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The El Niño event of 2015–2016: climate anomalies and their impact on groundwater resources in East and Southern Africa

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Supplementary Information

S1. Climatological context: El Niño and other drivers of climate over EASE/SA, the 2015-16 El Niño event and climate anomalies over SA

The climatological mean austral summer wet season of October-April rainfall (Fig. S1(a)) shows a maximum extending Northwest-Southeast from Democratic Republic of Congo (DRC)/Angola in the west, across Zambia, Malawi to northern Mozambique in the East. The leading mode of interannual variability in rainfall and SPEI-7, is a north/south dipole pattern of opposing anomalies across EASE and SA, with a divide at ~11^{o}S, the approximate mean latitude of rainfall maximum and is strongly related to ENSO. This structure clearly evidenced by the leading Empirical Orthogonal Function (EOF) of SPEI-7 (Fig. S1(b)) which explains 21.5% of total variance. The time coefficients correlate strongly with tropical SSTs (Fig. S1(d)) highly characteristic of the ENSO SST anomalies in both the Pacific and Indian Oceans, notably the SW/NE positive/negative correlation dipole across the southwest/equatorial Indian Ocean (e.g. Lindesay, 1988; Reason *et al.*, 2000, Lazenby *et al.*, 2016). As such, for Africa South of the equator the leading mode of climate variability is strongly related to ENSO, with wet (dry) anomalies during El Niño (la Niña) events across EASE (SA). The EOF pattern is largely insensitive to the length of choice of months in the wet season. This north-south dipole response across EASE/SA to ENSO has been well documented previously (Ropelewski and Halpert, 1987; Janowiak, 1988; Goddard and Graham, 1999; Manatsa *et al.*, 2011), although the physical mechanisms of teleconnection remain elusive (see Blamey *et al.* 2018 for a summary).

The climate anomaly pattern during 2015-16 was highly characteristic of this mode (compare Figs. 1(a) and S1b). Very strong SST anomalies over the Pacific and elsewhere in the tropics during 2015-16 (Fig. S1(d)) were associated with a strong north/south dipole in rainfall with drought in SA (Fig. 1(a)). The socio-economic impacts were pronounced, with much of SA affected by drought, leading to a regional drought disaster declaration by the Southern Africa Development Community (SADC). By September 2016, six SADC countries had declared ‘national drought emergencies’ (Botswana, Namibia Lesotho, Malawi, Swaziland and Zimbabwe) with drought emergency declared for seven of the South Africa’s nine provinces, and a temporary red alert also declared for central and Southern provinces of Mozambique (SADC 2016a). The drought resulted in an extensive loss of crops and livestock, an increase in food prices, driving an estimated 39 million people into deeper food insecurity (SADC 2016a; 2016b; Archer *et al.*, 2017). Surface water shortages further affected electricity generation and domestic supply, affecting economic activity and human health (SADC, 2016a; Siderius *et al.* 2018).

The 2015-16 El Niño was without doubt one of the strongest on record, and by some indicators was actually the strongest. There are many measures of ENSO strength (see e.g. https://www.esrl.noaa.gov/psd/enso/dashboard.html), which provide a mixed picture on the relative strength of the major events. 2015-16 appears strongest based on the Niño 3.4, Niño 4 and Bivariate El Niño – Southern Oscillation index, whilst 1997-98 is the strongest based on the (East pacific Niño 3 and 1+2 SST indices, east Pacific heat content and the Multivariate El Niño index. However, 2015-16 was certainly more persistent that 1997-98 with many indices turning positive at some time in 2014 related to the El Nino event that was predicted in 2014 but did not develop fully until 2015-16 (Levine and McPhaden, 2016).

However, there is substantial diversity in the character of El Niño events, in terms of both (i) the structure and magnitude of anomalies in the Pacific sector. For example, 2015-16 and 1997-98 differed in that the former was stronger in the Central Pacific sector (Niño3.4 and Niño SST region) and the latter in the East Pacific (Niño 1+2 and Niño 3 SST regions) (ii) the state and evolution of other regional drivers of climate variability which interact with ENSO teleconnection processes, such that the remote impacts over Africa can be quite variable (e.g. Ratnam *et al.*, 2014; Preethi *et al.*, 2015, Hoell *et al.*, 2017; Blamey *et al.*, 2018). Across Southern Africa (SA) multiple regional structures of ocean and atmospheric variability modulate the impacts of ENSO including the South Indian Ocean dipole (Reason, 2001) as well as the Angola low and Botswana High atmospheric features (Blamey *et al.*, 2018). Furthermore, intraseasonal variability associated with the Madden Julian Oscillation, with 30-60 day timescales can also modulate interannual drivers of variability, particularly over East Africa (Berhane and Zaitchik, 2014).

