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Key Points:

- Simple water balance models have less skill than weather prediction system soil moisture analyses
- Weather prediction system soil moisture analyses are unbiased and capture the seasonal variations
- The remotely sensed ASCAT soil wetness product is of good quality

Supporting Information:

- Supporting Information S1

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Comparison of soil wetness from multiple models over Australia with observations

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Abstract The McArthur Forest Fire Danger Index used in Australia for operational fire warnings has a component representing fuel availability called the Drought Factor (DF). The DF is partly based on soil moisture deficit, calculated as either the Keetch-Byram Drought Index (KBDI) or Mount's Soil Dryness Index (MSDI). The KBDI and MSDI are simplified water balance models driven by observation based daily rainfall and temperature. In this work, gridded KBDI and MSDI analyses are computed at a horizontal resolution of 5 km and are verified against in-situ soil moisture observations. Also verified is another simple model called the Antecedent Precipitation Index (API). Soil moisture analyses from the Australian Community Climate and Earth System Simulator (ACCESS) global Numerical Weather Prediction (NWP) system as well as remotely sensed soil wetness retrievals from the Advanced Scatterometer (ASCAT) are also verified. The verification shows that the NWP soil wetness analyses have greater skill and smaller biases than the KBDI, MSDI and API analyses. This is despite the NWP system having a coarse horizontal resolution and not using observed precipitation. The average temporal correlations (root mean square difference) between cosmic ray soil moisture monitoring facility observations and modeled or remotely sensed soil wetness are 0.82 (0.15 $\pm$0.02), 0.66 (0.33 $\pm$0.07), 0.77 (0.20 $\pm$0.03), 0.74 (0.22 $\pm$0.03) and 0.83 (0.18 $\pm$0.04) for NWP, KBDI, MSDI, API and ASCAT. The results from this study suggests that analyses of soil moisture can be greatly improved by using physically based land surface models, remote sensing measurements and data assimilation.

1. Introduction

Australia has a long history of frequent forest fires, owing to its hot and dry climate. The McArthur Forest Fire Danger Index (FFDI) [*McArthur*, 1967; *Luke and McArthur*, 1978; *Finkele et al.*, 2006; *Noble et al.*, 1980; *Griffiths*, 1998] was introduced in 1958 for operational fire warnings over Australia and is still used operationally. The formulation of FFDI is based on air temperature, wind speed, relative humidity, and a component representing fuel availability called the Drought Factor (DF). The FFDI is almost linearly related to the DF which is a relative measure with possible values between 0 and 10. The DF is a function of Soil Moisture Deficit (SMD) and recent rainfall and is defined on the assumption that the fuel moisture content (FMC) is affected by both long term and short term drying effects. The short term drying effects are based on the time since recent rain and past 20 days rainfall amount [*Griffiths*, 1998]. The long term drying effects are based on either the Keetch-Byram Drought Index (KBDI) [*Keetch and Byram*, 1968] or Mount's Soil Dryness Index (MSDI) [*Mount*, 1972]. KBDI and MSDI are estimates of the SMD and represent the degree of drought in the landscape. Studies [e.g., *Gellie et al.*, 2010; *Westerling et al.*, 2006; *Clark*, 1989; *Dutta et al.*, 2013] show that the occurrence of large destructive fires corresponds to very large SMD values. SMD therefore is a key variable in the FFDI calculations with accurate estimates of soil moisture crucial for effective wildfire management, rating and warning.

KBDI and MSDI are simple water balance models that do not take into account the majority of physical factors which affect soil moisture dynamics such as soil type, vegetation type, terrain or aspect. They oversimplify the evapotranspiration and runoff processes, which are critical in calculating accurate soil moisture states, potentially leading to large errors. Recent progresses in the remote sensing of soil moisture, data assimilation techniques and physically based land surface models has led to the development of new soil moisture products. Two examples of such data sets are the soil moisture analyses produced from the Bureau of Meteorology's operational Numerical Weather Prediction (NWP) system [*Puri et al*., 2013] and remotely sensed soil wetness measurements from the Advanced Scatterometer (ASCAT) [*Wagner et al*., 2013] instrument. This study undertakes an evaluation of the latter two data sets along with KBDI, MSDI and another simple water balance model called the Antecedent Precipitation Index (API) [*Crow et al*., 2005]. In-situ observations of soil moisture from the OzNet hydrological monitoring network [*Smith et al*., 2012] and Australian national cosmic ray soil moisture monitoring facility (CosmOz) [*Hawdon et al*., 2014] are used to validate the modeled and remotely sensed soil moisture data sets.

For a variety of reasons, models cannot accurately simulate the absolute magnitude of soil moisture. The reasons range from uncertainty in model parameters and parameterisations as well as the very high spatial variability of soil moisture. The very high spatial variability is due to factors such as the very high spatial variability of soil types, vegetation, topography and rainfall. Models are unable to capture this very high spatial variability. *Koster et al*. [2009] demonstrate that model soil moisture is highly model specific while *Brocca et al*. [2014] show that a large fraction of the soil moisture spatial variability is time invariant and that relative measures of soil moisture such as soil wetness are much less affected by spatial variability. *Brocca et al*. [2014] suggest that consideration of absolute soil moisture values may lead to misleading conclusions. Since the DF (used as input to FFDI) is a relative measure, it seems likely that for fire danger prediction it is the relative soil wetness that is most important, rather than the absolute magnitude of soil moisture. Consequently, this study verifies soil wetness (a relative measure) rather than the absolute magnitude of soil moisture.

2. Data and Methodology

2.1. Meteorologically Based Soil Moisture Indices

This study calculates gridded daily analyses of KBDI and MSDI using the same methodology as *Finkele et al*. [2006]. The primary difference is that this study calculates KBDI and MSDI at a resolution of about 5 km while *Finkele et al*. [2006] calculated KBDI and MSDI at a resolution of about 25 km. KBDI and MSDI are calculated using gridded analyses of daily rainfall and daily maximum temperature from the Australian Water Availability Project (AWAP) [*Jones et al*., 2009]. The AWAP gridded analyses are based on observations of precipitation and temperature and also have a resolution of about 5 km. The gridded fields of KBDI and MSDI are computed for 40 years, from 1974 to 2014. A spin-up period of 10 years, from 1964 to 1974 is used. API daily gridded analyses are also calculated at a resolution of about 5 km using AWAP daily gridded analyses of rainfall and maximum temperature. Unlike KBDI and MSDI which estimate soil moisture deficit, API estimates soil water.

