bnhcrc.com.au

EVALUATION OF DAILY SOIL MOISTURE DEFICIT USED IN AUSTRALIAN FOREST FIRE DANGER RATING SYSTEM

Vinodkumar and Imtiaz Dharssi
Bureau of Meteorology

Version	Release history	Date
1.0	Initial release of document	03/11/2017

Australian Government
Department of Industry, Innovation and Science

Business Cooperative Research Centres Programme

Disclaimer:
The Bureau of Meteorology and the Bushfire and Natural Hazards CRC advise that the information contained in this publication comprises general statements based on scientific research. The reader is advised and needs to be aware that such information may be incomplete or unable to be used in any specific situation. No reliance or actions must therefore be made on that information without seeking prior expert professional, scientific and technical advice. To the extent permitted by law, the Bureau of Meteorology and the Bushfire and Natural Hazards CRC (including its employees and consultants) exclude all liability to any person for any consequences, including but not limited to all losses, damages, costs, expenses and any other compensation, arising directly or indirectly from using this publication (in part or in whole) and any information or material contained in it.

Publisher:
Bushfire and Natural Hazards CRC

November 2017

Citation: Vinodkumar and Dharssi I (2017) Evaluation of daily soil moisture deficit used in Australian forest fire danger rating system. Melbourne: Bushfire and Natural Hazards CRC

Cover: Dry soil, Ricky Thrakar (CC BY-NC-ND 2.0)

Contents

List of Tables

List of Figures

ABSTRACT

The fuel availability estimates in McArthur Forest Fire Danger Index used in Australia for issuing operational fire warnings are partly based on soil moisture deficit, calculated as either the Keetch–Byram Drought Index (KBDI) or Mount's Soil Dryness Index (SDI). These indices are essentially simple water balance models designed to estimate soil moisture depletion in the upper soil levels. In the present study, daily values of the above two indices are calculated over Australia at 0.05^{o} resolution from 1974 onwards. A detailed verification of these two models against in-situ soil moisture measurements from CosmOz, OzNet and OzFlux networks are performed. The validations are done using soil moisture observations that represent both surface and deeper soil moisture. The verifications for deeper soil are restricted to OzNet and OzFlux, as only these two networks provide corresponding observations. The verification results show that both KBDI and SDI have relatively low skill in estimating shallow layer (0 – approx. 30 cm) soil moisture compared to a much deeper soil profile (0 – approx. 1m). The modest sensitivity of both KBDI and SDI to weather changes indicate that they are not an accurate measure for estimating duff layer soil moisture.

1 INTRODUCTION

Fire danger rating systems (FDRS) are devised to evaluate and integrate the individual and combined factors influencing fire danger. FDRS employed in different countries across the world are generally based on meteorological variables and fuel conditions. The ignition, spread, as well as the short temporal variations in fire danger, are shown to be dependent on fuel availability and prevalent weather conditions (Chandler *et al.,* 1983). Fuel availability is the proportion of fuel which will burn in a fire (Luke and McArthur, 1978). Because fuel availability measures are not always readily available, fire danger rating systems include sub-models to estimate these quantities from weather observations. The McArthur Forest Fire Danger Index (FFDI; McArthur, 1967) used in Australia for instance, has a component representing fuel availability called the Drought Factor (DF). DF was developed to predict the amount of fuel (i.e., vegetation, litter etc.) which would be available to be consumed in the flaming front of a fire. McArthur postulated that the amount of fuel left unburnt should be due to fuel moisture content (FMC), resulting from the influences of both soil and atmospheric moisture. He assumed that using cumulative soil moisture deficit as a proxy for long-term drying and rainfall for short-term drying would be an acceptable way of calculating the amount of fuel which could be burnt by a fire.

Research have revealed that the occurrence of large destructive fires corresponds to very large soil moisture deficit (SMD) values in Australian landscapes, thereby potentially increasing the availability and resulting flammability of the forest fuel structures (Gellie, 2010). It is also shown that correlation exists between soil moisture state and vegetation moisture content (Burgan, 1988; Viegas *et al.,* 1992). Hence, models for soil moisture estimation were developed that can be used as a proxy for FMC. Keetch–Byram Drought Index (KBDI; Keetch and Byram, 1968) and Mount's Soil Dryness Index (SDI; Mount, 1972) are two such models which measure cumulative soil water deficit in forested ecosystems. KBDI and SDI are basically water balance models with simplified and empirical formulations. These two models are used in the DF calculations in Australia for operational fire danger rating. Studies show that KBDI exhibits a strong relationship with FMC (Dimitrakopoulos and Bemmerzouk, 2003).

The Australian Bureau of Meteorology (the Bureau) operationally produces a 0.25 x 0.25 degree grids of KBDI and SDI daily (Finkele *et al.,* 2006) which is derived using an old spatial (gridded) analyses of daily rainfall and maximum temperature (Weymouth *et al.,* 1999). The Bureau recently upgraded these operational analyses to a higher resolution of 0.05 x 0.05 degree from Australian Water Availability Project (AWAP) (Jones *et al.*, 2009). It is the purpose of this report to describe the calculation of the new higher resolution daily KBDI and SDI product based on these latest high resolution temperature and rainfall analyses. These high resolution grids are calculated for the last 42 years. Such a long time-series is believed to of use for researchers looking at the climatology of fire danger, return period analysis (risk assessment), etc. The report also describes a quantitative verification of these high resolution drought indices against in-situ observations. The merits and limitations of these two indices are also discussed based on these verifications. The report is organized as follows. Section 2 of this report documents the KBDI and SDI methods used in some detail, as this forms the basis for the gridded calculations. Section 3 describes the qualitative comparison between the two products, and their general climatology. Section 4 discusses the verification of KBDI and SDI against in-situ observations. The report finishes with concluding remarks in Section 5.

2 DATA AND METHODS

2.1 Models

2.1.1 Keetch–Byram Drought Index (KBDI)

The KBDI was developed for United States Forest Service to estimate fuel conditions over a wide range of climatic and rainfall conditions in forested or wild land areas. The KBDI is based on a daily simple water balance, and was designed to account for cumulative soil water depletion from the upper soil layer and covering layer of duff. A duff layer contain moderately to highly decomposed leaves, needles, fine twigs, and other organic materials. KBDI ranges from 0 to 203.2 mm when rainfall is expressed in mm and temperature in degree Celsius. 0 mm indicate soil at field capacity and 203.2 mm represent soil at wilting point. The KBDI is one of the most widely used drought indices in wildfire monitoring and prediction. The significant advantage of the method lies in its easy implementation with a few meteorological variables (Ganatsas et al., 2011). Some of the underlying assumptions made in KBDI are:

(i) rate of moisture loss due to evapotranspiration is a function of vegetation cover density.
(ii) vegetation cover density is an exponential function of mean annual rainfall
(iii) evapotranspiration (ET) rate is also assumed to be an exponential function of the daily maximum temperature.
(iv) the depth of the soil layer is based on the maximum water holding capacity of 203.2 mm (8 inches), and,
(v) no distinction is made between interception and runoff processes and is approximated as the first 5.08 mm (0.2 inches) of rainfall within consecutive rainy days. A consecutive rainfall period ends on the first day where there is no measurable rain.

KBDI conceptually estimates the moisture deficit in a virtual soil layer. By assuming a maximum water holding capacity of 203.2, KBDI allows the soil layer depth to vary with soil type at each location. According to Keetch and Byram, for sites with a heavy soil type like clay, the soil layer would be about 76–89 cm (30–35 inches) deep. The simulated layer is even deeper for sites with sandy soil, since the water holding capacity of sand is lower.

Numerous studies have assessed the behaviour of KBDI in different regions and climates. For example, Dolling et al. (2005) studied the climatology and natural variability of KBDI in the Hawaiian Islands in relation to fire activity. Brolley et al. (2007) generated probabilistic KBDI forecasts based on initial KBDI and the ENSO signals to study the forecast probabilities of KBDI exceeding a threshold during El Nino and La Nina years. Liu et al. (2010) used KBDI calculations from projected climate change scenarios to identify trends in global wildfire potential due to the greenhouse effect. Because the index was developed for the south-eastern U.S.A, the exact functional form of this relationship may not be valid for annual rainfall amounts that differ significantly from those of this region (Snyder et al., 2006). Hence, modified versions adapted to local meteorological conditions have been widely proposed by various studies (Garcia-Prats, 2015). Ganatsas et al. (2011) proposed a modified version better adapted to Mediterranean conditions, by tuning parameters used in the original derivation of KBDI. However, the original KBDI formulation still maintains a respectable agreement with volumetric soil water content of duff and upper soil layers (Xanthopoulos et al., 2006). Dimitrakopoulos and Bemmerzouk (2003) found that KBDI is a good indicator of live fuel moisture content and hence flammability. The original formulation of KBDI is adopted for operational fire danger ratings in the Australian states of Victoria, New South Wales and Queensland (Finkele *et al.*, 2006).

For the present study, KBDI is generated for whole Australia using AWAP daily rainfall and maximum temperature data (Jones *et al.,* 2009). Both KBDI and the input AWAP data are at 0.05^{o} x 0.05^{o} resolution. The AWAP rainfall is a 24 hour accumulated field valid at 9 am (local time). AWAP data is available from 1900 (for rainfall) and 1911 (for temperature), and are produced near real-time. The gridded KBDI fields are calculated from 1964 and are produced near real time as well. However, the first 10 years (1964 - 1974) of KBDI data is discarded as spin-up.

