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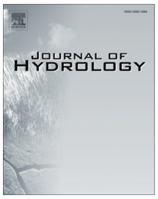

Towards soil property retrieval from space: An application with disaggregated satellite observations

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SUMMARY

Soil moisture plays a key role in most environmental processes, as evaporation and transpiration are heavily dependent on soil moisture variability. While it is one of the few important hydrological variables that can be directly observed, the high spatial and temporal variability makes it difficult to measure globally or even regionally. Reliance is therefore placed on land surface models to predict the evolution of soil moisture using low-resolution soil property information or typical values. But to make predictions with the required accuracy, more reliable and detailed soil parameter data are required than those currently available. This paper demonstrates the ability to retrieve soil hydraulic parameters from near-surface measurements, using Soil Moisture and Ocean Salinity (SMOS) observations disaggregated to 1 km resolution for a demonstration area the size of a single SMOS footprint. The disaggregated soil moisture product was first assessed against in-situ soil moisture observations, before testing the retrieval methodology using the disaggregated soil moisture data for individual soil columns co-located with three long-term monitoring sites in the Murrumbidgee Catchment. The retrieval methodology was then applied to the entire 40 km × 40 km demonstration area at 5 km spatial resolution. The results suggest that spatially variable soil hydraulic properties exist in the study area, while published soil texture maps show only a single soil type, meaning that a single set of soil hydraulic parameters would normally be used in soil moisture prediction models for this region. Use of a single set of soil hydraulic parameters, rather than the spatially variables ones, was estimated to have an approximate 0.06 m^3/m^3 impact on the soil moisture prediction.

1. Introduction

On a global scale, soil hydraulic parameters are currently obtained from look-up tables that are linked to a coarse resolution soil texture map, like the Food and Agricultural Organization (FAO) of the United Nations Soil Map of the World (Latham, 1981). Thus, the soil hydraulic parameters used in global land surface models are 'typical' values for a given soil texture. While these values come with an error estimate, the variation within a single soil texture group is larger than that between the different texture groups (Clapp and Hornberger, 1978). Although the soil texture map may be at a finer resolution at regional scale than at global scale, the same look-up tables typically apply. Due to the uncertainty of the soil hydraulic parameter data, there is therefore a high probability that the soil moisture prediction models will make erroneous soil moisture predications. Thus, there is an urgent need for global soil hydraulic parameter data sets at a higher spatial resolution and accuracy than those currently available.

Satellite remote sensing is able to supply time series information on near-surface soil moisture data with a 2–3 day repeat cycle globally, and with soil moisture information now available from several different satellites it is possible to obtain moisture time series observations as often as daily. Hence, there is the potential to derive more accurate soil hydraulic parameter datasets over large areas from these observations, but most work to date has focused on synthetic simulations at local scale (Ines and Mohanty, 2008; Montzka et al., 2011), or observations on engineered soils (Burke et al., 1997a, 1997b, 1998; Camillo et al., 1986; Ines and Mohanty, 2008); for a more detailed review of these studies refer to Bandara et al. (2013). There are only a few studies that have focused on estimating soil hydraulic properties from soils under transient flow or naturally occurring boundary conditions (Dane and Hruska, 1983; Ritter et al., 2003); a more detailed review of these studies can be found in Bandara et al. (2014).

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In Bandara et al. (2013), a methodology was developed for estimating the soil hydraulic properties of a heterogeneous soil column within a synthetic twin-experiment framework. According to this methodology, the soil hydraulic parameters were derived by calibrating a soil moisture prediction model to surface soil moisture observations, such as those which are available from satellite observations. This methodology was then applied to field conditions in Bandara et al. (2014) and the retrieved soil hydraulic parameters validated with field and laboratory experiments. The study presented in this paper advances that work by applying the methodology to a 40 km × 40 km test area with heterogeneous soil columns of 1–5 km resolution under natural conditions. The retrieved soil hydraulic parameters include: (a) Clapp and Hornberger exponent, (b) hydraulic conductivity at saturation, (c) soil matric suction at air entry, (d) volumetric fraction of soil moisture at saturation, (e) volumetric fraction of soil moisture at the critical point, equivalent to a soil suction of 3.364 m, and (f) volumetric fraction of soil moisture at wilting point, assumed to be for a soil suction of 152.9 m.

2. Site and data description

The work presented in this study focuses on a 40 km × 40 km area, encompassing a full SMOS pixel, positioned in such a way that five sites of the OzNet Soil Moisture Monitoring Network (http://www.oznet.org.au) (Smith et al., 2012) are located within it. Those sites are: Y2 (34.6548 S, 146.1103 E), Y3 (34.6208 S, 146.4239 E), Y5 (34.7284 S, 146.2932 E) and Y7 (34.8518 S, 146.1153 E), as shown in Fig. 1, located near Yanco, New South Wales, Australia. The soil of the Yanco region is duplex, with horizon A being approximately 0.30 m deep. The soil moisture has been measured continuously over depths of 0–0.05 m, 0–0.30 m, 0.30–0.60 m and 0.60–0.90 m as the average over 30 min intervals. The precipitation was measured by a tipping bucket rain gauge with the cumulative rainfall recorded every 6 min (Smith et al., 2012). Additionally, experimental data on the soil hydraulic properties of sites Y2, Y5 and Y7, derived from field and laboratory measurements as discussed in detail in Bandara et al. (2014), have also been utilized.

