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On the effectiveness of surface assimilation in probabilistic nowcasts of PBL profiles

Motivation

Surface observations comprise a wide, non-expensive and reliable source of information about the state of the near-surface planetary boundary layer (PBL). Operational data assimilation systems have encountered several difficulties in effectively assimilating them, among others due to their local-scale representativeness, the transient coupling between the surface and the atmosphere aloft and the balance constraints usually used.

A long-term goal of this work is to find an efficient system for probabilistic PBL nowcasting that can be employed wherever surface observations are present. Earlier work showed that surface observations can be an important source of information with a single column model (SCM) and an ensemble filter (EF). Here we investigate several questions that arise from ours and related studies using SCM and EF to estimate the state of the PBL:

- **What is the necessary complexity or sophistication of the model and assimilation scheme?**
- **Would the resulting nowcast PBL profiles be as accurate when assimilating the information in the surface observations into background profiles using simpler schemes than an EF?**
- **Do flow-dependent covariances derived from an SCM (including externally-imposed horizontal advection) ensemble contain the needed 3D flow information?**

SCM predictions and SCM/EF flow-dependent covariances (SCM/EF)

- **SCM resolved dynamics:** Momentum, thermodynamic and moisture equations.
- **SCM forcing and closure:** vertical turbulence, atmospheric surface layer, and land-surface as in WRF (ARW) version 2.2.1 (MYJ, similarity, Noah-LSM)

$$\frac{\partial u}{\partial t} = f(v - v_g) - \frac{\partial}{\partial z}\langle u'w'\rangle + \frac{u_u - u}{\tau_a}$$

$$\frac{\partial v}{\partial t} = -f(v - v_g) - \frac{\partial}{\partial z}\langle v'w'\rangle + \frac{v_u - v}{\tau_a}$$

$$\frac{\partial \theta}{\partial t} = -\frac{\partial}{\partial z}\langle w'\theta'\rangle + F_{rad} + \frac{\theta_u - \theta}{\tau_a}$$

$$\frac{\partial q_v}{\partial t} = -\frac{\partial}{\partial z}\langle w'q_v'\rangle + \frac{q_{vu} - q_v}{\tau_a}$$

- **Radiation:** Dudhia short-wave and RRTM long-wave schemes (in particular to improve night simulations when radiative cooling can be important in the PBL).
- **Externally-imposed horizontal advection:** upstream advection that relaxes the SCM state toward a prescribed 3D state, e.g. WRF forecasts, on the advective time scale.
- **A state-augmentation approach:** advection speed is dynamically tuned with the surface observations (simulating the effect of assimilating data in three spatial dimensions) to diminish unrealistically rapid growth in ensemble spread due to too wide variance in the WRF forecasts.
- **Vertical grid:** 81 vertical levels on a vertically-stretched column with model top at approximately 16 km to properly simulate radiative processes.
- **EF:** The SCM is coupled to the NCAR/DART system, default ensemble adjustment Kalman filter (EAKF, a square-root filter and implemented with serial observation processing).
- **Vertical covariance localization:** with an element-wise multiplication of a fifth-order piece-wise rational function (Gaspari and Cohn 1999) and the background error covariance estimates.
- **Ensembles of initial conditions, large scale forcing, advective tendencies and surface radiation (if not explicitly computed by the SCM):** imposed by starting with a WRF forecast column closest to the location of the surface observations for a given day and hour, then perturbing it with the scaled difference between that forecast and a randomly selected archived forecast from the same season; the scaling of the difference is drawn randomly from $\mathcal{N}(0; 1)$.

A column dressing approach with climatological covariances (CD)

- A deterministic mesoscale forecast (3D WRF) is adjusted using **surface-atmosphere 3D-climatological covariances** (σ_{xc}^2 , calculated within the 3D WRF sample and conditioned on the local time of day) and **surface-forecast errors** (d_y) where surface observations are available.
- **Surface-error model:** 30-min persistence.
- It can be interpreted as an **optimal interpolation technique** based on climatological covariances and a 30-min persistence error model:
  - **Observation increment:** $\Delta y = \sigma_c^2 \left(\sigma_c^2 + \sigma_o^2\right)^{-1} d_y$
  - **Climatological forecast variance:** σ_c^2
  - **Observation error variance:** σ_o^2 (assigned as in the EF)
  - **State increment:** $\Delta x = \frac{\sigma_{xc}^2}{\sigma_c^2}\Delta y$ (the adjustment applied to a WRF-column state variable)
- The adjusted profile is dressed with the in-sample uncertainty distribution scaled by the most recent observed error to provide a probabilistic nowcast.

