AMERICAN METEOROLOGICAL SOCIETY

Journal of Climate

EARLY ONLINE RELEASE

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The DOI for this manuscript is doi: 10.1175/JCLI-D-13-00149.1

The final published version of this manuscript will replace the preliminary version at the above DOI once it is available.

If you would like to cite this EOR in a separate work, please use the following full citation:

Bauer-Marschallinger, B., W. Dorigo, W. Wagner, and A. van Dijk, 2013: How Oceanic Oscillation Drives Soil Moisture Variations over Mainland Australia: An Analysis of 32 Years of Satellite Observations. *J. Climate*. doi:10.1175/JCLI-D-13-00149.1, in press.

1 **How Oceanic Oscillation Drives Soil Moisture Variations over**
2 **Mainland Australia: An Analysis of 32 Years of Satellite**
3 **Observations**

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ABSTRACT

Australia is frequently subject to droughts and floods. Its hydrology is strongly connected to oceanic and atmospheric oscillations (climate modes) such as the El Niño Southern Oscillation (ENSO), Indian Ocean Dipole (IOD) and Southern Annular Mode (SAM). A global 32-year dataset of remotely sensed Surface Soil Moisture (SSM) was used to examine hydrological variations in mainland Australia for the period 1978-2010. Complex Empirical Orthogonal Function (CEOF) analysis was applied to extract independent signals and to investigate their relationships to climate modes. The annual cycle signal represented 46.3% of total variance and a low but highly significant connection with SAM was found. Two multi-annual signals with a lesser share in total variance (6.3% and 4.2%) were identified. The first one had an unstable period of two to five years and reflected an east-west pattern that can be associated with ENSO and SAM, but not with IOD. The second one, a one to five year oscillation, formed a dipole pattern between the west and north and can be linked to ENSO and IOD. As expected, relationships with ENSO were found throughout the year and are especially strong during southern spring and summer in the east and north. Somewhat unexpectedly, SAM impacts strongest in the north and east during summer and is proposed as key driver of the annual SSM signal. The IOD explains SSM variations in the north, east and south-east during spring and also in the west during winter.

1. Introduction

Climate change is expected to accelerate the global hydrological cycle, with implications for ecosystems and feedback to regional and global climate (Huntington 2006). Precipitation is expected to be less reliable, with intensification of both dry and wet conditions and more extreme rainfall events (and floods) (Trenberth 2011) and an increased risk of aridity and droughts (Dai 2013). Globally, soil moisture, a good indicator of water availability for plant growth, is expected to decrease over large parts of the Earth (Gerten et al. 2007). Surface Soil Moisture (SSM), defined as the water in the top few centimeters soil, is very sensitive to changes in precipitation, temperature, solar irradiation, humidity and wind. It is an important integrator of climatic conditions and can be a driver of local climate (Legates et al. 2010) and weather (Taylor et al. 2012). Variations in heat fluxes are affected by spatial and temporal dynamics in soil moisture, which alter near-surface air temperature and humidity. Consequently, soil moisture estimation can be a critical skill in temperature, humidity and precipitation forecasts (Koster et al. 2004). Earlier research illuminated the feedbacks of large-scale soil moisture anomalies on atmospheric conditions for the particular case of Australia (Simmonds and Lynch 1992; Simmonds and Hope 1998). Soil moisture, being a state variable, has certain benefits for monitoring hydrological conditions when compared to flux variables such as precipitation or evapotranspiration, whose observation is generally more demanding. Since 2008, soil moisture is listed as an Essential Climate Variable (ECV) within the framework of the Global Climate Observing System (GCOS) (Blunden and Arndt 2012).

The hydrology of Australia is highly variable and the continent is frequently subject to droughts and floods. Recently, there have been several extreme dry and wet events, including a protracted drought from 1995/2001 to 2009 known as "Big Dry" or "Millennium Drought" (Ummenhofer et al. (2009); van Dijk et al. (2013)), continually dry conditions in south-west Western Australia since the 1970s and extensive floods from 2009 to 2012 (e.g. Channel Country 2009-2010, Queensland 2010-2011). Surrounded by oceans and located in

the tropics and subtropics, Australia’s hydrology responds strongly to changes in global ocean circulation patterns. Its mainly semiarid to arid characteristics and the lack of significant mountain ranges make it sensitive to climate modes.

Climate modes are large-scale oceanic or atmospheric oscillations which can have a global as well as a specific regional impact. Different climate modes interact directly or via teleconnections across the globe. Within a region, oceanic oscillations are coupled to atmospheric effects that appear as variations in the direction and strength of major winds patterns, giving rise to precipitation anomalies (Field et al. 2012). At least three major climate modes that are relevant for Australia’s hydrology have been identified (Nicholls (2009); Risbey et al. (2009); Verdon-Kidd and Kiem (2009); an overview is given by van Dijk et al. (2013)). (1) The El Niño Southern Oscillation (ENSO) refers to climate phenomena resulting from interactions between coupled large-scale oceanic and atmospheric circulation processes in the Pacific region (Solomon et al. 2007). It is driven by cyclic cooling and warming of the equatorial Pacific (termed El Niño and La Niña phases as opposite) coupled with fluctuations of an atmospheric global-scale tropical and subtropical surface pressure pattern. El Niño and La Niña events cause dry and wet anomalies, respectively in Australia and the entire western Pacific area (Chiew et al. 1998). (2) The Indian Ocean Dipole (IOD) is an irregular cycle of warming and cooling of ocean waters in the equatorial Indian Ocean and was first described by Saji et al. (1999). The phases of the IOD oscillation are termed positive, negative and neutral. During a positive event, evaporation, convective activities and precipitation are reduced in Indonesia and Australia and augmented in eastern Africa (Saji and Yamagata 2003). These effects are inverted during a negative event when north-westerly winds are generated that pick up moisture from the ocean and carry it deep into Australia’s south-eastern parts, as described earlier by Nicholls (1989) and examined by Simmonds (1990) and Simmonds and Rocha (1991). Yuan and Li (2008) described in detail the nature of the ENSO-IOD interactions, while Ummenhofer et al. (2009) and van Dijk et al. (2013) examined the relationship of south-east Australian droughts with Indo-Pacific interactions. (3) The Southern

