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ABSTRACT

Accurate soil dryness information is essential for the calculation of accurate fire danger ratings, fire behavior prediction, flood forecasting and landslip warnings. Soil dryness also strongly influences temperatures and heatwave development by controlling the partitioning of net surface radiation into sensible, latent and ground heat fluxes. Rainfall forecasts are crucial for many applications and many studies suggest that soil dryness can significantly influence rainfall. Currently, soil dryness for fire danger prediction in Australia is estimated using very simple water balance models developed in the 1960s that ignore many important factors such as incident solar radiation, soil types, vegetation height and root depth. This work presents a prototype high resolution soil moisture analysis system based around the Joint UK Land Environment System (JULES) land surface model. This prototype system is called the JULES based Australian Soil Moisture INformation (JASMIN) system. The JASMIN system can include data from many sources; such as surface observations of rainfall, temperature, dew-point temperature, wind speed, surface pressure as well as satellite derived measurements of rainfall, surface soil moisture, downward surface short-wave radiation, skin temperature, leaf area index and tree heights. The JASMIN system estimates soil moisture on four soil layers over the top 3 meters of soil, the surface layer has a thickness of 10 cm. The system takes into account the effect of different vegetation types, root depth, stomatal resistance and spatially varying soil texture. The analysis system has a one hour time-step with daily updating. For the surface soil layer, verification against ground based soil moisture observations from the OzNet, CosmOz and OzFlux networks shows that the JASMIN system is significantly more accurate than other soil moisture analysis system used at the Bureau of Meteorology. For the root-zone, the JASMIN system has similar skill to other commonly used soil moisture analysis systems. The Extended Triple Collocation (ETC) verification method also confirms the high skill of the JASMIN system.

1. INTRODUCTION

The Australian people, businesses and environment are all vulnerable to wildfires, floods and other natural hazards. Deloitte Access Economics (2016) estimate the 2015 total economic cost of natural disasters in Australia exceeded $9 billion. Some examples of recent extreme events are the 2016 West Australia Waroona-Yarloop bushfire, the 2015/16 Victoria Wye River Jamieson Track bushfire, the 2015 West Australia Esperance bushfire, the 2015 South Australia Pinery bushfire, the 2009 Victoria Black Saturday bushfires, and the Millennium drought spanning from 1998 to 2009. A recent United Kingdom Meteorological Office report concludes that investment in weather services provides around a ten fold return (Gray 2015; Lazo et al. 2009).

Fire intensity, spread rate and ignition are very sensitive to the fuel dryness which is strongly linked to soil dryness. For example, Dutta et al. (2013) show, using a neural network, that knowledge of soil dryness is essential for the accurate prediction of wildfire incidence. Gellie et al. (2010) shows that the occurrence of large destructive fires corresponds to very large soil moisture deficit values. For operational fire danger prediction, soil moisture deficit is currently estimated using simple models developed in the 1960s. In Australia, the most important of those used are the Keetch-Byram Drought Index (KBDI; Keetch and Byram 1968) developed by the US Forest Service, and the related Soil Dryness Index (MSDI; Mount 1972) developed by Forestry Tasmania. These simple models do not take into account different soil types, land-cover types, vegetation height and many other factors. They have significant limitations as drivers of the sophisticated fire models used by fire agencies and the Bureau of Meteorology to manage and warn for dangerous fire conditions and have been verified as less effective than soil dryness estimates from land surface models (Dharssi and Vinodkumar 2015; Vinodkumar et al. 2017). The current operational fire systems only use soil dryness assuming one soil layer, soil type and vegetation, at one point in the day. It is essential that recent advances in Numerical Weather Prediction (NWP), land surface modelling, satellite remote sensing and data assimilation are used effectively for natural hazards emergency management and incorporated into warnings systems.

2. HIGH RESOLUTION SOIL MOISTURE ANALYSIS SYSTEM

Soil moisture can vary greatly over short distances such as a few tens of meters (e.g. Famiglietti et al. 1999). This spatial variability is due to the very high spatial variability of vegetation properties, soil textures, orography and rainfall. Therefore, it is highly desirable to analyse soil moisture at the highest possible spatial resolution. Many applications, such as fire danger warnings, agriculture and weather forecasting, require soil moisture information at a spatial resolution of 5 km or better.

The JASMIN system is based around the Joint UK Land Environment System (JULES; Best et al. 2011) land surface model. The JASMIN system is run with daily updating at a spatial resolution of 5 km. JASMIN is configured with 4 soil layers. The top layer is 10 cm thick and the total thickness of the soil column is 3 m. JASMIN requires meteorological input data to drive the JULES land surface model. The JASMIN system provides analyses of soil moisture, soil temperature, evaporation, latent and sensible heat fluxes as well as other surface variables.

2.1 Physically based land surface model

JULES is used by the Bureau of Meteorology and other international weather centres for NWP and is also used for climate prediction. JULES can include many different land surface processes such as the hydrological cycle, surface energy balance, carbon cycle and dynamic vegetation (this study uses static land-cover). JULES models the partitioning of rainfall into canopy interception, through fall, runoff and infiltration. The JULES soil hydrology is based on a finite difference approximation of the Richards' equation and Darcy's law. The van Genuchten equations (van Genuchten 1980) are used to define the relationship between soil moisture and soil hydraulic conductivity. Transpiration by plants extracts soil water directly from the soil layers via the plant roots while bare soil evaporation extracts soil water from the top soil layer only. The ability of plants to access water from each soil layer is determined by the root density distribution and soil moisture availability. The soil moisture availability is a function of soil moisture and soil texture. A sophisticated photosynthesis model is used to calculate the bulk stomatal resistance. The photosynthesis model includes the effects of incident solar radiation, vegetation type, leaf area index (LAI), surface air temperature and humidity deficit.

JULES includes 5 plant functional types (PFTs; broad-leaf trees, needle-leaf trees, C3 (temperate) grass, C4 (tropical) grass and shrubs). JULES simulates 4 non-vegetation types (urban, inland open water, bare soil and land ice). JULES uses surface tiles to represent sub-grid-scale variations in land cover.

