

# Australian Root Zone Soil Moisture: Assimilation of Remote Sensing Observations

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**Abstract:** Knowledge of temporal and spatial variation in root zone soil moisture content across Australia is vital for a wide range of environmental and socio-economic activities. However, such information is not currently available, due to an inability to monitor with ground-based point measurement techniques at an appropriate spatial resolution, and the uncertainty associated with land surface model predictions. Advances in remote sensing instruments and algorithms have made possible monitoring of spatial variation in surface soil moisture content for areas of low to moderate vegetation, but these measurements are limited to the top few centimetres at most. While soil moisture measurements for such a thin surface layer are not very useful on their own, this surface data is used to constrain land surface model predictions through the process of data assimilation, yielding improved estimates of soil moisture not only in the surface layer, but also at depth. The C-band passive microwave remote sensing data from the Scanning Multi-frequency Microwave Radiometer (SMMR) is assimilated into a land surface model for the period 1979 to 1987. We are limited to this time period as there has been no appropriate space-borne passive microwave sensor from then until May 2002, when the Advanced Microwave Scanning Radiometer for the Earth observing system (AMSR-E) was launched. Moreover, SMMR has the same frequencies as AMSR-E making it an ideal developmental test bed until AMSR-E data become available. The disadvantage of the SMMR time frame is the lack of adequate soil moisture validation data, meaning that it is difficult to assess the improvement of skill in predicting root zone soil moisture content when surface observations are assimilated. We assess the improvement in skill by comparing with patterns in Normalised Difference Vegetation Index (NDVI) data and the limited soil moisture profile data available.

**Keywords:** *Soil Moisture; Land Surface Modelling; Remote Sensing; Data Assimilation*

## 1. INTRODUCTION

Knowledge of spatial and temporal variability in root zone soil moisture across Australia is crucial in a wide array of environmental fields. Such applications range from weather and climate prediction to early warning systems (e.g. flood forecasting), climate-sensitive socio-economic activities (e.g. agriculture and water management) and policy planning (e.g. drought relief and global warming). However, reliable information on root zone soil moisture content at the continental scale is not currently available for a variety of reasons. First, there is a limited area that can be monitored with an adequate spatial and temporal resolution using ground based point measurement techniques (Grayson and Western, 1998). This stems from the large variability in soil moisture content and soil properties over short distances (Western et al. 1999, 2002), and the cost involved with installation, calibration and maintenance of soil moisture monitoring equipment. Second,

there is a high level of uncertainty associated with continental scale land surface models, with a wide variation between the different models when using the same input parameters and atmospheric forcing (Houser et al., 2002).

Advances in passive microwave remote sensing have made possible the measurement of soil moisture content over large areas on a frequent basis under certain conditions. While this would appear to be an obvious alternative for gaining knowledge of spatial and temporal variation in soil moisture content across Australia, there are a few limitations. For instance, this only provides a soil moisture estimate of the top few centimeters at most and is limited to areas of low vegetation (Du et al., 2000, Engman 2000) away from large water bodies such as the ocean. Moreover, due to the relatively weak signal observed, space borne sensors have a coarse resolution, being on the order of 25km. While this resolution is appropriate for broad scale applications such as weather prediction and policy planning, it is not

appropriate for small scale applications such as on-farm water management. Further, surface soil moisture measurements are highly dependent on the meteorological conditions of the last few hours to days, and do not give a direct indication of the more relevant deeper layer soil moisture content. Thus methods for obtaining root zone soil moisture content from these surface measurements need to be developed. While there have been numerous synthetic experiments demonstrating such a capability through assimilation of these surface measurements into a land surface model (eg. Entekhabi et al., 1994; Walker and Houser, 2001; Reichle et al., 2001), there have been relatively few studies that have used real space-borne data.

