Model Error and Parameter Estimation in a Simplified Mesoscale Prediction Framework, Part I:

Model Description and Sources of Uncertainty

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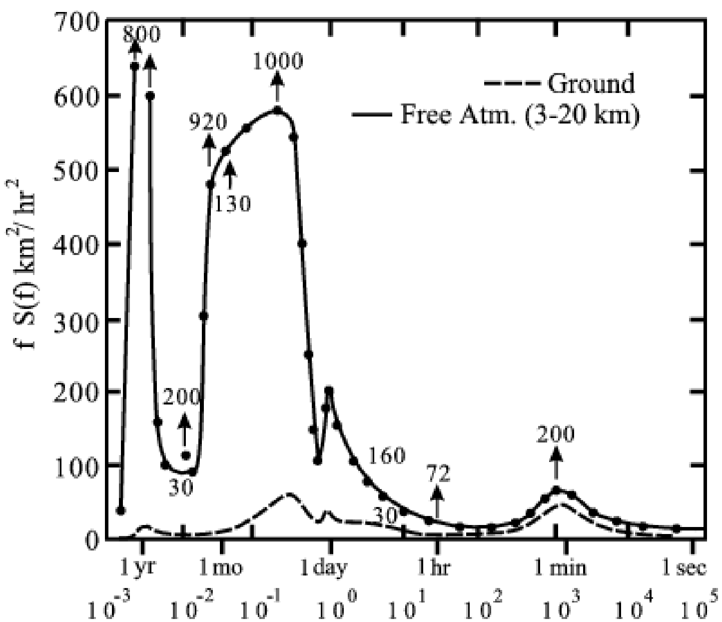
Topics

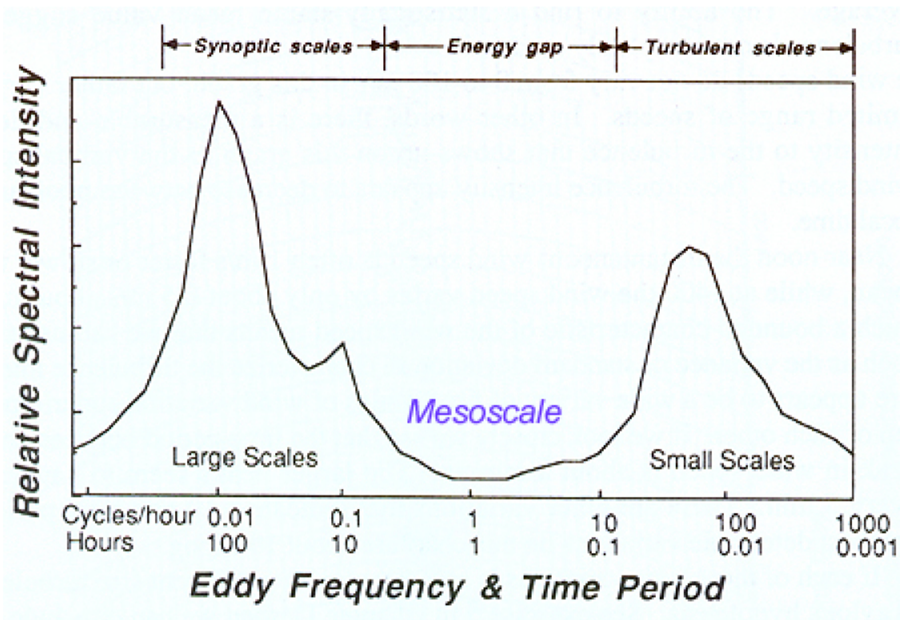
- Mesoscale forecasting - some background.
- Data assimilation at mesoscales.
- Types of error in mesoscale models.
- A column model to emulate a full 3D mesoscale model, and experience with it.
- Some naive parameter estimation experiments.

Mesoscales

Horizontal wind spectra in the frequency domain.



