Data Assimilation for Better Heat Flux Predictions from Land Surface Models

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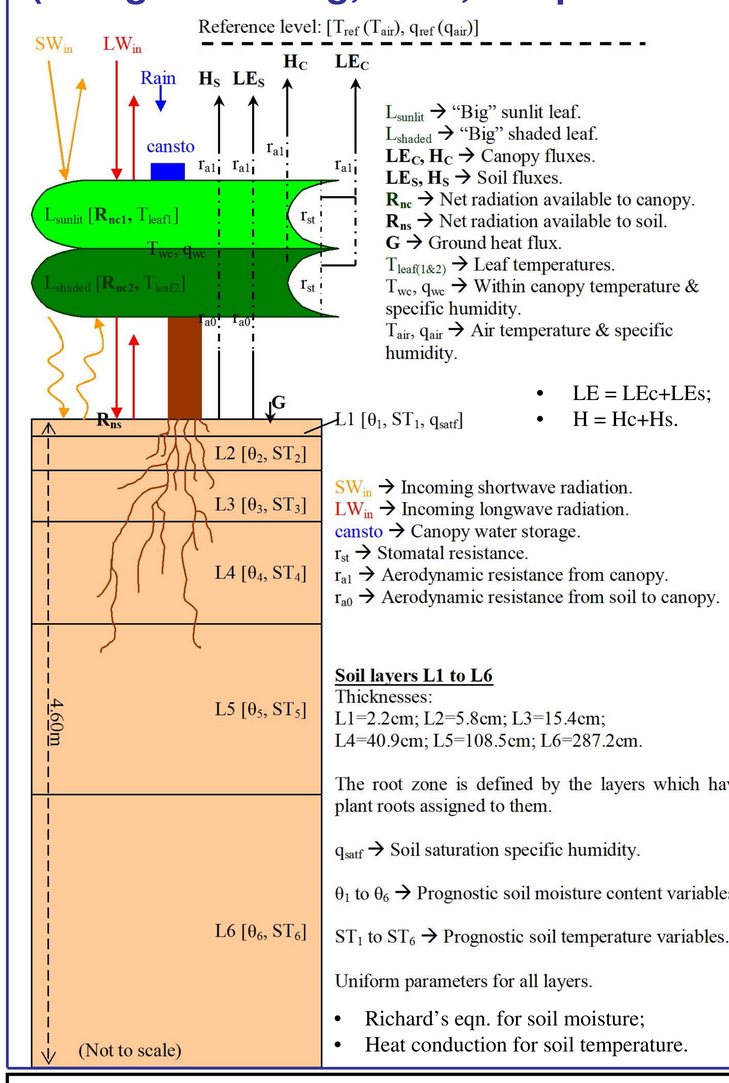
Introduction

Land Surface Models (LSMs) are designed to quantify components of the terrestrial water and energy cycle on continuous timescales. This is useful for agricultural applications or initialising weather and climate forecasting which requires accurate predictions of latent (LE) and sensible (H) heat fluxes. Data assimilation offers great potential for improving uncertain LSM predictions, by constraining prognostic state variables with available data observations. Various remote sensing observations and associated products are becoming more readily available and are potentially valuable for optimising spatially distributed LSM predictions via data assimilation. Soil moisture or skin surface temperature assimilation has dominated recent research efforts but LSM accuracy and structure, along with (in)adequacy of parameter data, will dictate whether these approaches can consistently translate to optimal LE and H predictions. Limited examples exist of LE and H data assimilation, which would presumably work best to constrain model states for the benefit of optimal LE and H predictions, where remotely sensed LE and H are emerging products (based on skin temperature observations). Using an offline version of the CABLE LSM, earmarked for Australia's weather prediction system, 3 data assimilation experiments were carried out in an attempt to answer following:

- **What impact do different observation types have on CABLE when assimilated, particularly for LE and H predictions? Can data assimilation highlight model limitations? Are there particular challenges to assimilating some data types?**

CSIRO Biosphere Model (CBM)/CABLE

(Wang & Leuning, 2001; Raupach *et al.*, 1997; Kowalczyk *et al.*, 2006)



L_{sunlit} → "Big" sunlit leaf.
L_{shaded} → "Big" shaded leaf.
LE_C, H_C → Canopy fluxes.
LE_S, H_S → Soil fluxes.
R_{nc} → Net radiation available to canopy.
R_{ns} → Net radiation available to soil.
G → Ground heat flux.
$T_{leaf(1\&2)}$ → Leaf temperatures.
T_{wc}, q_{wc} → Within canopy temperature & specific humidity.
T_{air}, q_{air} → Air temperature & specific humidity.

