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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

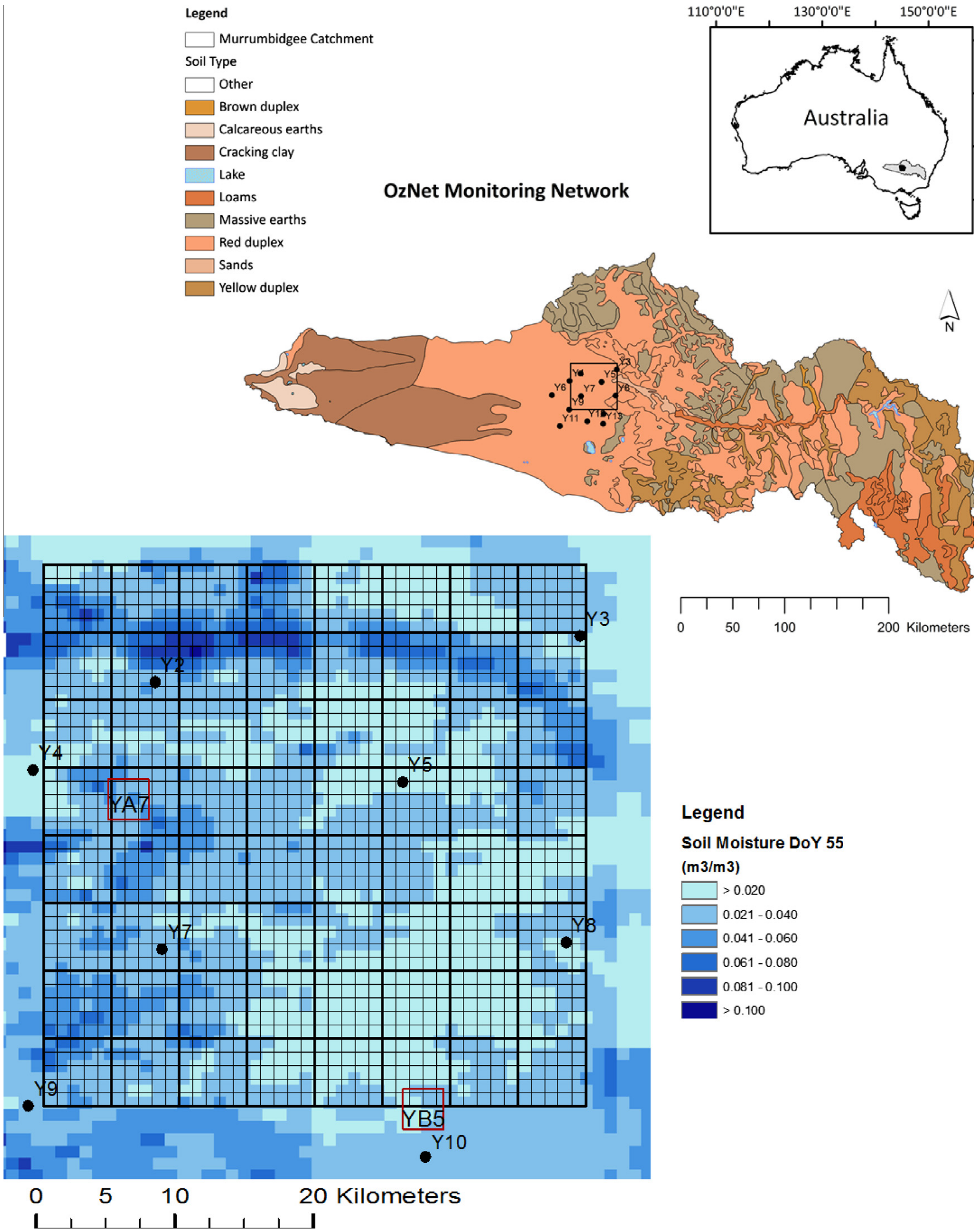


Fig. 1. The location of Yanco sites (indicated by black dots) of the OzNet Soil Moisture Monitoring Network within the Murrumbidgee Catchment, together with the published soil map. The two areas of intensive soil moisture sampling (YA7 and YB5), and an example of the disaggregated soil moisture data for a SMOS footprint (DoY 55 – February 24, 2010) are also shown. The 1 km grid of DISPATCH and the 5 km grid to which it is later aggregated are shown in the blowout. The extent of this grid indicates the coverage of the model simulations used for estimating the soil parameters.

position occurs when flown through a hyper-dimensional search space (Engelbrecht, 2005). Thus, changes to the position of particles within the search space are influenced by the experience and/or knowledge of its neighbour, in addition to its' own. The PSO algorithm comprises three components; (i) the momentum, so that the velocity of the 'swarm' cannot change abruptly, (ii) the 'cognitive' or personal component (c_1), representing that the particle learns from its own flying experience and fitness, and (iii) the 'social' component (c_2), representing the cooperation with other particles and thus learning from the flying experience of the group (Kennedy and Eberhart, 1995). However, when updating the velocity of the 'swarm' it may become too high and cause particles to leave behind 'good' solutions, or too slow such that the search space is not explored adequately. Therefore, Shi and Eberhart (1998) introduced an additional parameter termed as the 'inertia weight' to control the velocity, with the intension of overcoming this problem. The work presented in this paper uses the PSO code from Scheerlinck et al. (2009), with some modifications to facilitate parallelization.

For the work presented in this paper, $w = 0.4$, $c_1 = 1.4$ and $c_2 = 1.3$ were used as these were shown to be the best combination of parameters; Bandara et al. (2013) contains a detailed discussion about the selection of PSO parameters. Additionally, the root mean square error (RMSE) for the predicted minus observed soil moisture was used as the objective function in this study.

4. Methodology

The objective of this study was to retrieve the soil hydraulic properties of the demonstration area at a 5 km × 5 km spatial resolution. Consequently the study was approached in three steps. First, the DISPATCH data was evaluated with field observations at 1 km and 5 km resolution. Second, soil hydraulic parameters were retrieved for the Y2, Y5 and Y7 sites using the 1 km DISPATCH data, with the results compared to those from Bandara et al. (2014) where direct ground measurements were used. In this step, the derived soil hydraulic parameters and predicted root zone soil moisture were validated against field and laboratory measured soil parameters and observed root zone soil moisture, respectively. Finally, the methodology was applied to the 40 km × 40 km area to obtain a spatial map of soil hydraulic properties at 5 km × 5 km resolution, and evaluated against available spatial soil texture maps and associated soil hydraulic parameter estimates. The 5 km × 5 km resolution surface soil moisture data has been used in the spatial retrieval due to computational constraints in applying the methodology at the 1 km × 1 km spatial scale, and the availability of meteorological forcing data at 5 km × 5 km spatial resolution. Consequently, the DISPATCH data evaluation was conducted at two different spatial scales.