2.2 Meteorological driving data

When run off-line (un-coupled from the atmosphere model) JULES requires meteorological information to drive the land surface. This driving data consists of i) air temperature, ii) specific humidity, iii) wind speed, iv) surface pressure, v) downward surface solar radiation, vi) downward surface longwave radiation and vii) precipitation. The driving data is required with a temporal resolution of 3 hours or better. JULES can interpolate the driving data over time so that the model time-step can be shorter than the temporal resolution of the driving data. The driving data must be at the same spatial resolution as the JULES model grid.

The Bureau of Meteorology's Mesoscale Surface Analysis System (MSAS; Glowacki et al. 2012) performs hourly analyses of air temperature, dew-point temperature, wind components, surface potential temperature and mean sea level pressure at a spatial resolution of 4 km. This data is converted and re-gridded to provide the JULES driving data for air temperature, specific humidity, wind speed and surface pressure. The MSAS data is available in near real time (NRT).

The Bureau of Meteorology uses observations from the current operational Geostationary Meteorological Satellite (GMS) to model hourly values of downward surface solar radiation at a spatial resolution of about 5 km. Currently, only the daily solar exposure product is available in NRT and so a climatology of hourly surface solar radiation is used to disaggregate to hourly values.

The downward surface longwave radiation data is obtained from a Bureau of Meteorology NWP model (Puri et al. 2010). The NWP data is available in NRT, 6 hourly at a resolution of 12 km.

The Bureau of Meteorology's Australian Water Availability Project (AWAP; Jones et al. 2009) provides daily analyses of rainfall at a spatial resolution of 5 km. This data is available with a lag of about 1 day. The 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-in gaps in the AWAP data.

2.3 Soil and vegetation ancillary data

JULES uses ancillary input data which are static or only have a seasonal variation. JULES uses static information about land cover types, vegetation heights, soil texture, soil albedo, soil hydraulic and thermal properties. JULES uses seasonally varying information on LAI. Remotely sensed satellite measurements are used to derive the soil albedo (Houldcroft et al. 2009) , land-cover types (Loveland et al. 2000), LAI (Samanta et al. 2008) and forest canopy height (Simard et al. 2011). The ancillary data can have a significant impact on model results (Dharssi et al. 2009, 2015).

3. SOIL MOISTURE OBSERVATIONS

Unfortunately, there are few in-situ observation of soil moisture. However, these few observations are very useful for the validation of soil moisture analysis systems and land surface models. Vaz et al. (2013) have evaluated the accuracy of eight different types of electromagnetic soil moisture sensors. They find sensor accuracies of about $0.02\ m^3/m^3$ when using soil specific calibration functions. The observations also contain errors of representativity that depend on the scale of interest. For point observations of absolute volumetric soil moisture, the error of representativity will vary from about $0.04m^3/m^3$ at the 2.5 m scale to about $0.07m^3/m^3$ at the 50 km scale (Famiglietti et al. 2008). Quality control of the observations is required to filter out gross errors.

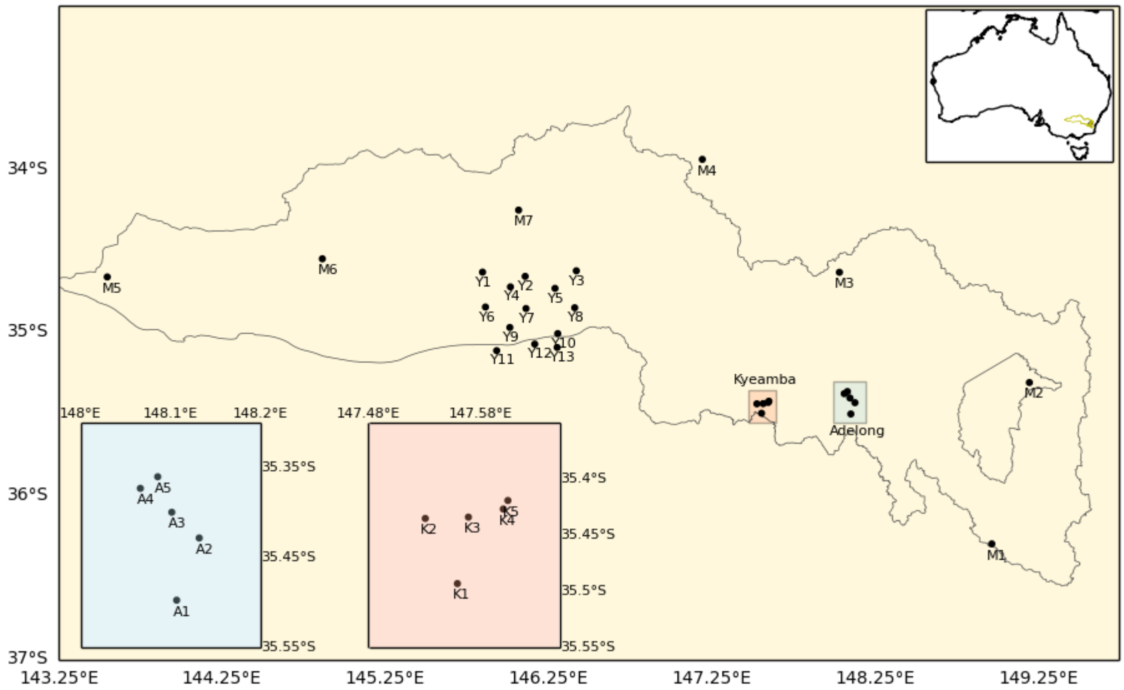

Figure 1 The OzNet soil moisture monitoring network.

3.1 OzNet

The OzNet monitoring network is located in the Murrumbidgee river catchment and managed together by Monash University and University of Melbourne (Young et al. 2008; Smith et al. 2012). The dataset consists of 38 observing stations situated in a semiarid to humid climate. The observations provide point measurements of soil moisture in the top 90 cm of soil. The OzNet soil moisture observations are visually inspected to identify quality issues, the quality control includes comparisons with rainfall observations (Smith et al. 2012). Most stations are located in crop-lands or grasslands. Figure 1 shows the location of the OzNet observing stations.

