The Planetary Boundary Layer and Uncertainty in Lower Boundary Conditions

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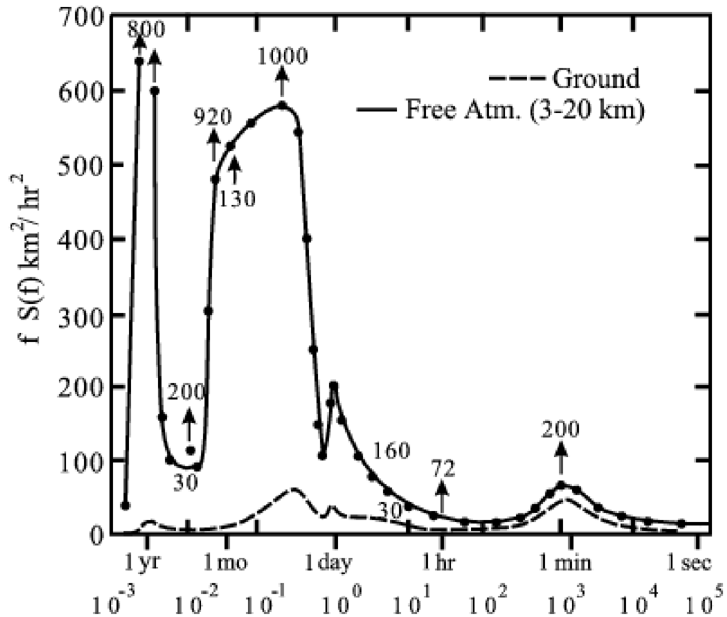
Topics

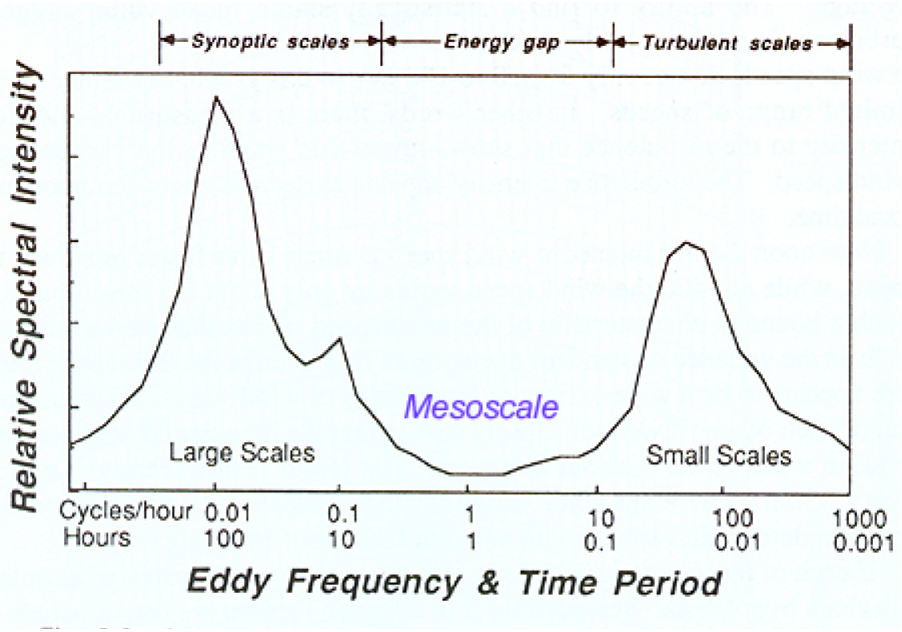
- The closure problem and physical parameterizations for NWP models.
- Basic structure and dynamics of the PBL.
- Some open questions in PBL parameterization and uncertainty in mesoscale forecasting.
- A column model to emulate a full 3D mesoscale model, and experience with it. Distinction from soil estimation for the sake of soil estimation.

Mesoscales

Horizontal wind spectra in the frequency domain.



Vinnichenko 1970



Vander Hoven 1957

Reynolds Averaging

- Key assumption is that Reynolds averaging is valid for numerical weather prediction scales.

- Viscous effects operate on scales much smaller than energetic eddies.

- Break variables into mean and turbulent (mean 0) components, where the filter length corresponds to a "spectral gap," or a minimum in energy at a particular range of scales:

$$\psi = \overline{\psi} + \psi'$$

- Find equations in the mean to solve, and parameterize the perturbation quantities, including covariance terms.

Closure

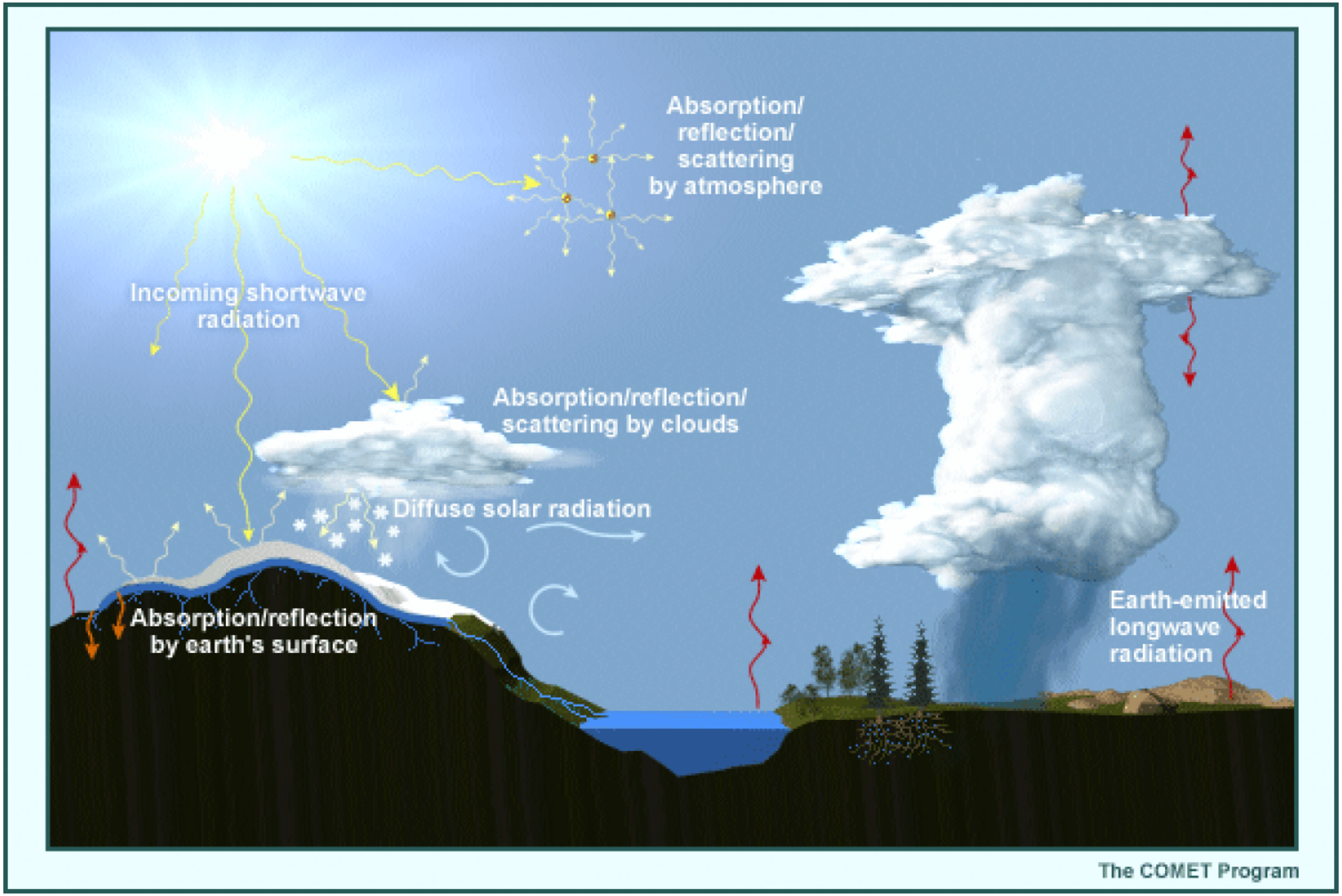
Prognostic equations for $\overline{\psi}$ can be written after averaging and other simplifications:

$$\begin{aligned}
\frac{\partial \overline{\psi}_i}{\partial t} &= Advection + body\ forcings + \frac{\partial \overline{u_j' \psi'}}{\partial x_j} \\
\overline{u_j' \psi'} &= f\left(U, V, W, T, Q, \mathbf{P}\right) \\
body\ forcings &= f\left(U, V, W, T, Q, \mathbf{P}\right)
\end{aligned}$$

- Subgrid-scale tendencies and body forcings are typically functions of resolved-scale variables and parameters $\mathbf{P}$.

