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DISAGGREGATION OF JASMIN SOIL MOISTURE PRODUCT TO 1 KM RESOLUTION: METHOD OVERVIEW AND FIRST VALIDATION RESULTS

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Cover: Dry cracked earth. Courtesy: http://www.publicdomainpictures.net/

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ABSTRACT

Fire intensity, spread rate, and ignition are very sensitive to fuel dryness which in turn is strongly linked to soil moisture deficit. Though the value of soil moisture deficit in predicting fire danger has been long established, very few fire danger rating systems employ a comprehensive methodology to estimate it. Most such fire danger rating systems use very simple empirical water balance models which are found to have errors. The Bureau of Meteorology has recently developed a prototype, high-resolution, land surface modelling based, state-of-the-art soil moisture analysis for Australia. The product, called Joint United Kingdom Land Environment Simulator (JULES) based Australian Soil Moisture Information (JASMIN), has a spatial resolution of 5 km at hourly timesteps. However, applications like fire danger mapping may require soil moisture information at higher spatial resolution due to the large spatial variability of soil moisture in the landscape. We focus on some of the research carried out to downscale the JASMIN product from 5 km to 1 km spatial resolution. We discuss the application of three downscaling algorithms: two regression-based methods and one with a theoretical basis. The three methods applied are based on the well-known surface temperature – vegetation index space. We present an overview of the application of each method, along with an evaluation and comparison against each other and against ground-based soil moisture observations. Results from comparison with ground-based soil moisture measurements indicate that there is no significant degradation of the bias in the three methods, when going into higher spatial resolutions. However, the regression methods, in general, fail to capture the observed temporal variability. The theoretical based method, on the other hand, provides a temporal correlation of 0.81 and captures the skill of the parent JASMIN product.

1. INTRODUCTION

Accurate and fine-scale soil moisture estimation is critical for the management and timely warning of natural hazards like landscape fires, floods, heatwaves, landslips. It has application to environmental management and to agricultural activities as diverse as livestock farming and silviculture. In a fire danger context, soil moisture status, usually provided in the form of moisture deficits, is a key parameter to assess the fuel availability. In Australia, there is evidence that the methods used to estimate soil moisture in operational fire prediction perform poorly (Vinodkumar and Dharssi, 2017). A prototype, high resolution, land surface modelling system has been developed by the Bureau of Meteorology (Dharssi and Vinodkumar, 2017) to provide soil moisture estimates with high accuracy and precision. This prototype system is based on the Joint UK Land Environment Simulator (JULES; Best et al. 2011) land surface model and is forced mainly by observation based meteorological analyses. The new system is called the JULES based Australian Soil Moisture Information (JASMIN) and estimates soil moisture at a spatial resolution of 5 km. Though JASMIN provides accurate soil moisture information at high spatial resolution, it is at a coarser scale than is ideal for fire and other environmental applications. A common practice to overcome such a problem is to employ downscaling methods to increase the spatial scale of the product.

Downscaling methods establish a functional relationship between soil moisture and associated feature variables (e.g., topography, land-use, land surface temperature), whose spatial distribution can more readily be measured. The downscaling methods generally differ in the type of auxiliary input data (e.g., optical/thermal data, elevation/slope, soil attributes) and the characteristics of the disaggregation method (i.e., physics-based or statistical). One of the most common and early frameworks used in soil moisture downscaling is the use of landscape indices, especially terrain indices, to downscale the coarser resolution soil moisture data. However, the downscaling methods using terrain attributes often establish the relationships by using extensive in-situ observations. Such methods are found to be catchment-specific, restricting their applicability to smaller spatial scales (Busch et al., 2012; Werbylo and Niemann, 2014).

Recent advances in optical remote sensing have allowed researchers to use different remote sensing products that reflect soil moisture variability as ancillary information. A method based on "universal triangle" concept is used in several studies where a relationship between soil moisture, vegetation index (VI) and surface radiant temperature (Ts) from optical remote sensing sensors is established. The universal triangle concept arises from the emergence of a triangular or trapezoidal shape when VI and Ts measures taken from heterogeneous areas are plotted in two-dimensional feature space – forming a Ts/VI scatterplot (Figure 1). Of the different land surface parameters, NDVI and LST are the most widely used. Theoretical and experimental studies have demonstrated the relationship between surface soil moisture, NDVI and LST for a given region under specific climatic conditions and land surface types. This method is used by several studies to downscale microwave remote sensing retrievals of soil moisture (Peng et al., 2017).