2.1.1. Keetch-Byram Drought Index

The KBDI [*Keetch and Byram*, 1968; *Janis et al*., 2002] is a widely used drought index designed for wildfire monitoring and prediction. The KBDI was developed by the United States Department of Agriculture's Forest Service for use in the forested and wildland areas of the south-eastern United States. However, KBDI has also been applied to many other regions and land-cover types. KBDI has been incorporated into the United States National Fire Danger Rating System to estimate the amount of dead fuel available for burning [*Burgan*, 1988; *Roads et al*., 2005]. KBDI is also used operationally for forest fire danger prediction in the Australian states of Victoria, New South Wales and Queensland [*Finkele et al*., 2006]. A near real time (NRT) mapping of KBDI has been developed and used operationally in the south-eastern United States [*Johnson and Forthum*, 2001]. KBDI has also been employed to study wildfire occurrence in the upper mid-western U. S. [*Lorimer and Gough*, 1988], Mediterranean regions [*Ganatsas et al*., 2011; *Garcia-Prats et al*., 2015], Hawaii [*Dolling et al*., 2009], Malaysia [*Ainuddin and Ampun*, 2008], South Africa [*Verbesselt et al*., 2006] and Lebanon [*Mitri et al*., 2015]. KBDI has also been used to assess changes to global wildfire potential due to climate change [*Liu et al*., 2010].

The KBDI can be expressed as mm equivalent of soil moisture deficit in the root-zone and surface litter (duff) layer, ranging from 0 (very wet conditions) to 203 mm (very dry conditions). KBDI is essentially a simple water balance model operating at a daily time scale. The significant advantage of using KBDI lies in the ease of implementation and requirement for only a few input variables. A major underlying assumption made in KBDI is that the evapotranspiration rate is a function of the mean annual rainfall. *Snyder et al*. [2006] tested KBDI for an arid grassland region in California and suggest that the KBDI method to estimate evapotranspiration may not be valid for regions where mean annual rainfall is significantly different from the south-eastern Unites States. In addition, KBDI assumes that a single number can be used to describe both the dryness of the root-zone soil and the surface duff layer. KBDI assumes a maximum water holding capacity of about 20 cm. *Keetch and Byram* [1968] suggest that for sites with a heavy clay soil, a water holding capacity of 20 cm equates to a soil depth of about 80 cm. The depth of soil assumed by KBDI is not well defined, since the soil water holding capacity varies significantly with soil texture and organic matter content [e.g., *Wosten et al*., 1999; *Balsamo et al*., 2009]. In particular, the presence of organic matter can significantly increase the soil water holding capacity and consequently significantly reduce the assumed depth of soil. *Garcia-Prats et al*. [2015] find for a planted pine forest in Spain, that KBDI is more representative of soil dryness at a soil depth of about 30 cm.

2.1.2. Mount's Soil Dryness Index

MSDI [*Mount*, 1972] is used operationally in the states of Tasmania, South Australia and Western Australia for fire danger prediction [*Finkele et al*., 2006]. MSDI was developed for the Tasmanian Fire Service as an alternative to KBDI. MSDI has a range of 0–200 mm. Rainfall interception and runoff in MSDI are based on seven vegetation categories. The MSDI vegetation map is derived using the Moderate resolution Imaging Spectrometer (MODIS) leaf area index (LAI) data set [*Paget and King*, 2008]. The vegetation map is derived from LAI using the same linear relationship as *Finkele et al*. [2006]. For each vegetation class, parameter values are defined for canopy rainfall interception fraction, canopy storage capacity, canopy loss per wet day, and flash-runoff fraction [*Finkele et al*., 2006]. The regression coefficients used to calculate evapotranspiration are the same as those used operationally by the Bureau of Meteorology's MSDI calculations. The regression coefficients are based on observations of evapotranspiration from the capital cities of south-eastern Australian states (Victoria, Tasmania and South Australia). Following the operational system, only one set of regression coefficients is used for the whole of Australia.

2.1.3. Antecedent Precipitation Index

API is another simple water balance model [*Crow et al*., 2005] and is based on the assumption that the amount of moisture in a soil column is related to precipitation at earlier times. API for day *i* is given by:

$$\mathrm{API}_i = \gamma \mathrm{API}_{i-1} + P_i \tag{1}$$

Following *Crow et al*. [2005], the loss coefficient $\gamma = 0.85 + 0.0075(293.15 - T_{\mathrm{max}})$ where P_i is the daily precipitation (mm) and T_{max} is the daily maximum temperature (Kelvin).

2.2. In Situ Soil Moisture Observations

Unfortunately, there are only a very few ground based observations of soil moisture. However, these few observations are extremely useful for the validation of remotely sensed and model soil moisture.

2.2.1. OzNet

The OzNet hydrological monitoring network is managed together by Monash University and the University of Melbourne, in Australia. Soil moisture observations from the Murrumbidgee river catchment (Figure 1a) [*Smith et al*., 2012] are available online from http://www.oznet.org.au for the period 2001–2011 (observations after May 2011 are unavailable at the time of this study). The Murrumbidgee data set consists of 38 soil moisture observing sites situated in a semiarid to humid climate over an area of $82,000\ \mathrm{km}^2$. The observations measure soil moisture in the top 90 cm of soil. The OzNet soil moisture observations are visually quality controlled and this process includes comparisons with rainfall observations [*Smith et al*., 2012].

The Murrumbidgee catchment is characterized by significant spatial variability in climate, soil, vegetation and land use. Climate variations are mainly associated with the change in elevation from west to east, which varies from 50 m to more than 2000 m. Soil types are predominantly of finer-texture in the plains of the western half of the catchment, whereas the eastern half is primarily dominated by medium to coarse-textured soils. Agricultural land constitutes the major portion of the catchment, except the steeper parts where a mixture of native eucalypt forests and exotic forest plantations are predominant.

2.2.2. CosmOz

CosmOz is a network of cosmic ray soil moisture probes established at thirteen locations around Australia [*Hawdon et al*., 2014]. A cosmic-ray probe measures the number of fast neutrons near the land surface. Fast neutrons are strongly moderated by the presence of hydrogen and soil moisture represents the largest and most variable source of hydrogen near the surface. Therefore, measured intensities reflect variations in the surface soil moisture. The effective depth of measurement depends strongly on soil moisture itself [*Zreda*

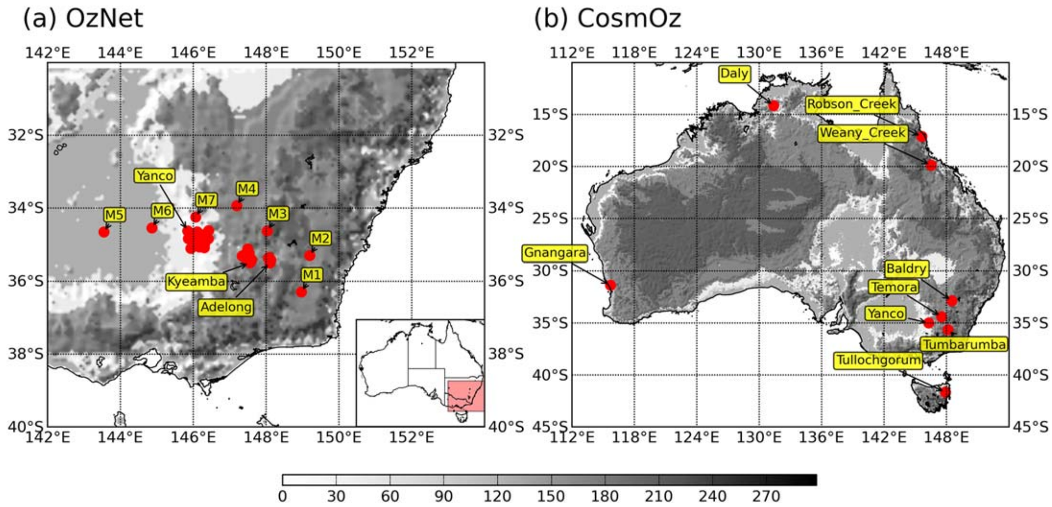

Figure 1. Site locations of (a) OzNet and (b) CosmOz network observing stations. Spatial extent of OzNet is shown by the map of Australia in the inset of Figure 1a. The filled contours represent surface elevation (m) at 10 km resolution.

