High resolution soil moisture mapping

J.P. Walker, G. Dumedah, A. Monerris, Y. Gao, C. Rüdiger & X. Wu
Civil Engineering, Monash University, Australia

R. Panciera
CRC – Spatial Information, University of Melbourne, Australia

O. Merlin
CESBIO, France

R. Pipunic & D. Ryu
Infrastructure Engineering, University of Melbourne, Australia

M. Zreda
Hydrology and Water Resources, University of Arizona, United States

ABSTRACT: Soil moisture information is of critical importance to real-world applications such as agriculture, water resource management, flood, fire and landslide prediction, mobility, soil hydraulic parameter estimation etc. Many of these applications require soil moisture information at high resolution. While this may be estimated from land surface models, the predictions are often poor due to inadequate model physics, poor parameter estimates and erroneous atmospheric forcing data. An alternative is remote sensing but most techniques only give a soil moisture estimate for the top few centimetres. Moreover, the sensors that give the most reliable soil moisture estimates (passive microwave) have relatively low spatial resolution from space, being on the order of 50km. Such sensors include the European Space Agency (ESA) Soil Moisture and Ocean Salinity (SMOS) mission launched in Nov 2009, and the National Aeronautics and Space Administration (NASA) Soil Moisture Active Passive (SMAP) mission scheduled for launch in Oct 2014. Other high spatial resolution satellite observations such as active microwave, visible and thermal have been shown to contain information on soil moisture, but their data is noisy and/or difficult to interpret. However, it is expected that the low resolution passive microwave data may be downscaled using the noisy high resolution data and/or modeling. For example, SMAP will provide a better than 10km resolution soil moisture product by merging 3km active microwave data with 40km passive microwave data. This paper presents some examples of high resolution soil moisture mapping from ground and airborne techniques, combined active-passive satellite soil moisture retrieval, optical downscaling, and assimilation into a high resolution land surface model.

1 INTRODUCTION

Accurate knowledge of spatial and temporal variation in soil moisture at high resolution is critical for achieving sustainable land and water management, and for improved climate change prediction and flood forecasting (Entekhabi et al. 1996, Alemaw et al. 2006). Such data are essential for efficient irrigation scheduling and cropping practices, and the accurate initialisation of climate prediction models, so that reliable climate forecasts can be obtained for land management. With agriculture being by far the largest water user in Australia, even moderate water savings of 10% in that sector would lead to a water saving equivalent to one third of the total consumptive use by our capital cities (ABS 2006). Moreover, soil moisture information is needed for setting the correct antecedent moisture conditions in flood forecasting models. The fundamental limitation is that spatial and temporal variation in soil moisture is not well known or easy to measure, particularly at high resolution over large areas. Techniques for estimating soil moisture include ground, airborne and satellite measurement technologies, and combinations with modeling systems.

Over the past three decades there have been numerous soil moisture remote sensing studies, using thermal infrared (surface temperature) and microwave (passive and active) electromagnetic radiation. Of these, microwave is the most promising approach due to its all weather capability and direct relationship with soil moisture through the soil dielectric constant. Whilst active (radar) microwave sensing at L-band (1.4GHz) has shown some positive results (Baghdadi & Zribi 2006), passive (radiometer) microwave measurements have a reduced sensitivity to land surface roughness and vegetation cover (Njoku et al. 2002), meaning that passive microwave techniques have the most promise. However, spaceborne passive microwave data suffers from being a low spatial resolution measurement and approaches for downscaling (improving the effective resolution) are required. Consequently, when considering airborne and satellite technologies, this paper places an emphasis on passive microwave approaches and the current downscaling options under consideration.

Moreover, this paper discusses the role of land surface models to both downscale the satellite observations and to yield a root-zone (top 1m) soil moisture map, rather than the near-surface (top 5cm) values typically observed. Calibrating land surface models to remotely sensed soil moisture also affords the possibility to retrieve soil hydraulic parameters.