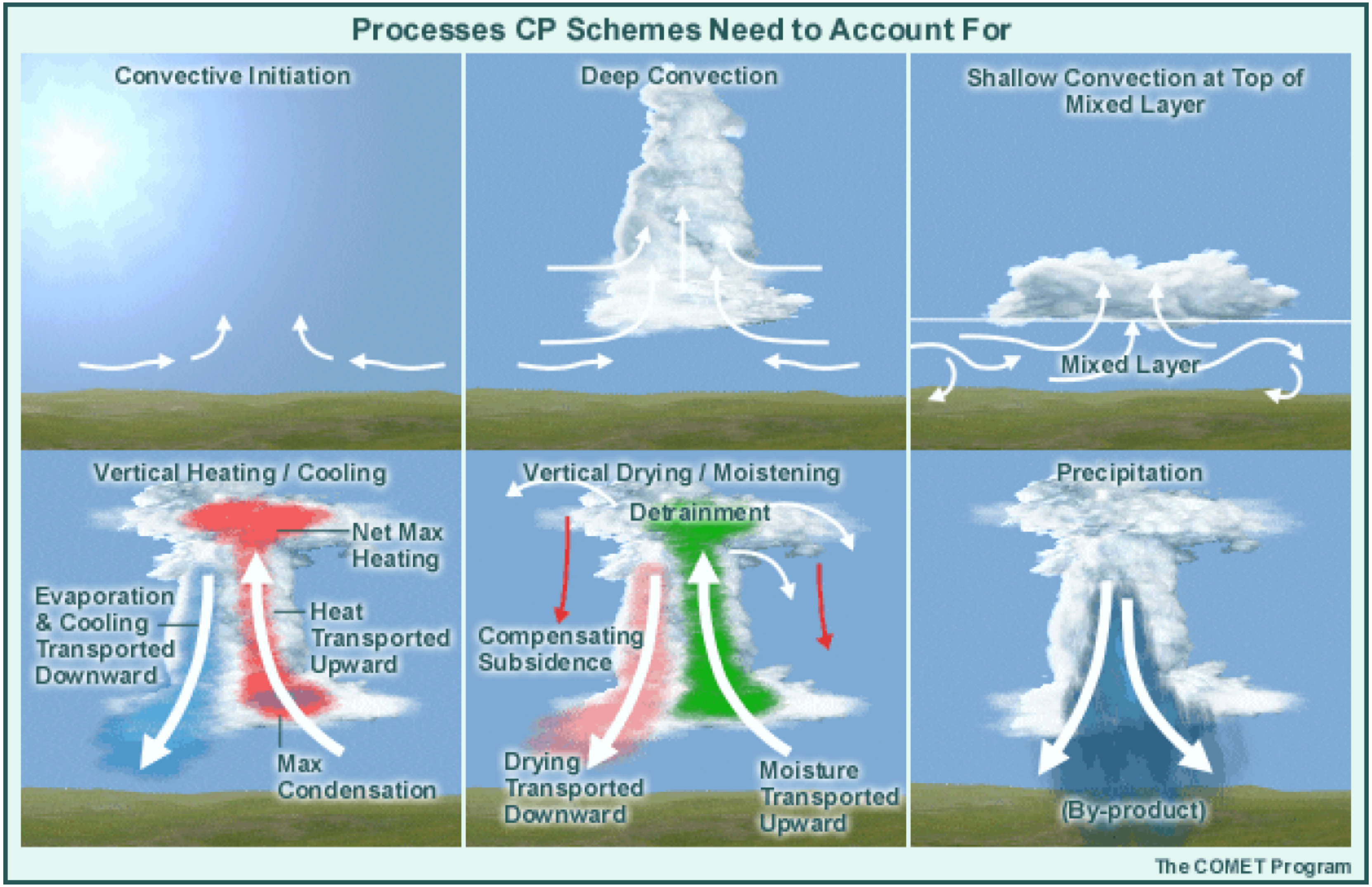
- Parameters are normally fixed values, and can be marginally physical.

Physical Parameterization



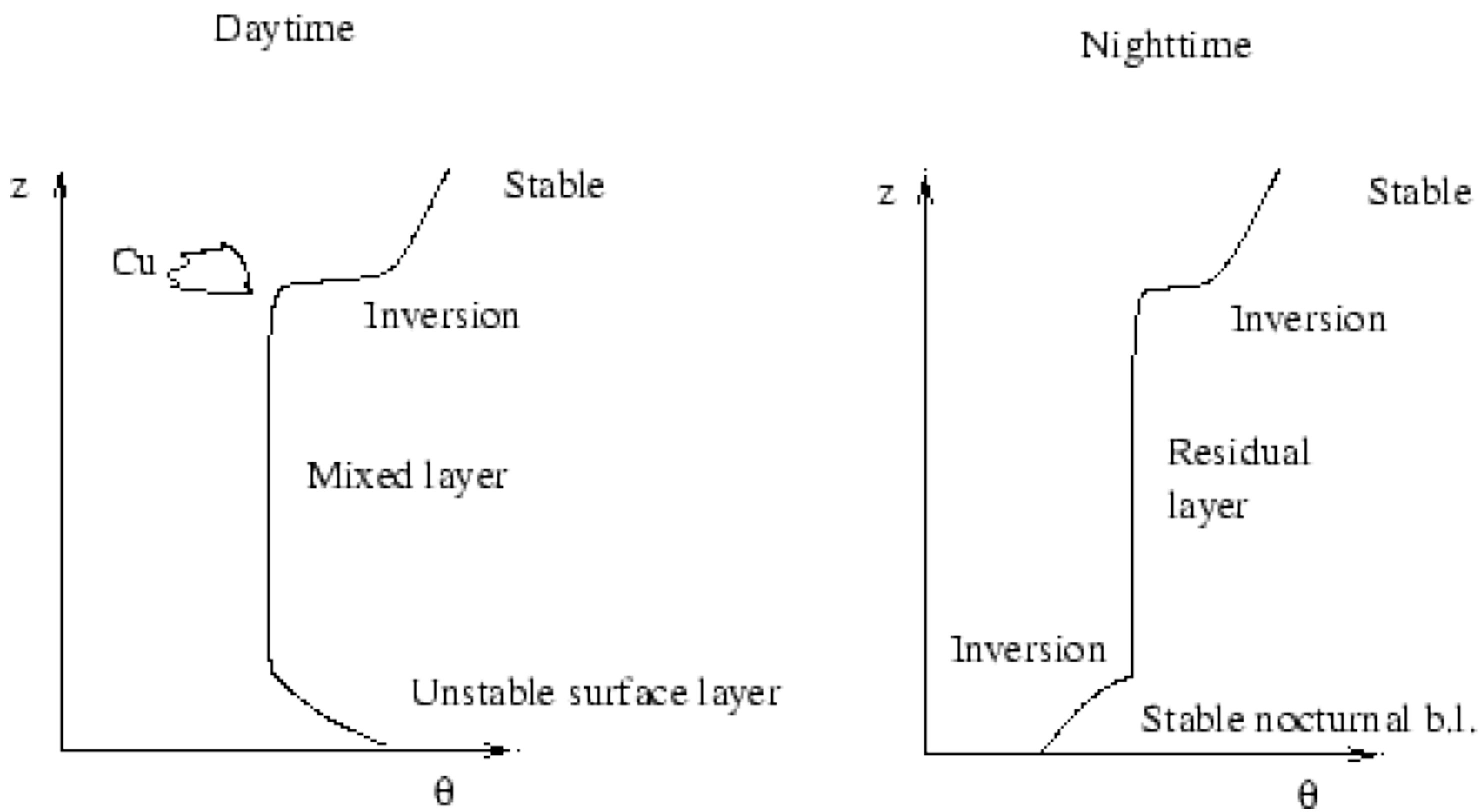
Any unresolved process that can affect resolved variables.

Physical Parameterization



Many cloud processes are below grid scale.