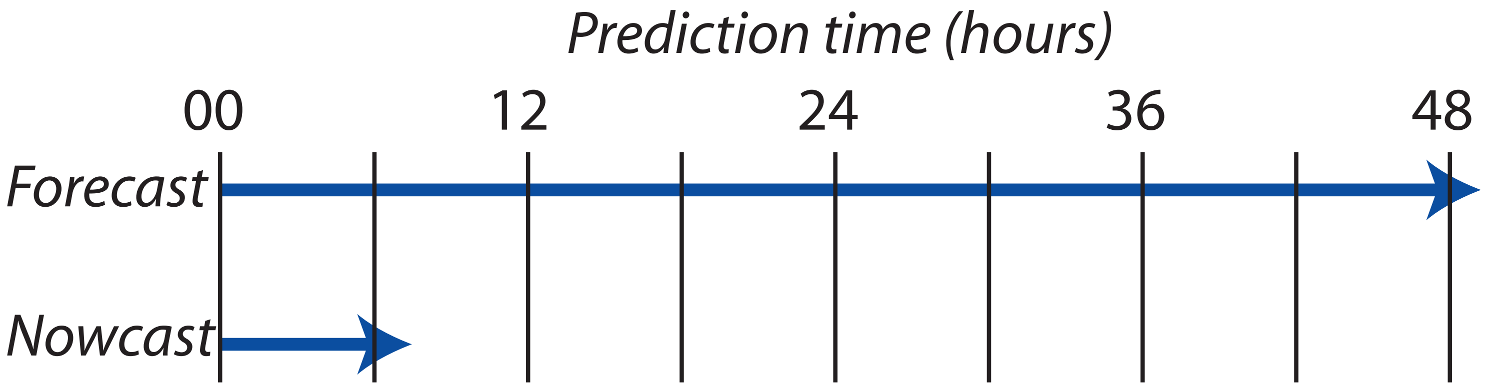
Vinnichenko 1970



Vander Hoven 1957

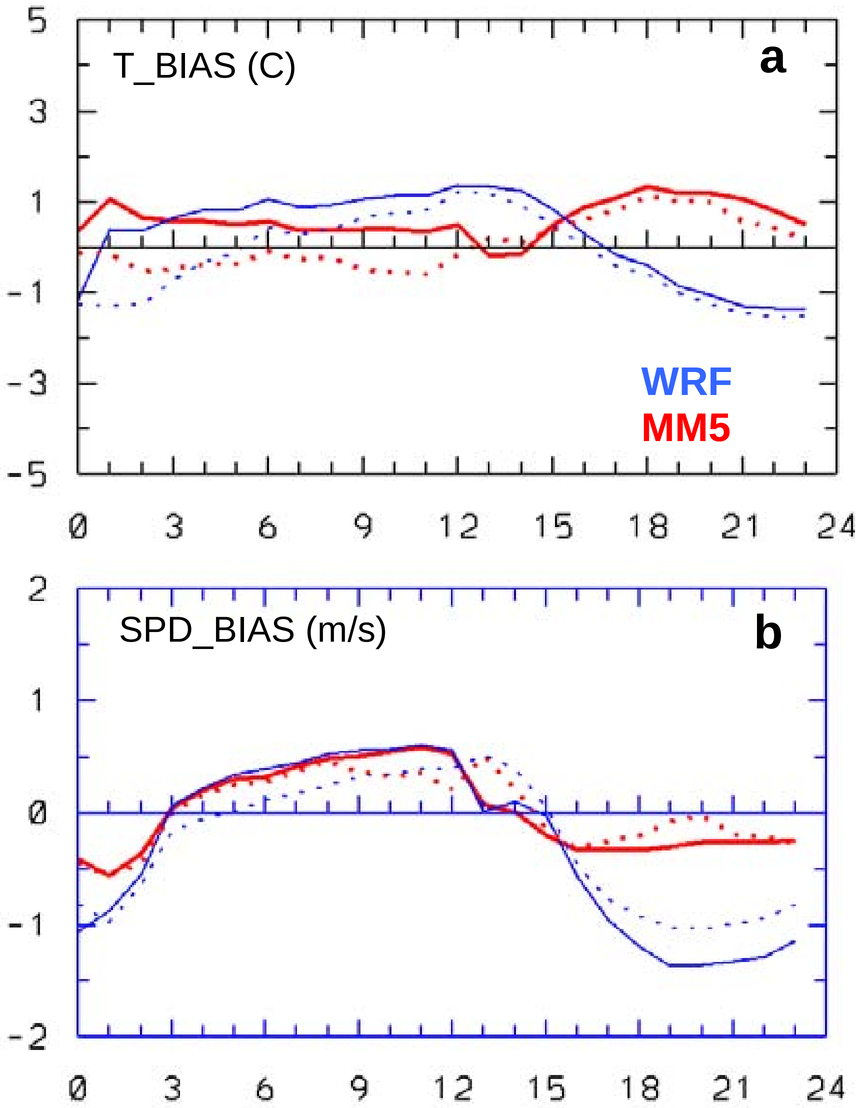
Mesoscale Prediction Times

- Mesoscale prediction is fundamentally an initial condition problem.



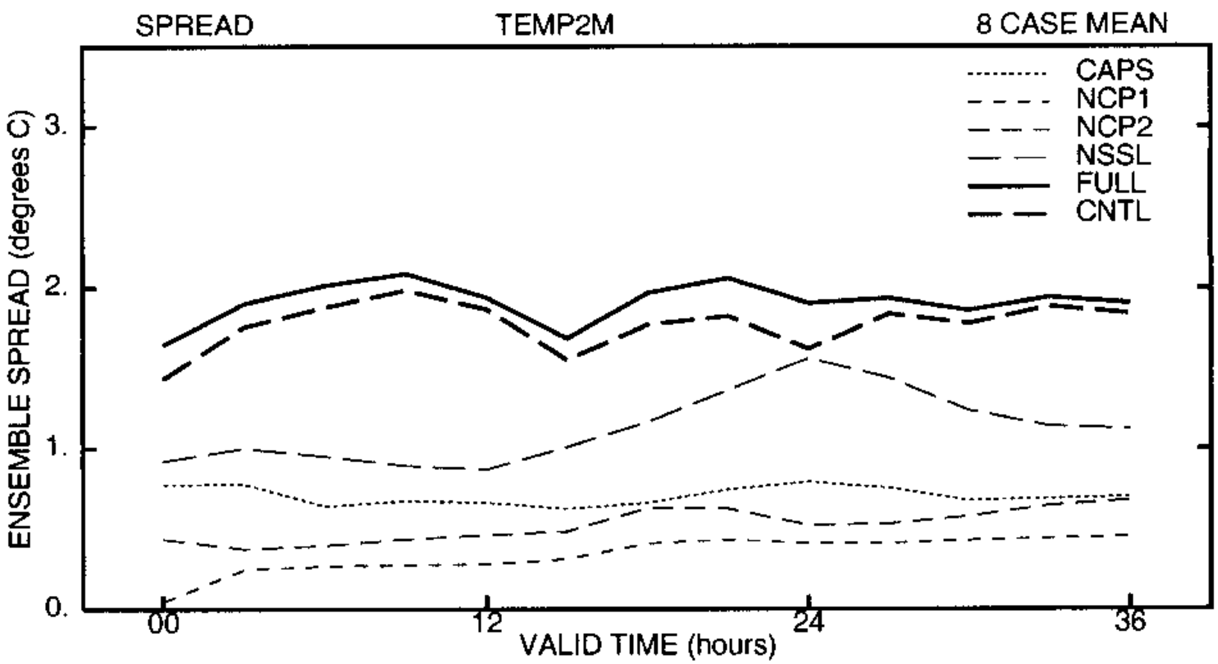
Nowcasting is typically done by extrapolating current conditions because dynamical models have less skill at these time scales. A place for better data assimilation and accounting for model error?

Forecast Error at the Surface



Errors near the surface are often dominated by bias, and show a diurnal evolution.

Lack of Variability the Surface



Ensembles are extremely underdispersive and show little intrinsic error growth near the surface in the short range, leading to experimentation with "multi-model" ensembles (FULL). From Hou et al. 2001 *MWR*.

Information in Surface Observations

- Surface observations are relatively dense and inexpensive to gather.
- Typically under-utilized in operational data assimilation.
  Model error?
  Constraints in the assimilation systems?
- Potential to to tell us something about the state of the overlying PBL.
- Potential to to tell us something about the model, including values of parameters.

Column Model Environment

- A 1-D PBL modeling framework: various land-surface and PBL parameterizations, forced. Original model development by Mariusz Pagowski, NOAA/ESRL.

- Internal dynamics for ageostrophic wind, diffusion equation, etc.

- Geostrophic and radiative forcing from a mesoscale model (e.g. RUC or WRF) or observations.