2 GROUND BASED MEASUREMENT

2.1 *Hydraprobe Data Acquisition System*

The Hydraprobe Data Acquisition System (HDAS) is a spatially enabled soil moisture, temperature and salinity measurement platform that logs all relevant information into GIS (Geographic Information System) format using ArcPad®. It has been developed over the last 5 years by authors of this paper and consists of a Stevens® Water hydraprobe and a GPS (Global Positioning System) enabled handheld computer running GIS software and a custom script (see Fig. 1). This pocket PC is used to:

- display a map of the sampling area and grid;
- communicate with the GPS receiver to get the real time position;
- display the location on a background map;
- communicate with the hydraprobe to take readings of soil moisture, temperature and salinity;
- obtain metadata including sample date, time, ID;
- input any additional observations as required;
- store the metadata, position information and hydraprobe readings in a GIS shape file; and
- display the location of the recorded measurements on the map.

The hydraprobe determines soil moisture and salinity by making a high frequency (50 MHz) complex dielectric constant measurement. The hydraprobe sensor provides four voltage outputs that can be converted to soil moisture, temperature and salinity using proprietary relationships of Stevens® Water, according to three pre-defined soil types. Additionally the real and imaginary parts of the soils dielectric constant are derived. Like most soil dielectric sensors, the output is soil temperature dependent, and is thus integrated with a thermocouple.

The accuracy of the hydraprobe soil moisture output has been found to be poorer than the stated manufacturer accuracy by several independent field tests; this was observed particularly in clay soils characterised by warm temperatures. Moreover, in clays, the standard output showed highly reduced sensitivity to changes in soil moisture when wetter than $0.3m^3/m^3$. Therefore the HDAS system uses an advanced soil moisture relationship developed though extensive laboratory analysis, with a demonstrated field accuracy of $0.035m^3/m^3$ over a variety of soil types (Merlin et al. 2007). It is also more reliable with respect to soil temperature variations, particularly in clay soils.

The HDAS allows rapid monitoring of top 5cm soil moisture for large areas as shown in Figure 2.

2.2 *COSMOS Rover*

The COsmic-ray Soil Moisture Observing System (COSMOS) is a stationary sensing device that gives soil moisture information averaged over a footprint size of approximately 600m and a depth of around from about 70cm in very dry soils to about 15cm in

Figure 1. The Hydraprobe Data Aquistion System (left) and COSMOS Rover (right).

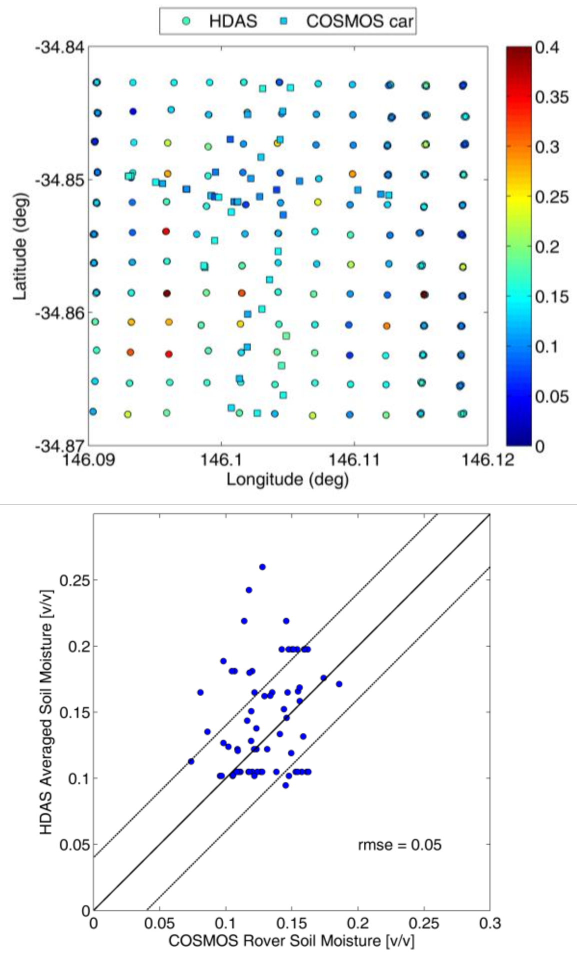

Figure 2. High resolution soil moisture map using the Hydraprobe Data Acquisition System (HDAS) at 250m spacing and the COSMOS Rover at a grassland site on 5th September 2011 (top). Comparison of HDAS and COSMOS Rover estimates of soil moisture (bottom).

