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Key Points:

- Introducing a data fusion-based drought index for weekly water stress monitoring
- Applying the proposed index in three areas with different climates and land use
- Comparative evaluations of the proposed index and commonly used indices

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A data fusion-based drought index

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Abstract Drought and water stress monitoring plays an important role in the management of water resources, especially during periods of extreme climate conditions. Here, a data fusion-based drought index (DFDI) has been developed and analyzed for three different locations of varying land use and climate regimes in Australia. The proposed index comprehensively considers all types of drought through a selection of indices and proxies associated with each drought type. In deriving the proposed index, weekly data from three different data sources (OzFlux Network, Asia-Pacific Water Monitor, and MODIS-Terra satellite) were employed to first derive commonly used individual standardized drought indices (SDIs), which were then grouped using an advanced clustering method. Next, three different multivariate methods (principal component analysis, factor analysis, and independent component analysis) were utilized to aggregate the SDIs located within each group. For the two clusters in which the grouped SDIs best reflected the water availability and vegetation conditions, the variables were aggregated based on an averaging between the standardized first principal components of the different multivariate methods. Then, considering those two aggregated indices as well as the classifications of months (dry/wet months and active/non-active months), the proposed DFDI was developed. Finally, the symbolic regression method was used to derive mathematical equations for the proposed DFDI. The results presented here show that the proposed index has revealed new aspects in water stress monitoring which previous indices were not able to, by simultaneously considering both hydrometeorological and ecological concepts to define the real water stress of the study areas.

1. Introduction

Australia's significant hydroclimatic variations lead to high spatiotemporal water fluctuations throughout the country [*Kirono et al*., 2011; *Gallant et al*., 2013], impacting on water resources, river, and terrestrial ecosystems, as well as irrigation and dryland agriculture areas [*Van Dijk et al*., 2013]. A variety of studies have documented droughts in Australia, and in some cases the final results have been found to be significantly different even between individual stations within small catchments; in fact, these conflicts represent high uncertainties and complexities which have led researchers to undertaking further investigations [*Mpelasoka et al*., 2008; *Verdon-Kidd and Kiem*, 2009; *Risbey*, 2011; *Van Dijk et al*., 2013].

Water stress monitoring has traditionally been characterized using drought indices (DIs) during the processes of water resources management [*Hayes*, 2003]. A variety of DIs have been introduced and applied in drought monitoring and forecasting over the past decades, but are often based on a single hydroclimatic variable, such as the Surface Water Supply Index (SWSI) [*Shafer and Dezman*, 1982], standardized precipitation index (SPI) [*McKee et al*., 1993], or the Soil Moisture Drought Index [*Hollinger et al*., 1993; *Hunt et al*., 2009]. Indices which incorporate a range of hydroclimatic variables, such as the Palmer Drought Index (PDSI) [*Palmer*, 1965, 1968] that has input variables of precipitation, potential evapotranspiration, soil moisture, runoff, and infiltration/percolation as well as the Vegetation-Temperature Condition Index (VTCI) [*Patel et al*., 2012] derived from spectral measurements, are also commonly used.

Drought (or water stress) conditions can be defined in various ways, depending on the perspective of the application [*Wilhite*, 2005]: (i) hydrological, (ii) biophysical, (iii) socioeconomic, and (iv) agricultural droughts (water stress). Consequently, they will provide different, if not conflicting, information under various climate conditions. A combination of those individual indices will therefore provide a more robust basis for the definition of droughts, as it will be based on a range of observable variables, rather than a very select subset (and in some cases only one). *Wilhite* [2000] and *Van Loon and Van Lanen* [2012] have argued that no single DI can be used in all circumstances, and that most individual DIs cannot comprehensively analyze the deficiency of available water resources within the water systems. To overcome these drawbacks, a number of studies suggested data fusion and aggregation concepts to derive new DIs which are more accurate and reliable than individual DIs alone [*Keyantash and Dracup*, 2004; *Balint and Mutua*, 2011; *Barua et al*., 2012; *Zhang and Jia*, 2013; *Li et al*., 2015]. The main aim of data fusion (which is the process of aggregating and combining information from multiple data sources and/or sensors) is to present the solution that is either more accurate or allows experts to retrieve more information beyond those that could be obtained through taking benefit from individual data sources [*Azmi et al*., 2010]. Unfortunately, previous data fusion-based drought indices (DFDIs) still have deficiencies which need to be addressed. Some of the main shortcomings are (i) the reliance on subjective selection of inputs, (ii) the subjective determination of weighting values in weighted-average fusion methods, (iii) only considering water content-based individual DIs (such as precipitation and streamflow) in the process of combinations, and (iv) the process of validation [*Keyantash and Dracup*, 2004; *Balint and Mutua*, 2011; *Barua et al*., 2012; *Zhang and Jia*, 2013; *Li et al*., 2015].

By considering a set of individual DIs, this study develops a methodology to monitor water stress conditions of terrestrial ecosystems by objectively linking water availability and vegetation conditions. The combination methodology makes use of advanced statistical methods (i.e., multivariate methods such as independent components analysis), and also considers the ecometeorological characteristics (i.e., land use, landcover, and climate) of an area to state the ultimate water stress conditions at each time step. In order to test the ability of the new approach to generalize a range of DIs, three case study areas, each with different combinations of land use and climate regimes, and subsequently a diverse range of surface and atmospheric conditions, are presented.

2. Data Fusion-Based Drought Indices (DFDIs)

2.1. Commonly Used DFDIs and Their Main Drawbacks

Before discussing the commonly used DFDIs, it is necessary to separate the monthly conditions of terrestrial ecosystems into two distinct aspects:

1. Wet/Dry months: a month can be named as a wet month if the mean of the historical precipitation for that month is higher than the total mean of all months of the year; otherwise it would be a dry month.
2. Active/Nonactive months: during active months, the mean air temperature is usually between 6° and 40°C with most plant types being physiologically active and growing [*Singh and Dhillon*, 2006]; however the degree of the plant activity depends on the plant available water [*Singh and Dhillon*, 2006] and the vegetation type. In contrast, during a nonactive month, mean air temperature is lower than 6° or higher than 40°C, with plants having a minimum physiological activity or are even shut down, unless the plant has adapted to the prevailing local conditions [*Brut et al*., 2009].

A number of different possible combinations of dry/wet, as well as active/nonactive months and their influences on choosing appropriate drought indices to evaluate the water stress of an area are presented in Appendix A.

The various drought indices presented in the literature can be divided into commonly used state-of-the-art DFDIs as summarized below:

1. Linear Aggregated Drought Index (LADI) [*Keyantash and Dracup*, 2004]:
   LADI is based on the combination of six hydrometeorological variables of precipitation, potential evapotranspiration, streamflow, reservoir storage, soil moisture content, and snow water content using the multivariate method of linear principal component analysis (LPCA) [*Hidalgo et al*., 2000]. LADI utilizes only the first principal component as it explains the largest fraction of the variance described by the full members.
2. Nonlinear Aggregated Drought Index (NLADI) [*Barua et al*., 2012]:
   NLADI is an extended form of LADI. Essentially, NLADI employs the nonlinear principal component analysis (NLPCA) [*Linting et al*., 2007] to combine the six hydrometeorological variables used in LADI. The combination process is similar to LADI.
3. Weighted Average-based Drought Index (WADI) [*Balint and Mutua*, 2011]:
   WADI is a combined drought index based on the weighted average method between precipitation

drought index (with the weight of 0.5), temperature drought index (with the weight of 0.25), and vegetation drought index (with the weight of 0.25).

4. Arithmetic Average-based Drought Index (AADI) [*Zhang and Jia*, 2013]:

   AADI is an index based on arithmetically averaging standardized variables of precipitation, soil moisture, and air temperature.

The different drought indices have their individual advantages and disadvantages. In particular, LADI and NLADI only consider hydroclimatological variables which reflect the water content of a system, which is insufficient for analyzing the water stress of a terrestrial ecosystem as it does not consider the level of plant-physiological activity, especially during the growing months. Consequently, it is necessary to broaden the considered data set and choose indices that also recognize the physiological stress of the vegetation, which may not be directly related to the water content-based indices. In addition, the aggregation of the variables is performed by only using the PCA method. One of the main assumptions of the PCA is the Gaussianity of its input variables and the underlying linear regressions to derive any aggregated variables. To rely solely on this multivariate method for combining data is a limiting approach, as most hydrometeorological variables do not necessarily follow Gaussian probabilistic distribution functions and therefore, complex relationships between the variables can be better assessed assuming nonlinear relationships. Moreover, these two DFDIs are already the first principal component (PC1) of six fixed hydroclimatological variables aggregated by the PCA, irrespective of the variances of the entire data set that can be covered by PC1. Finally, they cannot be applied easily for estimating and predicting waster stress in an area, because assessing the water stress for following time steps requires reperforming all combination stages from the beginning of the observations. Conversely, WADI is based on a weighted average combination in which the weights are determined subjectively (or through calibration) for a specific case study area. The advantage is that the index values are intercomparable between sites. However, by choosing standard weights they may lack physical meaning, as the relative importance of the included variables may change across seasons. Thus, there is no guarantee to get reliable results for any area with different climate and land use. Further, WADI and AADI are both derived based on averaging single DIs, an approach which may neither by naturally nor physically consistent.