2.1.2 Mount's Soil Dryness Index (SDI)

SDI is the second type of soil water balance model used in Australia for DF and FFDI calculations. It was developed by Mount (1972) for the Tasmanian Fire Service and is currently widely used in the states of Tasmania, South Australia and Western Australia. SDI ranges from 0 to 200 mm. Like KBDI, SDI also represents soil moisture deficit, but interception and runoff are treated separately here. The interception and runoff are a function of vegetation class defined at each point of calculation (Finkele *et al.,* 2006). The vegetation types are classified into seven categories based on forest and understory densities. For each vegetation class in SDI, parameters like canopy interception, canopy storage capacity, canopy loss per day and runoff fraction are defined. These parameters are used for interception and run-off calculations. For details, readers are referred to Kumar & Dharssi (2015). SDI vegetation categories in this study are derived using Moderate resolution Imaging Spectrometer (MODIS) leaf area index (LAI) data set (Paget and King, 2008). The MODIS dataset is available at 1 km resolution and was resampled to 0.05^{o} x 0.05^{o} resolution. The classifications were based on a mean dataset obtained from 10 years (2002-2012) of data. The linear relationship between SDI vegetation category and LAI discussed in Finkele et al. (2006) is used to derive the vegetation dataset. ET in SDI assumes a linear relationship with daily maximum temperature. The regression coefficients required to calculate ET are obtained from operations and are derived from the relationship between mean monthly pan evaporation and daily maximum temperature data available from the Bureau's Australian Integrated Forecaster Workstation (AIFS) for state capital cities. SDI calculations are also driven using AWAP daily rainfall and maximum temperature data at 0.05^{o} x 0.05^{o} resolution. The spin-up period is similar to that of KBDI calculations (1964-1974).

2.2 In-situ soil moisture observations

2.2.1 OzNet

One of the sources of in-situ data used for this study is from the Murrumbidgee Soil Moisture Monitoring Network (Smith *et al.,* 2012) which is part of the OzNet hydrological monitoring network, managed together by Monash University and University of Melbourne in Australia. The Murrumbidgee dataset primarily consists of 38 soil moisture observing sites situated in a semiarid to humid climate over an area of 82,000 km^2. The observations primarily constitutes of soil moisture measurements of top 90 cm (roughly the root zone). The catchment is characterized by significant spatial variability in climate, soil, vegetation, and land use. Agricultural land constitutes the major portion of the catchment, except the steeper parts where a mixture of native eucalypt forests and exotic forest plantations is predominant. The soil moisture observations from OzNet are given in volumetric content (m^3 m^{-3}) and the data is freely available from OzNet website (http://www.oznet.org.au). Out of 38, 30 sites (Figure 1a) which have the longest record of about ten years (2001 – 2011) are used in this study. The observed soil profiles used in this study correspond to 0 – approx. 30 cm and 0 – approx. 90 cm.

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 produced from land due to its interaction with cosmic rays (Desilets and Zreda, 2013). Because fast neutrons are strongly moderated by the hydrogen atom present in the soil, their measured intensities reflect variations in the soil moisture (Zreda et al., 2008). The effective depth of measurement, which is defined as the thickness of soil from which 86 per cent of counted neutrons arise, depends strongly on soil moisture (Zreda et al., 2008). The measurement depth decreases non-linearly with increasing soil moisture, and theoretically ranges from about 70 cm in soils with no water to about 10 cm in saturated soils. One of the major advantages of cosmic-ray probes over traditional point measurement approaches is that it has a much larger horizontal foot print, about 240 m in diameter at sea level (Köhli et al, 2015). The cosmic-ray probes provide reasonably accurate (±0.02 m^3 m^{-3}) estimates of root-zone soil moisture content over a large area (Franz *et al.,* 2012). All the probes in CosmOz network are stationary and are installed above the land surface at an height of 1–2 m. Data used for this study is obtained from the portal http://cosmoz.csiro.au/ managed by Commonwealth Scientific and Industrial Research Organization (CSIRO) of Australia. The study uses level 4 data available from the portal, which has undergone numerous corrections and quality control. The comprehensive methodology applied for data processing and probe calibration for the CosmOz network are given in Hawdon et al. (2014). The site locations of the CosmOz probes used in this study are provided in Figure 1b.

Although there are in total of thirteen sites in CosmOz network, only eight are selected (Figure 1b) in the current study. The five sites discarded are Mineral Banks in Tasmania, Namadgi in Australian

Capital Territory, Norwin in Queensland, Griffith in New South Wales and Gnangara in Western Australia. The first three sites have not been calibrated at the time of this study. The Griffith site, though calibrated, is located on a flood irrigation area. As a result, the measured percentage volumetric soil moisture values exceeds 100 per cent several times during the study period. Further, the site is susceptible to flooding from Mirrool Creek, one of which occurred in Feb/March 2012. Gnangara is the driest and sandiest site of all, and have issues with probe calibration (Hawdon et al., 2014). The sandy soil at Gnangara may result in very low soil moisture content, and it has been acknowledged that the calibration function does not perform well at such low soil moisture values (Hawdon et al., 2014).

2.2.3 OzFlux

OzFlux is an Australian wide network established to study regional ecosystems ranging from forests to grasslands. It is the Australian arm of a global initiative called Fluxnet. OzFlux consists of 37 flux towers and their associated soil moisture and micro-meteorological instrumentation. The present study uses level 3 data that are subjected to detailed quality control. Datasets can be downloaded directly from the OzFlux data portal (data.ozflux.org.au/portal). Profile soil moisture in the OzFlux network is measured at individual stations using Time Domain Reflectometry (TDR) sensors and are given in volumetric units. Data from the twenty publicly available OzFlux sites (Figure 1c) are used in this study. All these sites contain soil moisture observations for the top layer, the depths of which vary from site to site and are generally less than 15cm. The study also utilizes moisture data that corresponds to a deeper soil profile available at about thirteen sites out of the twenty two. The depths of these profiles are usually between 50 and 100 cm and also vary with sites.

3 DATA PROCESSING

Though all datasets used here represent soil moisture, they in their original form differ to each other in many aspects. For example, KBDI and SDI are indices that represent soil moisture deficit. The *in-situ* observation are in volumetric units. Also, the above two models are at a daily resolution whereas the *in-situ* measurements have a temporal resolution of 30 minutes or finer. Hence, in order to make a fair comparison, post-processing is done on each dataset. To match the daily time steps of the KBDI and SDI fields, *in-situ* data are averaged over each day. A spatially collocated sub-set of gridded KBDI and SDI fields with respect to *in-situ* observation locations are obtained using the nearest neighbour technique. KBDI and SDI are converted from deficit to soil moisture using their maximum values. Finally, all soil moisture datasets are scaled between [0, 1] using their own maximum and minimum values from the respective lengthy time series.

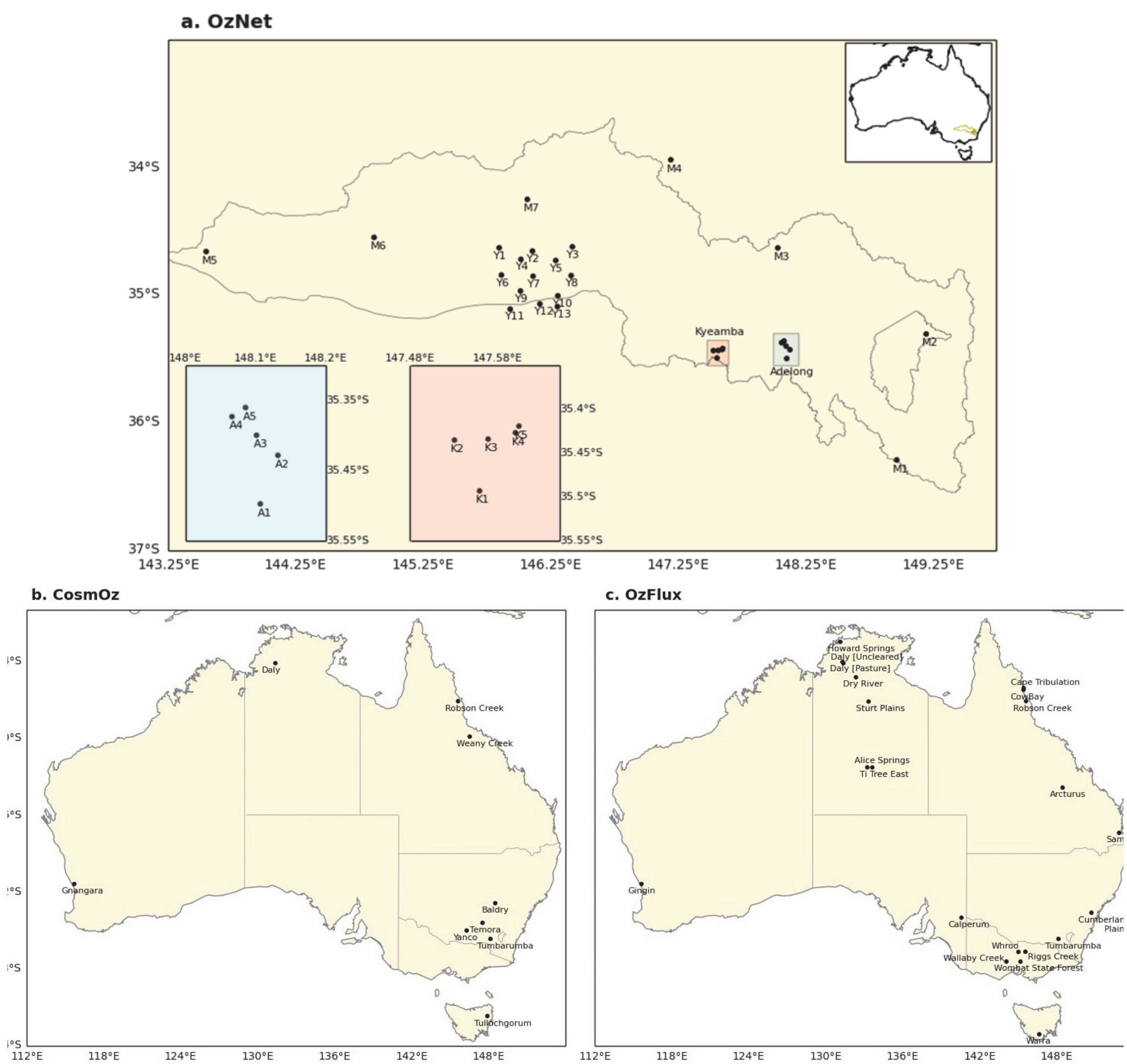

Figure 1 In-situ soil moisture monitoring networks. (a) OzNet (b) CosmOz, and (c) OzFlux. Details of each site from these networks are given in Appendix 1.