saturated soils, by measuring the fast neutron intensity in the air (Desilets et al. 2010, Zreda et al. 2011). A new mobile version of this system is called the COSMOS Rover (Fig. 1). In this implementation multiple cosmic ray sensing tubes are put into the back of a vehicle and driven around the sampling area, with time-integrated readings logged each minute together with a GPS location, altitude, pressure and time. Thus, this system yields soil moisture information averaged over a footprint approximately 600m wide and whose length depends on the speed of the vehicle (Zreda et al. 2011).

This system was installed in a 4WD vehicle and used to make soil moisture surveys over a 3km × 3km grassland area in the Murrumbidgee River catchment, NSW, Australia during September 2011. Area-averaged soil moisture from the COSMOS Rover measurements are compared to top 5cm HDAS soil moisture measurements on a 250m grid (Fig. 2). The root mean square error (RMSE) between ground sampled and estimated soil moisture was found to be $0.05m^3/m^3$, which is close to the HDAS systems accuracy. Thus, results are encouraging for the potential use of COSMOS Rover to fill the gap between detailed ground measurement systems such as HDAS and remote sensing systems.

3 AIRBORNE MEASUREMENT

A new airborne sensing system (Fig. 3) provides the capability to economically map near-surface soil moisture at spatial resolutions of 50m across large areas. This capability allows greater areas to be covered in better spatial and temporal detail than what is possible from traditional ground based techniques. The approach is based on brightness temperature measurements which represent the soil emission at microwave wavelengths. In this application measurements from an airborne Polarimetric L-band Multibeam Radiometer (PLMR) are used together with ancillary information on soil temperature and vegetation water content, in order to make the soil moisture measurement. Using such an airborne system, an area of $300km^2$ can be mapped in just a few hours at 50m resolution, for an equivalent cost of mapping an area two orders of magnitude smaller using advanced ground based techniques such as the HDAS. An example of results from such a soil moisture mapping system is shown in Figure 3 for wet and dry conditions (Walker et al. 2008).

The airborne PLMR observations and ground HDAS data for this example were collected during the National Airborne Field Experiment (NAFE) conducted during November 2005 in the Goulburn River catchment, NSW Australia (see www.nafe.unimelb.edu.au). A sequence of high resolution flights were made across a focus farm using the PLMR between October 31 and November 25.

To obtain soil moisture maps from PLMR brightness temperature observations, the effect of across-track angular variations in the aircraft data were first corrected by referencing to a common incidence angle of 38.5º, corresponding to the outer beams. Using simple averaging of all observations falling within each grid cell the brightness temperature data were then binned to a regular 50m grid. The land-cover type of each pixel was also estimated using a 30m LandSat Thematic Mapper land cover classification for the purpose of setting vegetation specific radiative transfer parameters from tables of best estimates. In this example ancillary data on soil texture and temperature were determined from data collected at the focus farm. Soil moisture was then retrieved using the dual-polarised brightness temperature observations and the standard tau-omega model (Wigneron et al. 2007), by matching predicted soil and vegetation brightness temperature contributions to the observations.

Figure 3 shows the derived high resolution soil moisture maps made across a focus farm in the Krui area of the Goulburn River catchment on two dates, together with the coincident ground survey maps made of that farm using the HDAS. The spatial pat-