Annular Mode (SAM) (also known as Antarctic Oscillation (AAO) as defined by Gong and Wang (1999)) describes an oscillating pattern of weaker and stronger westerly winds between mid and high latitudes on the southern hemisphere. The SAM positive phase is linked to negative sea level pressure anomalies over the polar regions and intensified westerly winds (Field et al. 2012). During a negative SAM event, an equator-ward expansion of the jet stream is experienced and the belt of (weaker) westerly winds expands towards the equator. Depending on the season of the year, this latitudinal shift of the westerly winds (and hence low pressure systems) can alter precipitation patterns in the southern hemisphere.

Present studies on the impact of climate modes on the hydrology of Australia show some agreement but also contradictions: Chiew et al. (1998) linked ENSO to long-term data on rainfall, droughts and streamflow in Australia, associating dry conditions during the latter part of the calendar year with El Niño. Liu et al. (2007, 2009) found evidence of strong connections of ENSO to remotely sensed SSM variation in spring and winter season, and to a lesser extent in autumn and summer. However, Verdon-Kidd and Kiem (2009) argued that ENSO alone cannot explain major droughts in south-east Australia (SEA). Ummenhofer et al. (2009) investigated observation and reanalysis datasets over SEA and found a clear impact of the IOD that exceeded the contribution of ENSO. García-García et al. (2011) and Forootan et al. (2012) examined water mass variations derived from Gravity Recovery And Climate Experiment (GRACE) data. The latter found that Indo-Pacific influences on Australia's hydrology are regionally different: ENSO affects predominantly northern and eastern Australia, while IOD impacts the south and SEA. This appears to contradict the findings of Timbal and Hendon (2011), who asserted that ENSO and IOD did not contribute to rainfall deficits during the Millennium Drought as they affect only spring rainfall only, whereas the main rainfall deficits were in fall and winter. This is supported by the work of Nicholls (2009), who concluded that southern Australia's rainfall variability during fall and winter can not be explained by changes in tropical phenomena like ENSO and IOD, but instead are driven by the extra-tropical SAM. Meneghini et al. (2007) found a positive

relation between rainfall variability in northern Australia with SAM and negative relation in southern Australia, but in the latter case for winter only.

For this study, we considered soil moisture as an integrator of near-surface hydrological processes over Australia, recognizing that previous studies examined the hydrology in different regions and periods and with diverse data. The relationship with precipitation is not necessarily a direct one, as soil moisture storage is the combined result of precipitation, evapotranspiration and soil moisture redistribution. Our study aimed to clarify the contribution of climate modes on the variability of soil hydrology over all of mainland Australia by investigating the multi-decadal remotely sensed surface soil moisture (SSM) dataset. Key questions were: 1) Does the remotely sensed SSM variation consist of separable signals? 2) If so, what are the spatial and temporal patterns of these separate signals? 3) Can these separate signal be linked to the climate modes ENSO, IOD and SAM?

Remote sensing has demonstrated capability in observing SSM in a globally consistent and comprehensive way (de Jeu et al. 2008). Liu et al. (2012) and Wagner et al. (2012) presented a global 32-year SSM dataset, covering the period from October 1978 to December 2010. This is the very first observation-based global dataset describing SSM over such a long period. Its data were collected from four passive and two active satellite microwave sensors. Our study was motivated by the very first possibility of analyzing remotely sensed SSM variations over a continuous period of 32 years.

In this study, the SSM history of Australia was first derived from the multi-decadal dataset and then decomposed into seasonal means. Complex Empirical Orthogonal Function (CEOF) analysis was then applied to the SSM data to extract the principal signals in Australia’s soil hydrology, in the form of paired spatial and temporal functions. The CEOF technique was chosen because of its proven capability to reveal propagating patterns in geophysical data fields. Connections between the principal SSM CEOF functions and candidate climate indices were examined with Spearman rank correlation analysis, to identify the spatial distribution and the strength of their relationship.

2. Data and Methods

a. Climate Mode Indices

Climatic oscillation patterns such as ENSO, IOD and SAM are described by normalized indices. The index' magnitude quantifies the strength and the sign indicates the phase of the oscillations.

The *Southern Oscillation Index (SOI)* defined by Troup (1965) is a measure of ENSO and is determined by differences of atmospheric pressure at Tahiti in equatorial Pacific and Darwin in northern Australia. SOI was preferred to other ENSO indices since it is based on conditions in the western Pacific. Strong positive values are associated with La Niña episodes and strong negative values with El Niño, respectively. The monthly SOI-data used in this study was available from the Australian Bureau of Meteorology (BOM <http://www.bom.gov.au/climate/enso/>).

