Assimilation of Fixed Screen-Height Observations in a Parameterized PBL

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Outline

- Lessons from predictability studies
- Major challenges for DA in the PBL
- Experiments with a column model
- Parameter estimation experiments

The Brutal Facts

- Initial condition error is guaranteed but unknown
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History shows the situation is not hopeless, but we need to recognize limitations and account for what we cannot know.

Predictability Lessons

- The forecast problem, particularly at small scales, is inherently probabilistic.
- We are obligated to include estimates of uncertainty in observations, analyses, and forecasts and how they relate to the "flow of the day."
- The only way we know how to do this is to combine ensemble forecasts with a data assimilation system, using our best dynamic models.

Challenges for ensemble DA in the PBL

- Model error
- Forward operator error
- Covariance localization shape and length

Model error in the PBL (a short list)

- Choice of "constants" in parameterization schemes
- Structural error in parameterizations
- Static land-surface descriptions
- Biases from misrepresentation of orography

Operator (H) error in the PBL

- Representativeness
- Deterministic error from model formulation
- Lack of error growth in forecast

Approaches to These Problems

The name of the game...

$$\begin{aligned} \mathbf{x}^{\mathsf{a}} &= \mathbf{x}^{\mathsf{b}} + \mathbf{P}^{\mathsf{b}} \mathbf{H}^{\mathsf{T}} \left(\mathbf{H} \mathbf{P}^{\mathsf{b}} \mathbf{H}^{\mathsf{T}} + \mathbf{R} \right)^{-1} \left(\mathbf{y}^{\mathsf{o}} - \mathbf{H} \mathbf{x}^{\mathsf{b}} \right) \\ \mathbf{P}^{\mathsf{b}} &= \mathbf{M} \mathbf{P}^{\mathsf{a}} \mathbf{M}^{\mathsf{T}} + \mathbf{Q} \end{aligned}$$

 ${\bf M}$ is the model propagator. ${\bf Q}$ is the model error covariance matrix.

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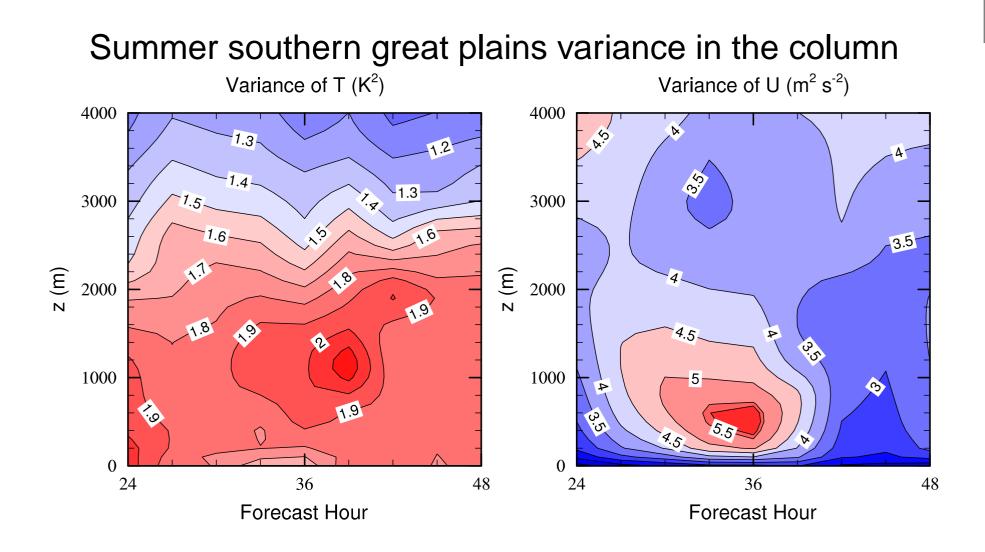
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- Ensemble Kalman Filter (EnKF) data assimilation in the PBL (estimate P^b).
- Augment x with model parameters and estimate them from the observations.