et al., 2008]. The measurement depth decreases nonlinearly with increasing soil moisture and, theoretically, ranges from about 70 cm (10 cm) in very dry (saturated) soils. One advantage over traditional point measurement sensors is that cosmic-ray probes have a horizontal footprint of about 240 m in diameter at sea level [*Kohli et al*., 2015].

CosmOz observations are obtained from the online portal http://cosmoz.csiro.au/managed by Commonwealth Scientific and Industrial Research Organisation (CSIRO) of Australia. This study uses 7 h moving averages of level 4 processed data which have been quality controlled and are available directly from the portal. Only observations from calibrated CosmOz sites are used. The data processing and calibration methods used by the CosmOz network are described by *Hawdon et al*. [2014]. The locations of the CosmOz probes, used in this study, are shown in Figure 1b.

2.3. NWP Soil Moisture

The operational global NWP system employed by the Bureau of Meteorology is part of the Australian community Climate and Earth System Simulator (ACCESS) [*Puri et al*., 2013]. The ACCESS Global NWP system first became operational in September 2009 with a horizontal resolution of about 80 km. The ACCESS Global NWP system was updated in March 2012 with an increase in horizontal resolution to about 40 km. Numerous improvements to the ACCESS model and data assimilation were also implemented. The ACCESS Global NWP system does not use observations of precipitation. This study uses soil moisture analyses from both the old and newer operational ACCESS Global NWP systems. This study refers to the old ACCESS Global NWP system as ACCESS_80km and the newer ACCESS Global NWP system as ACCESS_40km. The ACCESS global NWP system has in 2016 been upgraded with an improved horizontal resolution of 25 km.

ACCESS NWP incorporates a physically based land surface model (LSM) to represent processes which regulate the exchanges of water and energy through the soil-plant-atmosphere continuum. Soil moisture is one of the prognostic variables simulated by the LSM. Both ACCESS_80km and ACCESS_40km use the Met Office Surface Exchange Scheme version 2 (MOSES2) [*Essery et al*., 2001] LSM. The MOSES2 soil is 3 m thick and is discretized into four layers of 0.1, 0.25, 0.65 and 2 m thickness from top to bottom.

ACCESS Global NWP employs a physically based soil moisture nudging technique [*Best et al*., 2007] that adjusts the model soil moisture to minimize the errors in 6 h forecasts of daytime screen temperature and humidity. The nudging scheme is physically based as it uses the model equations and the model soil and vegetation parameters (e.g., wilting point, field capacity, fraction of bare soil, vegetation root depth). The model wilting point and field capacity parameters have a significant impact on the magnitude of the analysed soil moisture. While the fraction of bare soil and vegetation root depth parameters significantly modulate the vertical variation of the soil moisture nudges.

Since errors in forecasts of screen temperature and humidity are due to many factors, the soil moisture nudging scheme seeks to identify and correct for those errors in forecasts that are due to the model soil moisture. The ACCESS NWP soil moisture nudging scheme is only active in unstable conditions (negative Richardson number), where the errors in screen temperature and humidity are of opposite sign (i.e., model boundary layer too warm and dry or model boundary layer too cold and moist), where there is evaporation, and where there is no snow cover. Despite these precautions, a significant disadvantage of the soil moisture nudging scheme is that the model soil moisture can become updated for model errors that are unrelated to soil moisture (e.g., errors in model clouds). The soil moisture nudging is performed four times a day and only adjusts model soil moisture for the portion of the globe in daylight. The soil moisture nudging scheme can correct the model soil moisture not only for random errors but also for persistent systematic errors in the model such as biases in the model precipitation. The soil moisture nudging scheme only uses observations of screen level temperature and humidity and doesn't use any remotely sensed observations or any observed precipitation. More advanced soil moisture analysis schemes using remotely sensed measurements of soil moisture and Kalman filter data assimilation schemes have been implemented in ACCESS NWP and tested in research mode [*Dharssi et al*., 2011, 2015]. However, these schemes are currently not operational in ACCESS NWP. Many other NWP centres and researchers also only use observations of screen level temperature and humidity to analyse soil moisture [e.g., *de Rosnay et al*., 2013; *Vinodkumar et al*., 2008].

The ACCESS_80km soil moisture analyses are only available from 2009 to 2012 and therefore can be compared against OzNet soil moisture observations which are available from 2001 to 2011. ACCESS_40km soil moisture analyses are only available from 2012 and consequently cannot be compared against OzNet observations. ACCESS_40km soil moisture analyses can be compared with CosmOz observations which are available in near real-time (NRT) since 2011. The ACCESS NWP soil moisture content analyses (SMC_i) have units of mass per unit area (kg/m^2). While the soil moisture observations are in units of volumetric fraction (m^{3}m^{-3}). Two alternative methods are used to perform the vertical integration over model soil layers and convert to soil moisture volumetric fraction (θ). For simplicity, the Static Weight (S35) method uses

$$\theta=\frac{SMC_1+SMC_2}{\rho_w(d_1+d_2)} \quad . \tag{2}$$

$\rho_w=1000$ kg/m^3 is the density of water and d_i is the thickness of the ACCESS NWP soil layer i ($d_1=0.1$ m and $d_2=0.25$ m). SMC_i is the ACCESS soil moisture content in ACCESS NWP soil layer i. The Dynamic Weight (DW) method uses the approach of *Franz et al*. [2012];

$$\theta=\frac{\sum_i W_i \quad SMC_i/d_i}{\rho_w \sum_i W_i} \quad . \tag{3}$$

The value of the weights W_i depends on the reported sensing depth of the CosmOz observing system.

$$W_i=\int_{Z_{i-1}}^{Z_i} w(z) \quad dz \quad , \tag{4}$$

$$w(z)=\begin{cases} a\left(1-\left(\frac{z}{z^*}\right)^b\right) & z\le z^* \\ 0 & z>z^* \end{cases} \quad . \tag{5}$$

$b=1$, z^* is the reported CosmOz sensing depth and Z_i is the NWP model soil layer depth at layer i ($Z_0=0$, $Z_1=d_1 \ldots Z_3=d_1+d_2+d_3$). The constant a is defined by

$$1=\int_0^{z^*} a\left(1-\left(\frac{z}{z^*}\right)^b\right)dz \quad . \tag{6}$$

Only the S35 method is used for verification against OzNet observations. Both the S35 and DW methods are used for verification against CosmOz observations. The S35 method is equivalent to the DW method when $b=-\infty$ and $z^*=0.35$ m.

