Variational Data Assimilation for Soil Moisture Estimation

Rolf Reichle

Dennis McLaughlin

Dara Entekhabi

Dept. of Civil and Environmental Engineering, M.I.T.

MOTIVATION

Profile soil moisture is an important variable for capturing diurnal and day-to-day variations in hydrologic fluxes at the land surface.

Passive microwave remote sensing in the L-band (1.4 GHz) can provide information about the physical temperature and the dielectric properties of the land surface which are, in turn, related to soil moisture in the top few centimeters.

In this paper we describe a four-dimensional data assimilation (4DDA) algorithm which uses a physically-based model of soil moisture and heat transport in order to extract information about soil moisture profiles and land-atmosphere fluxes from L-band microwave measurements.

HYDROLOGIC MODEL & MEASUREMENT OPERATOR

State Equations

Soil moisture (Richards' eq.)

$\partial_t \theta = \nabla K(\theta) \nabla (\psi + z) +$ model error

Soil temp. (Force-Restore)

$\partial_t T_g = c_1 G - c_2 (T_g - \bar{T}) +$ model error

Parameterizations

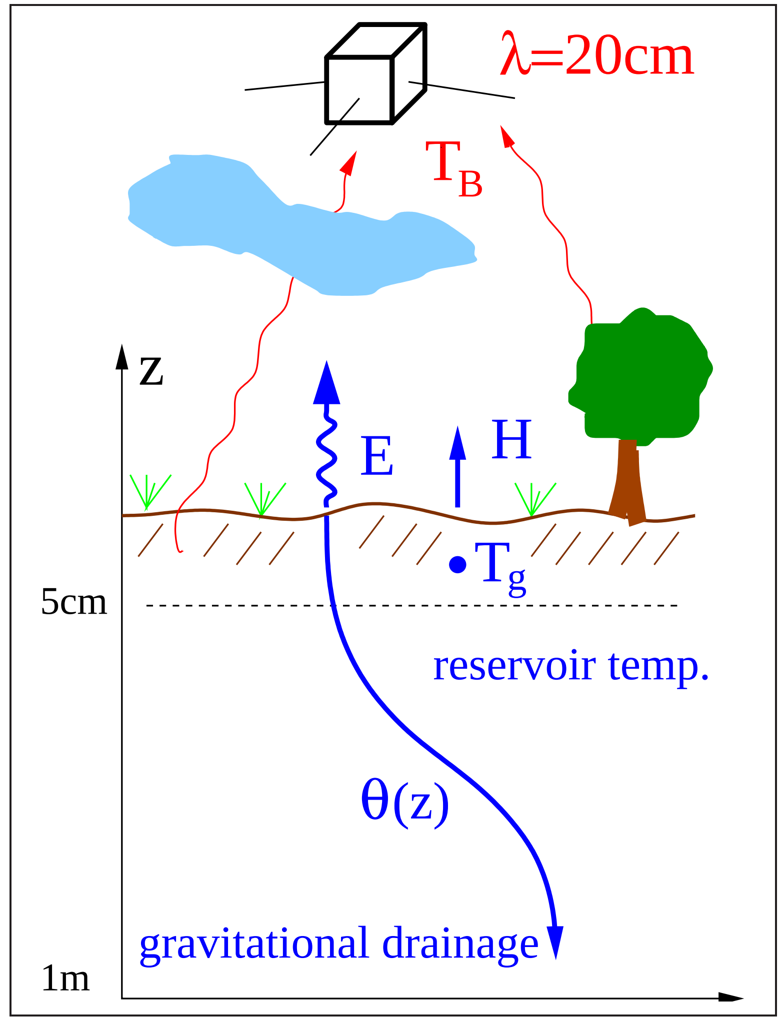
Vegetation, soil, radiation

Micro-meteorologic Forcing (15min)

Measurement Equation

Brightness temp. (RT model)