Over East Africa rainfall is more strongly related to the state of the Indian Ocean than to ENSO. The Indian Ocean Zonal mode (IOZM), an east-west pattern of atmosphere-ocean variability across the Equatorial Indian ocean, strongly modulates the regional Walker circulation and hence rainfall over East Africa. During positive IOZM events warmer ocean temperatures in the equatorial west Indian Ocean and cooler temperatures in the east lead to enhanced rainfall over EASE, with negative IOZM leading to a reduction in rainfall (see Nicholson 2017 for a review and references therein). The impact of ENSO on EASE is therefore intimately connected to the state of the IOZM (Black *et al.*, 2003, Manatsa *et al.*, 2011). During 2015-16 the IOZM was only weakly positive (see SST anomalies in Fig. S1(d)) and the seasonal de-trended IOZM index (Saji *et al.*, 1999) in 2015-16 was ranked 16th out of 150 years. As a result, the mean equatorial zonal Indian Ocean Walker cell with ascent (descent) in the east at ~100^{o}E (west at ~50^{o}E) of the basin is only weakly perturbed. The zonal cross section over the East Africa-Indian Ocean sector indicates that enhanced large-scale uplift is limited to a quite restricted region of EASE from ~33^o-40^{o}E. In this way, the weak reorganisation of the Indian ocean Walker circulation led to rather moderate rainfall anomalies over EASE (Section 3.1).

S2. SPEI-7 Intensity-Area-Frequency (IAF) curves and associated return period estimates, and attribution of anthropogenic influence on the SA drought 2015-16

Droughts are spatially extensive but variable features. We represent the spatial extent using IAF curves which show the intensity of SPEI-7 water balance anomalies across all spatial scales within a study domain. IAF curves are independent of the precise spatial patterns of SPEI-7 anomalies, and as such allow us to compare droughts between individual years, and to calculate the return periods for drought events across scales. This direct comparability of SPEI-7 IAF curves is valuable since no two drought events have exactly the same spatial pattern. The IAF curves are derived using the method of Mishra and Cherkauer (2010) separately over the two study domains of EASE and SA, by calculating the mean SPEI-7 value of grid cells lying within various areal extent intervals: The areas covered by the lowest (for SA) or highest (for EASE) 5th, 10th, 20th…100th areal percentiles of SPEI grid cell values within the domain area i.e. when all grid cells are ranked. This allows, for each season, the mean SPEI-7 IAF curve to be plotted (see Fig. 3).

We then estimate the return period of the 2015-16 El Niño event by comparing the observed SPEI-7 IAF curve of 2015-16 with IAF curves representing various 'benchmark' return periods (Fig. 3) and finding the closest match, by least squared error. Estimating these benchmark return periods of drought events is challenging given the relatively short observational record for what are relatively long duration events, and indeed because of non-stationarity in climate records under a changing climate. We address both these challenges in our approach. To counter the problem of insufficient sampling of the extreme tail of the distribution, we increase our sample of climate events beyond the observed record using large ensembles of climate model simulations from the HAPPI experiment (Mitchell *et al.*, 2017). HAPPI is designed specifically to quantify climate extremes, through the use of relatively high model resolution and large initial-condition ensembles. We use precipitation data from four atmospheric models, namely HadGEM3, CAM5, MIROC5 and NorESM, (degraded to common resolution of 1^{o}) each with 10 ensemble members, run over the period ~1950s-2010s, forced with observed SSTs and 'historical' greenhouse gases and aerosol radiative forcings. These simulations provide about 2400 years of simulated data, with greater statistical definition of the extreme tail of the distribution required for the extreme events, notably the 2015-16 drought over SA which is the strongest on record. As with the observations we derive the mean SPEI-7 for each areal extent interval (5th, 10th, etc. spatial percentiles over the domain), for each of the ~2400 model years. Estimation of return periods is based on the Extreme Value Theory (EVT), widely used for the description of rare climate events in the extreme tail of the parameter distribution. The Generalized Extreme Value distribution (GEV) is fitted to the distribution of only the extreme SPEI-7 values, for each areal extent separately (using maximum likelihood estimation and a chi-squared goodness-of-fit test, Coles *et al*., 2001). This distribution of extremes ('block maxima') is composed of the most intense SPEI-7 values (for drought over the SA domain SPEI-7 is multiplied by -1) within non-overlapping 'blocks' of 30 years, a standard climatological period. Then, return periods are estimated by inverting the resulting GEV cumulative probability distribution for a range of periods from 30-300 years, for each areal extent separately, providing IAF curves for benchmark return periods (see Fig. 3). Whilst our approach is similar to previous drought analyses (e.g. Robeson, 2015) we recognise a number of caveats. First, the estimated return periods are sensitive to the arbitrary choice of block size and we estimate the uncertainty associated with this using periods of 25-60 years. Second, whilst the large ensembles provided by the HAPPI experiment are designed specifically for analysis of extremes they necessarily provide only a partial representation of the climate variability 'space'.