$$\langle d_y^2\rangle = \alpha\sigma_c^2 + \sigma_o^2 \qquad \alpha = \frac{\langle d_y^2\rangle - \sigma_o^2}{\sigma_c^2}$$

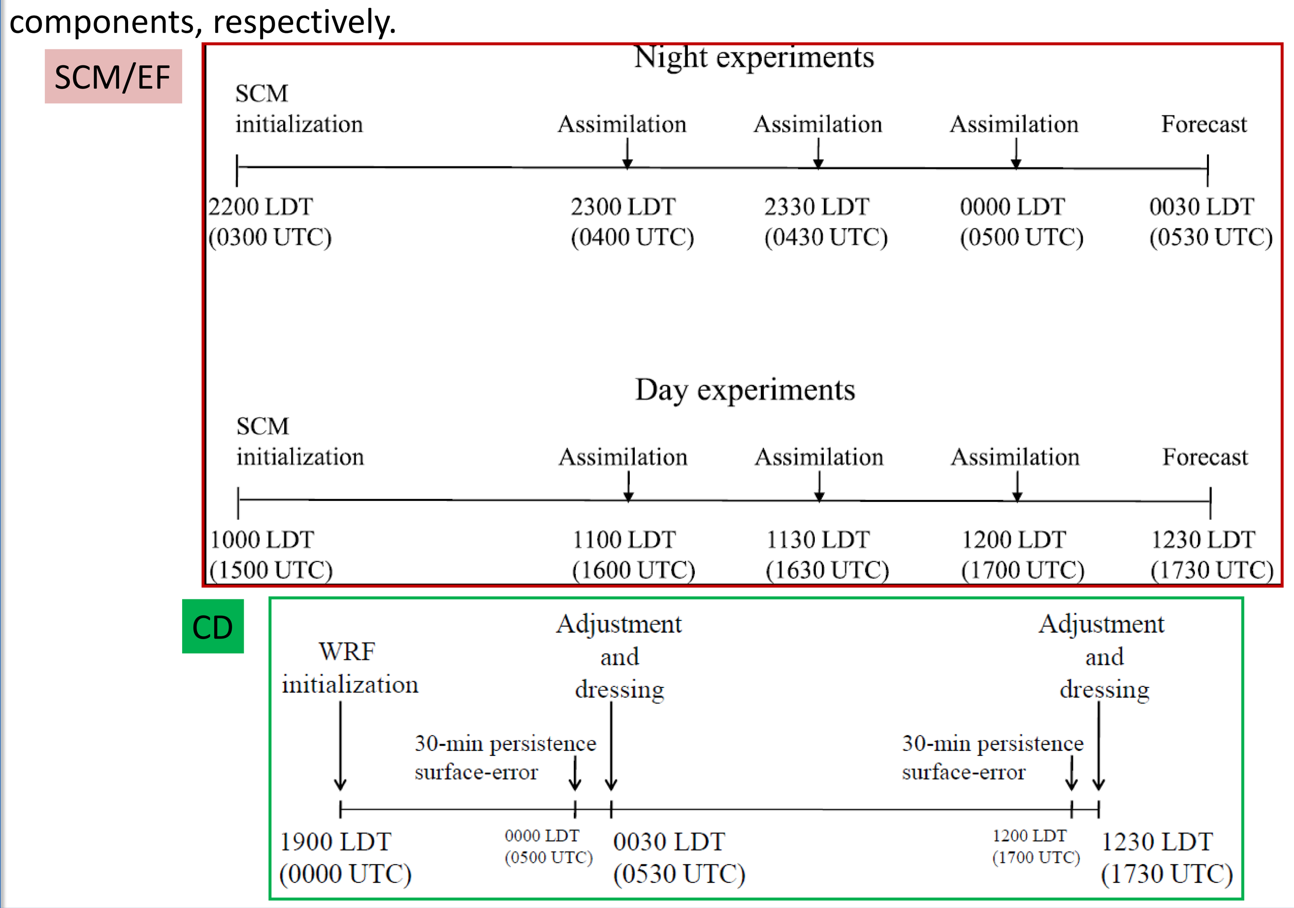
$$\langle d_x^2\rangle = (\alpha - 1)\sigma_x^2$$