IOD is characterized by the *Dipole Mode Index (DMI)*, which is the normalized difference between sea surface temperatures (SST) in the western and the south-eastern tropical Indian Ocean (Saji et al. 1999). The phases of the IOD are named positive and negative according to the sign of the DMI. The monthly data used here were obtained from http://www.jamstec.go.jp/frcgc/research/d1/iod/e/iod/dipole_mode_index.html

Finally, the *Southern Annular Mode Index (SAMI)* is the difference between the normalized monthly zonal mean sea level pressure (MSLP) in the Southern Ocean at 40° and 70° south, respectively. Proposed by Nan and Li (2003), SAMI is a modification of the original definition as *Antartic Oscillation Index (AOI)* by Gong and Wang (1999). We chose SAMI because of suitable time coverage and high correlation with other SAM indices as shown by Ho et al. (2012). The SAMI data was available from <http://ljp.lasg.ac.cn/dct/page/65572>

The monthly climate indices were resampled to seasonal means, to derive values for (southern) summer (DJF), fall (MAM), winter (JJA) and spring (SON) for the period from

December 1978 to November 2010.

b. ECV SM Multidecadal Surface Soil Moisture

The remotely sensed 32-year SSM dataset used here was constructed and distributed as part of the European Space Agency’s (ESA) Water Cycle Multimission Observation Strategy (WACMOS) and Soil Moisture Climate Change Initiative (Soil Moisture CCI) projects (Liu et al. 2012). The dataset (named the Essential Climate Variable Soil Moisture, ECV SM) combines two different types of microwave earth observation systems and six separate missions. It comprises data from four passive systems, including the Scanning Multichannel Microwave Radiometer (SMMR) onboard Nimbus-7 (1978-1987), the Special Sensor Microwave Imager (SSM/I) of the Defense Meteorological Satellite Program (1987-2007), the Tropical Rainfall Measuring Mission Microwave Imager (TMI) (since 1997) and the Advanced Microwave Scanning Radiometer-Earth Observing System (AMSR-E) onboard the Aqua satellite (since 2002). Data from active microwave sensors are from the Scatterometers (SCAT) onboard the European Remote Sensing satellites (ERS-1/2) since July 1991, and the Advanced Scatterometer (ASCAT) onboard the Meteorological Operational satellite program (MetOp-A) that was launched in October 2006.

SSM estimates from passive data were obtained with the Vrije Universiteit Amsterdam – National Aeronautics and Space Administration (VUA-NASA) algorithm, which is based on the Land Parameter Retrieval Model (LPRM, Owe et al. (2008)). For the active sensors, SSM estimates were provided by the Vienna University of Technology (TU-Wien) change detection algorithm originally developed for SCAT onboard ERS (Wagner et al. 1999) and applied with minor adaptations to ASCAT (Naeimi et al. 2009). The combination of passive and active microwave satellite-based retrievals in the ECV SM product offers enhanced data coverage and density for SSM at global scale (Liu et al. 2011, 2012). A global trend analysis was performed by Dorigo et al. (2012), showing consistency with trends in vegetation and precipitation data as well as with land surface models. The ECV SM data is available from

<http://www.esa-soilmoisture-cci.org/>. Detailed overviews at the quality and error characteristics of the merged ECV SM product are given in Albergel et al. (2013), Loew et al. (2013) and Dorigo et al. (in review).

The ECV SM dataset consists of time series of daily data at a 0.25° -grid over global land masses, excluding grid cells containing sea, lakes permanent snow/ice cover or dense vegetation. For Australia this includes about 11,000 grid cells each spanning a daily time series of 32 years. For this study, the SSM daily time series were resampled to seasonal means, the same way as done for the climate indices.

The dataset suffers from some data gaps (Loew et al. 2013; Dorigo et al. in review). There are gaps over vegetated areas in the north and east of Australia, especially for the period 1987 to 1991. This is due to the short wavelength used by the SSM/I sensors, which limits the retrieval of soil moisture to areas with no or sparse vegetation. Power supply degradation affected the observations of SMMR in 1986 and caused further discontinuity in the data. A calibration issue disturbed observations of ERS 1 SCAT in 2001 and caused anomalies in the data, too. To avoid artefacts from anomalies or partial data, we disregarded all data for MAM/JJA 1986, DJF-SON 1991 and DJF 2001-MAM 2003 and obtain a sample size for each season of 28 to 30, totaling 116 all seasons combined.

c. Complex Empirical Orthogonal Function (CEOF) Analysis

A Complex Empirical Orthogonal Function (CEOF) analysis was applied to the ECV SM data in order to derive the dominant signals and patterns of its variability (called *modes*). With this method, the ECV SM data, considered as a statistical field, was decomposed into uncorrelated complex-valued vectors in time (Complex Principal Components, CPC) and space (Complex Empirical Orthogonal Functions, CEOF). Specifically, we used Hilbert Empirical Orthogonal Functions Analysis, introduced by Rasmusson et al. (1981), based on the relation of the data samples with their (shifted) Hilbert transforms. The methodology followed the generic recipe by Hannachi et al. (2007) with computational improvements by

Wilks (2011). To deal with data gaps, the methods by von Storch and Zwiers (2002) were applied.

CEOF analysis was favored over non-complex EOF analysis due to its ability to detect the propagation of spatial patterns, enabling the analysis of moving modes. The main advantage for our study is that it reveals (in addition to the variance characteristics) the change of the geophysical processes (von Storch and Zwiers 2002) and so provides quantitative understanding of the underlying oscillating mechanisms (Esquivel and Messina 2008). Comparison with the results of non-complex EOF analyses suggested that the imaginary part of the CEOFs reflects the static, non-shifted patterns and therefore can be used for correlation analyses concerning climate modes.

Only grid points with a time series sample size greater than an empirically determined threshold of 86 out of 116 samples were considered valid. This was done to achieve a workable compromise between spatial and temporal integrity.