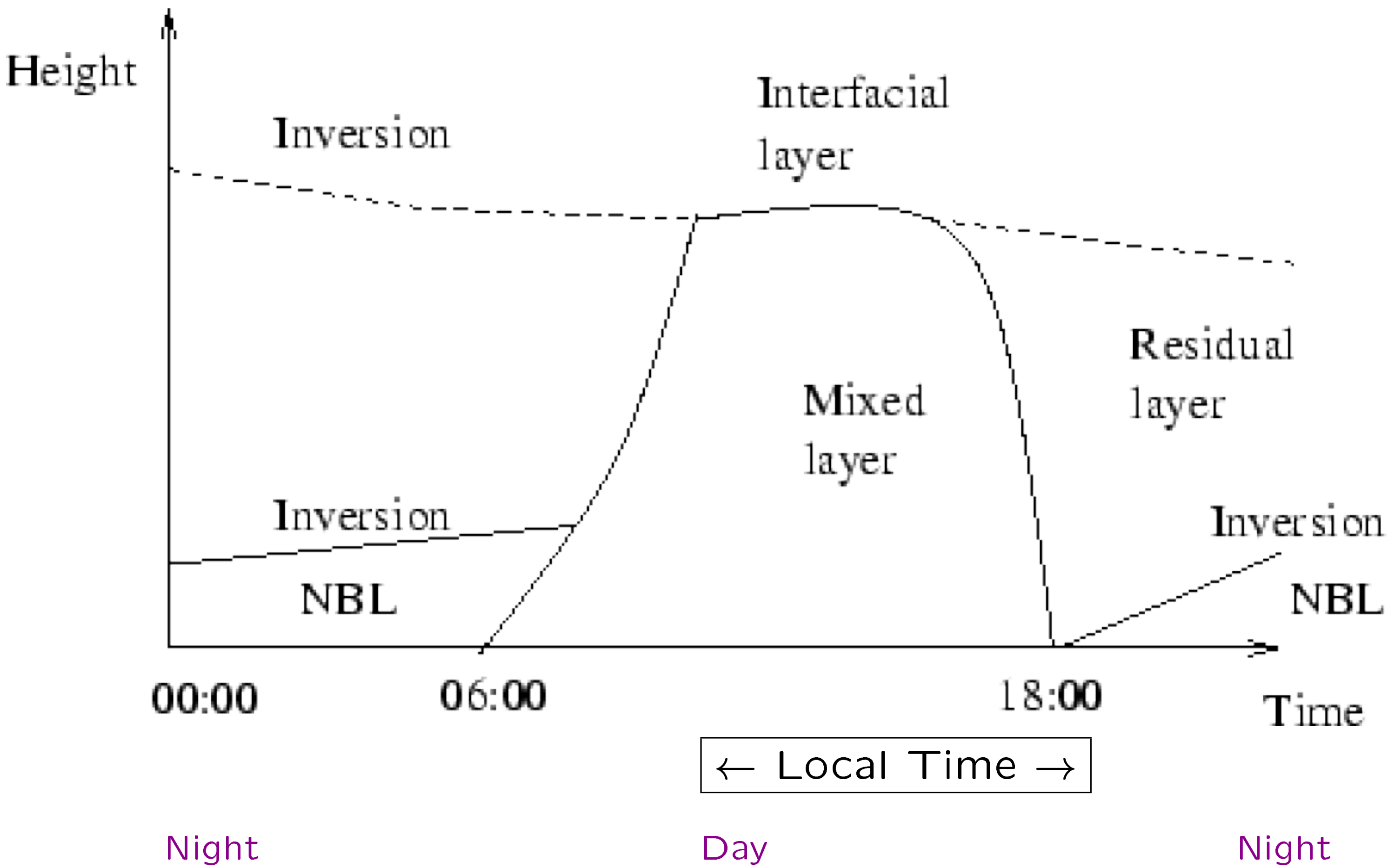
The Planetary Boundary Layer



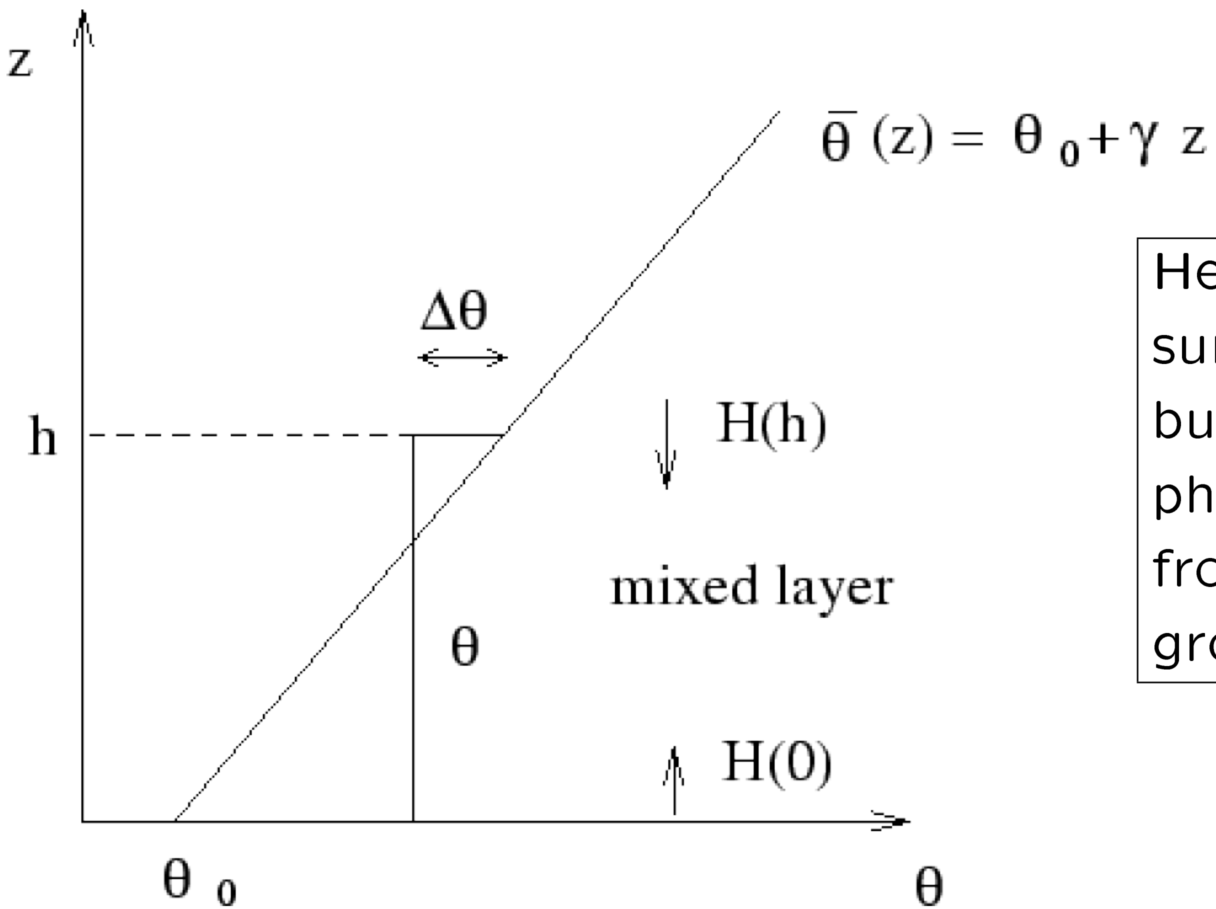
Strong coupling with surface; turbulence.

Weak or no coupling to surface; intermittency.

The Planetary Boundary Layer



Growth Through Entrainment



Heat fluxes from the surface generate turbulent eddies that physically mix the air from aloft into the growing PBL.

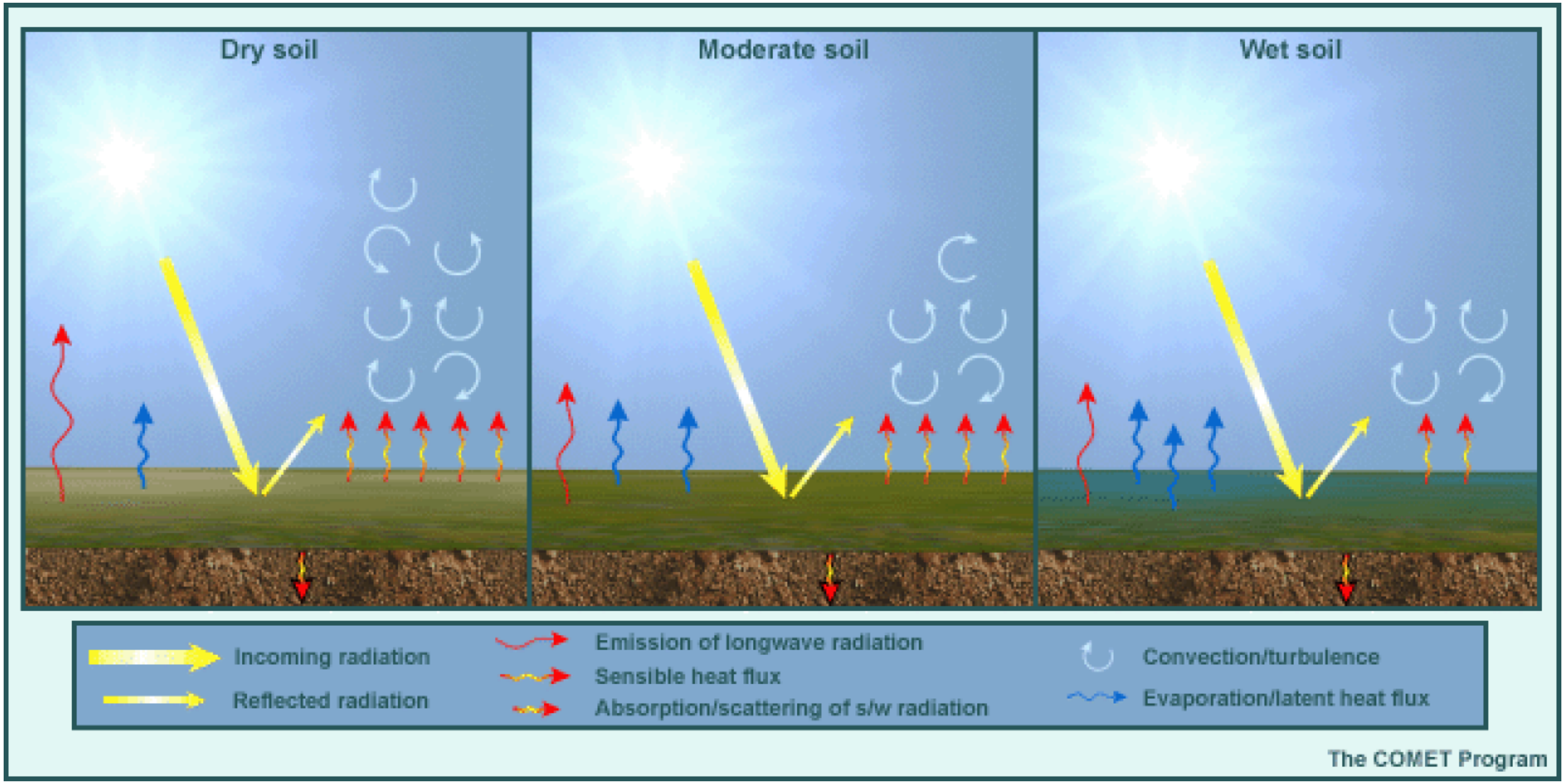
PBL Depth

- A difficult problem: how to parameterize the entrainment rate? Typically some function of the surface fluxes, with parameters.

- Conservative scalars (potential temperature, moisture, pollutants) are generally well-mixed within the PBL.

- Moisture and temperature in the PBL, and inversion strength, are key to thunderstorm prediction.

Soil Moisture



Soil moisture partitions the latent and sensible heat fluxes through the surface. It can be prognostic or diagnostic.

PBL Analysis and Forecasting

- Observations in the PBL above the surface are sparse or low-quality.

- Mesoscale models rely on parameterizations, which are generally deficient, to determine the PBL.

- Mesoscale models are necessary for both the analysis (data assimilation) and forecast problems, when high spatial resolution is required.

Better PBL analyses can improve thunderstorm nowcasting, air quality and plume forecasting.

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.

- Assimilation of any relevant observations. Here focus on surface obs: T_2, Q_2, U_{10}, V_{10} assimilated half-hourly to get information about the atmospheric state.

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

Model Formulation

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

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

A Parameter to Modify Soil Moisture

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.

Context (opinions)

- Numerical weather prediction (NWP) is messy and at times ugly, but its success is undeniable.

- An honest person will talk about parameter tuning in NWP.

- Community inertia toward more complex approaches.

- An alternative may be to seek simpler approaches that make use of objectively tunable parameters.

In many cases there is no reason to expect that parameters are stationary in time and space.

Observations to Inform the Model

- Observations are the only direct source of information about the truth.

- Observations and model are combined in data assimilation.

- In data assimilation, observations have the potential to tell us something about the model, including values of parameters.

Linear Statistical Analysis Equation

$$\begin{aligned} x^a &= x^b + K\left(y^o - Hx^b\right) \\ K &= P^bH^T\left(HP^bH^T + R\right)^{-1} \end{aligned}$$

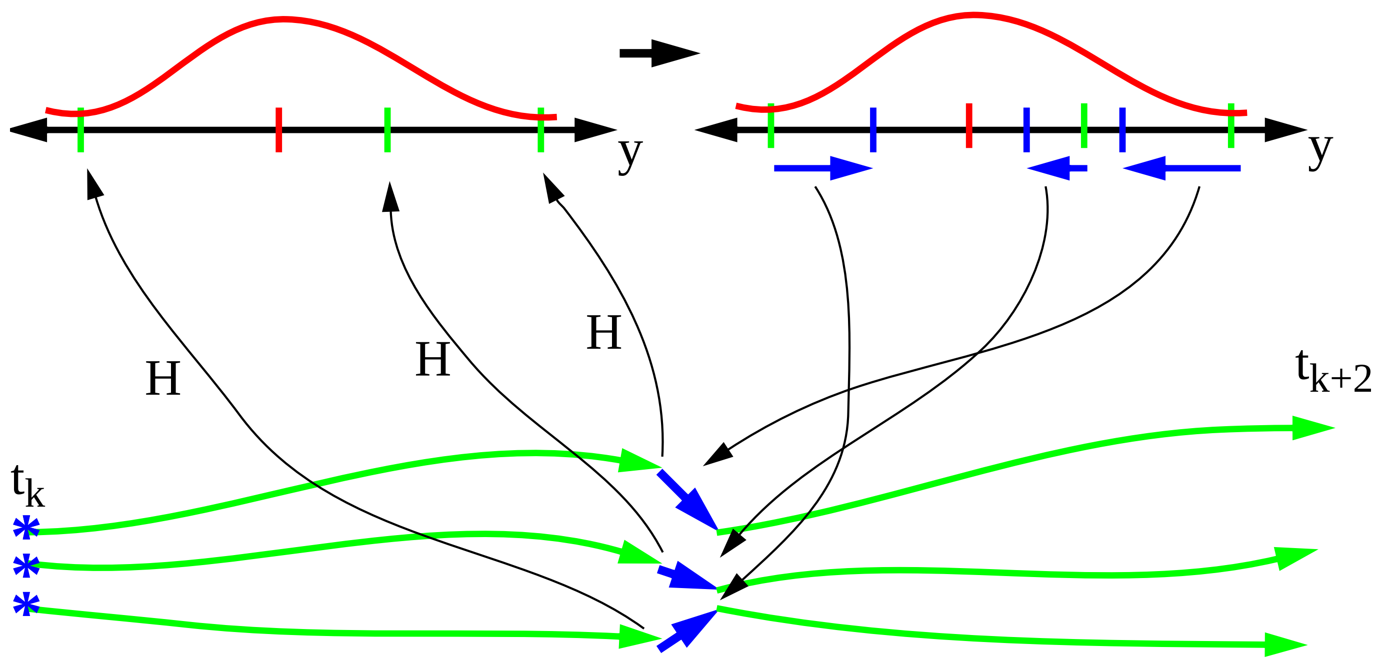
- $x^b = x^f$ from the previous forecast cycle (background)
- H is the forward operator, relating x to y^o
- K weights x^b versus y^o and describes the covariance between error at the observation sites and error on the model grid
- P^b is the background error covariance matrix (unknown!)
- R is the observation error covariance matrix, including instrument and representativeness error (unknown!)

