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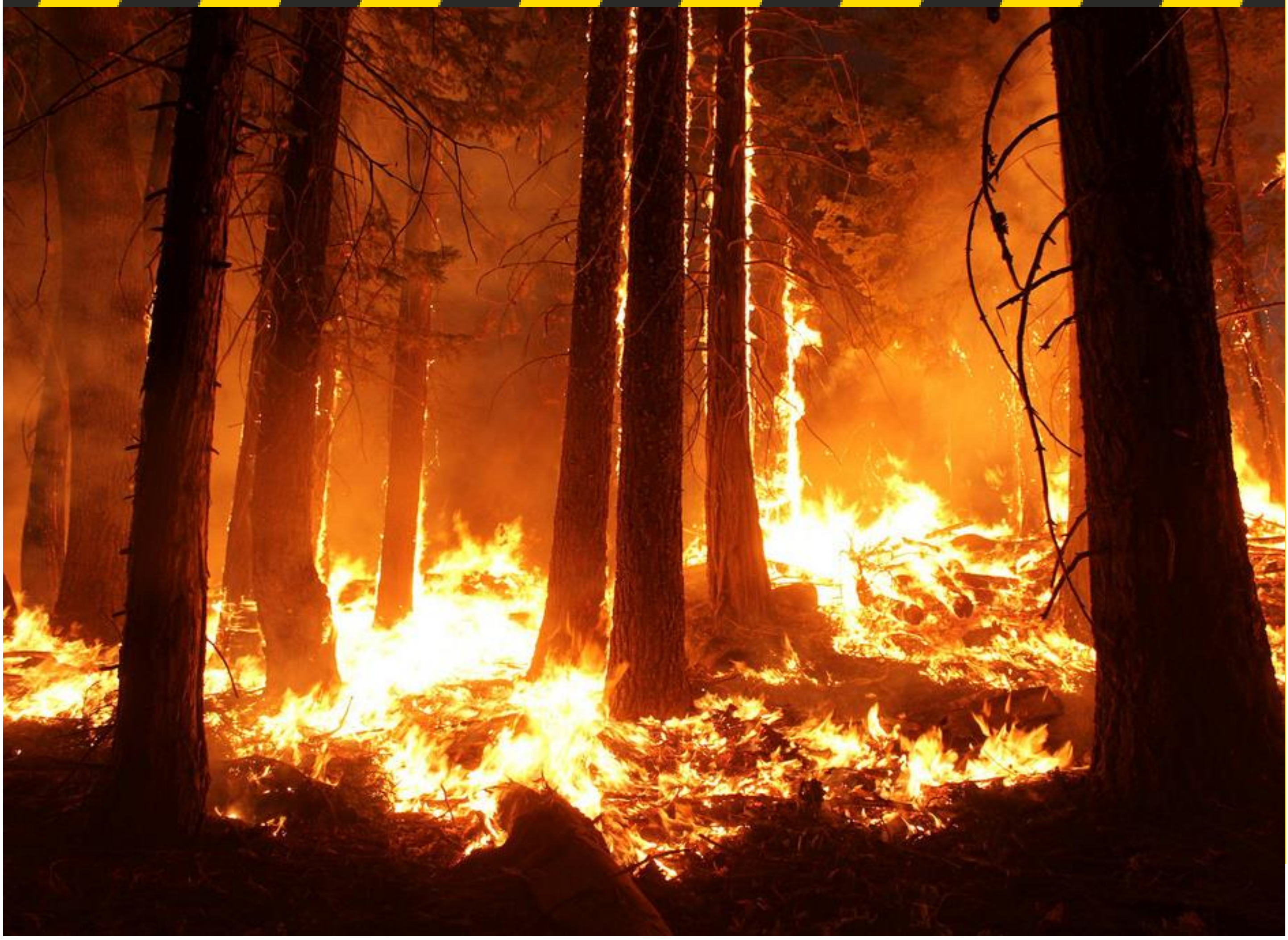
MITIGATING THE EFFECTS OF SEVERE FIRES, FLOODS AND HEATWAVES THROUGH THE IMPROVEMENTS OF LAND DRYNESS MEASURES AND FORECASTS

Annual report 2016-2017

Vinodkumar[1,2], Imtiaz Dharssi[1] and Alex Holmes [2,3]

[1] Bureau of Meteorology
[2] Bushfire and Natural Hazards CRC
[3] Monash University



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EXECUTIVE SUMMARY

The Bushfire and Natural Hazards CRC project titled "Mitigating the Effects of Severe Fires, Floods and Heatwaves through the Improvements of Land Dryness Measures and Forecasts" examines the use of detailed land surface models, satellite measurements and ground based observations for the monitoring and prediction of landscape dryness. This project will address a fundamental limitation in our ability to prepare for fires, floods and heatwaves and is directly linked to pre-event planning as well as forecasting of events.

Currently landscape dryness is estimated in Australia using simple empirical models developed in the 1960's. The most prominent of those used in Australia are the Keetch-Byram Drought Index (KBDI; Keetch & Byram 1968) and the Soil Dryness Index (SDI; Mount 1972). An initial study performed as part of this project suggest that analyses of soil moisture can be improved by using physically based land surface models, remote sensing measurements and data assimilation. The project has developed a stand alone prototype land surface modelling system to produce daily soil moisture analyses at 5km resolution and at 4 soil layers. Verification against ground based soil moisture observations show that this prototype system is significantly more skilful than both KBDI and SDI.

The present report documents the activities undertaken in 2016-2017. The main focus of the year has been on the calibration of soil moisture from a new high resolution land surface modelling system allowing for easier utilisation within existing operational fire prediction systems. The calibrated outputs will be evaluated against numerous case studies that include past bush fire occurrences and fuel reduction burns conducted by fire agencies. This work is in progress and eight case studies have been identified so far. These case studies were selected with the help of end users. All case studies will be documented and could be used as training documentation by fire agencies.

END USER STATEMENT

Mark Chladil, Tasmania Fire Service, Hobart

The Project has finished the initial stage with some provocative results. The traditional and simple to calculate soil moisture deficit models have been compared with the new JASMIN product and in situ soil moisture measurements. JASMIN shows better results than the SDI over the KBDI although there are regional differences. A pilot program now is underway to provide fire managers with a JASMIN product scaled to mimic the SDI and KBDI potentially suitable for a JASMIN based Drought Factor. This will give an alternative soil moisture input for evaluation over coming seasons. Case studies are also underway to learn more about the real world outcomes of the JASMIN based soil moisture estimates in terms of both dead and live fuel moisture content. Much validation needs to be done to realise the potential of better temporal and spatial resolution for multiple soil layers.