2.4. ASCAT Soil Water Index

The Advanced Scatterometer (ASCAT) instruments on board EUMETSAT meteorological satellites MetOp-A (launched 2006) and MetOp-B (launched 2012) provides NRT estimates of surface soil wetness. A third ASCAT instrument is expected to be launched on the MetOp-C satellite during 2017, thereby providing a continuous and long-term source of NRT soil moisture measurements. Daily global coverage from a single MetOp satellite is about 80% [*Wagner et al*., 2013]. A change detection method developed by the Vienna University of Technology [*Wagner et al*., 1999] is used to derive surface soil wetness from ASCAT backscatter measurements. The surface soil wetness retrievals (m_s) are in the form of percentage degree of saturation that range from 0 (dry) to 100% (wet). This study uses the EUMETSAT NRT 12.5 km resolution product from MetOp-A.

2.4.1. Exponential Filter

The ASCAT surface soil wetness product represents soil moisture in a thin surface layer of $\simeq 1$ cm thickness [*Albergel et al*., 2012]. However, the in-situ observations and model analyses of soil moisture used in this study are for a deeper layer of soil. Therefore, the exponential filter [*Wagner et al*., 1999] is applied to the time-series of ASCAT surface soil wetness measurements to approximate the soil wetness profiles (SWI) for a deeper layer of soil. This simple approach has been found to provide reliable estimates. A recursive formulation of the exponential filter [*Albergel et al*., 2009] is used in this study. This recursive formulation can be expressed as:

$$\mathrm{SWI}_n = \mathrm{SWI}_{n-1} + K_n\left((m_s)_n - \mathrm{SWI}_{n-1}\right) \quad , \tag{7}$$

where SWI is the soil wetness profile, m_s is the ASCAT surface soil wetness, K_n is the gain and n is the index of time. The gain K_n at time t_n is given by

$$K_n = \frac{K_{n-1}}{K_{n-1} + \exp\left(t_n - t_{n-1}\right)/T} \quad , \tag{8}$$

where T is the characteristic time length in days and K_n has a range from 0 to 1. For initialisation of the filter, $K_0 = 1$ and $\mathrm{SWI}_0 = (m_s)_0$.

The optimal value of T is derived by calculating ASCAT SWI for all integer values of T between 1 and 40 days, using ASCAT and in situ observations from the first 9 months of 2015. It is found that $T = 4$ days gives the best agreement with CosmOz soil moisture observations. Using $T = 4$ days, the temporal correlation between CosmOz observations and ASCAT SWI (ASCAT m_s) is 0.83 (0.76). The Root Mean Square Difference (RMSD) between normalized CosmOz observations and ASCAT SWI (ASCAT m_s) is 0.18 (0.20). See section 2.5 for an explanation of the normalisation procedure.

2.5. Data Processing

In order to match the daily time steps of the API, KBDI and MSDI analyses, the NWP model soil moisture analyses, ASCAT soil wetness measurements and in situ soil moisture observations are converted to daily averages. The nearest neighbour technique is used to colocate the data. KBDI and MSDI values are converted to soil moisture content by subtracting the values from their respective maximum.

The approach of *Albergel et al*. [2012] is used to calculate the soil moisture verification statistics. To calculate the average correlation, the method of *Corey et al*. [1998] is used that applies Fisher's Z transformations. To enable a fair comparison, all soil moisture time-series and indices are converted to soil wetness (normalized between [0, 1]) using their own maximum and minimum values from their own long time series, as also done by many other soil moisture verification studies [e.g., *Brocca et al*., 2011]. This rescaling approach is sensitive to outlier observations and therefore the OzNet and CosmOz observed soil moisture time-series have been visually inspected to remove erroneous measurements. Some studies [e.g., *Draper et al*., 2009] rescale the soil moisture time-series by matching the mean and standard deviation.

The anomaly correlations between models and observations are also calculated. Anomalies are computed for each time-series by using a 31 day sliding window to calculate the window mean ($\overline{\theta_i}$). The anomaly A is then computed using $A_i = \theta_i - \overline{\theta_i}$. The anomalies are calculated using the method of *Draper et al*. [2012]. A confidence interval (CI) of 95% is computed for each correlation value, after applying Fisher-Z transform. Time series of soil moisture are highly auto-correlated. Therefore, to estimate CI, the effective sample size [*Dawdy and Matalas*, 1964; *Draper et al*., 2012] is assumed to be

$$N_{eff}=N\frac{(1-r_a r_b)}{(1+r_a r_b)}, \quad (9)$$

where N is the number of samples, and r_a and r_b are the lag-1 auto-correlation of the two time-series being compared.

Taylor diagrams [*Taylor*, 2001] are used to show three verification statistics on a two dimensional plot. Correlation is shown on the azimuthal axis, normalized standard deviation (NSD) on the radial axes and unbiased RMSD is shown as the distance from the point corresponding to $R=1$ and $NSD=1$ [for a fuller explanation, see *Albergel et al*., 2012].

3. Results

Ground based soil moisture observations contain errors and consequently the verification statistics will be affected by errors in both the observations and the model or remotely sensed soil moisture. Throughout this paper the term RMSD is used rather than Root Mean Square Error (RMSE). This acknowledges that the CosmOz and OzNet soil moisture observations contain errors; both instrumental errors and errors of representativity. The errors of representativity will depend on the scale of interest. The Supporting Information S1 provides detailed verification and time-series plots for each OzNet and CosmOz soil moisture observing site. For brevity, a summary of the verification is presented here.

Verification against OzNet is only carried out for ACCESS_80km, API, KBDI and MSDI, since their temporal availability overlaps with that of the OzNet observations The verifications statistics are calculated from September 2009 to May 2011 when all the data are available. The evaluation against CosmOz is undertaken for ACCESS_40km, ASCAT, API, KBDI and MSDI. Since ACCESS_40km data set has the shortest availability, the verification period spans from May 2012 to December 2014. Verification statistics between ASCAT and OzNet can be found in *Albergel et al*. [2012].