2.2. Proposed DFDI

To address the abovementioned deficits of commonly used DFDIs, a new index is proposed at this point. The workflow schematic of the proposed algorithm is presented in Figure 1. First, an appropriate set of indices and proxies is determined based on the available data. Those consist of a pool of variables covering water contents, water consumption, and vegetation conditions. Then, the indices and proxies derived from the previous step are standardized based on an equiprobability transformation [*Shukla and Wood*, 2008] and are consequently labeled standardized drought indices (SDIs), and are finally clustered via the Probabilistic Similarities (PSs) method (Appendix B). In particular two of the formed clusters, which consist of (i) water content-based SDIs such SPI, and (ii) vegetation condition-based SDIs such as NDVI, can provide relevant enough information to precisely assess the water stress of an area, all subsequent steps are only applied to the two abovementioned clusters. It is well understood that the water stress conditions inside plants are closely related to the level of plant available water of an area. Consequently, considering indices from both groups can provide a more comprehensive evaluation of the ultimate water stress situations of an ecosystem, and potentially help exclude vegetation states that could be seen as drought-related from remotely sensed data sources, but are in fact false positives, caused by vegetation cover affected by pests and diseases.

In order to investigate the efficiency of performing multivariate methods to aggregate the SDIs located within the two main clusters, the Kaiser-Meyer-Olkin (KMO) test [*Kaiser and Rice*, 1974] is employed. Using this method, a value greater than 0.5 indicates the efficiency of multivariate methods in combining SDIs. Seeing that the clusters derived from the PSs method consist of similar indices (either water or plant-physiology driven), it is expected that the multivariate methods are appropriate to aggregate the SDIs located within the same cluster. This aggregation is then achieved, using three common multivariate methods, namely the Principal Component Analysis (PCA) [*Hotelling*, 1933], Factor Analysis (FA) [*Kim and Mueller*, 1978], and Independent Component Analysis (ICA) [*Hyvarinen and Oja*, 2000]. FA and ICA have the advantage of assuming the aggregated variables to not only be uncorrelated but also statistically independent, non-Gaussian, and also consider nonlinear regressions between variables [*Hyvarinen et al*., 2001].

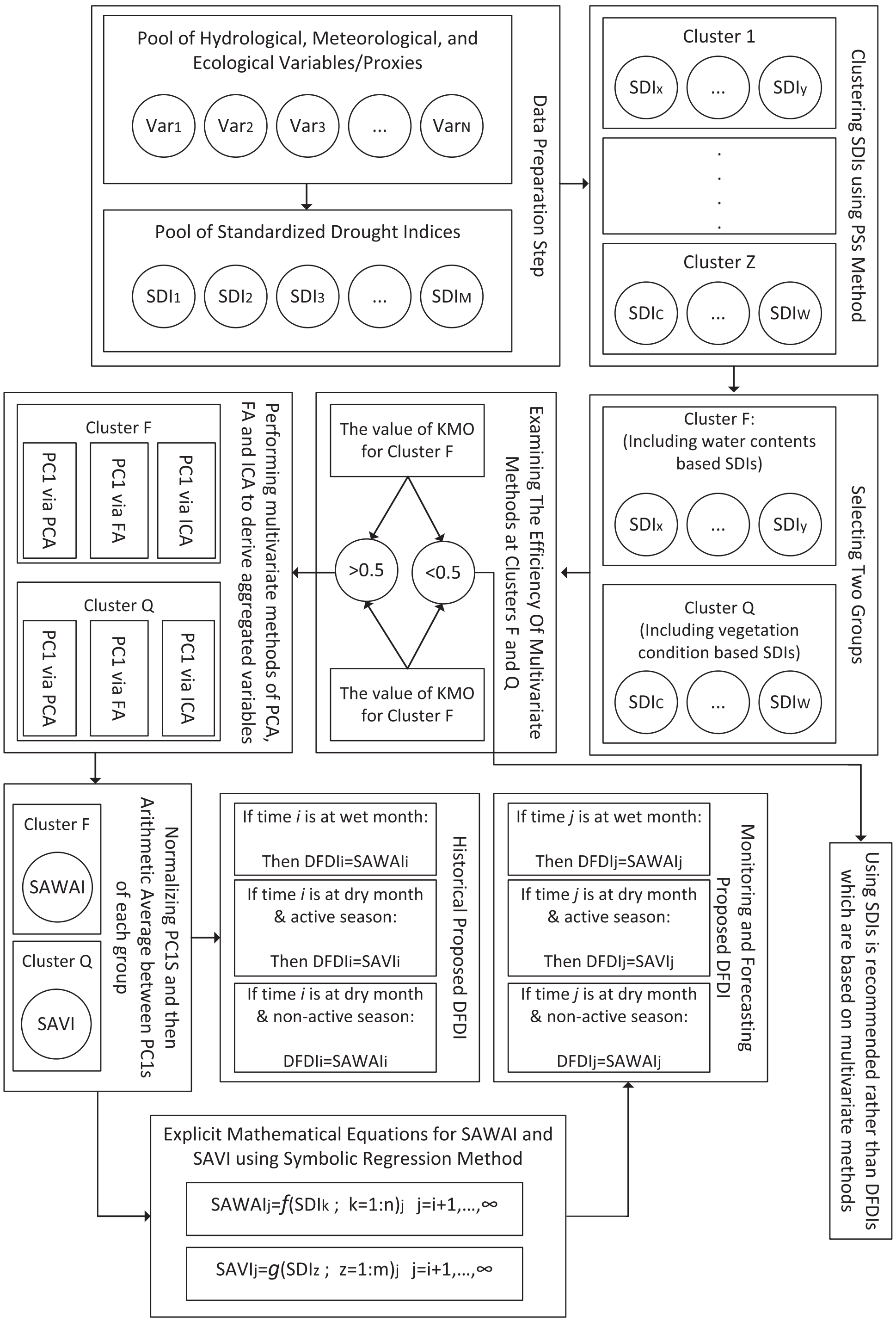

Figure 1. Schematic outline of the proposed drought index.

The indices obtained through the aggregation within the clusters are then standardized by dividing them by their individual standard deviations. To specify the best number of aggregated variables derived for the two mentioned clusters when using the different multivariate methods, the Kaiser1 method [*Kaiser*, 1960] is used. For the Kaiser1 method, the aggregated variables in which their Eigenvalues are greater than 1 are selected. Considering that the PS method forms consistent clusters, the first principal component (PC1) of each cluster will dominantly cover the highest amount of variance for all variables located in a group with

Table 1. Proposed Thresholds for the DFDI

Threshold Range	Gaussian Function Curve Areas				Classifications
DFDI < -1.65	5%			100%	Extreme dry
$-1.65 \le$ DFDI < -1.15	12.5%		90%		Severe dry
$-1.15 \le$ DFDI < -0.67	12.5%	75%			Moderate dry
$-0.67 \le$ DFDI ≤ 0.67	50%				Normal
$0.67 <$ DFDI ≤ 1.15	12.5%				Moderate wet
$1.15 <$ DFDI ≤ 1.65	12.5%				Severe wet
$1.65 <$ DFDI	5%				Extreme wet

Eigenvalues greater than 1; or the difference between the Eigenvalues of the first and second principal components is quite large enough to only consider PC1 as the aggregated variable of each cluster. After standardizing the PC1s by dividing them by their standard deviations; an arithmetic average between the PC1s of the two mentioned clusters derived from different multivariate methods (PCA, FA, and ICA) is calculated, giving the final aggregated variable of that specific cluster. Here, as those two clusters represent either water or vegetation, they are named Standardized Aggregated Water Availability Index (SAWAI), and Standardized Aggregated Vegetation Index (SAVI), respectively.

In order to make the current methodology more applicable in a real-time scenario, explicit mathematical equations are derived for SAWAI and SAVI by employing the Symbolic Regression Method [*Koza et al*., 2003]. The independent variables for the mathematical equations are drawn from a set of SDIs from within the SAWAI and SAVI clusters. Emphasis is given to select more readily available SDIs as independent variables, such as the standardized precipitation index (SPI), rather than more complex ones, in order to make the final drought index as practical and directly applicable as possible. Summarizing Appendix A, the final proposed data fusion-based drought index (DFDI) may be expressed as follows:

If time *i* is at a wet month, irrespective of whether that month is physiologically active or nonactive, the water stress monitoring can be appropriately evaluated by SAWAI:

$$DFDI_i = SAWAI_i;\ \& DFDI_j = SAWAI_j = f(SDI_k; k=1:n)_j \qquad j=i+1,\ldots,\infty \tag{1}$$

If time *i* is during a dry month, as well as an active season, the water stress monitoring should be assessed by SAVI, which reflects the water consumption and vegetation growth, therefore

$$DFDI_i = SAVI_i;\ \& DFDI_j = SAVI_j = g(SDI_z; z=1:n)_j \qquad j=i+1,\ldots,\infty \tag{2}$$

If time *i* is during a dry month, as well as a nonactive season, the water stress monitoring should be evaluated by SAWAI which reflects the amount of stored and plant-available water, again following equation (1).