Cheap! Thousands of realizations possible with a quick turn-around

Model Formulation

$$
\begin{aligned}
\frac{\partial U}{\partial t} &= f_c\,(V - V_g) - \frac{\partial}{\partial z}\overline{u'w'} \\
\frac{\partial V}{\partial t} &= -f_c\,(U - U_g) - \frac{\partial}{\partial z}\overline{v'w'} \\
\frac{\partial \theta}{\partial t} &= -\frac{\partial}{\partial z}\overline{w'\theta'} \\
\frac{\partial Q}{\partial t} &= -\frac{\partial}{\partial z}\overline{w'q'}
\end{aligned}
$$

Prognostic in U, V, θ, and Q with parameterization providing closure. Parameterization is the same as in the Weather Research and Forecast (WRF) model.

Model Formulation

$$
\begin{aligned}
\frac{\partial U}{\partial t} &= f_c\,(V - V_g) - \mathcal{U}\,(U, V, \theta, Q, \mathbf{P}) \\
\frac{\partial V}{\partial t} &= -f_c\,(U - U_g) - \mathcal{V}\,(U, V, \theta, Q, \mathbf{P}) \\
\frac{\partial \theta}{\partial t} &= -\mathcal{T}\,(U, V, \theta, Q, \mathbf{P}) \\
\frac{\partial Q}{\partial t} &= -\mathcal{Q}\,(U, V, \theta, Q, \mathbf{P})
\end{aligned}
$$

Closure terms are functions of the resolved state (forcing and diffusion), and myriad parameters $\mathbf{P}$.

Model Formulation with Advection

$$\frac{\partial U}{\partial t} = f_c\,(V - V_g) + \mathbf{V} \bullet \nabla U - \frac{\partial}{\partial z}\overline{u'w'}$$

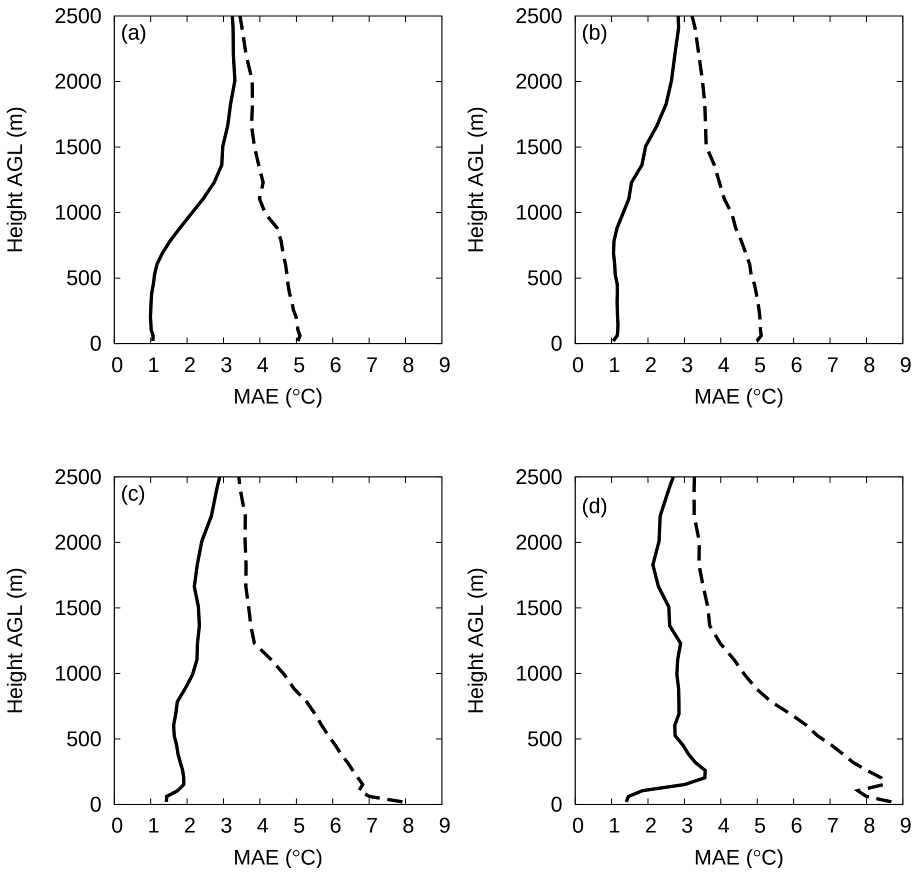
$$\frac{\partial V}{\partial t} = -f_c\,(U - U_g) + \mathbf{V} \bullet \nabla V - \frac{\partial}{\partial z}\overline{v'w'}$$

$$\frac{\partial \theta}{\partial t} = \mathbf{V} \bullet \nabla \theta - \frac{\partial}{\partial z}\overline{w'\theta'}$$

$$\frac{\partial Q}{\partial t} = \mathbf{V} \bullet \nabla Q - \frac{\partial}{\partial z}\overline{w'q'}$$

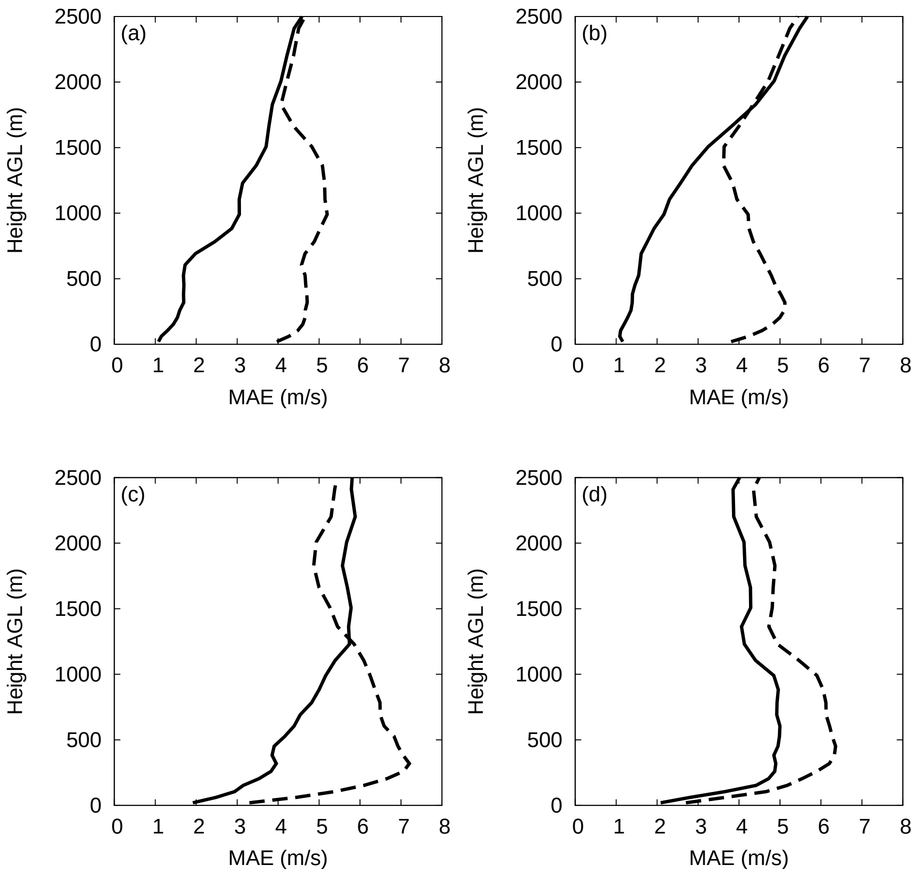
Advection acts to relax the column state toward an imposed 3D state.