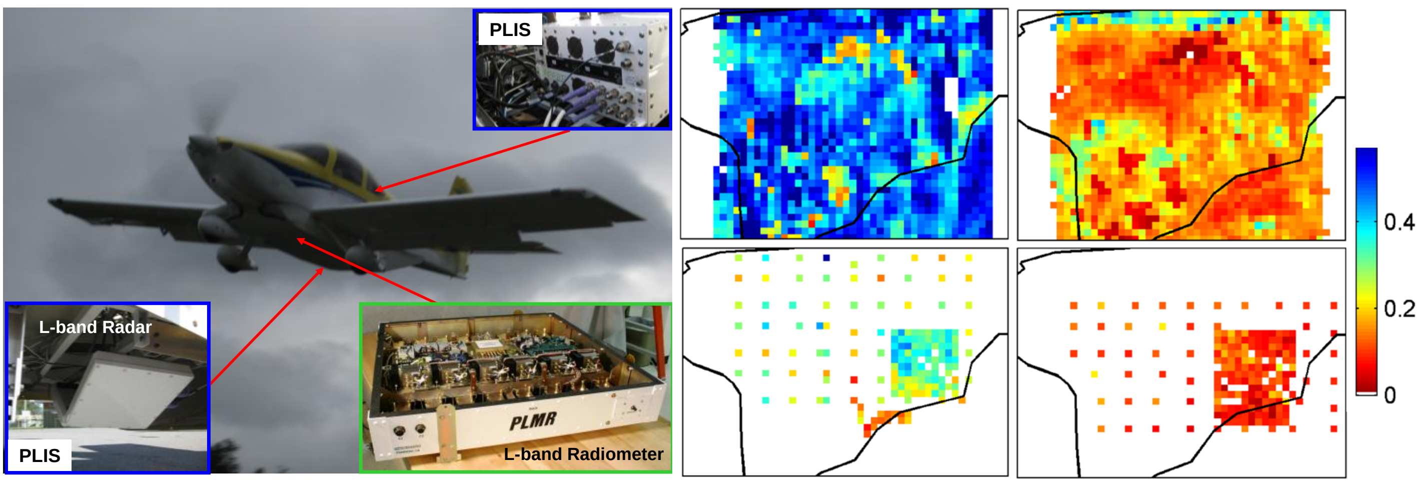

Figure 3. Airborne soil moisture mapping system including L-band radar and radiometer (left) and derived soil moisture maps at 50m spatial resolution on the 3rd and 17th November 2005 using the L-band radiometer (top right), as compared to ground measured soil moisture using the HDAS (bottom right). Units are volumetric soil moisture fraction.

terns in these plots show that the more highly elevated hill tops are typically drier than the lower valley bottoms, as expected. There is also a good general agreement with the ground data, when keeping in mind that the airborne sensor gives an integrated measurement over an area of approximately 2,500m^2 while the ground data are in most cases individual point measurements of 25cm^2. A quantitative comparison between the airborne and field soil moisture data gave an overall retrieval error less than 0.04m^3/m^3. On the 3rd November the RMSE was 0.033m^3/m^3 with zero bias while on the 17th November the RMSE was 0.027m^3/m^3 with a bias of 0.015m^3/m^3. Consequently, airborne passive microwave remote sensing provides a viable tool for high resolution soil moisture mapping across large areas, with an accuracy and detail that is not achievable from traditional ground based approaches.

4 SATELLITE MEASUREMENT

4.1 *L-band radiometer with optical downscaling*

The European Space Agency (ESA) launched the Soil Moisture and Ocean Salinity (SMOS) satellite in November 2009, being the first-ever dedicated soil moisture mission based on L-band passive microwave radiometry. However, space-borne passive microwave data at L-band suffers from being a low spatial resolution measurement, on the order of 40km, meaning methods need to be developed to provide the higher resolution products demanded by many applications. DisPATCh (Disaggregation based on Physical And Theoretical scale Change) is one algorithm under development for downscaling SMOS. This method uses high-resolution skin temperature data from optical sensors that are subsequently used to estimate evaporative fraction, which is correlated with soil moisture spatial variability (Merlin et al. 2008, 2012).

DisPATCh has been applied to SMOS data over the 500km × 100km AACES (Australia Airborne Calibration/validation Experiments for SMOS) area in the Murrumbidgee Catchment, NSW Australia (see www.aaces.monash.edu.au). The 40km resolution SMOS soil moisture was disaggregated to 1km resolution using the MODIS (Moderate Resolution Imaging Spectroradiometer) skin temperature data (Fig. 4). The 1km downscaled data were subsequently compared with the AACES intensive ground measurements aggregated at a 1 km resolution. Although a persistent dry bias of 0.08m^3/m^3 was present in the disaggregated data, the correlation between downscaled SMOS and in situ data at 1 km resolution was about 0.7 when applying DisPATCh.