In the above equations, *i* includes all previous time steps till the current time; *j* is all time steps after *i*; *f* and *g* are the optimum mathematical functions between the selected SDIs to calculate $SAWAI_j$ and $SAVI_j$, respectively; SDI_k and SDI_z are *k* and *z* selected SDIs as independent variables to derive SAWAI and SAVI, respectively.

Due to the fact that the output of the considered aggregating methods (PCA, FA, and ICA) is based on Gaussian distribution functions, thresholds of dry, normal, and wet events can also be defined based on the Gaussian variates of the standard deviations [*Barua et al*., 2012; *Keyantash and Dracup*, 2004]. Following the justifications for the thresholds used for the Probabilistic Similarities mentioned in Appendix B, the thresholds proposed are as shown in Table 1.

In terms of temporal resolution, weekly data sets, derived by averaging the daily information of that week, are considered for the evaluation of water stress in the present paper. This aggregated temporal window is necessary as the physiological conditions of plants are the main elements of the terrestrial ecosystems and reflect, or integrate, the water stress (wilting point) with a lag time of around one week. In fact, daily data products may show decorrelated results between the indices and the surface conditions for this same reason. Moreover, information of water stress monitoring with longer time spans (monthly, seasonally) cannot be practical for ecological water management due to the wilting point onset for many vegetation species [*Svoboda et al*., 2002; *Heim*, 2002].

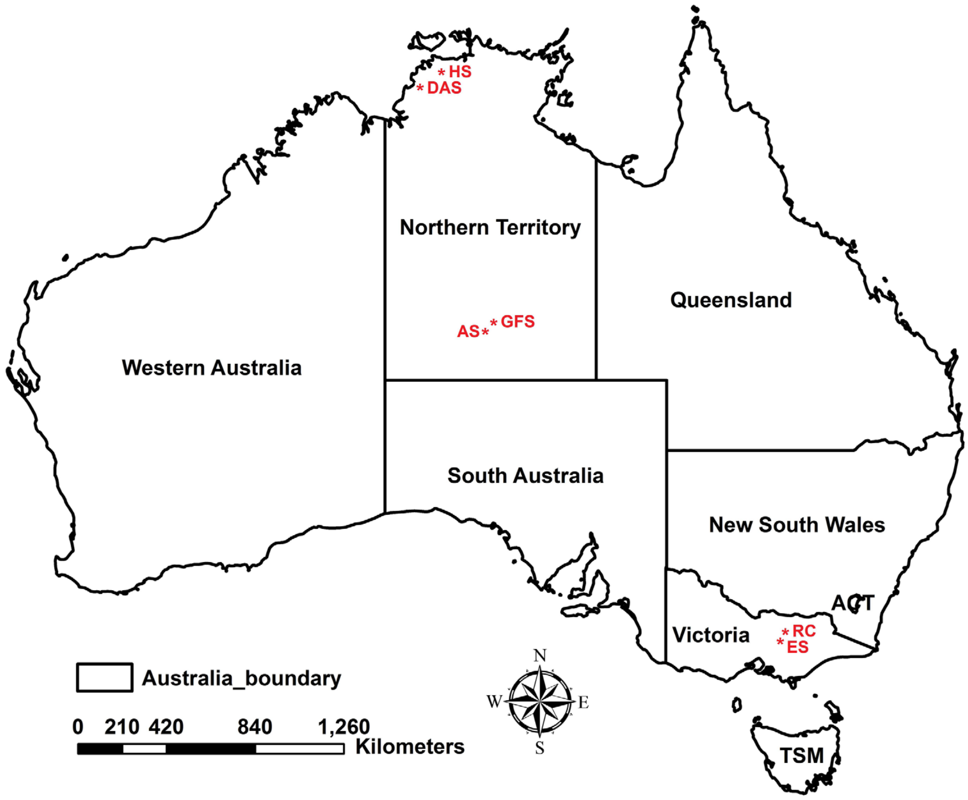

Figure 2. Locations of the three OzFlux tower sites and adjacent synoptic stations used in this study. HS: Howard Springs OzFlux Tower Site, DAS: Darwin Airport Station, AS: Alice Springs OzFlux Tower Site, GFS: Grape Farm Station, RC: Riggs Creek, and ES: Euroa Station.

3. Case Study Sites and Data Sources

Due to the fact that characteristics an ecosystem's water stress mainly depend on its climate and land use, three case study sites have been chosen (Figure 2), each having a different climate and land use, to evaluate the capacity of the proposed methodology.

3.1. Riggs Creek OzFlux Tower Site (RG)

The Riggs Creek OzFlux tower is located within the Goulburn-Broken catchment (Lat: −36.650°, Lon: 145.576°), in northern Victoria, Australia [*Beringer*, 2014]. The predominant land use in this temperate region consists of dryland agriculture and pasture. Carbon dioxide, water vapor, and latent/sensible heat are measured via the open-path eddy flux technique (at height of 2 m). The soil moisture contents and soil temperature are collected using installed sensors every 0.1 m across the profile. The utilized time series of verified data from this OzFlux tower is 1.5 years (minimum amount of data gaps) starting in December 2010.

3.2. Alice Springs OzFlux Tower Site (AS)

The Alice Springs flux station is located on Pine Hill cattle station (Lat: −22.287°, Lon: 133.640°), near Alice Springs in the Northern Territory, Australia [*Cleverly*, 2011]. The land use of this area is woodland characterized by a Mulga canopy in a generally arid to semiarid climate. The soil is overlying a 49 m deep water table. The tower is 13.7 m tall; and carbon dioxide, water vapor, and heat measurements are collected via the open-path eddy covariance technique at 11.6 m. Soil moisture and temperature measurements are collected in bare soil, Mulga, and understory habitats. For this study, considering the availability of verified data from this OzFlux tower with a minimum of gaps, data from 3 September 2010 to 30 June 2013 are considered for this site.

3.3. Howard Springs OzFlux Tower Site (HS)

The Howard Springs flux station is located in the Black Jungle Conservation Reserve in the Northern Territory, Australia (Lat: −12.495°, Lon: 131.150°) [*Beringer*, 2013]. The flux tower site is categorized as an open

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Table 2. Hydroclimatic Variables/Proxies Used in This Study[a]

Category	Data Sources	Primary Variables	Abbreviation	Units	Temporal Scale	Spatial Scale	Calculation
In situ observations	OzFlux Towers Network	Soil Moisture Content (Depth = 10 cm)	SM	mm	0.5 h	5* m	Direct measurement
		Precipitation	P	mm	0.5 h		
		Moisture flux (Latent Heat)	MF	W/m^2	0.5 h		
		Evaporative fraction index [*Shuttleworth et al.* 1989]	EFI		0.5 h		$EFI=\frac{H}{Rn-G}$
A combination of in situ observations, satellite information, and model output	Asia-Pacific Water Monitor (APWM) Section	Runoff and surface soil moisture	ROI	mm	1 day	500 m	A combination of the output of several sources and models
Satellite information	MODIS-Terra Satellite	Normalized difference Vegetation Index [*Maki et al.* 2004]	NDVI		1 day	250 m	$NDVI=\frac{NIR-VIS}{NIR+VIS}$
		Vegetation Condition Index [*Patel et al.* 2012]	VCI		1 day	250 m	$VCI=\frac{NDVI-NDVI_{min}}{NDVI_{max}-NDVI_{min}}$
		Temperature Condition Index [*Patel et al.* 2012]	TCI		1 day	500 m	$TCI=\frac{Tb_{max}-Tb}{Tb_{max}-Tb_{min}}$
		Perpendicular Drought Index [*Ghulam et al.* 2007]	PDI		1 day	250 m	$PDI=\frac{1}{\sqrt{M^2+1}}(VIS+M\times NIF)$

[a]*NIR*: the spectral reflectance measurements acquired in the near-infrared regions (700–1100 nm), *VIS*: the spectral reflectance measurements acquired in the visible (Red) regions (400–700 nm). $NDVI_{max}$ and $NDVI_{min}$: maximum and minimum *NDVI* for a given time series, *Tb*: brightness temperature of the spectral reflectance measurements acquired with band 4 of MODIS. Tb_{max} and Tb_{min}: maximum and minimum brightness temperature, respectively, *M*: the slope of soil line in the NIR-VIS spectral feature space. H: latent heat flux (Wm^{-2}), Rn: Net radiation (Wm^{-2}), G: ground/soil heat flux (Wm^{-2}). *This is an approximation.

woodland Savanna (average tree height is 14–16 m), and is found within a tropical climate. The tower is 23 m tall and instruments are installed at approximately 10 m above the ground. Carbon dioxide, water vapor, and heat measurements are collected via the open-path eddy covariance technique. Soil moisture content is also measured at the site. Again considering the data gaps, for this OzFlux tower, data from 1 January 2011 to 31 December 2013 are applied.