Though literature identifies the soils of Yanco as duplex, this study has allowed the soil profile to consist of three distinct soil horizons with potentially different soil properties; horizon A, horizon B_1 and horizon B_2, as in Bandara et al. (2014). This is because three distinct soil layers were observed in the field, with differences in the particle size distribution and soil hydraulic properties accordingly.

4.1. Assessing the DISPATCH data

As a first step, the disaggregated 1 km × 1 km resolution soil moisture data was evaluated with field observations. For this evaluation the intensive near-surface soil moisture measurements corresponding to the sites YA7 and YB5 were used. Since the sampling was done every 250 m, with three replicates for each point, the average and standard deviations of all such points falling within the 1 km × 1 km area was calculated. The DISPATCH footprints corresponding to these areas were then extracted for the day that the field observations were made. This procedure was applied to both sites, and for all days that the disaggregated data were available. The averaged soil moisture value and its standard deviation over the entire area of YA7 and YB5 were also calculated for each day of observations, so as to make an assessment of the product at 5 km × 5 km.

Additionally, in-situ soil moisture data from Y2, Y5 and Y7, three permanent stations of the OzNet monitoring network, were also used for evaluation. Of the many stations in the network, extensive field and laboratory experiments have been conducted on Y2, Y5 and Y7, as these three stations are well distributed within the one SMOS pixel. The methodology proposed in Bandara et al. (2013) was already tested on these three sites using ground observation in Bandara et al. (2014). Consequently, the 1 km × 1 km DISPATCH data corresponding to the location of the monitoring sites were extracted and compared with the soil moisture observations made at 6 am. The purpose of this assessment was to investigate the differences between the two data sources and to identify any persistent biases. However, it is recognized that point-to-spatial comparisons are difficult due to significant spatial variations over short spatial scales (Cosh et al., 2004; Crow et al., 2012). Consequently, differences between the point measurements of in-situ data are expected when comparing against the DISPATCH data, but the temporal evolution is expected to be similar in the case when the 1 km/5 km pixels do not contain irrigated fields.

4.2. One-dimensional (point) retrieval using DISPATCH data

The three sites (Y2, Y5 and Y7) for which field and laboratory measured soil hydraulic parameters are available were chosen to demonstrate the ability of retrieving root zone soil hydraulic parameters from surface soil moisture observations alone, with disaggregated soil moisture from SMOS. The methodology was tested using the three different scenarios summarized in Table 1; scenario A – using only the summer data with an objective function penalty (the parameter to be retrieved was given an initial best-guess value based on the pedo-transfer function estimates, and a search space of three times the standard deviation of that parameter based on the published values, thereby restraining the parameter from boundary values), scenario B – using the complete year of data with the same penalty as described in scenario A, and scenario C – using the complete year of data without the penalty. The results were contrasted against a fourth scenario; scenario D – using published values from Rawls et al. (1982).

It was identified from the synthetic study in Bandara et al. (2013). that the use of a year-long period is the most suitable approach, but Merlin et al. (2012) have shown that the correlation between DISPATCH and in-situ soil moisture observations is highest (0.7) during the summer period. Thus, this study investigated the trade-off between using only the summer soil moisture observations as opposed to the year-long record.

In scenarios A–C, the JULES simulated surface soil moisture for 6 am was compared with the disaggregated data, and the six soil hydraulic parameters retrieved for the complete soil profile using PSO, such that the objective function between the simulated and observed time-series was a minimum. The methodology recommended in Bandara et al. (2013) for multi-parameter retrieval has been followed, being a sequential approach that starts with the three most sensitive parameters for all soil types, followed by the remaining three soil parameters. The retrieved parameters were then compared with experimental observations, and the predicted root zone soil moisture compared with the observed root zone soil moisture.

4.3. Spatial retrieval using DISPATCH data

In this step, the focus was to obtain the spatial distribution of soil hydraulic parameters for the full SMOS footprint using the 5 km JULES model. The 1 km × 1 km DISPATCH data were averaged to a 5 km × 5 km grid that was aligned with the 5 km × 5 km grid established for the JULES soil moisture prediction model. Apart from the computational and forcing data reasons already discussed, the 5 km × 5 km resolution DISPATCH data has been used as the random errors in downscaled data are expected to be less at the coarser spatial resolution. However, any systematic errors, such as bias, in SMOS data will remain in DISPATCH data at all resolutions. Consequently, in this step the 6 am surface soil moisture predictions were compared with the averaged DISPATCH data, and the same six parameters retrieved for the complete soil profile using PSO.

Given that there were no field or laboratory observations of soil hydraulic parameters for the complete study area, the spatial distribution of each parameter was compared with the soil texture

Table 1
The different scenarios tested in the one-dimensional retrieval using DISPATCH data.

Scenario	Description
A	Using only the summer data with penalty, where the parameters to be retrieved were given a best-guess value with a variation of three times the standard deviation of that parameter (as explained in Section 4.2)
B	Using the complete year of data with the penalty
C	Using the complete year of data without the penalty
D	Using published values from Rawls et al. (1982)

distribution map and the corresponding soil property estimates of the region. It was also compared with an independent soil texture distribution map based on particle size distribution analysis data collected across the study area. Moreover, the spatial variation in predicted surface and root zone soil moisture estimates were also assessed.

5. Results and discussion

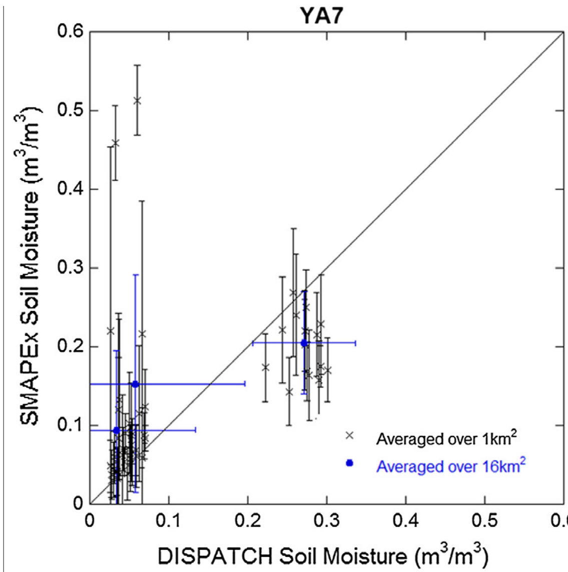
The disaggregated data was first evaluated with field measurements of soil moisture. This is because errors in the downscaled soil moisture data will propagate into the derived soil properties, and thus a good understanding of the soil moisture accuracy is required. The feasibility of using DISPATCH data with the proposed methodology was then tested for single soil columns, before being applied to the larger demonstration area.