4 VERIFICATION METRICS

For all stations, Pearson's correlation coefficient (R, Eq. (1)), root mean square difference (RMSD, Eq. (2)) and bias (Eq. (3)) are calculated for the whole period in which the comparing data overlaps.

$$R = \frac{\frac{1}{N}\sum_{i=1}^{N}(model_i - \overline{model})(in\ situ_i - \overline{in\ situ})}{\sigma_{model}\sigma_{in\ situ}} \qquad (1)$$

where σ is the standard deviation.

$$RMSD = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(in\ situ_i - model_i)^2} \tag{2}$$

$$bias = \frac{1}{N}\sum_{i=1}^{N}(in\ situ_i - model_i) \tag{3}$$

In order to avoid seasonal effects that can superficially enhance the temporal correlations, we also evaluate the anomalies using the Pearson's correlation. Given a 31-day sliding window defined to calculate the mean ($\overline{SM}$), the anomaly A is then computed using:

$$A(i) = SM(i) - \overline{SM}. \tag{4}$$

5 MONTHLY MEAN

The historical archives of daily gridded fields of KBDI and SDI from 1974 to 2014 are used to calculate mean monthly climatologies from the two models. Figure 2 depicts the mean climatology of KBDI for January (Figure 2a) and July (Figure 2b). Month of January occurs during the southern hemisphere summer, whereas July falls within the winter period. The two months are hence chosen to represent the two distinct seasons. Figure 3 depicts the same, but for SDI.

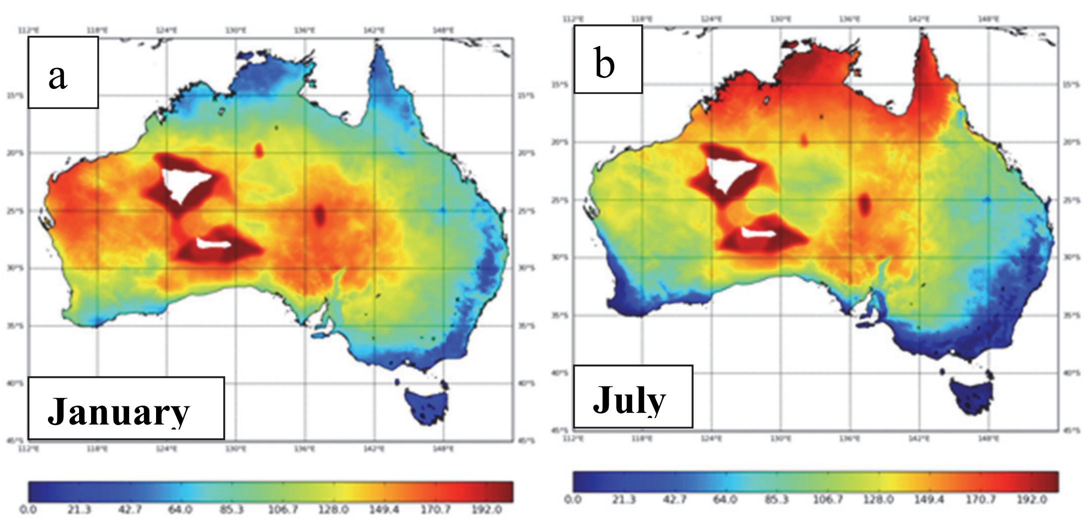

Figure 2 Mean monthly KBDI values for (a) January, and (b) July. The mean is calculated using a 41 year data from 1974 – 2014.

The largest values of KBDI in January are found in central and north-western Australia (Figure 2a). The northern and south-eastern regions are relatively wet. The anomalously large KBDI values over central Australia around data void regions are partially an artefact of highly varied and often low rainfall totals in arid regions, but also an impact of interpolation of rain-gauge measurements to daily data across data sparse regions. January in northern Australia (north of 16^{o}S) is within the northern wet season, where the dominant rainfall producing mechanism is the active phase of monsoon. The northern wet season occur mostly between November and April and accounts for at least 90% of the annual rainfall for all but tropical coastal Queensland. However, it is interesting to note that KBDI depicts wet soil even during summer in the southern parts. This is more predominant in Tasmania, where the whole state is fairly wet.

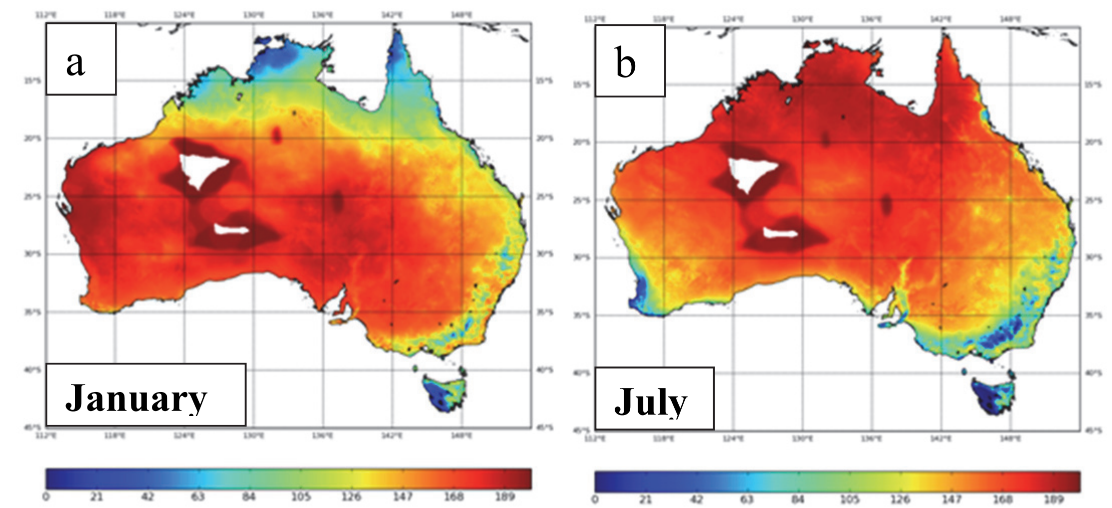

Figure 3 Same as in Figure 2, but for SDI.

In July, KBDI shows a distinct north-south pattern, when northern Australia is very dry and southern Australia is very wet (Figure 2b). The values in the “Top End” are generally above 170 mm. The onset of warm dry season in northern Australia coincides with southern hemisphere winter and is characterized by a sharp decline in humidity and rainfall. Continuous dry conditions over the next few months rapidly decrease the root-zone soil moisture content, and is captured by KBDI as manifested in Figure 2b. On contrary, the soil in the southern regions of Australia is close to field capacity owing to the wet winters. Southern parts of Australia usually experience a cool wet winter, with the region coming under the influence of westerly winds and rain-bearing cold fronts, with the high pressure systems now moving northwards, centred on the continent. The resulting dry soil state due to the frequent high pressure systems and low rainfall activity over Central Australia are also manifested in the monthly KBDI values for July.

SDI also shows a distinct wet soil in January over the northern Australia, which coincide with the higher rainfall amount owing to the monsoons. The soil dries rapidly as one moves inland and the gradient of this drying is larger than that with KBDI. The western and central Australia are markedly dry as well. Moving into the winter month of July, the major part of the north and central part of the continent remains relatively dry compared to the south. SDI appears to simulate drier soil than KBDI at most of the places. Comparisons between the KBDI and SDI made by Finkele et al. (2006) also noted a similar behaviour. They argued that the differences arising in the simulated soil moisture deficit between two schemes are mainly due to the representation of evapotranspiration rather than the infiltration/runoff process. The evapotranspiration in SDI is a linear function of maximum temperature and consequently follows the maximum temperature patterns, which is higher for inlands. Hence, Finkele et al. (2006) concluded that the use of SDI may not be appropriate at warm inland locations of Australia. They suggested that SDI is however suitable in predicting soil moisture deficits at cooler climatic zones, like the south eastern parts of Australia, where they observed that the differences between SDI and KBDI are minimal.

6 RESULTS

6.1 Verification against shallow layer observations

6.1.1 OzNet 0–30 cm

Figure 4 represents the model evaluation against OzNet in-situ observations of 0–30 cm soil profile in terms of box and whisker plots. The verification period is from 2001 to 2011. The median R value for KBDI and SDI is 0.61 and 0.74 respectively (Figure 4a). The highest correlation for KBDI is 0.82 obtained over site A1 in the Adelong catchment. The lowest correlation for KBDI is 0.4 at site Y4 in Yanco. SDI also displays a larger variability among stations, with a maximum value of 0.84 at site A5 and a minimum value of 0.49 over site Y6. In general, the correlation values of SDI are higher for shallow soil layers in Murrumbidgee, indicating a relatively stronger similarity in temporal soil moisture dynamics compared to KBDI.