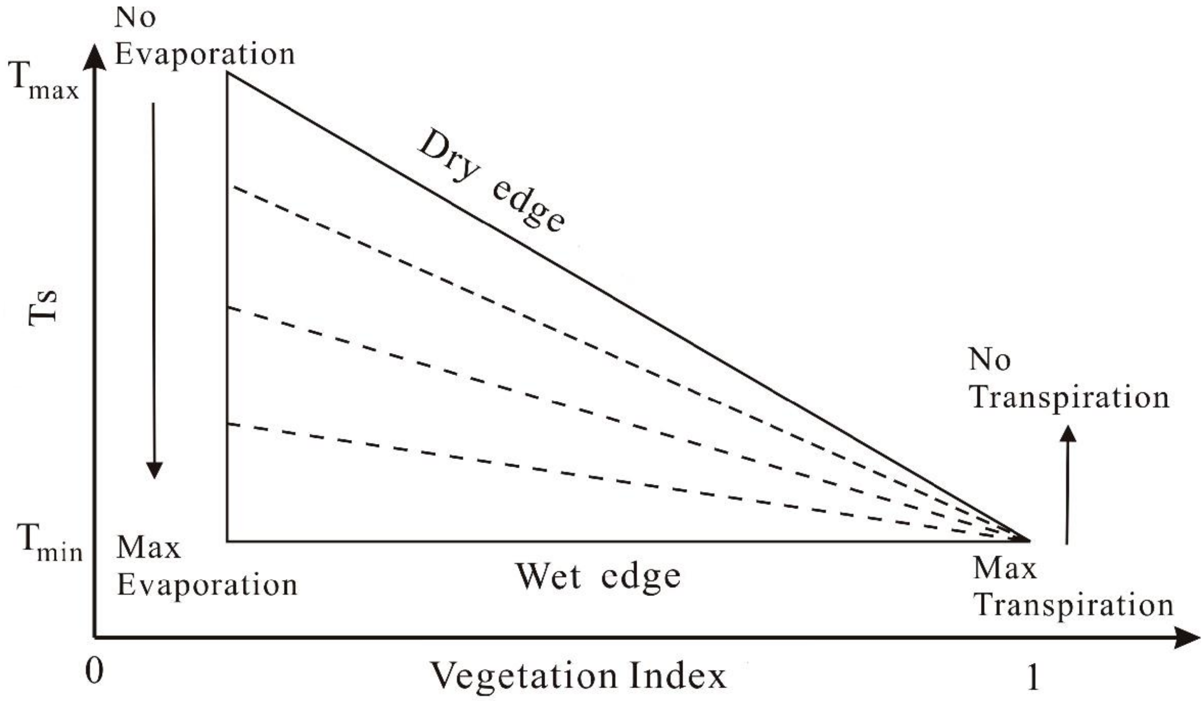

Figure 1. The Ts-VI feature space

Based on the triangular feature space, an empirical, polynomial fitting downscaling method was proposed by Zhan et al. [2002] and Chauhan et al. [2003]. Piles et al. (2011) employed a similar method over south-eastern Australia to retrieve soil moisture at 1 km resolution from Soil Moisture and Ocean Salinity (SMOS) mission using NDVI and LST data from Moderate Resolution Imaging Spectro-radiometer (MODIS). Piles et al. (2011) found that the downscaled soil moisture captures the spatial variability effectively without a significant degradation of the root mean square error. The polynomial fitting approaches are relatively simple to implement and use satellite measurements as input. However, one of the caveats with the regression approaches is that they do not necessarily conserve mass, implying that the aggregated downscaled soil moisture is not necessarily equal to the coarse resolution product.

Merlin et al. (2012) explored the relationship between fractional vegetation cover and soil evaporative efficiency over a catchment in south-eastern Australia using MODIS data. Prior to this study, Merlin et al. (2008) had developed a simple method to downscale soil moisture by using two soil moisture indices (SMIs): Evaporative Fraction (EF; the ratio of evapotranspiration (ET) to the total energy available at the surface) and Soil Evaporative Efficiency (SEE; the ratio of actual to potential evaporation). In addition to the direct relationship existing between soil moisture and EF/SEE, these SMIs are chosen because they have a constant diurnal characteristic, being less dependent on incoming radiation than ET (Nishida et al., 2003). The SEE-based disaggregation method was further improved leading to the emergence of the "Disaggregation based on Physical And Theoretical scale Change (DisPATCh)" model (Merlin et al., 2012). The DisPATCh method was found to yield a temporal correlation of 0.7 when compared to ground-based observations over the semi-arid Murrumbidgee catchment.

The present study explores the applicability of some of these methods based on the universal triangle concept to downscale JASMIN soil moisture from 5 km to 1 km spatial resolution. Specifically, the multiple linear regression method discussed in Piles et al. (2011) and the DisPATCh method discussed in Molero et al. (2016) are implemented and evaluated. The main reason for selecting these methods is that they have been tested and documented to derive soil moisture information at 1 km spatial resolution over Australian regions. Further, the input data used in these methods are readily available. To investigate whether the skill of the multiple linear regression method can be improved further by regularization, we implemented the Least Absolute Shrinkage and Selection Operator (LASSO) regression using the same feature variables used in the multiple linear regression method.

2. DATA SETS

2.1 JASMIN

The JASMIN system runs at 5 km resolution with an hourly time interval (Dharssi and Vinodkumar, 2017). The soil column extends from the surface to 3 m and is divided into four layers of thickness 100 mm, 250 mm, 650 mm and 2 m. JASMIN uses the van Genuchten soil hydraulic model (van Genuchten, 1980) to define the relationship between soil moisture and soil hydraulic conductivity. Except for tree heights, JASMIN use the default ancillary information provided along with JULES to account for spatial variability in soil and vegetation properties horizontally. The tree height information used in JASMIN is based on a global dataset of canopy height derived from a space-borne light detection and ranging instrument (Simard et al., 2011).

The BoM's Mesoscale Surface Analysis System (MSAS; Glowacki et al., 2012) data available near-real-time at 4 km resolution is converted and re-gridded to provide the JULES driving data for air temperature, specific humidity, wind speed and surface pressure. The downward surface solar radiation data is from a near-real-time BoM product derived from the Himawari Geostationary Meteorological Satellites and is available at about 5 km resolution. The downward surface longwave radiation data is obtained from BoM's regional NWP model at 12 km resolution (Puri et al., 2013).

Rainfall data is from AWAP (Jones et al., 2009) and available as daily accumulations. Tropical Rainfall Measuring Mission (TRMM; Huffman et al. 2007) data is used to disaggregate AWAP rainfall to 3-hourly values. The TRMM data is also used to fill spatial gaps in AWAP data.

2.2 IN-SITU SOIL MOISTURE OBSERVATIONS

2.2.1 OzNet

OzNet is a dedicated soil moisture observation network primarily located in the Murrumbidgee catchment (Smith et al., 2012). The OzNet–Murrumbidgee dataset consists of 46 sites, all of which are located on either grassland or cropland. Data from 2010 onwards are used in this study. The soil profiles in OzNet are generally mapped at 0 – 80 mm, 0 – 300 mm, 300 – 600 mm and 600 – 900 mm depths. For the present study, we choose 0 – 80 mm and 0 – 900 mm profiles for comparisons.

2.2.2 CosmOz

CosmOz is a soil moisture network consisting of 16 sites established at various locations around Australia (Fig. 1; Hawdon et al., 2014). The network uses cosmic-ray probes to measure soil moisture. The cosmic-ray probes provide a horizontal foot print of about 240 m in diameter at sea level (Köhli et al, 2015). Franz et al. (2012) estimated the accuracy of cosmic-ray probes as 0.02 m^3 m^{-3}. The present study uses level 4 data, which has undergone corrections, calibrations and quality control. The comprehensive methodology applied for data processing and probe calibration for the CosmOz network are given in Hawdon et al. (2014). For the present study, 14 sites out of the total 16 are selected. The two sites discarded are Griffith in New South Wales and Gnangara in Western Australia. The Griffith site is in an irrigation area. Such anthropogenic modifications are not represented in the models. Gnangara is discarded because the calibration function does not perform well here, a result of high sand fraction in the soil over this region (Hawdon et al., 2014).

2.2.3 OzFlux

OzFlux is a network established to study regional ecosystems ranging from forests to grasslands (Beringer et al., 2016). OzFlux consists of 37 sites located around Australia, measuring soil moisture and micro-meteorological fields. Soil moisture is given in volumetric units and is based on measurements from the Time Domain Reflectometry sensors set up at each site. The present study uses the quality-controlled level 3 data freely available from the OzFlux data portal (data.ozflux.org.au/portal). Data from the 21 non-embargoed, free, publicly available OzFlux sites are used in this study. All these sites contain soil moisture observations for a shallow layer of depth <150 mm, which varies from site to site.