5.1. Assessing the DISPATCH data

The surface soil moisture measurements from SMAPEx, averaged over areas of 1 km × 1 km, are compared with DISPATCH in Fig. 2. The same data averaged over the entire 3 km × 3 km areas of YA7 and YB5 are also plotted against the averaged 5 km × 5 km DISPATCH data on the same plot. The whiskers show the standard deviation of the observed soil moisture for each pixel. For the 1 km × 1 km resolution, the root mean square errors (RMSEs) between DISPATCH and measured soil moisture were calculated as 0.09 m^3/m^3 and 0.12 m^3/m^3 for YA7 and YB5 respectively. For both the YA7 and YB5 areas, it can be observed that the majority of the points lie above the 1:1 line, implying that there is a dry bias in DISPATCH. This is because any systematic errors in SMOS, like the dry bias in this case, propagate into a dry bias in the downscaled DISPATCH data. This dry bias was calculated as 0.05 m^3/m^3 for YA7 and 0.02 m^3/m^3 for YB5, with an unbiased RMSE of 0.07 m^3/m^3 and 0.11 m^3/m^3, respectively.

The SMAPEx observations were also averaged over the entire 3 km × 3 km areas, including four days of observations for YA7 and three for YB5. It was found that the overall field observations were wetter than DISPATCH, with DISPATCH again having a dry bias for YA7 of 0.05 m^3/m^3 and 0.02 m^3/m^3 for YB5. The RMSE without bias removal was 0.06 m^3/m^3 for both YA7 and YB5. When comparing the finer resolution (1 km × 1 km) with the coarser resolution (5 km × 5 km) results, it was observed that there was no change in the bias, but there was a considerable improvement in the RMSE.

While some field measurements of soil moisture were as high as 0.35 m^3/m^3, these were due to irrigation of crops within the YA7 area. However, the YB5 area is mainly pasture for grazing use. Importantly, these high values in field measurements are not borne out by SMOS, or the downscaled data by DISPATCH, which show much drier overall conditions. This is because SMOS has a coarse resolution, and assumes that the area of its footprint is relatively homogeneous in terms of both the soil and vegetation type. While the disaggregated data tries to account for heterogeneity,



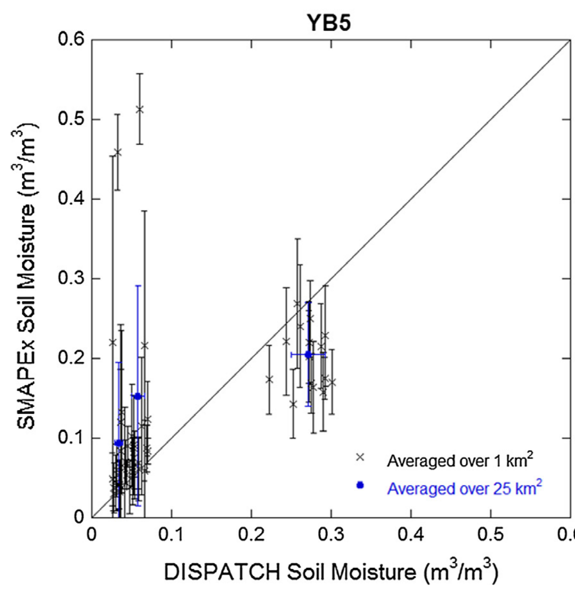


Fig. 2. Comparisons between the SMAPEx campaign soil moisture data and the disaggregated DISPATCH soil moisture product from SMOS for YA7 and YB5. The SMAPEx observations have been averaged at 1 km^2 and 16 km^2, and 1 km^2 and 25 km^2 for YA7 and YB5 respectively. DISPATCH soil moisture product has been averaged at 16 km^2 for YA7, and 25 km^2 for YB5. The whiskers represent the standard deviation of the measured value. The data are between July 5, 2010 and September 2011, with the disaggregated data from the corresponding ascending overpass of SMOS.

there are clearly limitations when compared with point measurements in areas that span the range of extremes. That is, in this case, the limitation of the DISPATCH data lies mainly in the spatial resolution (1 km) of the MODIS data, which is coarser than the typical size of fields in the area. The use of higher (about 100 m) resolution Landsat or Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data would overcome this limitation.

DISPATCH data were extracted for the three long-term monitoring sites Y2, Y5 and Y7 for 2010. Fig. 3(a) shows the comparison between the point observations and corresponding DISPATCH pixel at 1 km × 1 km spatial resolution, while Fig. 3(b) compares the multiple point observations with DISPATCH data averaged over an area of 5 km × 5 km. Fig. 3(c) compares the point observations pertaining to Y2, Y5 and Y7 with the original SMOS Level 3 data, under the assumption that it can be applied at the higher spatial resolution without any specific downscaling algorithm applied. However, there are several factors to be considered when comparing point data with large footprints. For example, assumptions about the homogeneous distribution of soil, vegetation, roughness and so on in the satellite products are propagated to the disaggregated product. And there are difficulties of comparing point observations against spatial averages, as already discussed.

Table 2 lists the statistics of these comparisons, showing that for Y2 the DISPATCH downscaling did not add any extra skill to the full SMOS pixel data when compared at annual scale, with the difference in RMSEs between these spatial resolutions typically less than 0.02 m^3/m^3. However, when looking at the data on seasonal time scale, the finding was different. During winter, where limited DISPATCH data were available, mainly due to cloud cover, the RMSE was higher than that during summer and with a dry winter-time bias. For example, the summer time RMSE was 0.09 m^3/m^3 at the 5 km spatial resolution while it was 0.16 m^3/m^3 during the winter at Y7. For Y5 at the 1 km spatial resolution, the summer RMSE was at 0.09 m^3/m^3 with the winter RMSE at 0.16 m^3/m^3. As shown in Fig. 4, the correct DISPATCH soil moisture dynamics are maintained during the dry summer period, but not in the winter. Moreover, dry-down events are better captured by DISPATCH as opposed to wet-up events. The reason behind DISPATCH performing better during dry conditions is due to the fact that the theoretical basis for this method is best suited for the water limited condition, such as in summer.

Keeping in mind the limitations of DISPATCH data, mainly due to the assumption that the area of the SMOS footprint is homogeneous when deriving the coarse scale soil moisture, and the coarse spatial resolution of the MODIS data, it is found that DISPATCH is comparable to field observations. Consequently, DISPATCH data at both 1 km and 5 km spatial resolutions have been utilized here to retrieve soil hydraulic parameters using the methodology that was applied and tested in Bandara et al. (2014) with in-situ data.