Skill in PBL State Estimates: T



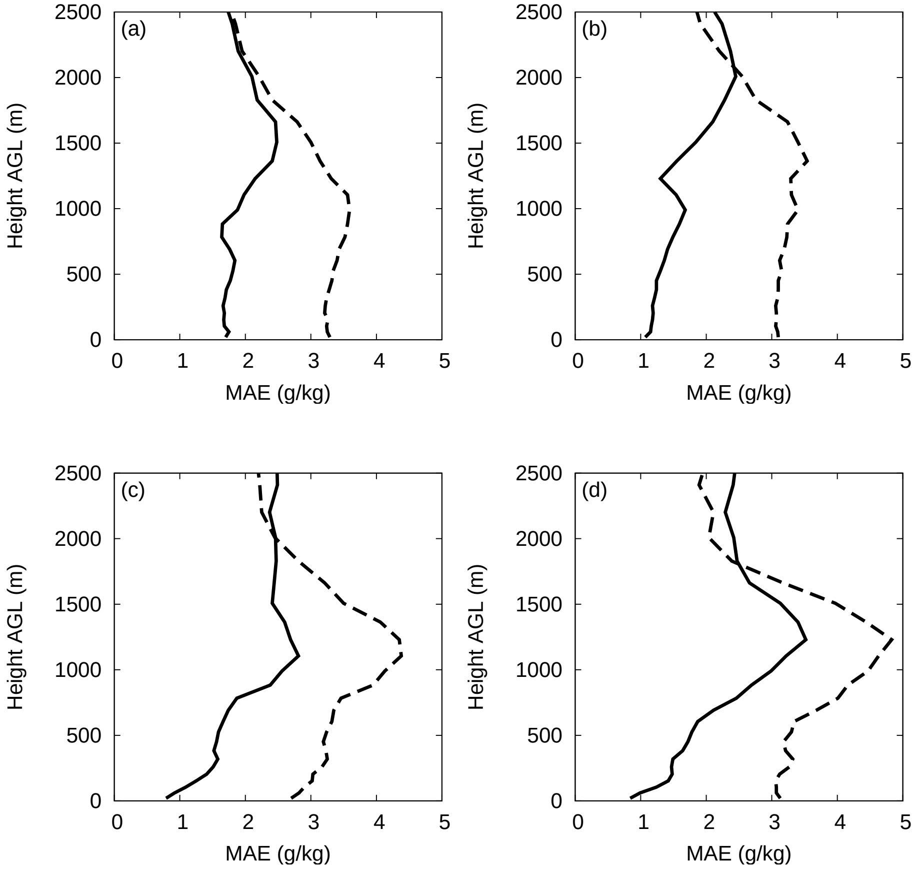
Using only screen-height (surface) observations, skillful profiles are estimated at all times of day: (a) 1PM LT, (b) 7PM LT, (c) 1AM LT, and (d) 7AM LT.

Skill in PBL State Estimates: U



Using only screen-height (surface) observations, skillful profiles are estimated at all times of day: (a) 1PM LT, (b) 7PM LT, (c) 1AM LT, and (d) 7AM LT.

Skill in PBL State Estimates: Q_v



Using only screen-height (surface) observations, skillful profiles are estimated at all times of day: (a) 1PM LT, (b) 7PM LT, (c) 1AM LT, and (d) 7AM LT.

State Augmentation

Data assimilation to estimate a discrete system state $\mathbf{Z}$ at time t.

$\mathbf{Z}$ is a joint state, with both state variables and parameters.

$\mathbf{X}$ represents state variables.

$\mathbf{x}$ is a set of parameters, which may or may not be physical.

Then $\mathbf{Z} = (\mathbf{X}, \mathbf{x})$.

Given all observations up to the current time, $\mathbf{Y}_t$, we want to estimate $\mathbf{p}(\mathbf{Z}_t|\mathbf{Y}_t)$.

These experiments are to estimate parameters in a land-surface scheme, given screen-height observations and an evolving model.

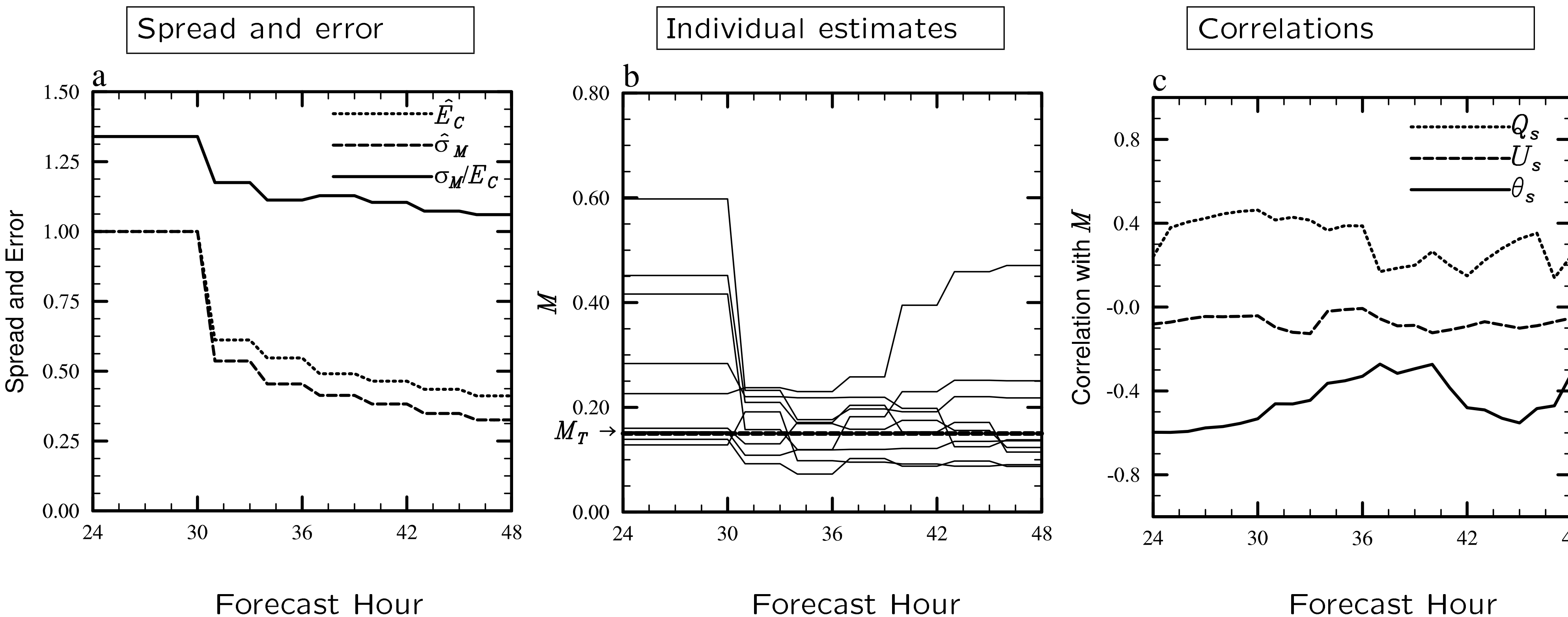
An exchange coefficient for moisture, Q_c, is computed:

