Data Assimilation for Better Heat Flux Predictions from Land Surface Models

Robert Pipunic¹, Jeffrey Walker¹, Andrew Western¹
1. Department of Civil & Environmental Engineering, University of Melbourne, Australia robp@unimelb.edu.au

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 initialise 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 CALBE when assimilated, particularly for LE and H predictions? Can data assimilation highlight model limitations? Are there particular challenges to assimilating some data types?

1D Kyeamba Creek field data assimilation study

Experiment 2:

<table>
<thead>
<tr>
<th>CSIRO Biosphere Model (CBM)/CABLE</th>
<th>Ensemble Kalman Filter (EnKF)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Wang &amp; Leuning, 2001; Raupach et al., 1997; Kowalczyk et al., 2006)</td>
<td>Observation</td>
</tr>
</tbody>
</table>

Assimilation updates prognostic model states #1 to #6 and S1 to S6

- LE & H assimilation better for LE & H predictions - despite sometimes poorer state estimates;
- Large observation uncertainty assigned for assimilation (≤50Wm⁻²);
- Difficult to validate/rescale/define uncertainty for product using single flux station.

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 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

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 assess model structure for targeting improvements.