2.3 MODIS

The Moderate Resolution Imaging Spectroradiometer (MODIS) is an instrument onboard both the Terra and Aqua satellites operated by the National Aeronautics and Space Administration (NASA). Terra's orbit around the Earth with equator crossing times of 10:30 AM/10:30 PM local time, while Aqua passes over the equator 3 hours after Terra, at 1:30 PM/1:30 AM local time. Terra MODIS and Aqua MODIS cover the entire Earth's surface in 1 to 2 days, collecting data in 36 spectral bands.

The MODIS data used in the present study are the MODIS/Terra and MODIS/Aqua 1 km resolution daily daytime LST (MOD11A1, version 5), MODIS/Terra 1 km resolution 16-day NDVI product (MOD13A2, version 5), and MODIS/Terra+Aqua 1 km resolution 16-day surface albedo product (MCD43A3, version 5). The surface albedo data set is only used in DisPATCh method, where it is used to estimate vegetation temperature at maximum water stress (Merlin et al., 2012). The MCD43A3 product provides both directional hemispherical reflectance (black-sky albedo) and bi-hemispherical reflectance (white-sky albedo). In this study, surface albedo refers to the MODIS shortwave white sky albedo, following Merlin et al. (2012).

The MODIS products used here were obtained from the TERN-AusCover data portal (http://www.auscover.org.au/, as of July 2018). The AusCover MODIS dataset is produced and managed by the Commonwealth Scientific and Industrial Research Organization (Paget and King, 2008). The original MODIS data are created and maintained by the Land Processes Distributed Active Archive Centre (LPDAAC), which is a as a partnership between the U.S. Geological Survey (USGS) and NASA. To facilitate the utilization of these datasets by the Australian environmental research community, CSIRO collate all available tiles for selected products covering the Australian continent. These collated tiles are then mosaiced and remapped into the same Geographic (rectilinear latitude/longitude) projection (Paget and King, 2008).

3. METHODOLOGY

3.1 Multiple linear regression method

The triangle concept has been used to develop a linking model that relates JASMIN soil moisture data to MODIS derived NDVI and LST datasets. The linking model in this case is a multiple linear regression method which uses NDVI and LST data as the feature variables. The relationship can generally be expressed through a regression formula such as:

$$SM_{1km} = \sum_{i=0}^{n} \sum_{j=0}^{n} a_{ij} NDVI^{i} LST^{j} \qquad (1)$$

Piles et al. (2010) effectively used a second order polynomial function to define the linking model between the LANDSAT surface radiant temperature/NDVI features and airborne soil moisture estimates. The surface radiant temperature and NDVI were normalized to reduce the dependence of each parameter on ambient conditions. A similar approach is adopted in the present study. However, the quadratic function was selected after experimenting with linking models of various order, ranging from first to ninth order. The experiments were conducted over a test domain in south-eastern Australia, comprising the Murrumbidgee catchment, for the year 2010. The results were then compared against OzNet observations. It is found that the quadratic function provided the best estimate among all functions examined. The linking model used in the present study can be written as:

$$SM_{hres} = a_{00} + a_{01}T_n + a_{10}f_v + a_{11}T_n f_v + a_{02}T_n^2 + a_{20}f_v^2 \quad (2)$$

Here, T_n stands for normalized LST (3) and f_v is the fractional vegetation cover defined as (4). T_n and f_v are calculated after masking cloud affected and land water pixels from respective datasets.

$$T_n = \left[\frac{T_s - T_s^{min}}{T_s^{max} - T_s^{min}}\right]_{hres} \quad (3)$$

$$f_v = \frac{NDVI - NDVI_{min}}{NDVI_{min} - NDVI_{max}} \quad (4)$$

T_s^{max} and T_s^{min} are the maximum and minimum LST values for a day and region under study. Similarly, $NDVI_{max}$ and $NDVI_{min}$ are the maximum and minimum NDVI values for a day and region after masking the cloud and water pixels.

3.2 Least Absolute Shrinkage and Selection Operator (LASSO) regression

The LASSO (Tibshirani, 1996) is an extension to linear regression technique, where the regression coefficients are optimally reduced (shrinkage). In some cases, the regression coefficients are even reduced to zero, thereby ignoring a feature (selection). LASSO minimizes the residual sum of squares as in classical linear regression, but the determination of regression coefficients is constrained by the sum of the absolute values of the coefficients being as small as possible. This is achieved by defining a regularization parameter (λ) in the cost function (Equation 5) that determines the influence of the classical least square contribution (first term in the right-hand side of Equation 5) relative to the sum of modulus of the coefficients (second term on the right-hand side of Equation 5).

$$J(\beta_k) = \frac{1}{N}\sum_{n=1}^{N}(Y_n - \sum_k \beta_k X_{k,n})^2 + \lambda \sum_k |\beta_k| \quad (5)$$

The LASSO technique applied in the present study also uses normalized LST and NDVI features to derive the linking model. In order to estimate the optimal regularization parameter (λ), experiments were conducted on a training dataset covering south-east Australia, spanning the whole year of 2010. Based on the subjective evaluation and on the objective verification against in-situ observations from OzNet network, a value of 80 was selected for λ.

3.3 Disaggregation based on Physical And Theoretical scale Change (DisPATCh)

The DisPATCh method is categorized as physics based as it links the land surface temperature data with surface soil moisture through soil evaporation process. The theoretical basis of the method is highlighted by the reliance on mathematical tools such as partial derivatives, Taylor series expansions, and projection techniques (Merlin et al., 2005). The development of the DisPATCh method can be found in Merlin et al. (2006) and Merlin et al. (2008).

The DisPATCh method in this study uses the soil evaporative efficiency (SEE) concept, defined as the ratio of actual to potential evaporation, to model the sub-pixel spatial variability of surface soil moisture. The advantage of using SEE is that it is much more directly linked to remote sensing and a SEE model can be readily developed in conjunction with land surface temperature and surface soil moisture. The disaggregation method in DisPATCh can be written as:

$$SM_{hres} = SM_{lres} + \left[\frac{\partial SM}{\partial SEE}\right]_{lres} . \left(SEE_{hres} - \overline{\langle SEE_{hres}\rangle_{lres}}\right) \quad (6)$$

SM_{hres} is the 1km downscaled soil moisture, and SM_{lres} is the coarse scale JASMIN soil moisture. Here, we upscale the JASMIN soil moisture to 50 km resolution by averaging. This is in order to construct an accurate Ts-VI space, which is otherwise impossible in a 5 km resolution JASMIN grid, which encompasses only 25 MODIS LST pixels. From now on, coarse-scale JASMIN grid in DisPATCh refers to the 50 km resolution grid. SEE_{hres} is the MODIS-derived soil evaporative efficiency and $\overline{\langle SEE_{hres}\rangle_{lres}}$ its average within a JASMIN grid. ∂SM/∂SEE is the partial derivative of soil moisture with respect to soil evaporative efficiency evaluated at the coarse scale. Here, a linear model is used to define the sensitivity of soil moisture to SEE, as this is found to be a good approximation at kilometre scales (Merlin et al., 2013).