The reason for this little use of space-borne data is the lack of a dedicated soil moisture remote sensing mission. However, global soil moisture data has recently become available from the 6.6GHz channels (C-band) of the Scanning Multichannel Microwave Radiometer (SMMR) flown from October 1978 to August 1987. There was no replacement C-band sensor until May 2002 when the Advanced Microwave Scanning Radiometer for the Earth observing system (AMSR-E) was launched, once again making global measurement of surface soil moisture content possible. Since C-band data is the best that we can hope for over the next several years, the historic SMMR data set provides an excellent data source in preparation for using AMSR-E observations when its' calibration and soil moisture retrieval algorithm has been finalised.

In this paper the spatial and temporal variation in soil moisture content across the Australian continent is estimated during the period 1979 to 1987, by assimilating the space-borne SMMR observations in a land surface model forced with observation-constrained European Center for Medium-range Weather Forecasts (ECMWF) re-analysis data. Evaluation with soil moisture measurements is difficult due to the time frame of SMMR data, and the fact that SMMR cannot measure soil moisture for areas within 100km of the coast. Hence this paper relies heavily upon the patterns in Normalised Difference Vegetation Index (NDVI) data, using vegetation vigor as a measure of soil moisture availability.

## 2. MODELS

### 2.1. Land Surface Model

The land surface model used in this study is the catchment-based land surface model (CLSM) of Koster et al. (2000). The key innovations of this model are the explicit inclusion of sub-catchment spatial variability and the model domain, which is



**Figure 1.** Catchment delineations for Australia.

based on the hydrologic watershed as defined by the topography (Figure 1) rather than an arbitrary grid.

The model physics are based on TOPMODEL (Beven and Kirkby, 1979) concepts for relating the water table distribution to the topography. Soil moisture status is modelled using three prognostic variables (defined as catchment deficit, root zone excess and surface excess) and a special treatment of transfer between them. These prognostic variables consider the water table distribution and non-equilibrium conditions in the root zone. From these prognostic variables it is possible to calculate surface (top 2cm), root zone (top 1m) and profile soil moisture content, and the fraction of the catchment under saturated, unstressed and stressed soil moisture conditions. A complete description of this land surface model is given by Koster et al. (2000) and Ducharme et al. (2000), and is summarised further by Walker and Houser (2001).

### 2.2. Kalman Filter

The Kalman filter is a statistical data assimilation approach that tracks the mean and covariances of a state vector (ie. soil moisture content in our case) using a series of forecast and update steps. An update is made whenever observations become available. The correction made to the state estimate is the difference between the actual observation and the model prediction of the observation, weighted by the ratio of covariance of the model states to covariance of observation and model predicted observation, multiplied by a matrix for mapping between model states and observations. Starting from an initial estimate of the model uncertainty, the covariances of the model states are forecast using standard error propagation theory. The reader is referred to

Walker and Houser (2001) for a more detailed discussion of the Kalman filter, the Kalman filter equations and their application to the catchment-based land surface model.

We have used a one-dimensional Kalman filter for updating the CLSM prognostic state variables in this study. A one-dimensional filter has been used because of its computational efficiency, the fact that spatial correlations would be weak at the scale of catchments used, and that model calculations are performed independent of the adjacent catchments. Spatial correlations in soil moisture content for distances greater than 50km would be due to large scale correlations in atmospheric data, soil properties, vegetation and topography (Western et al., 2002).

Diagonal terms for the initial covariance matrix were specified to have a standard deviation equal to the maximum difference between the initial prognostic state value and the upper and lower limits, with the off diagonal terms as zero. The diagonal terms of the model error covariance matrix were the predefined values of 0.00025, 0.0025 and 0.025 mm/min for surface excess, root zone excess and catchment deficit respectively, with the off-diagonal terms specified to be zero. The assumption of model error independence for the three soil moisture prognostic variables is valid, as the physics used for forecasting these three prognostic variables are different.

### **3. DATA SETS**

#### **3.1. Model Parameters**

The CLSM requires topographic, soil and vegetation parameters. The topographic parameters are the mean, standard deviation and skewness of the compound topographic index. The catchment delineations and topographic data were taken from the GEODATA 9" digital elevation model of Australia, and topographic parameters scaled to 100m equivalent. The catchments used in this application (Figure 1) have an average area of 2,500km<sup>2</sup>.

