Maximizing the value of satellite soil moisture products

Chun-Hsu Su*, Dongryeol Ryu, Andrew W. Western

Department of Infrastructure Engineering, The University of Melbourne, Victoria, Australia

* csu@unimelb.edu.au

INTRODUCTION

Soil Moisture is a key variable in hydrological and meteorological processes. It has been regarded as an Essential Climate Variable in the *ESA Climate Change Initiative* framework (esa-soilmoisture-cci.org).

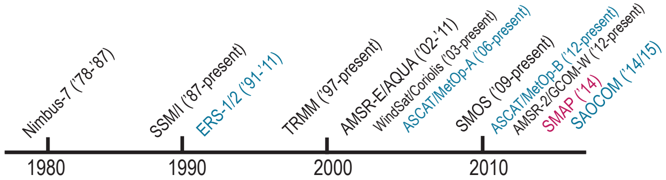


FIGURE 1: Historical, active and upcoming satellites with soil moisture remote sensing capabilities.

Spaceborne radiometers and scatterometers provide global mapping of surface soil moisture in 2-3 days repeat time.

The active missions can provide near real-time retrievals of soil moisture for many prospective operational applications in hydrological and numerical weather prediction modelling,

Satellite records dating back to 1978 are also valuable inputs for re-reanalysis.

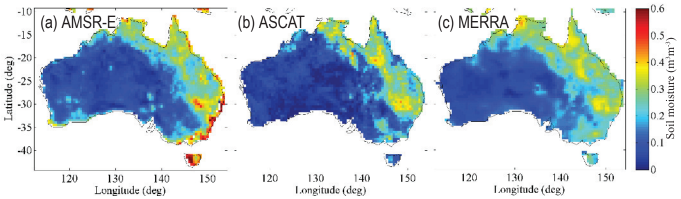


FIGURE 2: Average soil moisture by AMSR-E, ASCAT, and NASA-GMAO MERRA model from 1/1/2011-3/1/2011.

To interpret satellite data correctly or assimilate them into models, we need to,

1. **Estimate and characterise their error structures;**
   - Suitable for modelling end users
   - Allowing probabilistic model forecast
   - Optimal Kalman filtering
2. **Define an observation operator to translate the moisture information from observation space to model space;**
   - Suitable for modelling end users
   - Allowing direct comparisons between different soil moisture products
   - Data fusion
3. **Remove the errors to allow better interpretation of trends and variations.**
   - Enabling direct inspection of soil moisture dynamics
   - Suitable for non-modelling end users

ERROR CHARACTERISATION & OBSERVATION OPERATOR

Estimates of soil moisture by satellite remote sensing and from land-surface and hydrometeorological models, can show considerable differences, due to their differences in support and the presence of measurement errors (sensors, background, attenuations, retrieval, etc). This undermines our ability to make direct comparisons of different estimates, and to undertake data fusion and assimilation.

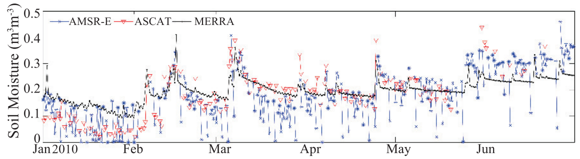


FIGURE 3: Time series of soil moisture estimates at Kyeamba Creek, SE Australia.

Triple collocation [1] solves this problem by assuming an affine, stationary model and using covariances amongst 3 coincident and independent data sets.

Using model and satellite soil moisture with triple collocation enables an understanding of the influence of vegetation and land cover on the retrieval errors [2].

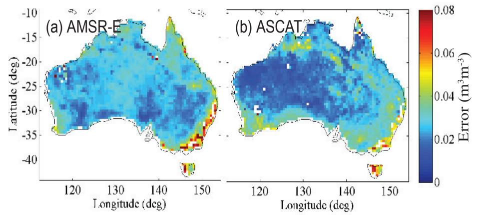
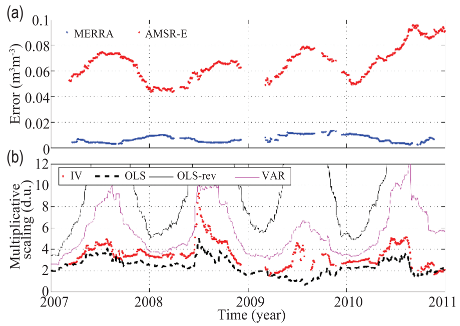


FIGURE 4: Spatial errors of AMSR-E and ASCAT soil moisture products, estimated using 2007-2011 data with triple collocation.

The requirements of 3 independent data, large data sample, stationary statistics and linearity of the scaling model within estimation periods are difficult to realise in practice.

Triple collocation can be generalised as the method of instrument variables (IV), allowing for possibility of estimating error and scaling relationships based on 2 autocorrelated time series by using a short-time windowing and lagged variables [3].



There exists seasonal variations in errors and multiplicative biases between model and satellite soil moisture. This information is vital for data assimilation.

Standard 2-data estmators, ordinary least-square (OLS) and variance-matching (VAR), are sub-optimal [3,4].

FIGURE 5: Estimation of time varying (a) errors in AMSR-E and MERRA, and (b) multiplicative biases between them at Kyeamba Creek.

DE-NOISING IN FOURIER DOMAIN

Spectral analysis provides a powerful method to examine satellite data; and combined with digital signal processing theory, the means to optimally remove the stochastic noise in the data.

Small-time scale surface soil moisture time series are a mixture of diurnal cycle from surface heating, irregular fluctuations from individual rainfall wetting, and transient exponential-like decay by loss. The water balance and these physical processes suggests that the small-time scale soil moisture dynamics will mimic *Brownian motion* with a brown spectrum.

However satellite data shows the presence of stochastic noise and systematic periodic errors. **Accordingly, a spectral model of erroneous satellite soil moisture was developed [5].**

Wiener filtering formalism combined with a spectral description of satellite data defines an optimal low pass filter H_L that retains the brown spectrum characteristics. Bandstop filters H_B remove extraneous spectral peaks.

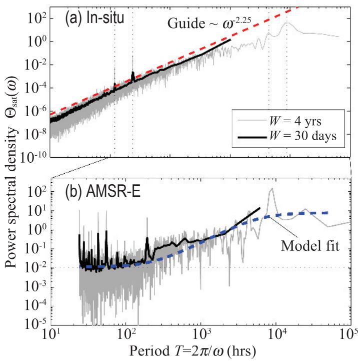


FIGURE 6: Power spectral density of (a) in situ and (b) AMSR-E soil moisture time series at Kyeamba. Their spectra can be fitted with a water balance model.

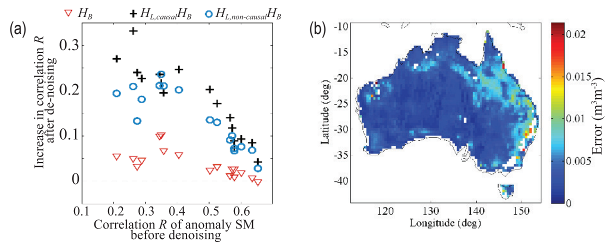


FIGURE 7: (a) Evaluation of the de-noised AMSR-E product against (a) in situ measurements at Murrumbidgee. (b) Spatial error map of denoised product using triple collocation (compare with Fig. 4a).

The Wiener and bandstop filters have shown to remove the stochastic noise in the data and improve its correlations against ground truth. Together with gap-filling, they can produce continuous global soil moisture maps.

REFERENCES AND ACKNOWLEDGEMENTS

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