$T_B = M(\theta, T_g) +$ measurement error



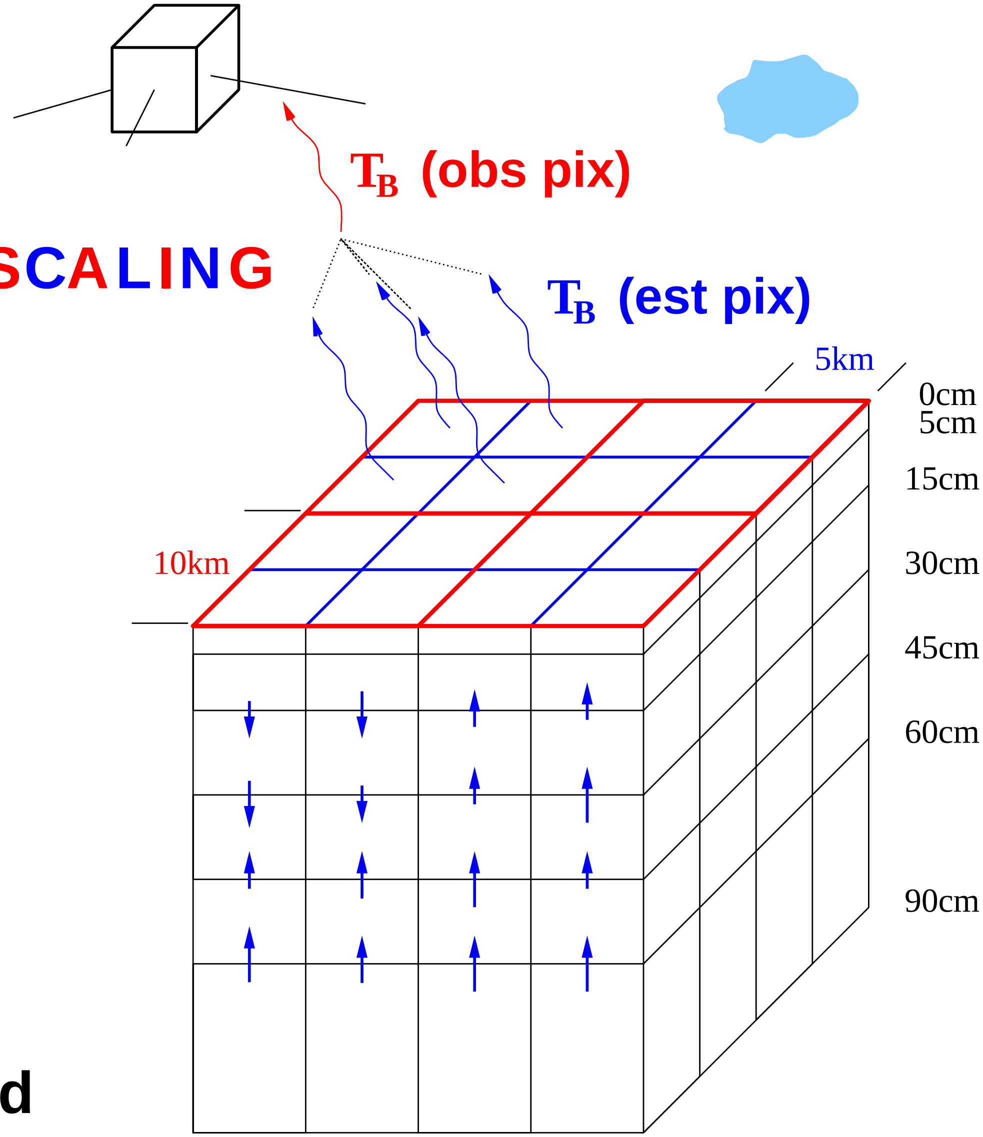
The **coupled soil moisture and temperature model** which forms the basis of the 4DDA algorithm is designed to capture the key physical processes while remaining computationally efficient.

We account for **model errors** by treating the surface forcings and the initial conditions in different pixels as random fields which are **correlated over time and space**.

Vertical fluxes dominate

We *neglect lateral unsaturated* moisture and heat flow and divide the computational region into 1-dim. vertical cells (or pixels).
Moisture transport in each pixel is described with Richards' equation while energy transport is described with a force-restore model.
The measurement operator corresponds to a non-coherent Radiative Transfer (RT) model [*Jackson et al.*, 1995].