Soil parameters include porosity, wilting point, saturated hydraulic conductivity, the Clapp and Hornberger (1978) soil texture parameter, saturated matric potential and total soil depth. Apart from soil depth, soil parameters were inferred from dominant soil texture information given by the 5' × 5' resolution Food and Agriculture Organisation (FAO) digital soil map of the world, using the values in Cosby et al. (1984). Total soil depth was taken from the first International Satellite Land Surface Climatology Project (ISLSCP) initiative (Sellers et al., 1996a) 1° × 1° resolution global data set. Catchment

partitioning and timescale parameters required by the CLSM were pre-processed using the topographic and soil parameters by the methodology of Ducharme et al. (2000).

Vegetation parameters include vegetation type, greenness fraction and Leaf Area Index (LAI). Vegetation type information was taken from the ISLSCP Initiative 1 data set. Monthly values of greenness fraction and LAI were derived from Advanced Very High Resolution Radiometer (AVHRR) measurements of NDVI at 1° × 1° resolution using the relationships of Sellers et al. (1996b). Climatologies were obtained by averaging the parameter estimates over the time period of 1982 to 1990, and used for simulation of the years outside this time period. The snow free albedo was calculated from the LAI, greenness fraction, vegetation type and a look-up table (Koster and Suarez, 1991), while zero plane displacement height and momentum roughness length was calculated from the month of year, vegetation type and a look-up table (Koster and Suarez, 1996).

#### **3.2. Forcing Data**

Atmospheric forcing data were from an observation-constrained 15-year (1979-1993) ECMWF Re-Analysis (ERA-15) data set (Berg et al., 2001). The atmospheric data fields used include: air temperature and humidity at 2m, wind speed at 10m, total and convective precipitation, downward solar and longwave radiation and atmospheric pressure.

The atmospheric data fields from re-analysis are subject to significant model bias, so the re-analysis fields were constrained to monthly average observations using a bias correction technique. Observation constraints were imposed using a difference or ratio correction, depending on the field. The reader is referred to Berg et al. (2001) for a complete description of the observation constrained forcing data set.

#### **3.3. Initial Conditions**

The initial land surface model states for 1 January 1979 were derived by driving the CLSM to equilibrium. The spin-up equilibrium states were obtained by cycling the land surface model with the 1979 atmospheric forcing data for 10 years. This is the typical way that initial conditions for land surface models are obtained.

#### **3.4. Observations**

Surface soil moisture observation data were derived from the 6.6GHz vertically and horizontally polarised brightness temperature