For estimation of return periods shorten than the duration of one 'block' (30 years), we follow Mishra and Cherkauer (2010) and Philip *et al.* (2018) in fitting a distribution to the historical record of SPEI-7 data. For each areal extent interval (5th, 10th, etc. spatial percentiles) we fit a GEV distribution to the 116 historical SPEI-7 data points. We then invert the cumulative distribution to derive return periods for every spatial percentile, giving a set of IAF benchmark return period curves. Finally, we conduct all the above IAF curve return period analysis using SPEI-7 derived with each of the three PET equations and provide the average return period estimates and the associated range to represent this component of uncertainty.

It is likely that anthropogenic climate change is, and will continue to, affect large-scale hydrology. As such, climate risks are changing and non-stationarity in climate records complicates the interpretation of return periods. However, the IPCC recent assessment report concludes that there is only low confidence in detection and attribution of observed changes in drought extremes globally (Bindoff *et al.*, 2013), largely due to uncertainties in distinguishing relatively small trends in precipitation from decadal variability, especially given limitations in precipitation data. Nevertheless, attribution of recent temperature rises is robust even down to the regional/continental scale (Bindoff *et al.,* 2013). In recent probabilistic event attribution analyses of tropical drought events the contribution of anthropogenic temperature effects is discernible, in contrast to that of precipitation (Marthews *et al.*, 2015). As such, the full causal chain from climate anomaly through water balance to agricultural drought is complex and typically not well represented in models such that attribution of drought remains extremely challenging. Therefore, here we estimate the effects purely of anthropogenic temperature trends on drought risk over SA through a simplified attribution experiment. The SPEI-7 IAF return period analysis above is repeated, but in deriving the benchmark return period curves the temperature data, used in calculating PET, has the signal of anthropogenic climate change removed. Specifically, PET is estimated using the HAPPI multi-ensemble mean temperature from a counterfactual world without human influence on radiative forcing: the ‘natural’ runs, in which only the natural forcings (solar variability and volcanic aerosols) are provided to the models. To ensure space-time consistency in all the climate variables whilst changing the temperature data, we used the 30-year smoothed temperature from the ‘natural’ model runs to which is added the anomalies of temperature from the ‘historical’ run with respect to a 30-year running mean. Not that we derive the SPEI-7 over both datasets merged together so that the effect of the temperature perturbation between the ‘natural’ and ‘historical’ runs is reflected in the resulting SPEI-7 values, given that the index is standardised across the timeseries. The benchmark return period IAF curves are then derived from the SPEI-7 values for each dataset separately. Thus, comparing the estimated SPEI-7 IAF return periods from the climate with ‘historical’ temperature with those from a counterfactual climate with the ‘natural’ only temperature, provides an indication of the influence of the anthropogenic temperature trend effects on drought risk over SA. We note that the SPEI is quite temperature dependent through PET calculation such that other drought indices may yield different sensitivity to warming.

We must emphasise that this analysis deliberately considers only the effects of the slowly evolving anthropogenic influence on temperature. We do not consider anthropogenic influences on rainfall and the other determinants of PET i.e. wind speed, humidity, radiation budget, no any changes to variability in temperature or any other variables. Further, the difference in model estimated temperatures between the 'natural' and 'historical' run will include the effects not just of anthropogenic radiative forcing but also the surface energy budget which itself is affected by precipitation and other near surface variables whose response to radiative forcing we do not consider. However, in utilising a large model ensemble to define the statistics of extreme events, we retain some features of the probabilistic event attribution method (e.g. Allen *et al.*, 2003, Stott *et al.*, 2014) but focus solely on that aspect of climate change (near surface temperatures) for which we have greatest confidence in the ability of models to represent with credibility.