Andrew Sturgess, Queensland Fire & Emergency Services, Brisbane

This project has the potential to provide significant enhancements to one of the underpinning elements of understanding fire behaviour. Severe soil moisture deficits are one of the drivers of extreme weather events. It is expected that the project will lead to improved soil moisture estimation. This in turn will lead to better fuel moisture calculations, one of the critical determinants of fire behaviour.

Fire and emergency agencies have an appreciation of the shortcomings of the current soil moisture models but at the same time there exists a degree of comfort with the existing models. As such, change management will be an important part of establishing this research into operations. End users are encouraged to provide case studies and to engage with the researchers to evaluate the products as the research transitions to operations.

With the development of the new National Fire Danger Rating the timing of the prototyping provides an ideal opportunity for agencies to establish case studies that can be used to test potential improvements to the existing FDR inputs. The moisture values for four soil layers will also enhance understanding the links between soil dryness and live/dead fuel moisture content. It is hoped that future developments will allow further downscaling to better account for variations attributed to topography including aspect.

Being better able to predict severe weather events provides agencies with an opportunity to enhance planning, preparedness, response and recovery. If these potential benefits are realised through this research it will lead directly to more resilient communities, a goal that is shared across all agencies.

PROJECT BACKGROUND

Fire intensity, spread rate and ignition are very sensitive to the fuel dryness which in turn is strongly linked to soil moisture content. Estimates and forecasts of fuel and soil moisture are the foundation of the fire danger calculations used to rate and manage wildfires and to warn of developing fire danger. Similarly, estimates and forecasts of soil moisture are essential ingredients to be able to forecast with accuracy river flows on a seasonal scales (one to three months), which is very much in demand by water managers and reservoir operators.

Currently landscape dryness is estimated using simple, empirical water balance models developed in the 1960's. The most prominent of those used in Australia are the Keetch-Byram Drought Index (KBDI; Keetch & Byram 1968) developed by the US Forest Service, and the related Soil Dryness Index (SDI; Mount 1972) developed by Forestry Tasmania. These models were designed for easy hand calculations over a small number of locations. The KBDI and SDI are found to have limited skill in estimating soil moisture, particularly in shallow soil layers (Vinodkumar et al., 2017).

The dependency of fire potential to moisture in a particular layer of soil may change with season (Haines et al., 1976). A good soil moisture estimation system should therefore work throughout the seasons and should not depend upon a fixed depth of soil horizon (like KBDI and SDI) to indicate fire danger. A model system employing a multi-layer soil model is suggested to be the best solution (Haines et al., 1976). 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.

A prototype high resolution soil moisture information system based on Joint UK Land Environment Simulator (JULES) LSM to estimate soil moisture has been developed (Dharssi and Vinodkumar, 2017). This system, called the JULES based Australian Soil Moisture Information (JASMIN); estimates soil moisture at a spatial resolution of 5 km. JASMIN provides information at 4 soil layers, with a 10 cm thick surface layer and a soil column of 3 m thickness to represent the root-zone. This design, allow the JASMIN system to estimate surface soil moisture which is representative of dead fuel moisture content and root-zone soil moisture that provides information on live fuel moisture content. Verification against ground based soil moisture observations shows that this prototype system is significantly better than the simple KBDI and SDI models currently used operationally (Dharssi & Vinodkumar, 2017).

WHAT THE PROJECT HAS BEEN UP TO

1. Calibration of JASMIN product

The JASMIN soil moisture is in units of mass per unit area (kg m^{-2}). However, the drought factor (DF) calculations require soil moisture deficit (SMD) values specified in a range between 0 – 200. This requires appropriate calibration (also known as rescaling or matching) techniques for the use of JASMIN soil moisture in the current operational DF calculations. A considerable number of studies have explored several matching techniques for verification (Draper et al., 2009; Su et al., 2013; Vinodkumar et al., 2017) and for data assimilation (Houser et al. 1998; Walker and Houser 2001; Sabater et al. 2007).

The present study applies commonly used rescaling methods, including minimum-maximum matching, mean-variance matching and cumulative distribution function (CDF) matching. As a pre-processing step, JASMIN soil moisture is converted to volumetric units for a selected soil profile. Here we use two soil profiles for rescaling. The first one has a depth 0.35 m comprising of the top two model layers. The second profile has a depth of 1 m and uses the top three model layers. It is possible to rescale all soil profiles that could arise from any rational combination of the four available model soil layers. However, we have limited our efforts to the above mentioned profiles as the original indices were developed to estimate dryness in a shallow layer of soil.

1.1 Calibration methods

1.1.1 MINIMUM-MAXIMUM MATCHING

The first approach involves rescaling JASMIN time series to match its minimum (Θ_{min}) and maximum (Θ_{max}) to those of SMD in FFDI ($\vartheta_{min} = 0$, $\vartheta_{max} = 200$).

$$\hat{\Theta} = \vartheta_{min} + (\Theta - \Theta_{min})(\frac{\vartheta_{max} - \vartheta_{min}}{\Theta_{max} - \Theta_{min}})$$

This is mathematically equivalent to the approach by Albergel et al. (2012) and Vinodkumar et al. (2017), where they normalized soil moisture data sets to a standard range 0 – 1. We refer this approach as minimum–maximum (MM) matching. The volumetric soil moisture values are normalized based on their minimum and maximum values from a six and a half year long daily time series (1st Jan 2010 to 1st July 2016). This normalized soil moisture is then subtracted from its maximum (i.e., 1.0) to yield soil moisture deficit.

1.1.2 MEAN-VARIANCE MATCHING

In the second approach, JASMIN data (Θ) is normalized ($\hat{\Theta}$) to have same mean (μ) and variance (σ^2) as the reference (KBDI/SDI) data (ϑ). This is achieved through,

$$\hat{\Theta} = \mu_{\vartheta} + \frac{\sigma_{\vartheta}}{\sigma_{\Theta}}(\Theta - \mu_{\Theta})$$

We denote this method as the μ - σ matching. The mean and variance at each grid point, is calculated using a six and half year long time series spanning from 1st January 2010 to 1st July 2016.

1.1.3 CDF MATCHING

The cumulative distribution function (CDF) matching (Reichle & Koster, 2004) is a non-linear method that matches higher order statistical moments of the distributions in addition to the mean and variance. The CDF characterizes the cumulative probability of a continuous random variable (X) up to a specific value (x). That is,

$$F(x) = \Pr[X \leq x]$$

In CDF-matching, the two datasets are ranked and an operator is calculated. In the present study, this operator is a cubic spline fit of ranked JASMIN soil moisture values to their corresponding KBDI/SDI values. The cumulative distribution of the result now matches the whole range of KBDI/SDI values. CDF matching in this study is done by performing a fit on either the daily spatial samples of two datasets or by using a long time series of two datasets (temporal sampling).

