

# Centennial-scale variability of soil moisture in Eastern Australia

**A.J. Gibson<sup>1</sup>, G.R. Hancock<sup>1</sup>, D.C. Verdon-Kidd<sup>1</sup> and T. Wells<sup>2</sup>**

<sup>1</sup>*School of Environmental and Life Sciences, Faculty of Science, The University of Newcastle, Australia*

<sup>2</sup>*School of Engineering, Faculty of Engineering and the Built Environment, The University of Newcastle, Australia*

Email: [abraham.gibson@uon.edu.au](mailto:abraham.gibson@uon.edu.au)

**Abstract:** Soil moisture is of critical importance to maintaining agricultural productivity and is used as an indicator of agricultural drought. Antecedent soil moisture conditions are also important in forecasting catchment runoff and water storage levels. In-situ measurements of soil moisture, however, are exceedingly sparse at a global scale compared to most other hydroclimatic variables, and the temporal coverage of most records is limited to 15–20 years at best. To overcome this, water balance models have been developed and applied to evaluate soil water availability at centennial-scales. These include the Australian Water Availability Project (AWAP) Waterdyn model, and the Australian Water Resource Assessment (AWRA-L) models; two of the major water balance models used in Australia.

This study looks to extend on their validation and application using a unique in-situ soil moisture data set from the Scaling and Assimilation of Soil Moisture and Streamflow (SASMAS) project for the Krui and Merriwa River catchments in eastern NSW, Australia. The two catchments are predominantly grazed and can be considered representative of the wider East Coast of Australia. Modelled outputs were compared against catchment average in-situ data and validated using correlation analyses. Both models performed similarly across both catchments, with the AWAP upper and lower soil moisture layers returning correlation coefficients of 0.60–0.75, while the AWRA-L root zone layer returned correlation coefficients of 0.76–0.78. Following this, long term temporal trends in soil moisture anomalies from 1908–2015 were examined against trends in rainfall cumulative deviation. Soil moisture deficits and cumulative deviation of rainfall were well correlated from 1908–2015 ( $r = 0.79$ – $0.84$ ), as was shown by the response of soil moisture to major droughts across SE Australia. Across the entire timeseries, no significant trend could be found.

Many studies exist that look at this issue in response to the recent Millennium Drought across the Murray-Darling Basin, however, the East Coast of Australia is identified as its own separate climate entity. Understanding soil moisture trends in this understudied area, where agricultural, environmental and industrial water needs intersect is important. A key finding was that rainfall and soil moisture deficits were more severe during the WWII Drought than the Millennium Drought. This needs to be accounted for in drought management strategies.

**Keywords:** *Soil moisture, AWAP, AWRA-L, rainfall, agriculture, drought*

## 1. INTRODUCTION

Soil moisture is a key environmental variable in regulating erosion, runoff, deep water storage, plant growth, soil health and a critical component of the carbon cycle (Holgate *et al.*, 2016). Its management is critical to agricultural productivity, and it is a key indicator of agricultural drought. Quantification of soil moisture, therefore, is required to predict and measure drought in this space. However, there are few in-situ measurement datasets that are both spatially and temporally extensive. Soil moisture monitoring networks, such as the SASMAS network, utilise point-based instrument measurements. These networks are costly to establish and intensive to maintain, resulting in tradeoffs between spatial and temporal resolution (Rüdiger *et al.*, 2007). While alternate methods include field campaigns (also labour intensive) and remotely sensed products, both of which have limited temporal resolution and varying spatial resolutions (Holgate *et al.*, 2016).

In the absence of field data, continental-scale water balance models provide a means to understand trends in soil moisture to inform management decisions (Frost *et al.*, 2015, Raupach *et al.*, 2009). Two of these are the AWAP Waterdyn and AWRA-L models. These models not only estimate current conditions of the Australian water balance but also provide the opportunity for hindcasting. Studies using these model outputs are extensive and use point-based validation across a variety of locations (Frost *et al.*, 2015, Holgate *et al.*, 2016, Raupach *et al.*, 2009). Few studies, however, have looked at catchment-scale trends across the entire output record in the high rainfall zone of eastern Australia (Frost *et al.*, 2015, Holgate *et al.*, 2016, Raupach *et al.*, 2009). To better inform drought management in agriculture, this study aims to extend on the validation of the AWAP and AWRA outputs for two catchments in eastern NSW, and to use these model outputs to assess the temporal variation in soil moisture over a centennial-scale.