S3. Groundwater storage estimates from GRACE and LSMs

To address uncertainty associated with different GRACE processing strategies to resolve ΔTWS (Eq. 1) we apply an ensemble mean of three GRACE TWS. Namely, the CSR land (version RL05.DSTvSCS1409, Swenson and Wahr, 2006; Landerer and Swenson ,2012) and JPL Global Mascon (version RL05M_1.MSCNv01, Watkins *et al.*, 2015; Wiese *et al.*, 2015) solutions, from NASA's *GRCTellus* data dissemination site (http://grace.jpl.nasa.gov/data), and a third GRGS GRACE solution (CNES/GRGS release RL03-v1) (Biancale *et al.,* 2006) from the French Government space agency, Centre National D'études Spatiales (CNES).

GRCTellus CSR land solution (version RL05.DSTvSCS1409) is post-processed from spherical harmonics released by the Centre for Space Research (CSR) at the University of Texas at Austin. *GRCTellus* gridded datasets are available at a monthly time step and a spatial resolution of 1° × 1° (~111 km at equator) though the actual spatial resolution of GRACE footprint is ~450 km or ~200,000 km^2 (Scanlon *et al.,* 2012). To amplify TWS signals we apply the dimensionless scaling factors provided as 1° × 1° bins that are derived from minimising differences between TWS estimated from GRACE and the hydrological fields from the Community Land Model (CLM4.0) (Landerer and Swenson, 2012). JPL-Mascons (version RL05M_1.MSCNv01) data processing involves the same glacial isostatic adjustment correction but applies no spatial filtering as JPL-RL05M directly relates inter-satellite range-rate data to mass concentration blocks (mascons) to estimate monthly gravity fields in terms of equal area 3° × 3° mass concentration functions in order to minimise measurement errors. Gridded mascon fields are provided at a spatial sampling of 0.5° in both latitude and longitude (~56 km at the equator). Similar to *GRCTellus* CSR product, dimensionless scaling factors are provided as 0.5° × 0.5° bins (Shamsudduha *et al.*, 2017) that also derive from the Community Land Model (CLM4.0) (Wiese *et al.*, 2016). The scaling factors are multiplicative coefficients that minimize the difference between the smoothed and unfiltered monthly ΔTWS variations from the CLM4.0 hydrology model (Wiese *et al.*, 2016). GRGS monthly GRACE products (version RL03-v1) are processed and made publicly available (http://grgs.obs-mip.fr/grace) by CNES (Shamsudduha *et al.*, 2017). Further details on the Earth's mean gravity-field models can be found on the CNES official website of GRGS/LAGEOS (http://grgs.obs-mip.fr/grace/). GRACE ΔTWS time-series data have some missing records as the satellites are switched off for conserving battery life (Shamsudduha *et al.*, 2017); these missing records are linearly interpolated (Shamsudduha *et al.*, 2012).

To derive ΔGWS from GRACE ΔTWS (eq. 1) we use simulated soil moisture to represent ΔSMS and surface runoff, as a proxy for ΔSWS (Mishra *et al.*, 2016), from LSMs within NASA's Global Land Data Assimilation System (GLDAS). We apply monthly ΔSMS and surface runoff data at a spatial resolution of 1° × 1° from 4 GLDAS LSMs: The Community Land Model (CLM, version 2) (Dai *et al.*, 2003), NOAH (version 2.7.1) (Ek *et al.*, 2003), the Variable Infiltration Capacity (VIC) model (version 1.0) (Liang *et al.*, 2003), and MOSAIC Mosaic (version 1.0) (Koster and Suarez, 1992). The respective total depths of modelled soil profiles are 3.4 m, 2.0 m, and 1.9 m and 3.5 m in CLM (10 vertical layers), NOAH (4 vertical layers), and VIC (3 vertical layers), and Mosaic (3 vertical layers) (Rodell *et al.*, 2004). In the absence of in situ ΔSMS and ΔSWS data in the study areas, we apply an ensemble mean of the 4 LSMs-derived ΔSMS and ΔSWS data in order to disaggregate GRACE ΔTWS signals across our study regions, for the period August 2002 to July 2016, similar to the approach applied for other locations by Shamsudduha *et al.* (2012, 2017). To help interpretation of these mean

ΔGWS signals we also present the total uncertainty in estimates of ΔGWS which result from the uncertainty in estimates of ΔTWS, ΔSMS and ΔSWS (blue shading in Fig. 5(c)). The uncertainty in these individual water balance components is shown in Fig. S2 i.e. the range in estimated GRACE ΔTWS across the three retrieval estimates, and the ranges in estimates ΔSMS and ΔSWS across the four LSMs. Overall, the total uncertainty in ΔGWS can be substantial and receives roughly equal contribution from uncertainty in ΔTWS and ΔSMS with uncertainty in ΔSWS important only occasionally. There is some indication that during the periods of greatest ΔGWS uncertainty, the ΔTWS uncertainty is most important e.g. 2009-10 and 2015-16 at Limpopo. To understand this uncertainty in GRACE ΔTWS further we show the time series of the three individual ΔTWS retrievals of CSR, JPL-Mascons and GRGS (Fig. S3), which we examine in more detail in Section 3.2.2. For further understanding of the uncertainty in the estimates water storage from LSMs with respect to GRACE readers are referred to Scanlon *et al.* (2018).