1.2 Results

Figure 1 shows KBDI and the corresponding rescaled JASMIN soil moisture deficits using four calibration methods from the 1 m profile for 1st January 2013. The spatial variability seen in JASMIN product obtained by using the MM method (Figure 1b) may correspond to the variability in soil, vegetation, and topographical parameters that JASMIN take into account to calculate soil moisture. Given the linearity of MM method, rescaling preserves the spatial structure and temporal correlation in the original data. This is an important property, as land surface based soil moisture products exhibit very good temporal correlations with observations (Vinodkumar et al, 2017; Dharssi & Vinodkumar, 2017). Since the MM method do not use KBDI/SDI as reference for rescaling, like other methods, they do not inherit missing land values seen in these reference products.

The JASMIN product from 1 m profile, re-scaled to KBDI using *μ-σ* method for 1st January 2013 is shown in Figure 1c. The *μ-σ* approach appears to smooth out the JASMIN soil moisture field, compared to that from MM method (Figure 1b). Also the *μ-σ* rescaled product (Figure 1c) is wetter than the MM product. The south eastern part, especially Tasmania, becomes wetter when using *μ-σ* approach compared against the MM method is used. The missing land points in the reference dataset are carried over to the rescaled dataset in this approach. Also, at locations which are very dry and have very low temporal variability in the JASMIN dataset, the *μ-σ* rescaling method tend to exceed the theoretical maximum of reference dryness index.

The temporal CDF matching (figure 1e) seem to introduce the wet bias in the reference KBDI data. This is evident over south-eastern Australia and especially Tasmania, where KBDI is known to have a large wet bias (Vinodkumar et al., 2017). However, matching the temporal distributions of the two datasets is found to give a better correlation than that using the spatial distributions (Table 1). The spatial CDF matching (Figure 1d) seem to have reduced some of this bias, if not all. The JASMIN system simulate mainly wet soils in the eastern half of the country (not shown), which is captured in the rescaled outputs. The western half is generally drier compared to the KBDI.

The cumulative probability curves of the KBDI and their corresponding rescaled products for 1st January 2013 are given in Figure 1f. These probabilities are a good representative of the cumulative probabilities of the whole time series for each product. The probability of having values lower than 100 mm in the MM matched JASMIN product is very low. The KBDI (black line) displays a wet bias compared to the MM matched product (orange line). The shift towards a wetter soil in JASMIN products rescaled using μ-σ method (Figure 1c) is evident from their CDF (green line) compared with that from MM method (orange line). Normalization using the mean and variance of a wet KBDI makes JASMIN product wetter, resulting in a decrease of Kolmogorov-Smirnov (K-S) statistics from 0.25 in MM method to 0.09 for *μ-σ* method. Since spatial CDF matching corrects all moments of the distribution, regardless of its shape, the cumulative probabilities of KBDI (black line) and spatial CDF matching (light purple line) looks almost identical. However, the statistical errors associated with limited sample size may result in small differences in the cumulative probability of two distributions, as depicted by the K-S statistics. The cumulative probability curve of temporal CDF matching (maroon curve, figure 1f) shows that this product is wetter than KBDI.

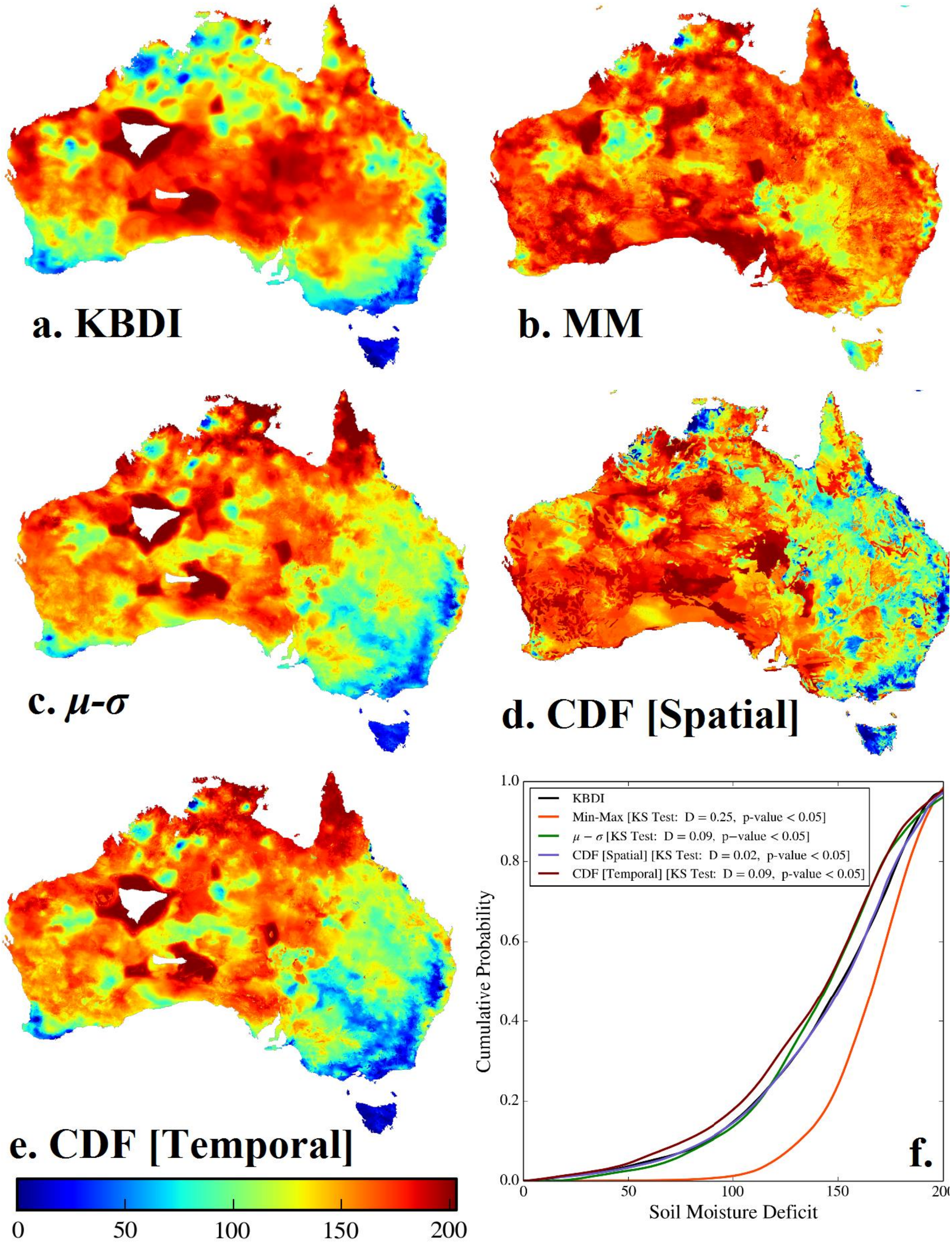

Figure 1. a) KBDI and the corresponding JASMIN sm rescaled using four methods for 1st January 2013: b) MM, c) μ–σ, d) CDF spatial and e)CDF temporal matching. (f) the cumulative probability from KBDI and the four corresponding rescaled products. The recaled JASMIN soil moisture corresponds to the 1 m profile.