In addition to long-term in-situ soil moisture observations, this study utilizes a 1 km × 1 km resolution disaggregation of the SMOS soil moisture product, as opposed to a single value over its 40 km × 40 km footprint. The downscaled soil moisture data were obtained using a disaggregation method named DISPATCH (DISaggregation based on Physical And Theoretical scale CHange (Merlin et al., 2005, 2008, 2012, 2013). DISPATCH distributes fine scale soil moisture values around the coarse (40 km resolution SMOS) observation, using the soil evaporative efficiency derived at high resolution from available red/near-infrared/thermal infrared data, and a soil evaporative efficiency model. This study utilized 1 km resolution MODIS optical data and version 2 DISPATCH algorithm (Merlin et al., 2013). Data were created in August 2012 using the level 3 SMOS soil moisture product (Merlin, 2012). During July 2010 and September 2011, three intensive soil moisture sampling campaigns were conducted over some selected areas of the Murrumbidgee Catchment (SMAPEx-1, SMAPEx-2 and SMAPEx-3). Each of these campaigns mapped surface soil moisture at 250 m spacing across focus areas of approximately 3 km × 3 km in size. The measurements from these areas, known as YA7 and YB5 (shown in Fig. 1), were used in this study to compare with and assess the DISPATCH data, where YA7 is irrigated cropping while YB5 consists of native grassland. Further details on these campaign data are available from (www.smapex.monash.edu.au) (Panciera et al., 2013). While other sites were also included in these campaigns, these two were selected for their coverage by DISPATCH and because they were geographically diverse, being located to the north and south of the study area respectively.

Two data sources were used to derive the spatially distributed forcing data required for the study area. They were the Australian Community Climate and Earth-System Simulator (ACCESS) (BoM, 2010) dataset and the Australian Water Availability Project (AWAP) (Jones et al., 2007) data at 12 km and 5 km spatial resolutions respectively. The ACCESS data consisted of long and short wave radiation, precipitation, air temperature, dew-point temperature, and horizontal and vertical components of wind and surface pressure at hourly intervals, while precipitation data from AWAP was provided on a daily scale. The hourly ACCESS precipitation was scaled to match the daily AWAP precipitation according to the methods described in Berg et al. (2003). This approach was chosen, as the AWAP precipitation, which is a daily gauge-interpolated product at a resolution of 5 km, was used to disaggregate the 12 km × 12 km ACCESS precipitation to 5 km × 5 km, thereby enhancing the JULES soil moisture predictions at 5 km resolution. By using weighted averages, all forcing data were brought to the AWAP grid with a spatial resolution of 5 km × 5 km.

Fig. 1 shows an example of the disaggregated SMOS data at a 1 km × 1 km scale for the study area near Yanco in the Murrumbidgee Catchment. These data were available for 2010 and 2011 for both the ascending and descending overpasses. However, only the ascending (6 am) overpass data are used in this study as it is widely accepted that morning overpass data better conform to the assumptions of the soil moisture retrieval algorithms. This is because the soil temperature profile is closer to equilibrium at this time, meaning that the assumption of vegetation and near-surface soil temperatures being the same is appropriate. The DISPATCH dataset was averaged to 5 km × 5 km resolution before being used in the spatially distributed soil hydraulic parameter retrieval. Thus, a total of 64 such 25 km^2 grid cells covering the 40 km × 40 km area were simulated, corresponding to a single SMOS pixel.

3. Modelling algorithms

3.1. Land Surface Model (LSM)

The Joint UK Land Environment Simulator (JULES) is used as the soil moisture prediction model (Best et al., 2011; Clark and Harris, 2009; Clark et al., 2011) in this paper. It is a process based land surface model that simulates the fluxes of carbon, water, energy and momentum between the land surface and the atmosphere. JULES is a derivative of the Met Office Surface Exchange Scheme (MOSES) (Cox et al., 1999).

Of the four sub-models in JULES – soil, snow, vegetation and radiation – the focus in this study is on the soil sub-model and the simulation of soil moisture. Herein, JULES is run with 7 soil layers of 0.025 m, 0.025 m, 0.125 m, 0.125 m, 0.30 m, 0.30 m, and 2.0 m thickness respectively, resulting in an overall soil depth of 2.9 m. The time-step used by the model was 1 h, to conform to the time-step of the forcing data. A 2 year pre-run initialized at saturation was used to set the initial conditions of the land surface model (Bandara, 2013).

3.2. Particle Swarm Optimizer (PSO)

The Particle Swarm Optimization (PSO) algorithm is based on the collective behaviour of individuals in decentralized self-organizing systems. These systems are created through a population of individuals that interact both with each other and with the community (Kennedy and Eberhart, 1995). Given that PSO is population-based, it has the capability to control the balance between the local and global search space, thereby being less susceptible to getting trapped in a local minimum (Engelbrecht, 2005).

Based on the social–psychological tendency of an individual to mimic the success of others, any changes to an individual particle's