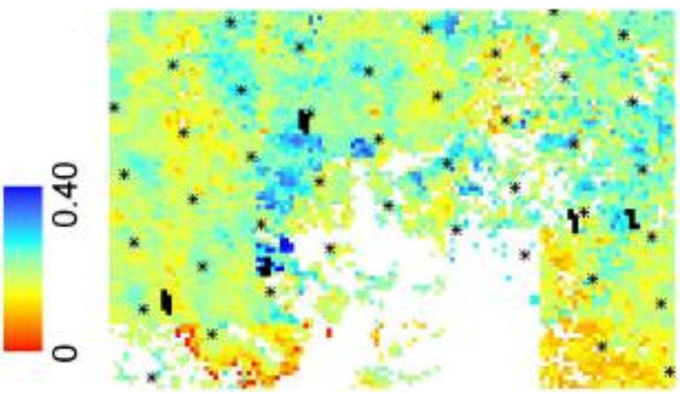

Figure 4. Possible 1km resolution downscaled soil moisture from SMOS using an optical downscaling scheme with data from MODIS. Results are from 18th February 2010 in the Murrumbidgee Catchment, NSW Australia. Units are volumetric soil moisture fraction.

4.2 *L-band radar and radiometer retrieval*

The National Aeronautical and Space Administration (NASA) is currently developing its soil moisture dedicated mission called Soil Moisture Active Passive (SMAP), with a scheduled launch date of 2014. The basis of SMAP is that high resolution (3km) but noisy soil moisture data from a L-band radar will be used to downscale accurate but low resolution (40km) soil moisture data from a radiometer to 10km. While the active passive downscaling algorithm for this mission is still under development, the potential for enhancing low-resolution passive microwave soil moisture retrieval using noisy but high-resolution active microwave data has been demonstrated.

Information from the two sensors has been combined within the framework of a system state estimation model based on Bayesian probabilistic theory (Zhan et al. 2006). However, this study relied upon synthetically generated radar and radiometer observations produced by land surface models, thus requiring significant assumptions to be made. It was found that the Bayesian merging method produced the best soil moisture retrievals compared with traditional numerical inversions of the radar or radiometer observations alone, with an average RMSE of 3km soil moisture retrievals of 0.038m^3/m^3 (Fig. 5).

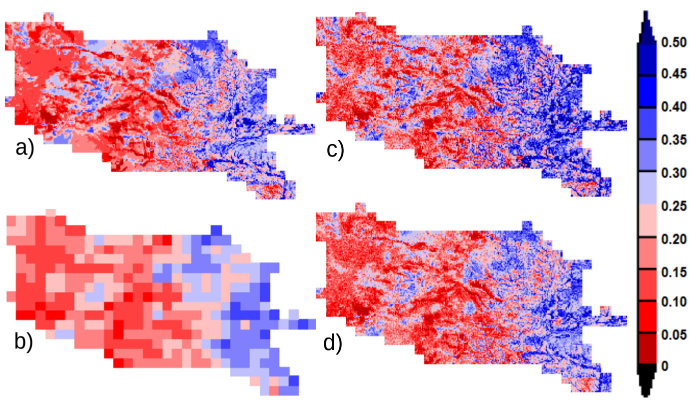

Figure 5. Soil moisture data expected from SMAP for the Red Arkansas River basin with simulated fields of a) 3km truth soil moisture, and satellite retrieved soil moisture for b) 40km L-band radiometer observations, c) 3km L-band radar observations and d) 3km merged L-band radiometer and radar observations. Units are volumetric soil moisture fraction (from Zhan et al, 2006).

In comparison the direct radar backscatter inversions resulted in a RMSE of $0.060m^3/m^3$. Likewise the direct radiometer inversion had a RMSE of $0.063m^3/m^3$ when evaluated against the 3km spatial resolution truth.