Experiments

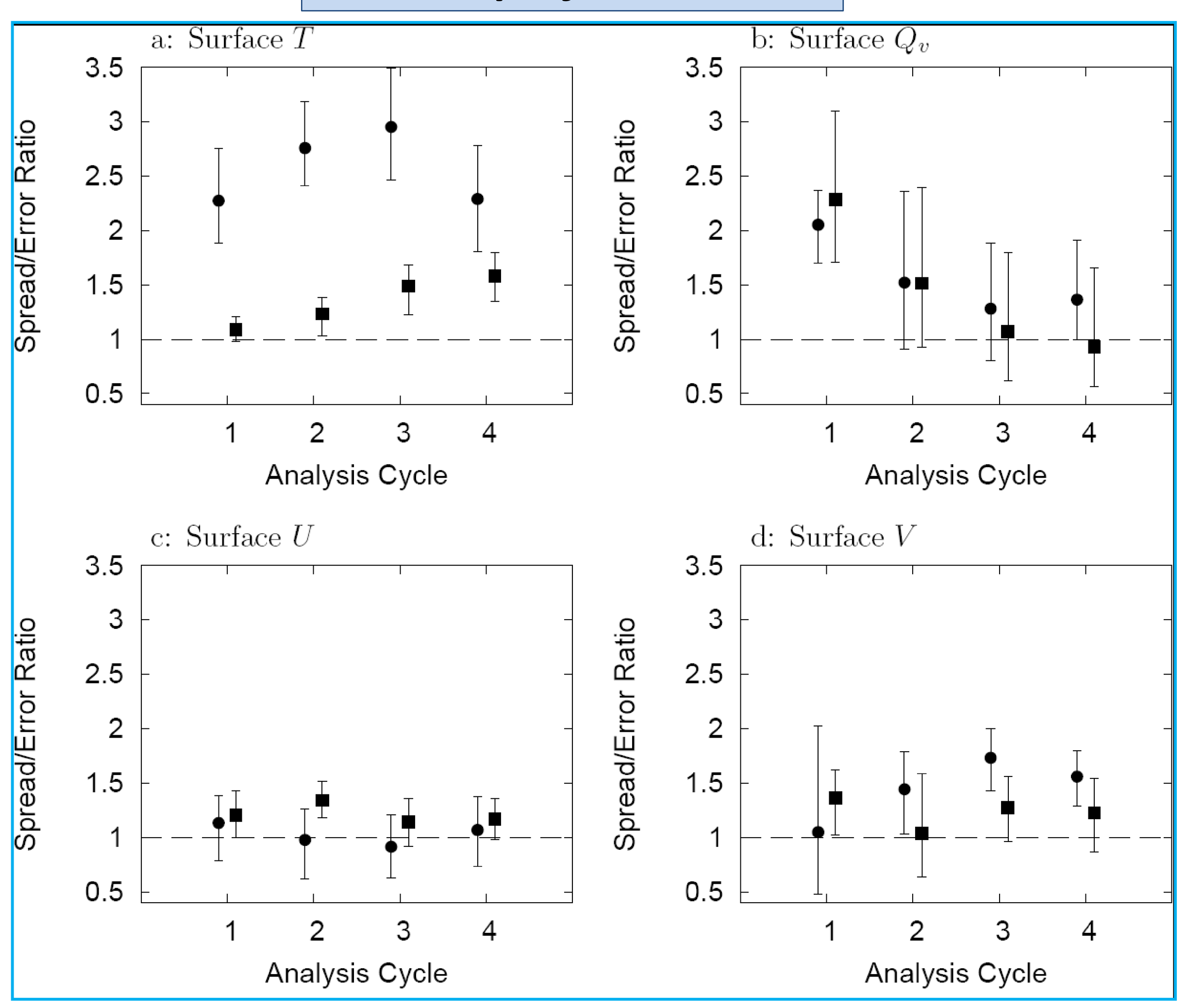
Experiment period and location: 3 May – 15 July 2003, over the Atmospheric Radiation Measurement (ARM) Central Facility near Lamont, Oklahoma.