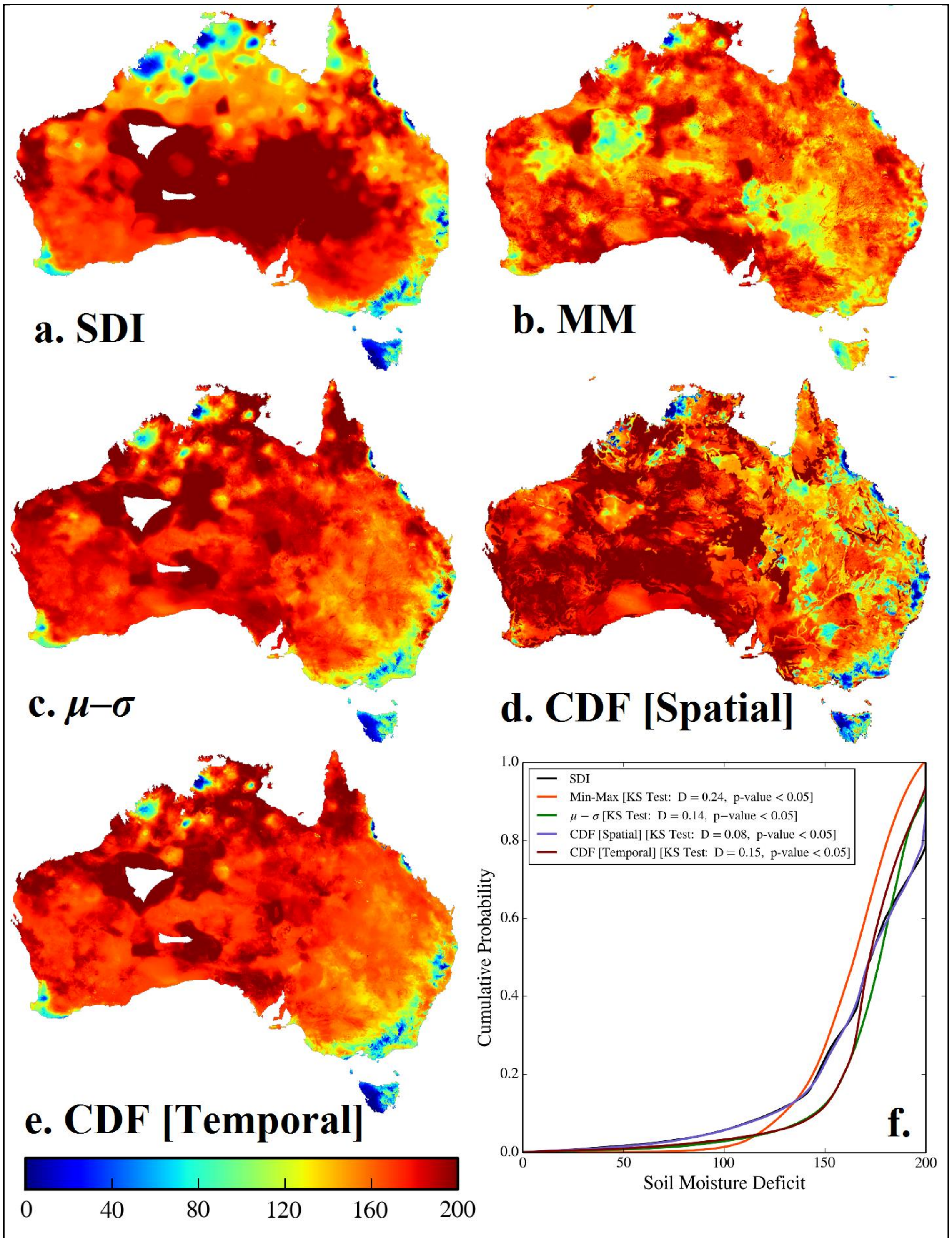

Figure 2. a) SDI and the corresponding JASMIN sm rescaled using four methods for 1st January 2013: b) MM, c) μ–σ, d) CDF spatial and e)CDF temporal matching. (f) the cumulative probability from SDI and the four corresponding rescaled products. The recaled JASMIN soil moisture corresponds to the 1 m profile.

The JASMIN product rescaled to SDI using MM method (figure 2b) have a similar spatial structure to the JASMIN product rescaled to KBDI using the same method, and differ only in their magnitude due to slight difference in respective maxima of SDI (200 mm) and KBDI (203.2 mm). Use of SDI mean and variance to normalize makes JASMIN product wetter (figure 2c) compared to that from the MM product. The spatial CDF matching produce a wetter eastern half compared to the other products (figure 2d). Also, the soil moisture deficit from the spatial CDF matching appears to be noisier than the other products. The product obtained from the temporal CDF matching is fairly similar to that obtained from μ–σ matching (figure 2c) in spatial structure.

Figure 2f depict the cumulative probabilities from SDI and four rescaled JASMIN products for 1st January 2013. There is a high probability for SDI (black line) to have values equal to 200 (i.e., maximum). This is possibly due to the maximum values observed over large portion of central Australia. The cumulative probability from MM method is given by the orange line. The soil moisture deficit up to about 135 mm in the MM method has a dry bias compared to that in SDI. Above this value, the product based on the MM approach has a wet bias. Interestingly, the use of the SDI mean and variance to normalize, results in a drier JASMIN product (green line) for values below ~180 mm. Here, the K-S statistics are reduced from 0.24 to 0.14, indicating a closer probability distribution. The matching of higher order moments using the spatial samples give an almost identical distribution (light purple line) to that of SDI. The cumulative probabilities of temporal CDF matching (brown line) in the lower spectrum of soil moisture deficit values are fairly identical to that from the μ–σ method (green line). However, for higher soil moisture deficit values, the CDF temporal matching product is observed to be wetter than that from μ–σ method.