$$Q_c = \frac{M\rho_1 \overline{w'q'}}{q_0 - q_1}$$

- M is a moisture availability parameter $\{0,1\}$.
- ρ_1 is density at the first atmospheric model level.
- q_0 and q_1 are moisture contents at the surface and the first atmospheric level, repsectively.
- $\overline{w'q'}$ is the parameterized kinematic moisture flux.

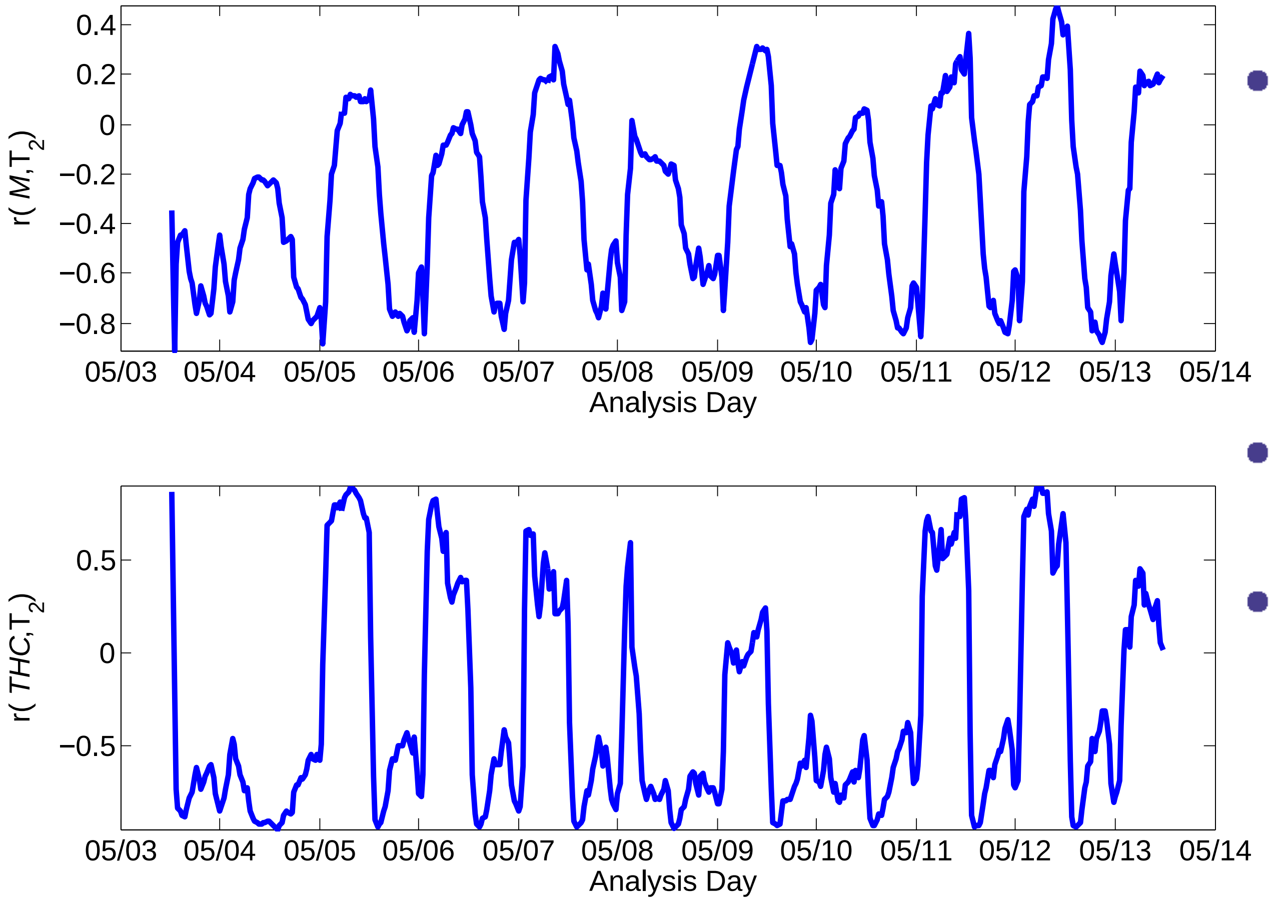
Provides a lower boundary condition (forcing) for the atmospheric model.