MODIS derived soil evaporative efficiency is expressed as a linear function of MODIS-derived soil temperature (T_s) and is given as:

$$SEE_{hres} = \left[\frac{T_{soil}^{max} - T_{soil}}{T_{soil}^{max} - T_{soil}^{min}}\right]_{hres} \tag{7}$$

T_{soil}^{max} and T_{soil}^{min} are the soil skin temperature at SEE=0 and SEE=1 respectively. The MODIS land surface temperature is linearly decomposed into soil temperature and vegetation temperature based on the Ts-VI feature space. The soil temperature is expressed as:

$$T_{soil} = \left[\frac{T_{LS} - f_v . T_v}{1 - f_v}\right]_{hres} \tag{8}$$

T_{LS} is the MODIS land surface temperature, f_v is the fractional vegetation and T_v is the vegetation temperature. The fractional vegetation cover is given as:

$$f_v = \frac{NDVI - NDVI_{soil}}{NDVI_{veg} - NDVI_{soil}} \tag{9}$$

$NDVI_{soil}$ is the NDVI corresponding to bare soil, and $NDVI_{veg}$ is the NDVI corresponding to full-cover vegetation. For the present study, $NDVI_{soil}$ and $NDVI_{veg}$ values are set to 0.10 and 0.80, respectively.

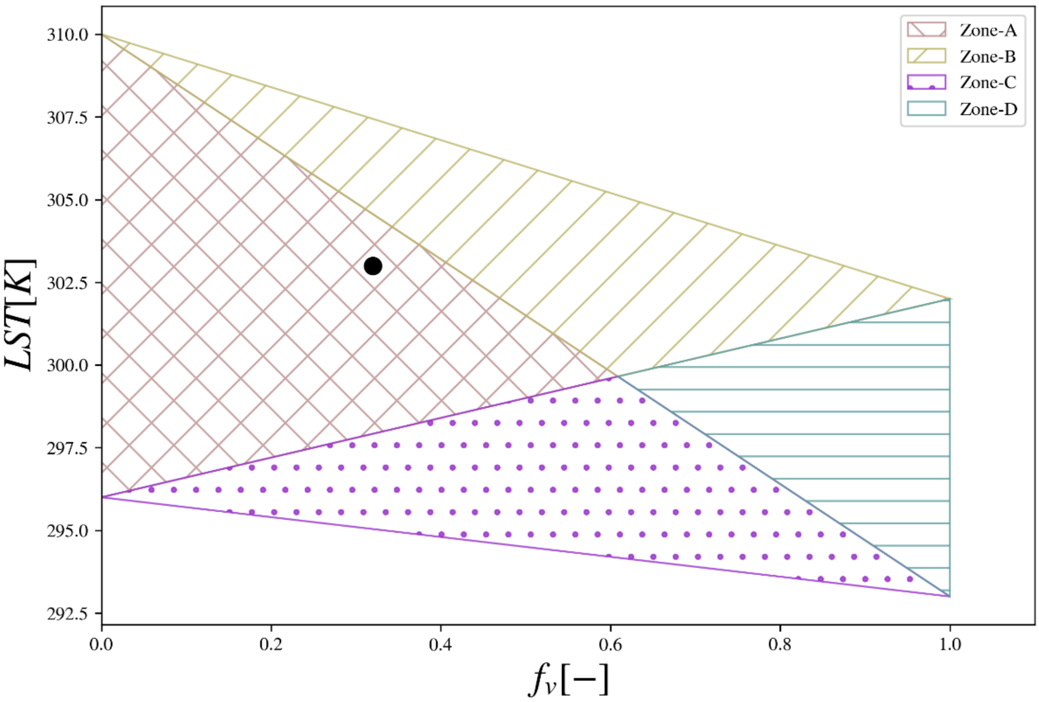

Figure 2: Estimation of vegetation temperature using the "hourglass" approach.

The vegetation temperature is estimated using the "hourglass" approach described in Moran et al. (1994) and Merlin et al. (2012). By plotting the diagonals of the Ts-VI quadrilateral for each coarse-scale grid, four areas are distinguished in the feature space defined by surface temperature and fractional vegetation cover (Figure 2). In zone A, LST is mainly controlled by soil evaporation leading to optimal sensitivity of LST to surface soil moisture. In zone D, LST is mainly controlled by vegetation transpiration with no sensitivity to surface soil moisture. In zones B and C, LST is controlled by both soil evaporation and vegetation transpiration with intermediate sensitivity to surface soil moisture. Based on this understanding, vegetation temperature is estimated for each zone as:

$$Zone\ A:\ T_v = \frac{T_v^{min} + T_v^{max}}{2} \tag{10}$$

$$Zone\ B:\ T_v = \frac{[T_v^{min}]_{SEE=0} + T_v^{max}}{2} \tag{11}$$

$$Zone\ C:\ T_v = \frac{T_v^{min} + [T_v^{max}]_{SEE=1}}{2} \tag{12}$$

$$Zone\ D:\ T_v = \frac{[T_v^{min}]_{SEE=0} + [T_v^{max}]_{SEE=1}}{2} \tag{13}$$

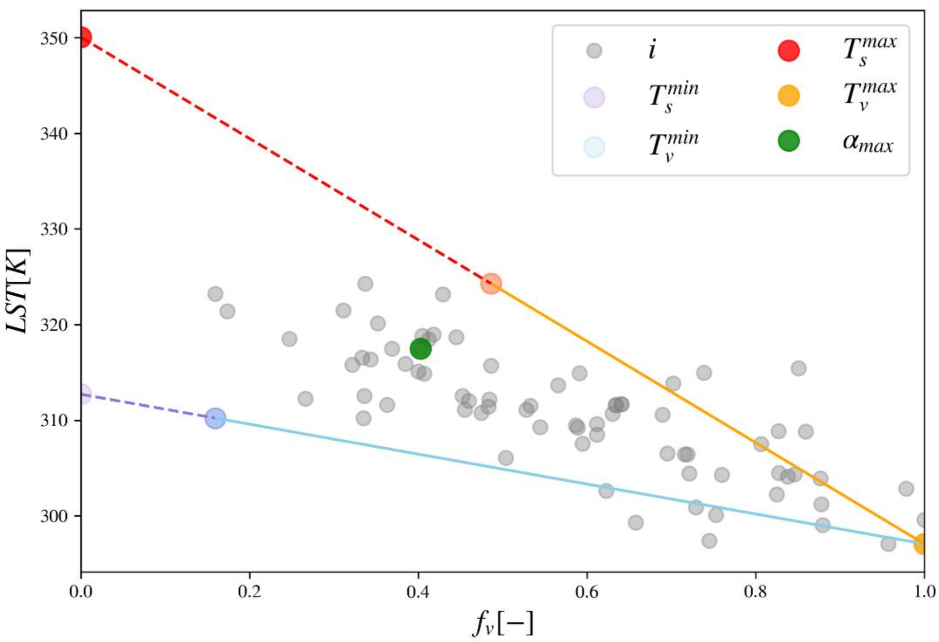

Figure 3: Estimation of end members

T_v^{min} and T_v^{max} being the vegetation temperature at minimum and maximum water stress respectively. End-members T_{soil}^{max}, T_{soil}^{min}, T_v^{min} and T_v^{max} are estimated at 1 km resolution by combining the spatial information provided by the LST-f_v and the LST-albedo feature space developed using the MODIS data within each coarser JASMIN grid point (Figure 3). Here, T_v^{min} is set to the minimum MODIS LST within each coarse-scale JASMIN grid. T_v^{max} is set to the LST of the MODIS pixel with the maximum albedo value (Figure 3). If fv < 0.5 for the corresponding MODIS pixel, the vegetation T_v^{max} is set to T_v^{min}. The above condition is set to increase the robustness of the determination approach, particularly for the JASMIN grids where all surface conditions are not met.

T_{soil}^{min} is calculated by extrapolating along the wet soil edge at f_v=0. The wet soil edge is defined as the line passing through (SEE=1, T_v^{min}) and through the data point such that all the data points with f_v < 0.5 are located above the wet soil edge (Figure 3). T_{soil}^{max} is estimated by extrapolating along the dry soil edge at f_v = 0. The dry soil edge is defined as the line passing through (SEE=1, T_v^{max}) and through the data point such that all the data points with f_v < 0.5 are located below the dry soil edge.

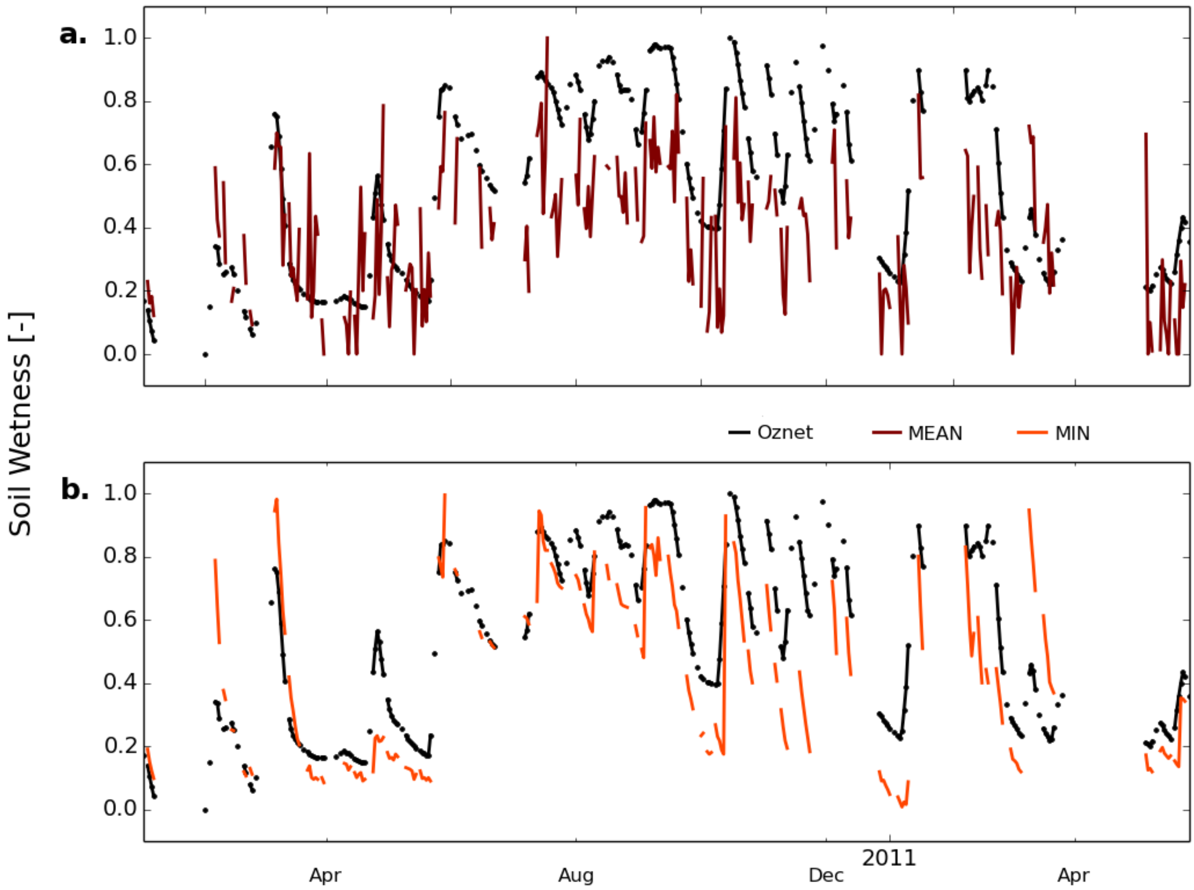

Figure 4. Calibration of DisPATCh soil parameter. The upper panel shows the comparison of in-situ soil moisture (black line) against downscaled soil moisture obtained by applying the mean soil parameter value (brown line). The lower panel depicts the same, except that downscaled soil moisture is obtained by applying the minimum soil parameter value.

A key factor in the performance of the DisPATCh algorithm is the correct calibration of the model depicting the relationship between soil moisture and SEE. Here, a linear assumption is made. The model is calibrated from daily SEE and SM estimates at low resolution. In studies applying DisPATCh to disaggregate microwave soil moisture retrievals, calibrated values of the soil moisture parameter were obtained by averaging estimates over multiple images collated over a few days (e.g.: Merlin et al., 2010). In the present study, calibration is done using the MODIS and JASMIN datasets spanning the whole year of 2010. However, during the calibration phase, it was found that averaging led to large parameter values which introduced random errors in the downscaled soil moisture, thereby reducing the temporal skill of the product (Figure 4a). This is demonstrated through the comparison against ground observations from OzNet-Yanco site 9. Choosing the minimum parameter value rather than the mean is found to reduce these random errors (Figure 4b). Hence, in the present study, the calibrated parameter values are set to the minimum of SM_p values at each grid point from the 2010 timeseries.