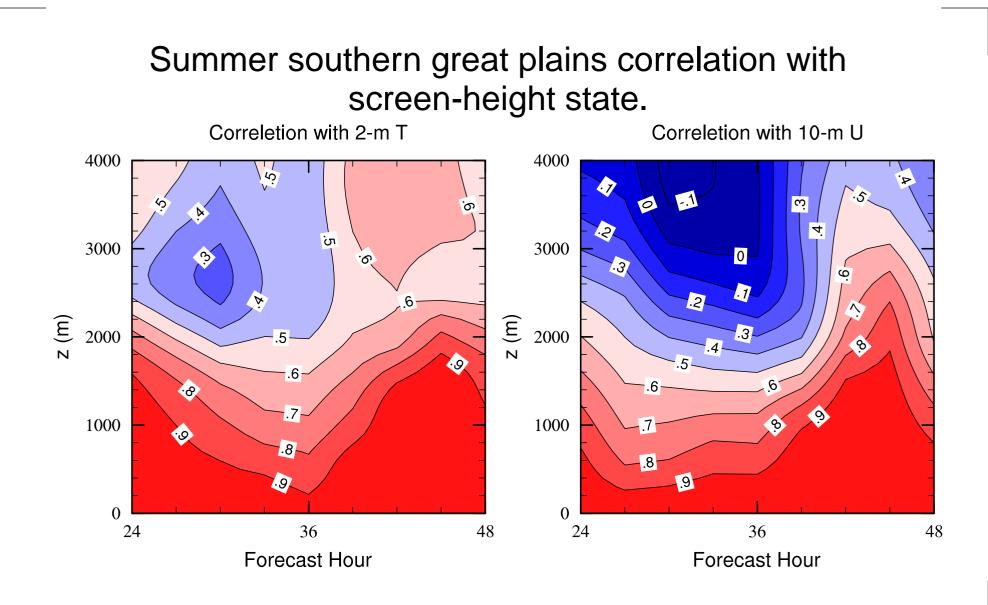
Experiment

- Analyze summer WRF climatology of PBL forecasts.
- Design off-line single-column model (MRF PBL parameterization).
- Large-scales forced by WRF climatology.
- Perform assimilation experiments on 500 cases ("truth" randomly chosen) with 100-member ensembles.
- Perform parameter estimation experiments with moisture availability parameter.