- LE = LEc+LEs;
- H = Hc+Hs.

SW_{in} → Incoming shortwave radiation.
LW_{in} → Incoming longwave radiation.
cansto → Canopy water storage.
r_{st} → Stomatal resistance.
r_{a1} → Aerodynamic resistance from canopy.
r_{a0} → Aerodynamic resistance from soil to canopy.

Soil layers L1 to L6
Thicknesses:
L1=2.2cm; L2=5.8cm; L3=15.4cm;
L4=40.9cm; L5=108.5cm; L6=287.2cm.

The root zone is defined by the layers which have plant roots assigned to them.

q_{satf} → Soil saturation specific humidity.

θ_1 to θ_6 → Prognostic soil moisture content variables.

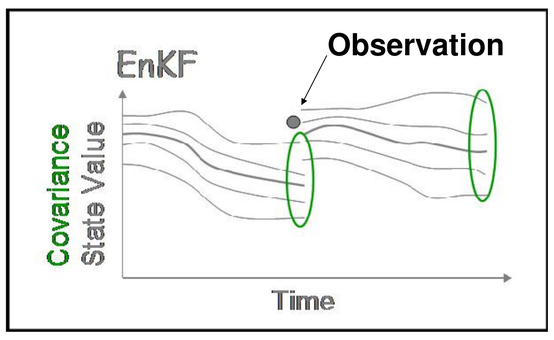
ST_1 to ST_6 → Prognostic soil temperature variables.

Uniform parameters for all layers.

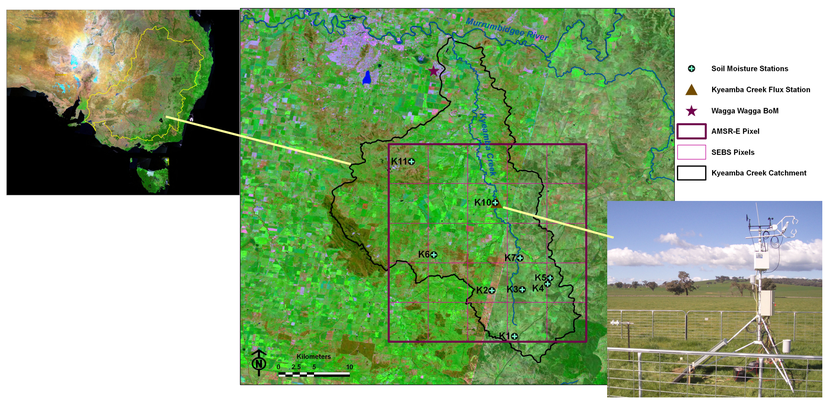
- Richard's eqn. for soil moisture;
- Heat conduction for soil temperature.

Assimilation updates prognostic model states θ1 to θ6 and ST1 to ST6

Ensemble Kalman Filter (EnKF)



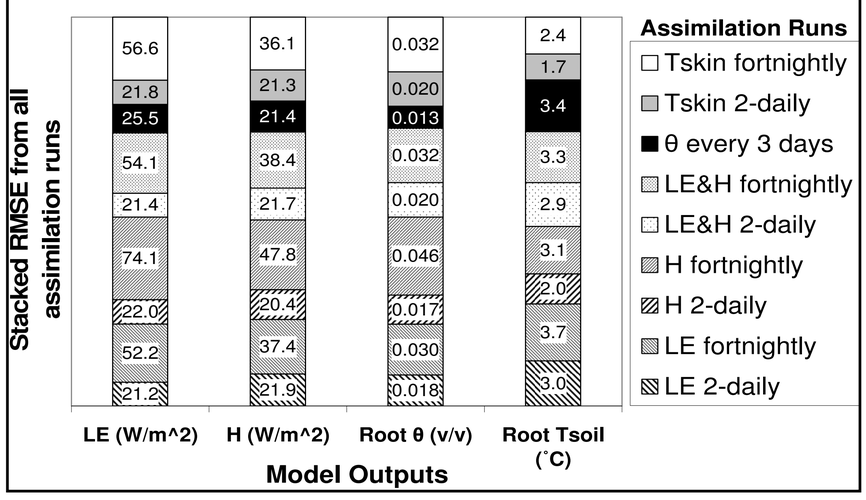
- Propagate ensemble of forecasts by perturbing initial state condition estimates and meteorological forcing data;
- Ensemble spread represents uncertainty → Model error covariance;
- Correction towards observation via innovation (observed minus predicted);
- Relative uncertainty (Kalman gain) between observation and model determines magnitude of correction.