Except for the observed data from the OzFlux network [*Finnigan et al.*, 2003; *Finnigan*, 2004], the remaining two data sources used in this study are obtained from model output (APWM) [*Van Dijk*, 2010] and satellite data from MODIS on NASA's Terra (Table 2). In the current study, standard, processed, freely available satellite data products are being used. Data quality flags, e.g., for cloudiness or significant retrieval errors, were considered and the respective data points were filtered out. As this study uses point observations, it is assumed that the MODIS products used here (with native resolutions of 250–500 m) are representative of the location where the towers are found, and that no further processing is required in that regard. Considering the main elements of the hydrological cycle as well as drought types, a diverse set of variables/proxies was taken into consideration to derive the single DIs for this study (Table 2). For each DI, the category of the utilized data sources (in situ observations, satellite information, and/or a combination of them), their spatial and temporal scale, and the method of deriving values for the DIs (direct measurement, measurement-calculations) are summarized in Table 2.

3.4. Data Limitations

The generally accepted approach to calculate long-term drought and water stress conditions requires time series data that extend beyond 30 years, so as to cover the full dynamical range of the local hydrology, while retaining sufficient data for validation purposes. The development of a general drought or water index, such as presented here, would therefore require a complete set of variables, including soil moisture, land surface water, and energy fluxes, among others. However, such a data do not exist in situ for such an extended range of variable and length of time. The only observational data available for such a study come from comprehensive tower sites, such as the FluxNet network [*Oak Ridge National Laboratory Distributed Active Archive Center*, 2015], which provides data for selected sites of up to 15 years, but with most sites in the range of 4–7 years of data availability. Hence, it is necessary to develop new algorithms with the limited data that are currently available. For all sites, the period chosen for this paper covered a wide dynamical range of the local hydrology including the 2010 period when Australia transitioned from an extreme drought condition to a significantly wetter climate with significant precipitation events in the following years. It was therefore possible to capture almost the full range of conditions within a short-time window.

Table 3. Primary Statistical Information of Individual SDIs for the Aggregation Step at Different Regions[a]

Regions	Clusters	$\overline{PSs}$	KMO Test	Eigenvalues of PC1	Variance of Variables Covered by PC1
RG	Cluster 1: SPI, SSMI, SMFI, SROI, SPDI	62	0.59	2.3	77%
	Cluster 2: SNDVI, SVCI, STCI	75	0.61	2.2	70%
	Cluster 3: SEFI			N/A	
AS	Cluster 1: SPI, SSMI, SMFI, SEFI, SPDI	80	0.78	3.5	72%
	Cluster 2: SNDVI, SVCI, STCI	62	0.56	2.1	70%
HS	Cluster 1: SPI, SSMI, SMFI, SEFI, SPDI	87	0.84	3.7	75%
	Cluster 2: SNDVI, SVCI, STCI	62	0.59	2.4	81%

[a]$\overline{PSs}$: The average of PSs between members of each cluster; PC1: first principal component of variables located at a same cluster; RG: Riggs Creek; AS: Alice Springs; HS: Howard Springs; and N/A: nonapplicable for a single member cluster.

While not optimal, the simplifying assumption is made that this wide range of conditions has the same statistical properties as a longer time series, therefore allowing for the development of the drought and water stress index presented here. This aspect is taken up again in the conclusion section to address this limitation for future studies.

4. Results and Discussion

For the calculation of the time series of the Perpendicular Drought Index (PDI), the values of the soil line slope in the NIR-Red spectral feature space were found to be 1.4, 0.94, and 1.02 for the Howard Springs, Alice Springs, and Riggs Creek tower sites, respectively. Depending on the environmental conditions and the available data (and therefore the derived DIs), the number of DI clusters may be more than two. This is actually expected, in particular for environmental conditions that are significantly different to the arid and semiarid examples in this study, as the underlying physical drivers may be different from region to region. In addition, inaccurate primary selection of individual DIs (i.e., selecting irrelevant indices with water stress issue which leads to forming more clusters) and/or inconsistencies stemming from data errors may influence the clustering. For the present study, considering only two clusters consisting each of water content and vegetation conditions, is enough to evaluate water stress conditions of an ecosystem appropriately (as shown in Appendix A). For example, Table 3 shows the SDIs of RG categorized into three clusters, of which Cluster 3 had only a single member (SEFI). This suggests that the information contained within SEFI (at least at RG), can be considered redundant or even irrelevant for the derivation of the main index, maybe due to data errors rooted within the measurements. As SEFI basically shows the output of a terrestrial ecosystem in form of evapotranspiration, it should consequently be located within the cluster representing water content-based indices. As for AS and HS, the SDIs were distributed into two clusters, in which Cluster 1 includes indices generally representing water availability, while Cluster 2 consists of proxies which describe vegetation conditions. The average values of PSs between members of each cluster, greater than 60%, represent the accuracy of categorizing SDIs. Further, having values of the KMO test greater than 0.5 shows that performing multivariate methods on each cluster to derive aggregated variables was effective. In addition, with the Eigenvalues of PC1 (all exceeding 1) as well as variable variances covered by PC1 (with the minimum value of 70%), it can be stated that the PC1 derived from each cluster appropriately represents that cluster, as it can properly cover the majority of the statistical characteristics of the members of that particular cluster.

In this study, the lack of runoff data at the Alice Springs (AS) and Howard Springs (HS) OzFlux tower sites meant that the standardized runoff and surface soil moisture index (SROI) was only calculated and subsequently used to derive the SAWAI for the Riggs Creek (RG) OzFlux tower site. To determine the sensitivity of SAWAI to SROI at Riggs Creek, the process of deriving SAWAI was repeated but this time without considering the SROI (named SAWAI*). The four goodness-of-fit criteria of Spearman rank correlation coefficients (Scc), Pearson correlation coefficients (Pcc), Root Mean Square Error (RMSE), and Volume Error (VE) were then derived to compare SAWAI and SAWAI*. The values of $Scc = 0.96$, $Pcc = 0.97$, $RMSE = 0.028$, and $VE = 0.44$ suggest that the impact of missing the runoff variable in deriving SAWAI can be carried by other variables such as precipitation (e.g., Standardized Precipitation Index (SPI)) and soil moisture (or Standardized Soil Moisture Index (SSMI)). Based on the presented sensitivity analysis and given that the main drivers of runoff are precipitation and antecedent soil moisture conditions, the assumption has been made that

Table 4. Specification of Wet/Dry Months, Active/Nonactive Months, and Proposed DFDI Based on SAWAI/SAVI for Each Month at the Different Locations

	Riggs Creek			Alice Springs			Howard Springs		
Month	Wet/Dry	Active/Nonactive	Proposed DFDI	Wet/Dry	Active/Nonactive	Proposed DFDI	Wet/Dry	Active/Nonactive	Proposed DFDI
January	Dry	Nonactive	SAWAI	Wet	Active	SAWAI	Wet	Active	SAWAI
February	Dry	Nonactive	SAWAI	Wet	Active	SAWAI	Wet	Active	SAWAI
March	Dry	Nonactive	SAWAI	Dry	Active	SAVI	Wet	Active	SAWAI
April	Dry	Active	SAVI	Dry	Active	SAVI	Dry	Active	SAVI
May	Wet	Active	SAWAI	Dry	Non-Active	SAWAI	Dry	Active	SAVI
June	Wet	Nonactive	SAWAI	Dry	Non-Active	SAWAI	Dry	Active	SAVI
July	Wet	Nonactive	SAWAI	Dry	Non-Active	SAWAI	Dry	Active	SAVI
August	Wet	Nonactive	SAWAI	Dry	Non-Active	SAWAI	Dry	Active	SAVI
September	Wet	Active	SAWAI	Dry	Active	SAVI	Dry	Active	SAVI
October	Wet	Active	SAWAI	Dry	Active	SAVI	Dry	Active	SAVI
November	Dry	Active	SAVI	Wet	Active	SAWAI	Wet	Active	SAWAI
December	Dry	Nonactive	SAWAI	Wet	Active	SAWAI	Wet	Active	SAWAI

SROI may not be needed for the two other case studies, as SPI and SSMI implicitly contain the key information provided by SROI. A further analysis of the validity of this assumption and its transferability to other climatic zones, in particular temperate and humid regions is required, but it is suggested to be valid here, given the closeness of the surface hydrological characteristics of the three sites.

In order to implement the proposed methodology, the wet and dry, as well as the plant-physiologically active and nonactive months were determined for each of the case study areas (Table 4) according to section 2.1 and Appendix A. For that purpose, 30 years of monthly data were used to classify active/nonactive months. At Riggs Creek, the monthly historical data of precipitation, mean minimum and mean maximum air temperature of the synoptic station of Euroa (1980–2010), as well as historical information of monthly pasture growth in Victoria [*Department of Environment and Primary Industries, State Government Victoria*, 2014] were used for this purpose. Also, historical data of the synoptic stations at Grape Farm and Darwin Airport (1980–2010) were used to define wet/dry as well as active/nonactive months for Alice Springs and Howard Springs, respectively (Table 4).

