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Continental satellite soil moisture data assimilation improves root-zone moisture analysis for water resources assessment

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SUMMARY

A framework was developed for the continental assimilation of satellite soil moisture (SM) into an operational water balance modelling system. The ensemble Kalman filter (EnKF) was implemented to assimilate AMSR-E and ASCAT-derived SM products into the landscape model of the Australian Water Resources Assessment system (AWRA-L) and generate ensembles of daily top-layer and shallow root-zone soil moisture analyses for the continent at 0.05° resolution. We evaluated the AWRA-L SM estimates with and without assimilation against *in situ* moisture measurements in southeast Australia (OzNet), as well as against a new network of cosmic-ray moisture probes (CosmOz) spread across the country. Results show that AWRA-L root-zone moisture estimates are improved though the assimilation of satellite SM: model estimates of 0–30 cm moisture content improved for more than 90% of OzNet sites, with an increase in average correlation from 0.68 (before assimilation) to 0.73 (after assimilation); while estimates 0–90 cm moisture improved for 60% of sites with increased average correlation from 0.56 to 0.65. The assimilation of AMSR-E and ASCAT appeared to yield similar performance gains for the top-layer, however ASCAT data assimilation improved root-zone estimation for more sites. Poor performance of one data set was compensated by the other through joint assimilation. The most significant improvements in AWRA-L root-zone moisture estimation (with increases in correlation as high as 90%) occurred for sites where both the assimilation of satellite soil moisture improved top-layer SM accuracy and the open-loop deep-layer storage estimates were reasonably good. CosmOz SM measurements exhibited highest correlation with AWRA-L estimates for modelled root-zones layer thicknesses ranging from 20 cm to 1 m. Slight improvements through satellite data assimilation were observed for only 2 of 7 CosmOz sites, but the comparison was affected by a short data overlap period. The location of some of the CosmOz probes was not optimal for evaluation of satellite SM assimilation, but their utility is demonstrated and the observations may become suitable for assimilation themselves in future.

1. Introduction

Over the past decade many researchers have demonstrated that the assimilation of remotely-sensed soil moisture (SM) products into land surface models can improve soil water balance predictions which can in turn lead to improved estimates of evaporative fluxes, drainage and runoff (e.g. Reichle and Koster, 2005; Brocca et al., 2010; Dharssi et al., 2011; Draper et al., 2011; Pipunic et al., 2013). The ability to constrain water balance estimation over large areas offers great potential for continental water resource assessment, particularly in parts of the landscape where traditional ground observation networks have sparse or intermittent coverage.

Conventional use of satellite observations for water balance studies is *via* the direct or indirect measurement of key components of the water cycle, including precipitation (e.g. Joyce et al., 2004; Huffman et al., 2007; Hou et al., 2008), evapotranspiration (e.g. Anderson et al., 2007; Mu et al., 2007; Kalma et al., 2008; Guerschman et al., 2009), surface soil moisture (Wagner et al.,

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1999; Njoku et al., 2003; Owe et al., 2008), terrestrial water storage through gravitational anomalies (e.g. Rodell et al., 2006, 2009; Van Dijk et al., 2011), river water storage and runoff (Alsdorf and Lettenmaier, 2003; Berry et al., 2005). However, observation-driven attempts to attain water balance closure with these remotely-sensed data have identified errors and biases in the individual data sets, as well as inconsistencies between linked variables, as limiting factors to closure (e.g. McCabe et al., 2008; Sheffield et al., 2009; Gao et al., 2010; Pan et al., 2012).

A water balance modelling system constrained with multiple remotely-sensed and ground-based observations would maximise consistency (closure) among water balance variables and in principle result in improved estimation (particularly in ungauged areas) provided the data are integrated into the modelling system in ways that incorporate both model and observation uncertainties. Data assimilation is one approach to model-data integration that allows optimal combination of model with observations, and improved estimation, provided respective errors are adequately specified. To-date, however, there are very few, if any, such data assimilation systems that are capable of exploiting satellite remote sensing data for operational water resources assessment. Van Dijk and Renzullo (2011) argue that this may be due to the small number of operational missions (and hence data continuity issues) and the generally coarse spatial scale of the satellite data and models used – this is the impetus of the grand challenge of hyper-resolution (1 km) satellite remote sensing proposed for water resource monitoring by Wood et al. (2011).

The Australian Water Resources Assessment (AWRA) system is a high-resolution modelling framework for continental water resources assessment and accounting with model-data integration at the core of its development. Unlike most global land surface models, the AWRA system runs at a fine (~5-km) resolution, is extensively calibrated with surface networks of streamflow, and is driven by high-quality meteorological surfaces derived from surface observations. The AWRA system currently operational in the Bureau of Meteorology does have a component specifically for the assimilation of satellite data into the system, but this functionality remains dormant pending further development and testing. The work presented here describes an aspect of the testing of this data assimilation component.