4. RESULTS AND DISCISSIONS

4.1 Seasonal means

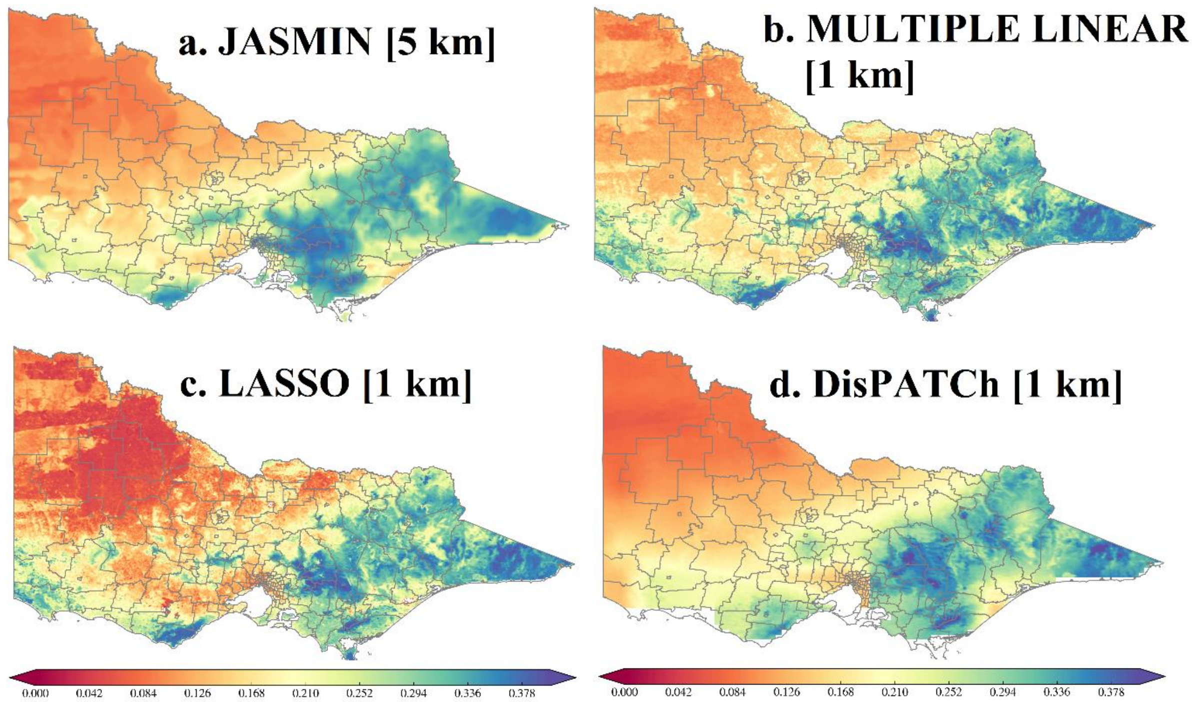

Figure 5. Seasonal average volumetric soil moisture for southern-hemisphere autumn (March – April) from (a) JASMIN at 5 km resolution, (b) multiple linear regression method at 1 km, (c) LASSO regression method at 1 km resolution, and (d) DisPATCh at 1 km resolution.

The daily gridded volumetric soil moisture fields from each of the three downscaled products, spanning from 2011 to 2016, are used to calculate seasonal mean climatologies. Figure 5 depicts the seasonal mean of each downscaling product for the southern-hemisphere autumn, extending from March to April. The seasonal climatology from the 5 km JASMIN product is also provided for comparison (Figure 5a). The spatial plots reveal some interesting aspects of each downscaling method. All the downscaling methods generally preserve the wet and dry regions in the coarse scale product, thereby providing similar spatial patterns. However, each downscaling product differs in the magnitude of spatial variability. Thus, the regression-based approaches have a higher spatial variability than DisPATCh. Further, the LASSO method tends to produce drier soil over arid-inland areas compared to the other two downscaling methods. DisPATCh is found to have smaller spatial variability than the two regression methods. This is especially pronounced over the arid inland regions. It is found that the soil parameter (SM_p) values in DisPATCh are quite low over these arid regions. Further, the spatial variability of SEE over arid regions is smaller, leading to DisPATCh adding smaller perturbations to the coarse scale soil moisture product. The nine-point-smoothing applied to eliminate the "chequered" patterns obtained in DisPATCh (Merlin et al., 2013) further smooths out these small spatial variabilities over the arid inland regions.

4.2 Comparison against observations

This section discusses the temporal skill of each downscaling product against ground-based observations. Good temporal skill is critical for soil moisture products used in fire prediction, as cumulative measures of soil moisture status are often considered in fire management and prediction. The verification period selected for the present study is 1st January 2010 to 1st March 2017. Completeness of in-situ temporal records vary from site to site and only sites with a complete seasonal cycle are selected for statistical analysis. This results in a total of 60 sites for the present analysis. Pearson's product-moment correlation (R), unbiased root-mean-square difference (ubRMSD) and bias metrics are used here to evaluate the skill of each product against in-situ observations. Bias is defined as the mean in-situ value minus model value. Several studies have used the above metrics to compare different soil moisture products (e.g., Vinodkumar et al., 2017; Brocca et al., 2014). The scores are computed for all stations and for the whole period where data overlaps. Only scores for correlations with p-values<0.001 are presented.

An evaluation of each model's skill over different land use / land cover (LULC) is presented in Figure 6. The LULC classification is made based on the types over which the observation sites are located. CosmOz and OzFlux provide this information via the site description and images given in the web portal. The LULC information for OzNet is provided in Young et al. (2008). We broadly classify the land cover types into forests, woodlands, grasslands and croplands. The northern Australian savannahs are classified as woodlands. All pasture and grazing paddocks are included under grasslands. Of the 60 sites in total across three networks, 12 are classified as croplands, 12 as forests, 9 under woodlands, and the remaining 27 under grasslands.