Research is currently underway by the authors of this paper to develop and validate the SMAP downscaling concept using real airborne observations in place of the synthetic observations, using the airborne simulator shown in Figure 3. Here radiometer (PLMR) and radar (PLIS) observations collected at 1km and 10m resolution, respectively, will be used directly and aggregated to the SMAP resolutions of 40km and 3km to simulate the SMAP data streams. The Bayesian methods proposed by Zhan et al. (2006) will then be applied, to combine the observations and their relative uncertainty, and estimate soil moisture at intermediate resolutions.

5 LAND DATA ASSIMILATION

Land surface models such as the Joint UK Land Environment Simulator (JULES) can be used to estimate the spatio-temporal variation in soil moisture throughout the soil root-zone. The resolution of such estimates is limited only by the spatial information content in the input variables such as soil and vegetation properties, and precipitation. The advantage of using models over observational data is that soil moisture estimates can be made continuous through time, and information on the root-zone can be obtained in addition to the near-surface layer. While such model estimates are limited by the accuracy of the model physics, model input parameters and precipitation forcing, it has been demonstrated that these effects can be reduced by constraining the model predictions with near-surface soil moisture observations such as those available from SMOS.

Figure 6 shows an example of near-surface and root-zone soil moisture estimates from JULES on 10th March 2010. The JULES land surface model implementation here has used (i) soil data from the Australian Soil Resource Information System, (ii) land cover data from the National Dynamic Land Cover Dataset, and (iii) hourly forcing data from the Australian Community Climate and Earth-System Simulator numerical weather predictions. Consequently the JULES soil moisture has been estimated at the resolution of the forcing data of approximately 10km, with spatial variation in soil moisture reflecting the spatial variation in soil properties, land cover, and precipitation across the catchment. Also shown is the near-surface soil moisture observed by SMOS on the same day. Whilst some similarities in patterns exist, there are also substantial differences.

These preliminary comparisons are important to quantify the level of correction to be applied to the JULES model soil moisture estimates, and to identify areas with erroneous satellite observations. An added advantage of determining soil moisture from models is that with the generation of ensemble predictions, satellite observations can be used to correct the impact of uncertainties from input data (land cover, soil, and precipitation). Consequently, the use of ensemble prediction and correction allows a learning capability to improve model outputs.

6 CONCLUSIONS

Soil moisture is an important variable for a range of applications. Moreover, there is a demand for information on its spatio-temporal variation at better than 10km spatial resolution over the root-zone.