2. Verification of calibrated products against in-situ observations

Each of the products discussed here is compared by calculating Pearson's product moment correlation against in-situ soil moisture observations. We have not limited the verification of KBDI, SDI and JASMIN rescaled to either of these traditional indices to regions where they are used operationally. Imposing such a limit on verification would severely limit the sample size and ability to deduce a meaningful statistical conclusion. The period of verification is from January 2012 to February 2013. Measurements used here comprise of 17 sites from OzFlux network and 6 from CosmOz network. The details of the sites used are given in Figure 3. Readers are referred to Vinodkumar et al. (2017) for more information on these two soil moisture networks.

The correlation scores for both actual and anomaly time series are provided in

Table 1. 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 ($\boldsymbol{\Theta}$). The anomaly A is then computed using $A_i = \boldsymbol{\Theta} - \theta_i$, where 'i' is the day of interest. The correlation values presented here are a network average. To calculate the average correlation, the method of Corey et al. [1998] is used to apply a Fisher's Z transformations.

Table 1 depicts the Pearson's product moment correlation for KBDI and three rescaled JASMIN products from the 0.35 m model soil profile. The highest correlation for both standard (0.85) and anomaly (0.66) time series over CosmOz network is obtained for the MM method. The correlation against CosmOz for full KBDI time series is 0.72. The corresponding anomaly correlation is 0.46. Against OzFlux surface observations, the highest correlation of 0.84 is obtained for MM matching method and the lowest of 0.75 is obtained for spatial CDF matching method. The correlation for KBDI is 0.76. The largest anomaly correlation of 0.74 is also obtained for the MM method. KBDI has the lowest anomaly correlation at 0.58. When compared against OzFlux root-zone observations, MM matching method and μ–σ method deliver the highest correlation for full (0.86) time series whereas the highest anomaly correlation (0.68) is obtained for temporal CDF matching method.

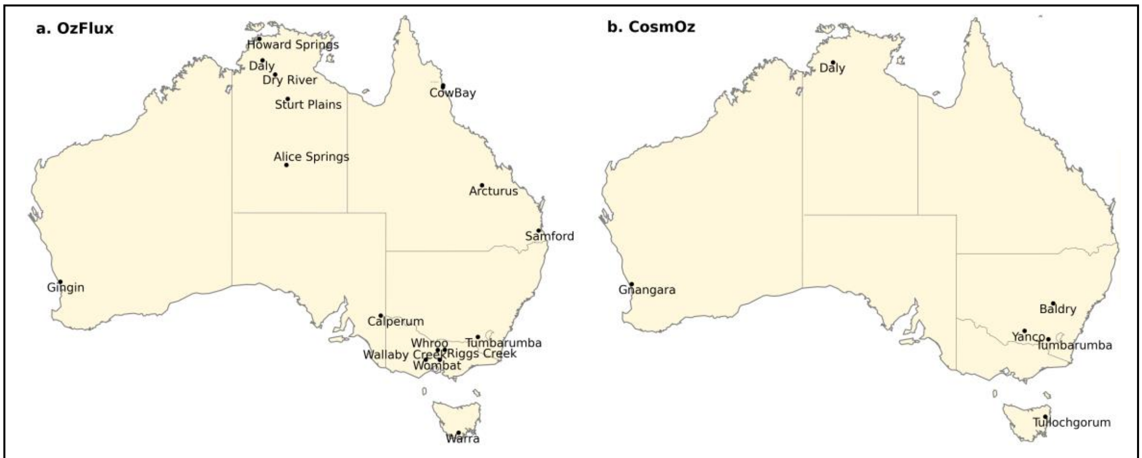

Figure 3. Observation sites: a) OzFlux, b) CosmOz.

The correlation for normal and anomaly time series from all JASMIN products are generally higher than that of KBDI. The MM and μ–σ methods give a higher correlation than the CDF matching techniques. The correlation from μ–σ method is fairly close to MM method. The linear transformation in both methods has preserved the correlations. The temporal CDF matching consistently give a higher correlation than the spatial CDF matching technique.

In situ network	Correlation					Anomaly correlation				
	KBDI	MM	μ–σ	CDF		KBDI	MM	μ–σ	CDF	
				Spatial	Temporal				Spatial	Temporal
CosmOz	0.72	0.85	0.84	0.79	0.82	0.46	0.66	0.60	0.49	0.55
OzFlux (surface)	0.76	0.84	0.83	0.75	0.82	0.58	0.74	0.71	0.60	0.69
OzFlux (root zone)	0.85	0.86	0.86	0.77	0.85	0.66	0.67	0.66	0.56	0.68

Table 1. Pearson's correlation for KBDI, JASMIN soil moisture rescaled using minimum-maximum matching, mean-variance matching and two CDF matching methods. The values represent a network average. JASMIN products correspond to 0.35 m model soil profile.

Correlations for the JASMIN product rescaled from the 1 m soil profile moisture using different methods is presented in Table 2. The correlations obtained for CosmOz from each rescaling method that uses 0.35 m JASMIN soil profile shown in Table 1 is generally greater than that use 1 m profile (Table 2). This is not surprising as CosmOz observations represent shallow layer soil moisture. The comparison of the JASMIN product rescaled with respect to KBDI and OzFlux surface and root zone observations also indicate that the rescaling done on the JASMIN product from the 0.35 m profile, in general, yield a higher correlation than that from a 1 m profile. About 42% of the deep layer observations in OzFlux have probes located at 0.5 m. Only 16% of total sites have probes located at 1 m. This possibly made the 0.35 m model profile more representative of observations than the 1 m profile.

In situ network	Correlation					Anomaly correlation				
	KBDI	MM	μ–σ	CDF		KBDI	MM	μ–σ	CDF	
				Spatial	Temporal				Spatial	Temporal
CosmOz	0.72	0.77	0.77	0.70	0.74	0.46	0.56	0.53	0.46	0.51
OzFlux (surface)	0.76	0.76	0.75	0.64	0.73	0.58	0.64	0.62	0.56	0.59
OzFlux (root zone)	0.85	0.84	0.84	0.72	0.83	0.66	0.65	0.64	0.53	0.64

Table 2: Pearson's correlation for KBDI, JASMIN soil moisture rescaled using minimum-maximum matching, mean-variance matching and two CDF

matching methods. The values represent a network average. JASMIN products correspond to 1 m model soil profile.