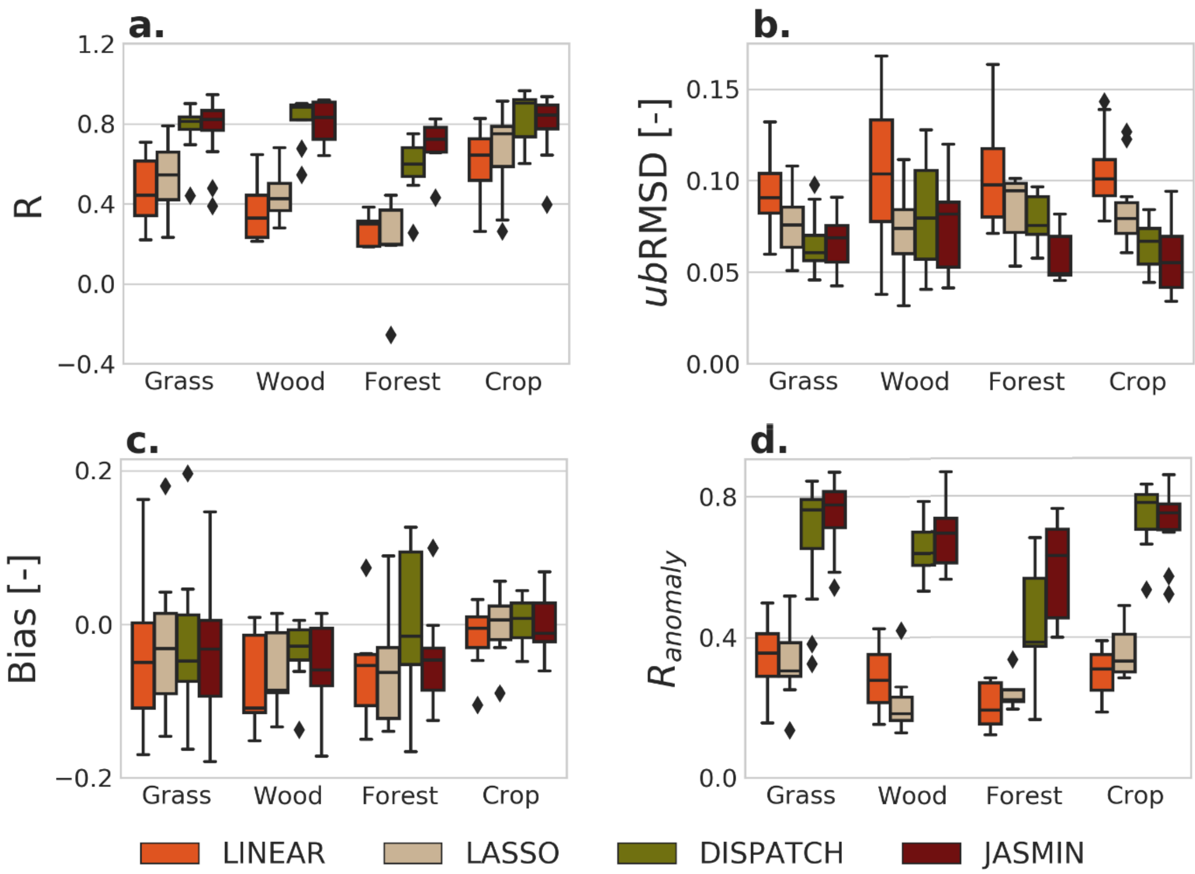

Figure 6. Skill of soil moisture products over various land cover types: a) Pearson's correlation, b) unbiased RMSD, c) bias, and d) anomaly correlation. The grouping is done based on the land cover type of the observing site. The outliers are marked as diamonds. The orange boxes represent multiple linear regression method, light khaki colour represents LASSO method, the green boxes represent DisPATCh and the magenta coloured boxes represent the original JASMIN product at 5 km resolution.

JASMIN performs consistently over all land cover types considered here. In terms of correlations, JASMIN exhibits noticeably higher skill over grasslands and croplands. The correlation over forested sites ranges from 0.43 to 0.78. The ubRMSD for forested sites ranges between 0.46 and 0.08 and is the lowest among the four land use types. The median bias for forest sites is -0.05. The range of the anomaly correlation for forest sites is 0.40 to 0.76. JASMIN has good skill in simulating moisture regimes over woodlands and the median values as indicated by the box plot for correlation, ubRMSD, bias and anomaly correlation are 0.81, 0.07, -0.05 and 0.75 respectively.

Interestingly, the temporal skill is reduced when JASMIN is downscaled using the two regression-based methods. For example, the median values obtained by the LASSO method over woodlands for correlation, ubRMSD, bias and anomaly correlation are 0.41, 0.08, -0.08, and 0.26 respectively. For the multiple linear regression method, the above scores are 0.37, 0.11, -0.1 and 0.32 respectively. The LASSO method is found to have similar bias and random errors to the original dataset. The LASSO method produces a higher skill than the multiple linear regression, highlighting the fact that there was some overfitting in the multiple linear regression method which is reduced in the LASSO method. Because of the safeguarding against high sensitivity to noise, LASSO has a higher correlation and lower ubRMSD than the multiple linear regression method. This is demonstrated through the timeseries plot over the Weany Creek site in the northern Queensland, which is part of the CosmOz network (Figure 7). This site is in a grazed open woodland with grassy and shrubby understory. The multiple linear regression method is found to have larger temporal variability than the LASSO method and the other two products (JASMIN and DisPATCh). This is particularly noticeable during the dry seasons where the multiple linear regression method shows large variability compared to the observations. A possible reason for this is the large sensitivity of estimated soil moisture in multiple linear regression to noise in the LST data. The uncertainties involved in the thermal infrared based LST retrievals are found to be about 2 K (Li et al., 2014). By applying regularization through LASSO, this sensitivity is reduced to some extent, but not to a point where the LASSO estimates match the temporal skill of the JASMIN product at 5km (Figure 7c).

In the case of DisPATCh, the temporal skill is similar to the JASMIN 5 km product and better than the other two downscaling methods. The average correlation of DisPATCh over the three networks is 0.81, identical to JASMIN. In the woodland, cropland and grassland cases, disaggregation either marginally improves or retains the mean R, bias and ubRMSD. The similar skill of DisPATCh and JASMIN can be appreciated from the box and whiskers provided in Figure 6. Specifically, DisPATCh shows an increase in R and reduction in bias over the woodland sites. The good performance of the DisPATCh over woodlands is re-affirmed by the timeseries plot at the Weany Creek, which is an open woodland site (Figure 7d). The DisPATCh shows similar temporal variability to the observations and does not produce the large variability observed in the other two downscaling methods.

However, it is observed that DisPATCh has lower skill than the JASMIN product over forested sites, possibly due to the increase of random uncertainties attributable to the models and data used by DisPATCh. Studies have shown that DisPATCh performs better over low-density vegetated areas in semi-arid environments (Merlin et al., 2012). A possible reason for this behaviour is the weaker coupling between evaporation and surface soil-moisture in temperate (where most forested sites are located) than in semi-arid climates. Further, the presence of dense vegetation poses a challenge in the retrieval of the soil temperature from thermal infrared data. The vegetation water stress may increase the remotely sensed land surface temperature independent of near-surface soil moisture.