ESTIMATION & OBSERVATION GRIDS



Vertical fluxes dominate

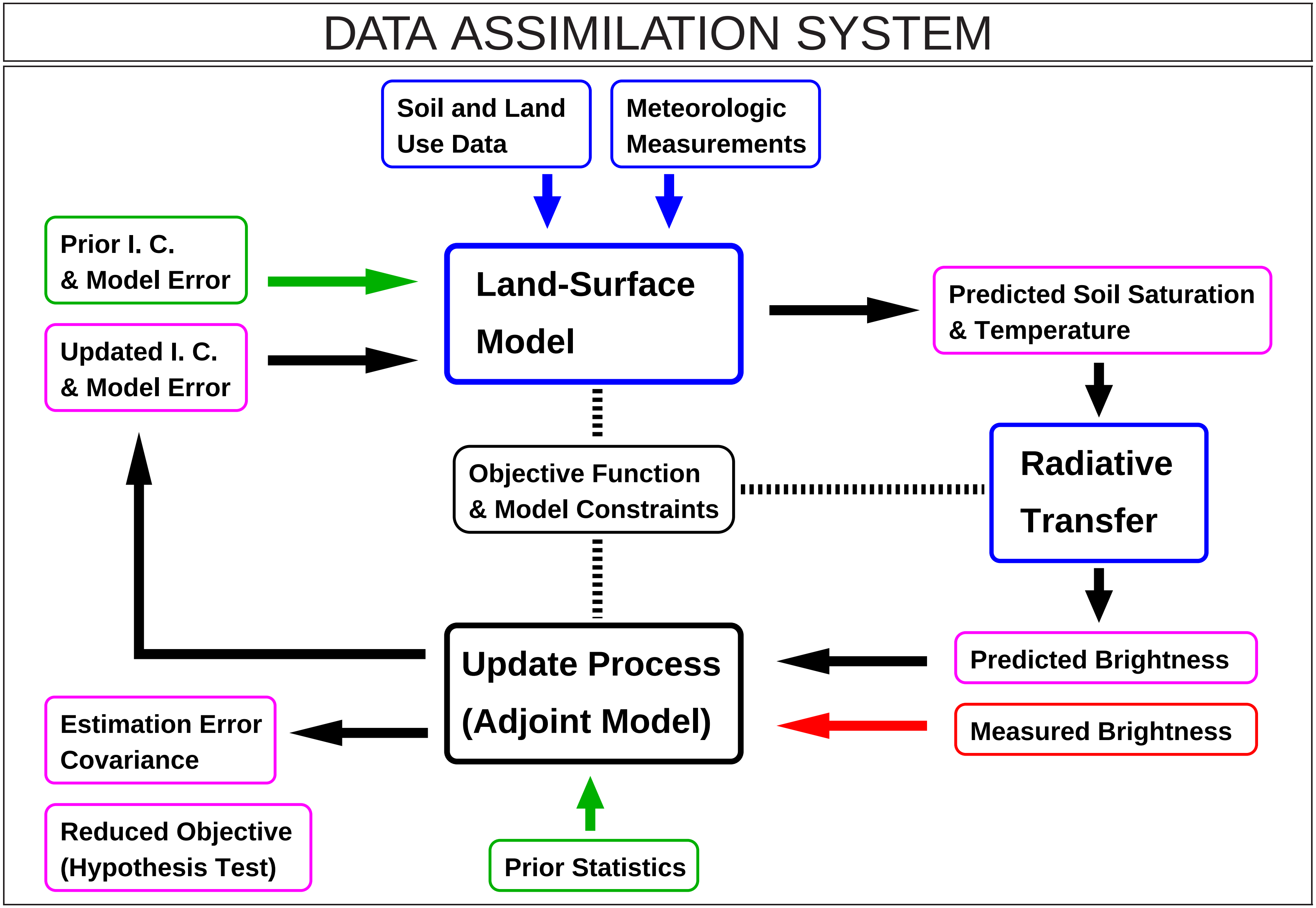
- neglect lateral unsat. moisture & heat flow
- forcing & parameters horizontally correlated

DOWNSCALING

The meteorologic and soil parameter inputs to the model are available at a finer scale than the brightness measurements.