Time series of SAVI, SAWAI, and the proposed DFDI for the study sites are shown in Figure 3. Figures 3a, 3d, and 3g present the time series of SAWAI along with SSMI at the different locations. For all sites, SSMI and SAWAI appear to have similar trends; however, SSMI usually reflects water stress conditions more gradually and smoothly throughout a specified time span, and consequently cannot show significant sensitivities to short-term water stress fluctuations. This pattern is due to the long-term hydrologic memory of soil moisture (equivalent to low-frequency variability), in particular in comparison with other hydrological variables such as precipitation, which is spectrally white [*Blender and Fraedrich*, 2006]. This is one of the main reasons why drought indices such as SNDVI and DFDIs are preferred at weekly temporal resolution [*Keyantash and Dracup*, 2004; *Barua et al.*, 2011, 2012]. Further, Figures 3b, 3e and 3h show that the time series of SAVI are close to SNDVI at all three case study sites. The reason of this high similarity lies in this fact that all SDIs which are located in Cluster 2 are derived from spectral measurements directly related to the vegetation conditions. In general points of view, the highest values for SAVI are associated with growing months and lowest ones related to nongrowing months or growing months with high water stress. In terms of memory, both SNDVI and SAVI have a relatively short-term memory when compared to SSMI.

After deriving the time series of the aggregated variables SAWAI and SAVI, the final proposed DFDI can be derived based on the results of Table 4 and equations (1) and (2). Therefore, according to Table 4, at Riggs Creek the proposed DFDI was equal to SAVI for the months of April and November, and equal to SAWAI for the remainder of the year. While the soil moisture conditions in April and November may be described as “normal” (Figure 3a), the vegetation water stress are between moderate wet and severe wet (Figure 3b). The reason for this difference lies in the water consumption of the natural system. In fact, for both of these months, mean maximum air temperature is usually mild (at Riggs Creek it is between 10°C and 25°C) and therefore evapotranspiration is moderate and energy limited, rather than water limited. For Riggs Creek, the drought conditions in April and November cannot comprehensively be described by water content-based indices such as SSMI and SAWAI, because at Riggs Creek these 2 months are categorized as Dry and Active months (Table 2), and consequently, it is necessary to employ a vegetation condition-based index such as NDVI or SAVI to obtain more accurate information on the prevailing conditions (Figure 3c).

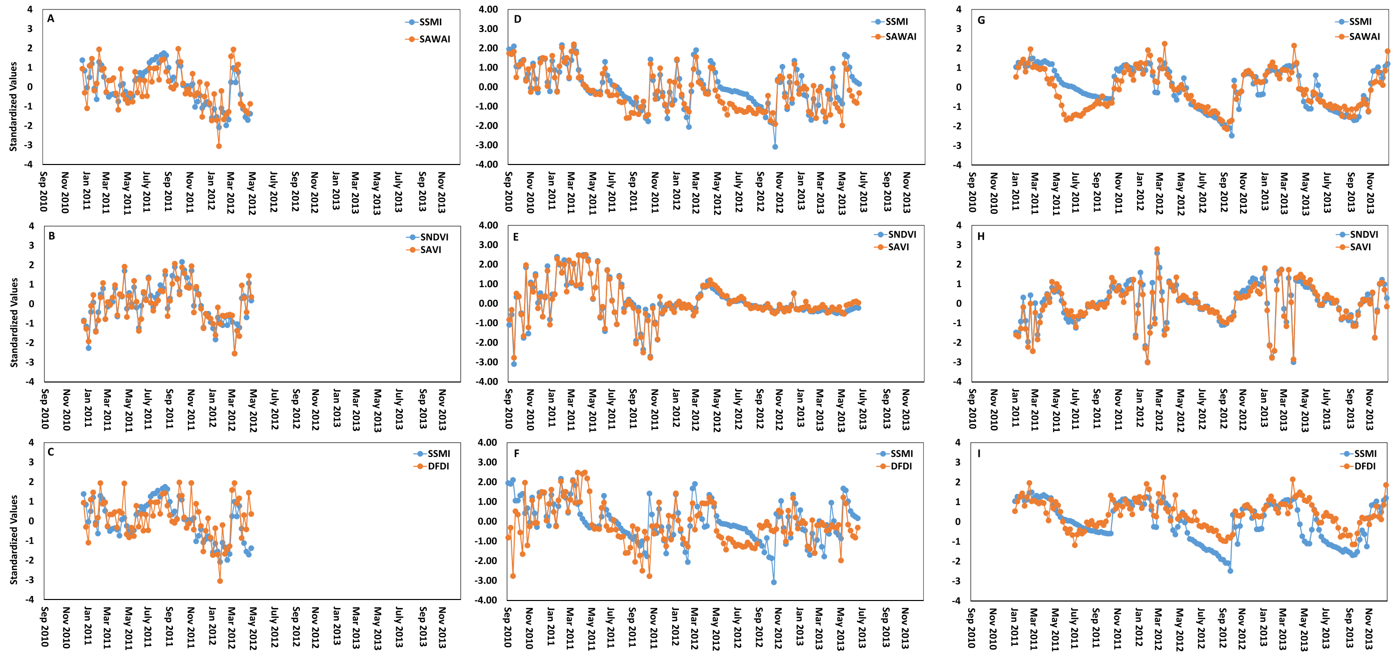

Figure 3. Time series of (a) SAVI compared with SSMI, (b) SAWAI compared with SNDVI, and (c) the proposed DFDI compared with SSMI at Riggs Creek OzFlux tower site. Descriptions of Figures 3d, 3e, and 3f are same as 3a, 3b, and 3c but for the Alice Springs OzFlux tower site. Descriptions of Figures 3g, 3h, and 3i are same as 3a, 3b, and 3c but for the Howard Springs OzFlux tower site.

At Alice Springs, the DFDI values were equal for the months March, April, September, and October based on SAVI. Performing cross-correlation analyses between SAWAI and SSMI showed a 2 month time lag which can also be noticed in Figure 3d. This is explained with the vegetation conditions of this area in September and October 2011 being associated with the soil moisture of July and August 2011, or rather the deeper root-zone conditions that are a consequence of the antecedent surface soil moisture. This is also reflected in an upward trend for DFDI between September and October 2011, while SSMI drops remarkably (Figure 3f).

The overall climate conditions and vegetation cover at Howard Springs may be considered as being between that of Riggs Creek and Alice Springs. Thus, the water stress conditions for this area should be analyzed based on a combination of reasons already considered at Riggs Creek and Alice Springs. According to Table 4, the months of April–October are active and dry. Therefore, according to equations (1) and (2), the proposed DFDI was determined based on SAVI. In this region, the average of mean maximum air temperature and average of mean minimum air temperature from April to October are around 22°C and 31°C, respectively. Those local conditions result in a moderate level of evapotranspiration, which can also be defined as the water consumption of the full terrestrial system, which is a combination of the lack of precipitation and lower average daily temperatures in winter. Based on the available data, both SAWAI and SSMI indicate significant levels of water stress, while the ecosystem is now defined as slightly under stress by the DFDI (within the range of 0 to -1). Consequently, throughout the period April–October, SSMI (or SAWAI) determined the water stress of this region to be higher than that proposed by DFDI (Figure 3i). Similar to Alice Springs, a 2 month time lag was also found between SAVI and SAWAI. For example, in March 2011 SAWAI started decreasing until May 2011, before increasing again until July 2011. This behavior was imitated by SAVAI from May 2011 with a minimum in June 2011. However, during this period, SSMI was only decreasing (Figure 3i), showing that individual SDIs such as soil moisture (SSMI) cannot be used to evaluate and interpret all different aspects of water stress of a terrestrial ecosystem [*Wilhite*, 2000; *Van Loon and Van Lanen*, 2012].