5.2. One-dimensional (point) retrieval using DISPATCH data

Though the disaggregated dataset from DISPATCH at 1 km × 1 km was biased relative to the selected stations, there was better agreement when comparing with the larger area. The dry winter-time bias can again be observed from Fig. 4, whilst maintaining the correct soil moisture dynamics during the dry summer period. This difference is as much as 0.15 m^3/m^3 during some instances. Moreover, dry-down events are better captured by DISPATCH as opposed to wet-up events. Thus, this section investigates the potential of using the 1 km resolution DISPATCH dataset for the retrieval of soil hydraulic parameters from surface soil moisture observations.

Table 3 contains the RMSEs calculated between the observed and predicted soil moisture when using the soil hydraulic parameters as retrieved according to scenarios A, B, C, and D (refer to Table 1). While Bandara et al. (2013) showed that the best results were achieved when using a year-long period, scenario A was included as the DISPATCH downscaling algorithm was shown to have more accurate soil moisture data during the water-limited summer period. Scenario C was included in this work for completeness, to test the applicability of the methodology if best-guess values were unavailable. However, it is seen from Table 3 that of the three sites, scenario A only outperformed scenario D once, being for Y5. When comparing scenario C to scenario D, it is seen that the soil moisture predictions of C only outperformed those of D for the near-surface of site Y7 and root zone of Y5. Thus, retrieving

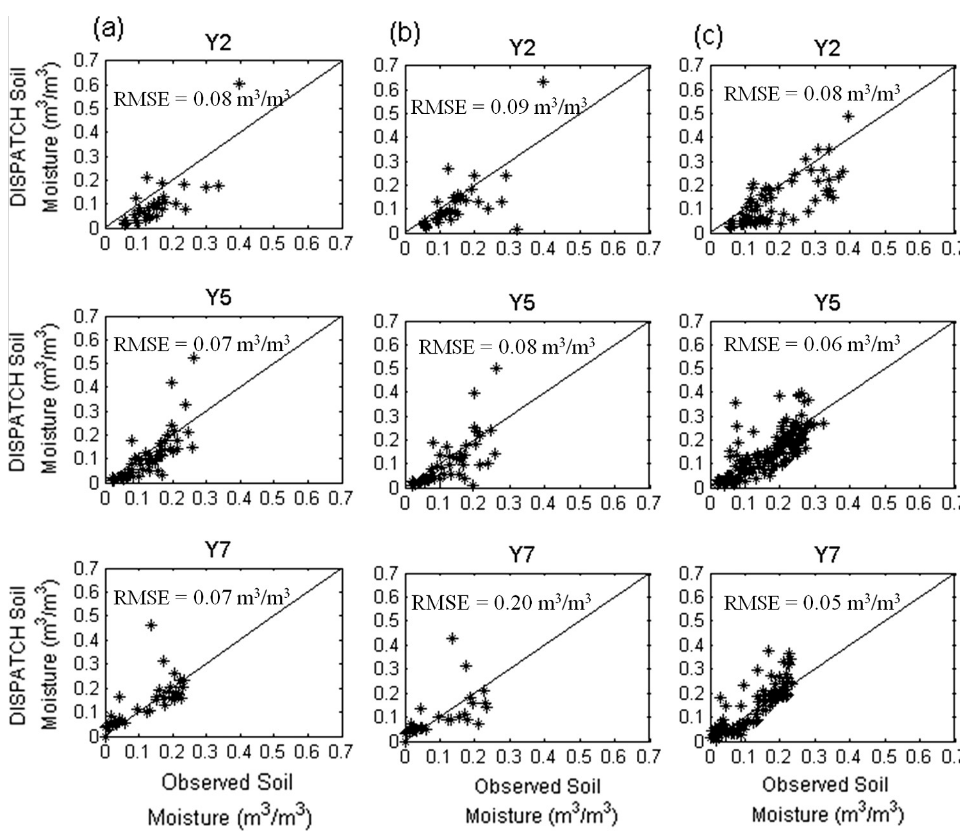


Fig. 3. Comparisons of observed soil moisture and the disaggregated DISPATCH soil moisture for the long-term monitoring sites Y2, Y5 and Y7; (a) DISPATCH data at 1 km spatial resolution, (b) DISPATCH data averaged to 5 km spatial resolution, and (c) original SMOS soil moisture data. The root mean square error (RMSE) shown in the figure is **before** bias removal.

Table 2
The root mean square errors (RMSE) calculated between field observed soil moisture and DISPATCH/SMOS data, in m^3/m^3. The dry bias is indicated with a plus (+) mark and the wet bias with a minus (−) mark.

Site	Spatial resolution								
	1 km			5 km			SMOS footprint		
	RMSE	Bias	Unbiased RMSE	RMSE	Bias	Unbiased RMSE	RMSE	Bias	Unbiased RMSE
Y2	0.08	+0.05	0.07	0.09	+0.03	0.08	0.08	+0.05	0.07
Y5	0.07	+0.02	0.06	0.08	+0.02	0.07	0.06	+0.02	0.06
Y7	0.07	−0.02	0.07	0.20	−0.01	0.08	0.05	−0.02	0.05