3.2 OzFlux

OzFlux (van Gorsel 2015) is a network of observing stations located at various sites within Australia providing continuous data over a long time period. Many of the stations

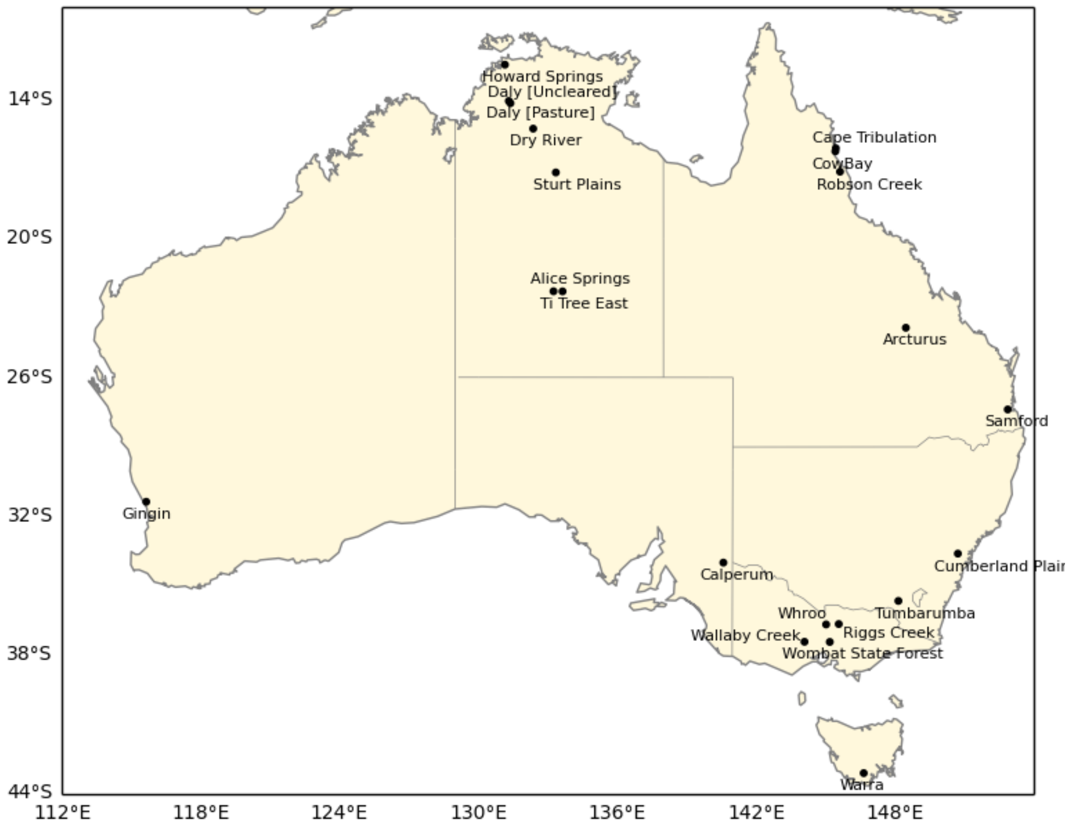

Figure 2 The OzFlux soil moisture monitoring network.

are located in wooded or forested areas. Figure 2 shows the location of the OzFlux observing stations.

3.3 CosmOz

A cosmic-ray probe measures the number of fast neutrons near the soil surface and measured intensities reflect variations in soil water. CosmOz is a network of cosmic ray soil moisture probes installed at a number of locations around Australia (Hawdon et al. 2014). The effective sensing depth depends strongly on soil moisture itself, decreasing non-linearly with increasing soil moisture and ranges from about 70 cm to 10 cm. One advantage over traditional point measurement sensors is that cosmic-ray probes have a horizontal footprint of about 200 m in diameter at sea level. This study uses level