SCM initialization and forcing (100 members), CD first guess and climatological covariances: Use of archived runs of the ARW version 2.1 with Δx = 4 km, initialized at 00 UTC (19 LDT) and coinciding with the experiment period.

Observation-error variances: 1 K^2, 10^{-6} kg^2kg^{-2} and, 2 m^2s^{-2} for temperature, mixing ratio and wind components, respectively.



Filter performance



Ratio of ensemble spread (sum of std dev squared of the ensemble and observation variance) to MSE in 30-min SCM/EF surface forecasts. Circles and squares are results of night and day time experiments respectively. Analysis cycles numbered 1–4 correspond either to 2300-0030 LDT and 1100-1230 LDT for night or day time experiments respectively. Error bars represent 90% confidence intervals derived using the BCa bootstrapping technique.

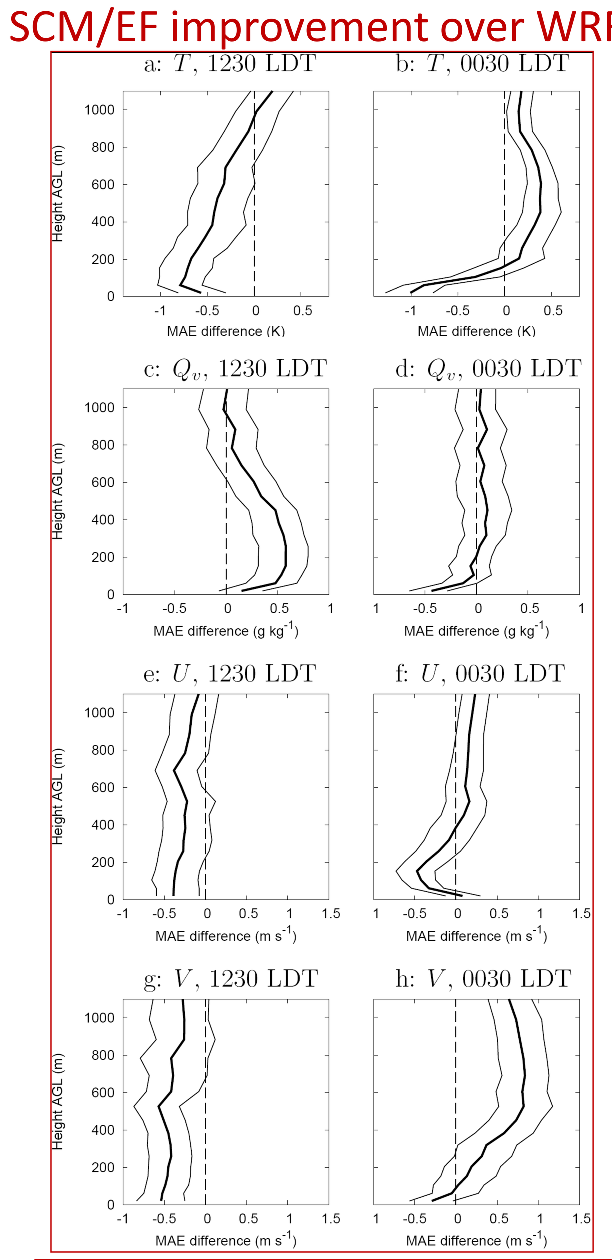
References

1. Rostkier-Edelstein, D. and J. P. Hacker, 2010: The roles of surface-observation ensemble assimilation and model complexity for nowcasting of PBL profiles: a factor separation analysis. *Wea. Forecasting*, **25,** 1670–1690, doi:10.1175/2010WAF2222435.1.

2. Rostkier-Edelstein, D. and J. P. Hacker, 2012: Flow-dependence, column covariance, and forecast model in assimilating surface observations for probabilistic nowcasts of PBL proles. Submitted to *Wea. Forecasting*.