Linear Statistical Analysis Equation

$$
\begin{aligned}
x^a &= x^b + K\left(y^o - Hx^b\right) \\
K &= P^bH^T\left(HP^bH^T + R\right)^{-1}
\end{aligned}
$$

- If K is correct, this gives the best linear unbiased estimate of the state x^a
- Estimating P^b and R is the crux
- Ensemble methods provide an approach: estimate P^b directly from an ensemble forecast (an ensemble filter)

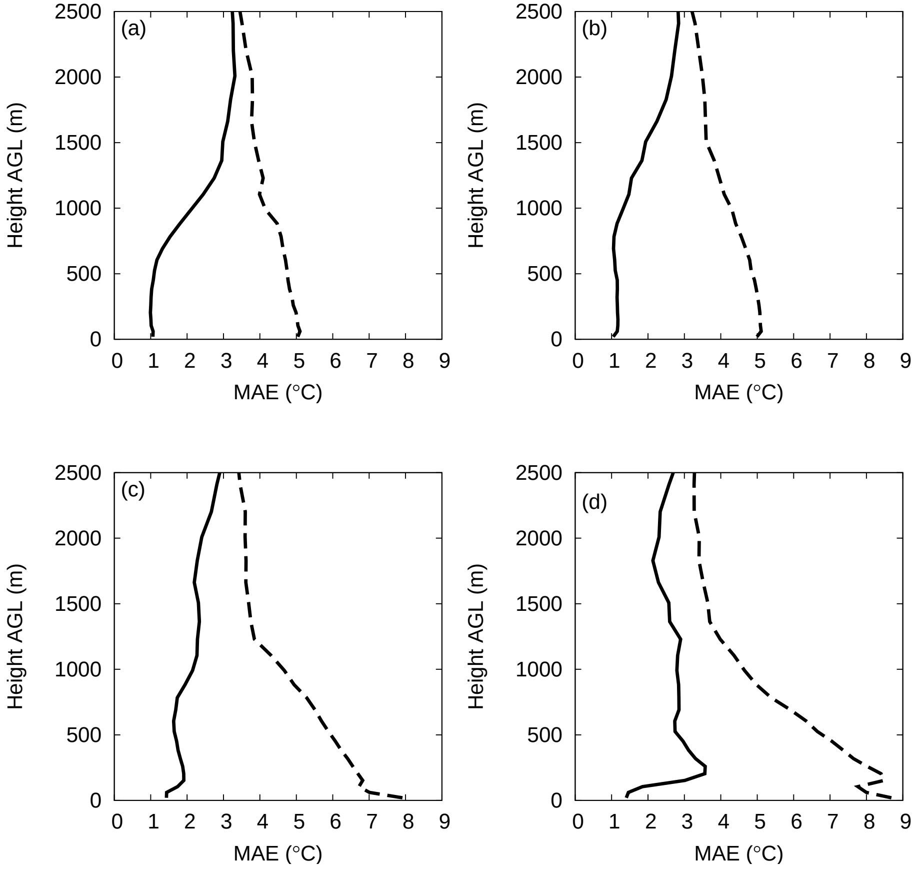
An Ensemble Filter



Model	Observation	Increment/Update

$$x^a = x^b + P^bH^T\left(HP^bH^T\right)^{-1}\left(HP^bH^T\right)\left(HP^bH^T + R\right)^{-1}\left(y^o - Hx^b\right) \quad (1)$$

Skill in PBL State Estimates



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.

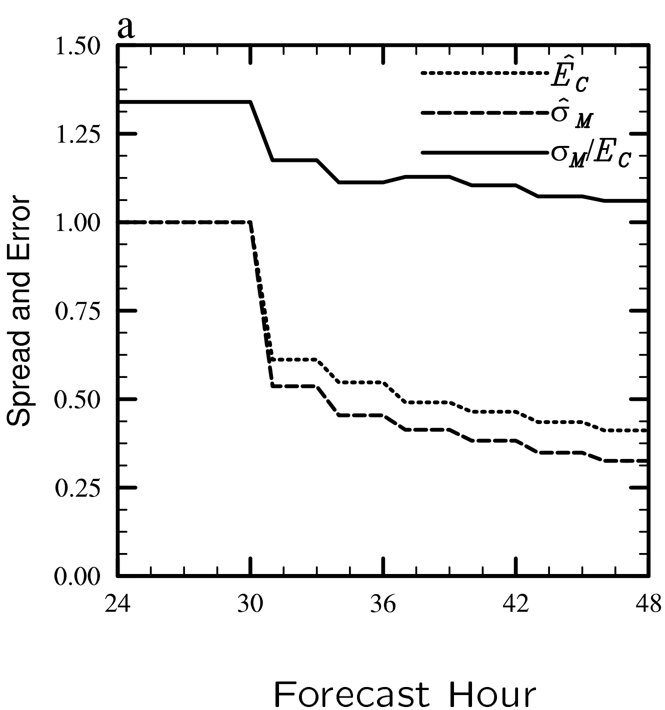
Then $\mathbf{Z} = (\mathbf{X}, \mathbf{x})$.

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

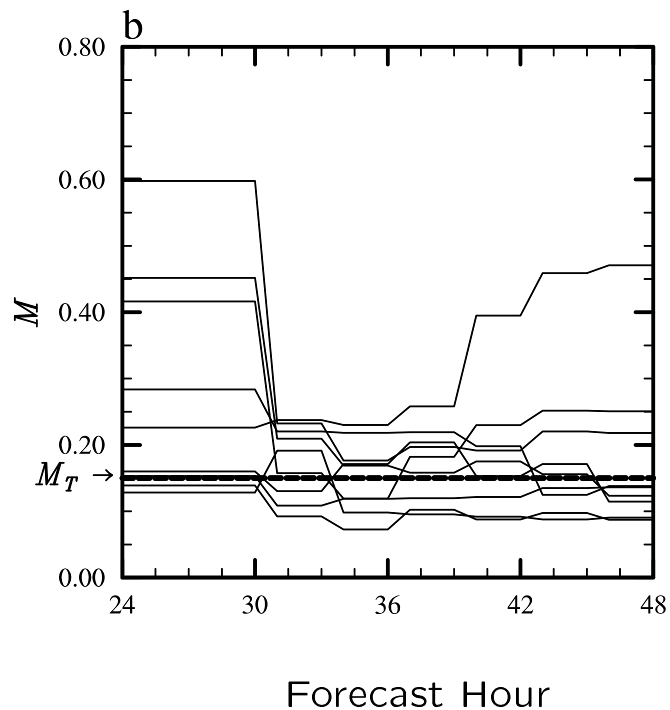
These experiments are to estimate parameters in a land-surface scheme, given screen-height observations and an evolving model.