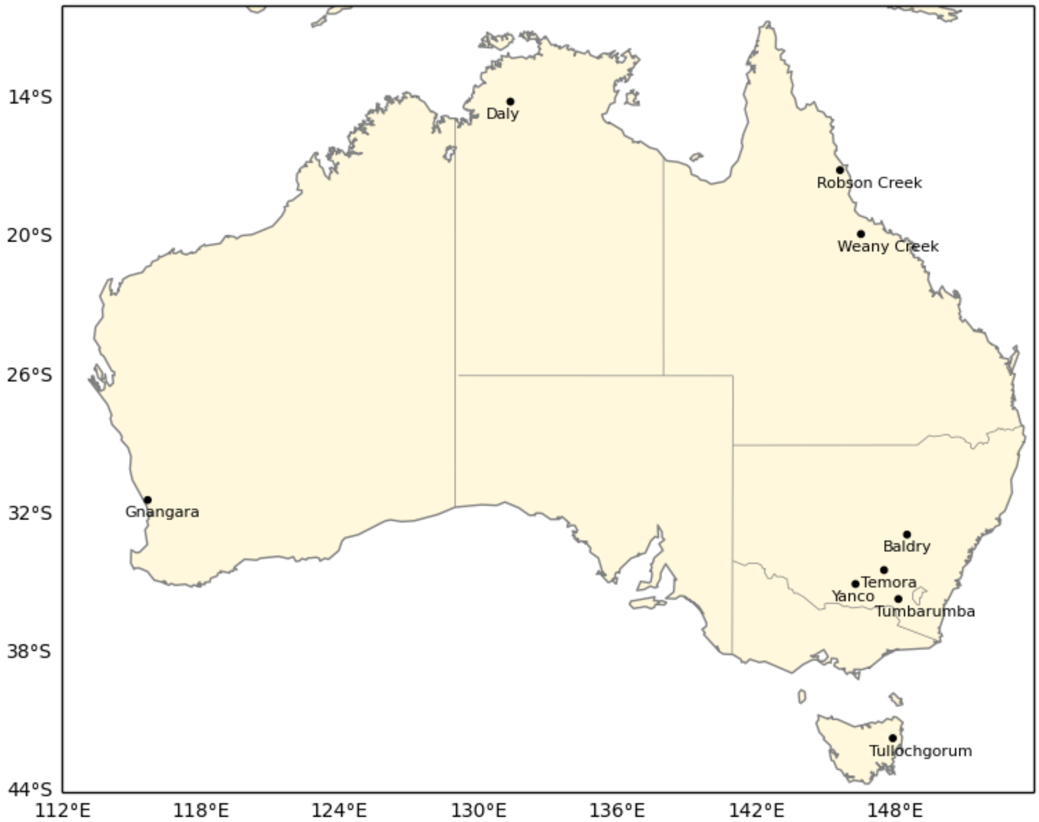

Figure 3 The CosmOz soil moisture monitoring network.

4 processed data which are seven hour moving averages that have been quality controlled. Only observations from calibrated CosmOz sites are used in this study. Figure 3 shows the location of the CosmOz observing stations.

4. AUSTRALIAN WATER RESOURCE ASSESSMENT LANDSCAPE MODEL

The Australian Water Resource Assessment landscape model (AWRA-L; Hafeez et al. 2015) was developed jointly by the Bureau of Meteorology and CSIRO through the Water Information Research and Development Alliance (WIRADA) initiative. The AWRA-L model has three soil layers (top: 0-10 cm, shallow: 10 cm-1 m, deep: 1 m-6 m)

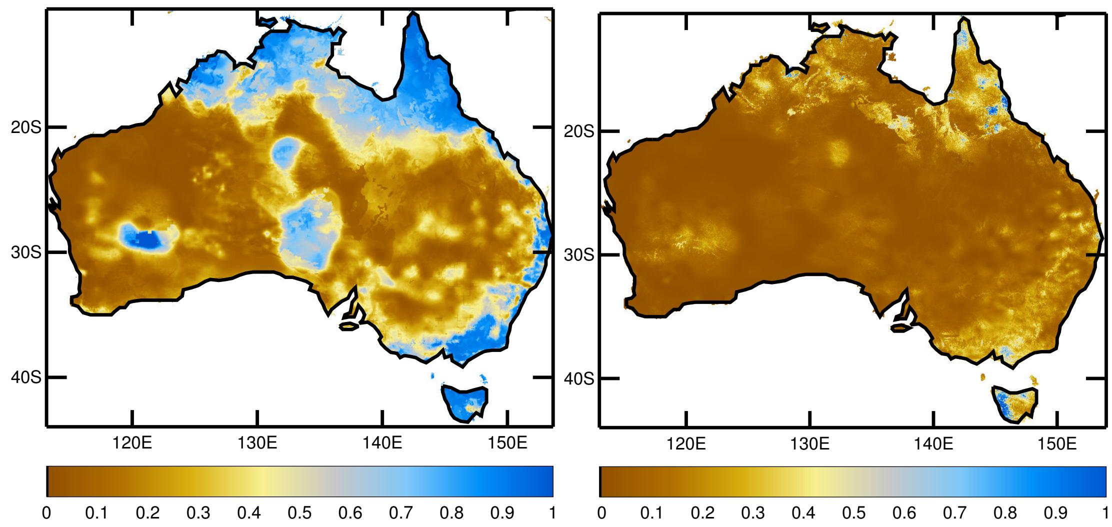

Figure 4 Example analyses, at a spatial resolution of 5 km, from the JASMIN (left panel) and AWRA-L (right panel) systems of the top 10 cm soil wetness for 19th March 2016 .

and two hydrological response units (shallow rooted versus deep rooted vegetation). AWRA-L estimates the stores and fluxes of water in the Australian landscape including soil moisture, evapotranspiration (ET), runoff and deep drainage. The AWRA-L model has a spatial resolution of 5 km and is driven by AWAP analyses of daily rainfall and temperature, as well as satellite derived analyses of daily incoming shortwave radiation. The AWRA-L model has been calibrated to stream-flow, catchment average soil moisture and ET for around 300 unimpaired catchments across Australia and validated on another approximately 300 unimpaired catchment. AWRA-L has been found to perform better than other continental-scale models and is better able to capture the observed soil moisture patterns than previous models (Bureau of Meteorology 2016). The results of the operational AWRA-L model outputs have been released to the public through the Australian Landscape Water Balance website (`http://www.bom.gov.au/water/landscape/`). The information is updated daily and is available at daily, monthly and annual time-scales from 1911 onwards. This work uses AWRA-L soil moisture analyses from the Bureau of Meteorology's operational system. Figure 4 shows example high resolution surface soil wetness analyses from the JASMIN and AWRA-L systems. The figure shows that while AWRA-L is much drier, the spatial patterns of wet and dry soils is similar for the two systems. A comparison of the parameters and parameterisations used by the AWRA-L and JASMIN systems is beyond the scope of this report.

5. ASCAT SURFACE SOIL WETNESS MEASUREMENTS

This study uses the EUMETSAT NRT $12.5\ km$ resolution product from the Advanced Scatterometer (ASCAT; Wagner et al. 2013) instrument on the MetOp-A satellite. The remotely sensed ASCAT surface soil wetness measurements are representative of a thin surface layer of soil $\simeq 1\ \ cm$ thick (Albergel et al. 2012). However, the CosmOz observations and JASMIN analyses used in this study are for a significantly deeper layer of soil. Therefore, an exponential filter (Wagner et al. 1999) is applied to the time-series of ASCAT surface soil wetness measurements to approximate the soil wetness profiles for a deeper soil layer. This simple approach has worked reasonably well in past studies with the exponential filter parameter value set to $T = 4$ days (Vinodkumar et al. 2017).