First, the analysis was carried out for ECV SM data from all seasons combined (but partially truncated for 1986, 1991, 2001-2003). Hendon et al. (2007), Nicholls (2009), Liu et al. (2009) and others found season-dependent impacts of climate oscillations on Australia's hydrology, and therefore, a separate analysis was also performed, examining time series for individual seasons only. This procedure reduced the maximum sample size at each location from 116 to 28 (MAM), 29 (DJF, JJA) or 30 (SON), respectively. Again, periods with insufficient data are disregarded and the minimum sample size per location was set at 20. To improve readability, the resulting (arbitrary scaled) values of the spatial CEOF amplitudes were normalized by their individual maximum and the temporal CPC amplitudes by their individual standard deviation.

d. Correlation Analysis

To quantify the strength of the relationship between the SSM modes and climate modes, the Spearman rank correlation coefficients between the conjugate imaginary parts of the all-

season-combined and individual-season CPC time series and the climate indices (SOI, DMI and SAMI) were calculated. We chose the non-parametric Spearman correlation because it does not require assumptions about the probability distributions of the samples. Rebel et al. (2012) found that the temporal autocorrelation of SSM, estimated from remote sensing, in-situ and modeling, is certainly not more than three months. However, we applied formulas from Wilks (2011) to account for any autocorrelation and to determine the effective sample size of CPC and climate index time series.

3. Results and Discussion

a. Spatiotemporal CEOF Analysis of ECV SM data

The first mode of the CEOF decomposition using data from all seasons represents 46.3% of total variance in SSM from 1979 to 2010 (Fig.1). The spatial amplitude (CEOF 1 Amplitude, Fig.1a) shows highest magnitude in the north and in the south-eastern and south-western edges of the continent. These locations coincide with Australia's humid regions, excluding the east coast.

The spatial phase (CEOF 1 Phase, Fig.1c) together with the temporal phase (CPC 1 Phase, Fig.1d) illustrate the propagating nature of the pattern: it is a clear annual signal characterized by one phase revolution per year (Fig. 1c, with $0^\circ = 360^\circ$). This is related to the spatial phase, which shows a propagation from north to south during one cycle (365 days $\approx 360^\circ$): at the beginning of the year (15 January) the phase is zero degrees, hence maximum amplitude is reached in the north around January-February (i.e. 30°) and in the south around July-August (i.e. 225°). The signal remains stable throughout all 32 years. The irregular peaks in the phase graph with 360° stem from small shifts in the annual cycle, i.e. earlier onsets of wet or dry periods. It becomes also apparent that the data truncation in 1986, 1991 and 2001-2003 does not degrade the analysis, even though particular seasons are excluded.

The findings for mode 1 reflect the general seasonal rainfall pattern. First, the north receives predominately monsoonal precipitation during southern summer season (December to March). Second, the south receives most rainfall during southern winter season (June - October). Third, low amplitudes on the actual humid central east coast reflects the lack of a distinct rainfall seasonality and a seasonal SSM signal is not necessarily expected here. Finally, the continent's interior is arid without clear seasonality and consequently features no relevant amplitude at all. The first principal component, representing the temporal amplitude of the first CEOF mode (CPC 1 Amplitude, Fig.1b), reflects the magnitude of the mode's SSM signal over time. It peaks regularly during summer, which coincides with the monsoon season that impacts predominantly the northern regions (CEOF 1 has the highest amplitudes there), where the spatial phase already highlighted maximum amplitude during January-February. The varying maximum value can mainly be linked to the variation in monsoon strength from year to year. For example, strong monsoons were recorded in (January) 1991, 1997, 1999-2002, 2004, 2008, 2009 and weak monsoons in 1983, 1988, 1990, 1998, 2005, 2007 as reported in Kajikawa et al. (2009). The comparison of the amplitudes of summer maxima in CPC 1 with these strong and weak monsoons, respectively, shows a high level of agreement, especially in the period from 1998 to 2005. This does not apply for the 1983 and 2010 maxima, but the latter can be explained by an exceptional La Niña event. Minima are experienced in the mid of the year and reflect the overall low average precipitation across Australia during winter. The relatively low values in 2003, 2005, 2007 and 2008 agree with the worst years of the Millenium Drought as reported by van Dijk et al. (2013). Overall, the patterns of mode 1 agree very well with the results of García-García et al. (2011), who applied a CEOF decomposition to water mass variations of Australia derived from GRACE gravity anomaly data. However, our study investigated a much longer period and thus extends this previous research, demonstrating the usefulness of the ECV SM data.

The second mode (CEOF 2, Figure 2), represents 14.5% of total variance and has a rather

uniform, continent-wide pattern (Fig. 2a). The CEOF 2 phase (Fig. 2c) features only a small range between 315° and 30° and thus suggests that mode 2 is a rather static, non-oscillatory, SSM variation component. The CPC 2 amplitude (Fig. 2b) and phase (Fig. 2d) are not easy to interpret with ambiguous cycle lengths, giving this mode a random character. Obviously, the CEOF method fails to properly resolve temporal amplitude and phase of non-oscillatory patterns, as it induces arbitrary Hilbert transforms. Nonetheless, the variance represented by this mode could be considered as base signal of Australian inland SSM. Its varying amplitude may be linked with the inland penetration of the northern monsoon and tropical cyclone storms, accounting for the maxima of CPC 2 appearing often (but irregularly) early in the year.