Estimate a Single Parameter



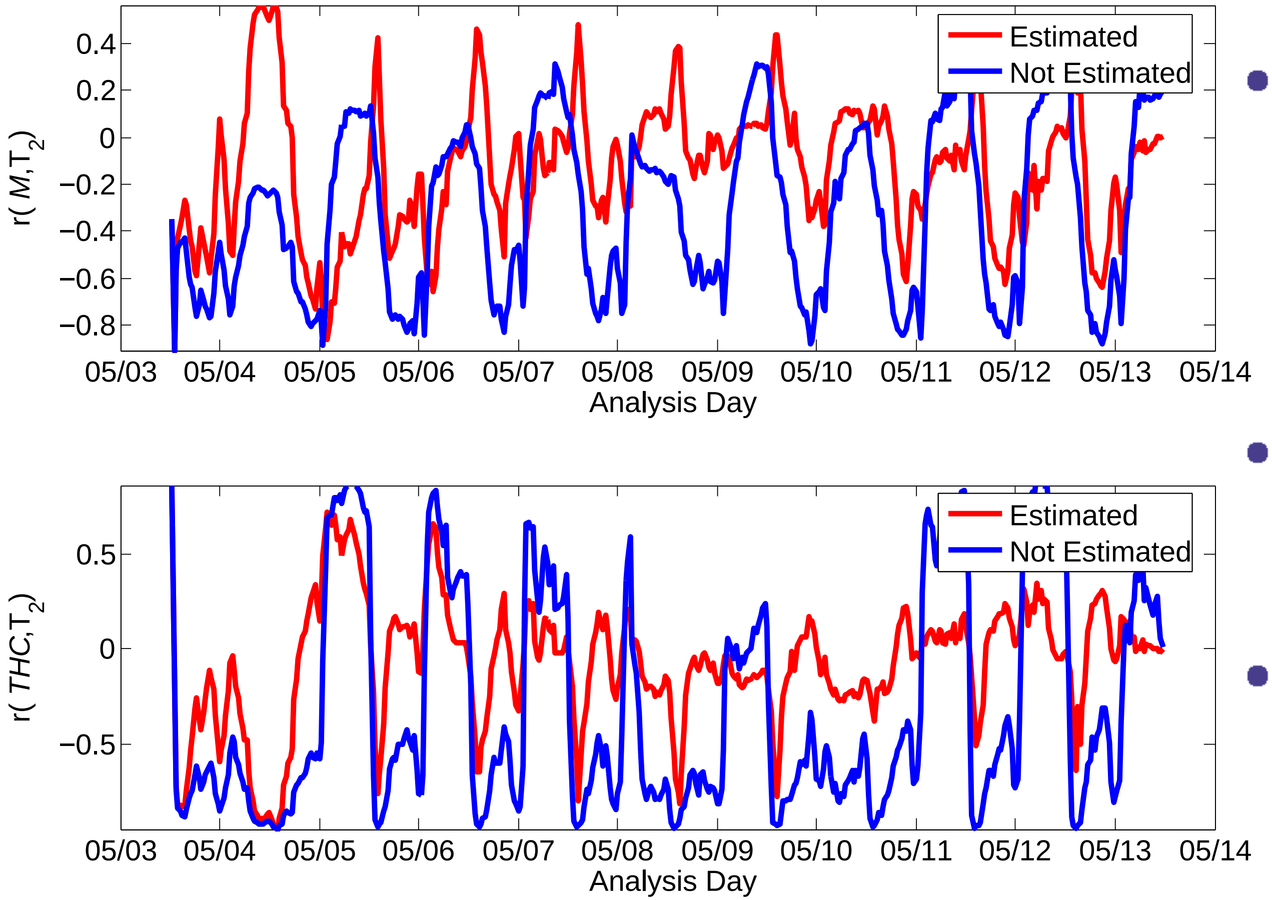
Single parameters (moisture availability) can be estimated when the true value is known.

Correlations Without Assimilation



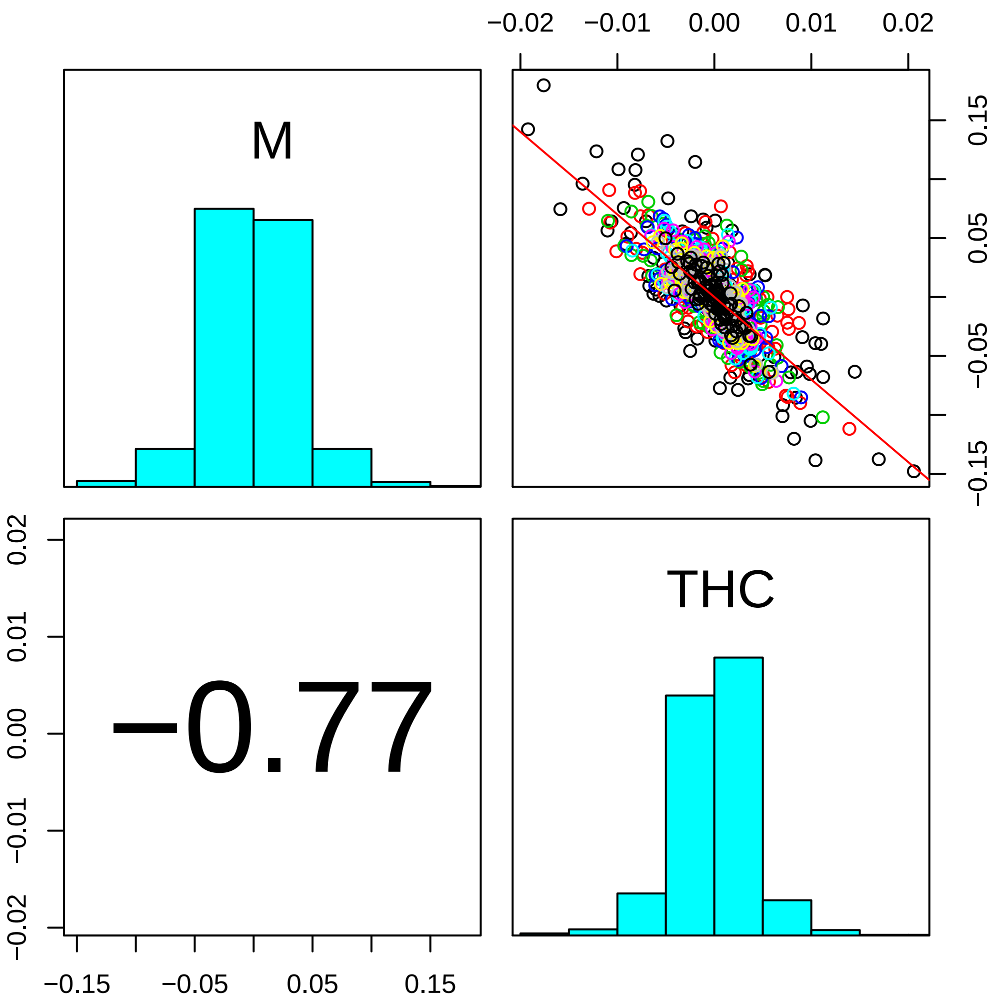
- Correlation coefficients of T_2 with parameters M and THC, for 100 ensemble members integrated for 10 days.
- Parameter distributions are fixed.
- Distributions chosen as β with $\sigma = 0.1M$ and $0.01THC$.