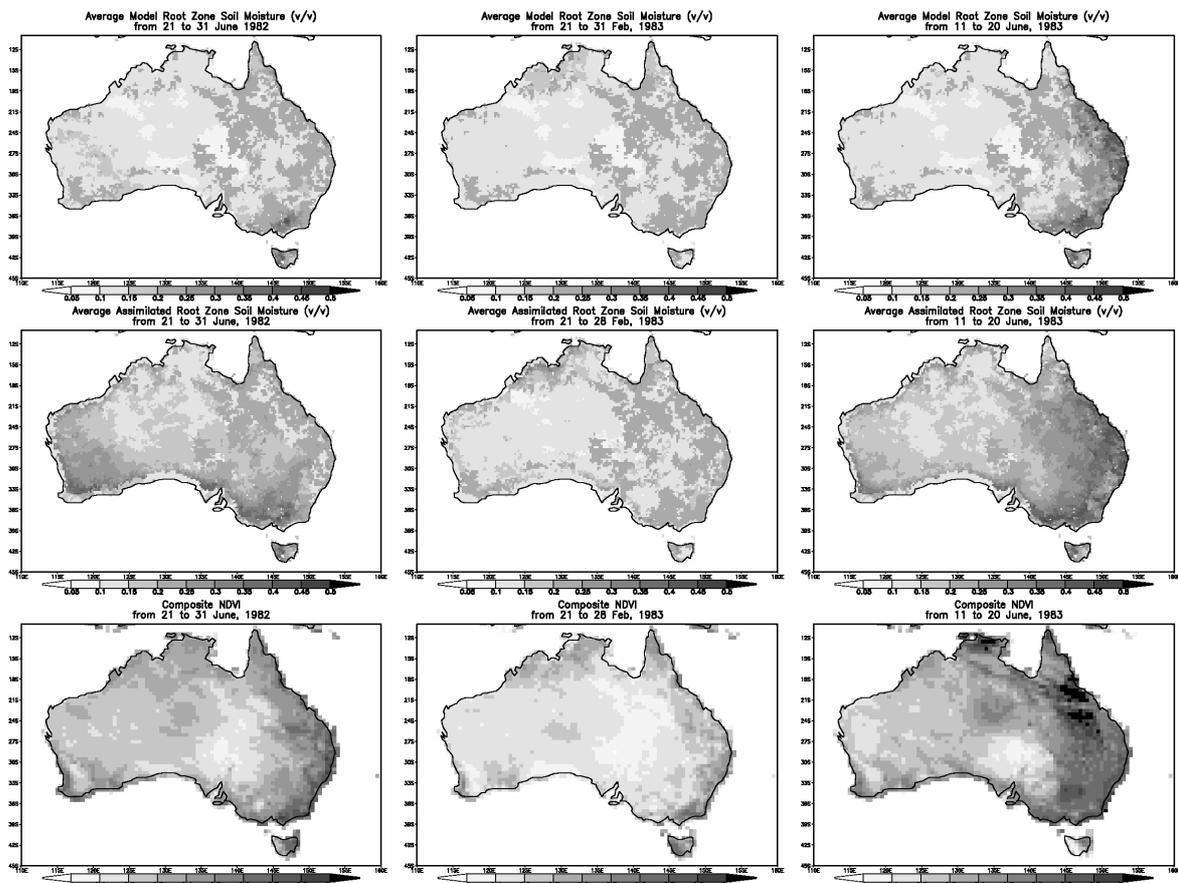
measurements from the space-borne SMMR instrument on board the Nimbus-7 satellite. The radiative transfer model of Mo et al. (1982) was used to solve for the surface soil moisture content and vegetation optical depth simultaneously using the microwave polarisation difference index non-linear iterative optimisation procedure of Owe et al. (2001). Constant values for single scattering albedo and roughness, and equal horizontal and vertical polarisation optical depth values were assumed. Soil temperature was estimated from the 37GHz vertically polarised brightness temperature measurements, soil properties were from the FAO soil map, and dielectric constant was related to soil moisture content by the Wang and Schmugge (1980) dielectric mixing model.

While there was no calibration of the surface soil moisture retrieval algorithm to ground measured soil moisture data, results compared well with point measurements of soil moisture in the top 10 cm layer and satellite-derived NDVI data (Owe et al., 2001). The comparisons were for two test sites in Illinois, USA that maximised the number of soil moisture stations in each site. The test sites had a mixture of pasture, cropland and woodland.

### 3.5. Evaluation Data

There is little soil moisture data for Australia during the SMMR time period (1979-1987). Moreover, due to the coastal dwelling nature of the Australian population, a large proportion of the data available is within 100km of the coast. This means that while simulation results can be compared for those locations, no improvement due to assimilation can be expected. A similar caveat applies to data in heavily vegetated areas. The soil moisture data for evaluation were from a database of soil moisture observations around Australia collated by Ladson et al. (2002). These data consist mostly of information on total profile dynamic water storage, and in some cases, time series of changes in profile soil water storage. While these data are not ideal, they do provide some information on spatial and temporal variability over the observation period. However the results of these comparisons were inconclusive and are not discussed further here.