## 2. DATA AND METHODS

### 2.1. Study Site

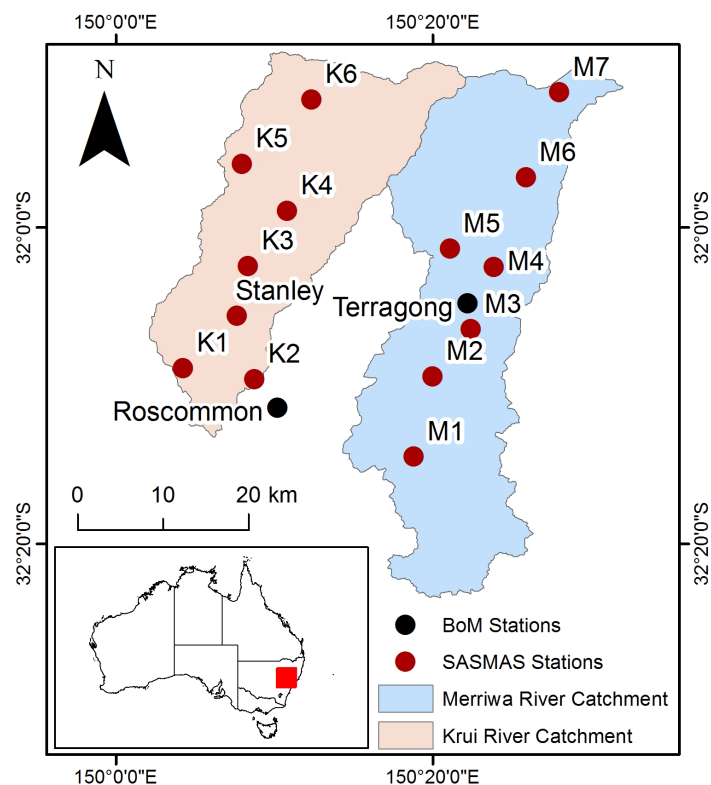
The analyses were carried out in the Krui (585 km<sup>2</sup>) and Merriwa (808 km<sup>2</sup>) River catchments in eastern NSW. The catchments have a strong elevation gradient, ranging from 500 m in the south to >1000 m in the north. Associated with this is a strong rainfall gradient, with average annual totals ranging from 500–1000 mm.yr<sup>-1</sup>. Underlying geology is Tertiary basalt on the hillslopes with Jurassic sedimentary sequences exposed in the river valleys. Dominant soil types are; eucrozerms, chromosols, vertisols and dermosols. These soils are highly fertile with high clay content and so are agriculturally significant. The predominant land use is grazing, with some cropping occurring on the floodplains, while the northern reaches of both catchments are densely forested. The catchments are considered hydrologically and geomorphologically identical (Kunkel *et al.*, 2019). These characteristics are representative of the wider East Australian Coast.

### 2.2. SASMAS Soil Moisture Data

The SASMAS network consists of 23 monitoring stations distributed across the greater Goulburn River catchment. Here, catchment-average soil moisture from six stations within the Krui catchment (K1–K6) and seven within the Merriwa catchment (M1–M7) was used for validation of the modelled datasets (Figure 1). The seven stations located in the Stanley subcatchment were not included as to not bias the catchment average. Soil moisture at each site is recorded using a vertically inserted Campbell Scientific CS616 water content reflectometer at depths of 0–300 mm, 300–600 mm and 600–900 mm. Soil moisture is recorded every twenty seconds and then aggregated at five-minute intervals (Rüdiger *et al.* 2007). This data extends from 2003 to 2015, and so represents conditions during and after the Millennium Drought (Gibson *et al.*, 2019). These datasets were, on average, 84.4 % complete. For comparison with modelled outputs, this data was aggregated to a monthly time-step.

