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Can assimilating remotely-sensed surface soil moisture data improve root-zone soil moisture predictions in the CABLE land surface model?

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Abstract

The ability to quantify soil moisture content over depths including the root zone is important for predicting key hydrological processes for a range of applications in agriculture, emergency planning, and weather prediction. Remote-sensing provides a large amount of spatially distributed information related to water balance quantities. This includes brightness temperature data from passive microwave sensors such as the Advanced Microwave Scanning Radiometer for the Earth Observing System (AMSR-E), which is used to estimate surface soil moisture content. Such observations can add valuable information to hydrologic/land surface modelling when combined using data assimilation techniques. However soil moisture from sensors such as AMSR-E can only be retrieved for the top couple of centimetres of soil at most, so assimilating this information into the surface layer of a model needs to constrain soil moisture in deeper layers. This will depend partly on the accuracy of model structure in relating surface moisture dynamics to deeper soil profiles, and also on assumptions made about model errors that can affect how the assimilation algorithm adjusts the model. Here we assimilated AMSR-E soil moisture observations into a CSIRO Atmosphere Biosphere Land Exchange model (CABLE) simulation over the Yanco region in the Murrumbidgee catchment, Australia. We then examined the impact it had on deeper soil moisture profiles (0-30cm and 0-60cm) in CABLE compared to in-situ validation data for two sites. CABLE was not calibrated, however the AMSR-E data were rescaled to match CABLE's soil moisture time series for the year 2005 (where annual rainfall was representative of long term climatology in the study region). The latest remotely-sensed Leaf Area Index (LAI) product from MODIS was also used as a key model parameter input. Initial results after perturbing this data and other inputs, to represent model error for the assimilation process, indicated the stability of assimilation applied to CABLE is sensitive to large perturbations. From subsequent experiments, the impact on predictions over 0-30cm and 0-60cm depth ranges from assimilating AMSR-E surface soil moisture was minimal compared to CABLE predictions with no assimilation, even though there were clear impacts on surface moisture predictions. This study provides direction for more focused research into understanding and representing model error and sensitivity with the help of remotely-sensed information.

Introduction

The growth in remotely-sensed data products related to the terrestrial water cycle is providing opportunities to improve our understanding of hydrological processes, which will ultimately lead to better water management decisions. Remote sensing provides spatially distributed information on fairly regular time intervals that can add value when combined with hydrologic models. This study examines the impact that remotely-sensed surface soil moisture data has on land surface model predictions of root zone soil moisture when it is assimilated. Available in-situ soil moisture data were used only for validation – the aim was to test the assimilation for a realistic scenario (for most of Australia) where the only soil moisture data available is from remote sensing.

Soil moisture content is a key land surface state. Over deeper soil profiles incorporating the root zone it is linked to processes such as groundwater recharge, surface run-off and evapotranspiration, thus quantifying is important for flood forecasting, agriculture and numerical weather prediction. Remotely-sensed soil moisture products derived from passive microwave sensors are considered relatively reliable but are limited by large spatial scale (>10 km) and shallow sensing depth in the soil (~1-2cm). This poses a problem when aiming to constrain a model's root zone moisture with remote sensing over spatial regions – the impact from assimilating a surface observation must be able to translate positively to the model's deeper layers. Many past studies that have demonstrated positive impacts on deeper soil moisture by assimilating surface observations have been controlled synthetic studies (e.g. Pipunic *et al*., 2008; Walker and Houser, 2001). Reichle *et al*. (2007) showed small improvements to deeper soil moisture from assimilating real remotely-sensed data and Draper (2011) showed some improvement in MOSES model (Essery *et al*., 2001) simulations for the Murrumbidgee catchment in Australia. More research is needed into the assimilation of actual remotely-sensed surface soil moisture products and their usefulness for constraining deeper moisture content, specifically for Australian conditions and with models such as the CSIRO Atmosphere Biosphere Land Exchange model (CABLE; Kowalczyk *et al*., 2006) which is planned for implementation in Australia's weather and climate simulation system.