The measurement operator M of the 4DDA algorithm accounts for this difference in scales as well as for the nonlinear relationship between soil moisture, soil temperature, and brightness temperature.

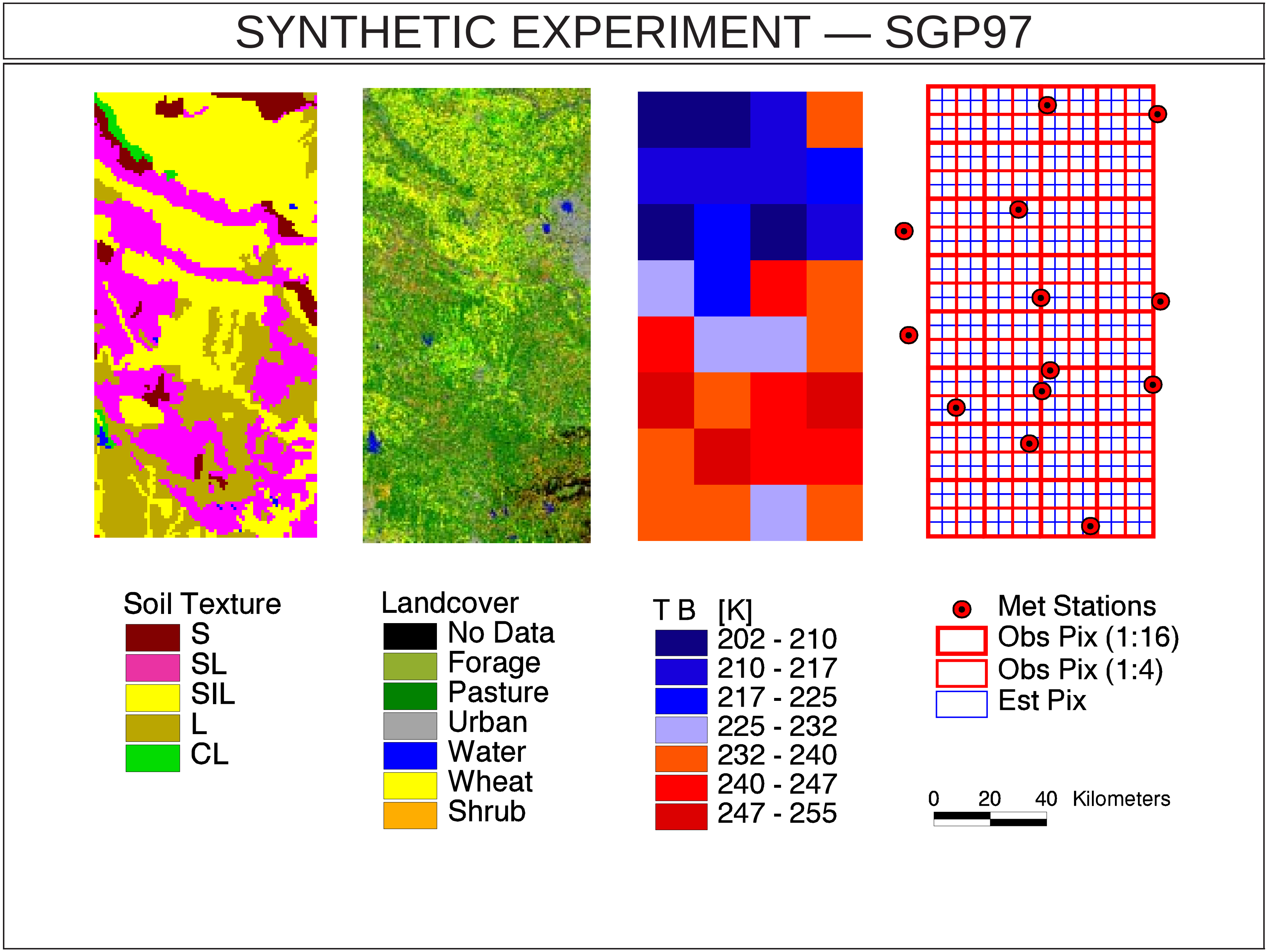
This makes it possible to estimate soil moisture profiles at a finer scale than the resolution of the brightness data.