4.1. Deriving Mathematical Equations for SAVI and SAWAI

To complete the proposed methodology, explicit mathematical formulations for SAVI and SAWAI were derived using the symbolic regression method (Table 5), such that the proposed index could be applied in

Table 5. Derived Mathematical Equations Along With Goodness-of-fit Criteria Calculated on Validation Data for SAVI and SAWAI at the Different Locations

Regions	Dependent Variable	Independent Variables	Mathematical Equations	Goodness-Of-Fit Values Calculated on Validation Data: r^2	Max. Error	Mean Abs. Error	Formula Evaluations	Confidence Stability	Confidence Maturity
RG[a]	SAVI	SNDVI	$SAVI = SNDVI - 0.19^{a}sin[delay(SNDVI,3) + sin(110.79^{a}SNDVI)]$	96%	0.34	0.14	$3.4e^{10}$	91.2%	99.5%
	SAWAI	SPI, SSMI	$SAWAI = 0.58^{a}SPI + 0.54^{a}SSMI + 0.15^{a}delay(SSMI,2) + 0.15^{a}SPI\text{^}2 - 0.09^{a}SSMI\text{^}2$	93%	0.66	0.19	$8\ e^{10}$	93.3%	98.2
AS[a]	SAVI	SNDVI	$SAVI = SNDVI + 0.07^{a}SNDVI^{a}sin(2.13^{a}SNDVI + 1.15^{a}SNDVI\text{^}2)$	94%	0.36	0.11	$5.5\ e^{10}$	98.4%	99.5%
	SAWAI	SPI, SSMI, SEFI	$SAWAI = 0.13 + 0.52^{a}SEFI + 0.27^{a}SSMI + 0.23^{a}\ SPI$	96%	0.37	0.08	$5.3\ e^{10}$	99.6%	99.8%
HS[a]	SAVI	SNDVI	$SAVI = SNDVI - 0.003/(1 + sin(1.17 + 130.17^{a}SNDVI - 11.48^{a}SNDVI\text{^}2))$	95%	0.70	0.17	$3e^{11}$	94.5%	96.5%
	SAWAI	SPI, SSMI, SEFI	$SAWAI = 0.06 + 0.55^{a}SEFI + 0.34^{a}SSMI + 0.07^{a}SPI^{a}SEFI + 0.09^{a}SSMI\text{^}2 - 0.12^{a}SPI\text{^}2$	96%	0.30	0.10	$6.5\ e^{10}$	99.8%	99.8%

[a]RG: Riggs Creek; AS: Alice Springs; HS: Howard Springs; Formula Evaluation is the total number of equations which are examined; "Confidence Stability" refers to how long the solution list has not changed; "Confidence Maturity" relates to how much computational effort has been put into the current listed solutions. (Adapted from Eureqa User-Manual/website, http://formulize.nutonian.com/documentation/eureqa/).

a practical way. As mentioned in the methodology section, the SDIs should be selected as independent variables of SAVI and SAWAI, as these indices are usually easy to quantify and have high similarities with dependent variables. At the study sites of Alice Springs and Howard Springs, considering the time series of available SDIs (as independent variables) and dependent variables (SAWAI and SAVI), three indices of SPI, SSMI, and SEFI were applied to estimate SAWAI values. The SNDVI was used for deriving SAVAI values. At Riggs Creek, because of omitting SEFI after the clustering step, only two indices of SPI and SSMI were considered as independent variables to estimate the values of SAWAI.

In order to derive the final equations for the DFDI, the "Eureqa Formulize" software developed by *Schmidt and Lipson* [2009] was chosen to derive explicit mathematical equations between independent and dependent variables. In recent years, this software has been utilized in a variety of environmental issues as a reliable and accurate tool to evaluate symbolic regression-based problems [*Abrahart and Beriro*, 2012; *Drobot et al*., 2014]. Five main mathematical operators, exponential, trigonometry, and delay functions to derive the optimum mathematical equations subject to a variety of the regression complexities have been considered. The level of equation complexities grows when the number of contributing independent variables and mathematical functions increases. The optimum solution is an equation in which by increasing its complexity, the degree of its accuracy would not be changed meaningfully. This optimum explicit equation can be easily used to derive the values for the dependent variable. According to suggestions of previous research in modeling data by data-driven methods [*Azmi et al*., 2010; *Araghinejad et al*., 2011; *Gharun et al*., 2015], 50% of the entire data should be considered for the calibration stage, 25% for the validation stage, and 25% for the verification stage; and for all these three stages both normal and extreme events should be present among the considered data set. As discussed above, only limited temporal data coverage is available for this study, which affects the approach that can be taken to derive and validate these equations. In order to include a diverse range of hydrologic and vegetation conditions, a partial sampling approach is therefore considered here for the different stages of calibration, validation, and verification [*Araghinejad et al*., 2011]. This approach also overcomes the problem of overfitting the regression to dynamic regimes that may not be representative of the entire data set, as would be the case for a short and very dynamic data range when applying the traditional split sampling technique, and generally results in a better performance when compared to other approaches. The advantages and limitations of different sampling strategies for hydrological models have been presented in other papers, such as *Juston et al*. [2009], and therefore are not discussed in detail here.

Table 5 presents selected mathematical equations for modeling SAVI and SAWAI in the different regions. The goodness-of-fit results, confidence stability, and confidence maturity criteria show that the selected solutions were accurate and reliable. Among the selected equations, the regression which belongs to SAWAI at Howard Springs had the highest accuracy (Deterministic coefficient (r^2) = 96%, maximum error = 0.3, and mean absolute error = 0.1) and reliability (confidence stability = 99.8% and confidence maturity = 99.8%). Confidence stability

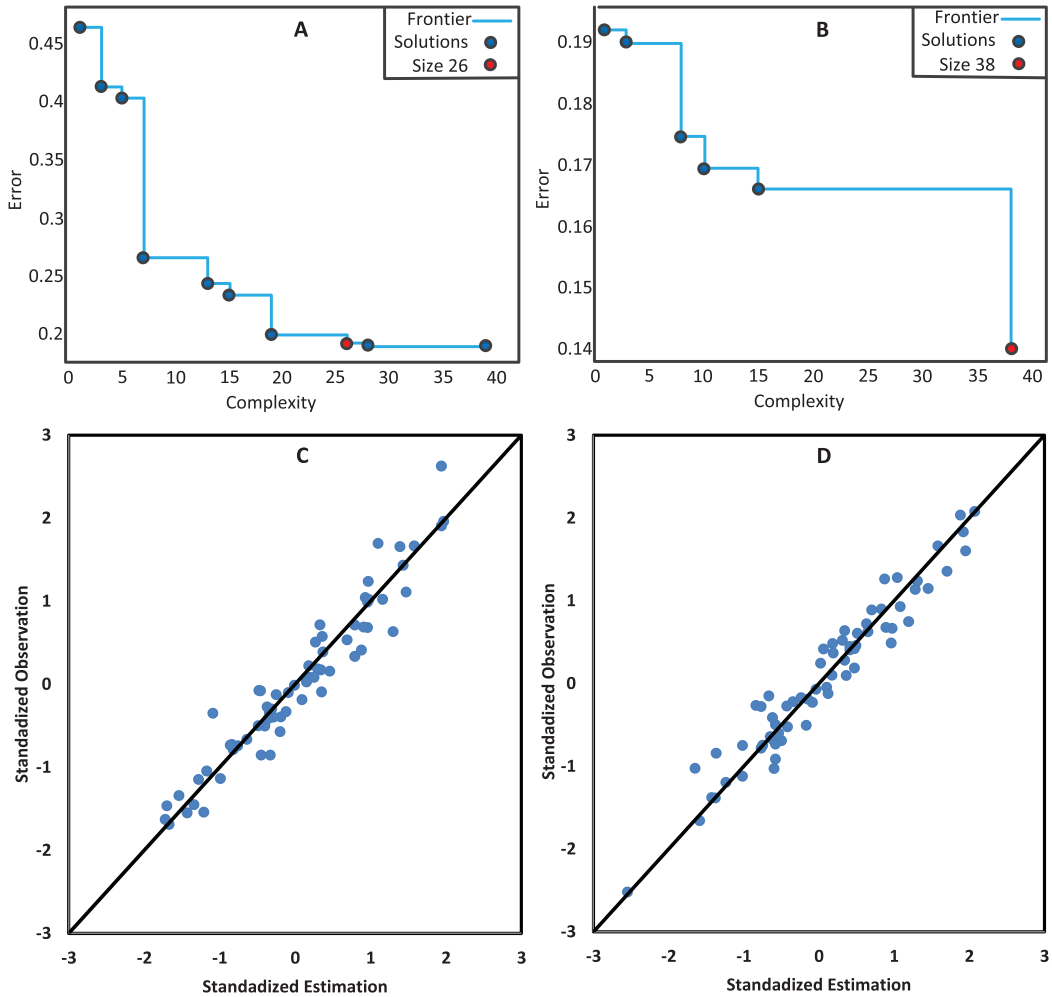

Figure 4. (a and b) Accuracy of the mathematical solution versus complexity within the Symbolic Regression method for SAWAI and SAVI at Riggs Creek, respectively; (c and d) observations versus predicted values derived from the selected mathematical equation for SAWAI and SAVI at Riggs Creek, respectively.

and maturity values close to 100% show that the final list of solutions is strongly reliable (Eureqa User-Manual/website, http://formulize.nutonian.com/documentation/eureqa/). By using these explicit mathematical equations, users can easily derive the values of the proposed DFDI for future water stress monitoring over the considered case study areas; which presents a user-friendly and practical characteristic of the proposed methodology.

For the Riggs Creek OzFlux tower site, the accuracy of the mathematical solution versus its complexity is presented in Figure 4a and 4b. Figure 4a indicates that the optimum equation for SAWAI at Riggs Creek has a complexity size of 26 with mean absolute error of 0.19; while Figure 4b presents the optimum equation for SAVI at Riggs Creek as having a complexity size of 38 with mean absolute error of 0.14. Further, the plot of observations versus predicted values of SAWAI and SAVI are shown in Figure 4c and 4d, respectively. These scatter plots show that the selected equations have the ability to model both nonextreme as well as extreme events appropriately, which is a desirable outcome for water stress monitoring issues.