Specifically, we investigated whether the assimilation of satellite soil moisture products into the landscape water balance model component of the AWRA system (AWA-L) leads to improved moisture estimation in both the top (near surface) layer and in the shallow (<1 m) root zone. The AWRA-L model (described in Section 2.1) is part of a larger modelling system designed to augment surface metering where available and provide comprehensive coverage of key water balance terms for national scale water resources assessment and accounting. The method of satellite data assimilation employed (described in Section 2.2) is a popular and demonstrably effective technique for sequential updating of model soil moisture states where and when satellite data are available.

Evaluating root-zone soil moisture estimation may be considered one of the first steps towards quality assurance of the model performance, as soil moisture is a key variable in the partitioning of rainfall into evaporation, infiltration and runoff, as well as being a quantity of interest (e.g. for drought assessment) in its own right that is reported in annual Australian Water Resources Assessments (Bureau of Meteorology, 2013). While both the satellite soil moisture data used (described in Section 3.1), the data preprocessing and error characterisation (triple collocation, Section 3.2), and the water balance modelling are continental in extent, our evaluations focuses on an *in situ* monitoring network in southeastern Australia (Section 3.3). In addition, this is the first study to evaluate assimilation results against the new cosmic-ray soil moisture probe that is being deployed across Australia. We present (in Section 4) the results of the evaluation of the assimilation results against both ground-based soil moisture monitoring networks, and assess improvement against the unconstrained (open-loop) model estimates.

2. Method

2.1. The Australian Water Resources Assessment landscape model: AWRA-L

The Australian Water Resources Assessment (AWRA) system was developed by Australia's Commonwealth Scientific and Industrial Research Organisation (CSIRO) and Bureau of Meteorology (BoM). The system is comprised of 3 model components: the landscape (AWRA-L), river (AWRA-R) and groundwater (AWRA-G) models. The system generates the water balance terms that underpin the BoM's mandatory reporting on the state of Australia's water resources and is under continual development (Van Dijk and Renzullo, 2011; Stenson et al., 2011). For the investigation presented here, we limited our focus to the landscape model AWRA-L (Van Dijk, 2010).

AWRA-L describes the temporal evolution of water stores and fluxes across a region of interest. Gridded forcing data (spatial estimates of meteorological observations, see Section 2.2) drive the model to produce spatial water balance estimates on a grid of $0.05^\circ \times 0.05^\circ$ cells across Australia. Note that in this system component each cell is modelled independently of its neighbours (i.e. there is no lateral transport of water). Fig. 1 provides a schematic for the AWRA-L model representation of the soil column. Fig. 1a shows the unsaturated zone partitioned into three conceptual soil water stores: the first corresponding to the uppermost soil layer, called the *top layer*; the second corresponding to the part of the soil where water is extracted by shallow-rooted vegetation, referred to as the *shallow root layer*; and the third is where deep-rooted vegetation extract water, referred to the *deep root layer*. Each layer is characterised by a maximum water holding capacity (field capacity) parameter, denoted S_{0FC}, S_{sFC} and S_{dFC} for the top-layer, shallow and deep root soil layers respectively.

Unlike many land surface models, AWRA-L specifies only the water storage, S_z, in the soil layers rather than prescribing a layer thickness and porosity (and θ_{FC} and θ_{WP}) based on pedotransfer functions. This was done to avoid the model parameter estimation equifinality issues (Beven and Freer, 2001) associated with introducing mathematically equivalent parameters into the AWRA-L model. The free parameters with regard to soil layer specification are the field capacity values (i.e. S_{0FC}, S_{sFC} and S_{dFC}); the water availability in Fig. 1b is only used to provide indicative soil layer thicknesses and to aid in the evaluation of the AWRA-L storage estimates against ground data. Viney et al. (2011) describe the method for estimating these field capacity values (among other model parameters) for application of the AWRA system across Australia. Here we have used the values specific to the currently operational version 3.0 of AWRA-L.

The physical thicknesses of the soil layers, Z (mm), can be approximated as,

$$Z = \frac{S_{zFC}}{(\theta_{FC} - \theta_{WP})} \tag{1}$$

where S_{zFC} is field capacity water storage (in mm) for soil layer z, and the difference between field capacity and wilting point for each soil layer in volumetric units, $\theta_{FC} - \theta_{WP}$, represents the soil available water. Spatial estimates of soil water availability from the Australian Soil Resource Information System (Fig. 1b) (http://www.asris.csiro.au) are used to provide indicative estimates of soil layer thicknesses for the top, shallow-root and deep-root layers following