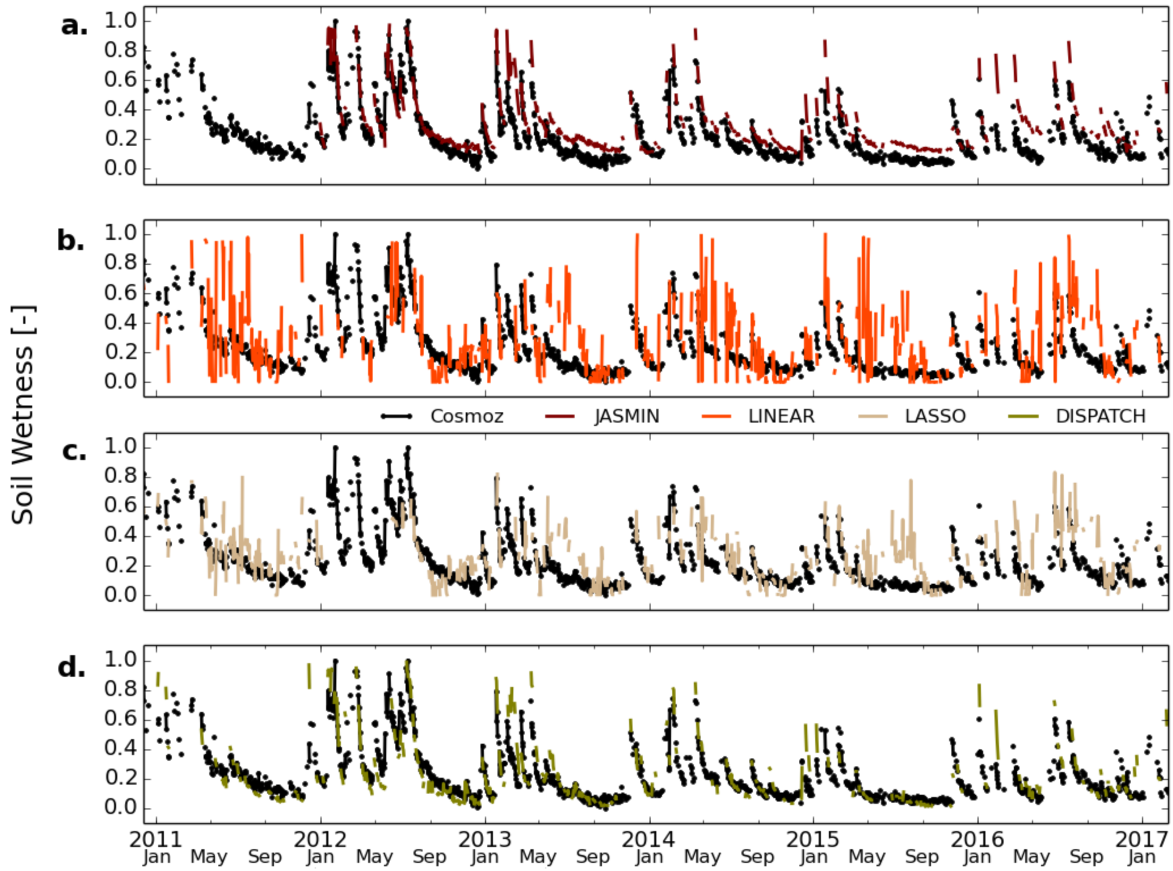

Figure 7. Soil wetness time-series at the Weany Creek site in Queensland, part of the CosmOz network. The brown lines show JASMIN analyses at 5 km resolution, orange line represent multiple linear regression method, light khaki depict LASSO method and the green line represent DisPATCh. The black dotted lines show the in-situ observations.

5. SUMMARY AND CONCLUSIONS

Three algorithms to improve the spatial resolution of the JASMIN product from 5 km to 1 km are investigated. The selected algorithms are based on the well-known surface temperature-vegetation index feature space and are applied using the thermal and optical infrared data from the MODIS instrument. The rationale for choosing these algorithms is: (a) they can be applied at a continental scale, (b) input data is readily available, and (c) they have been tested and documented over Australian regions. The present study applies a step-by-step approach, where the algorithm identified as the simplest is implemented, tested and evaluated first, before moving to the next algorithm to explore any added skill that can be potentially gained. In that respect, we started off with the multiple linear regression method discussed in Piles et al (2010). To investigate whether the skill of the multiple linear regression method can be improved further by regularization, we implemented LASSO regression using the same feature variables used in the multiple linear regression method. Further, a more theoretical based method, in the form of DisPATCh, was tested to identify any potential gain in skill that could be achieved.

Results from the application indicate that it is feasible to improve the spatial resolution of JASMIN using all three disaggregating algorithms and preserve the general large-scale spatial structure seen in JASMIN soil moisture estimates. However, the seasonal means obtained at 1 km shows that each product displays characteristic soil moisture spatial variability at fine scales. Results from comparison with ground-based soil moisture measurements indicate that there is no significant degradation of the bias in the three methods when moving to higher spatial resolution. However, the regression methods degrade the temporal correlations and the ubRMSD scores. The DisPATCh method produces the best skill among the three algorithms tested here, and the skill scores from DisPATCh are comparable to those of the original JASMIN timeseries.

The low skill observed in regression methods possibly resulted from the large random errors attributable to the methods or uncertainties in the feature variables. It is worth noting that even the minimum and maximum limits applied to calculate the normalized LST and NDVI datasets (feature variables in the regression method) can introduce uncertainties in the downscaled soil moisture output. Further research is required to identify and minimize some of the uncertainties associated with both MODIS LST and NDVI datasets and to provide robust quality control.

Uncertainties in the MODIS input datasets have an important influence on the DisPATCh results as well, in addition to the uncertainties arising from the model assumptions and calibrations. It is found that calibration has a significant influence on the DisPATCh model behaviour. Further research is needed to calibrate the model so that the spatial variability in soil moisture is accurately captured. One aspect of DisPATCh that needs to be revisited is the modelling of soil moisture sensitivity to the soil evaporative efficiency. The model in the present study was chosen for its simplicity and its ability to represent the general behaviour of soil evaporative efficiency over the full range of soil moisture. However, studies have shown that the soil moisture sensitivity to soil evaporative efficiency can be non-linear and influenced by various factors including atmospheric demand, soil texture etc. It is important to note that the DisPATCh algorithm is evolving and will continue to do so. Further work is required to test and evaluate the new ideas that will be developed in relation to DisPATCh and will be a focus of future research.

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