Due to the shortcomings in available soil moisture data, this study has placed an emphasis on evaluation by comparing patterns in root zone soil moisture with patterns in NDVI data. The basis



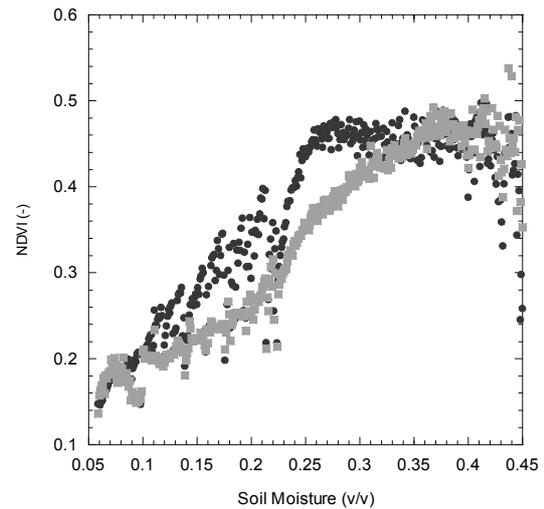
**Figure 2.** Comparison of model predicted root zone soil moisture content with (centre row) and without (top row) assimilation against NDVI data (bottom row), for prior to onset of the 1982/83 drought (left column), at the peak of the drought (centre column) and return to normal conditions (right column).

for this is that Australian native vegetation consists predominantly of evergreen species, meaning that changes in NDVI should be strongly related to soil moisture and climate. The NDVI data used for evaluation are from the  $0.1^\circ \times 0.1^\circ$  NOAA/NASA Pathfinder AVHRR Land (PAL) data sets that cover the period from July 1981 through to present. These data are 10-day composites of the daily data with the fewest clouds. The three composites per month are for days 1 through 10, 11 through 20, and then the remaining days.

#### 4. RESULTS

Comparisons between NDVI and root zone soil moisture data were made by firstly calculating the 10-day average root zone soil moisture content from the 6-hour simulation output with and without assimilation. Figure 2 shows a comparison of the spatial soil moisture and NDVI data prior, during, and following the 1982/83 drought. These results are representative of other times, and cover the range from dry through wet. From a qualitative sense, it is quite clear that there is a better agreement in the spatial pattern of root zone soil moisture from assimilation with that from the NDVI data, particularly in the south-eastern (June 1982) and eastern (June 1983) parts of the continent. There is little difference between the root zone soil moisture with and without assimilation in February 1983, with the observed pattern being largely a function of the underlying patterns in soil properties.

A quantitative comparison between the NDVI and soil moisture data was made by mapping both the root zone soil moisture and NDVI data onto a  $0.5^\circ$  grid, and comparing on a pixel-by-pixel basis. Figure 3 shows the results for mean NDVI response for soil moisture in  $0.01\text{v/v}$  bins. While there was a large amount of scatter across the range of soil moisture content values (average standard deviation was approximately 0.15 in NDVI for both cases), there is an obvious trend in the mean. The assimilation results show a near linear relationship across all soil moisture contents, while the results without assimilation show a saturation of the NDVI values for soil moisture content greater than about  $0.25\text{v/v}$ . This linear relationship for the assimilation data suggests a stronger correlation between root zone soil moisture and NDVI than for without assimilation. The saturation suggests that the CLSM has a dry bias, as can also be observed in Figure 2. However, it is difficult to draw exhaustive conclusions from this comparison due to complicating effects, such as temporal variations in NDVI values from seasonal, climatic and vegetation variability. Current work is



**Figure 3.** Comparison of mean NDVI against root zone soil moisture with (squares) and without (circles) assimilation.

focused on making comparisons that eliminate these complications.

#### 5. CONCLUSIONS

This paper has presented results from the first known study to use space-borne measurements of surface soil moisture content to estimate the spatial and temporal variation of soil moisture content across Australia by the process of data assimilation. Unfortunately the lack of appropriate soil moisture data and mismatch in scale between model output and available data made it difficult to draw any conclusive statements regarding improvements in soil moisture predictions. There was however an obvious increase in correlation between soil moisture predictions and NDVI data when SMMR surface soil moisture data were assimilated. This provides some encouragement for pursuing assimilation experiments using the new AMSR-E data, and the collection of more appropriate ground-based soil moisture data for validation purposes.

#### 6. ACKNOWLEDGEMENTS

This research was supported by a University of Melbourne International Collaborative Grant. Processing of catchment definitions by Stephen Wealands and data manipulation by Robert Pipunic is acknowledged.

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