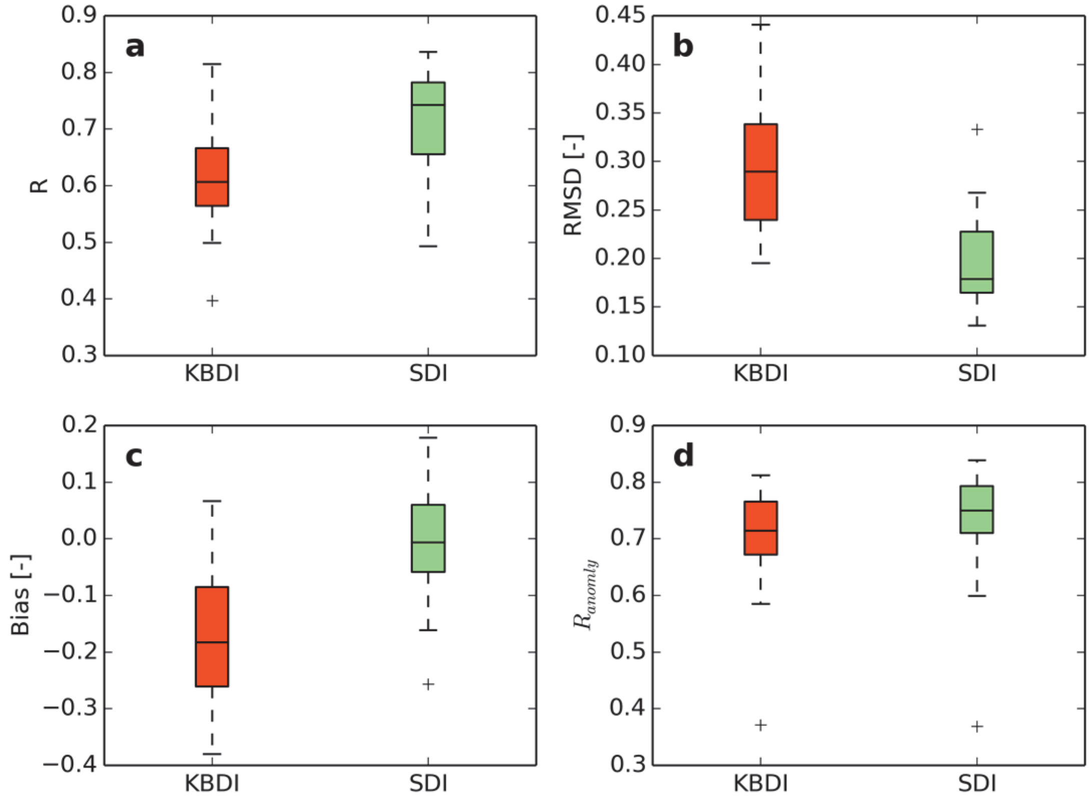

Figure 4 Box and whisker plots depicting (a) correlation, (b) RMSD, and (c) bias and, (d) anomaly correlation of KBDI and SDI against OzNet surface observations. Black line within each box represent median value. Width of the box represent inter-quartile range. The top and bottom edges of whisker represent maximum and minimum values (excluding outliers). The outlier is depicted as a '+' symbol. An outlier is any value that lies more than one and a half times the length of the box from either end of the box.

The median bias obtained for KBDI and SDI is -0.19 and -0.01 respectively. KBDI in general displays a large wet bias, except for two sites (Y1 and Y9). The biases obtained at Y1 and Y9 are 0.01 and 0.07 respectively. The maximum wet bias is observed at site A2 (-0.38). KBDI displays a large wet bias at all Adelong and Kyeamba sites. This is demonstrated in the time series plot for site A4 (Figure 5a). During the winter months, KBDI exhibits very small temporal variability and are often close to field capacity (i.e., soil dries too slowly). Further, it usually underestimates the drying phase that follows a typical winter. This features are clearly seen in the time series of site A4 (Figure 5a). SDI shows no such characteristics over A4 and follows the observations quite closely.

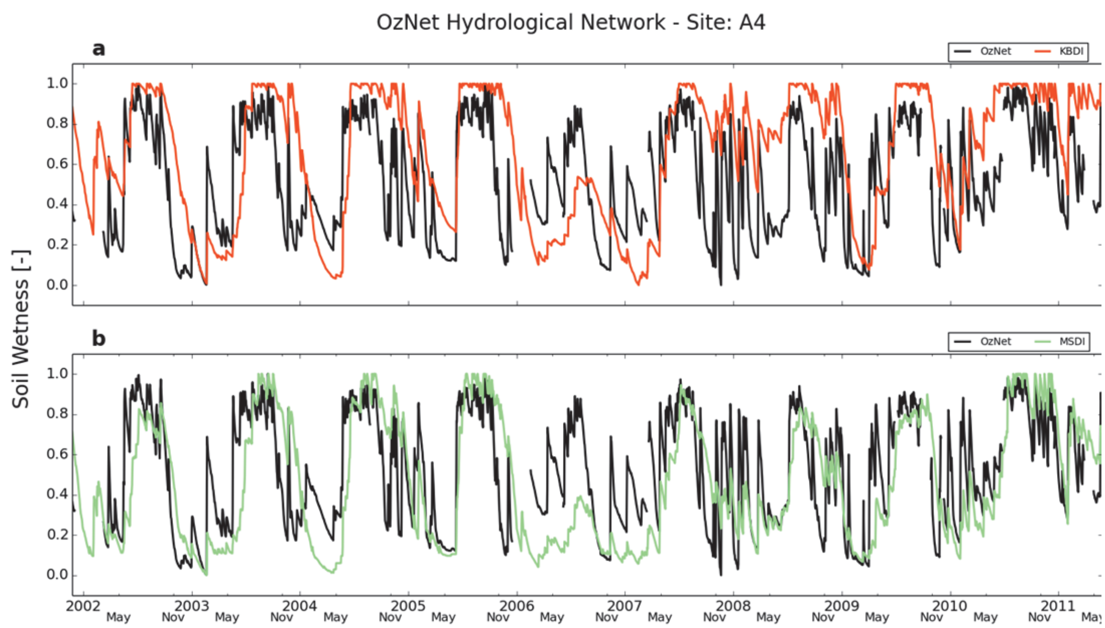

Figure 5 Time series of soil wetness at K4 from (a) KBDI (orange line) and SDI (green line). OzNet in-situ observations are in black.

The median value of bias in SDI presents a small negative value indicating wet bias. Out of the 30 sites, SDI display a wet bias over 17 sites and a dry bias over the rest 13 sites. The largest dry bias in SDI is observed at site M1 (0.15) and largest wet bias is observed at site K1 (-0.16). The median RMSD value for KBDI and SDI are 0.29 and 0.18 respectively. The largest RMSD for KBDI (0.44) is over site K1 and the lowest is 0.20 at Y12. For SDI, the largest error is observed at A2 (0.33) and smallest at M4 (0.13). Compared to KBDI, RMSD in SDI is lower and is more consistent across the sites.

Though soil moisture used in FFDI represents the seasonal drying effects, the short term drying could be of significance as well. This is particularly true for Australia, where frequent heatwaves could cause extreme drying in a short span. These dryness indices were designed to represent moisture variations in the duff layer, which is heavily influenced by the weather events. KBDI and SDI capture the short term variability reasonably well, with median values being 0.72 and 0.75 respectively. The anomaly correlations for KBDI and SDI are generally greater than that of normal time series. This implies that KBDI and SDI capture the variations in local precipitation reasonably well, a feature of using high resolution rainfall analyses to drive them.

6.1.2 CosmOz

The soil moisture estimates from KBDI and SDI are also evaluated against daily averaged measurement from CosmOz cosmic ray probes in the same way. The period of verification is from March 2011 to January 2016.