3.1. Comparison With OzNet

3.1.1. Top 30 cm Soil Layer Observations

The temporal correlation, bias, RMSD and unbiased RMSD (ubRMSD) calculated for ACCESS_80km, KBDI, MSDI and API with respect to the OzNet observations of soil moisture in the top 30 cm of soil are given in Table 1. The values represent averages over 30 stations. 95% confidence intervals are also provided. The soil moisture time-series have high values of auto-correlation which reduces the effective sample size and results in large confidence intervals for correlation and anomaly correlation. The temporal correlations between observed and modeled soil moisture varies considerably from station to station and no single model is always best or worst. The results show that the ACCESS_80km and MSDI soil wetness analyses have the best overall agreement with the OzNet 30 cm observations. The ACCESS_80km and MSDI soil wetness analyses have the smallest bias, RMSD and ubRMSD. Average biases are 0.03 $\pm$0.03 (ACCESS_80km), $-$0.26$\pm$0.04 (KBDI), $-$0.02$\pm$0.04 (MSDI) and 0.15 $\pm$0.03 (API). KBDI in general display a large wet bias, which suggest that KBDI underestimates evapotranspiration. Averaged RMSD for ACCESS_80km, KBDI, MSDI and API are 0.20 $\pm$0.01, 0.36 $\pm$0.03, 0.22 $\pm$0.02 and 0.27 $\pm$0.02 respectively. These results suggest that the

Table 1. Verification Scores With 95% Confidence Intervals for the ACCESS_80km NWP Model, KBDI, MSDI and API Against OzNet In Situ Soil Moisture Observations for the Top 30 cm of Soil[a]

	Normal Time Series				Anomaly Correlation
Data Set	Correlation	Bias	RMSD	ubRMSD	95% Confidence Intervals
All Soil Wetness Conditions					
ACCESS_80km	0.67–0.81	0.03 ± 0.03	0.20 ± 0.01	0.18 ± 0.01	0.67–0.72
KBDI	0.53–0.78	−0.26 ± 0.04	0.36 ± 0.03	0.23 ± 0.02	0.70–0.75
MSDI	0.60–0.81	−0.02 ± 0.04	0.22 ± 0.02	0.19 ± 0.02	0.75–0.79
API	0.65–0.74	0.15 ± 0.03	0.27 ± 0.02	0.21 ± 0.01	0.71–0.75
OzNet 30cm Observations Indicate Soil Wetness Values Less Than 0.5					
ACCESS_80km	0.49–0.69	−0.06 ± 0.03	0.16 ± 0.02	0.13 ± 0.01	0.58–0.67
KBDI	0.40–0.74	−0.32 ± 0.04	0.40 ± 0.04	0.22 ± 0.01	0.72–0.79
MSDI	0.42–0.74	−0.07 ± 0.03	0.19 ± 0.03	0.16 ± 0.01	0.75–0.81
API	0.43–0.58	0.08 ± 0.02	0.18 ± 0.02	0.15 ± 0.01	0.63–0.70

[a]Scores for both normal and anomaly time series are presented. The values represent an observing network average.

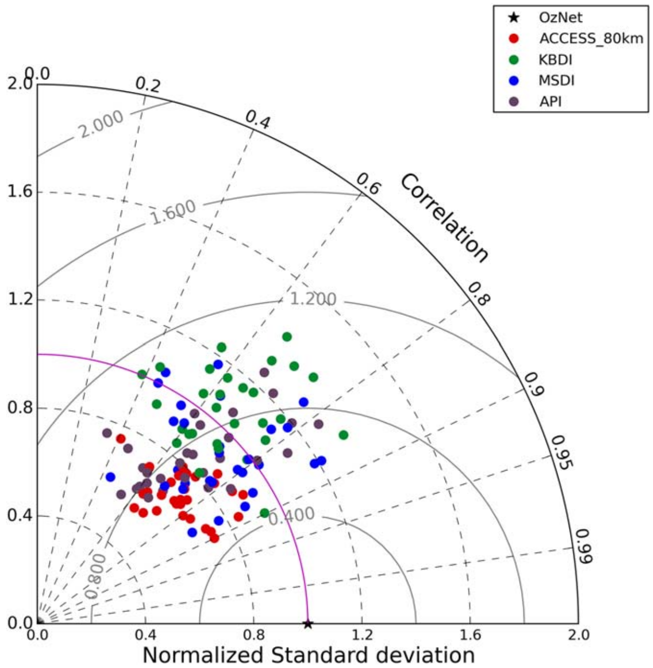

Figure 2. Taylor diagram illustrating the verification scores of ACCESS_80km, KBDI, MSDI and API against soil moisture observations at 30 OzNet observing stations.

MSDI analyses are more accurate than KBDI primarily because KBDI shows a significant wet bias. Table 1 also shows verification results for dry conditions when the observed soil wetness is less than 0.5. These additional verification statistics show that KBDI also has a large wet bias during dry conditions (-0.32 ± 0.04) and that the ACCESS soil wetness analyses are more skillful. Figure 2 shows a Taylor diagram comparing ACCESS_80km, KBDI, MSDI and API soil moisture against OzNet soil moisture observations at the 30 stations. The figure suggests that the ACCESS_80km model underestimates the soil wetness variability, as depicted by the normalized standard deviation values.

Figure 3 shows the time series of soil wetness from ACCESS_80km, KBDI, MSDI and the OzNet observations at sites M1, A1, Y1 and K1 in the Murrumbidgee catchment. The time-series plots from other sites are not shown here for brevity. Generally, the crests and troughs in the time series are captured by all the models. The time series plots clearly show that the KBDI is much wetter than

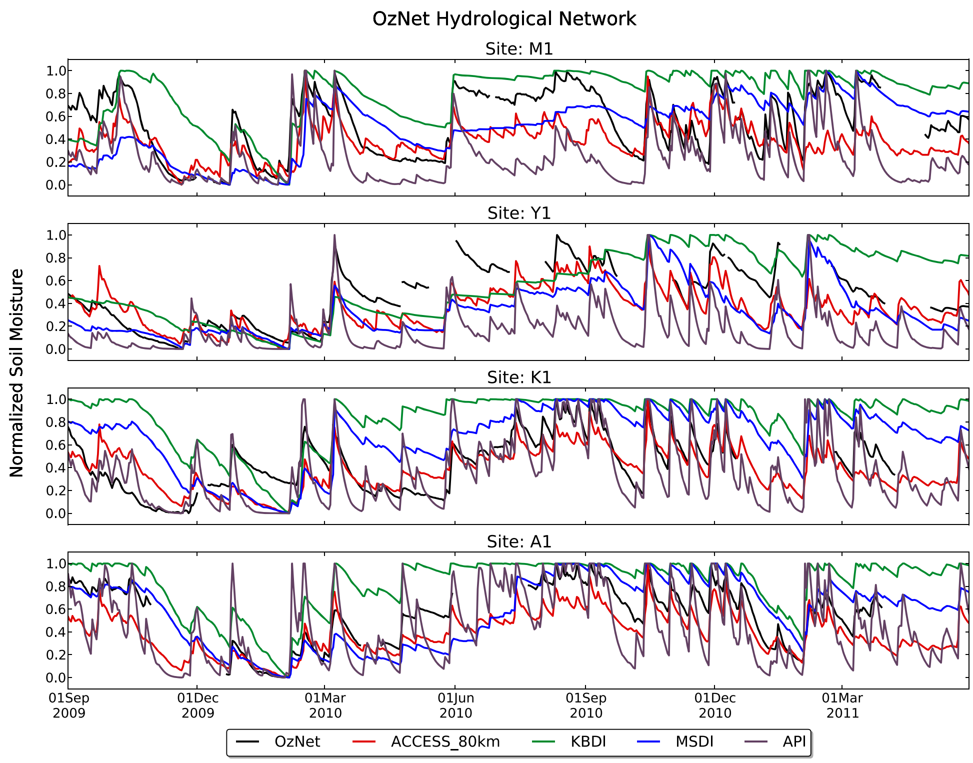

Figure 3. Normalized soil moisture time-series at four OzNet sites. Plots from top to bottom are for sites M1, Y1, K1 and A1 in the Murrumbidgee catchment. The red lines show ACCESS_80km normalized soil moisture analyses, green lines show KBDI, blue lines MSDI, and black lines show the in-situ OzNet observations

the observations. During the winter months, KBDI is wet and erroneously exhibits very little temporal variability. The MSDI displays higher temporal variation and shows better agreement with the observations. Although, MSDI generally underestimates the rate of change (Figure 3). The ACCESS NWP soil wetness follows the observation most closely.