In this study, AMSR-E remotely-sensed surface soil moisture data (Owe *et al*., 2008) were assimilated into the CABLE model using the ensemble Kalman filter (EnKF) algorithm (Evensen, 1994). Raw AMSR-E measurements are of brightness temperature and surface soil moisture is derived using an algorithm, in this case from Owe *et al*. (2008). This algorithm is shown to produce good quality soil moisture data relative to other algorithms in a global evaluation by Crow *et al*. (2010). The EnKF used the remotely-sensed surface data to update soil moisture and temperature state variables for all of CABLE's six soil layers. Implementing the EnKF requires an ensemble of predicted model states to estimate model errors – generated by prescribing input errors to initial state values, meteorological forcing and parameters. An important parameter related to the water balance is Leaf Area Index (LAI) and one of the latest remotely-sensed spatial data products from MODIS (MYD15A2) was used here. The impact of error perturbations on this data was briefly examined.

The Yanco region within the Murrumbidgee catchment in south eastern Australia (Figure 1) was chosen for the study due to the multi-year meteorological and in-situ soil moisture data available from the Oznet network (http://www.oznet.org.au/) that was used for model input and validation. CABLE was run at 5km spatial resolution and the broader 25km scale AMSR-E observations (Figure 1) were assimilated once per day for the descending overpass time of the satellite sensor (~1:30am local time). Analysis of the assimilation focused on two subset domains in the region – one defined by the single AMSR-E pixel containing the in-situ station Y1, and the other defined by the AMSR-E pixel containing the station Y3 (see Figure 1). The impact from assimilating the 25km scale remote sensing product was assessed for both the single 5km model pixels containing in-situ data, and also for the

average across all model pixels within the AMSR-E domain. Moreover, assimilation outputs of soil moisture for the 5km model pixels collocated with in-situ Oznet stations Y1 and Y3 were compared with in-situ soil moisture over the depths 0-30cm and 0-60cm (depth averaged from 0-30cm and 30-60cm field measurements) to assess the impact of assimilating surface moisture data on deeper predictions. Stations Y1 and Y3 were chosen for comparison based on the contrast between uniform soil properties within the AMSR-E domain for Y1 and variable soil properties for model parameterisation within the AMSR-E domain for Y3 (Figure 1).