Estimate a Single Parameter

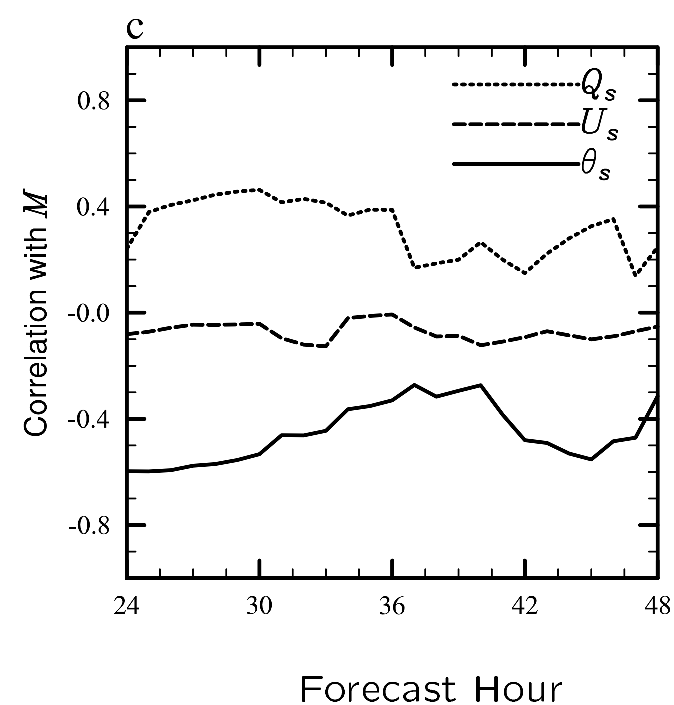
Spread and error



Individual estimates

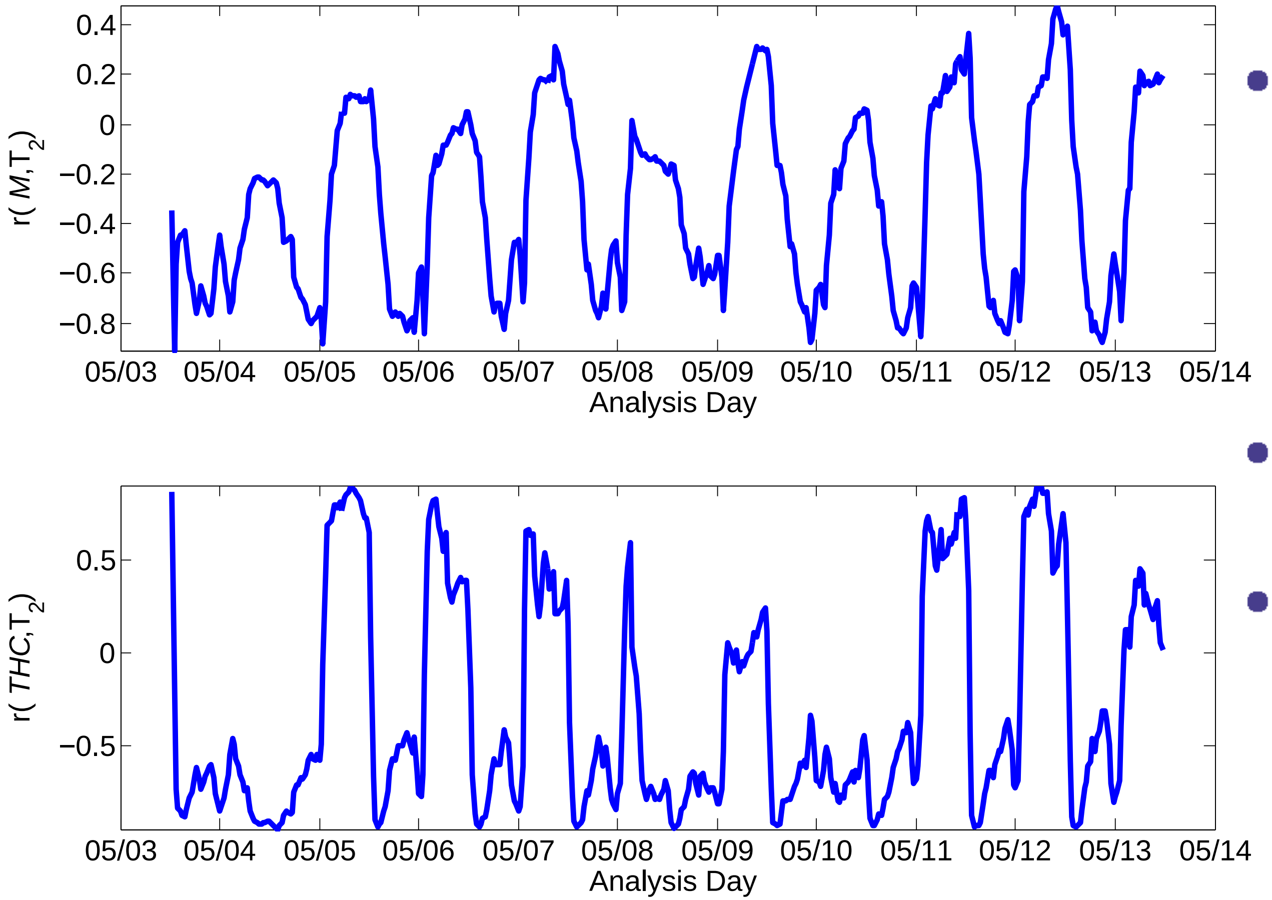


Correlations



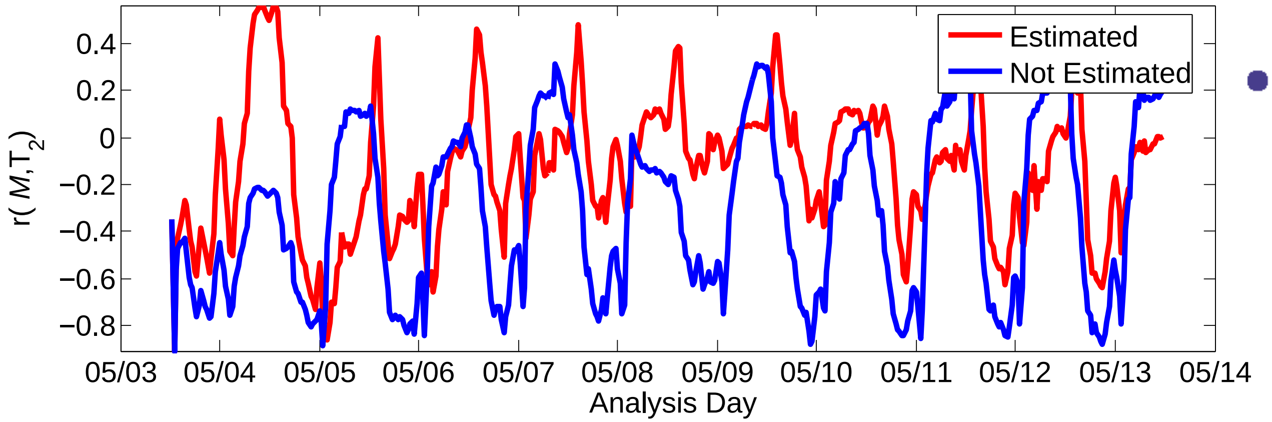
Single parameters (moisture availability) can be estimated when the true value is known.

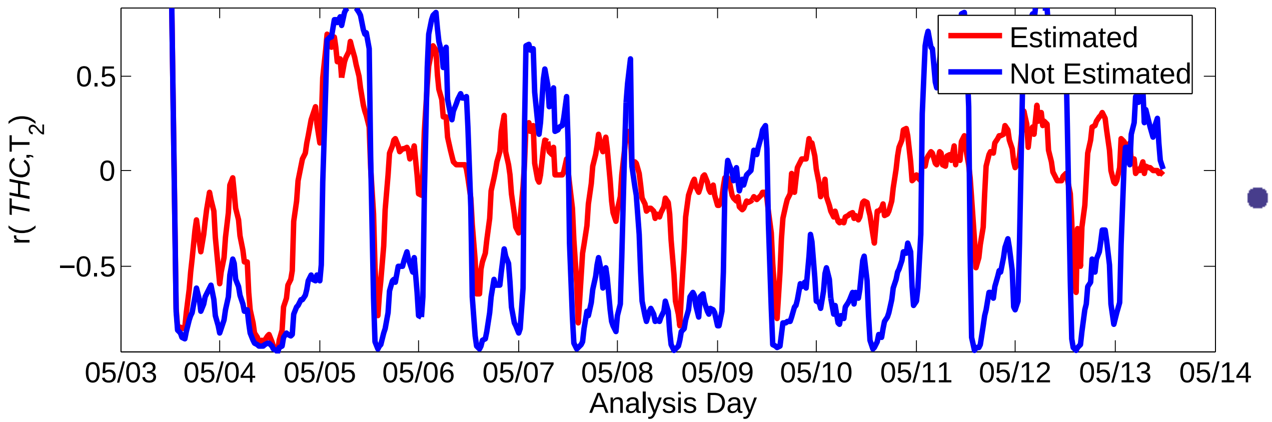
Correlations Without Assimilation



- 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 $0.01THC$.