It is expected to have different mathematical equations for areas with different climate regimes and/or land use-land cover conditions. To apply this methodology spatially (i.e., national scale), the following steps need to be undertaken: (1) following the proposed methodology of this paper, SAWAI/SAVI values would be derived for each grid point, (2) the area would be regionalized once, subject to climate regimes and also according to the land cover/landscape (the outcome of this step would be two regionalization maps), and (3) for each regionalized map, a mathematical equation would be derived between SAWAI (SAVI) and the corresponding independently observed variables.

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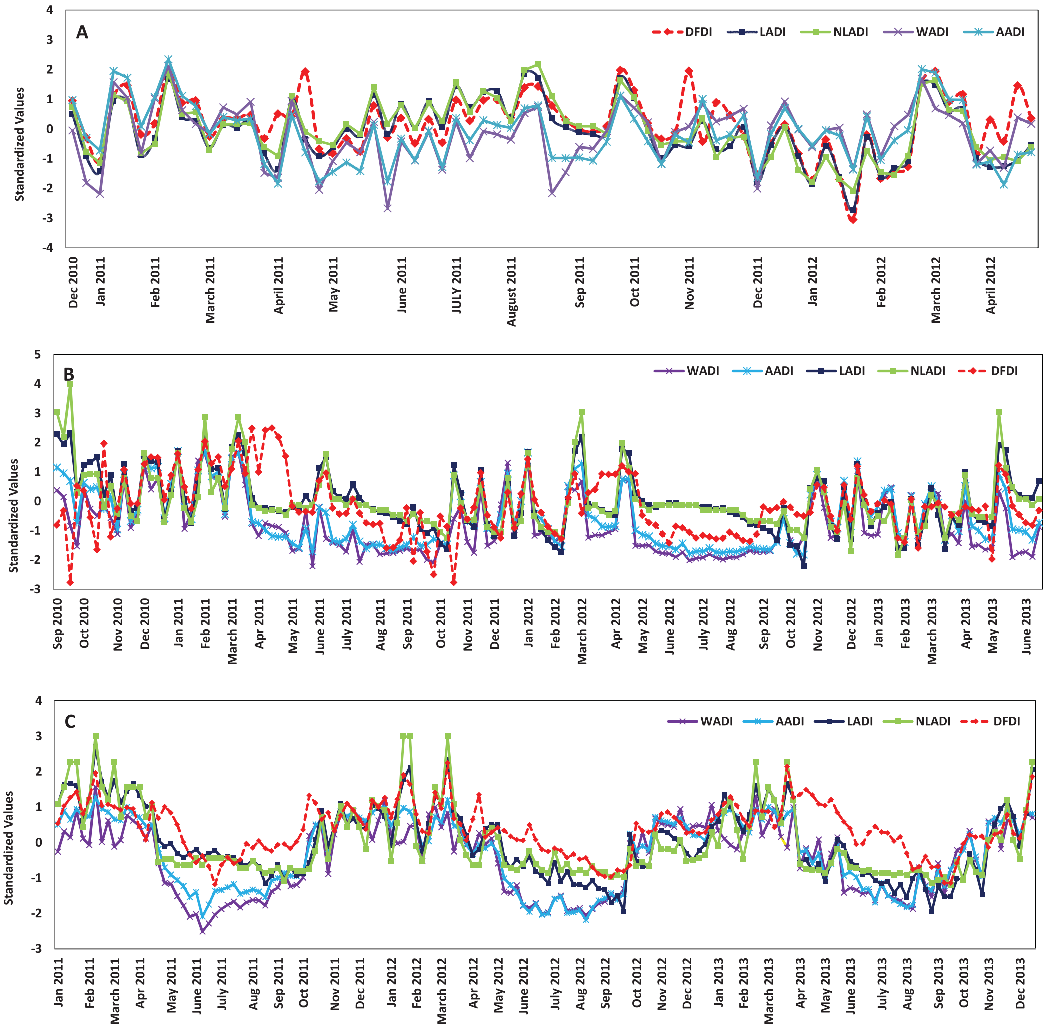

Figure 5. Comparison between commonly used and proposed DFDIs at (a) Riggs Creek, (b) Alice Springs, and (c) Howard Springs.

4.2. Proposed DFDI Versus Commonly Used DFDIs

So far, the proposed DFDI was derived on the basis of addressing the deficits of commonly used SDIs and DFDIs, and its superiorities presented in comparison to single SDIs. Here a quantitative comparison between the proposed DFDI and previously used DFDIs is presented. Time series of four commonly used DFDIs and the proposed DFDI are presented in Figure 5 for the three case studies. It is worth noting that to be able to compare the time series, each of the commonly used DFDIs was standardized by their standard deviation. To comparatively evaluate between commonly used DFDIs and the proposed DFDI, Spearman Rank Correlation (constrained between ±1) were used for determining the best aggregate correlation [*Wilks*, 1995; *Keyantash and Dracup*, 2004], as it removes the problem of non-Gaussian distributions. According to Table 6, the highest Rank correlations were between LADI and NLADI (97%), as well as between WADI and AADI (89%), due to their similar base and foundations. The average of Rank correlation between proposed DFDI and other DFDIs ranged from 60% (proposed DFDI vs NLADI) to 65% (proposed DFDI vs AADI), which shows a moderate correlation.

According to Figure 5, all DFDIs present similar trends from a general point of view. Interestingly, under circumstances in which the proposed DFDI is considered equal to SAWAI, the values of the proposed DFDI are mostly located between the maximum and minimum values derived from other DFDIs. Nevertheless, in other cases in which the DFDI is equal to SAVI, the proposed DFDI mostly presents maximum or minimum values with reference to others. For all three cases, AADI and WADI tend to reflect minimum values from

Table 6. Comparison Between Commonly Used Data Fusion-Based Drought Indices and the Proposed Drought Index Using the Spearman Rank Correlation Coefficient at the Different Locations[a]

	LADI			NLADI			WADI			AADI		
DFDIs	RG	AS	HS	RG	AS	HS	RG	AS	HS	RG	AS	HS
PDFDI	0.72	0.47	0.72	0.72	0.42	0.67	0.55	0.67	0.67	0.58	0.62	0.76
LADI				0.97	0.97	0.97	0.55	0.54	0.73	0.68	0.66	0.87
NLADI							0.44	0.46	0.71	0.58	0.59	0.84
WADI										0.85	0.91	0.91

[a]RG: Riggs Creek; AS: Alice Springs; HS: Howard Springs.

April to September in comparison with others. In fact, the abovementioned period covers the end of autumn, winter, and early spring in the southern hemisphere, therefore the values of air temperature are the lowest, and consequently the values of AADI and WADI which are based on a weighted average of air temperature and two other hydrological variables drop regardless of the actual water availability situation and vegetation conditions. Considering that LADI and NLADI are in fact aggregated drought indices of a set of SDIs derived from water contents variables, it was expected to have high similarities between these two indices and the proposed DFDI in months in which it is calculated based on SAWAI. However, during other months (proposed DFD is equal to SAVAI) at times remarkable discrepancies are apparent. This occurs because the reference of the proposed DFDI to detect the water stress of an area during those months is based on the vegetation conditions which depends on the water availability of the area during a previous time steps (here previous weeks) due to the presence of a lag time between water availability and its influence on vegetation.

One limitation of any statistical model is the requirement for data that describe the diverse hydroclimatological and plant physiological variables, both in space and time. This study benefits from a variety of stations that provide such local data sets. In areas without advanced instruments, the current algorithm can be applied using input data from nearby synoptic stations (suitable where there is a comparatively low spatial variability in the surface conditions), along with global distributed data sources such as model outputs (e.g., reanalysis data sets such as NCEP/NCAR) and remotely sensed data products (e.g., MODIS and Landsat).

5. Conclusions

A comprehensive, robust, and user-friendly water stress (drought) index is required by decision support system models to obtain more information for an improved water resources management and planning. Nonetheless, evaluation and monitoring of water stress over a terrestrial ecosystem is much more complicated than using single drought indices such as SSMI or PDSI. In the current study, a data fusion-based drought index (DFDI) has been introduced to describe water stress based on coincident information from different single drought indices. In this way, the proposed DFDI uniquely describes water stress conditions beyond the traditional individual meteorological, hydrological, and agricultural subcategories. The proposed DFDI considers simultaneously the water availability of the system and the water stress conditions of vegetation to analyze different situations. Three case studies, with different climate and land use conditions, were selected to describe the ability to generalize the proposed methodology. The high-resolution data and information required were provided from three sources; the OzFlux Network, the Asia-Pacific Water Monitor (APWM), and the MODIS-Terra satellite. The main findings of this study include:

1. Confirmation of previous studies showing that individual SDIs are not sufficient to be applied in all circumstances, particularly in terms of diverse land use and climate conditions.
2. Some DFDIs, such as WADI and AADI, which are formed on the basis of empirical equations along with subjective assumptions, cannot be generalized as a comprehensive index.
3. Two DFDIs (LADI and NLADI) always consider fixed hydrometeorological variables/proxies during their aggregating process. However, in some cases, such as human or measurement errors, some of those variables may be inconsistent with others, and therefore ignoring those at times would make the final results more precise. In the current study, the process of filtering the SDIs was performed using Probabilistic Similarity Method to allow for this.