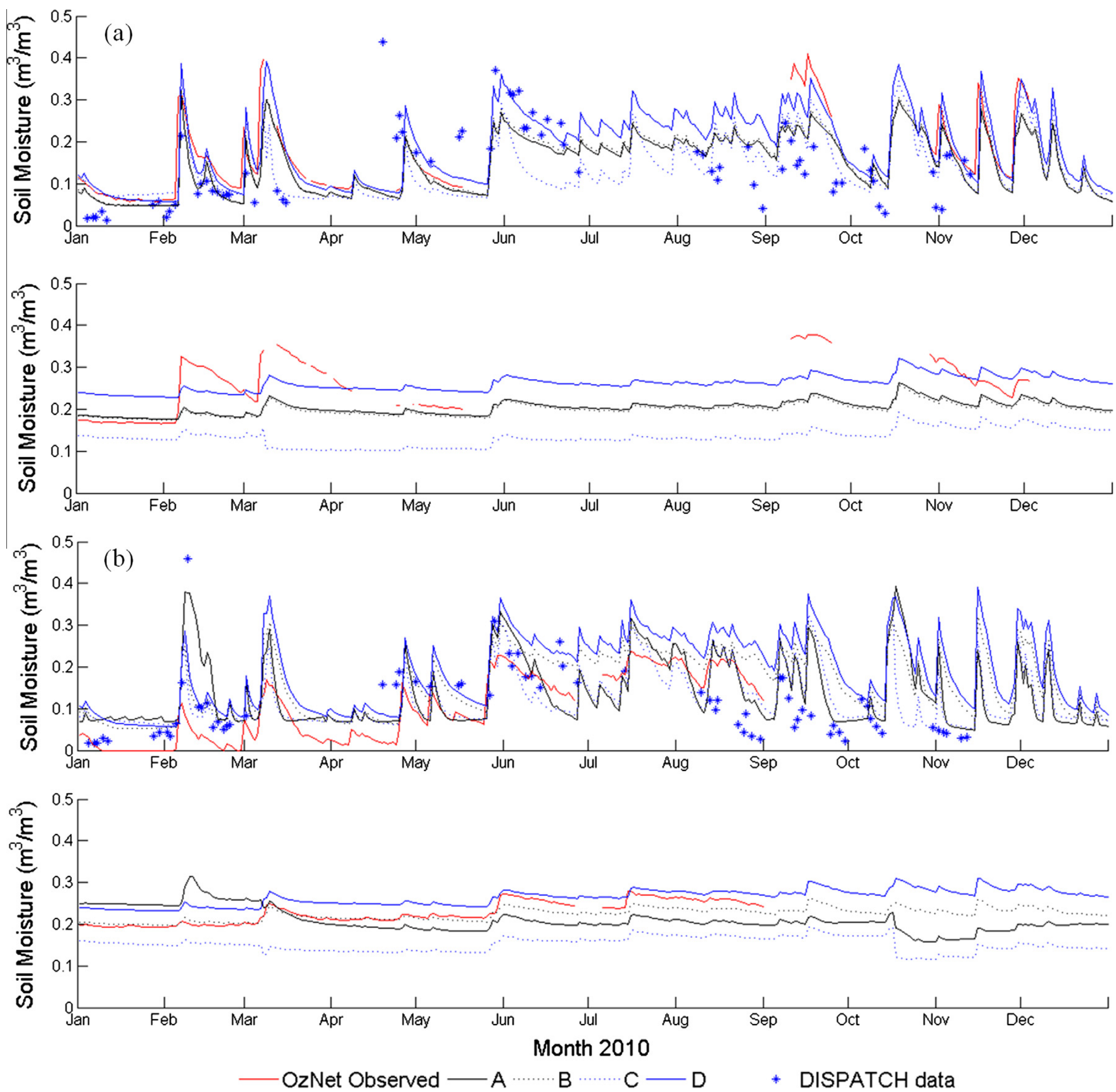


Fig. 4. The measured and predicted soil moisture from scenarios A–D, according to Table 1; (a) Y2 and (b) Y7 with the top panel corresponding to the surface and the bottom panel to the root zone soil moisture content accordingly.

soil hydraulic parameters with scenarios A and C showed negligible improvement in soil moisture predictions over those from published soil hydraulic parameters. In contrast, the results indicate that Y5 and Y7 both out-performed the soil moisture predictions made by published values for both the near-surface and the root zone when the full year of DISPATCH data according to scenario B are used. Scenarios A and B both outperformed scenario C for the surface and root zone of Y2, but had no improvement over scenario D.

Since sites Y2 and Y7 have similar soil properties and provide similar results, only Y2 and Y5 results will be discussed from here on. Fig. 4(a) shows that soil moisture predictions from parameters

Table 3
The root mean square error (RMSE) between the field-measured and predicted soil moisture, for the surface and root zone when using the parameter source according to the four scenarios.

Scenario	RMSE (m^3/m^3)					
	Surface			Root zone		
	Y2	Y5	Y7	Y2	Y5	Y7
A	0.05	0.03	0.09	0.08	0.08	0.05
B	0.05	0.03	0.06	0.08	0.08	0.02
C	0.06	0.05	0.06	0.14	0.06	0.08
D	0.03	0.03	0.08	0.05	0.10	0.03

retrieved with scenarios A and B were best able to capture the dynamics of the observed soil moisture, especially for the root zone of Y2. Fig. 4(b) shows that the near-surface soil moisture dynamics of Y5 are best captured when retrievals used scenario A and B. However, there is a significant difference in the soil moisture predictions for the root zone, despite the dynamics being well captured. Even though it was shown that DISPATCH had a better match with field observations under the water limited summer conditions, the above results indicate that best parameter retrieval is still achieved when using a complete year of DISPATCH data.

Fig. 5 shows the soil water characteristic curves obtained from the different retrieval scenarios, together with the hydraulic conductivity curves. Each of the soil water characteristic curves are also compared with the published ones, where it is seen that the retrieved parameters fall within the ranges given in Clapp and Hornberger (1978) for the soil texture of this area, and with field measured values. For site Y2, the parameters retrieved using scenarios A and B (apart from the soil hydraulic conductivity at saturation) tend to fall close to each other, as opposed to Y5 where they are farther apart. The retrievals with scenario C are almost at the lower end of the range given in Clapp and Hornberger (1978), but are still close to the curve derived from field measurements.

Apart from the soil hydraulic conductivity at saturation, the parameters retrieved with scenarios A and B are very close to the experimentally derived parameters for Y2, almost to the point of overlapping. For site Y5, parameters retrieved from scenario B have the closest match with the observed values. Unlike Y2, retrievals from scenario A do not fall close to the experimentally derived values of parameters. These results further strengthen the fact that the complete year of data yields the best parameter estimates, even though the winter time soil moisture from DISPATCH did not agree well with field observations.

In Bandara et al. (2014), the soil hydraulic parameters were retrieved for the same sites using in-situ near-surface soil moisture observations. Soil hydraulic parameters retrieved with scenarios A and B with DISPATCH data compare well to the retrieved parameter values from in-situ soil moisture observations, as seen from the soil water characteristic curves in Fig. 5.