### 2.3. AWAP Soil Moisture: The Waterdyn Model

The AWAP project is a cooperative effort to assess the water balance of Australia between the Commonwealth Scientific and Industry Research Organisation (CSIRO), BoM and the Australian Bureau of Agricultural and Resource Economics and Sciences. Using the Waterdyn model, soil moisture, as a percent of volumetric saturated water content, was calculated at a resolution of 0.05° across the whole of Australia. Here, soil moisture for the model upper (0–200 mm) and lower (>200 mm) layers are compared with the 0–300 mm and an average taken from 300–900 mm depth from the SASMAS field data, respectively (Raupach *et al.*, 2009). Data is available from 1900 to present day years and stationarity was tested for using the Augmented Dicky-Fueller test. This test uses a null hypothesis that a timeseries is non-stationary (has a systematic pattern present). Large critical values reject this hypothesis (Rashid and Beecham, 2019).



**Figure 1.** Location of study catchments and SASMAS monitoring stations.

#### 2.4. AWRA-L Soil Moisture Model

The AWRA-L model derived by CSIRO and BoM, also aims to derive estimates of the nation's water balance and is used to assess drought conditions using soil moisture estimates. Similar to the Waterdyn model, outputs are calculated on  $0.05^\circ$  resolution across Australia. Root zone (0-1000mm) soil moisture as a percent of available water holding capacity were taken from the Version 5 model estimates. This was compared with average soil moisture for the entire SASMAS profile (0-900 mm) as it was the closest corresponding depth (Frost *et al.*, 2015, Viney *et al.*, 2015). For both model datasets, catchment averages were determined from all grid cells in each catchment. Data is available from 1911 to the present, and as for AWAP, stationarity was tested for using the Augmented Dicky-Fueller test.

#### 2.5. Rainfall Data and Soil Moisture Deficit

In the absence of a single, long-term local rainfall record, a composite record was created using data from the Terragong, (1908–1970; no. 61073), and Roscommon, (1970–present; no. 61287) BoM stations. The stations are 20 km apart (Figure 1) but were found to be analogous through regression analyses; Terragong =  $1.03 \times$  Roscommon ( $R^2 = 0.93$ ,  $p < 0.01$ ) (Gibson *et al.*, 2019). Annual average rainfall from this timeseries is  $578 \text{ mm}\cdot\text{yr}^{-1}$ . From this record, monthly rainfall Cumulative Deviation (CD) (to match the soil moisture records) was calculated to highlight periods of water excess and limited availability. For comparison, monthly soil moisture CD was calculated from the two model records from 1908-2015, as this was better correlated than the raw soil moisture data. CD is calculated as the successive deviation from the long-term mean.