6. SOIL MOISTURE VERIFICATION

Figure 4 shows an example high resolution surface soil wetness analysis from the JASMIN system. The JASMIN soil moisture analyses are verified against in-situ soil moisture observations from the OzNet, OzFlux and CosmOz networks following the approach of Vinodkumar et al. (2017); Albergel et al. (2012). Also verified against observations are KBDI, MSDI and the AWRA-L model. Verification is performed for the surface and root-zone soil. All soil moisture time-series are converted to soil wetness (normalised between [0, 1]) using their own maximum and minimum values from their own long time series. Brocca et al. (2014) show that absolute values of soil moisture have a much higher spatial variability (and consequently errors of representativity) than relative measures such as soil wetness. Consequently, it is preferable to use a relative measure such as soil wetness for verification. The calculation of temporal correlations is un-affected by a linear rescaling of absolute soil moisture values to soil wetness.

Soil moisture observations contain errors and consequently the verification is affected by errors in both the model analyses and observations. Therefore the standard deviation of the model errors will be lower than the computed Root Mean Square Difference

(RMSD) or unbiased RMSD (ubRMSD) values. The observation errors are due to the sensor and also the errors of representativity. For fire danger ratings, the scale of interest is about 1 km and therefore the point observations and model analyses are both likely to contain significant errors of representativity. The CosmOz soil moisture observations will have smaller errors of representativity since the horizontal footprint is several hundred meters in diameter.

Bias is defined as Bias $= \overline{\text{Analysis} - \text{Obs}}$. Consequently, a positive bias value implies that the model is too wet. Albergel et al. (2012) calculates anomalies as:

$$\text{anom}(t) = \frac{x(t) - \overline{x(t-15:t+15)}}{\sigma(x(t-15:t+15))}. \tag{1}$$

Where $x(t)$ is the soil wetness time-series. $\overline{x(t-15:t+15)}$ is the average value of x for a 31 day moving window. $\sigma(x(t-15:t+15))$ is the standard deviation of $x(t)$ in the 31 day moving window. Equation 1 gives reasonable results at most locations. However, at the CosmOz Daly and Weaney Creek sites the computed anomaly correlations are very low. During the dry season $\sigma(x(t-15:t+15))$ becomes very small at the Daly and Weaney Creek sites causing very low values of the anomaly correlation. Dharssi and Vinodkumar (2015) calculate anomalies as

$$\text{anom}(t) = x(t) - \overline{x(t-15:t+15)} \tag{2}$$

and find much higher anomaly correlations. Therefore, in this work soil moisture anomalies are calculated using equation 2.

6.1 OzNet

The verification period is 1st January 2010 to 31st May 2011. Verification results are shown in tables 1 and 2. Results indicate that the JASMIN system has significantly greater skill for surface soil wetness than AWRA-L, KBDI and MSDI. Holgate et al. (2016) have also found that AWRA-L performs relatively poorly for surface soil moisture. The poor performance of KBDI is consistent with the results of both Holgate et al. (2016) and Vinodkumar et al. (2017). For the top 1 m of soil, JASMIN, AWRA-L and MSDI have similar skill, although AWRA-L appears to have a dry bias. KBDI has a large wet bias and less skill than the other models.

Table 1 Verification scores with 95% confidence intervals for the JASMIN, AWRA-L, KBDI and MSDI against OzNet in situ soil moisture observations for the top 30cm of soil. Scores for both normal and anomaly time series are presented. The values represent an observing network average.

Data set	Normal Time Series				Anomaly Correlation
	Correlation	Bias	RMSD	ubRMSD	95% Confidence intervals
JASMIN	0.80 to 0.86	0.04±0.04	0.19±0.02	0.15±0.01	0.82 to 0.85
AWRA-L	0.62 to 0.68	-0.25±0.04	0.32±0.03	0.20±0.01	0.73 to 0.77
KBDI	0.59 to 0.74	0.27±0.04	0.36±0.03	0.23±0.02	0.56 to 0.65
MSDI	0.66 to 0.79	0.03±0.04	0.22±0.02	0.19±0.01	0.63 to 0.69

Table 2 Verification scores with 95% confidence intervals for the JASMIN, AWRA-L, KBDI and MSDI against OzNet in situ soil moisture observations for the top 90cm of soil. Scores for both normal and anomaly time series are presented. The values represent an observing network average.

Data set	Normal Time Series				Anomaly Correlation
	Correlation	Bias	RMSD	ubRMSD	95% Confidence intervals
JASMIN	0.66 to 0.86	0.00±0.04	0.20±0.03	0.17±0.02	0.73 to 0.78
AWRA-L	0.65 to 0.82	-0.08±0.04	0.21±0.03	0.18±0.02	0.71 to 0.77
KBDI	0.58 to 0.86	0.26±0.05	0.35±0.04	0.20±0.02	0.62 to 0.69
MSDI	0.58 to 0.85	0.01±0.05	0.23±0.02	0.19±0.02	0.68 to 0.74

6.2 CosmOz

The verification time period is 1st January 2012 to 31st December 2015 and results are shown in table 3. Verification again shows that the JASMIN system has high skill, particularly in terms of temporal correlation and unbiased RMSD.

6.3 OzFlux

The verification period is 1st January 2012 to 31st December 2015 and results are shown in tables 4 and 5. In this study, the OzFlux observations are quality controlled (QC) using an automated system based on Dorigo et al. (2013). The automated QC scheme rejects about 2% of the observations. For surface soil wetness, verification

Table 3 Verification scores with 95% confidence intervals for the JASMIN, AWRA-L, KBDI and MSDI against CosmOz in situ soil moisture observations. Scores for both normal and anomaly time series are presented. The values represent an observing network average.

Data set	Normal Time Series				Anomaly Correlation
	Correlation	Bias	RMSD	ubRMSD	95% Confidence intervals
JASMIN	0.82 to 0.88	0.08±0.06	0.17±0.04	0.13±0.02	0.67 to 0.71
AWRA-L	0.61 to 0.67	0.00±0.04	0.16±0.02	0.15±0.02	0.67 to 0.71
KBDI	0.58 to 0.72	0.25±0.07	0.34±0.06	0.21±0.02	0.44 to 0.44
MSDI	0.68 to 0.79	0.05±0.04	0.18±0.03	0.17±0.03	0.47 to 0.53

again shows that the JASMIN system has high skill and perform better than the other models. AWRA-L displays a large dry bias while KBDI displays a large wet bias. For the top 1 m of soil, all the models perform well and show similar skill.