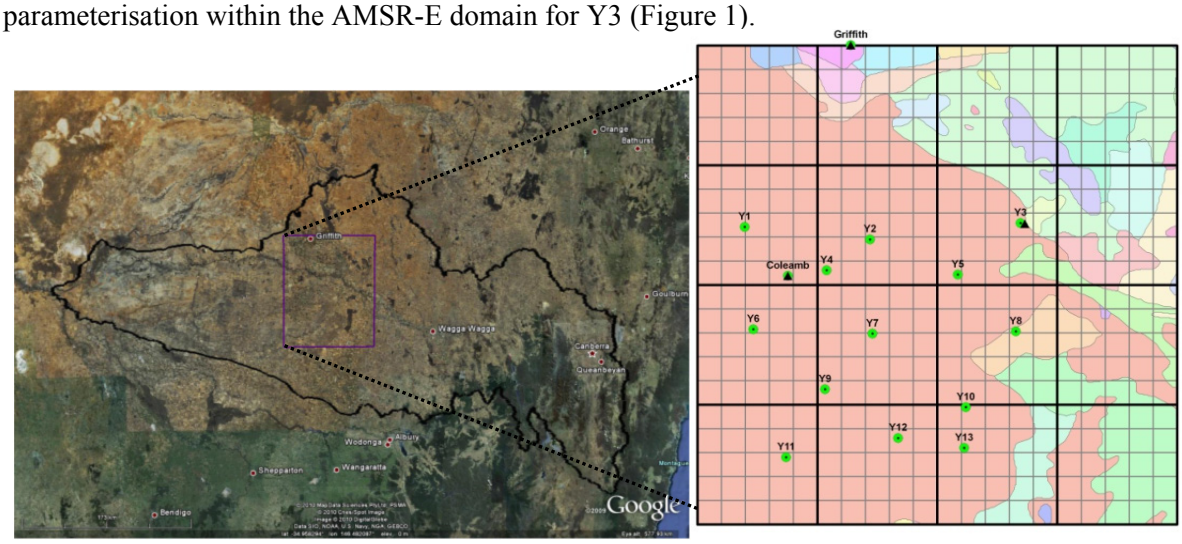


Figure 1: *The square study region within the Murrumbidgee Catchment (black boundary) in the left hand image. A close up on the right shows in-situ soil moisture and meteorological data stations, with coloured polygons representing soil units. The large black squares over the study region are 25km AMSR-E footprints for remotely-sensed surface soil moisture. Grey squares are 5km model simulation pixels. In-situ soil moisture and rainfall stations are represented by yellow points and meteorological forcing data stations by black triangles.*

Data and Models

CABLE calculates water and energy exchanges at the land surface for both bare soil and vegetation surfaces. It consists of six soil layers with thicknesses of 2.2, 5.8, 15.4, 40.9, 108.5 and 287.2cm respectively from top to bottom with the movement of water between layers based on Richard's equation. Bare soil evaporation is based on a Penman-Monteith calculation for potential evaporation which is then weighted by a water availability term based on soil moisture content of the top soil layer. Meteorologic forcing data determines the model time step intervals and drives its integration forward in time and the essential variables include short and long wave incoming radiation, air temperature, rainfall, wind speed and specific humidity. The forcing data and hence model time step integration for this study was 30 minutes.

From Figure 1, forcing inputs were available from Griffith, Yanco (station Y3) and Coleambally (Coleamb), while rainfall which was available at all 15 stations shown. Key soil parameters in the model include wilting point, porosity, and hydraulic conductivity at saturation and were taken from interpretations by McKenzie *et al*. (2000) of Atlas of Australian Soils units displayed in Figure 1. CABLE only accepts a single set of soil parameter data for each soil layer, which may be a limitation if modelling areas with highly contrasting vertical properties in the soil profile. The LAI parameter influences the model energy balance partitioning between soil and vegetation surfaces and hence has implications for moisture use by vegetation. The MYD15A2 MODIS remotely-sensed product used here has 8-day temporal and 1km spatial resolution.

All model inputs (meteorological forcing and parameters) were assigned to the 5km modelling pixels based on collocation with the pixels or on nearest proximity where input data were point scale. The 1km LAI product was spatially averaged within each 5km modelling pixel.

The EnKF is based on the standard form of the Kalman Filter where the differences between modelled and predicted quantities, or the innovation, (in this case between surface soil moisture) are used to determine state update increments, added to state variable predictions (in this study moisture and temperature for all six CABLE soil layers). Innovations are weighted by the Kalman gain, representing the relative uncertainty between model state predictions and observations – a higher uncertainty in model predictions translates to the observations being more trusted with greater weight placed on the innovations, and *vice-versa*. Uncertainty for the EnKF is estimated from the spread of an ensemble of values about the mean or "true" model prediction and observation values, created by prescribing error perturbations to various model inputs and the observations. Forcing data perturbation was guided by analysing differences between station data within the study region. Rainfall is a key input for the water balance and perturbations within ~35% of measured values were added. Perturbations to initial soil moisture and temperature state variable values were arbitrarily done (0.05vol/vol and 5°C respectively), as for key soil parameters including wilting point, porosity and field capacity done within a very small range (~0.001vol/vol). For an initial test simulation, MODIS remotely-sensed LAI data was perturbed based on error analysis from a parallel study by McColl *et al*. (2011).