By contrast, CEOF mode 3, containing 6.3% of variance, reveals a clear multi-annual, east-west contrasting pattern (Figure 3c). The CEOF 3 amplitude (Fig. 3a) highlights two regions, one in the north-west towards the Indian Ocean and the other in the north-east towards the Pacific Ocean. The CEOF 3 phase plot (Fig. 3c) indicates that the occurrence of the CEOF 3's maxima alternate as a dipole oscillation from west to east. From the CPC 3 phase plot (Fig. 3d), an irregular period length of two to five years can be inferred. This evidence suggests a connection with ENSO and IOD: the east-west character meets typical ENSO patterns and the CPC extremes coincide with ENSO extremes (with minima in 1987 and 1997 coinciding with El Niños and maxima in 1998, 2006, 2008 and 2010 with La Niñas, Fig. 3b). The detected multi-year-cycle is also in accordance with the nature of ENSO, for which de Viron et al. (2013) found quasi-biennial and quasi-quadrennial periods. Abundant rainfall during southern summer 2009/10 and 2010/11 have been related to La Niña (Blunden and Arndt 2012) and caused record-breaking floods in Queensland and New South Wales. Mode 3 accounts for these wet events: CEOF 3 features high amplitude in the inland areas of NSW and at the greater coastal area of QLD, while CPC 3 shows maximum values in summer 2009/10 and 2010/11.

The fourth mode, explaining 4.2% of variance, shows similar CPC graphs in amplitude

(Fig. 4b) and in phase (Fig. 4d) as mode 3. However, its spatial pattern (Fig. 4a) is strongest in the north and in the north-west. From the spatial phase map (Fig. 4c), it appears that these both focus areas reach peak values consecutively with about one half cycle difference ($\phi \approx 90^\circ$ in the west and $\phi \approx 225^\circ$ in the north). As a note, phase maps are not meaningful in areas where the associated amplitude is close to zero. The period varies from one to five years and does not show a stable behavior (Fig. 4b). Noticeable is the high number of peaks in the CPC 4 amplitude in the middle of the year which cannot be associated with the monsoonal rainfall regime.

DATA SYNTHESIS FROM PRINCIPAL CEOF'S

Since a CEOF analysis is a decomposition of the original data field, the latter can be reconstructed by summing up the vector products of CEOF and CPC of the respective principal modes. The first four modes comprise 71.3% variance. A synthesis using these four modes gives a rebuild of the initial dataset such that, as an example, the correlation maps of SOI with the fields (initial and CEOF-synthesized) match satisfactorily (Fig. 5). The initial dataset is built from 11000 times 128 samples, while the synthesized from 4 times 116. This demonstrates the efficiency of the CEOF method and its skill to fill successfully data gaps. A compression of the huge original data field into a smart set of CEOF and CPC functions preserves most of total variance by taking advantage of redundancy from spatial and temporal dependencies.

The remaining differences between Figure 5 a and b cannot be used to attribute the remaining variance (28.7%). Any EOF or CEOF analysis cannot resolve meaningful patterns for modes of lower variability (Wilks 2011). This limitation is a consequence of the method's mathematical design, which demands mutual orthogonality between EOFs. Hence, the distinction between measurement noise, mathematical artifacts and minor signals is not possible for lower-ranked modes. Nonetheless, the results obtained with the synthesized data provides more confidence in the empirically found threshold for the number of values required;

here 86 out of 116 were sufficient. Comparison with results from analyses using a higher or lower threshold showed either less coverage or more deviations, but no improvements when reconstructing the original data.

CEO F ROBUSTNESS

The CEO F synthesis approach can also be used to test the robustness of the calculated CEO F and CPC patterns. In this application, the ECV SM dataset is repeatedly synthesized through summation of all modes, but each time skipping one leading mode more. The datasets produced this way are then decomposed again into new CEO Fs and the results are compared to the initial CEO Fs. Modes that are not reproduced by this procedure are considered as degenerated, since their patterns appear to be dependent on the method instead on the data. For the above modes 2, 3 and 4 (mode 1, as being the leading mode, can not be compared obviously), all CEO F spatial and temporal patterns are also obtained through this procedure, showing only small deviations. Of course, the new modes' share in total variation increases proportionally to the sum of previously skipped variance. Moreover, a masking over 51 gridpoints, visible as distinctive spots in the CEO F 1 phase map (Fig.1c), was necessary since these outliers disturb this procedure.

Above assessment receives support from conventional tests for EOF robustness, which provide criteria for the reliability of the obtained functions. The Kaiser's Rule as in (Wilks 2011) suggests to retain the first 25 modes. Rule N, following Overland and Preisendorfer (1982) as contrasting the modes' eigenvalues with eigenvalues from randomized (noise-like) data, accepts above modes too. The Rule of Thumb by North et al. (1982) suggests to retain the first five modes, but classifies lower ranked modes as degenerate.

Furthermore, the stability of CEO Fs as a function of the analysis period was examined. To this end, several CEO F analyses of individual ECV SM sub-samples were carried out and evaluated against the reference CEO Fs of the complete 1979-2010 time series. 30 sub-samples were created, each starting one year later from 1980 on and all ending in 2010, accounting

for the gradually increasing quality of the remotely sensed observations over the years. For every sub-sample, the CEOF spatial amplitude value was compared to the reference at each grid point. Figure 6 shows the mean of these differences over all grid points per CEOF mode 1 to 4. It becomes apparent that sub-samples containing time series spanning more than 16 years (starting before 1994) feature only little deviation in the mean values below 10% for each mode, relative to the maximum amplitude of the four individual reference CEOFs. Further reduction of the sub-sample period introduces considerable deviations to all modes, with less impact on the seasonal signal (CEOF 1). Deviations of CEOF 3 and CEOF 4 increase considerably after 1993, which is plausible since they represent multi-annual signals and thus demand a longer observation period. Therefore, for analyses such as those carried out here a lower limit for the investigated time series length of about 10-15 years would seem appropriate. Interestingly, CEOF 2 has second lowest mean difference for the longest sub-samples, but when reducing sample sizes, it exceeds soon the lower-ranked CEOF 3 and CEOF 4. This confirms that CEOF 2 is not captured well by complex EOF analysis because it reflects a quasi-static pattern.