The short term variation in model soil wetness is assessed through verification of anomaly time-series. Such short term soil wetness variations may be significant for calculation of fire danger, particularly for Australia, where heatwaves can cause rapid drying. The 95% confidence intervals for the mean anomaly correlation between model and in-situ soil wetness observations are presented in Table 1. The 95% confidence intervals for anomaly correlation averaged over 30 OzNet observing sites are 0.67–0.72 (ACCESS_80km), 0.70–0.75 (KBDI), 0.75–0.79 (MSDI) and 0.71–0.75 (API). The results suggest that ACCESS_80km is better able to capture the soil wetness seasonal variations rather than the short term variations.

3.1.2. Top 90 cm Soil Layer Observations

The correlation, bias and RMSD calculated for ACCESS_80km, KBDI, MSDI and API with respect to the OzNet observations in the top 90 cm of soil are given in Table 2. The values represent averages over 28 stations. The top three model soil layers of ACCESS_80km have a total thickness of 1 m and therefore the ACCESS_80km soil wetness is calculated using information from the top three model soil layers. The root zone soil moisture time series have very high auto-correlations and therefore at many OzNet observing stations the effective sample size is less than 3. Consequently, confidence intervals cannot be calculated for the temporal correlation between model soil wetness and the 90 cm observations. Since the uncertainty in the calculated correlation values is very high, it is not possible to use temporal correlation to make conclusions about model skill. However, for completeness the temporal correlation values are still provided in table 2. The effective sample size is much larger for anomaly correlation and 95% confidence intervals have been calculated. The anomaly correlation suggest that all the models have similar skill with MSDI perhaps performing slightly better. KBDI also shows a significant wet bias for the thicker top 90 cm soil layer of -0.26 ± 0.04. This large bias results in much higher RMSD values for KBDI of 0.34 $\pm$0.04. The ACCESS_80km and MSDI soil wetness analyses have the smallest bias and RMSD. The performance of ACCESS_80km is very acceptable, considering the coarse spatial resolution of the model.

3.2. Comparison With CosmOz

3.2.1. Normal Time Series

The soil wetness analyses from ACCESS_40km, KBDI, MSDI, API and ASCAT are evaluated against daily average measurements from the CosmOz cosmic ray probes. Although there are a total of 13 sites in the CosmOz observing network, only the nine sites which are fully calibrated and are not subjected to irrigation are selected (Figure 1) for this study. Measurements from Gnangara are included even though there are major issues with site calibration [*Hawdon et al*., 2014]. The sandy soil at Gnangara results in very low soil moisture content so that the calibration does not perform well.

Table 3 shows the verification scores at CosmOz locations using either the static (ACCESS_S35) or dynamic (ACCESS_DW) weighted vertical integration of ACCESS_40km NWP soil analyses. The scores for ACCESS_S35

Table 2. Verification Scores With 95% Confidence Intervals for the ACCESS_80km NWP Model, KBDI, MSDI and API Against OzNet In Situ Soil Moisture Observations for the Top 90 cm of Soil[a]

Data Set	Normal Time Series: Correlation	Bias	RMSD	ubRMSD	Anomaly Correlation 95% Confidence Intervals
All Soil Wetness Conditions					
ACCESS_80km	0.69	0.00 ± 0.04	0.22 ± 0.02	0.20 ± 0.02	0.60–0.66
KBDI	0.76	-0.26 ± 0.04	0.34 ± 0.04	0.20 ± 0.02	0.63–0.69
MSDI	0.76	-0.01 ± 0.04	0.21 ± 0.02	0.18 ± 0.02	0.69–0.74
API	0.59	0.16 ± 0.04	0.29 ± 0.03	0.23 ± 0.01	0.64–0.70
OzNet 90 cm Observations Indicate Soil Wetness Values Less Than 0.5					
ACCESS_80km	0.62	-0.08 ± 0.03	0.19 ± 0.02	0.16 ± 0.02	0.61–0.70
KBDI	0.72	-0.31 ± 0.05	0.38 ± 0.05	0.20 ± 0.02	0.69–0.77
MSDI	0.69	-0.07 ± 0.03	0.17 ± 0.03	0.14 ± 0.02	0.74–0.81
API	0.45	0.07 ± 0.02	0.19 ± 0.01	0.17 ± 0.01	0.61–0.69

[a]Scores for both normal and anomaly time series are presented. The values represent an observing network average. The effective sample size is too small to calculate confidence intervals for the correlation.

Table 3. Verification Scores for Normalized ACCESS_40km Soil Moisture Analyses Against Ground-Based CosmOz Observations[a]

Site	Sensing Depth (*m*) Mean	Max	Min	Correlation S35	DW	Bias S35	DW	RMSD S35	DW	Anomaly Correlation S35	DW
Baldry	0.22	0.38	0.11	0.89	0.87	0.02	0.01	0.12	0.13	0.82	0.79
Daly	0.40	0.55	0.16	0.82	0.84	−0.02	−0.03	0.13	0.13	0.60	0.61
Gnangara	0.40	0.56	0.24	0.57	0.66	−0.07	0.05	0.21	0.19	0.54	0.68
Robson Creek	0.13	0.21	0.08	0.80	0.82	0.06	−0.06	0.16	0.15	0.40	0.45
Temora	0.17	0.27	0.09	0.90	0.90	−0.01	−0.05	0.12	0.13	0.72	0.77
Tullochgorum	0.20	0.47	0.08	0.76	0.75	0.05	−0.05	0.17	0.18	0.67	0.73
Tumbarumba	0.10	0.14	0.06	0.82	0.81	0.03	−0.05	0.15	0.16	0.55	0.54
Weaney Creek	0.23	0.35	0.11	0.74	0.75	−0.02	−0.05	0.15	0.17	0.77	0.78
Yanco	0.20	0.37	0.08	0.87	0.88	−0.03	−0.05	0.13	0.13	0.76	0.77
Mean				0.82	0.82	0.00	−0.03	0.15	0.15	0.67	0.71

[a]S35 (DW) represents the static (dynamic) weighting method used for vertical integration over the ACCESS soil layers.

and ACCESS_DW are similar at most locations. The biggest sensitivity to the vertical integration method is at Gnangara, where the CosmOz sensing depth is consistently high and on average about 0.4 m. However, Daly also has an average sensing depth of 0.4 m but there the verification scores are not significantly affected by the vertical integration method. Therefore, other factors such as the calibration might explain the sensitivity to the vertical integration methods. ACCESS_S35 only uses information from the top two model soil layers while ACCESS_DW can also use information from the third model soil layer, when the CosmOz sensing depth is greater than 0.35 m.