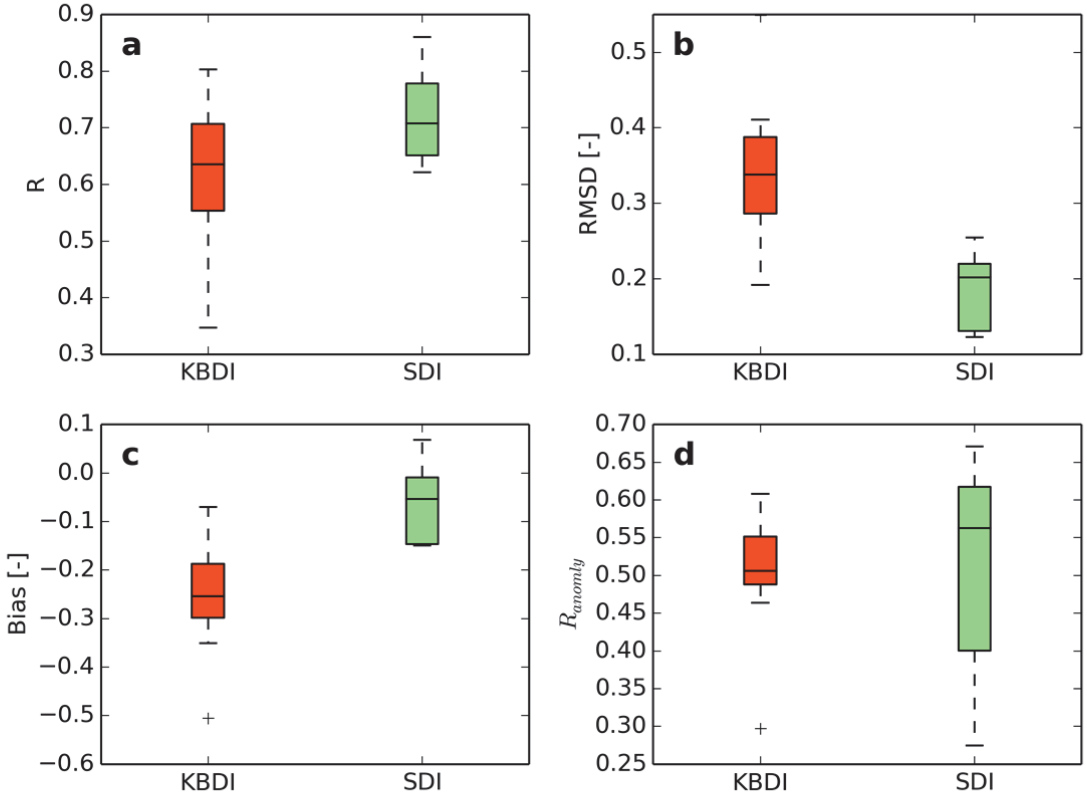

Figure 6 Box and whisker plots depicting (a) correlation, (b) RMSD, (c) bias, (d) anomaly correlation of KBDI and SDI against CosmOz surface observations.

The verifications against CosmOz highlight a similar pattern to that from the OzNet, where the SDI soil moisture product exhibits a better skill than KBDI (Figure 6). The median correlation coefficient for KBDI is 0.63 and that for SDI is 0.71 (Figure 6a). The median bias exhibited by KBDI and SDI is -0.25 and -0.06 respectively (Figure 6c). KBDI show a wet bias at all station, with the maximum bias observed at Tullochgorum (-0.51) and minimum at Robson Creek, QLD (-0.07). Since the CosmOz observations have a wider spatial distribution, the consistent wet bias seen at all sites suggests a location or region independent characteristics. SDI does not exhibit any consistent wet or dry bias spatially. The spatial variability of bias is larger in KBDI than SDI. KBDI also exhibits larger random errors compared to SDI, as depicted by the RMSD scores (Figure 6b) for respective models. Figure 6d depicts the correlation coefficient of anomalies for both KBDI and SDI obtained from the comparison against CosmOz observations. The correlations are generally lower for KBDI and SDI compared to that from the verification against OzNet. However, verification with CosmOz probably is more representative of the skills of each model across the continent due to a wider variety of climatic conditions over which the verification has been made, although the sample size is relatively smaller.

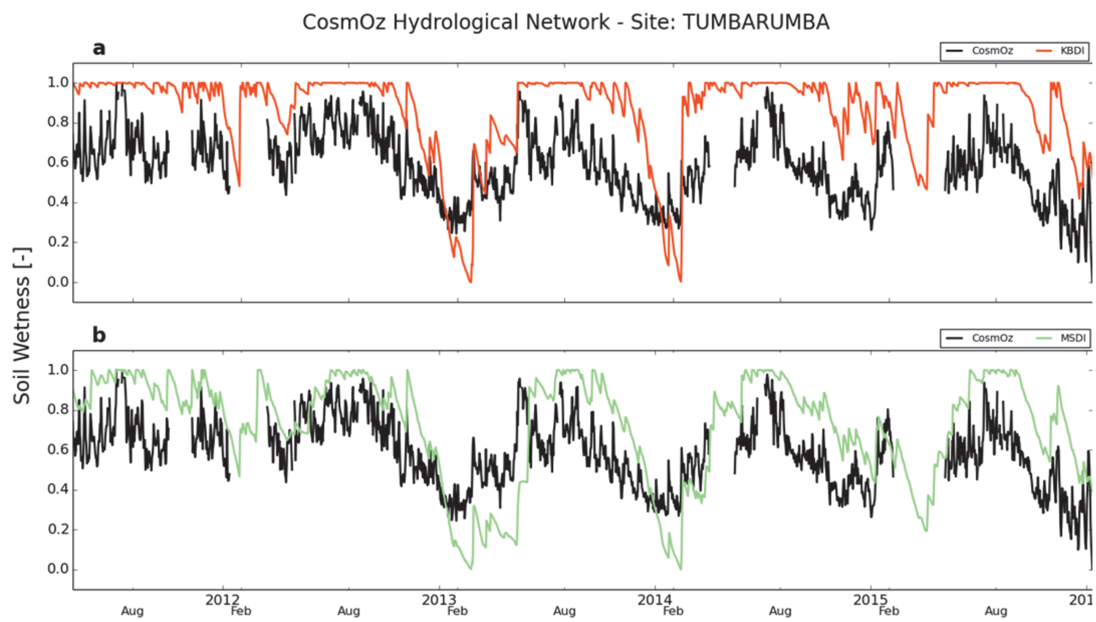

Figure 7 Time series of soil wetness at Tumbarumba from (a) KBDI (orange line) and (b) SDI (green line). CosmOz in-situ observations are in black.

A time series comparison of both soil moisture product observations over Tumbarumba is presented in Figure 7. This site is located in a wet sclerophyll eucalyptus forest. Tumbarumba is a good representative site to evaluate KBDI and SDI, as they are designed to simulate soil dryness in forested ecosystems. The mean depth of CosmOz measurements over this site is 10 cm, and the maximum and minimum are 14 cm and 6 cm respectively. A shallow observation layer means that the soil moisture shows high frequency fluctuations, by being easily influenced by weather events and radiative forcing. However, both KBDI and SDI fail to capture the high frequency variations observed in situ, and only have modest responses to weather forcing. This indicates that these two models poorly represent the duff layer moisture in a typical forest region of south-eastern Australia. Studies have shown that fire potential during spring and autumn are highly dependent on duff layer soil moisture. The poor simulations of duff layer soil moisture by KBDI and SDI hence question the applicability of these methods under such conditions.

6.1.3 OzFlux

A total of 20 sites from OzFlux network are used here for verification. The period of verification is variable for OzFlux. Each of these sites was set up at different times and hence has varying length of data record. For active sites, the end time of verification is 1st June 2015 and corresponds to the latest model estimate at the time of verification. Sites decommissioned before 1st June 2015, have end time matched accordingly. The longest record available is for Tumbarumba, which is about 15 years. The shortest record of observation is about 3.5 years. The depths of shallowest soil profile also vary from site to site. The deepest of surface soil moisture observations are at 15cm (2 sites) and the shallowest is 5cm (5 sites).

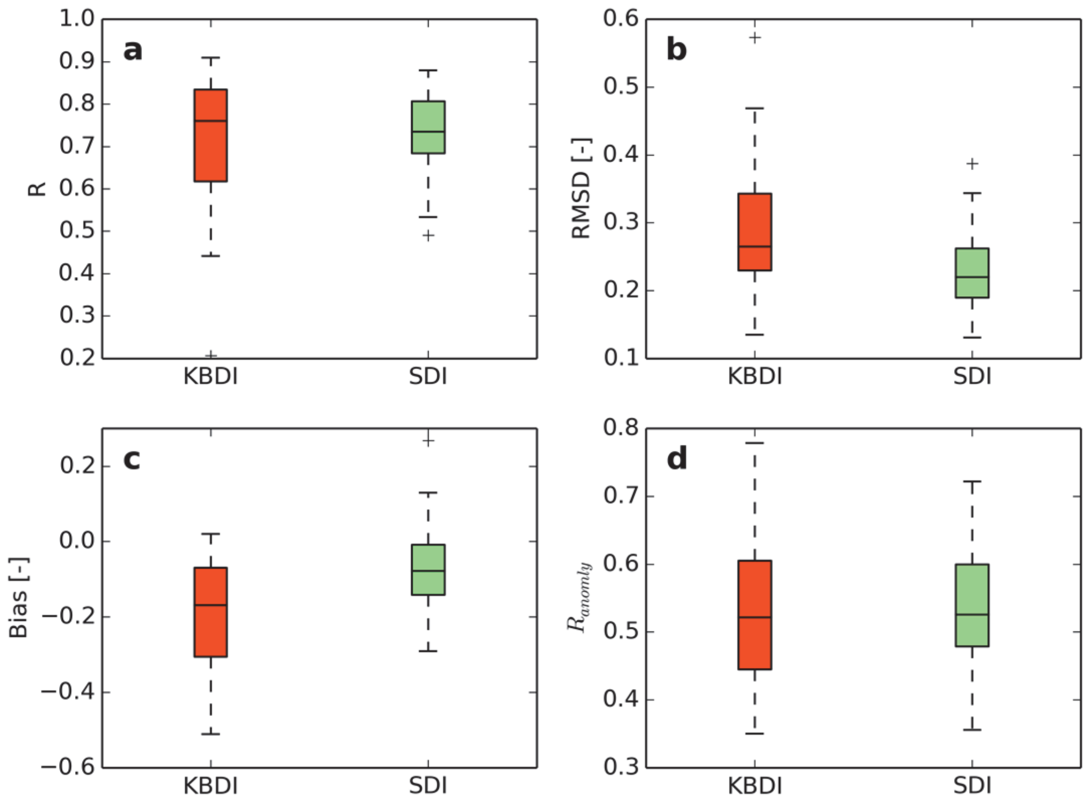

Figure 8 Box and whisker plots depicting (a) correlation, (b) bias, (c) RMSD and, (d) anomaly correlation of KBDI and SDI against OzFlux surface observations.