Table 4 Verification scores with 95% confidence intervals for the JASMIN, AWRA-L, KBDI and MSDI against OzFlux in situ soil moisture observations for the top 10cm of soil. Scores for both normal and anomaly time series are presented. The values represent an observing network average.

Data set	Normal Time Series				Anomaly Correlation
	Correlation	Bias	RMSD	ubRMSD	95% Confidence intervals
JASMIN	0.78 to 0.83	0.10±0.05	0.21±0.03	0.16±0.01	0.71 to 0.74
AWRA-L	0.65 to 0.70	-0.17±0.06	0.26±0.05	0.18±0.02	0.67 to 0.70
KBDI	0.68 to 0.81	0.22±0.07	0.30±0.06	0.19±0.02	0.52 to 0.58
MSDI	0.69 to 0.82	0.09±0.06	0.23±0.03	0.18±0.01	0.53 to 0.59

7. EXTENDED TRIPLE COLLOCATION

McColl et al. (2014) have developed the Extended Triple Collocation (ETC) method to estimate the temporal correlation between a model or observation system and the unknown truth. The ETC method makes the same assumptions as the more widely known Triple Collocation (TC; Scipal et al. 2008; Vogelzang and Stoffelen 2012; Zwieback et al. 2012; Dorigo et al. 2010; Yilmaz and Crow 2014; Gruber et al. 2016; Draper et al. 2013) method. ETC and TC require three mutually independent time-series estimates of the same quantity. For example, the three time-series could be i) outputs from a model, ii) a remotely sensed product and iii) ground based observations. The three

Table 5 Verification scores with 95% confidence intervals for the JASMIN, AWRA-L, KBDI and MSDI against OzFlux in situ soil moisture observations for the top 1m of soil. . Scores for both normal and anomaly time series are presented. The values represent an observing network average.

Data set	Normal Time Series				Anomaly Correlation
	Correlation	Bias	RMSD	ubRMSD	95% Confidence intervals
JASMIN	0.73 to 0.90	0.11±0.07	0.22±0.04	0.16±0.03	0.63 to 0.69
AWRA-L	0.74 to 0.90	0.07±0.01	0.21±0.06	0.15±0.02	0.61 to 0.69
KBDI	0.78 to 0.91	0.15±0.09	0.25±0.06	0.17±0.02	0.64 to 0.70
MSDI	0.74 to 0.91	0.07±0.08	0.22±0.05	0.17±0.02	0.58 to 0.65

time-series are each assumed to be linearly related to the unknown truth. The errors in the time-series are assumed to to be un-correlated to each other and with the unknown truth. Following McColl et al. (2014), the temporal correlation between a time-series i and the unknown truth is given by

$$R_{i,TC} = \sqrt{\frac{Q_{ij}Q_{ik}}{Q_{ii}Q_{jk}}} \tag{3}$$

where Q_{ij} represents the covariance between time-series i and j. McColl et al. (2014) show that $R_{i,TC}$ is closely related to the unbiased signal to noise ratio $SNR_{ub,i} = R^2{}_{i,TC}/(1-R^2{}_{i,TC})$ and the $fRMSE$ metric defined by Draper et al. (2013); $fRMSE_i = (1-R^2{}_{i,TC})^{1/2}$.

In this work, equation 3 is re-written more simply as

$$R_{i,TC} = \sqrt{\frac{R_{ij}R_{ik}}{R_{jk}}} \tag{4}$$

where R_{ij} represents the Pearson's correlation between between time-series i and j. Since the Pearson's correlation is unaffected by a linear rescaling of the time-series, $R_{i,TC}$ will also be un-affected by a linear rescaling of the input time-series. Equation 4 also indicates that ETC is only useful when all the Pearson's correlations in equation 4 are greater than a threshold value ($\simeq\ 0.5$). If R_{jk} approaches zero then $R_{i,TC}$ could take un-physical values greater than 1. The ratio of two ETC derived correlations is given by

$$\frac{R_{i,TC}}{R_{j,TC}} = \sqrt{\frac{R_{ij}R_{ik}}{R_{jk}}\frac{R_{ik}}{R_{ij}R_{jk}}} = \frac{R_{ik}}{R_{jk}}\ . \tag{5}$$

This result shows that the ETC method doesn't change the relative ranking of the time-series compared to using Pearson's correlations.

Following McColl et al. (2014), the standard deviation of the error in time-series i is given by

$$\sigma_{i,TC} = \sqrt{Q_{ii} - \frac{Q_{ij}Q_{ik}}{Qjk}} \; . \tag{6}$$

In this work, equation 6 is re-written more simply as

$$\sigma_{i,TC} = \mu_i \sqrt{1 - R^2{}_{i,TC}} \; , \tag{7}$$

where μ_i is the standard deviation of time-series i ($\mu_i^2 = Q_{ii}$). Time-series with a large dynamic range will have larger values of μ than time-series with a small dynamic range. If the computed value of $R^2{}_{i,TC}$ is greater than 1 then $\sigma_{i,TC}$ will have an imaginary value. Equation 7 shows that it would be possible to "game" TC by choosing model parameter values that produce a low value for μ. Therefore, $R_{i,TC}$ is a more useful measure of skill than $\sigma_{i,TC}$.