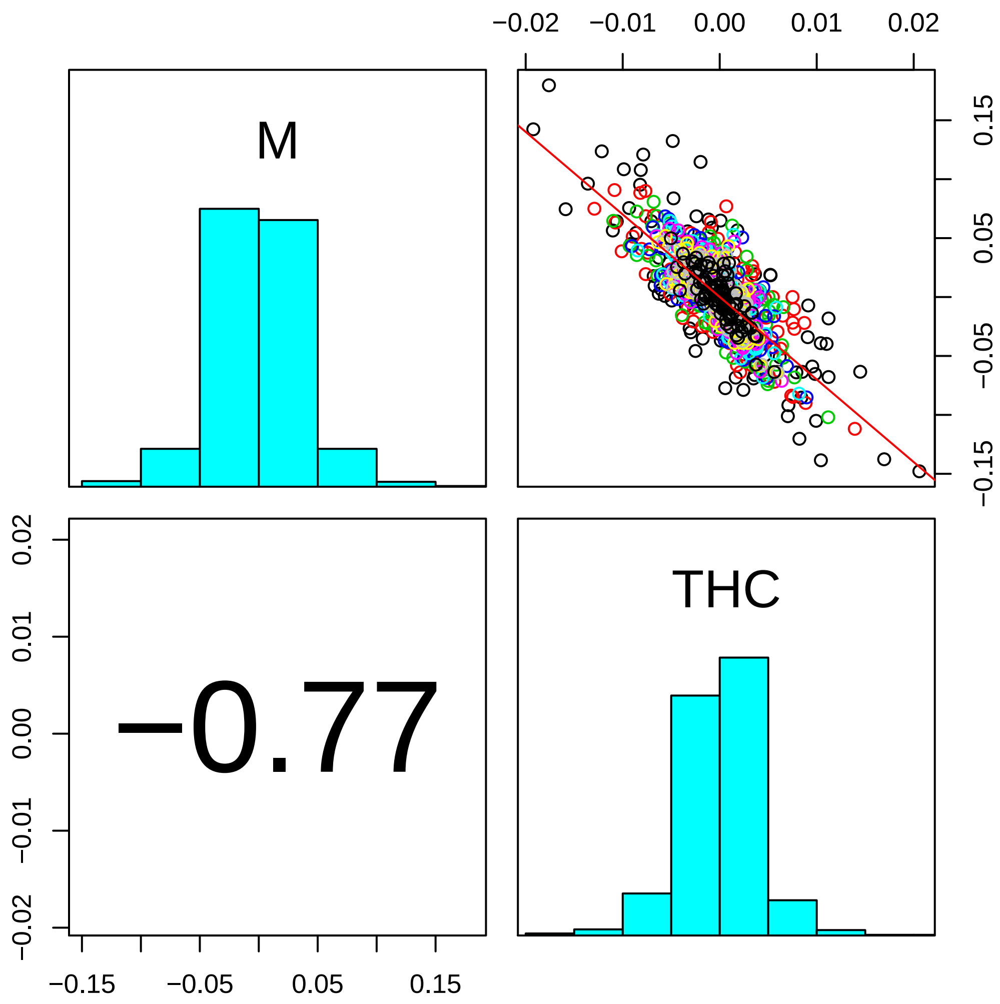
Correlations With Assimilation





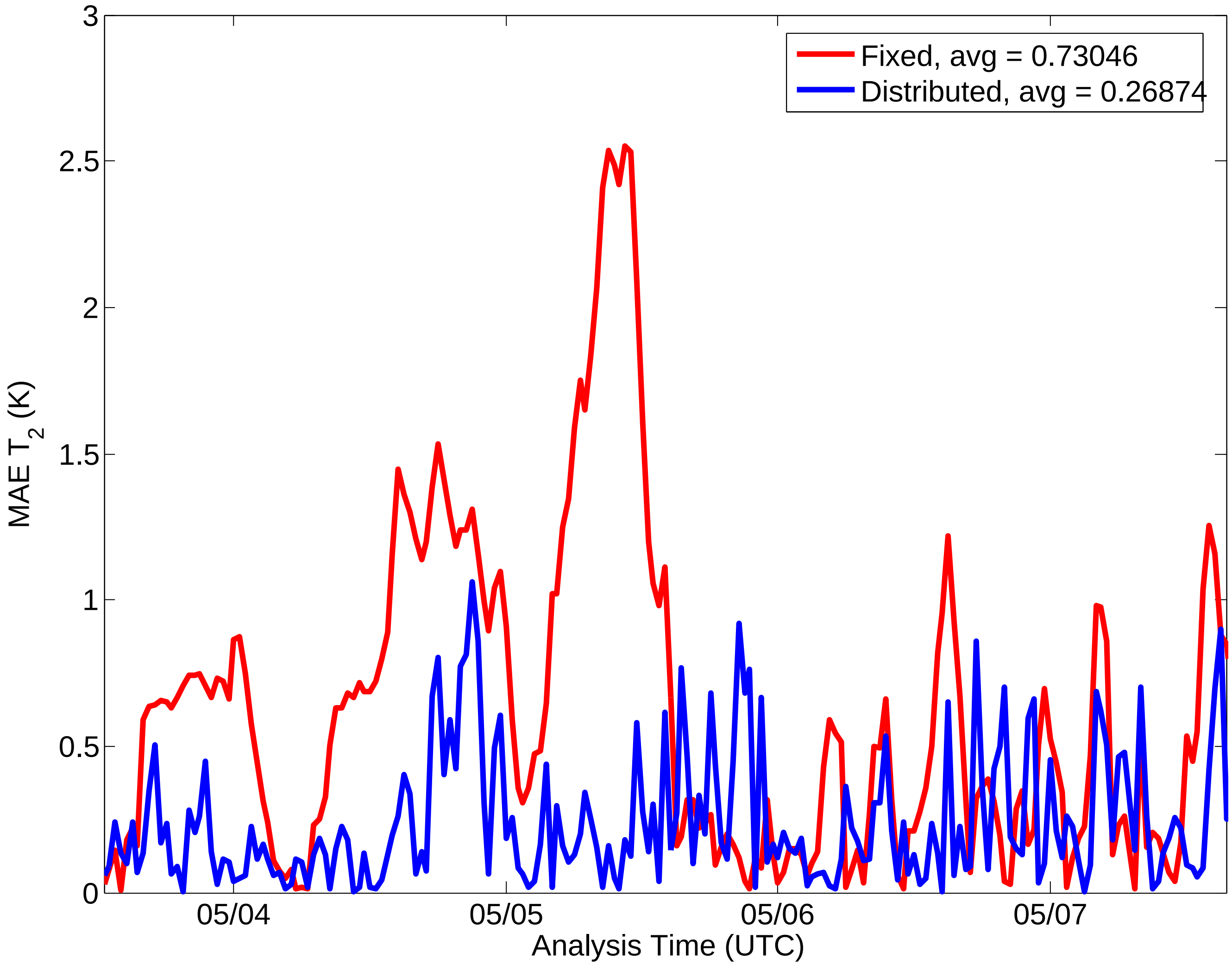
- Correlation coefficients of T_2 with parameters M and THC, for 100 ensemble members integrated for 10 days.
- Parameter distributions are estimated while assimilating.
- Correlations change, transitions more pronounced.

Dependent Parameters



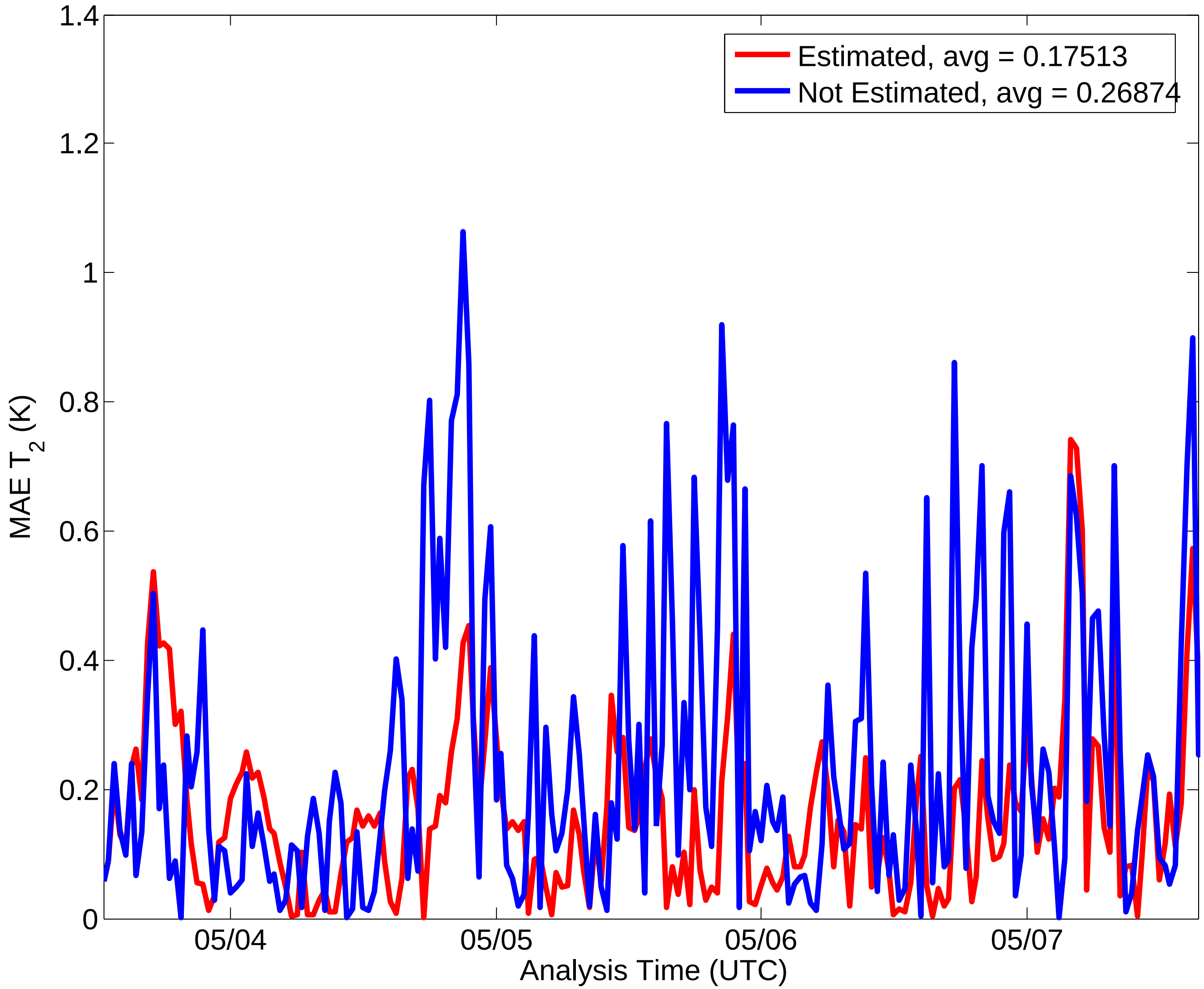
- M and THC are linearly dependent when estimated. Here is at 00 UTC for over 10 days, but this is true at any time.
- Cannot be distinguished, thus could be replaced by a single parameter.

Distribution Improves Assimilation



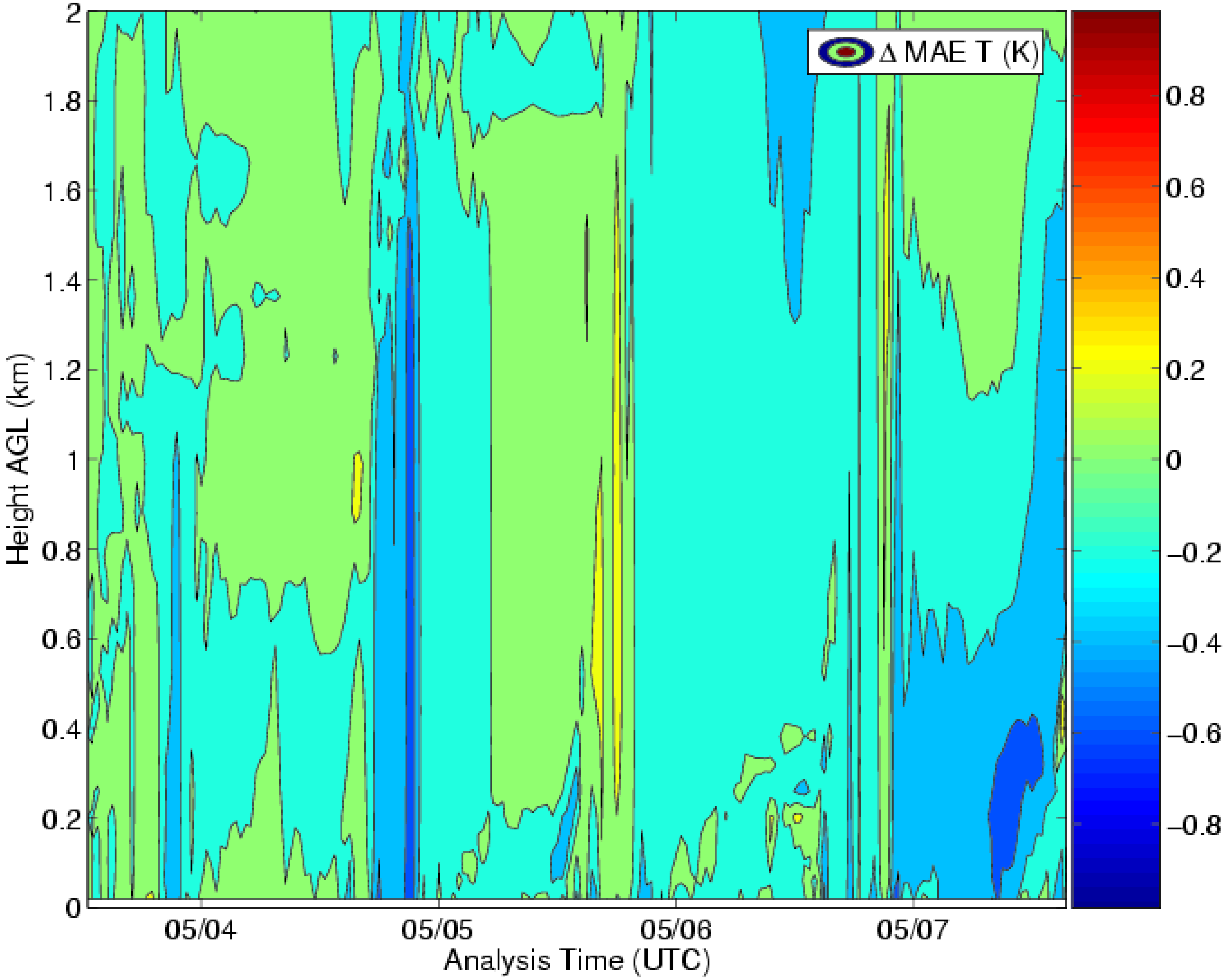
Compared to single fixed parameter values, distributed parameters result in a better fit to observations. The effect is particularly true during transitions.