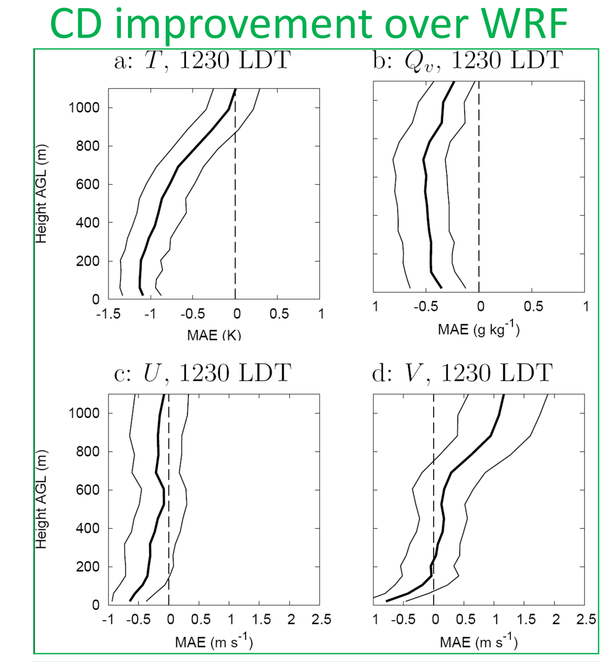
Deterministic SCM/EF and CD skill

SCM/EF improvement over WRF



Differences in MAE between 30-min SCM/EF-forecasts and their corresponding WRF-forecast profiles

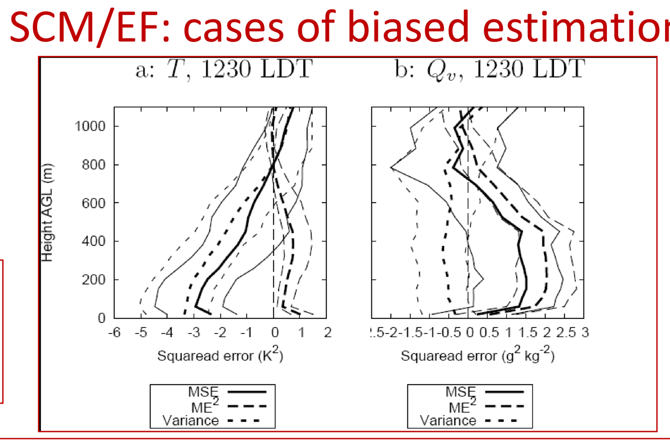
CD improvement over WRF



Differences in MAE between 30-min CD-forecasts and their corresponding WRF forecast profiles

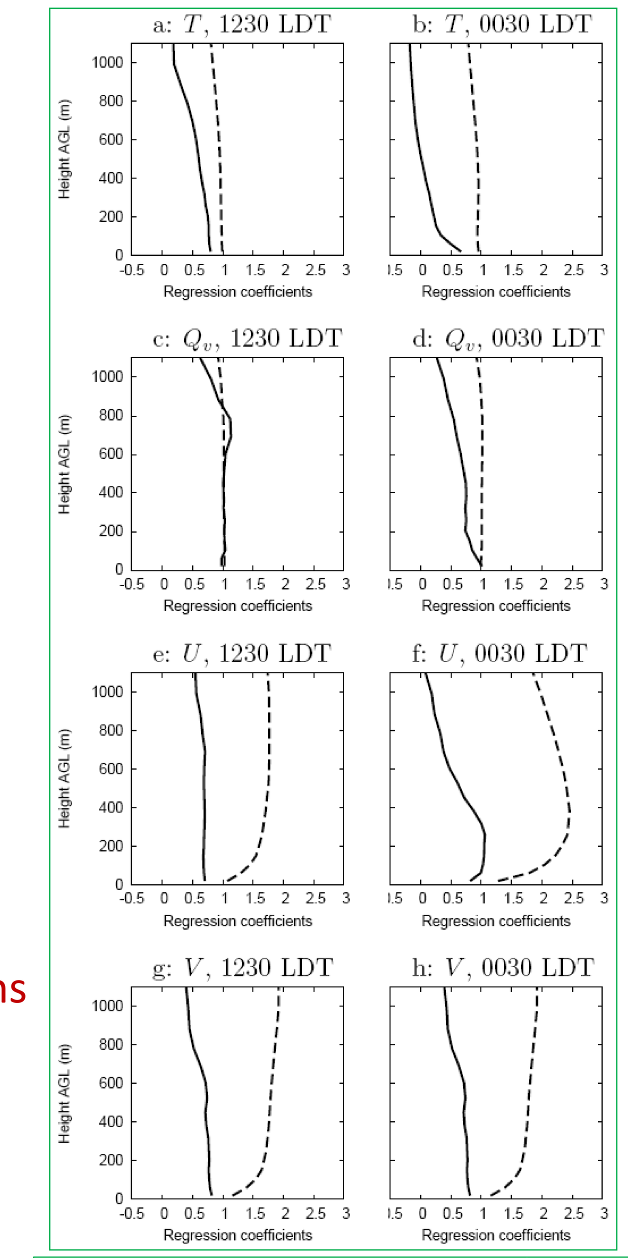
Bold lines → experiment results
Thin lines → 90% confidence intervals