DATA ASSIMILATION SYSTEM
Soil and Land Use Data
Meteorologic Measurements
Prior I. C. & Model Error
Updated I. C. & Model Error
Land-Surface Model
Predicted Soil Saturation & Temperature
Objective Function & Model Constraints
Radiative Transfer
Update Process (Adjoint Model)
Predicted Brightness
Measured Brightness
Estimation Error Covariance
Reduced Objective (Hypothesis Test)
Prior Statistics

The data assimilation algorithm optimally combines the information from the hydrological model with the information from the remote sensing data and yields a best estimate of the true state of the system.

The estimates are derived from a **variational least-squares algorithm**. Variational methods are particularly well-suited for assimilation applications which rely on highly nonlinear state equations, such as those used in our model of soil moisture and temperature variability.
The approach is widely used in oceanographic research and in operational weather forecasting [*Bennett*, 1992; *Thépaut and Courtier*, 1991].
Variational assimilation methods interpolate and extrapolate the data in a **dynamically consistent** way.

Through its implicit propagation of the error covariances, the algorithm is **very efficient** and thus able to provide **optimal** estimates without the simplifications that are needed in large-scale Kalman filtering applications.

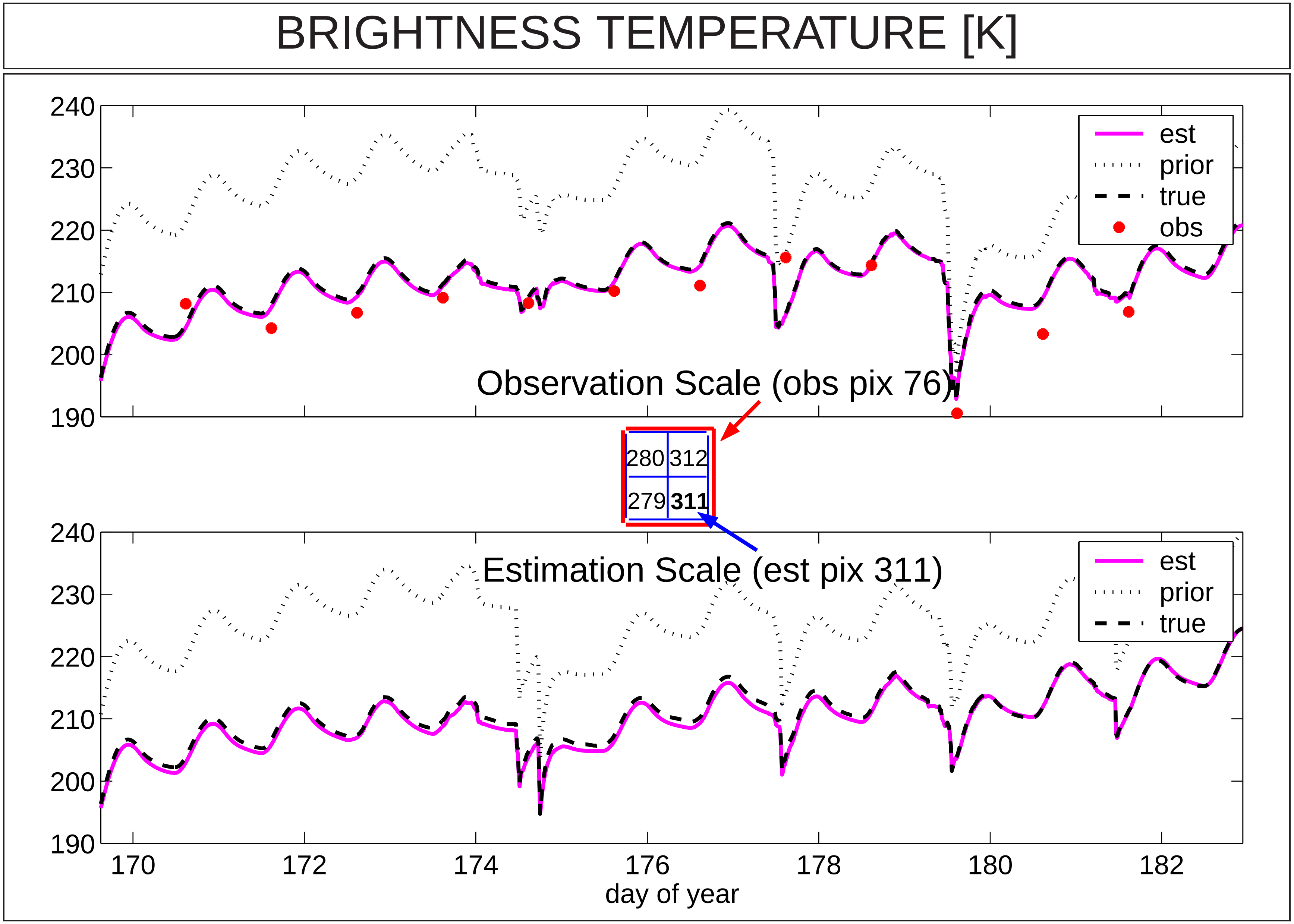

SYNTHETIC EXPERIMENT — SGP97
Soil Texture
S
SL
SIL
L
CL
Landcover
No Data
Forage
Pasture
Urban
Water
Wheat
Shrub
T B [K]
202 - 210
210 - 217
217 - 225
225 - 232
232 - 240
240 - 247
247 - 255
Met Stations
Obs Pix (1:16)
Obs Pix (1:4)
Est Pix
0 20 40 Kilometers

Our test problem is based on the **SGP97** field experiment.
The algorithm is used to run a series of twin-experiments with synthetically generated **“true”** parameter, model, and measurement errors.
Such experiments are best suited to evaluate the performance of the algorithm as all of the uncertain inputs are known.

The assimilation is performed for a two-week period. Observations of brightness temperatures are available once daily in the morning.

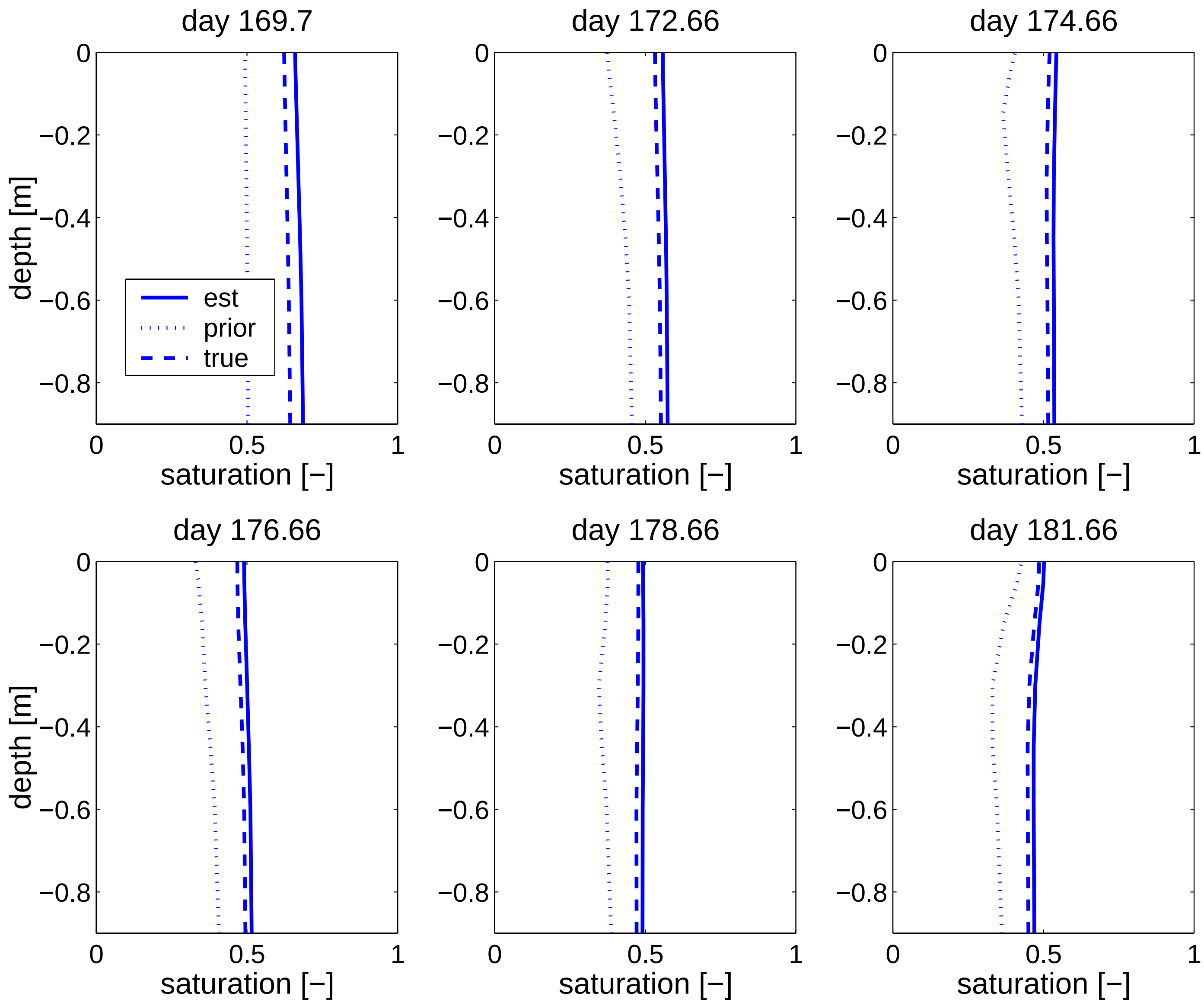
The **prior** is our best guess using the hydrologic model but without assimilating the brightness data. The **estimate** contains both the information from the model and from the brightness data.