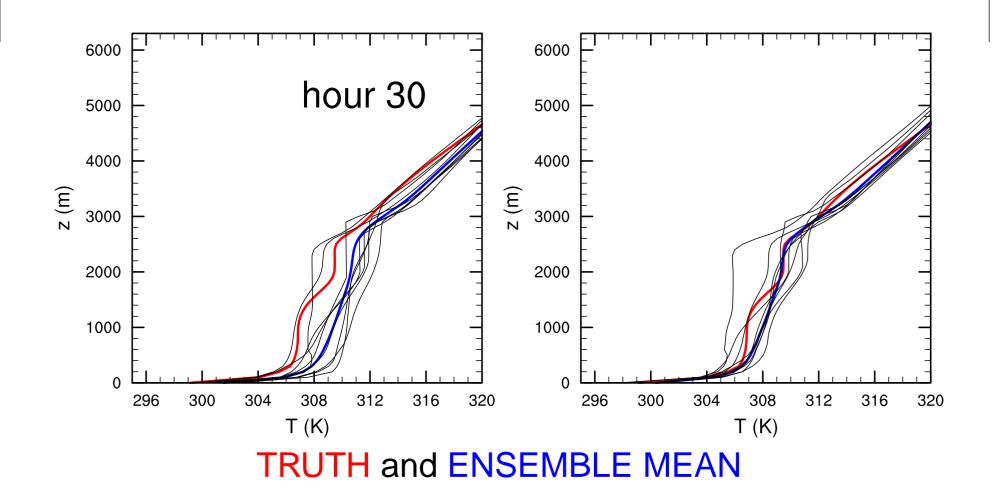
WRF Climatology



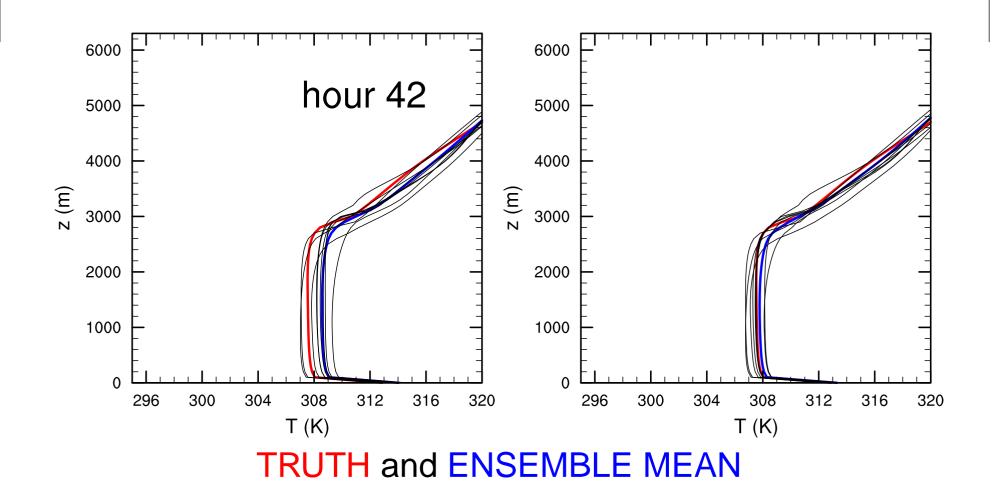
WRF Climatology



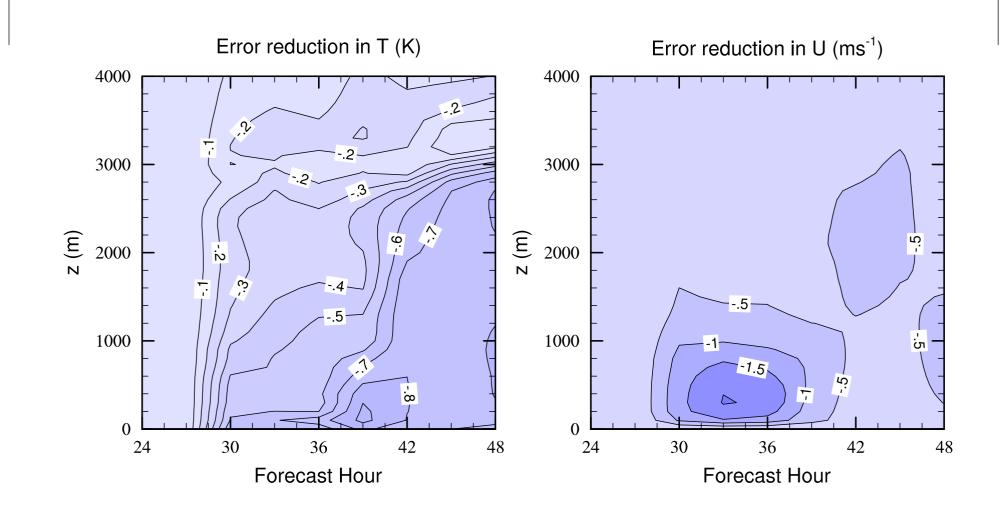
Assimilation Example: Nighttime



Assimilation Example: Daytime

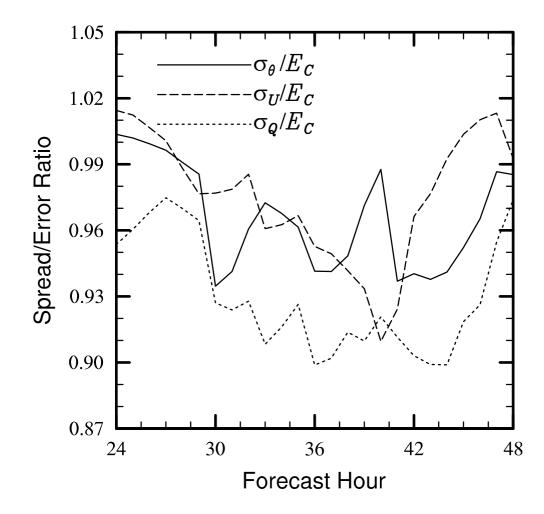


Average Error Reduction for Assimilation

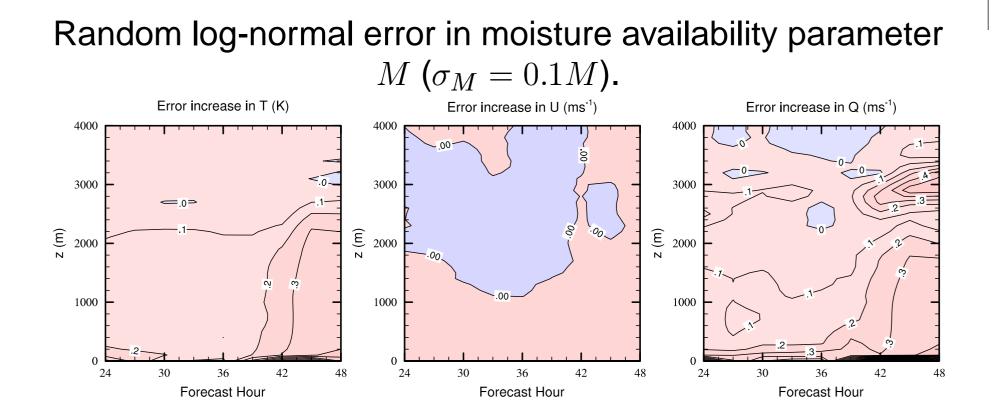


Is the Assimilation Working?