Estimating observational uncertainty was guided by the work of Draper *et al*. (2009) who assessed the AMSR-E soil moisture product used in this study (Owe *et al*., 2008) against in-situ surface data in different Australian locations including the Murrumbidgee catchment. They determined an overall error range of $\sim\pm 0.03$vol/vol and a conservative range of ± 0.04vol/vol was used for perturbing observed values in this study.

The depth of AMSR-E soil moisture (~1-2cm) is similar to the top soil layer depth in CABLE (2.2cm) however the large spatial disparity required that the spatial average of all 5km simulation pixels within each 25km AMSR-E footprint domain be calculated prior to the innovation calculation. With the 25km scale innovations, subsequent updates were made to individual 5km modelling pixels.

Methods

Initial analysis is required to ensure meaningful comparisons can be made between AMSR-E soil moisture and models as systemic differences are common. They are typically artefacts of the differences between particular retrieval algorithms applied to remotely-sensed data, and the land surface model structure and soil parameter data used in them (especially wilting point and porosity). These issues have been discussed in past studies (e.g. Drusch *et al*., 2005) where the current accepted solution is rescaling the remotely-sensed data series to the model prior to assimilation so that the soil moisture climatology between them matches. This ensures relative changes in moisture storage between the two are comparable and constraints on the model more meaningful.

Two years of data – 2005 and 2006 – were used for the experiments. Rescaling of AMSR-E soil moisture data to CABLE was done for the year 2005 after it was spun-up (5 yearly repeats). The Oznet station forcing datasets produced for modelling the region span from the year 2000 to 2011, generally a very dry period in south-eastern Australia. Compared to long term climate statistics from BoM data for locations in the vicinity of the study region (Bureau of Meteorology climate statistics: (http://www.bom.gov.au/climate/data/), the 2005 annual rainfall total across the 15 Oznet stations used in this study (Figure 1) are representative of the long term annual rainfall climatology. The 2005 AMSR-E data series was rescaled by matching its mean and standard deviation to the spun-up CABLE predictions for the top soil layer using the following:

$$\theta'_{AMSR-E} = \left(\theta_{AMSR-E} - \mu(\theta_{AMSR-E})\right) \times \left(\sigma(\theta_{CABLE}) \Big/ \sigma(\theta_{AMSR-E}) \right) + \mu(\theta_{CABLE}) \,. \qquad (1)$$

From equation (1) the rescaled AMSR-E moisture θ'_{AMSR-E} was calculated using the means ($\mu()$) and standard deviations ($\sigma()$) of both the original AMSR-E moisture (θ_{AMSR-E}) and CABLE moisture (θ_{CABLE}). Other rescaling methods such as CDF matching are common in the literature however there is no consensus yet as to which method is superior. For this study we confined our scope to matching the mean and standard deviation, although future work comparing these methods would be valuable.

To maintain independence the rescaling relationship from 2005 (representative of longer term climate) was applied to the 2006 series of observations and CABLE simulations and assimilation performed for the year 2006 (a severe drought year). Results were examined for two separate AMSR-E domains in the study region – one containing station Y1, and one containing Y3.