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 can we deal with non-Gaussianity in the parameters?
- 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?

- Theoretical: uncertainty in model parameterization is rarely addressed in a meaningful way.

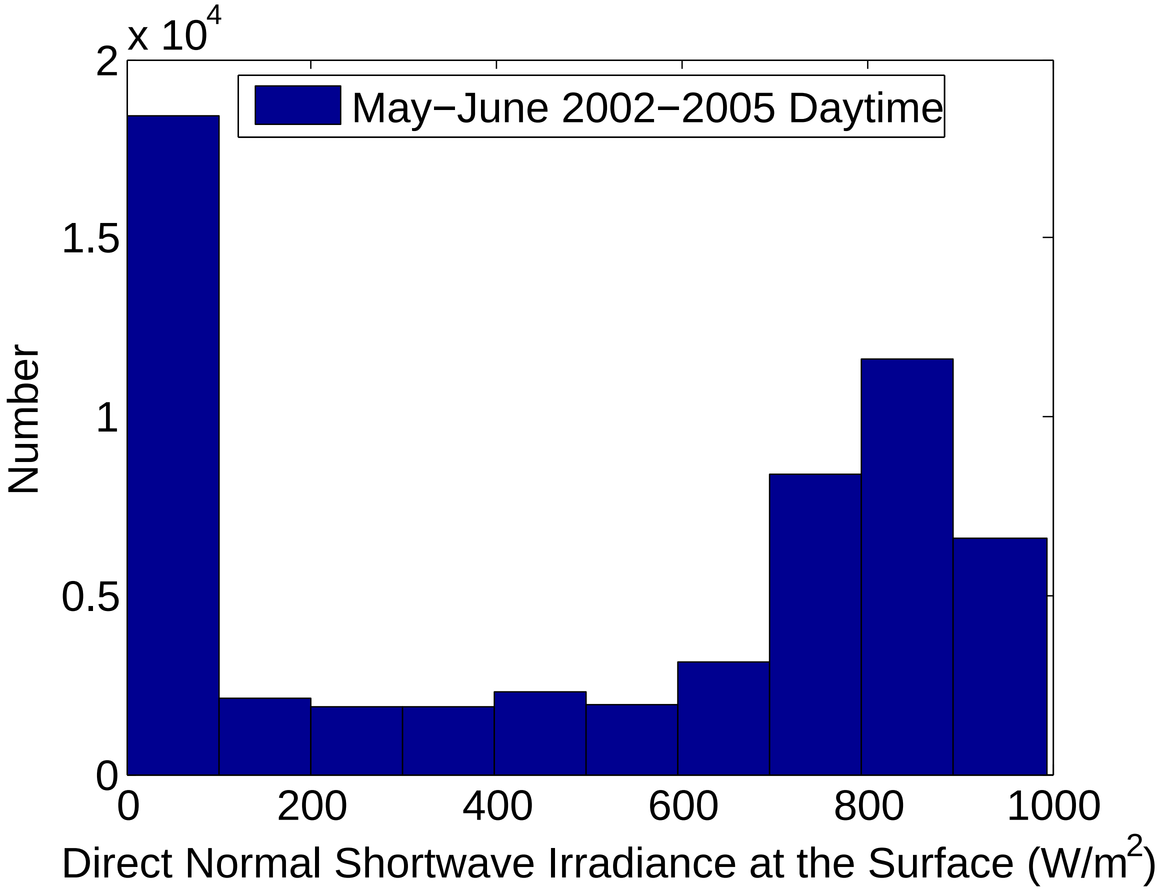
- Empirical: ubiquitous underdispersion in mesoscale ensemble forecasts suggests that something to approximate model uncertainty is needed.

- Practical: as a function of the resolved state, parameterizations respond to errors in the resolved state (and thus other parameterization schemes).

- Process: the response of the PBL to stochasticity, which certainly exists in the real atmosphere, is not well understood.

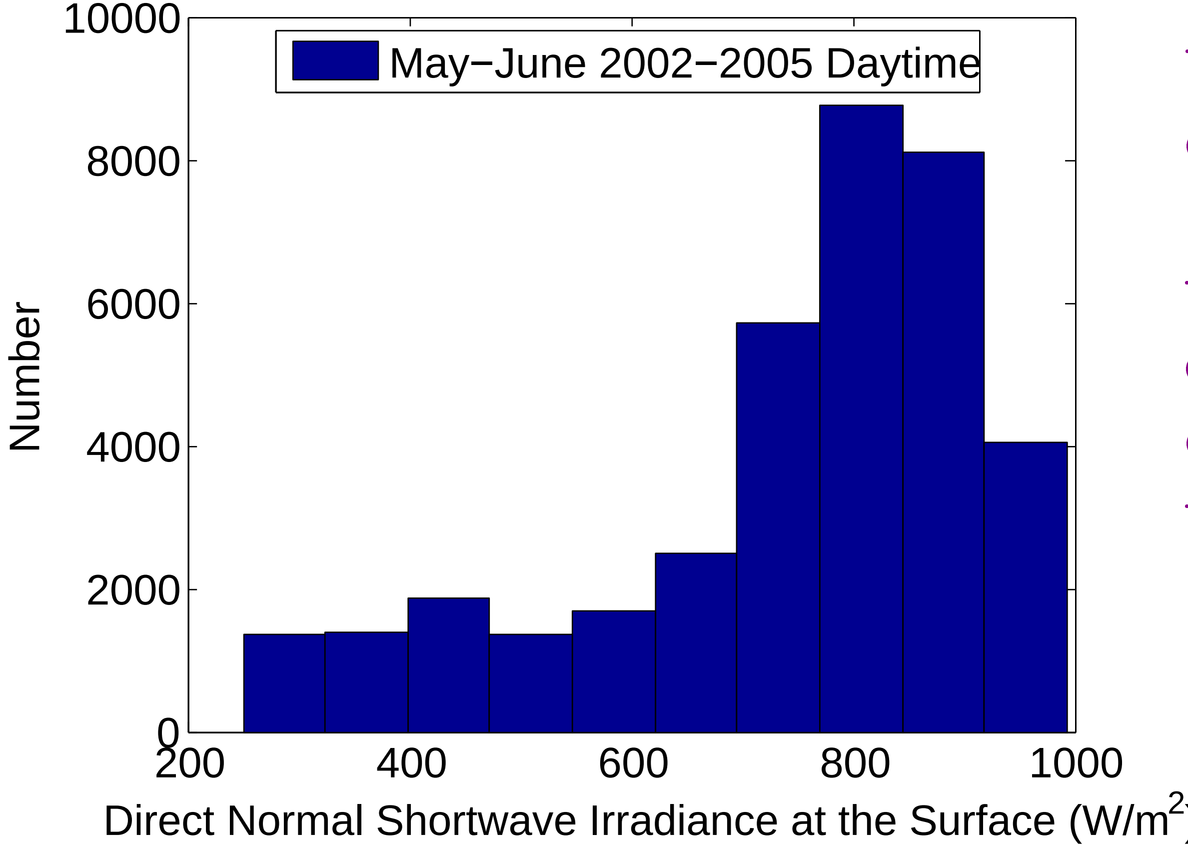
- Incoming solar radiation and outgoing infrared radiation interact with clouds.
- Do PBL winds, either modeled or in the real atmosphere, react to the modulated radiation in a meaningful way?
- What temporal and spatial scales of clouds are important?

Daytime Radiative Flux at the Surface



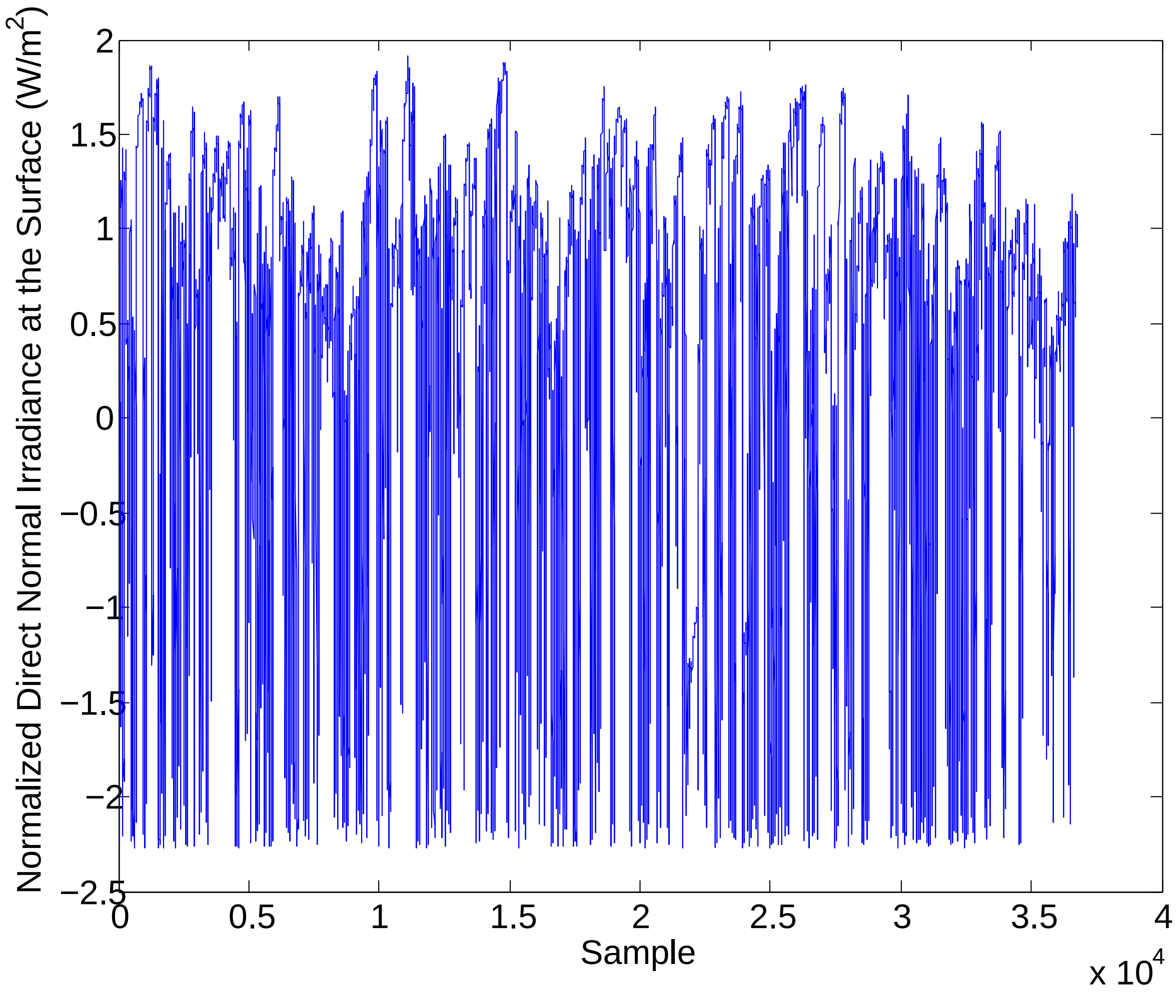
May-June daytime distribution is bimodal with a broad range of whiteness. This results from shallow convection (boundary layer clouds), and frequent longer-lived thick clouds associated with deep convection.