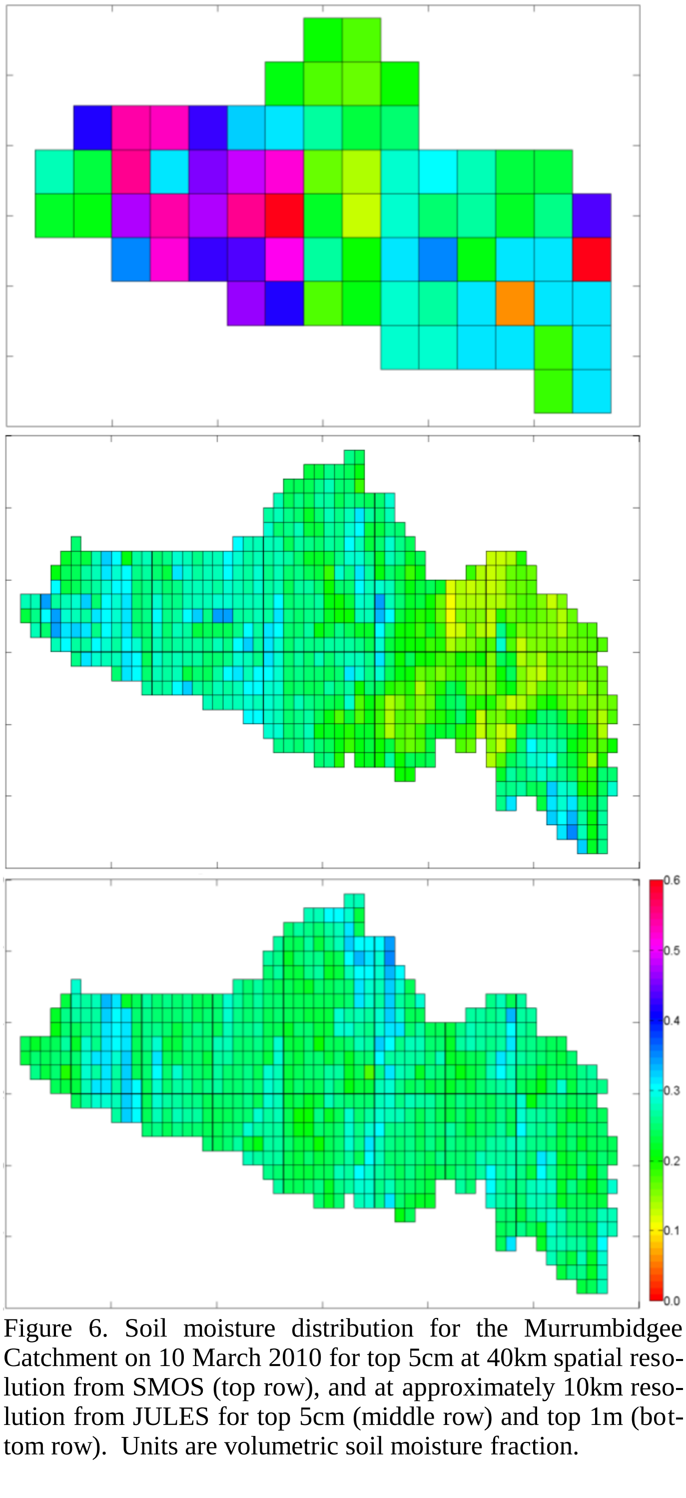

Figure 6. Soil moisture distribution for the Murrumbidgee Catchment on 10 March 2010 for top 5cm at 40km spatial resolution from SMOS (top row), and at approximately 10km resolution from JULES for top 5cm (middle row) and top 1m (bottom row). Units are volumetric soil moisture fraction.

Significant challenges currently exist for providing this information in near-real-time to applications. However, advances have been made and more are expected within the next 5 years.

There is already a capability to undertake rapid ground-based near-surface soil moisture mapping across focus areas with an accuracy better than $0.05m^3/m^3$ for validation of model, airborne and other approaches. There is also a capability to make near-surface soil moisture maps at spatial resolutions from 50m to 1km across areas of $500km^2$ to $5,000km^2$ respectively, with an accuracy better than $0.04m^3/m^3$. However, the implementation of these approaches is limited by the ability to provide regular information through time across large areas, and throughout the entire soil profile.

Passive microwave observations from satellites such as SMOS and SMAP can provide near-surface soil moisture data with a 2-3 day repeat and spatial resolution better than 10km when downscaling techniques using optical and/or radar data are applied. However, these products are still being matured, and do not provide any direct information on root-zone soil moisture.

Models can be used to estimate the soil moisture variation through space and time but are limited by the accuracy of model physics and input data.

Consequently a combination of the above approaches is required, including ground and airborne data for validation of emerging satellite products and downscaling methodologies, and satellite data used collectively with land surface model predictions to provide observational constraint to model predictions, thus offsetting errors from model physics and input data. The land surface model not only interpolates the satellite data through time, but extrapolates it to deeper depths in the soil profile, and can additionally downscale the low resolution satellite data where higher spatial information content are available through precipitation and/or soil and vegetation property inputs is available. The ground and airborne data can also play an important role in the validation of such model data assimilation results.

7 ACKNOWLEDGEMENTS

The research results in this paper have been made possible through infrastructure (LE0453434 and LE0560930) and research (DP0557543, DP0556941, DP0879212, DP09845861) funding from the Australian Research Council, and an infrastructure grant (ATM-0838491) from the National Science Foundation (USA). Initial setup of the study catchments was funded by research grants (DP0209724 and DP0557543) from the Australian Research Council, NASA and the CRC for Catchment Hydrology. The authors also wish to thank all the members of the ground and air crew of NAFE'05, SMAPEx-3 that contribute to the collection of data presented here.