Results

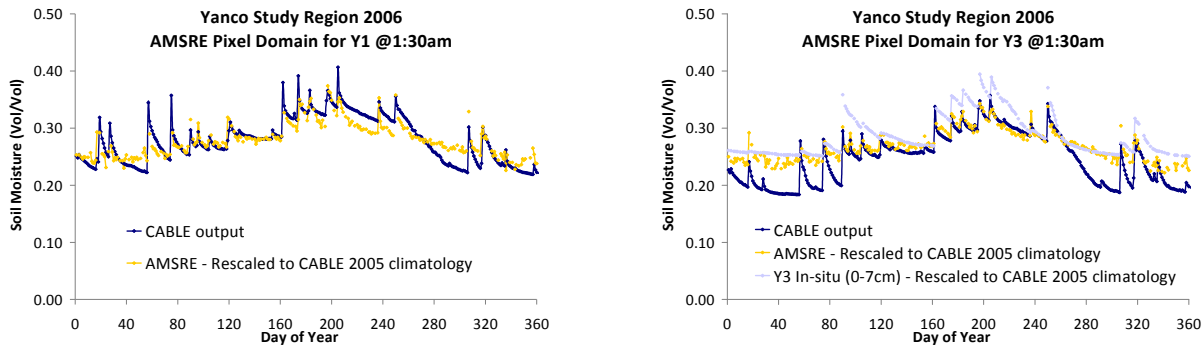


Figure 2: *Rescaled AMSR-E and CABLE top layer soil moisture for 2006 with Y1 domain on the left and Y3 on the right (see Figure 1 map). Available in-situ surface soil moisture data is also shown (available only for Y3).*

Prior to rescaling, the AMSR-E soil moisture data had a very large dynamic range spanning from less than 0.05vol/vol to over 0.50vol/vol across the rescaling year of 2005 for both the Y1 and Y3 domains. Figure 2 illustrates that the rescaling relationship applied to 2006 AMSR-E data resulted in a reasonable fit with CABLE for that year, especially for the Y1 domain. In-situ surface soil moisture data covering this experiment period was only available for Y3 amongst all the Oznet stations and was measured over 0-7cm depth. After also rescaling this data to the 2005 CABLE climatology it was used to independently validate the 2006 rescaled AMSR-E for the Y3 domain. Given the discrepancy in measurement depths and the spatial disparity (point scale v's 25x25km) the AMSR-E data corresponds reasonably well to the in-situ surface soil moisture from Y3 as indicated in Figure 2 and in the statistics in Table 1 below.

Table 1: *Quantitative comparison between the rescaled in-situ surface soil moisture from Y3 and corresponding AMSR-E soil moisture product for years 2005 and 2006. The anomaly correlation is relative to the 2005 mean surface soil moisture from CABLE used in rescaling.*

Year	Correlation coefficient	Anomaly correlation
2005	0.81	0.81
2006	0.88	0.72

Assimilation experiments were subsequently carried out with AMSR-E data and CABLE for 2006. An initial experiment with LAI perturbations (within ± 0.82) based on analysis by McColl *et al.* (2011) produced degraded soil moisture output (not shown here) indicating sub-optimal EnKF performance with large LAI perturbation.