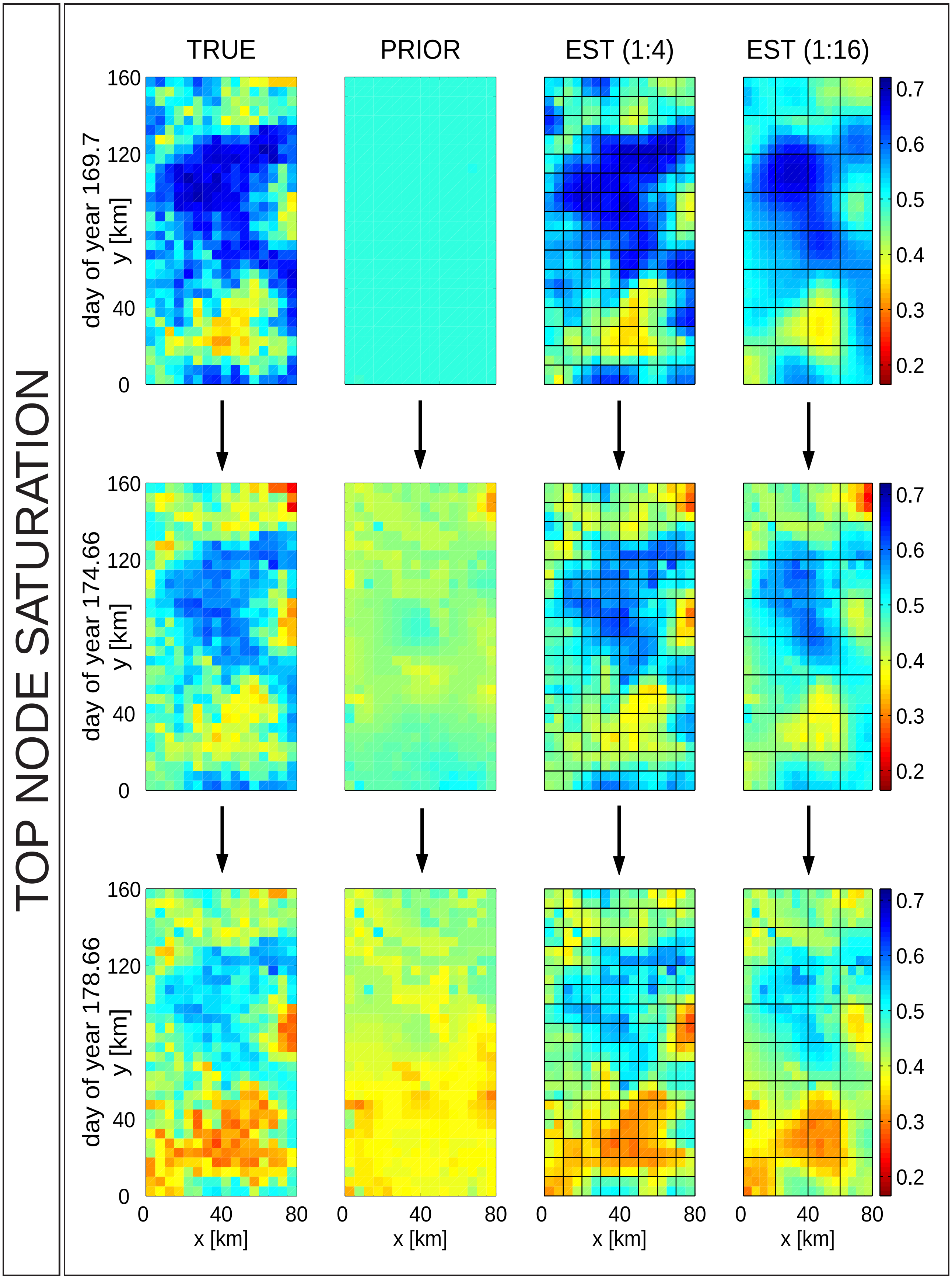
The algorithm recovers the brightness temp. on the scale of the observations *and* on the finer scale of the (downscaled) soil moisture estimates.
For a representative pixel, we also compare the prior and the estimated soil moisture profiles. The estimated profile is close to the truth.