b. Impact of Climate Modes on all-season ECV SM Modes

A correlation analysis was performed to assess the overall impact of the ocean oscillations on Australia's SSM signals. Spearman correlation coefficients were calculated for the four obtained CEOFs as well as non-complex EOFs on the one hand, and the ENSO, IOD and SAM indices on the other hand (Tab. 1). The table lists the correlation of climate indices with the imaginary part of the complex-conjugate CPCs for the CEOF case and with the PCs in the EOF case. It is apparent that the CEOF modes better capture the impact of climate modes than the EOF modes; the results from the CEOF analysis are better for both measured correlation coefficient and correlation significance. The propagating nature of CEOF modes 1, 3 and 4 supports this conclusion.

For CEOF mode 1, which comprises almost half of total variance and reflects the annual

north-south shift of Australia’s rainfall regime, a weak but highly significant connection ($p < 0.01$) to SAM was found. This suggests that the variation of the seasonal SSM signal is influenced by the state of SAM. This can be explained by the relation between SAM and the latitudinal position of westerly wind belt that drives location and strength of cold fronts and mid-latitude storm systems (Ho et al. 2012). Indeed, the normalized imaginary and real part amplitudes of CEOF 1 depict a clear gradient from -1 in the north to $+1$ in the south (see Supplementary Material). This supports the results of Meneghini et al. (2007), who proposed that SAM is directly related to rainfall variance in northern Australia and inverse in southern Australia. Hendon et al. (2007) found a contrast in SSM influence between seasons: in fall and winter, positive SAM is associated with decreased rainfall in south-east and south-west of Australia. During the cool season, the low pressure belt is usually located south of Australia and when it contracts towards the south pole, rainfall tends to be reduced. By contrast, during spring/summer, positive SAM conditions are associated with increased rainfall in these regions. To eliminate the possibility of spurious correlation due to similar seasonal patterns in SAMI and SSM, the seasonality in CPC 1 was removed by subtracting the seasonal averages (the climatologies). The correlation between the CPC 1 anomalies with SAMI is then even stronger ($\rho = -0.33$, see plots in Figure 7). Thus, SAM appears to be a driver of the variation of the seasonal SSM signal in Australia.

CEOF Mode 2 (14.5% variance) appears to contain non-seasonal, rather static variations lacking a systematic pattern (based on Fig. 2). Sure enough, no significant connections between complex mode 2 and climate modes were found. Comparison with the non-complex results provokes the assumption that some SAM-related variance captured by CEOF 1 is incorporated in EOF 2 (which features a seasonal-like signal; not shown). That said, non-periodic signals may not be disentangled properly from periodic signals by the regular EOF analysis. Indeed, EOF data synthesis excluding mode 2 and consecutive CEOF analysis produces a less smooth gradient for mode 1 in the spatial phase and a lower correlation with SAMI (reduced from $\rho = -0.27^{**}$ to $\rho = -0.23^{*}$).

CEOF Mode 3 captures a multi-year, east-west signal and 6.3% of total variance and correlates like mode 1 with SAMI. Thus, SAM seems to contain also a longitudinal element. High correlation was also found with SOI, confirming the findings of Chiew et al. (1998) and Liu et al. (2007) and further emphasizing the connection between ENSO and SSM in north-eastern Australia (Fig. 3 ab and Fig. 5). The absence of any correlation with DMI is curious, as the spatial and temporal pattern of mode 3 would be expected to be at least partially IOD-induced.

However, for CEOF mode 4 (4.2% of total variance) a correlation with DMI of $\rho = -0.30$ is found. The maxima of CPC 4 appear mid-year or later in the year (Fig. 4), suggesting this mode is a cool season component of the SSM signal. The imaginary part of CEOF 4 features strong negative amplitudes in the west of the continent, towards the Indian Ocean and positive amplitudes north of the center (not shown). ENSO is positively correlated with this mode and thus can be the reason for these positive amplitudes.

c. Impact of Climate Modes on seasonal ECV SM Modes

The ECV SM dataset was also decomposed into CEOFs for each season (DJF/MAM/JJA/SON) separately. The robustness of these seasonal CEOFs was determined using the conventional rules mentioned before. This suggested the following modes to be degenerated (only North's Rule of Thumb was critical): DJF mode 3 and 4; MAM mode 2 and 3; JJA mode 4; SON mode 4 (failed the Rule N test too). However, the following modes were recovered by the synthesis-re-analysis approach: DJF all modes except 4; MAM all modes; JJA all modes; SON all modes except 4. Overall, DJF and SON mode 4 may be considered as degenerated and therefore all modes of rank lower than 3 were disregarded in further analyses.

Analogous to the analysis of all-season-combined ECV SM data, the correlations coefficient between imaginary parts of CPCs from seasonal data and seasonal climate indices were calculated. The results for the leading three CEOF modes are listed in Table 2. The ECV SM data were synthesized from these first three CEOF modes for each season and the

Spearman correlation with climate modes is mapped in Figure 8. Even though comprising only about 60% of total variance each, the correlation plots in Figure 8 agree qualitatively with those of the initial ECV SM data (not shown) satisfactorily, underlining the efficiency of the CEOF analysis.