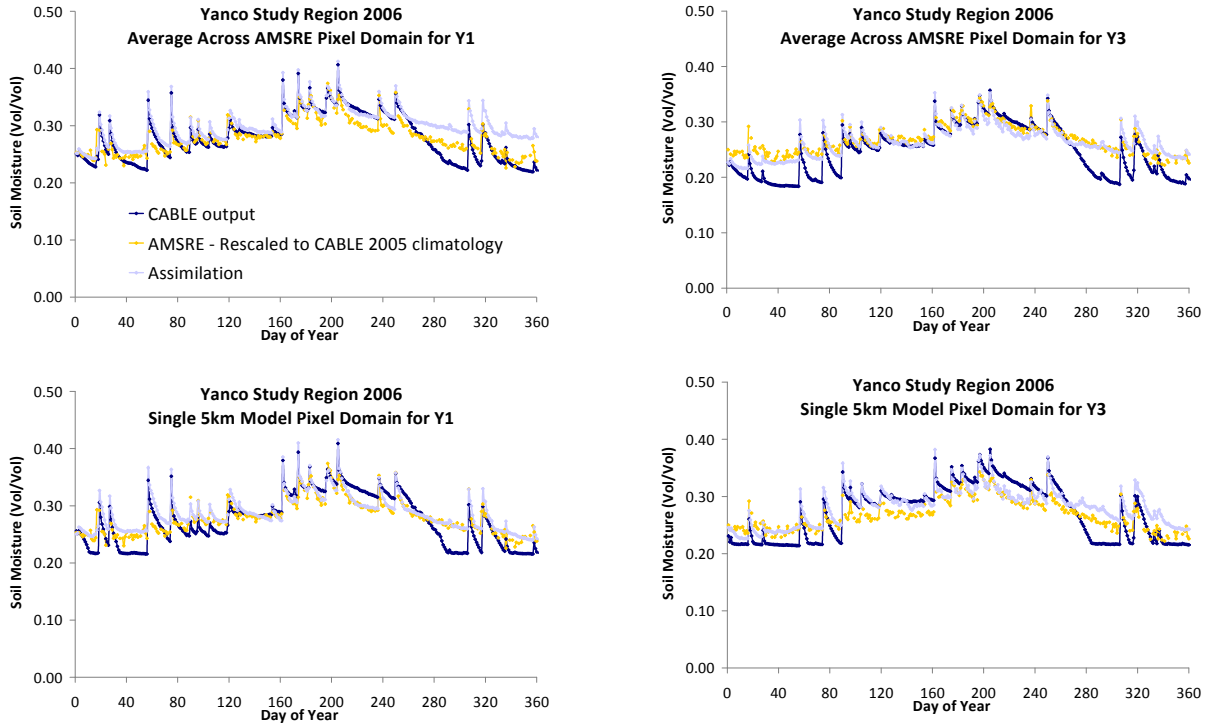


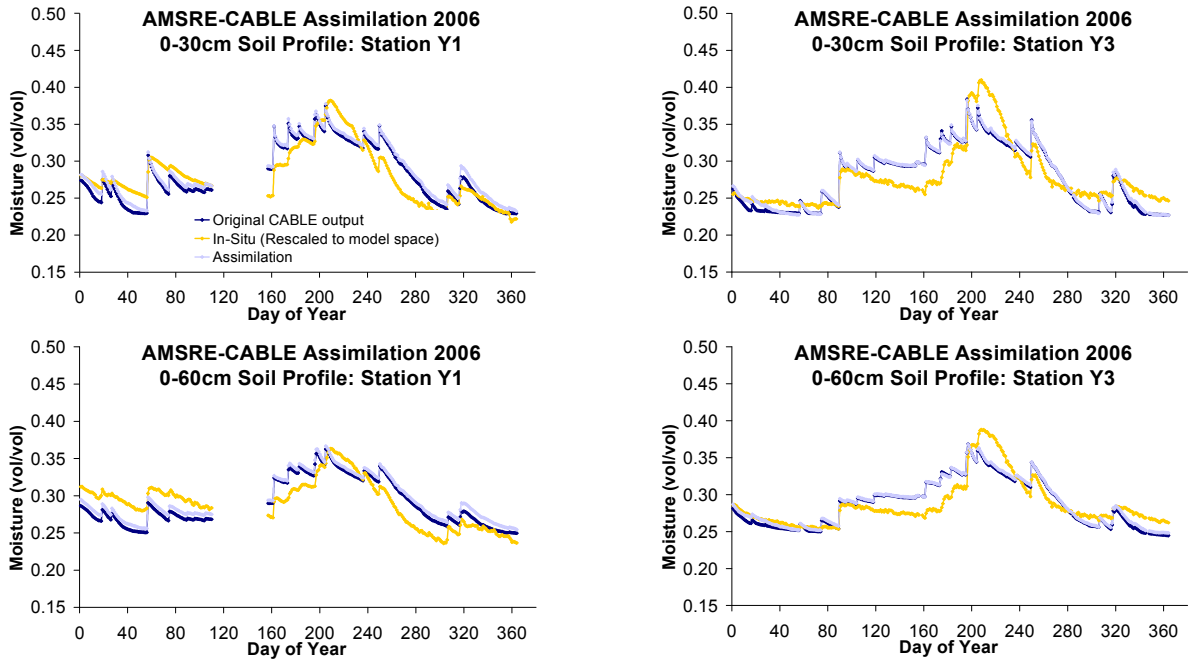
Figure 3: *Assimilation results and original CABLE output for the top soil layer, with assimilated AMSR-E observations at the AMSR-E overpass time (1:30am). Left hand plots correspond to simulation domains for Y1 and right hand plots to Y3. Full AMSR-E domain averages are on the top row and on the bottom are single 5km model pixel outputs collocated with the in-situ stations (see Figure 1).*