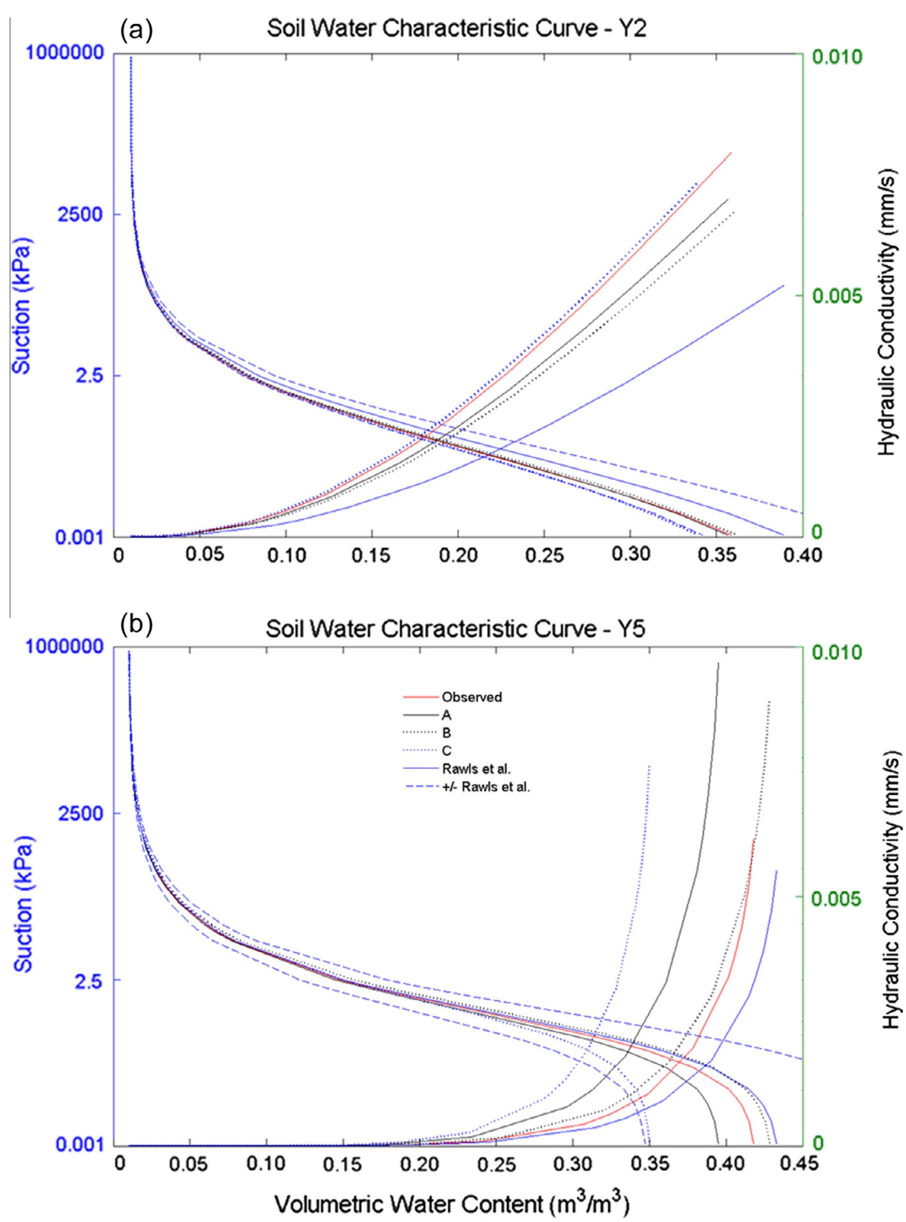


Fig. 5. The soil water characteristic curves for Y2 and Y5, showing the parameters retrieved under different methodologies.

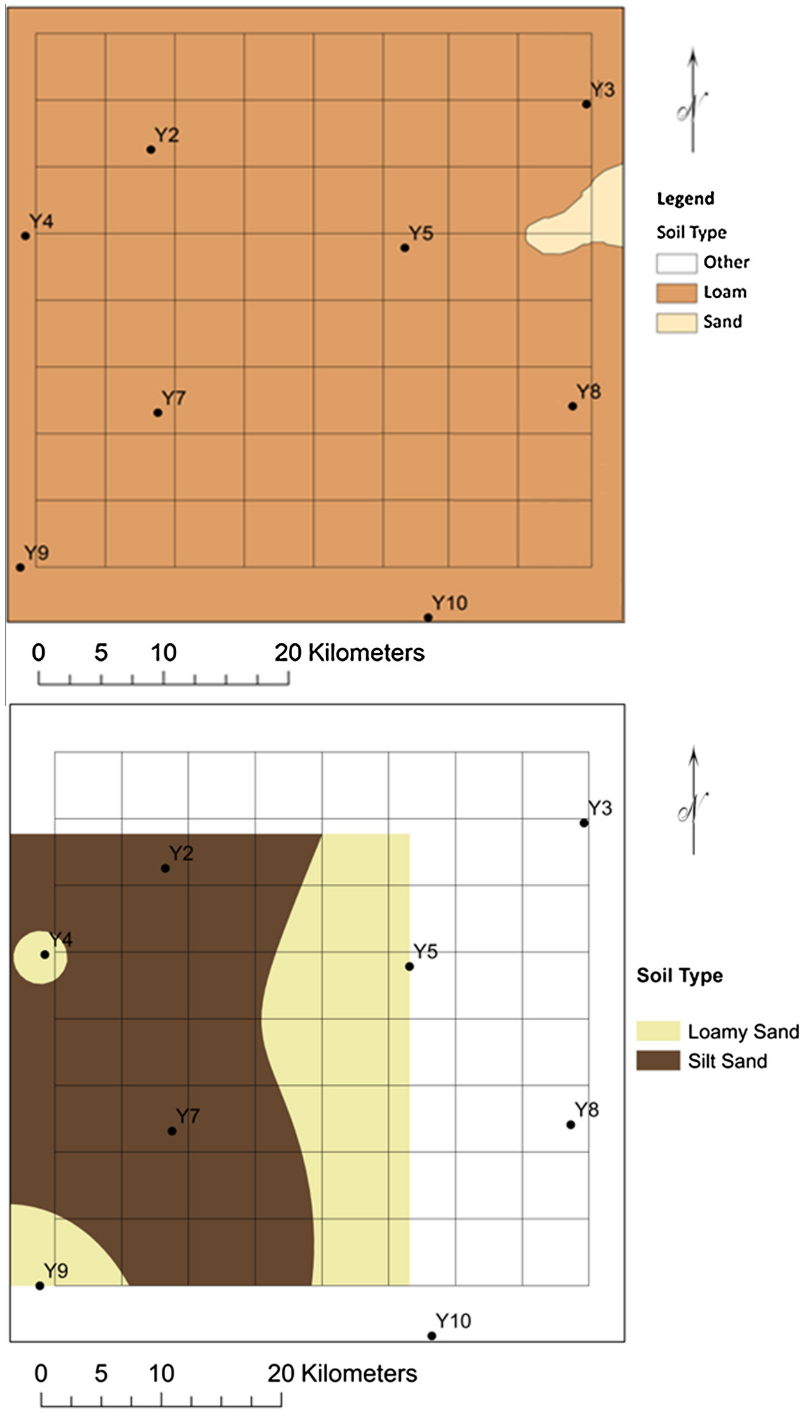


Fig. 6. The 5 km grid with the Yanco stations overlaid on (a) the soil type distribution across the demonstration area (*Source:* Bureau of Rural Sciences, Australia) and (b) the soil texture map interpolated from particle size distribution analysis data over the study area.

Table 4
Representative hydraulic parameter values for the typical soil types in Fig. 6. The standard deviation for each parameter is given in parenthesis. *Source:* Clapp and Hornberger, 1978.