Model the Effects of Shallow Convection



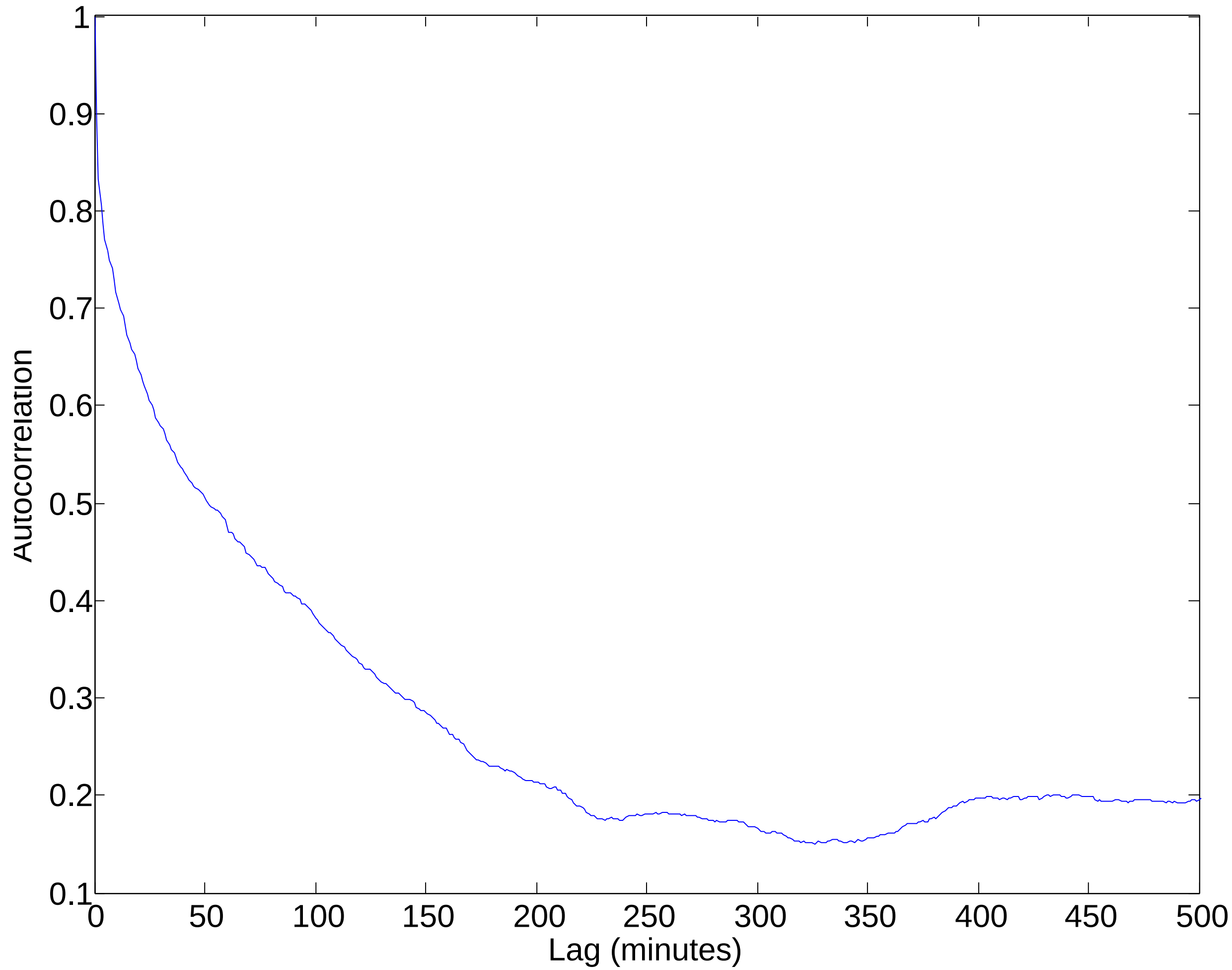
The effect of the thickest clouds ($I < 250$ W/m^2) removed somewhat arbitrarily. To model the full effects, we need a process to switch between the regimes.

Normalized Series



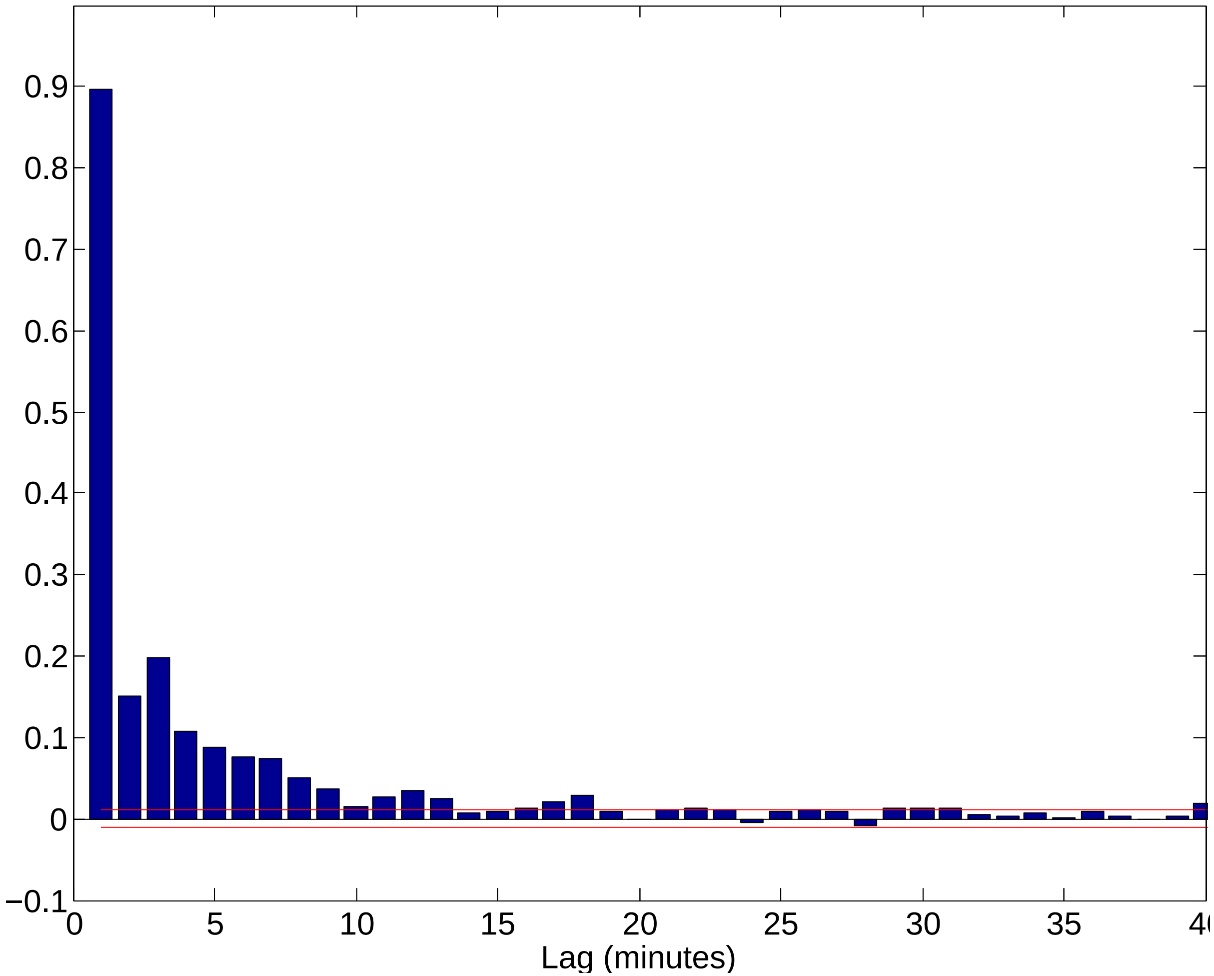
Normalized series shows intermittency.

Autocorrelation



Very slow decay with oscillations from lag ≈ 250. Weak to moderate autocorrelations are evident.

Partial Autocorrelation



Statistical significance is high through about 10 lags. Results seem to suggest that an ARMA model is appropriate for the part of the distribution representing shallow convection.

Next Steps

- Fit ARMA model, and find process to switch cloud regimes regimes.

- Introduce statistical model in column system.

- Investigate response of the column to variations in the statistical model, in terms of time scale and physical mechanism.

- What is the expected effect on PBL winds? How can we use this to produce a forecast system that accounts for uncertainty?

Another Potential Focus

- The stable (nocturnal) boundary layer is characterized by intermittent bursts of turbulence that appear random.
- Parameterization generally handles laminar flow, and does not account for the intermittency.
- An extra term could be added to the equations to account for it.

Stochastic approaches have been proposed for dealing with the stable boundary layer, but not pursued.

Closing Thoughts

- The assumptions that go into Reynolds or other averaging techiques, are violated daily in NWP applications.

- It is time to re-think parameterization; statistical and stochastic approaches are one viable approach.

- Relatively speaking, deep convection has received the most attention, but the PBL is important at both NWP and climate time scales.

- I propose a column model to efficiently address some of the challanges in PBL parameterization, but caution is necessary to ensure results will extrapolate to the 3D problem.