Figure 8 depict the box and whisker plots of each model's skill against OzFlux shallow soil moisture observations. The median correlation coefficient for KBDI is 0.77 and that for SDI is 0.75 (Figure 8a). Median bias values are -0.18 and -0.1 for KBDI and SDI respectively (Figure 8b). The median RMSD value for KBDI is 0.27 and for SDI is 0.23 (Figure 8c). The skill of KBDI is relatively higher for OzFlux, compared to OzNet and CosmOz networks. KBDI is known to perform well in regions with higher annual rainfall total (Spano et al., 2006). This is typical of the region (south-eastern US) for which KBDI was designed and calibrated. Plotting correlations against mean annual rainfall from OzFlux indicates an increase in correlation coefficient with mean annual rainfall amount (Figure 9).

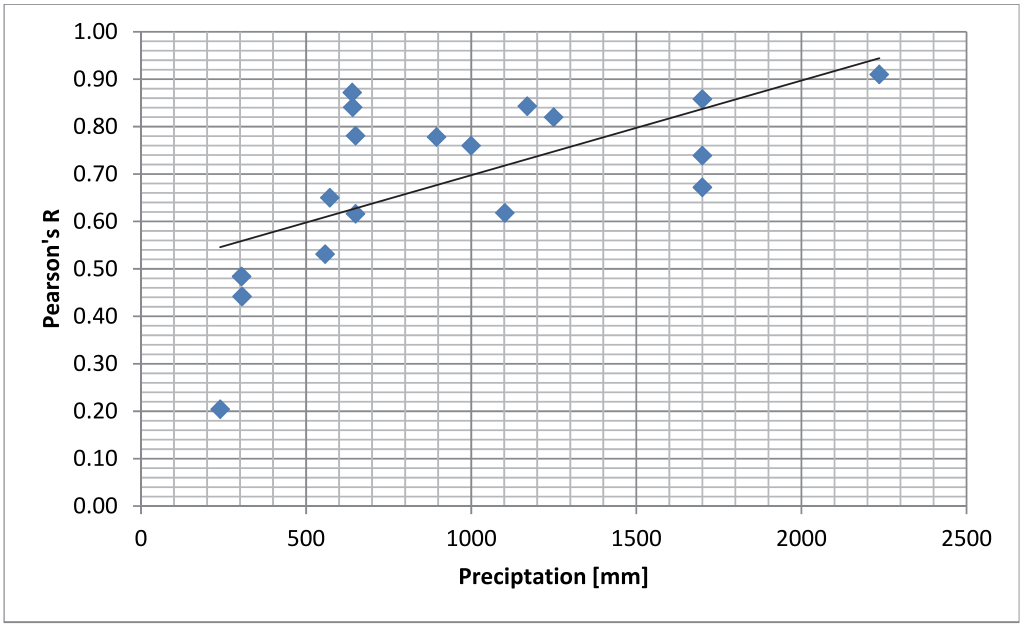

Figure 9 Correlation between KBDI and OzFlux shallow layer observations against mean annual rainfall total (mm).

The spatial distribution of OzFlux sites in different climate zones and ecosystems provides an opportunity to evaluate the performance of these two models at different conditions. It is noted that the skill of two models are generally better over sites in the northern half of the country than in the southern half. The median values of R, bias and RMSD for northern sites are 0.8, -0.09 and 0.23 respectively. The median values for southern sites are 0.71, -0.36 and 0.32 respectively. The southern sites are generally situated in a low rainfall region where median value of annual rainfall total is 650 mm. For northern sites, this value amounts to 999 mm. Recall that ET in KBDI is an exponential function of the mean annual rainfall, higher annual rainfall total leads to higher ET rates. Since mean annual rainfall is low in southern sites, ET from the KBDI seems to be underestimated during most of the year. SDI also displays a better skill for the northern sites, even though the differences in skills are not big as that for KBDI.

6.2 Verification against deep soil moisture observations

6.2.1 OzNet 0-90 cm

An additional comparison is made for KBDI and SDI with deep soil moisture observations from OzNet. The assumption of a maximum water holding capacity of 203.2 mm means that the depth of soil profile that KBDI represents may vary with soil type. The OzNet soils are predominantly silty loam, which generally have a water holding capacity of about 20%. This means that the simulated depth of KBDI over these sites are about 1 m. The closest available observation to this depth is the 0-90 cm soil moisture profile from OzNet, which is used here for comparison.

Catchment	**KBDI**				**SDI**			
	R	**RMSD**	**Bias**	**R_{an}**	**R**	**RMSD**	**Bias**	**R_{an}**
All	0.66	0.30	-0.20	0.68	0.70	0.18	0.00	0.72
Adelong	0.83	0.28	-0.22	0.77	0.83	0.19	0.00	0.76
Murrumbidgee	0.66	0.30	-0.22	0.65	0.75	0.18	0.03	0.78
Yanco	0.59	0.27	-0.12	0.59	0.61	0.19	0.01	0.63
Kyeamba	0.66	0.38	-0.30	0.75	0.82	0.16	-0.07	0.78

Table 1 Skill scores from comparison of KBDI and SDI against OzNet 0–90 cm soil moisture observations. R and R_{an} is the Pearson's product moment correlation coefficient for normal and anomaly time series respectively.

The skills scores from this comparison are depicted in Table 1. The median correlation for KBDI is 0.66 and the median bias and RMSD scores are -0.20 and 0.30 respectively. It is observed that the sites within the Adelong catchment consistently show a higher correlation (median R = 0.83) than observations from other sites. The Yanco sites display the lowest median correlation with a value of 0.59. The annual rainfall total of Adelong catchment (1144) is higher than that over the Yanco sites (426 mm). This may have reflected in the higher correlations obtained over Adelong compared to other catchments. However, the bias and RMSD scores from Adelong are not consistently better over other catchments. The median anomaly correlation for KBDI is 0.68. Disaggregation of anomaly correlation for KBDI over each catchment gives 0.77 for Adelong, 0.75 for Kyeamba, 0.66 for Murrumbidgee sites and 0.59 for Yanco.

The median values of correlation, bias, RMSD and anomaly correlation obtained for SDI are 0.70, 0.0, 0.18, and 0.72 respectively. The highest correlation for SDI is observed in Adelong (0.83) followed by Kyeamba (0.82), Murrumbidgee (0.75) and Yanco (0.61). ET in SDI is not a function of mean annual rainfall as such, and the skill scores from each catchment doesn't reflect any particular dependence to rainfall totals. As observed in earlier comparisons, SDI has a much lower bias and RMSD values than

KBDI counterparts. The anomaly correlation from this comparison is also higher in SDI (0.72) compared to KBDI (0.68). This indicates that the short term variations in the deep soil profiles are captured relatively well by SDI than by KBDI.

6.2.2 OzFlux

The deep soil moisture observations are available from 12 out of 20 sites considered in this study. The depths of these deep level observations also vary from site to site, similar to the surface observations. We have selected observation depth which is closer to 1m. The soil at most of these sites are of heavy type (large organic and clay content), and the representative depth of KBDI is assumed to be about 1 m. The calculated statistics are presented in Table 2. The median correlation, bias, RMSD and anomaly correlation obtained for KBDI is 0.81, -0.15, 0.27 and 0.62 respectively. Out of these 12 sites, 9 sites are in the northern half of Australia and only 3 sites are in the southern half. The KBDI skills over the northern sites are significantly better compared to the southern sites. The median correlation for KBDI in the northern sector is 0.83 compared to 0.68 in the southern sector. More importantly, the bias in KBDI is reduced to -0.09 in the north from -0.38 in the south. This implies that KBDI has good skill only in warm, high rainfall regions and have generally poor skill in colder regions. The anomaly correlation for sites in the northern half is 0.66 and that in the southern half is 0.58. KBDI thus appears to be more responsive to weather events in northern part of the country compared to the southern part, as reflected in the anomaly correlation.

Site	KBDI				SDI			
	R	RMSD	Bias	R_{an}	R	RMSD	Bias	R_{an}
Cape Tribulation	0.89	0.31	-0.27	0.72	0.81	0.42	-0.38	0.65
Cow Bay	0.87	0.18	-0.08	0.77	0.84	0.25	-0.13	0.73
Daly Pasture	0.83	0.22	-0.09	0.66	0.78	0.22	-0.07	0.57
Daly Uncleared	0.90	0.21	-0.11	0.61	0.86	0.21	-0.09	0.53
Dry River	0.80	0.28	-0.20	0.51	0.79	0.23	-0.12	0.48
Gingin	0.88	0.29	-0.25	0.58	0.87	0.12	0.00	0.60
Howard Springs	0.91	0.16	-0.01	0.62	0.92	0.18	-0.08	0.55

Robson Creek	0.96	0.10	-0.04	0.76	0.85	0.17	0.04	0.57
Sturt Plains	0.79	0.23	0.13	0.59	0.77	0.33	0.28	0.44
Ti Tree East	0.77	0.26	-0.20	0.83	0.84	0.15	-0.12	0.80
Warra	0.64	0.44	-0.38	0.45	0.71	0.26	-0.17	0.66
Wombat State Forest	0.68	0.45	-0.42	0.62	0.78	0.22	-0.12	0.64
Median	**0.85**	**0.24**	**-0.15**	**0.62**	**0.82**	**0.22**	**-0.10**	**0.59**

Table 2 Skill scores from comparison of KBDI and SDI against OzFlux observations. R and R_{an} is the Pearson's product moment correlation coefficient for normal and anomaly time series respectively.