8 REFERENCES

ABS, 2006. *Water Account, Australia 2004-05*. Australian Bureau of Statistics (ABS).

Alemaw, B. F., Chaoka, T. R. & Totolo, O. 2006. Investigation of sustainability of rain-fed agriculture through soil moisture modeling in the Pandamatenga Plains of Botswana. *Physics and Chemistry of the Earth* 31(15-16): 960-966.

Baghdadi N. & Zribi M. 2006. Evaluation of Radar Backscatter Models IEM, OH and Dubois Using Experimental Observations. *International Journal of Remote Sensing* 27(18): 3831-3852.

Desilets, D., Zreda, M. & Ferre, T.P.A. 2010. Nature's neutron probe: Land surface hydrology at an elusive scale with cosmic rays. *Water Resources Research* 46: W11505.

Entekhabi, D., Rodriguez-Iturbe, I. & Castelli, F. 1996. Mutual interaction of soil moisture state and atmospheric processes. *Journal of Hydrology* 184(1-2): 3-17.

Merlin, O., Rüdiger, C., Al Bitar, A., Richaume, P., Walker, J. & Kerr, Y. 2012. Disaggregation of SMOS soil moisture in southeastern Australia. *IEEE Transactions on Geoscience and Remote Sensing* 99:1-16.

Merlin, O., Walker, J. P., Chehbouni, A. & Kerr, Y. 2008. Towards deterministic downscaling of SMOS soil moisture using MODIS derived soil evaporative efficiency. *Remote Sensing of Environment* 112: 3935-3946.

Merlin, O., Walker, J. P., Panciera, R., Young, R., Kalma, J. D. & Kim, E. J. 2007. Calibration of a Soil Moisture Sensor in Heterogeneous Terrain with the National Airborne Field Experiment (NAFE) Data. In Oxley, L. and Kulasiri, D. (eds), *MODSIM 2007 International Congress on Modelling and Simulation*. *Modelling and Simulation Society of Australia and New Zealand, December 2007*, pp: 2604-2610. ISBN : 978-0-9758400-4-7

Njoku, E. G., Wilson, W. J., Yueh, S. H., Dinardo, S. J., Li, F. K., Jackson, T. J., Lakshmi, V. & Bolten, J. 2002. Observations of soil moisture using a passive and active low-frequency microwave airborne sensor during SGP99. *Transactions on Geoscience and Remote Sensing* 40: 2659-2673.

Walker J. P., Panciera, R. & Kim, E. 2008. High Resolution Airborne Soil Moisture Mapping. *Proceedings of the 14th Australasin Remote Sensing and Photogrammetry Conference, Darwin, Australia, 30 Sept - 2 Oct, 2008.*

Wigneron, J. P., Kerr, Y., Waldteufel, P., Saleh, K., Escorihuela, M. J., Richaume, P., Ferrazzoli, P., de Rosnay, P., Gurney, R., Calvet, J. C., Grant, J. P., Guglielmetti, M., Hornbuckle, B., Matzler, C., Pellarin, T. & Schwank, M. 2007. L-band Microwave Emission of the Biosphere (L-MEB) Model: Description and calibration against experimental data sets over crop fields. *Remote Sensing of Environment* 107(4): 639-655.

Zhan, X., Houser, P. R., Walker, J. P. & Crow, W. 2006. A Method for Retrieving High Resolution Surface Soil Moisture from Hydros L-Band Radiometer and Radar Observations. *Transactions on Geoscience and Remote Sensing* 44(6):1534-1544.

Zreda, M., Zeng, X., Shuttleworth, J., Zweck, C., Ferre, T., Franz, T., Rosolem, R., Desilets, D., Desilets, S. & Womack, G. 2011. Cosmic-ray neutrons, an innovative method for measuring area-average soil moisture. *Global Energy and Water Cycle Experiment News* 21(3): 6-10.