Soil texture	Clapp and Hornberger exponent (–)	Suction at air entry (cm)	Volumetric water content at saturation (m^3/m^3)	Hydraulic conductivity at saturation (mm/s)
Loam	5.39 (1.87)	–47.8 (51.2)	0.451 (0.078)	0.0069
Sand	4.05 (1.78)	–12.1 (14.3)	0.395 (0.056)	0.1761
Loamy Sand	4.38 (1.47)	–9.0 (12.4)	0.410 (0.068)	0.1564
Silt Loam	5.30 (1.96)	–78.6 (51.2)	0.485 (0.059)	0.0072

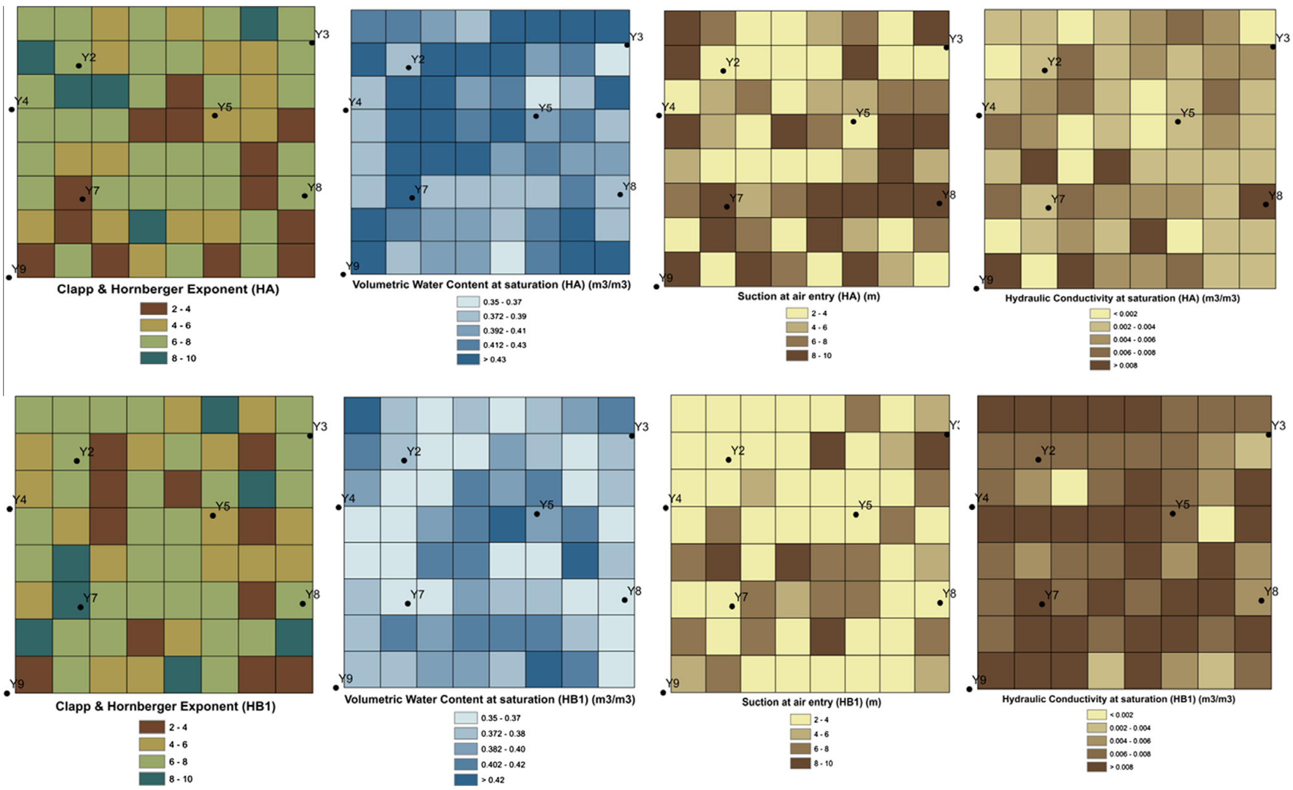


Fig. 7. The spatial distribution of retrieved parameters – left to right, Clapp and Hornberger exponent, Volumetric water content at saturation, Suction at air entry and Hydraulic conductivity at saturation – for Horizon A (top row) and Horizon B_1 (bottom row), over each 5 km × 5 km pixel within the demonstration area.

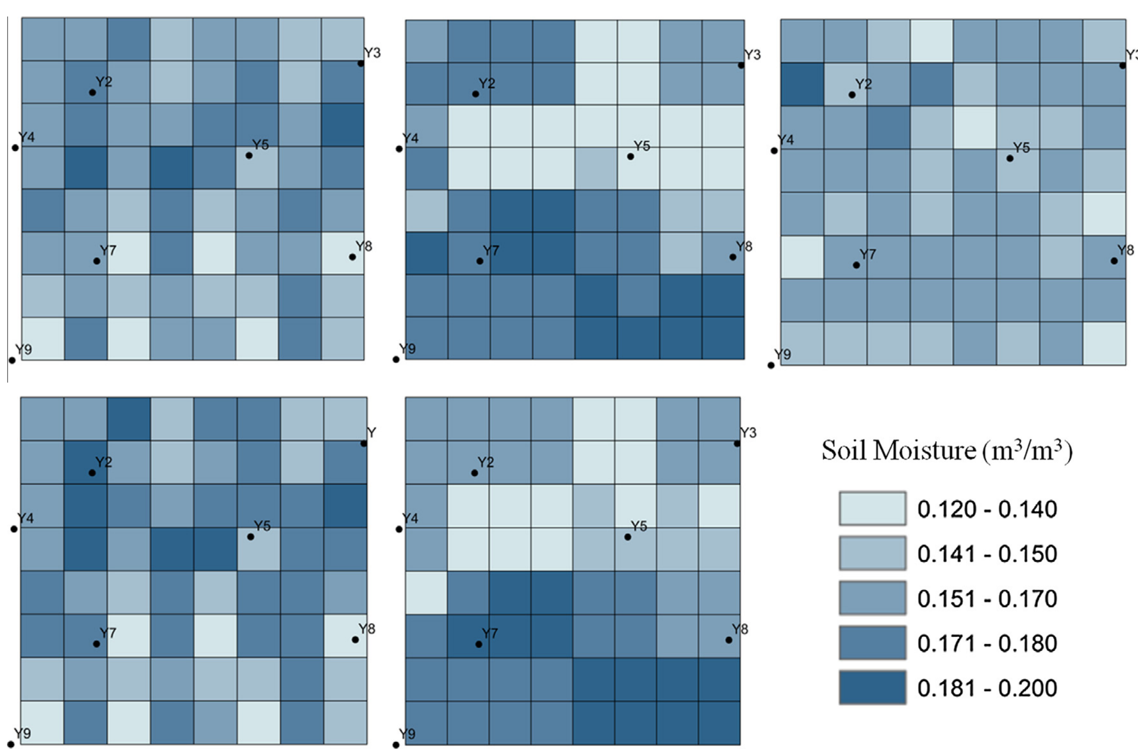


Fig. 8. Example of the predicted soil moisture using the retrieved parameters (left), published parameters from Rawls et al. (1982) (middle), and observed near-surface soil moisture from DISPATCH (right). The top row is for the near-surface and bottom row is for the root zone, for August 14, 2010 (DoY 257).