The median correlation, bias, RMSD and anomaly correlation obtained for SDI is 0.80, -0.10, 0.20, and 0.59 respectively. SDI displays a wet bias at all but three sites. The distinction in skill scores between northern and southern sites are relatively lower in SDI, compared to. However, the anomaly correlation in the southern sites (0.64) is higher than at the northern sites (0.57). A large dry bias of 0.28 is observed at Sturt Plains for SDI. Incidentally, KBDI, which generally has a wet bias also displays a dry bias at this site. The observations show a clear seasonal pattern, where soil moisture tends to decrease slowly as the dry season progresses. Though the models, especially KBDI, capture the wetting phase reasonably well, they tend to dry out more quickly than the observations. This is more evident in SDI. Thus the model have a large dry bias during winter months (dry season in northern Australia) resulting in an overall dry bias. It is therefore fair to assume that the ET rates are over estimated in the two models over this site. The mean annual rainfall at this site is relatively lower at 640 mm. The maximum temperature ranges from 28.4°C (in June/ July) to 39.1°C (in December). ET in SDI is linearly related to maximum temperature, and over relatively hot locations like Sturt Plains, it could possibly overestimate ET. What is more interesting is the dry bias observed in KBDI. Generally, KBDI gives a wet bias at low rainfall regions. However, the exponential nature of the multi-variate relationship that exist between ET, rainfall and maximum temperature means that, temperature also exerts a great influence in ET estimation of KBDI at hot regions.

7 DISCUSSIONS

The spatial patterns of KBDI and SDI monthly means are comparable to that of the current operational system produced based on Finkele et al (2006). For example, like the operational system, our SDI calculations generally show higher soil moisture deficit compared to KBDI. On our verification of both high resolution and operational systems against CosmOz and OzFlux observations, we found the station averaged skill of both systems to be fairly similar (not shown). It is acknowledged that the

AWAP rainfall analyses only provide a modest improvement to the coarser resolution analyses. Evidence suggest that a denser observation network and a very different analysis technique will be required to improve the daily rainfall analyses (Jones et al., 2009). However, the AWAP maximum temperature analysis has been found to have a lower root means square error compared to the previous operational analysis (Jones et al, 2009). This could produce some difference in our high resolution analyses of land dryness and the current operational ones. We also expect to see some potential dissimilarity between the high resolution and operational SDI, owing to the different leaf area index (LAI) data used to derive SDI vegetation class. The present study uses a MODIS based LAI index data, resampled to 0.05^0 resolution from the native 1km grids. The operational calculations use Graetz's LAI data (Finkele et al., 2006). We use MODIS LAI instead of Graetz's data, as the later was not available at a 5 km (or finer) resolution.

The verification of KBDI and SDI against in-situ soil moisture observations reveals some interesting features of two systems. Both models have only moderate skill in capturing the high frequency moisture fluctuations observed in shallow soil layer. The shallow soil layer can be considered as a good representation of duff layer. The moisture fluctuations in both duff and shallow soil layer are influenced by weather events and radiative forcing. The modest representation of duff layer soil moisture in these two models partly reflects the limitation of ET estimation methods in them. The ET process in both KBDI and SDI are overly simplified. For example, both of these models do not take into account the majority of physical factors like soil type, vegetation type, or terrain aspect which affect ET. Further, no information on atmospheric controls of ET like net radiation, wind speed, relative humidity is used. KBDI models ET as an exponential function of the mean annual rainfall in the denominator. This leads to higher ET rates in regions of larger annual rainfall total. These higher ET rates, in general, are found to have a positive impact in terms of improving skill of KBDI over regions of high annual rainfall. ET in SDI is a linear regression function of maximum temperature, where regression coefficients are calculated by linearly fitting monthly pan evaporation and monthly maximum temperatures (Finkele et al., 2006). It is probably difficult to capture the wide range of climate zones seen in Australia using a single set of coefficients. This could introduce errors, particularly biases, in the calculated ET in SDI.

The general improvement in the skill of KBDI from shallow to deep soil layers indicates that it represents the deep layer soil moisture variations better. This is evident in their time series plots as well. The gradual decreases in soil moisture from wet winter to summer indicate the less dynamic nature typical of deep soil moisture. SDI also shows an improvement in correlations. Thus, it could be argued that KBDI and SDI are a better proxy for live fuel moisture content than duff moisture. In summer, living vegetation gradually draws moisture from upper and lower level and a number of other phenomena cause water loss from all soil layers. The relatively small differences seen in the results of two (shallow and deep) OzNet verifications possibly result from the fact that the surface soil layer variability are reflected in the 0–90 cm observations. As mentioned earlier, both models have only modest skill in mimicking shallow layer observations. It is worth noting that, even though the temporal variations are captured better by the model over OzFlux sites for deep layers, large errors still exist due to the crude formulations.

The metrics used here for verification are commonly used in soil moisture studies. However, it is worth noting that these skill estimates may be biased. Reasons for this are two fold. First, the observation does not necessarily represent the "truth" and may contain errors. The reason for using root mean square "difference" instead of root mean square "error" in this study is to emphasize that observations are not perfect. Second, there is a significant difference in the spatial scale of observations and models. In comparing different soil moisture products with different spatial supports, we implicitly assume that they refer to the same physical variable. This may introduce error of representativity in the skill estimates. The metrics used here do not account for the errors of representativity and hence the analysis based on them may not be complete. However, they do give a good indication of the limitations of each model. There are emerging techniques like triple collocation [TC; Vogelzang and Stoffelen, 2012, Gruber et al., 2016] that is a more powerful method to estimate errors in models and observations and can address the representativity issues to some extent. However, the present formulation of TC contains a number of assumptions [Zwieback et al., 2012; Yilmaz and Crow, 2014] that has to be carefully evaluated for soil moisture datasets discussed here. Further, TC requires using a third independent dataset. Remotely sensed soil moisture products along with in-situ and model estimates are a widely used triplet. However, such an analysis is beyond the scope of present study and will be considered in future work.

8 CONCLUSIONS

The present study evaluates two models of soil moisture deficit used in McArthur's Forest Fire Danger Index against in-situ hydrological observations. These two models, called KBDI and SDI, are designed to estimate soil moisture depletion in the duff and upper soil layers. KBDI and SDI are basically empirical water balance models with very simplified formulations. Though designed to simulate soil moisture in both duff layer and upper soil layers, skill scores from the verification of these models against shallow layer soil moisture observations from all three networks (OzNet, CosmOz and OzFlux) indicate only a moderate agreement with observations. The two models represent the deep layer soil moisture dynamic better, highlighted by their comparison against deeper layer observations. The results from both shallow and deep layer verification also highlight a lack of consistency from the two models in capturing the soil water dynamics spatially. KBDI in general has a large wet bias. This is more prominent over sites in the southern half of the country. SDI is overall better than KBDI. We believe that the limitations of these models stem from the over-simplified account of processes like evapotranspiration and runoff which are critical in calculating accurate soil moisture states. This leads to large uncertainties in the estimated soil moisture.

The dependency of fire potential to moisture in a particular layer of soil may change with the seasons. For example, in spring, moisture at surface and extreme upper layer largely determines the condition of the available fuels (Haines et al., 1976). The duff layer and ground vegetation that draw moisture from shallow soil layers will be in a cured state. Vegetation with deeper roots can still access moisture that is available in the deeper layers. However, in summer, the deep soil dries up as well, limiting the access to water for live vegetation and reducing live fuel moisture content. Thus the fire potential dependency extents from surface to deeper layer in summer. This dependence of fire potential to moisture with seasons is possibly true for the southern half of Australia. Haines et al (1976) argued that a good soil moisture estimation system should work throughout the seasons and should not depend upon a fixed depth of soil horizon (like KBDI and SDI) to indicate fire danger. They suggested a model system employing a multi-layer soil model is the best solution. Land surface modelling is an emerging technique that could potentially fill this gap.

Land surface models (LSMs) are capable of estimating soil moisture at different layers and more systematically than the empirical methods. LSMs provide a detailed representation of the transport of momentum, heat and water in the soil–plant–atmosphere continuum; and depict thermal and hydrological processes in the soil and snow. Land surface models can also account for plant physiology, vegetation dynamics, carbon assimilation and groundwater dynamics. With the advances made in remote sensing of soil moisture from space, especially in the microwave spectra which has shown to be correlated to soil moisture (Su et al., 2013), a detailed description of its current state is available. Almost complementary to the land surface modelling technique, remote sensing can provide accurate estimate of soil moisture at the topmost soil layers. In order to obtain the best of two worlds estimate of soil moisture, remote sensing data could be ingested through advance data assimilation techniques to produce an optimal analysis of soil moisture that accounts for the errors in observations and model. The land surface data assimilation has shown to produce much better estimates of soil moisture states (Dharssi et al., 2012) and are deemed to be an improvement over the current empirical methods employed in fire danger rating. Following up on this study, we intend to perform research for estimating soil moisture using satellite remote sensing measurements, land surface model simulations and advanced data assimilation techniques. This consequently leads to the provision of soil dryness with greater accuracy at a much higher spatial and temporal resolutions for operational fire danger rating applications.

ACKNOWLEDGMENTS

The support of the Commonwealth of Australia through the Bushfire and Natural Hazards Cooperative Research Centre program is acknowledged. We also acknowledge Rob Smalley and Chun-Hsu Su for their helpful comments during the preparation of this manuscript.