Correlations With Assimilation



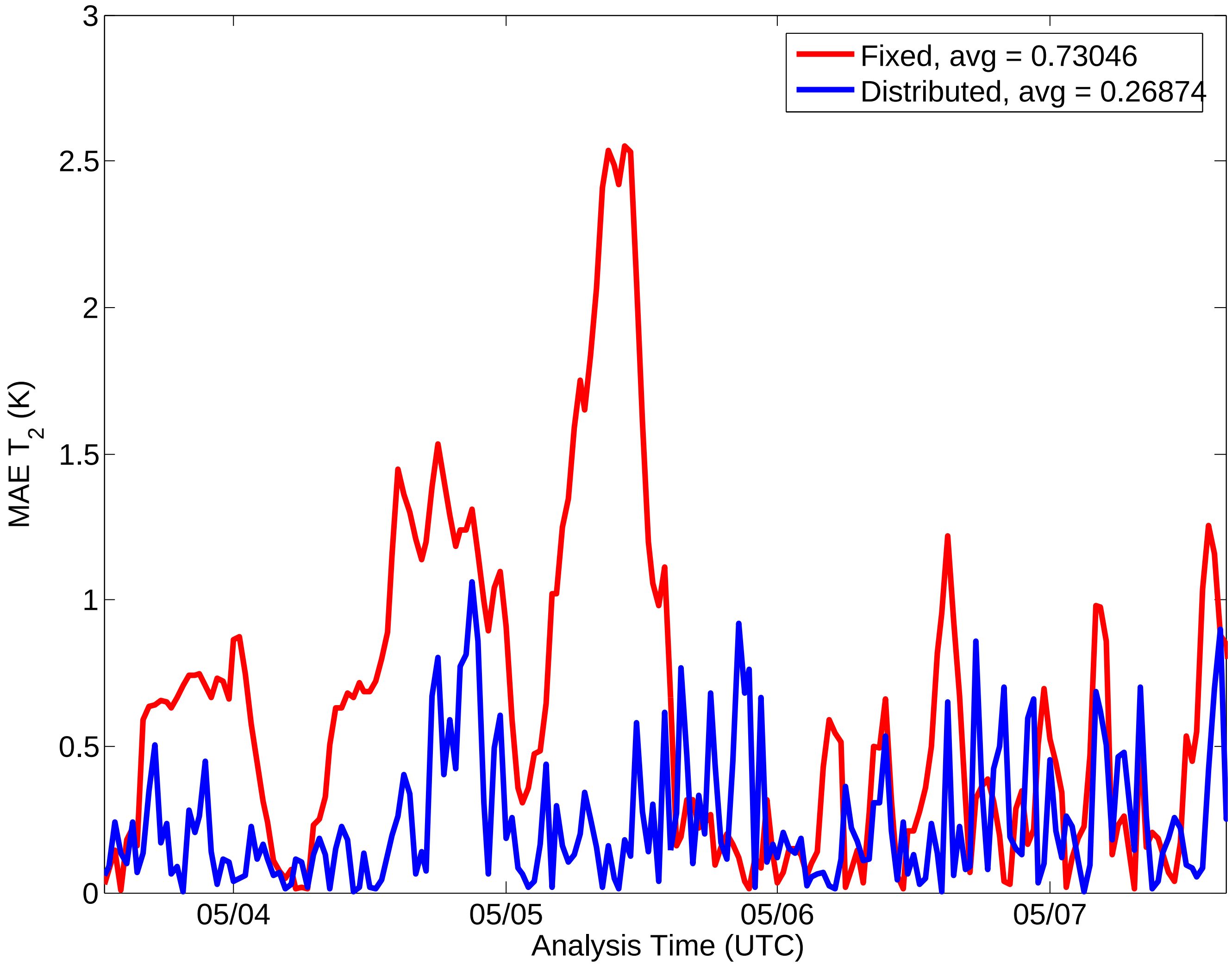
- Correlation coefficients of T_2 with parameters M and THC, for 100 ensemble members integrated for 10 days.
- Parameter distributions are estimated while assimilating.
- Correlations change, transitions more pronounced.

Dependent Parameters



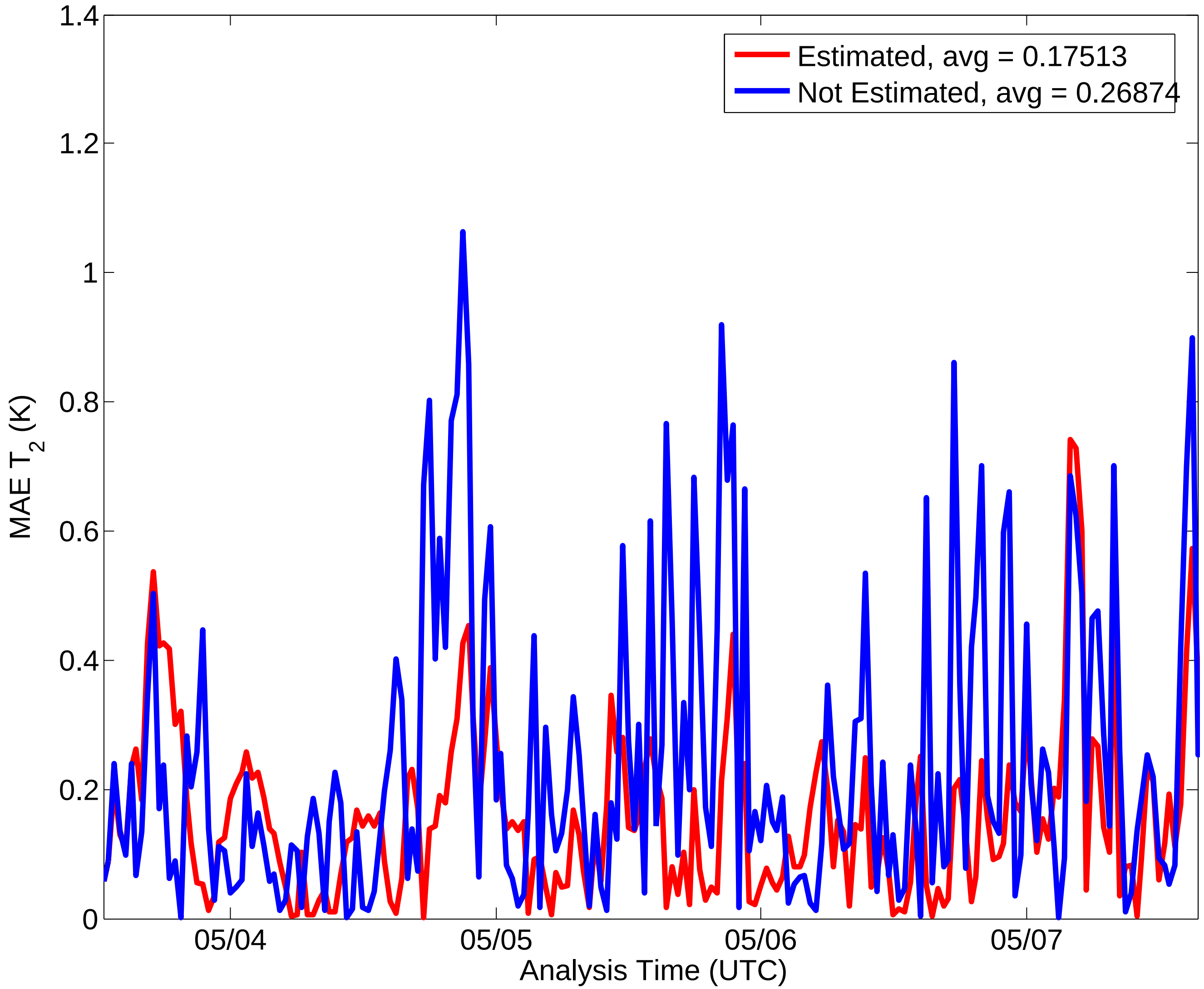
- M and THC are linearly dependent when estimated. Here is at 00 UTC for over 10 days, but this is true at any time.
- Cannot be distinguished, thus could be replaced by a single parameter.