In situ network	Correlation					Anomaly correlation				
	SDI	MM	μ–σ	CDF		SDI	MM	μ–σ	CDF	
				Spatial	Temporal				Spatial	Temporal
CosmOz	0.83	0.84	0.84	0.72	0.83	0.55	0.66	0.65	0.50	0.61
OzFlux (surface)	0.80	0.84	0.84	0.79	0.84	0.60	0.74	0.74	0.61	0.71
OzFlux (root zone)	0.86	0.86	0.86	0.81	0.86	0.66	0.67	0.67	0.60	0.66

Table 3: Pearson's correlation for SDI, JASMIN soil moisture rescaled using minimum-maximum matching, mean-variance (μ–σ) matching and two CDF matching methods. The values represent a network average. JASMIN products correspond to 0.35 m model soil profile.

The comparisons with SDI and JASMIN products rescaled from 0.35 m model soil profile are given in table 3. The correlation obtained from comparison with CosmOz for full (anomaly) time series of SDI is 0.83 (0.55), JASMIN rescaled using MM method is 0.84 (0.66), μ–σ method is 0.84 (0.66), spatial CDF matching method is 0.72 (0.50) and temporal CDF matching is 0.83 (0.61). The spatial CDF matching has a poorer skill than even the traditional SDI. The anomaly correlations from the JASMIN MM method are the highest closely followed by the μ–σ method. This indicates that these two methods are able to better capture the short term variations.

The correlations with surface soil moisture observations show that the MM, μ–σ and temporal CDF matching methods have similar correlations with a value of 0.84. SDI correlation is 0.80. The highest anomaly correlation value is 0.74 observed for both the MM and μ–σ methods. SDI has the lowest anomaly correlation with a value of 0.60. For OzFlux root-zone observations, all the products except that from spatial CDF matching provide a correlation of 0.86. The spatial CDF matching method gives the lowest correlations for both full and anomaly time series. The anomaly correlations of all other methods are fairly similar.

Table 4 depict the same as Table 3, but for JASMIN rescaled products from a 1 m model soil profile. Again, for CosmOz, the use of first two model layers (table

3) give a better skill over that of first three model layers (table 4). The correlations are reduced when using the first three model profiles, indicating an increase in representativity error between observations and model. The comparison against both OzFlux surface and root zone observations has a similar pattern to that observed for CosmOz. Overall, the spatial CDF matching method is inferior to other three methods in terms of correlation. The difference in correlations between the MM method and μ–σ matching method is negligible.

In situ network	Correlation					Anomaly correlation				
	SDI	MM	μ–σ	CDF		SDI	MM	μ–σ	CDF	
				Spatial	Temporal				Spatial	Temporal
CosmOz	0.83	0.77	0.77	0.59	0.77	0.55	0.56	0.55	0.39	0.51
OzFlux (surface)	0.80	0.76	0.76	0.73	0.77	0.60	0.64	0.63	0.54	0.59
OzFlux (root zone)	0.86	0.84	0.84	0.78	0.86	0.66	0.65	0.63	0.53	0.61

Table 4: Pearson's correlation for SDI, JASMIN soil moisture rescaled using minimum-maximum matching, mean-variance (μ–σ) matching and two CDF matching methods. The values represent a network average. JASMIN products correspond to 1 m model soil profile.

3. Comparison of calibrated JASMIN products with fire radiative power data

Following methods shown in Holmes et al (2016), evaluation of soil dryness products against Moderate resolution Imaging Spectro-radiometer (MODIS) fire radiative power (FRP) data are presented in this section. FRP estimates are available with every active fire pixel reported in the MOD14 and MYD14 fire products derived from the MODIS instrument on-board Terra and Aqua satellites [Giglio et al., 2003]. The MODIS FRP retrieval is based on the relationship between the emitted fire energy and infrared brightness temperature estimates in the 4 μm region (Kaufman et al., 1998). The algorithm is valid for FRP retrievals of fires with flaming temperatures greater than 600 K and occupying a pixel fraction less than 0.1 [Wooster et al., 2003]. The FRP is given in a unit of mega-watts (MW) per pixel.