5.3. Spatial retrieval from DISPATCH data

While the 1 km DISPATCH data showed large RMSEs when compared with in-situ measurements, they were comparatively smaller at 5 km resolution. Moreover, when comparing the retrieved soil hydraulic parameters from 1 km resolution DISPATCH data for the monitoring sites with experimental values they were found to be in good agreement, and the derived soil moisture predictions for the root zone performed better than the published values, being in agreement with field observations. Therefore, the methodology developed in Bandara et al. (2013) and tested in Bandara et al. (2014) at the point scale with in-situ data, is now applied to the 40 km $\times$ 40 km demonstration area of this study at a 5 km $\times$ 5 km spatial resolution.

Fig. 6(a) shows the published soil type distribution map for the demonstration area of the Yanco region in the Murrumbidgee catchment. The dominant soil type is loam with a small pocket of sand on the western side. Fig. 6(b) is the soil map derived from independent particle size distribution analysis of some sites in the focus area. Table 4 contains the representative hydraulic parameter values that relate to these soil types, as given in Clapp and Hornberger (1978), together with the standard deviation for each parameter. Of the six parameters that are the focus of this paper, only four (volumetric water content at saturation, Clapp and Hornberger exponent, soil matric suction at air entry and soil hydraulic conductivity at saturation) parameters have typical values. Therefore, only these parameters are discussed in detail here.

According to the standard deviation for the Clapp and Hornberger exponent, this parameter value can be expected to range from 3.52 to 7.26 for a loamy soil. The retrieved spatial distribution of this parameter as shown in the top panel of Fig. 7 is within this range. For the pocket of sandy soil, the expected range of the same parameter value is 2.27–5.83, and again the retrieved soil property values fall within this range. However, over the entire demonstration area there are five pixels (for example: fourth pixel in the second row) that have values between 8 and 10 for this parameter, which is above the typical value for the soil type. While it difficult to identify any particular spatial patterns in the retrieved soil hydraulic properties that might subsequently be compared against soil texture data, the fact that retrieved soil parameter values are within the range of expected values gives some confidence in the results.

The volumetric water at saturation has been assessed in a similar fashion, with the expected range calculated using the standard deviations given by Clapp and Hornberger (1978). Thus, the ranges were from 0.373 m^3/m^3 to 0.529 m^3/m^3 for a loamy soil, 0.342 m^3/m^3 to 0.478 m^3/m^3 for a loamy sand, and 0.426 m^3/m^3 to 0.544 m^3/m^3 for a silt loam. Apart from one pixel located above Y5, as seen from the top panel of Fig. 7, the rest of the pixels show values over 0.370 m^3/m^3. In contrast to the spatial variation of parameters derived here, according to the normal soil texture mapping approach there would be only a single value for the hydraulic conductivity at saturation for each soil type for the area.

Soils are highly heterogeneous and can vary significantly even within a few metres. Moreover, soil properties have a wide variation even for a soil of the same type. Therefore, it is expected and realistic to have the variation in soil hydraulic parameters as shown in the top panel of Fig. 7 for the A horizon. Similarly, the bottom panel of Fig. 7 shows the spatial distribution of soil hydraulic parameters for the horizon B_1. Certain parameters, especially the volumetric water content at saturation, vary quite significantly between layers of the same soil column. The suction at air entry shows more variation within pixels for the surface, but for horizon B_1 the variations within the layer are more homogeneous. For the Clapp and Hornberger exponent, the change between layers is gradual within a single soil column.

Fig. 8 is an example of the near-surface and root zone soil moisture of the demonstration area for a snapshot in time from the 2010 time series simulation. It was observed that the difference between the model predicted and observation derived DISPATCH soil moisture is quite low, as expected, due to its role in the optimization process. Moreover, it is observed from the middle panel that the soil moisture patterns are less varied when predictions are made using published values, given that most of the focus area consists of one soil type only. Similar soil moisture values are normally observed within an area of 10 km $\times$ 10 km. This is the approximate resolution of the ACCESS forcing data, and therefore the variation in soil moisture of the middle panel is mainly due to the changes in forcing rather than changes in soil type. When predictions are made with the retrieved values, there is a larger variation in the soil moisture, as each pixel has different soil parameters.

6. Conclusions

This spatially distributed application of the proposed soil hydraulic parameter methodology used a downscaled SMOS product called DISPATCH. First the accuracy of the 1 km near-surface soil moisture data from DISPATCH was assessed against field observations of soil moisture, having RMSEs of between 0.07 and 0.08 m^3/m^3.

Three different approaches were investigated to retrieve soil hydraulic parameters from DISPATCH, including (i) using only the summer data with a penalty (the parameters to be retrieved were given a best-guess value with a variation of three times the standard deviation of that parameter) included in the objective function, (ii) using the complete year of data with the penalty, and (iii) using the complete year of data without the penalty. While the synthetic study showed that use of a long period was the preferred approach, a summer period was used here as the DISPATCH downscaling algorithm provided more accurate soil moisture data during the water-/non-energy limited summer period. Despite this, the predicted root zone soil moisture was closest to field observations when the full 12-month period was used in the optimization. Therefore, the 12-month period was used in the optimization process when the methodology was applied spatially, rather than focusing on specific short-term datasets. The retrieved soil hydraulic parameters were validated against the field and laboratory measured values for Y2, Y5 and Y7, and found to both be comparable and in agreement with earlier results from use of in-situ soil moisture data. Thus, it was concluded that DISPATCH data could be used to obtain optimal soil hydraulic parameters for the surface and root zone.

The retrieval of optimal soil hydraulic parameters for the demonstration area was for three horizons, as three distinct horizons were observed during field experiments of Y2, Y5 and Y7. Therefore, spatial maps of optimal soil hydraulic parameters were obtained for the surface and horizons B_1 and B_2. Given that the soil texture map is only available for the surface, the spatial validation of soil hydraulic parameters was limited to the surface. Moreover, the existing texture map is of a coarse resolution with 98% of the demonstration area indicated as loam sand and the remaining 2% a small pocket of sand. The spatial map of the soil hydraulic properties for the near-surface was mostly within the values given for a typical loam and sand soil, but there were some instances where the retrieved values differed significantly. For example, the retrieved hydraulic conductivity at saturation was significantly lower than the typical value for the sandy soil (0.004–0.006 mm/s as opposed to the typical value of 0.1761 mm/s). However, soils are extremely heterogeneous and show contrasting characteristics within a few metres. Thus, this paper has demonstrated the feasibility of retrieving the spatial distribution of soil hydraulic parameters throughout the soil column, utilizing near-surface soil moisture observations from satellite remote sensing in conjunction with a soil moisture prediction model.

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