REFERENCES

Brolley, J.M., O'Brien, J.J., Schoof, J. and Zierden, D. (2007). Experimental drought threat forecast for Florida. *Agricultural and Forest Meteorology, 145*, 84-96.

Burgan, R.E. (1988). *Revisions to the the 1978 Bational Fire-Danger Raing System.* Asheville: U.S. Department of Agriculture.

Chandler, C., Cheney, P., Thomas, P., Trabaud, L. and Williams, D. (1983). *Fire in forestry, forest fire behaviour and effects.* New York: John Wiley & Sons.

Desilets, D., Zreda, M. and Ferre, T.P. (2010). Nature's neutron probe: Land surface hydrology at an elusive scale with cosmic rays. *Water Resources Research, 46*(11).

Dharssi, I., Bovis, K.J., Macpherson, B. and Jones, C.P. (2011). Operational assimilation of ASCAT surface soil wetness at the Met Office. *Hydrology and Earth System Science, 15*, 2729-2746.

Dimitrakopoulos, A.P. and Bemmerzouk, A.M. (2003). Predicting live herbaceous moisture content from a seasonal drought index. *International Journal of Biometeorology, 47*, 73-79.

Finkele, K., Mills, G.A., Beard, G. and Jones, D.A. (2006). *National daily gridded soil moisture deficit and drought factors for use in prediction of forest fire danger index in Australia.* Melbourne: Australian Bureau of Meteorology.

Franz, T.E., Zreda, M., Rosolem, R. and Ferre, T.P. (2012). Field validation of a cosmic-ray neutron sensor using a distributed sensor network. *Vadose Zone Journal*.

Ganatsas, P., Antonis, M. and Marianthi, T. (2011). Development of an adapted empirical drought index to the Mediterranean conditions for use in forestry. *Agricultural and Forest Meteorology, 151*, 241-250.

Garcia-Pratsa, A., Del Campo, A., Del Campo, F. and Tarcísio, F. (2015). Development of a Keetch and Byram—Based drought index sensitive to forest management in Mediterranean conditions. *Agricultural and Forest Meteorology, 205*, 40-50.

Gellie, N.J., Gibos, K.E. and Johnson, K. (2010). Relationship between severe landscape dryness and large destructive fires in Victoria. *VI International Conference on Forest Fire Research.* Coimbra, Portugal.

Gruber, A., Su, C.-H., Zwieback, S., Crow, W., Dorigo, W. and Wagner, W. (2016). Recent advances in (soil moisture) triple collocation analysis. *International Journal of Applied Earth Observation and Geoinformation, 45*, 200-211.

Hains, D.A., Johnson, V.J. and Main, W.A. (1976). *An assessment of three measures of long-term moisture deficiency before critical fire periods.* MN: USDA FS.

Hawdon, A., McJannet, D. and Wallace, J. (2014). Calibration and correction procedures for cosmic-ray neutron soil moisture probes located across Australia. *Water Resources Research, 50*(6), 5029-5043.

Jones, D.A., Wang, W. and Fawcett, R. (2009). *Climate data for the Australian Water Availability Project: Final milestone report.* Melbourne: National Climate Centre, Bureau of Meteorology.

Keetch, J.J. and Byram, G.M. (1968). *A drought index for forest fire control.* Asheville: U.S. Department of Agriculture and Forest Service.

Köhli, M.S. (2015). Footprint characteristics revised for field-scale soil moisture monitoring with cosmic-ray neutrons. *Water Resources Research, 51*(7), 5772-5790.

Liu, Y., Stanturf, J. and Goodrick, S. (2010). Trends in global wildfire potential in a changing climate. *Forest Ecology and Management, 259*, 685-697.

Luke, R.H. and McArthur, A.G. (1978). *Bushfires in Australia.* Canberra, Australia: Australian Government Publication Service.

McArthur, A.G. (1967). *Fire behaviour in Eucalypt forest.* Australian Coommonwealth Forestry and Timber Bureau Leaflet.

Mount, A.B. (1972). *The derivation and testing of a soil dryness index using runoff data.* Hobart: Tasmanian Forestry Commission.

Paget, M.J. and King, E.A. (2008). MODIS Land data sets for the Australian region. *Internal Report, 004*, 96 pp. Canberra, ACT, Australia: CSIRO Marine and Atmospheric Research.

Smith, A.B., Walker, J.P., Western, A.W., Young, R.I., Ellett, K.M., Pipunic, R.C., et al. (2012). The Murrumbidgee Soil Moisture Monitoring Network data set. *Water Resources Research, 48*(07).

Snyder, R.L., Spano, D., Duce, P., Baldocchi, D. and Xu, L. (2006). A fuel dryness index for grassland fire-danger assessment. *Agriculture and Forest Meteorology, 139*, 1-11.

Spano, D., Duce, P., Snyder, R.L., Zara, P. and Ventura, A. (2005, October 24-27). Assessment of fuel dryness index on Mediterranean vegetation. *Proceedings of the 6th Symposium on Fire and Forest Meteorology*. Cammore, Canada.

Su, C., Ryu, D., Young, R., Western, W.A. and Wagner, W. (2013). Inter-comparison of microwave satellite soil moisture retrievals over the Murrumbidgee Basin, southeast Australia. *Remote Sensing of Environment, 134*, 1-11.

Vogelzang, J.S. (2012). *Triple collocation.* UK: EUMETSAT NWP-SAF.

Weymouth, G., Mills, G.A., Jones, D., Ebert, E.E. and Maton, M.J. (1999). A continental scale daily rainfall analysis system. *Australian Meteorological Magazine, 48*, 169-179.

Yilmaz, M.T. (2014). Evaluation of Assumptions in Soil Moisture Triple Collocation Analysis. *Journal of Hydro-meteorology*.

Zreda, M., Desilets, D., Ferre, T.P. and Scott, R.L. (2008). Measuring soil moisture content non-invasively at intermediate spatial scale using cosmic-ray neutrons. *Geophysical Research Letters, 35*, L21402.

Zwieback, S.S. (2012). Structural and statistical properties of the collocation technique for error characterization. *Nonlinear Processes in Geophysics, 19*, 69–80.

APPENDIX 1: OBSERVATION SITE DETAILS

Site	Latitude	Longitude	Annual Rainfall [mm]	Land Use
A1	-35.497	148.106	1360	Grazing
A2	-35.428	148.132	1193	Grazing
A3	-35.400	148.101	1329	Grazing
A4	-35.373	148.066	900	Grazing
A5	-35.360	148.085	936	Grazing
K1	35.493	147.559	730	Grazing
K2	-35.435	147.531	728	Grazing
K3	-35.434	147.569	725	Grazing
K4	-35.427	147.600	732	Crop/Grazing
K5	-35.419	147.604	749	Grazing
M1	-36.293	148.971	555	Grassland
M2	-35.305	149.201	643	Grassland
M3	-34.630	148.037	668	Grassland
M4	-33.938	147.196	506	Grassland
M5	-34.658	143.549	333	Grazing
M6	-34.547	144.867	368	Grazing
M7	-34.249	146.070	437	Grassland
Y1	-34.629	145.849	416	Crop/Grazing
Y2	-34.655	146.110	426	Grazing
Y3	-34.621	146.424	442	Grassland
Y4	-34.719	146.020	417	Irrigated crop/grazing
Y5	-34.728	146.293	435	Crop
Y6	-34.843	145.867	411	Irrigated crop
Y7	-34.852	146.115	424	Grazing
Y8	-34.847	146.414	451	Grazing
Y9	-34.968	146.016	416	Irrigated crop
Y10	-35.005	146.310	437	Grazing
Y11	-35.110	145.936	406	Grazing
Y12	-35.070	146.169	428	Crop/Grazing
Y13	-35.090	146.306	439	Grazing

Table 1. OzNet sites.

Site	Latitude	Longitude	Annual Rainfall [mm]	Land Use
Alice Springs, NT	-22.283	133.249	306	Forest
Arcturus, NT	-23.859	148.475	572	Crop
Calperum, SA	-34.002	140.589	240	Bushes
Daly [Pasture], NT	-14.063	131.318	1250	Pasture
Daly [Uncleared], NT	-14.1592	131.388	1170	Savanna
Dry River, NT	-15.259	132.371	895	Savanna
Gingin, WA	-31.375	115.650	641	Forest
Howard Springs, NT	-12.495	131.150	1700	Forest
Riggs Creek, VIC	-36.656	145.576	650	Grazing
Robson Creek, QLD	-17.118	145.630	2236	Forest
Samford, QLD	-27.388	152.878	1102	Pasture
Sturt Plains, NT	-17.151	133.350	640	Grazing
Ti Tree East, NT	-22.287	133.640	305	Savanna
Tumbarumba, NSW	-35.657	148.152	1000	Forest
Wallaby Creek, VIC	-37.429	145.187	1700	Forest
Warra, TAS	-43.095	146.655	1700	Forest
Whroo, VIC	-36.673	145.029	558	Forest
Wombat State Forest, VIC	-37.422	144.094	650	Forest

Table 2. OzFlux sites.

Site	Latitude	Longitude	Annual Rainfall [mm]	Land Use
Baldry	-32.871	148.526	618	Pasture
Daly	-14.159	131.388	1445	Forest
Gnangara	-31.377	115.713	649	Forest
Robson Creek	-17.120	145.630	1300	Forest
Temora	-34.405	147.533	526	Crops
Tullochgorum	-41.669	147.912	610	Grazing
Tumbarumba	-35.656	148.152	1412	Forest
Weany Creek	-19.882	146.536	659	Forest
Yanco	-35.005	146.299	437	Grazing

Table 3. CosmOz sites.