The temporal correlation, bias, RMSD and ubRMSD calculated for ACCESS_40km, KBDI, MSDI, API and ASCAT with respect to the CosmOz observations of soil moisture are provided in Table 4. Results shows that ACCESS_40km soil wetness analyses have better overall agreement with the CosmOz observations than KBDI, MSDI and API. The ACCESS_40km soil wetness analyses have the smallest bias, RMSD and ubRMSD. The temporal correlation and anomaly correlation values also indicate that ACCESS_40km has high skill. KBDI again shows a large wet bias over all stations (-0.23 ± 0.08). Since the CosmOz observations are scattered all over Australia, this implies that KBDI under-predicts the soil moisture deficit substantially, regardless of the climate zone. API, unlike KBDI, exhibits a dry bias at all CosmOz sites. MSDI doesn't exhibit any consistent wet or dry bias.

ASCAT skill is generally very good with temporal correlations greater than 0.8, except at the Tumbarumba and Tullochgorum observing stations. The Tumbarumba site is located in a eucalyptus forest and the Tullochgorum site is surrounded by high terrain. ASCAT has difficulties in measuring soil wetness accurately in regions with high vegetation density or complex terrain [*Dharssi et al*., 2011; *Brocca et al*., 2011].

Figure 4 shows time-series plots of modeled and observed soil wetness for the Tullochgorum observing station. KBDI shows a large wet bias. The MSDI time-series is too smooth with the rate of wetting and drying

Table 4. Verification Scores With 95% Confidence Intervals for the ACCESS_40km NWP Model, KBDI, MSDI, API and ASCAT Against CosmOz In Situ Soil Moisture Observations[a]

Data Set	Normal Time Series Correlation	Bias	RMSD	ubRMSD	Anomaly Correlation 95% Confidence Intervals
All Soil Wetness Conditions					
ACCESS_40km	0.78–0.86	-0.03 ± 0.03	0.15 ± 0.02	0.14 ± 0.01	0.67–0.72
KBDI	0.57–0.74	-0.23 ± 0.08	0.33 ± 0.07	0.22 ± 0.03	0.44–0.52
MSDI	0.70–0.83	-0.07 ± 0.06	0.20 ± 0.03	0.17 ± 0.03	0.48–0.55
API	0.69–0.78	0.13 ± 0.04	0.22 ± 0.03	0.17 ± 0.02	0.67–0.72
ASCAT	0.77–0.88	-0.05 ± 0.08	0.18 ± 0.04	0.13 ± 0.04	0.64–0.70
CosmOz Observations Indicate Soil Wetness Values Less Than 0.5					
ACCESS_40km	0.58–0.73	-0.04 ± 0.03	0.14 ± 0.03	0.13 ± 0.02	0.64–0.72
KBDI	0.43–0.66	-0.29 ± 0.11	0.38 ± 0.10	0.23 ± 0.03	0.45–0.56
MSDI	0.59–0.76	-0.12 ± 0.06	0.20 ± 0.05	0.14 ± 0.04	0.48–0.65
API	0.52–0.67	0.08 ± 0.04	0.15 ± 0.02	0.12 ± 0.03	0.70–0.76
ASCAT	0.67–0.83	-0.09 ± 0.05	0.15 ± 0.03	0.12 ± 0.01	0.65–0.74

[a]Scores for both normal and anomaly time series are presented. The values represent an observing network average. The dynamic weighting method is used for the vertical integration of the ACCESS soil moisture analyses.

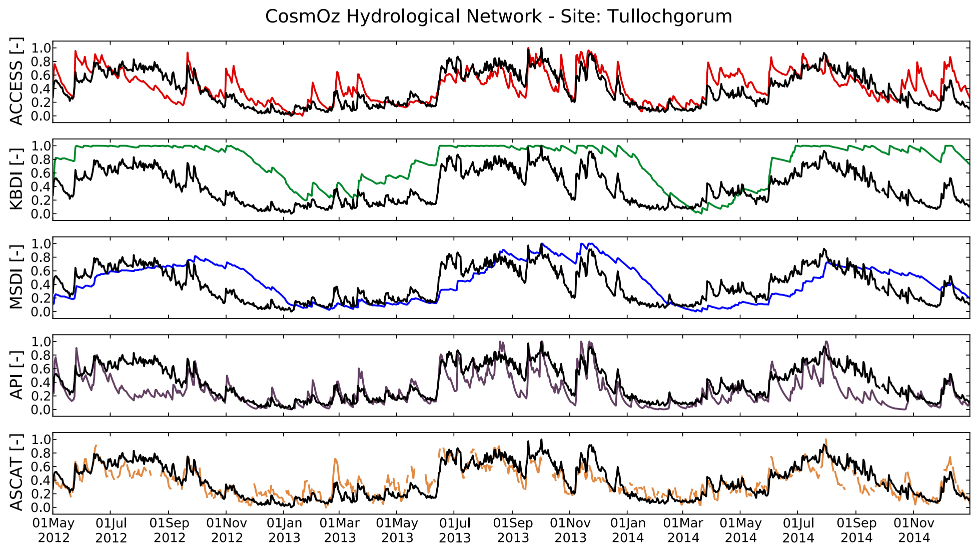

Figure 4. Time series of normalized soil moisture for the CosmOz Tullochgorum site in Tasmania, Australia. Panels from top to bottom show normalized: ACCESS_40km, KBDI, MSDI, API and ASCAT. ACCESS_40km uses the dynamic weighting method. The black line shows the CosmOz soil moisture observations.

misrepresented at most instances. In contrast, the API temporal variations appear to be too rapid. ACCESS_40km and ASCAT both show good agreement with the observations.

Figure 2 shows that the ACCESS_80km model underestimates the soil wetness variability. The Taylor diagram in Figure 5 shows that ACCESS_40km does not have this problem. A possible explanation is that ACCESS_40km uses the *Van Genuchten* [1980] equations to model soil hydraulic conductivity while ACCESS_80km uses the older Campbell equations [*Campbell*, 1974; *Clapp and Hornberger*, 1978]. The use of the van Genuchten equations reduces the soil hydraulic conductivity and increases the soil moisture dynamic range [*Balsamo et al.*, 2009]. The higher spatial resolution of ACCESS_40km may also explain this result.