The connection between SSM and climate indices is season-dependent, with correlation coefficients that vary strongly during the year (Tab. 2). It is noted that the sign of the coefficients also depend on the polarity of the imaginary part of the CEOF functions. Their (linked) spatial and temporal amplitudes are either positive or negative and these signs are configured by higher-ranked CEOFs. In Figure 8, the season-dependency is even more apparent and the changing locations of influence of the climate modes illustrates the dynamic character of the interactions. Also evident from Figure 8 is that SOI and SAMI have similar behavior during summer and fall, but not during winter and spring. The Spearman correlation between the indices confirms this (DJF $\rho = +0.50$ ($p < 1\%$); MAM $\rho = +0.45$ ($p < 1\%$); JJA $\rho = -0.07$ (not significant); SON $\rho = 0.21$ (not significant)). The IOD does not seem to share impact patterns with ENSO or SAM.

For ENSO, strong connections were found in summer (DJF mode 1, 31.7%: $\rho = +0.36$) and spring (SON mode 2, 18.7%: $\rho = +0.37$ and mode 3, 10.2%: $\rho = -0.63$). To a lesser extent, ENSO impact was found for fall (MAM mode 2, 11.1%: $\rho = +0.44$) and winter (JJA mode 3, 10.8%: $\rho = +0.52$).

SAM could be identified as notable SSM driver in summer (DJF mode 1, 31.7%: $\rho = +0.57$). The positive SAM-impact in large parts in northern Australia during this period can be seen in Figure 8. A minor contribution to SSM variance was found for fall (MAM mode 2, 11.1%: $\rho = +0.42$) in the north and off-coast SEA. No significant contribution was found for the other seasons. This agrees with the all-season CPC 1 (Fig. 1), which has maximum amplitude at the end and start of the year and was already found to be related to SAM.

For IOD, a strong connection to SSM was found for spring (SON mode 1, 33.8%: $\rho =$

473 -0.36). A smaller share of total SSM variation is explained by IOD in winter (JJA mode
 474 2, 18.0%: $\rho = -0.41$). This agrees with the interpretation of the all-season CEOF mode 4,
 475 which was related to IOD and peaks during the cool season. Looking at patterns in Fig. 8,
 476 IOD appears to drive SSM variances in the south-east and south central parts of Australia
 477 during spring and in the west during winter.

478 Our study confirms findings of Liu et al. (2007) who related ENSO and IOD to remotely
 479 sensed Australian SSM for 1998-2005. However, we also found strong correlation between
 480 SSM and SOI for summer, and IOD in winter. The much longer observation period can
 481 explain this difference. Liu et al. (2009) analyzed data for the period 1979-2006 and, contrary
 482 to our findings, they localized ENSO impact during summer mainly in the west. Nicholls
 483 (2009) asserted that the tropical climate modes ENSO and IOD, contrary to the extra-
 484 tropical SAM, did not explain southern Australian rainfall deficits during fall and winter in
 485 the period of 1958 to 2007. However, our results do not show a relation of SAM to Australian
 486 SSM during winter, and only some during fall. By contrast, ENSO shows a winter influence
 487 in SEA, and IOD in the south-west. Interestingly, CEOF summer mode 1 and fall mode 2
 488 show similar patterns and feature high positive amplitude in northern Australia as well as in
 489 SEA (recognizable also in the impact maps in Figure 8). Both modes correlate significantly
 490 with SOI and SAMI, suggesting that ENSO and SAM are connected to SSM in northern and
 491 south-eastern Australia during summer and fall. The fall influence of ENSO is not expected
 492 according to Timbal and Hendon (2011), who noted that the Millennium Drought was mainly
 493 a consequence of SEA's rainfall deficits during fall, driven by extra-tropical rather than by
 494 tropical processes. This may be due to antecedent rainfall deficits that integrate to dryer fall
 495 SSM conditions, but nevertheless, ENSO is diagnosed to have a stronger impact than SAM
 496 in that area. The results of Ummenhofer et al. (2009), who propose IOD as main driver of
 497 the Big Dry, are also not supported by the results of our study, as IOD appears to impact
 498 SEA in spring only. It should be noted, however, that results from hydrological studies
 499 on anomalies or extreme events may not be necessarily comparable with those of studies

on long-term variations. For example, van Dijk et al. (2013) found differences between the long-term rainfall variance explained by climate modes and their predicted contributions to rainfall anomalies during the Millennium Drought.

4. Conclusion

A new dataset of 32 years of remotely sensed surface soil moisture (SSM) was examined for mainland Australia and related to oceanic climate oscillation indices. We extended previous research on Australia’s hydrology to a longer observation period of over three decades and also addressed earlier research on the interaction of climate modes with hydrological conditions, represented by SSM observations. Our results demonstrated the merit of a multi-decadal dataset such as the ECV SM.

The CEOF analysis shed light on the nature of SSM conditions over Australia and our findings are in strong accordance with climatic understanding and previous studies (e.g. García-García et al. (2011)). The CEOF technique’s ability to extract moving oscillatory signals was demonstrated and thus made it possible to determine not only where, but also when variations occur. Furthermore, the capability of the CEOF technique to compress multidimensional geophysical data in a meaningful and efficient manner is highlighted. Only four leading modes comprised almost the complete variation with physical relevance and allowed proper spatiotemporal analysis. The CEOF analysis enabled the extraction of both seasonal and multi-annual signals. The seasonal signal (CEOF mode 1) explained about the half of all SSM variation, peaking in February-March in the north and in August-September in the south. A low, but highly significant influence of SAM was found in the seasonal signal. Two multi-annual signals explaining a lesser share of total variance (6.3% and 4.2%) were identified: one (CEOF mode 3) had an unstable period of two to five years and an east-west pattern that can be associated with ENSO and SAM, but not with IOD. The second one (CEOF mode 4) had a one to five year oscillation, formed a dipole pattern between the west

and north and was linked to ENSO and IOD. In addition, a similar analysis were performed for individual seasons. Strong relationships were found between ENSO and SSM in northern and eastern Australia for southern spring and summer, and to a lesser extent for fall. During winter, 10% of the total SSM variation in SEA can be linked to ENSO. SAM shows no clear impact during winter or spring but does during summer and fall in northern and eastern Australia, in similar ways as ENSO. In spring, IOD is clearly impacting SSM variations in the entire east, south-east and center. After spring, IOD disappears as a SSM driver, recurring in winter in the west and south.