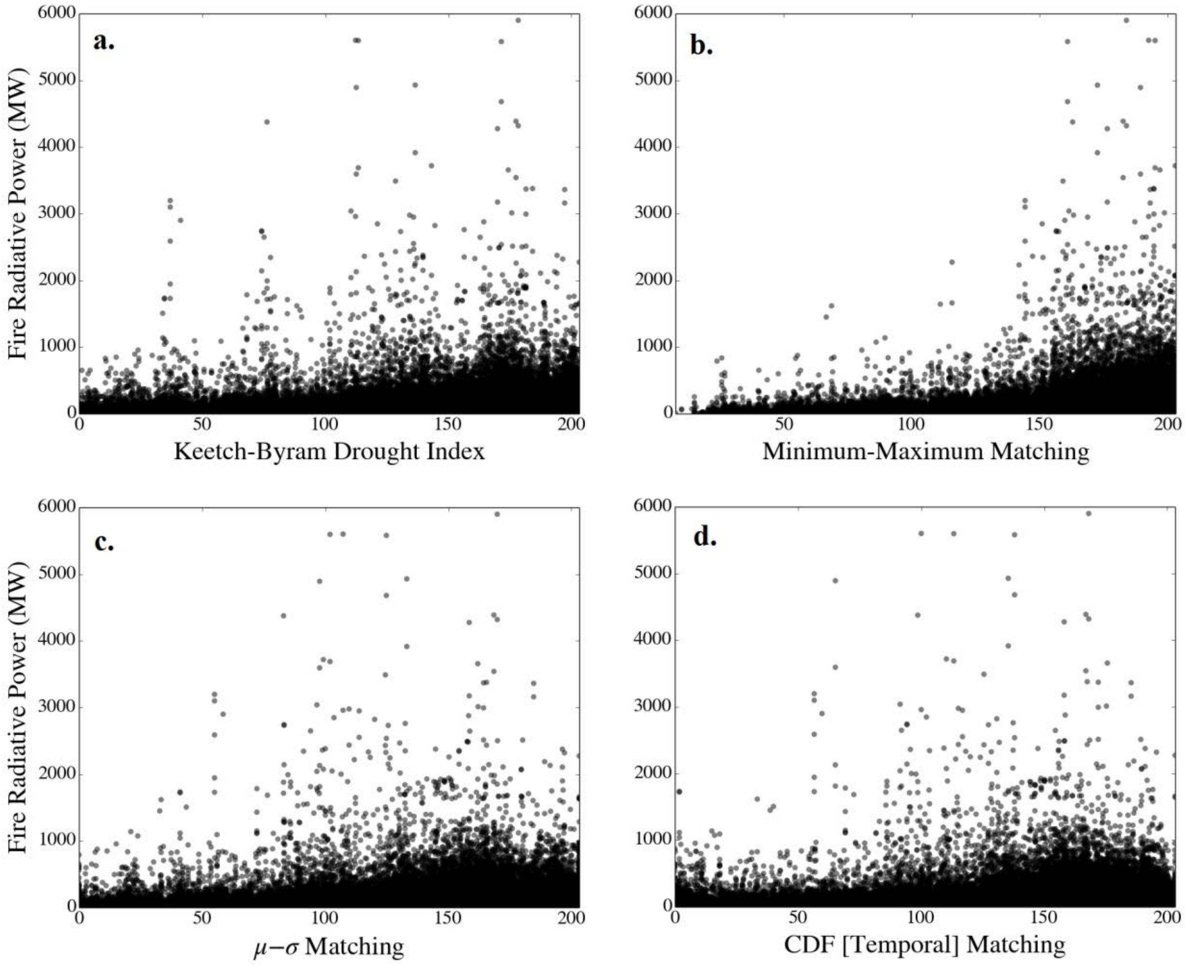

Figure 4. Scatter plot depicting MODIS FRP product against a) KBDI, JASMIN rescaled using b) MM method, c) μ–σ method and, d) temporal CDF matching method. JASMIN products correspond to 0.35 m model soil profile. The datasets span from January 2013 to February 2013.

Figure 10 depict scatter plots of MODIS FRP against KBDI and JASMIN products rescaled to KBDI using various methods. The KBDI display wet soils with dryness values < 100 mm for some fires with intensity > 2000 MW. The shift towards a drier soil in JASMIN MM rescaled product (figure 10b) attributes these large intensity fires to higher soil moisture deficits. Results from the scatter plot for μ–σ method (figure 10c) are quite different to that from MM method. Most of the high intensity fires in μ–σ method occur at SMD values 50 – 180. This is also true for JASMIN product rescaled using both spatial (not shown for brevity) and temporal CDF matching (figure 10d).

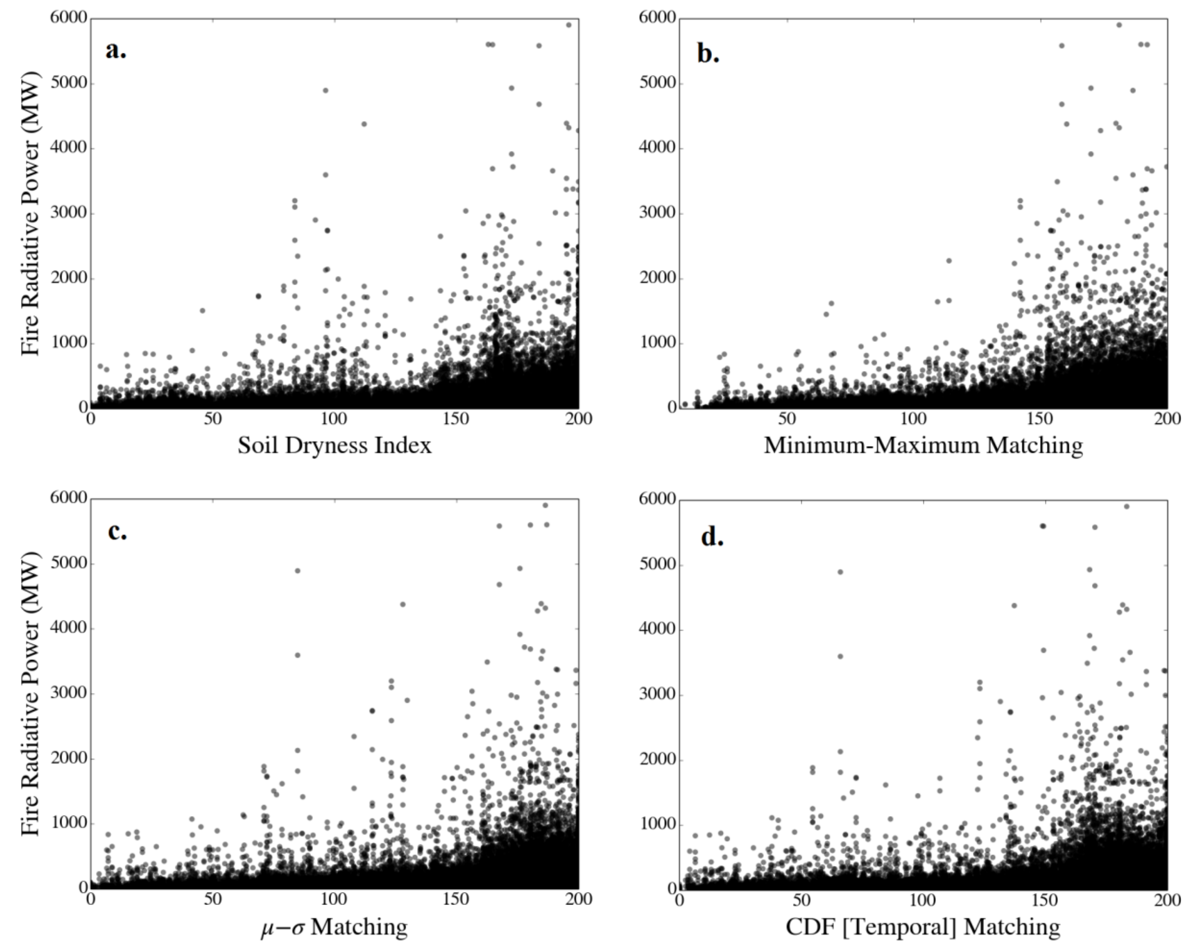

Figure 5. Scatter plot depicting MODIS FRP product against a) SDI, JASMIN rescaled using b) MM method, c) μ–σ method and, d) temporal CDF matching method. JASMIN products correspond to 0.35 m model soil profile. The datasets span from January 2013 to February 2013.

The scatter plots of MODIS FRP against SDI and JASMIN products rescaled to SDI using various methods are given in figure 11. The dry bias in SDI compared to KBDI is evident in the respective scatter plots. The high intensity fires in SDI (figure 11a) are associated with drier soils than KBDI (figure 10a), resulting in data points being shifted towards the dry end of SDI scale. The MM matching method (figure 11b) is drier than SDI. The difference between μ–σ (figure 11c) and temporal CDF matching (figure 11d) seem only marginal, even with matching of higher order statistical moments in the later method.