### 3. RESULTS

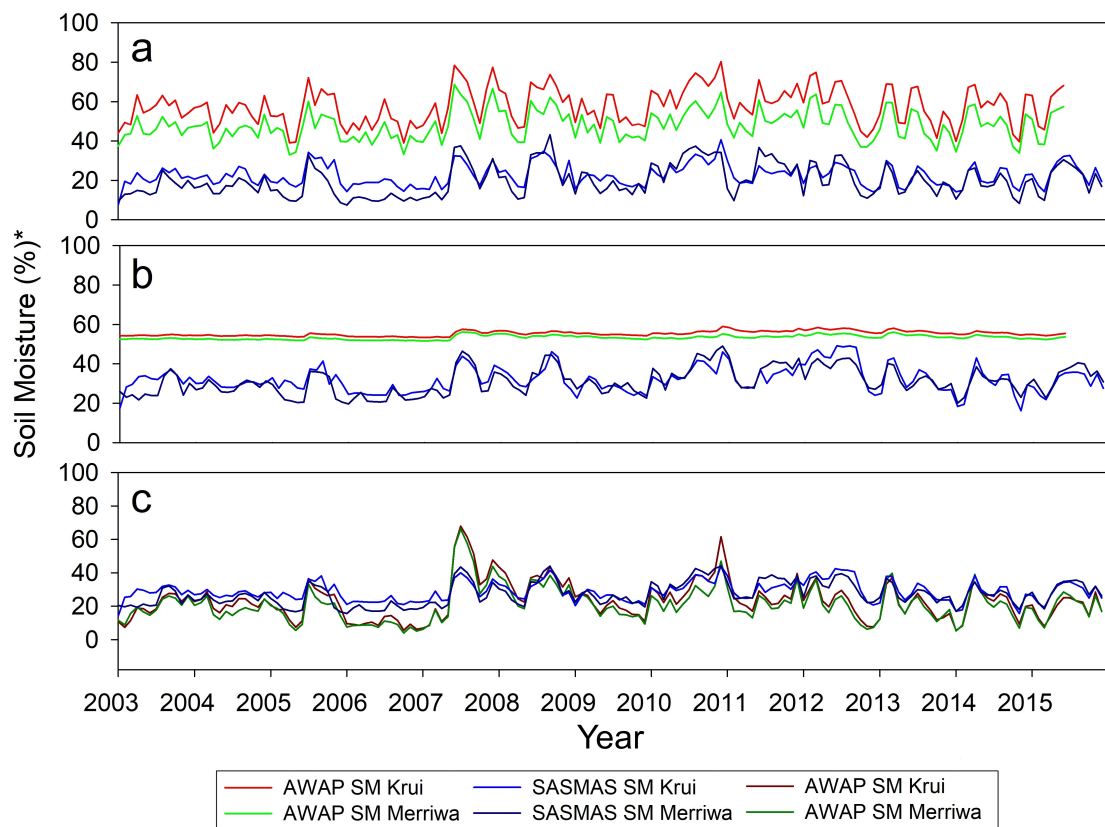
#### 3.1. Model Data Validation

Summary statistics for the SASMAS and the modelled datasets from 2003–2015 are presented in Table 1. Also presented are the correlation coefficients between the field and modelled datasets. Mean values cannot be

directly compared between the three datasets due to the differences in units, however, coefficient of variation (CV) values demonstrate a large degree of variability among the three datasets. CVs decrease with depth in the field data, which is to be expected. This trend is captured in the AWAP data, but CVs for both depths are systematically lower than the field data. In contrast, CVs for the AWRA data (48–50%) are greater than the SASMAS and AWAP datasets (2–16%); highlighting a discrepancy in the variability between the two models. Correlation coefficients are strong (0.75–0.87) between the field data and the corresponding depth of both models, indicating the models are able to capture trends in soil moisture. This is highlighted in Figure 2a-c. These values are similar to published values (Frost *et al.*, 2015, Holgate *et al.*, 2016).

**Table 1:** Mean, standard deviation and coefficient of variation (CV) of the datasets for the Krui (left) and Merriwa (right) catchments from 2003–2015. Correlation coefficients (r) are between modelled data and corresponding field depth ( $p < 0.01$ ). \*% as units outlined in Section 2.

Dataset	Depth (mm)	Mean (%*)		Std. Dev. (%*)		CV (%)		r	
SASMAS	0–300	22.49	19.87	5.55	8.33	24.66	41.94		
	300–600	30.90	30.13	8.15	9.41	26.38	31.24		
	600–900	33.35	32.40	5.78	5.80	17.32	17.90		
AWAP	Upper (0–200)	57.75	48.07	9.40	7.71	16.28	16.04	0.87	0.85
	Lower ( $\geq 500$ )	55.44	53.40	1.27	1.10	2.29	2.05	0.75	0.75
AWRA-L	Root Zone (0–1000)	23.42	20.94	11.46	10.51	48.94	50.18	0.76	0.78



**Figure 2.** Soil moisture timeseries for the SASMAS and modelled data for the AWAP Upper Layer (a) AWAP Lower Layer (b), and, AWRA-L root zone layer(c). \*Units for each dataset are outlined in Section 3.