ETC is used with i) the ground based CosmOz soil moisture observations, ii) JASMIN soil moisture analyses and iii) soil wetness measurements from ASCAT. Table 6 shows ETC derived values of R_{TC} and σ_{TC} for CosmOz, JASMIN and ASCAT soil wetness anomalies.The results indicate high skill for JASMIN at all the CosmOz sites with R_{TC} values greater than 0.76 at all sites. ASCAT also shows high skill at all sites except Tumbarumba which is a wet sclerophyll eucalyptus forest site and Tullochgorum which is surrounded by high terrain. ASCAT has already been shown to perform less well in regions with dense vegetation or complex terrain (Dharssi et al. 2011). CosmOz appears to have only moderate skill at Tumbarumba and this may be because of the high vegetation density. The ETC results suggest that at Daly, CosmOz is significantly less accurate than JASMIN or ASCAT. CosmOz appears to have high skill at Gnangara despite the calibration problems. Table 7 shows ETC results using time-series of CosmOz, AWRA-L and ASCAT. The results indicate that JASMIN is more skillful than AWRA at all CosmOz sites except Tumbarumba. At Tumbarumba, both the JASMIN and AWRA models appear to be much more skillful than CosmOz and ASCAT. At Daly and Gnangara the CosmOz skill appears to be much higher when using AWRA rather than JASMIN for the ETC calculations. This indicates that the ETC results are noisy and need to be treated with caution. At Weany Creek, ETC computes a correlation greater than 1 and an imaginary value for the error standard deviation. Zwieback et al. (2012) suggests that the relative error in the TC estimate of the standard deviation of the error is $\sqrt{5/N}$ where N is the number of triplets. Therefore, at least 500 triplets are required to estimate σ_{TC} with a relative uncertainty of 10%. However, positive time-series autocorrelation will reduce the effective number of triplets and consequently far more than 500 triplets will be required to estimate σ_{TC} with a relative uncertainty of 10%.

Tables 8 and 9 show ETC results using time-series of KBDI and MSDI soil wetness anomalies. The computed values of R_{TC} suggest that KBDI is less skillful than MSDI and that both are less skillful than JASMIN and AWRA. However, the computed σ_{TC} values are generally lower for KBDI and MSDI than for the other datasets. The reason for this is that the time-series of KBDI and MSDI anomalies have a much smaller dynamic range. That is, the standard deviation of the time-series (μ) is much lower for the KBDI and MSDI soil wetness anomalies. Typically, μ values for KBDI and MSDI soil wetness anomalies are about half of those for JASMIN, AWRA, CosmOz and ASCAT. Equation 7 shows that low values of μ lead to low values of σ_{TC}. Therefore, as already explained, R_{TC} is a more reliable indicator of skill than σ_{TC}.

Table 6 ETC based calculations of correlation (R_{TC}) and the standard deviation of the error (σ_{TC}) using time-series of CosmOz, JASMIN and ASCAT soil wetness anomalies.

		R_{TC}			σ_{TC}		
Site	Triplets	CosmOz	JASMIN	ASCAT	CosmOz	JASMIN	ASCAT
Baldry	494	0.95	0.83	0.77	0.03	0.07	0.05
Daly	542	0.71	0.85	0.89	0.08	0.05	0.03
Gnangara	490	0.79	0.80	0.85	0.07	0.06	0.06
Temora	404	0.86	0.87	0.79	0.07	0.06	0.06
Tullochgorum	755	0.92	0.76	0.73	0.03	0.06	0.08
Tumbarumba	666	0.68	0.77	0.60	0.08	0.08	0.09
Weany Creek	579	0.87	0.85	0.93	0.05	0.06	0.04
Yanco	748	0.88	0.90	0.80	0.04	0.04	0.05

Table 7 ETC based calculations of correlation (R_{TC}) and the standard deviation of the error (σ_{TC}) using time-series of CosmOz, AWRA and ASCAT soil wetness anomalies.

		R_{TC}			σ_{TC}		
Site	Triplets	CosmOz	AWRA	ASCAT	CosmOz	AWRA	ASCAT
Baldry	497	0.98	0.78	0.76	0.02	0.08	0.05
Daly	639	0.88	0.77	0.71	0.05	0.06	0.04
Gnangara	569	0.94	0.67	0.71	0.04	0.12	0.07
Temora	410	0.92	0.81	0.74	0.04	0.07	0.04
Tullochgorum	763	0.83	0.75	0.80	0.05	0.09	0.07
Tumbarumba	669	0.59	0.88	0.69	0.09	0.06	0.08
Weany Creek	586	1.01	0.79	0.81	-	0.05	0.06
Yanco	748	0.88	0.89	0.80	0.04	0.04	0.05

Table 8 ETC based calculations of correlation (R_{TC}) and the standard deviation of the error (σ_{TC}) using time-series of CosmOz, KBDI and ASCAT soil wetness anomalies.

		R_{TC}			σ_{TC}		
Site	Triplets	CosmOz	KBDI	ASCAT	CosmOz	KBDI	ASCAT
Baldry	497	0.84	0.68	0.88	0.06	0.04	0.04
Daly	639	0.62	0.72	1.01	0.08	0.04	-
Gnangara	569	0.65	0.55	1.03	0.08	0.04	-
Temora	410	0.78	0.64	0.87	0.06	0.03	0.03
Tullochgorum	763	0.94	0.52	0.71	0.03	0.04	0.08
Tumbarumba	669	0.70	0.43	0.58	0.08	0.07	0.09
Weany Creek	586	0.83	0.59	0.98	0.06	0.05	0.02
Yanco	748	0.79	0.67	0.89	0.05	0.03	0.04

Table 9 ETC based calculations of correlation (R_{TC}) and the standard deviation of the error (σ_{TC}) using time-series of CosmOz, MSDI and ASCAT soil wetness anomalies.