4. Identification and evaluation of case studies

The results presented above provide only a part of the evaluation carried out on different matching algorithms applied to JASMIN soil moisture. One of the key aims of this rescaling exercise is to make use of the calibrated JASMIN product in operational fire danger ratings. Hence, work has been undertaken to evaluate JASMIN products for multiple fire cases occurred over a range of time and locations. We intend to evaluate at least a dozen fire cases. So far, 8 case studies have been identified which include bushfire occurrences and fuel reduction burns. The cases under consideration at present are:

i. **Bushfire cases**

a. State Mine Fire, NSW, October 2013
b. Dunalley Fire, Tasmania, January 2013
c. Wuthering Heights Fire, Tasmania, Jan 2016
d. Lake Mackenzie fire, Tasmania, January 2016
e. Ballandean fire, Queensland, October 2014

ii. **Fuel reduction burns**

a. Lancefield, Victoria, September 2015
b. North-east Victoria, March 2017
c. Orbost, Victoria, March 2017

A sample plot of soil moisture deficit within the final fire boundary, valid on 18th October 2013 for the State Mine fire in New South Wales is shown in figure 6.

This evaluation will be carried out with the help of end users who have experience in evaluating such products in an operational environment. We also plan to produce near real-time outputs for end users as a pilot project to evaluate the products on a day-to-day basis.

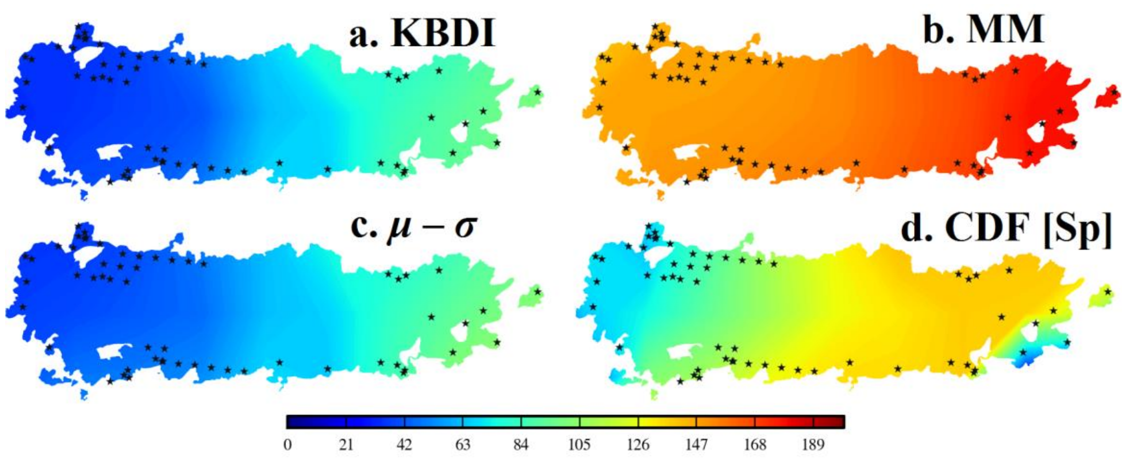

Figure 6. (a) The Keetch-Byram Drought index and rescaled JASMIN soil dryness using (b) MM, (c) μ–σ and (d) CDF Spatial matching methods for the State Mine fire in New South Wales. The plot is valid for 18th October 2013. The shape of the plot represent final fire boundary. The black stars depict hot spots detected by MODIS instrument.

NEWS

SEMINARS, WORKSHOPS AND CONFERENCES

AFAC 2016

Dr Vinodkumar and Dr. Imtiaz Dharssi attended the 2016 AFAC Conference held in Brisbane. Dr Imtiaz Dharssi gave a presentation titled "*A new high resolution land dryness analysis system for Australia*". Dr Vinodkumar presented a poster titled "*Soil dryness in fire danger rating: Time for a change in approach?*".

BUREAU OF METEOROLOGY R&D SEMINAR 2017

Dr Vinodkumar gave a presentation titled *Towards an Improved Land Dryness Estimate for Fire Prediction* at Melbourne on 17th May 2017. The seminar was open to End-users and others at sites outside the Bureau of Meteorology through Video Conferencing.

PUBLICATIONS LIST

JOURNAL PAPERS

Vinodkumar, I. Dharssi, J. Bally, P. Steinle, D. McJannet, and J. Walker, 2017: Comparison of soil wetness from multiple models over Australia with observations. Water Resources Research, 53(1) 633–646. ISSN 1944-7973. doi:10.1002/2015WR017738.

REPORTS

Vinodkumar and I. Dharssi, 2016: Downscaling of soil dryness estimates: A short review. BNHCRC Milestone Report.

Vinodkumar and I. Dharssi, 2017: Evaluation of daily soil moisture deficit used in Australian forest fire danger rating system. Bureau Research Report No. 022.

Dharssi, I. and Vinodkumar, 2017: A prototype high resolution soil moisture analysis system for Australia. Bureau Research Report, Under review.

Vinodkumar and I. Dharssi, 2017: Use of remote sensing measurements and data assimilation techniques to improve estimates of landscape dryness. BNHCRC Milestone Report.

CURRENT TEAM MEMBERS

- Imtiaz Dharssi, Project Lead, R&D Division, Bureau of Meteorology, Melbourne.
- Vinod Kumar, Scientist, R&D Division, Bureau of Meteorology, Melbourne.
- Claire Yeo, Severe Weather Meteorologist, Bureau of Meteorology, Melbourne.
- Jeff Kepert, Senior Scientist, R&D Division, Bureau of Meteorology, Melbourne.
- Peter Steinle, Senior Scientist, R&D Division, Bureau of Meteorology, Melbourne.
- Jeff Walker, Professor, Dept. of Civil Engineering, Monash University.
- Adam Smith, Scientist, Bureau of Meteorology, Melbourne.
- Ian Grant, Senior Scientist, Bureau of Meteorology, Melbourne.
- Alex Holmes, PhD Student, Monash University.
- John Bally, Lead End User, Bureau of Meteorology, Hobart.
- Paul Fox-Hughes, End User, Bureau of Meteorology, Hobart.
- Mark Chladil, End User, Tasmania Fire Service, Hobart.
- Adam Leavesley, End User, ACT Parks.
- Andrew Sturgess, End User, Predictive Services Unit, QFES, Brisbane.
- Rob Sandford, End User, Country Fire Service, South Australia.
- Ralph Smith, End User, Department of Fire and Emergency Services, Western Australia.
- David Taylor, End User, Parks Tasmania.
- Stuart Matthews, End User, NSW RFS.

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