### 3.2. Centennial-Scale Soil Moisture Variability

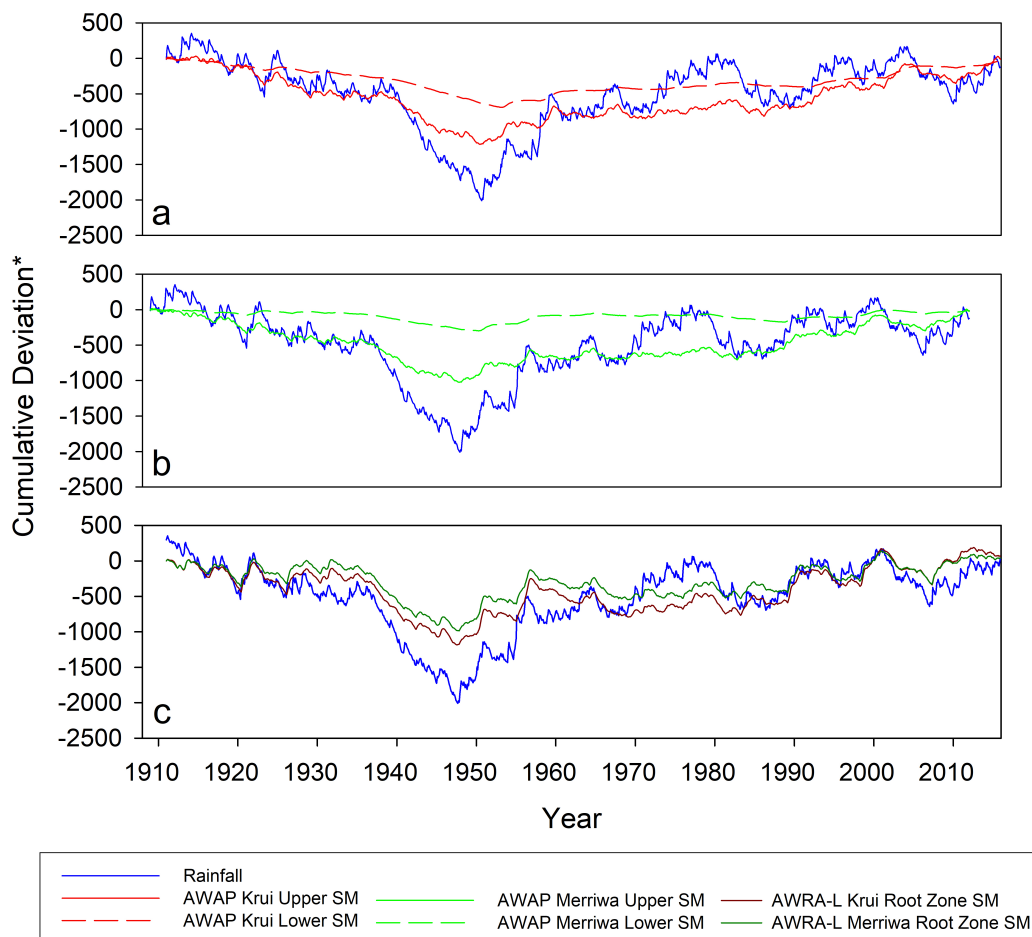
Table 2 presents the CVs for the modelled datasets across their entire timeseries for the two catchments, as well as the correlation coefficients between rainfall and soil moisture monthly CD. Here, all datasets show strong correlation between the monthly cumulative deviation in soil moisture and rainfall and there is also no evidence of non-stationarity in the datasets as determined by using an Augmented Dicky-Fueller Test. CVs are

different across the model timeseries, further highlighting the differences between the models shown in Section 3.1.

**Table 2:** Coefficient of Variation (CV) of entire timeseries soil moisture for each dataset and correlation coefficients (*r*) between monthly rainfall and soil moisture CD for the Krui (left) and Merriwa (right) catchments.  $p < 0.01$  for all correlation coefficients. The large Augmented Dicky-Fueller (ADF) values reject the null hypothesis that the timeseries is non-stationary.

Dataset	Depth (mm)	CV (%)		<i>r</i>		ADF	
AWAP	Upper (0–200)	18.74	18.40	0.84	0.84	-19.18	-20.18
	Lower ( $\geq 500$ )	3.51	2.81	0.79	0.84	-6.37	-7.30
AWRA-L	Root Zone (0–1000)	59.78	61.30	0.81	0.83	-11.37	-12.64

Figure 3a–c shows the timeseries soil moisture data for both modelled datasets across each catchment. CD of both soil moisture and rainfall were used to better visualise water deficits and highlight changes in water availability. Monthly cumulative deviation in rainfall and soil moisture was also better correlated than monthly rainfall and soil moisture; values of 0.3–0.4, compared to those in Table 2. During the period of the WWII drought (1935–1945), strong declines in water availability are evident in the study area, followed by a steady increase to water surplus just prior to 1980. The 1980s and Millennium Droughts show less significant declines in rainfall and soil moisture compared to the WWII event. During these events, the AWAP Upper layer and AWRA-L Root Zone layer are more responsive than the AWAP Lower layer across both catchments. This is further illustrated by the CV values in Table 2. Despite this variation however, there is no evidence of non-stationarity in soil moisture as indicated by the Augmented Dicky-Fueller test results indicating stationarity.



**Figure 3.** Timeseries of monthly cumulative deviation of rainfall and AWAP modelled soil moisture for the Krui (a) and Merriwa catchments (b), and, AWRA-L modelled soil moisture for the Krui and Merriwa catchments (c). \*Units for each dataset are outlined in Section 2.