4. The presence of more SDIs during the process of combination may lead to a more robust DFDI, and selective ignorance of some SDIs does not appear to affect the results significantly. For instance, the inclusion of the standardized runoff and surface soil moisture index (SROI) at Riggs Creek showed that the proposed DFDI does not have sensitivity to this indicator due to the presence of individual precipitation and soil moisture indices. Therefore, the unavailability of the SROI at Alice Springs and Howards Springs was assumed to be no issue for the results of the proposed DFDI, as long as the other indices are available.
5. One of the main advantages of this study is the explicit inclusion of vegetation condition-based indices alongside water content-based indices to derive the proposed DFDI. Regarding the physical concepts of terrestrial ecosystems during dry and active months, employing only water content-based SDIs during the process of combination is quite insufficient. Therefore, to have a comprehensive DFDI, it is necessary to consider both aggregated indices such as the Standardized Aggregated Water Availability Index (SAWAI) and Standardized Aggregated Vegetation Index (SAVI), subject to different months in terms of wet/dry conditions and active/nonactive situations.
6. In order to make the proposed DFDI as user-friendly and applicable as possible, a symbolic regression approach was used to derive explicit mathematical equations for SAVI, SAWAI, and consequently the proposed DFDI. Here, the three considered case studies resulted in average values of the goodness-of-fit criteria for SAVI and SAWAI as follows: $r^2 = 95\%$, Maximum Error = 0.45, and Mean Absolute Error=0.13. In this case, users such as water managers and other decision makers can rely on the equations to derive values of the proposed DFDI at any specific time for the considered areas.
7. In the past, new proposed indices have been validated based on their degrees of similarities (correlation) when compared to SPI or PDSI [*Keyantash and Dracup*, 2004; *Balint and Mutua*, 2011; *Barua et al*., 2012; *Zhang and Jia*, 2013; *Li et al*., 2015]. i.e., in case the new indices followed the behavior of SPI and or PDSI, they were considered as validated. However, this negates the development of new indices, as they then mimic the behavior of the existing ones. According to a recent review [*Hao and Singh*, 2015], no reliable "ground truth" exists (for a drought index) that may be used as an ultimate reference for the exact validation of a new index. In particular, the traditional indices (e.g., SPI and PDSI) have limitations and follow assumptions which have led to the development of new indices [*Keyantash and Dracup*, 2002; *Van Loon and Van Lanen*, 2012]. The present study independently validated the behavior of the proposed DFDI by comparing the physics and nature of the considered terrestrial ecosystems in addition to the climate conditions (classifying each month to wet and dry) and land use of the area (clustering each month into active and nonactive, subject to the type of dominant plants of the area). For this purpose, the two main elements of the terrestrial ecosystem consisting of the water balance (input water, storage water, output water) and the vegetation growth were considered for each month to identify the most appropriate driver responsible for the actual system water stress. According to the proposed methodology, SAWAI can specify the status of the water balance in terms of input (i.e., SPI), the storage (i.e., SSMI), and the output (i.e., SEFI and SROI) elements together, and SAVI can reflect the period of active vegetation (i.e., SNDVI), which together may indicate the water stress of the ecosystem.
8. The methodology section of this paper has presented as the first step the acquisition of an appropriate set of hydroclimatological variables to cover different aspects of water contents, plant water consumption, and vegetation conditions. It does not mean that the current set of the considered individual DIs is a fixed and strict selection. The selected indices will ultimately be driven by data availability, but will need to represent those three main domains. Moreover, regional differences may be found, as the underlying hydrological and plant-physiological drivers are unlikely to be the same between water and energy-limited environments.
9. This paper presents a proof-of-concept study, developing a robust index for comprehensive water stress monitoring using advanced statistical methods and sources. The temporal coverage of the full range of variables is very limited throughout the world, making the development and validation of such an approach challenging. This study focused on data collected from flux stations throughout Australia, providing a broad range of climatological and hydrological conditions across their short observation period. Despite the limited length of data, the results of the validation process are nonetheless promising and show the value of the methodology when confronted with significant data deficits. As with any statistics-based approach, longer data sets will make this type of model more robust in its estimating and

predictive skills. However, no monitoring site provides observations across the full spectrum of variables for a sufficiently long period. Consequently, future studies should assess the use of modelled data from climatological reanalyses to provide a consistent, long-term data set. This approach will then also allow quantifying the uncertainty introduced by the initial assumption that the long-term statistics of the hydrological dynamics throughout the monitoring stations were indeed covered by the short period of available data. Despite the limitations of the data set, it was shown that it is possible to derive useful information and create meaningful variable clusters by using an appropriate drought index which can be further developed for evaluating water stress-based issues.

Appendix A: The Relationship Between Dryness/Wetness Criteria and Active/Non-active Vegetation Conditions

The relationship between the status of a month in terms of dryness/wetness and active/nonactive vegetation, as well as the selection of the appropriate drought indices can be described based on one of the following categories:

1. If time i falls within a wet month, no matter that the month is plant-physiologically active or nonactive, the water stress monitoring can be appropriately evaluated by drought indicators such as the standardized precipitation index (SPI) which reflect the water contents. This is because the water balance of the system is much more sensitive to inputs such as precipitation and streamflow than outputs such as real evapotranspiration.
2. If time i falls within a dry and active month, the water stress monitoring can be assessed by drought indicators such as the normalized difference vegetation index (NDVI), which can be seen as a proxy reflecting the water consumption and vegetation growth. This is because the water balance of the system is much more sensitive to outputs such as actual evapotranspiration rather than inputs such as the amount of precipitation, which are usually reduced during this period.
3. If time i falls within a dry and nonactive month, the water stress monitoring can be appropriately evaluated by drought indicators which reflect the stored water such as the soil moisture drought index. This is because plants are usually in shut-down conditions and their water consumption would be insignificant, in addition to there being no remarkable input to the system in these cases.1

Appendix B: The Probabilistic Similarities-Based Clustering Method

The Probabilistic Similarity Method includes following steps:

1. Providing two new sets of SDIs based on imposing time lags of 1 and 2 on the primary set of SDIs. These two data sets along with the primary set of SDIs are considered as input data sets;
2. Considering two sizes of clusters equal to 3 (three main drought types) and 4 (e.g., to represent an interstitial group between main groups) for the current study;
3. Employing three linkage methods of Single, Average, and Ward, as well as three distance functions of Euclidean, Pearson correlation, and Spearman rank Correlation;
4. Considering all different combinations of cluster sizes, linkage methods and distance functions (2 cluster's size $\times$ 3 linkage methods $\times$ 3 distance functions $=$ 18 different combinations);
5. Clustering all variables based on the 18 different combinations of the previous step;
6. Calculating the probabilistic similarities between a pair of variables (with and without time lags) (PS_{ij}) as follows:

$$PS_{ij}=\frac{n}{N}\times 100=\frac{n}{C\times L\times S}\times 100 \tag{B1}$$

where n is the number of times that two variables (ij) are located in the same cluster; N is the total number of all different combinations of clustering (in the present case, this is equal to 18); C is the number of considered cluster sizes (here 2); L is the number of considered linkage methods (here 3); and S is the number of considered similarity functions (here 3);

Calculating the average between all PSs of a pair of SDIs (with and without time lags) to derive a final probabilistic similarity for each pair of drought indices;

In addition to deriving probabilistic similarities between each pair of SDIs, by defining thresholds for PSs, it is possible to reach a deterministic clustering for SDIs. We have proposed PSs greater than 60% as "strong similarity", between 40% and 60% as "moderate similarity" and finally less than 40% as "weak similarity."

To define the thresholds, first, it is assumed that the degree of consistency between members of a cluster has a linear correlation with average PSs of a set of variables, and further that PSs between a set of variables statistically follow a standard normal probabilistic distribution function. Therefore, Z scores between -0.67 and $+0.67$ cover 50% of all events which are defined as moderate conditions, while the remainder represent extreme conditions. Transferring this range of Z scores to the 0–100 scale, this would be represented by 40–60. Therefore, PSs between 40% and 60% ($-0.67<Z<+0.67$) represent those moderate conditions, or in other words "moderate similarity." Consequently, PSs greater than 60% ($Z>+0.67$) and less than 40% ($Z<-0.67$) can show "strong" and "weak" similarities, respectively (extreme conditions). All SDIs with a "strong similarity" can definitely be located in one cluster; while SDIs which have "weak similarity" with others may be considered as a single-member cluster.

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