The detected influence of the tropical modes ENSO and IOD on SSM variation in the north and east during spring was already clear from previous research. However, except for spring, no connection of IOD to the hydrological signal over SEA was found. Instead, IOD only seems to drive also a small share of the variance in the north and west, with varying intensity, following a multi-annual cycle. By contrast, ENSO contributes to the northern and eastern SSM signal throughout the year (but in winter only in SEA), following also a multi-annual cycle. This persistence has not been found so clearly in the existing literature. SAM however, shows a relation to the seasonal SSM signal of entire Australia, which comprises half of the total variation. Thus, SAM can be suggested as key driver of the continent's seasonal soil moisture variation. Furthermore, its influence in the north is found to be higher than expected.

When applied in hydro-climatological studies, CEOF analysis appears to be a powerful technique to identify climate mode induced signals. This could be useful for long-term trend analyses of e.g. regional or global precipitation, evaporation or SSM (as in Dorigo et al. (2012)), as multi-year phenomena like ENSO, IOD or SAM can significantly change the magnitude and even the sign of simple trends in the data, and therefore may need to be removed and analyzed separately.

Climate indices as SOI, DMI or SAMI are simplified but representative measures of oceanic circulations. Predicting oceanic oscillation patterns may be possible one to two

seasons in advance: there are already operational forecasts for ENSO (e.g. by BOM) and successful studies for IOD (e.g. Luo et al. (2008)). With further improvement of such climate mode prediction capabilities, seasonal forecast of SSM and the hydrology of Australia in general should be improved. Hudson et al. (2011) highlighted already that predicting ENSO, IOD and SAM enhances intra-seasonal forecast skills for winter and spring rainfall in Australia. Exploiting knowledge of correlations between climate modes and hydrological patterns provides a promising potential to increase seasonal hydrological forecasts, especially in Australia which is so strongly affected by ocean circulations.

Acknowledgments.

This study was performed in the framework of the STSE Water Cycle Multimission Observation Strategy (WACMOS) project funded by the European Space Agency (contract 22086/08/1-EC) and ESA's Climate Change Initiative (CCI) for Soil Moisture (contract 4000104814/11/I-NB).

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Mode	Variance	SOI	SAMI	DMI
	%	Spearman R		
CEOF CPC				
I	46.3	—	−0.27**	—
II	14.5	—	—	—
III	6.3	−0.41**	−0.28*	—
IV	4.2	−0.27*	—	+0.30**
EOF PC				
I	37.5	—	−0.17	—
II	20.0	—	−0.26**	—
III	6.1	−0.36**	—	—
IV	5.2	−0.22	−0.20	—

TABLE 1. Spearman correlation coefficients between climate indices SOI, SAMI and DMI and PC time series of CEOF and EOF analysis. For the CEOF, the imaginary part of the (complex conjugate) CPCs are used. Double asterisks indicate correlation at high significance ($p < 0.01$, **), single asterisk indicate significance ($p < 0.05$, *). No asterisk means significance $0.05 < p < 0.10$. Blanks indicate no or insignificant correlation. The mode's share in total SSM variance is also displayed.

Mode	Variance	SOI	SAMI	DMI
	%	Spearman R		
Summer - DJF				
I	31.7	+0.36*	+0.57**	—
II	15.0	—	—	—
III	10.7	—	—	—
Fall - MAM				
I	37.9	—	—	—
II	11.1	+0.44*	+0.42*	—
III	10.3	—	—	—
Winter - JJA				
I	32.1	—	—	—
II	18.0	—	—	−0.41*
III	10.8	+0.52**	—	—
Spring - SON				
I	33.8	—	—	−0.36*
II	18.7	+0.37*	—	—
III	10.2	−0.63**	—	—

TABLE 2. Spearman correlation coefficients between climate indices SOI, SAMI and DMI and imaginary part of (complex conjugate) CPC time series of seasonal CEOF analysis. Each season was decomposed separately. Notation as for Table 1.

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FIG. 1. First CEOF mode which explains 46.3% of total variance in the SSM field in Australia. The spatial amplitude in a). The temporal amplitude in b). The mode's spatial phase is depicted in c) and the phase revolution each year is seen in d). Dots indicate phase-values at DJF for better readability.

FIG. 2. As for Figure 1 but for the second EOF mode, which explains 14.5% of total variance.

FIG. 3. As for Figure 1 but for the third CEOF mode, which explains 6.3% of total variance.

FIG. 4. As for Figure 1 but for the forth CE0F mode, which explains 4.2% of total variance.

FIG. 5. Spearman correlation coefficient of SOI with seasonal SSM means from a) original data time series and from b) synthesized time series from first four CEOF modes.

FIG. 6. Mean difference of spatial amplitude values of CEOF modes 1 to 4 to reference modes for all sub-samples, indicated by the starting year. The scale is relative to maximum amplitude of the four reference modes, respectively.

FIG. 7. Plots of imaginary parts of CPC 1, 3 and 4, together with relevant climate indices. In c), IODMI is inverted, accounting for its negative correlation with SSM.

FIG. 8. Spearman correlation coefficient of climate indices with SSM time series synthesized from first three seasonal CEOF modes. White areas are masked out due to poor significance ($p < 0.05$).