## 4. DISCUSSION

### 4.1. Model Data Validation

The comparison between observed and model results are similar to previously published values using the AWRA-L and AWAP outputs (Frost *et al.*, 2015, Holgate *et al.*, 2016). However, using catchment-average soil moisture resulted in correlation coefficients that are approximately 0.3 higher than the point-based comparisons in previous studies. This is believed to be most likely due to the hierarchy of controls on soil moisture across the catchment. Point-based controls on soil moisture, such as soil properties and vegetation type and density can be highly variable at much finer scales than the resolution of the models. When an average is taken of these conditions across a large catchment, larger-scale drivers of soil moisture, such as climate and broad land use, exert more influence than point-based controls. As these factors are more homogenous at the resolution of the models, the trends between the observed and modelled data become closer.

In contrast to this, there is a discrepancy between the variability in the field data and the two models. Using CV values allows for the variability of the three datasets to be compared despite the differences in units. It is possible that these differences could be due to the differences in the formulation of the models. Firstly, different spatial datasets are used to describe drainage in the models. Secondly, the calibration of the Waterdyn model to streamflow was limited, while the AWRA-L model was calibrated to estimate whole water balance fluxes and so performs better than the Waterdyn model in estimating streamflow (Raupach *et al.*, 2009, Frost *et al.*, 2015). Monthly CV of rainfall is 88% for the study area from 1908–2015, and so variation in the models could be linked to the allocation of rainfall. However, CVs in the field data are closest to those of the AWAP data in the Krui, while shallow depths in the Merriwa reflect the higher CVs of the AWR-L data. Overall, these results highlight that, while these model products adequately represent trends in soil moisture, the scale and performance of the models for the intended application needs to be considered, particularly if variance/magnitude is important.

### 4.2. Temporal Variation in Soil Moisture

The Millennium Drought (~1995–2009) is often referred to as ‘the worst drought on record’. Verdon-Kidd & Kiem (2009), however, demonstrated that the WWII drought was more severe for certain regions of SE Australia, particularly the east coast. This is demonstrated in the rainfall and soil moisture deficits over the timeseries. Below average rainfall, essentially from the beginning of the record, led to major deficits in water availability, which were only recovered around 1980. Following this, water deficits were much smaller in magnitude in response to major drought. As a result, recent dry periods appear less sustained and intense than others in the observed record for the east coast. Additionally, the results show that rainfall, and in response soil moisture, are stationary and that drying shifts, identified in studies for other areas of SE Australia are not apparent here (Dai *et al.*, 2011, Verdon-Kidd *et al.*, 2014). Rather, the region has experienced a series of protracted droughts interrupted by a return to average (or even wet) periods (Gibson *et al.*, 2019).

Rainfall across SE Australia is widely recognised to be modulated by four major climate modes, and the short-lived but highly impactful 1980s drought is one of the only instance within the historical record where all four of these modes were in their “dry-phase” (Verdon-Kidd & Kiem 2009). Therefore, a repeat of this occurrence sustained over a period similar to the WWII drought would be of concern for water management in the region. Further, paleoclimate reconstruction studies have shown that there have been far more severe and persistent droughts than those seen in the historical record (Ho *et al.*, 2015, Palmer *et al.*, 2015). Similarly, studies indicate that more severe and frequent droughts may occur under climate change (Dai, 2011). As a result, future drought management needs to be prepared for more severe soil moisture deficits than those seen during the Millennium Drought

## 5. CONCLUSION

The importance of soil moisture as a key soil variable regulating ecosystem health and agricultural productivity is increasingly being recognised. In-situ measurements are globally sparse, and temporally limited and therefore alternatively measures need to be identified. In this study, two continental-scale model products were compared with catchment-scale in-situ data and found to be representative of soil moisture trends in an agricultural site in NSW, Australia. Soil moisture has been found to be responsive to drought but no observable trend was found in the timeseries over the last century for the site. Furthermore, given the varied outlooks on drought under paleoclimate records and climate change, it is important that temporal variability in soil moisture conditions is extended beyond the last 15–20 years of field and satellite observations using alternative methods.

Areas such as this may be important due to their reliable water availability for future management and agricultural production, or conversely, at risk to sustained changes in climatic variability.

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