SCM/EF: cases of biased estimations



Decomposition of squared-errors differences between 30-min SCM/EF forecasts minus their corresponding WRF-forecast profiles

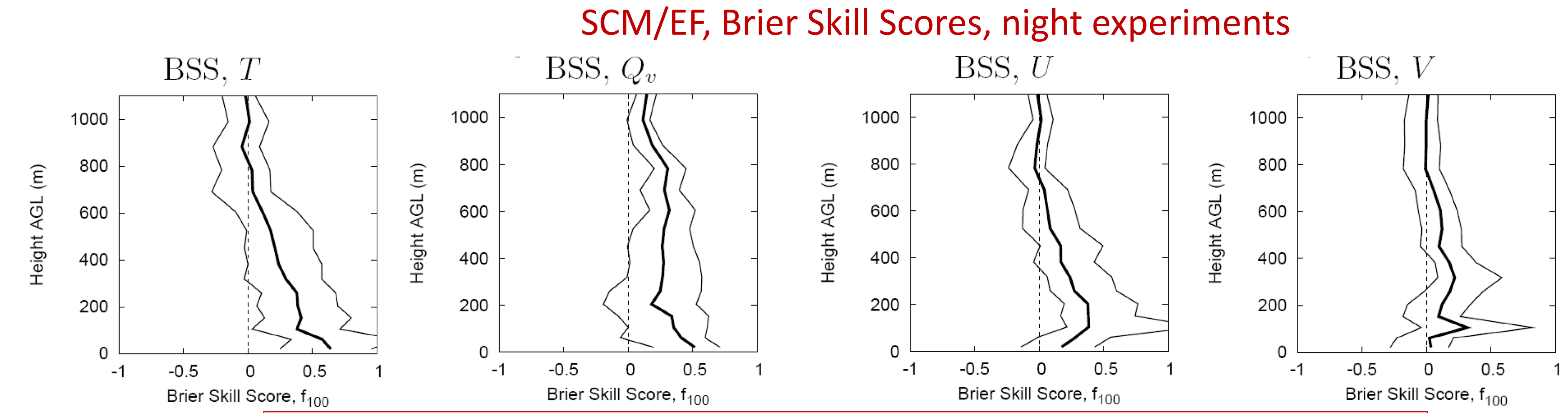
CD: WRF vs. error covariances



Adjustment factor in CD, σ_{xc}^2/σ_c^2.
Solid lines: using WRF-observations error covariances.
Dashed lines: using WRF covariances.

Impact of assimilation on SCM/EF probabilistic skill

SCM/EF, Brier Skill Scores, night experiments



Contribution from surface assimilation to brier-skill score (BSS) in 30-min SCM/EF forecasts

Summary

- Superior deterministic skill from the SCM/EF results during night when flow-dependent covariances are more accurate than climatological covariances. Further improved may be achieved through better vertical localization or sampling.
- CD is deterministically more skillful for temperature and moisture profiles during daytime because the SCM-PBL parameterization yields biased covariances, illustrating the need for explicit bias removal when assimilating observations into biased background estimates. Some of CD features could be used in a simple bias correction scheme for the SCM/EF
- The SCM/EF is most probabilistically skillful because:
  - (a) the EF covariances accommodate large seasonal variability (not shown here)
  - (b) the 30-min error persistence assumption fails during nighttime (not shown here)
  - (c) vertical error covariance estimates from archived forecasts are generally poor estimates of actual error covariances.
- A deterministic and probabilistic factor separation analysis of the SCM/EF shows the relative importance of surface assimilation, radiation parameterization, and advection (not shown here):
  - (a) <u>Results confirm surface assimilation as the most important factor</u>
  - (b) A factor can be deterministically beneficial and probabilistically detrimental, or vice versa, depending on its role in reducing mean error or improving sharpness
  - (c) <u>Assimilation results in notable improvement for nowcasts of low-level jet structures.</u>