Kyeamba Creek catchment: Flux station and in-situ soil moisture used for experiments 2 and 3. Single 25km pixel of AMSR-E soil moisture (Owe, *et al.*, 2001), and 5km pixels for beta/experimental set of SEBS derived LE and H (Su, *et al.*, 2002; Wood *pers. Comms.*, 2008), used in experiment 3.

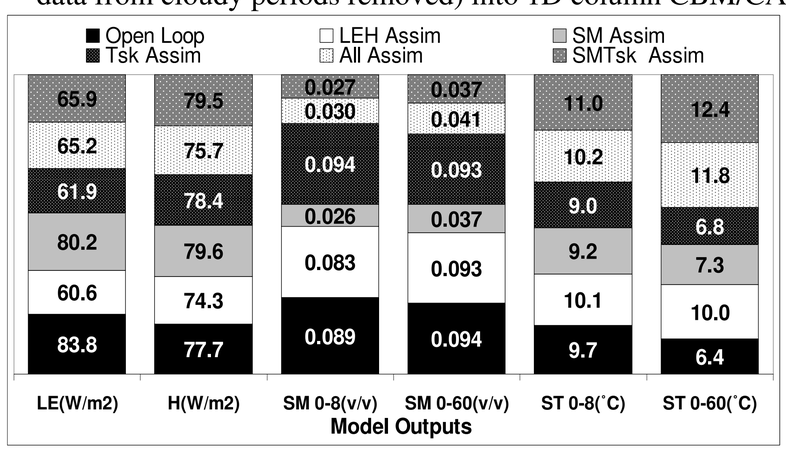
Experiment 1: Synthetic-twin study (Pipunic *et al.*, 2008)

Synthetically derived observations assimilated into "degraded" model scenario on remotely sensed time scales. RMSE between designated "truth" data series and assimilation outputs below:



Experiment 2: 1D Kyeamba Creek field data assimilation study

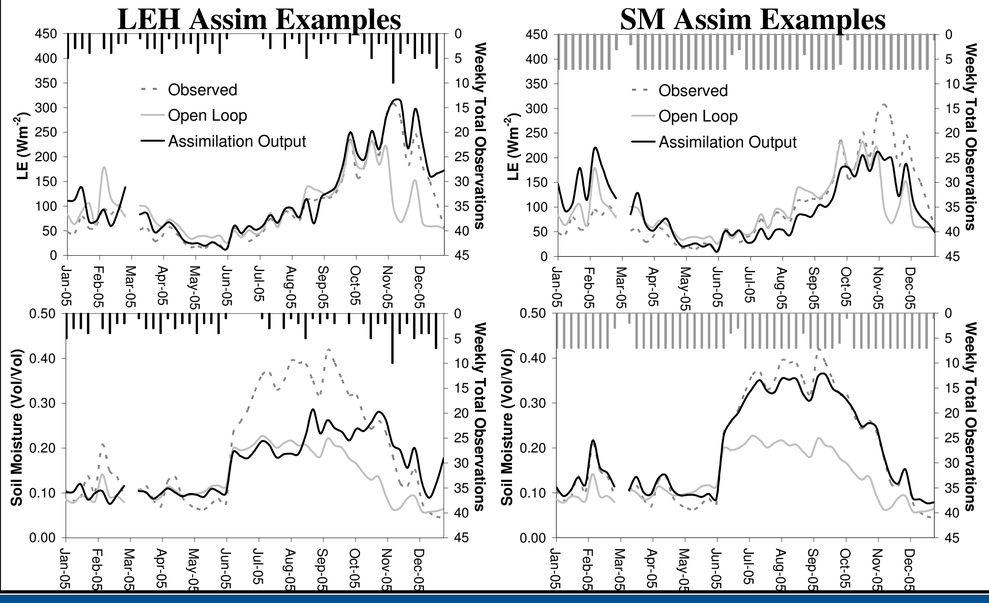
Assimilated in-situ point scale data on remote sensing timescales (LE, H & Tsk data from cloudy periods removed) into 1D column CBM/CABLE set-up