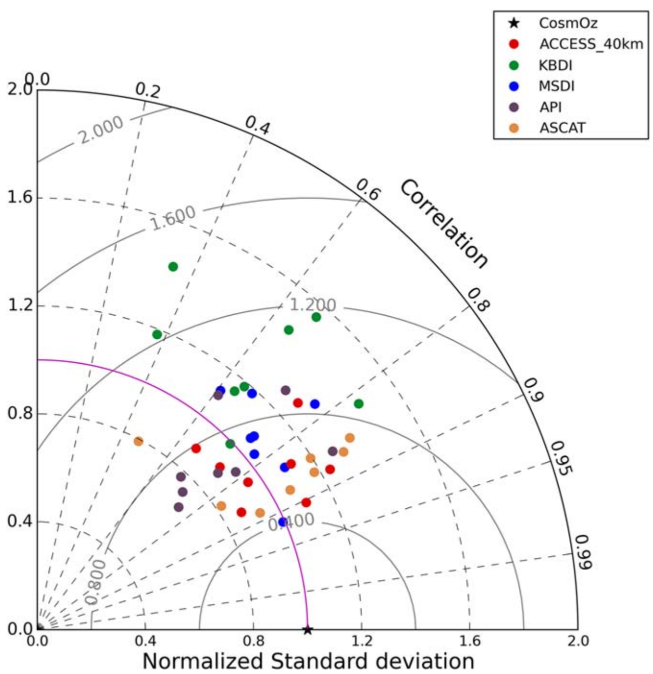

Figure 5. Taylor diagram illustrating the verification scores of ACCESS_40km, KBDI, MSDI, API and ASCAT against soil moisture observations from nine CosmOz sites. ACCESS_40km uses the dynamic weighting method.

3.2.2. Anomaly Time Series

Table 4 shows mean anomaly correlation between CosmOz observations and models. The ACCESS_40km, API and ASCAT best captures the short term soil wetness variations. The 95% confidence intervals for mean anomaly correlation are 0.67–0.72 (API), 0.67–0.72 (ACCESS_40km), 0.48–0.55 (MSDI) and 0.44–0.52 (KBDI). The 95% confidence interval for mean anomaly correlation between CosmOz and ASCAT is 0.64–0.70. Mean anomaly correlation between KBDI and CosmOz observations is lower than the mean anomaly correlation between KBDI and OzNet observations. Most likely, this is due to sensor locations. The OzNet Y10 site and CosmOz Yanco sites are located nearby and show similar anomaly correlation values. Anomaly correlation values are 0.59 (OzNet Y10 versus KBDI) and 0.55 (CosmOz Yanco versus KBDI).

4. Conclusions and Future Work

KBDI is still widely used in many areas of the world for wildfire monitoring and prediction. However, KBDI was developed in the 1960s and does not make use of the many developments in remote sensing, land surface modeling or data assimilation. This study compares and verifies KBDI and MSDI against ground based soil moisture observations. It is already widely known that KBDI indicates significantly wetter conditions than MSDI [*Finkele et al*., 2006]. The verification results in this study clearly shows that KBDI has a large wet bias and that MSDI agrees more closely with ground based soil moisture observations. KBDI is found to have a large wet bias at all the OzNet and CosmOz observing stations used for verification. The results show that overall MSDI has a small bias. *Burrows* [1987] has compared KBDI and MSDI against observations of soil moisture and log moisture at a few sites in western Australia and has also found that MSDI is more skillful than KBDI.

This study verifies ACCESS NWP soil wetness analyses and remotely sensed ASCAT soil wetness measurements against ground based observations. This is also one of the few studies to use CosmOz soil moisture observations for verification. Comparison against CosmOz observations shows that ACCESS NWP analyses and ASCAT measurements have more skill than KBDI and MSDI. The ACCESS NWP performance is particularly impressive given that KBDI and MSDI are computed on a much higher resolution grid and use observation based rainfall and temperature analyses. ACCESS NWP has a much coarser resolution and doesn't use any observations of precipitation. Results show that the ACCESS NWP soil wetness analyses have small biases and are particularly good at capturing the seasonal variations. Results also indicate that the more recent ACCESS_40km model soil moisture analyses agree more closely with the in-situ observations than the older ACCESS_80km model. This is likely to be due to the higher spatial resolution of ACCESS_40km as well as improvements to the model (e.g., use of the *Van Genuchten* [1980] equations) and data assimilation. Another significant advantage of ACCESS NWP is the ability to produce 10 day forecasts of soil moisture. Such forecasts will be very useful for medium range forecasting of fire risk. Future work is planned to assess the skill of the 10 day soil moisture forecasts.

As well as higher accuracy, the ACCESS NWP system is much more flexible and provides analyses of soil moisture on four clearly defined soil layers over a 3 m depth of soil. In contrast, the simple water balance model (KBDI, MSDI, API) outputs are ambiguous since the assumed depth of soil is not clearly defined. Since KBDI and MSDI assume very similar water holding capacities they are expected to be representative of nearly the same soil depth. The depth of soil assumed by KBDI and MSDI will depend strongly on soil type, which has a very high spatial variability. Linear rescaling cannot fully remove the difference in soil depth between the models and observations. However, results show that for verification of ACCESS against CosmOz observations, the verification results are very similar whether the dynamic weighting method or static method is used for vertical integration. The dynamic weighting method takes into account the variable sensing depth of CosmOz observations while the static method simply assumes a constant sensing depth of 35 cm.

Many studies have shown that ASCAT can provide good quality information about the surface soil wetness [e.g., *Brocca et al*., 2011; *Albergel et al*., 2012]. This work finds good agreement between the remotely sensed ASCAT surface soil wetness and CosmOz observations. The ASCAT surface soil wetness product has similar skill to the ACCESS_40km surface soil wetness in terms of correlation, anomaly correlation, bias and RMSD.

This study suggests that the best way to improve the analyses of soil moisture for operational fire warnings is to combine the strengths of the different systems. Therefore, a prototype 5 km resolution soil moisture analysis system is being developed that uses a physically based land surface model driven by observations based rainfall and temperature analyses (Dharssi, I., and V. Vinodkumar, A prototype high resolution soil moisture analysis system for Australia, technical report, Bureau of Meteorology, Melbourne, Victoria, Australia, in preparation, 2017). The system is also capable of assimilating remotely sensed observations of soil wetness such as ASCAT and land surface temperature.

Triple Collocation (TC) [*McColl et al*., 2014; *Scipal et al*., 2008; *Dorigo et al*., 2010; *Zwieback et al*., 2012; *Vogelzang and Stoffelen*, 2012; *Yilmaz and Crow*, 2014; *Gruber et al*., 2016] is a powerful and useful method to estimate errors in models and observations. Therefore, future work will also use TC to verify soil moisture data sets. Additional work is also planned to evaluate the verification results to understand the effects of soil types, vegetation, topography, climate and other factors on model skill.

5. Author Contribution

Imtiaz Dharssi, John Bally and Peter Steinle planned this work. Vinodkumar calculated KBDI and MSDI. Imtiaz Dharssi calculated API. Vinodkumar and Imtiaz Dharssi calculated the verification statistics. Vinodkumar and Imtiaz Dharssi prepared the manuscript. David McJannet provided advice on the CosmOz observations and contributed significant improvements to the manuscript. Jeff Walker provided advice on the OzNet observations and helped to improve the manuscript.

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