Distribution Improves Assimilation



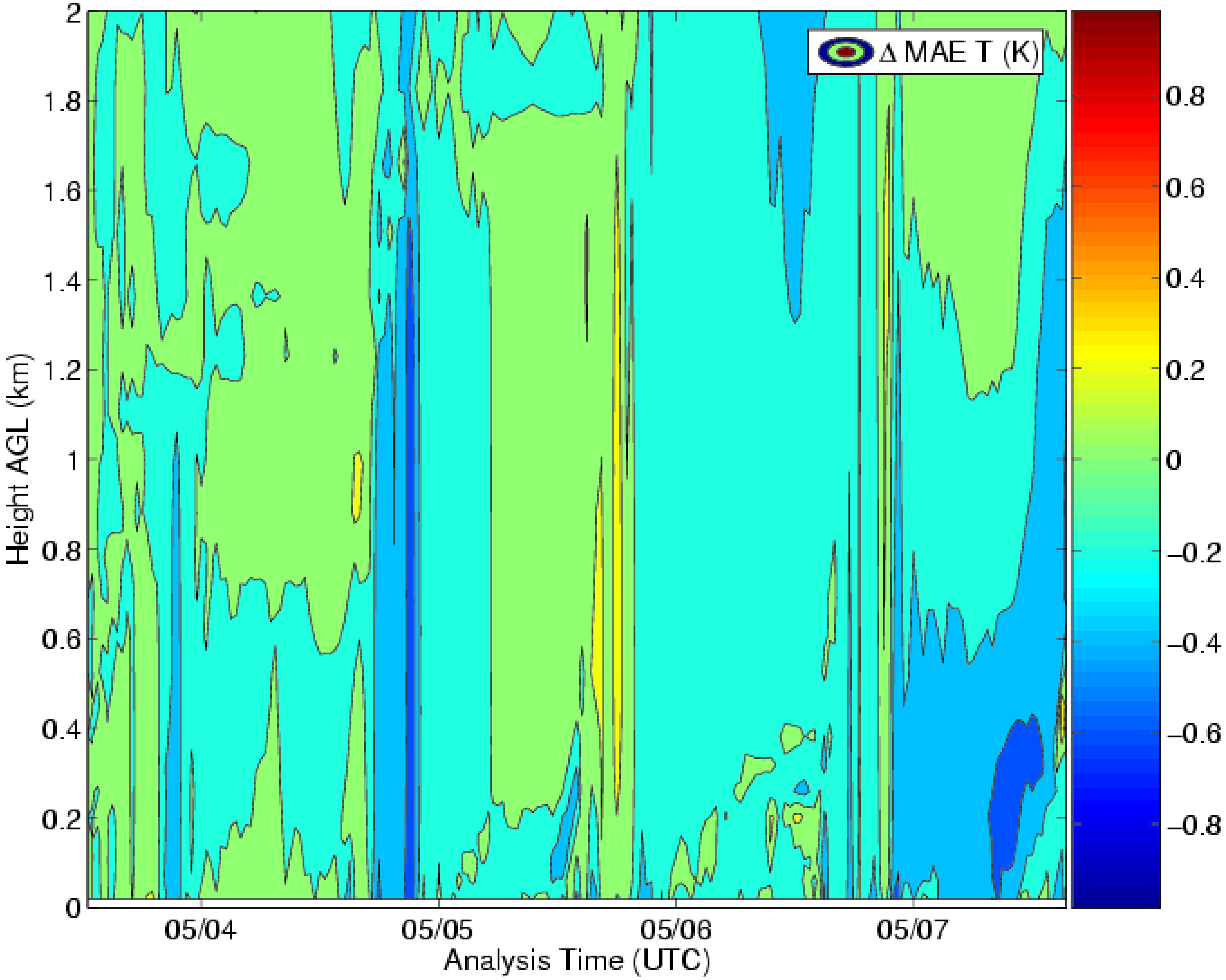
Compared to single fixed parameter values, distributed parameters result in a better fit to observations. The effect is particularly true during transitions.

Estimation Improves Assimilation



Compared to fixed distributed parameter values, estimated parameters result in a better fit to observations.

Error in the Profile



Differences in error (estimated – fixed distribution) show the profile is generally improved, especially during the growth phase of the PBL.

- State augmentation is a useful parameter estimation approach in observation system simulation experiments (OSSEs), but is much more difficult in real-data applications.

Much more work to do:

- How will a free bias parameter behave?
- Can we find distributions that make a better forecast in the face of other, unknown, model errors?
- Can we find appropriate stochastic processes to propagate the parameter distributions in time?