SM → once daily soil moisture

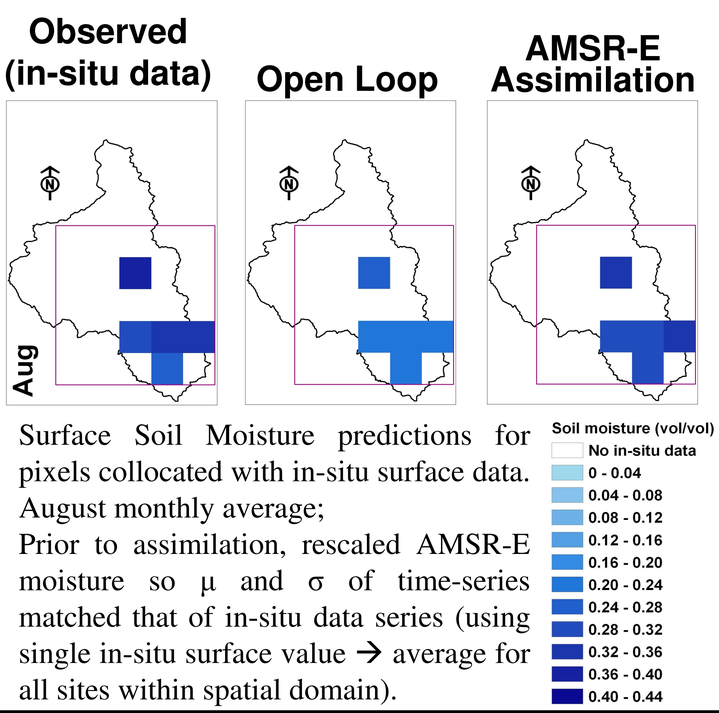
LEH → twice daily LE and H

Tsk → twice daily skin temperature

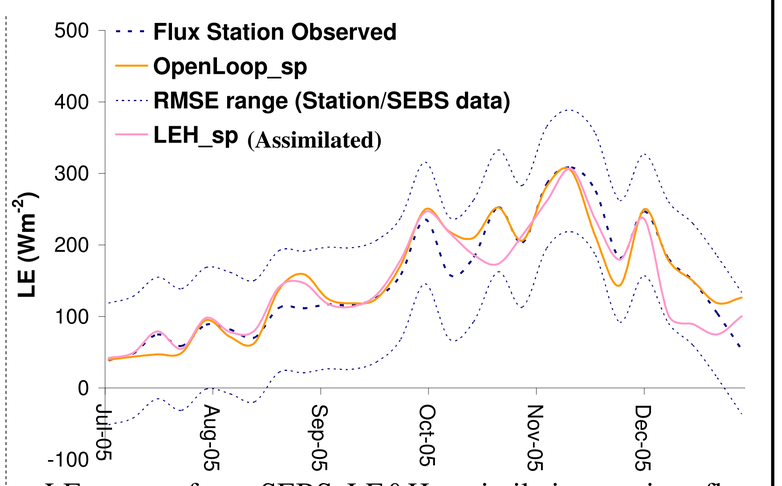


Experiment 3: Spatial modelling (5km res.) for remotely sensed data assimilation study

Separately Assimilated 25km AMSR-E soil moisture data and 5km res. SEBS LE and H data – MODIS AQUA times



- Surface Soil Moisture predictions for pixels collocated with in-situ surface data. August monthly average;
- Prior to assimilation, rescaled AMSR-E moisture so μ and σ of time-series matched that of in-situ data series (using single in-situ surface value → average for all sites within spatial domain).



- LE output from SEBS LE&H assimilation against flux station data (for pixel with flux station);
- Improved model relative to assimilated SEBS data, but not consistent relative to more certain flux station data;
- Large observation uncertainty assigned for assimilation (+/-80Wm^{-2}), Difficult to validate/rescale/define uncertainty for product using single flux station.

Conclusions

- Soil moisture assimilation good for soil moisture predictions but due to imperfect model, limited parameter data etc…….
- LE & H assimilation better for LE & H predictions – despite sometimes poorer state estimates;
- Need more ground validation data for LE and H remote sensing products → could use network of ground monitored data in future work for rescaling uncertain products prior to assimilation;
- Data assimilation has potential as tool to asses model structure for targeting improvements.