BRIGHTNESS TEMPERATURE [K]
Observation Scale (obs pix 76)
est
prior
true
obs
280
312
279
311
Estimation Scale (est pix 311)
240
230
220
210
200
190
170
172
174
176
178
180
182
day of year

PROFILE SATURATION — ESTIMATION SCALE (PIX 311)




TOP NODE SATURATION
TRUE
PRIOR
EST (1:4)
EST (1:16)
day of year 169.7
day of year 174.66
day of year 178.66
y [km]
x [km]
0
40
80
120
160
0.2
0.3
0.4
0.5
0.6
0.7

Two downscaling scenarios with brightness assimilation are shown:
In the 1:4 scenario, 5km $\times$ 5km estimates are obtained from 10km $\times$ 10km brightness observations (each obs pix contains 4 est pix).
In the 1:16 scenario, 5km $\times$ 5km estimates are obtained from 20km $\times$ 20km brightness observations (each obs pix contains 16 est pix).

In both cases, the top node saturation can be well recovered over the entire domain at a scale finer than the observation scale.

New Project (NRA-98-OES-11)

Soil Moisture Data Assimilation for Continental-Scale Land Surface Hydrology Applications

- Joint tasks between MIT and NASA-GSFC/DAO (Dr Paul Houser)
- Transition towards operational capability
  - Identify forward models appropriate for continental scales
  - Further improve computational efficiency of the algorithm
  - Develop methods for assessing the accuracy of the estimates
- Generate SGP97 soil moisture and temperature estimates from remote sensing and ground-based data

REFERENCES

Bennett, A. F., 1992: *Inverse methods in physical oceanography*, Cambridge University Press, Cambridge, UK.

Jackson, T. J., D. M. Le Vine, C. T. Swift, T. J. Schmugge, and F. R. Schiebe, 1995: Large area mapping of soil moisture using the ESTAR passive microwave radiometer in Washita 92, *Remote Sens. Environ.*, **53**, 27-37.

Thépaut, J.-N., and P. Courtier, 1991: Four-dimensional variational data assimilation using the adjoint of a multilevel primitive-equation model, *Q. J. R. Meteorol. Soc.*, **117**, 1225-1254.