		R_{TC}			σ_{TC}		
Site	Triplets	CosmOz	MSDI	ASCAT	CosmOz	MSDI	ASCAT
Baldry	497	0.90	0.79	0.83	0.05	0.05	0.04
Daly	639	0.61	0.72	1.01	0.08	0.04	-
Gnangara	569	0.67	0.64	1.00	0.08	0.03	-
Temora	410	0.79	0.76	0.86	0.06	0.03	0.03
Tullochgorum	763	0.92	0.63	0.72	0.03	0.03	0.08
Tumbarumba	669	0.59	0.57	0.70	0.09	0.04	0.08
Weany Creek	586	0.83	0.63	0.98	0.06	0.06	0.02
Yanco	748	0.80	0.77	0.88	0.05	0.03	0.04

8. CONCLUSIONS AND FUTURE WORK

This work presents a prototype high resolution soil moisture analysis system with daily updating. The analysis system is based around the JULES land surface model that is also used by the Bureau of Meteorology for NWP. The analysis system has four soil layers and a spatial resolution of 5 km. The analysis system uses a combination of surface and satellite observations to drive the land surface. The system is flexible and can assimilate satellite measurements of surface soil wetness and land surface temperature. The analysis system can be run in different science configurations, for example an ensemble approach can be used where members use different model settings, soil and vegetation ancillary fields. The analysis system could also be used with other land surface models such as the Community Atmosphere Biosphere Land Exchange model (CABLE; Law et al. 2012). The analysis system can be used for many applications such as i) the initialisation of the land surface state in weather forecasting models ii) forecasting of soil water for agriculture. However, the primary purpose of this analysis system is to improve predictions of fire danger.

Verification against in-situ observations show that the JASMIN system can provide fire agencies with far more accurate information than the simple models currently used (Dharssi and Vinodkumar 2015). Verification shows that the new system has greater skill than AWRA-L for surface soil moisture. For root-zone ($\simeq$ top 1 m) soil moisture, both JASMIN and AWRA-L have similar skill. For fire danger prediction, both the surface and root-zone soil moisture are important. Bovio and Camia (1997); Haines et al. (1976) suggest that in Spring, it is the surface moisture that is most important for fire danger. Root-zone soil moisture is strongly correlated to the live fuel moisture content that influences fire propagation (Chuvieco et al. 2004). While surface soil moisture is more strongly correlated with the dead fuel moisture content which is important for fire ignition (since dead fuels have a faster time scale and are usually drier). For example, the Canadian Forest Fire Weather Index (FWI; Field et al. 2015; Van Wagner et al. 1987) requires three moisture codes with significantly different drying time scales; i) a Fine fuels moisture code with a time constant of about 3 days, ii) a Duff layer[1] moisture code with a time constant of 14 days and iii) a Drought code with a time constant of 51 days. Originally the Drought code was developed to represent soil moisture (Dowdy et al. 2009; Turner 1972) and provides good estimates of the moisture state of slow

[1] fallen leaves, decomposing stems, branches and bark on the forest floor

drying fuels.

Data assimilation is the process through which the maximum amount of useful information can be extracted from observations and models. New flexible land data assimilation systems have been developed that can assimilate a wide variety of measurements such as 2 m temperature and humidity, satellite derived surface soil wetness, satellite derived land surface temperature and vegetation properties such as LAI (e.g. Dharssi et al. 2012, 2011). The data assimilation can also propagate the surface information into the deeper soil layers. Currently, the prototype JASMIN system doesn't assimilate measurements of satellite derived surface soil wetness or satellite derived land surface temperature (LST). Many other off-line land surface data assimilation systems also don't currently assimilate satellite derived surface soil wetness or satellite derived LST. Examples of such off-line systems are; i) the North American Land Data Assimilation System (NLDAS; Xia et al. 2014), ii) the ERA-Interim/Land reanalysis (Balsamo et al. 2015) and iii) the Modern-Era Retrospective analysis for Research and Applications (MERRA) land system (Reichle et al. 2011). Recently, the JULES land surface model has been incorporated into the NASA Land Information System (LIS; Kumar et al. 2008) and it is anticipated that a future JASMIN system will use LIS for data assimilation to assimilate remotely sensed measurements of surface soil wetness and land surface temperature. LIS also includes the CABLE land surface model making it less difficult to adapt the JASMIN system to use CABLE instead of JULES.

Future work will also look at the blending of JASMIN and AWRA-L soil moisture analyses to provide more accurate soil moisture products. Additional verification work will also be performed to better understand how factors such as land-cover affect the skill of soil moisture analyses. Future work will use the TERN soils database (Grundy et al. 2015) to improve the soil hydraulic and thermal parameters used by the JASMIN system.

Due to the lack of accurate very high resolution meteorological driving data it is not possible to simply increase the resolution of the soil moisture analysis system. Therefore, downscaling methods will also be used to produce a 1 km soil moisture product. These downscaling methods are essential since many applications require very high resolution soil moisture information at spatial scales better than 1 km. JASMIN soil moisture analyses for the period 2010 to 2017 are available to all researchers at the National Computational Infrastructure (NCI). The JASMIN system is expected to continue providing soil moisture analyses for the foreseeable future and these analyses will be archived at NCI.

9. AUTHOR CONTRIBUTION

Imtiaz Dharssi planned this work and developed the high resolution analysis system. Vinodkumar preformed the observation quality control and verification. Vinodkumar provided figures 1, 2 and 3. Imtiaz Dharssi suggested the use of equation 2 to calculate soil wetness anomalies. Imtiaz Dharssi wrote this report. Vinodkumar reviewed the manuscript and helped to improve it.

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Mike Liddell (2013)	Cape Tribulation OzFlux tower site	hdl: 102.100.100/14242
Mike Liddell (2013)	Cow Bay OzFlux tower site	hdl: 102.100.100/14244
Elise Pendall (2015)	Cumberland Plain OzFlux Tower Site	hdl: 102.100.100/25164
Jason Beringer (2013)	Daly Pasture OzFlux tower site	hdl: 102.100.100/14238
Jason Beringer (2013)	Daly Uncleared OzFlux tower site	hdl: 102.100.100/14239
Jason Beringer (2013)	Dry River OzFlux tower site	hdl: 102.100.100/14229
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Jason Beringer (2013)	Howard Springs OzFlux tower site	hdl: 102.100.100/14234
Jason Beringer (2014)	Red Dirt Melon Farm OzFlux tower site	hdl: 102.100.100/14245
Jason Beringer (2014)	Riggs Creek OzFlux tower site	hdl: 102.100.100/14246
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