• Compare spread and error for 0 < z < 1000 m

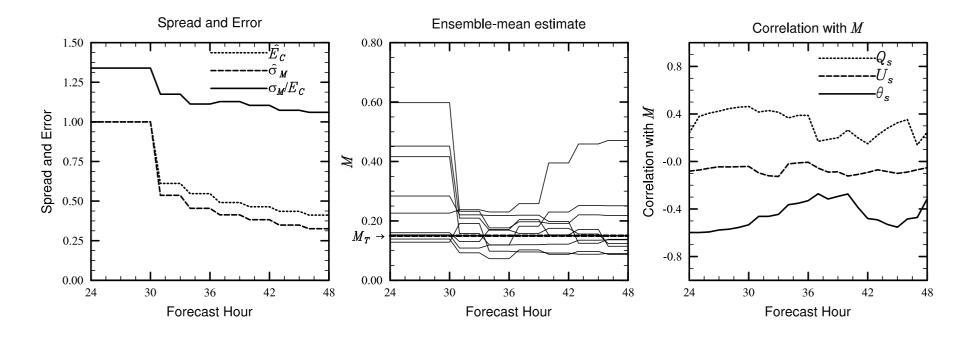


Add Some Model Error



Estimate M

Augment the state vector with M and allow the observations to modify the distribution.



WRF experiments

- Weather Research and Forecast model
- Domain over northern Utah
- $\Delta X = 3 \text{ km}$
- 40-member ensembles
- Assimilation of single profile
- Perfect U, V, T obs with noise

Prior error at 3 h

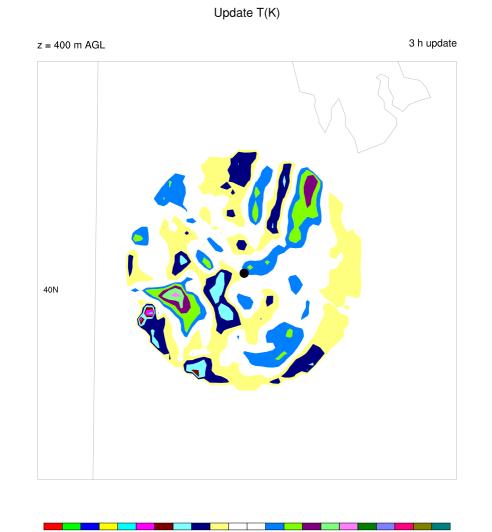
Ensemble Mean Error T(K)

3 h prior error z = 400 m AGL

-1-.9-.8-.7-.6-.5-.4-.3-.2-.10 .1 .2 .3 .4 .5 .6 .7 .8 .9 1

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Update from a single profile



 $-1 \ -.9 \ -.8 \ -.7 \ -.6 \ -.5 \ -.4 \ -.3 \ -.2 \ -.1 \ .0 \ \ .1 \ \ .2 \ \ .3 \ \ .4 \ \ .5 \ \ .6 \ \ .7 \ \ .8 \ \ .9 \ \ 1$

Error reduction at 3 h



-1 -.9 -.8 -.7 -.6 -.5 -.4 -.3 -.2 -.1 .0 .1 .2 .3 .4 .5 .6 .7 .8 .9 1

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Conclusions

- In a current-generation mesoscale model, the state at screen height is strongly coupled to the PBL through most of the diurnal cycle.
- Off-line modeling experiments show that these strong covariances can be exploited to determine the structure of the PBL with surface observations.
- Model error can be mitigated by augmenting the state vector with model parameters, and estimating their distributions.

To do:

 Continue 3D investigations — boundary conditions, nesting, cost

An Analysis of Record for the PBL

- Model error: uncertainty in H, structural and parameter errors
- In situ observation platforms: what are the responses?