Qualitative comparisons shown in Figure 3 indicate the assimilation is working correctly. The assimilation had an overall positive impact in adjusting CABLE's surface soil moisture closer to the assimilated AMSR-E data for both the 25km AMSR-E domain and the 5km modelling domain. An exception is the AMSR-E domain output for Y1 from approximately day 260 onwards where moisture has been adjusted too high. This could be the result of variable impacts across the smaller scale model output in the AMSR-E domain due to spatial variation of forcing data.

The final comparisons in this study were for both Y1 and Y3 modelling pixel domains. In-situ soil moisture measurements for 2006 from the two stations were compared with CABLE soil moisture for 0-30cm and 0-60cm depths to examine whether the surface assimilation of the remotely-sensed information could improve CABLE root-zone predictions. Table 2 summarises of CABLE predictive skill compared to in-situ observations and qualitative comparisons are shown in plots in Figure 4.

Table 2: *Quantitative comparisons between simulation outputs and in-situ soil moisture observations (rescaled to model space). The anomaly correlation is relative to the annual mean from CABLE output used in rescaling.*

		Nash Sutcliffe		Correlation coefficient		Anomaly correlation	
		CABLE	***Assim.***	***CABLE***	***Assim.***	***CABLE***	***Assim.***
Y1	***0-30cm***	0.97	0.96	0.86	0.86	0.86	0.84
	0-60cm	0.96	0.96	0.74	0.75	0.74	0.73
Y3	***0-30cm***	0.78	0.79	0.82	0.83	0.83	0.84
	0-60cm	0.85	0.86	0.84	0.85	0.85	0.86



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The original CABLE outputs are generally well matched with observations at both sites according to the statistics in Table 2 and from Figure 4 plots. The main discrepancy between CABLE and in-situ data appears to be in the rates of change in the wetter mid-year months, where in-situ data displays a quicker wetting to peak moisture and quicker dry-down (especially for Y3). Assimilation impacts for both sites and over both depth ranges are very minimal, despite relatively strong impacts on the surface soil moisture (Figure 3). The most noticeable impacts are slight moisture increases at dryer times in the beginning and at the end of the year, where impacts on the surface moisture were greatest.

Conclusions

The remotely-sensed AMSR-E soil moisture product based on Owe *et al*. (2008) was a reasonable match with CABLE surface soil moisture seasonal trends for the dry year 2006 after rescaling to 2005 moisture climatology (representative of long term rainfall average in the region). Moreover, it was reasonably well correlated with independent in-situ surface soil moisture data that was available for the Y3 site. Hence the AMSR-E product was considered suitable for assimilation.

Assimilation into CABLE's surface layer correctly impacted on the surface layer moisture even for single modelling domain pixels within the larger AMSR-E footprint. Therefore broad scale remotely sensed data can still provide useful information to CABLE for finer scale simulations. With the very minor impact on CABLE root-zone soil moisture, there was no clear evidence of an ability to strongly improve soil moisture prediction for deeper layers using only surface information. The inability to set depth varying parameters in CABLE may contribute to this along with other possible factors such as limitations in model physics or poor error representation in the EnKF. Large LAI error perturbations led to a degraded impact on surface soil moisture from assimilation, highlighting the sensitivity of CABLE and the EnKF performance to error (mis)specification. Further work is warranted to assess AMSR-E data using other surface in-situ data in the region and to examine root-zone impacts across the 11 other in-situ stations in the region to draw more robust conclusions.

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