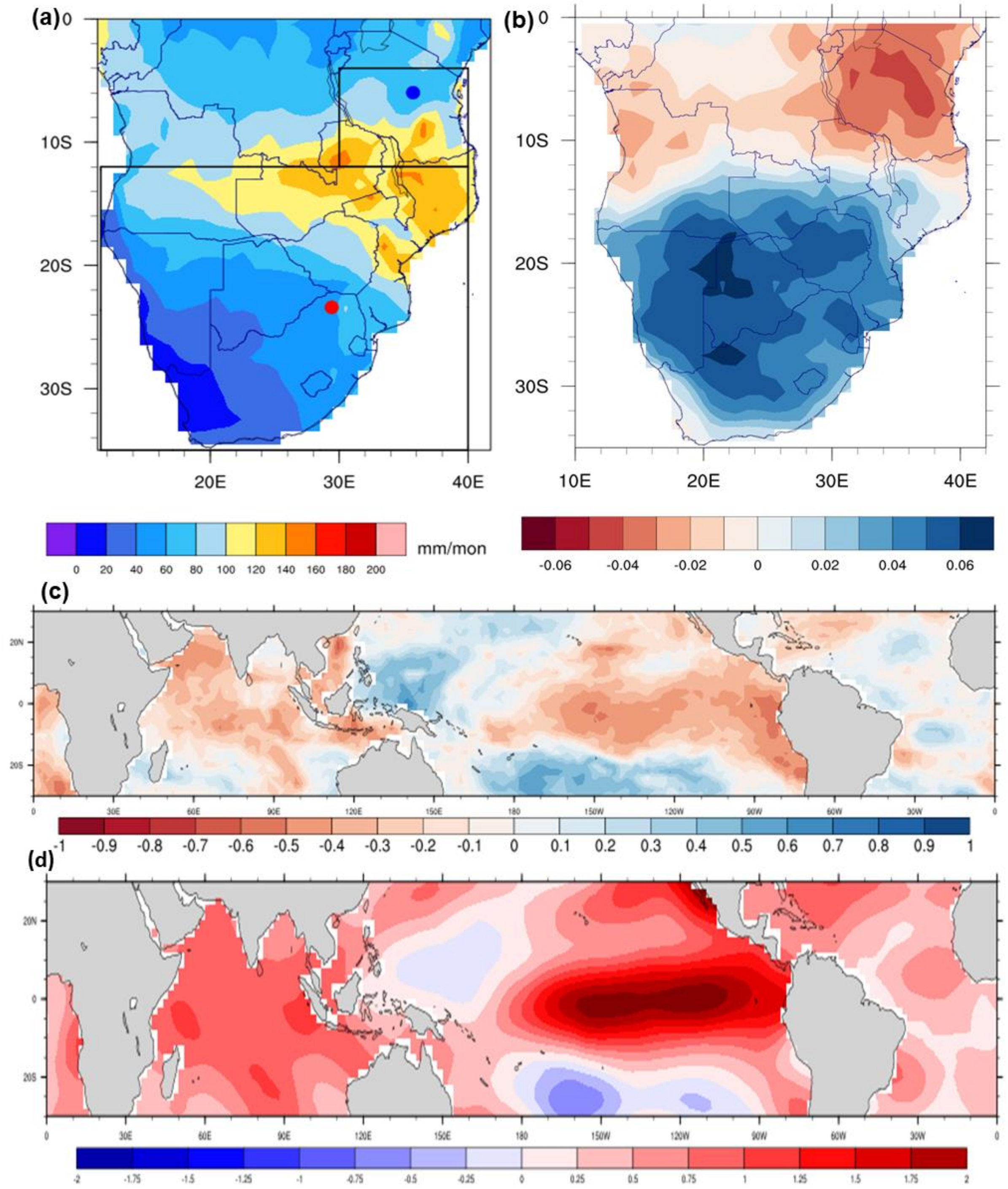
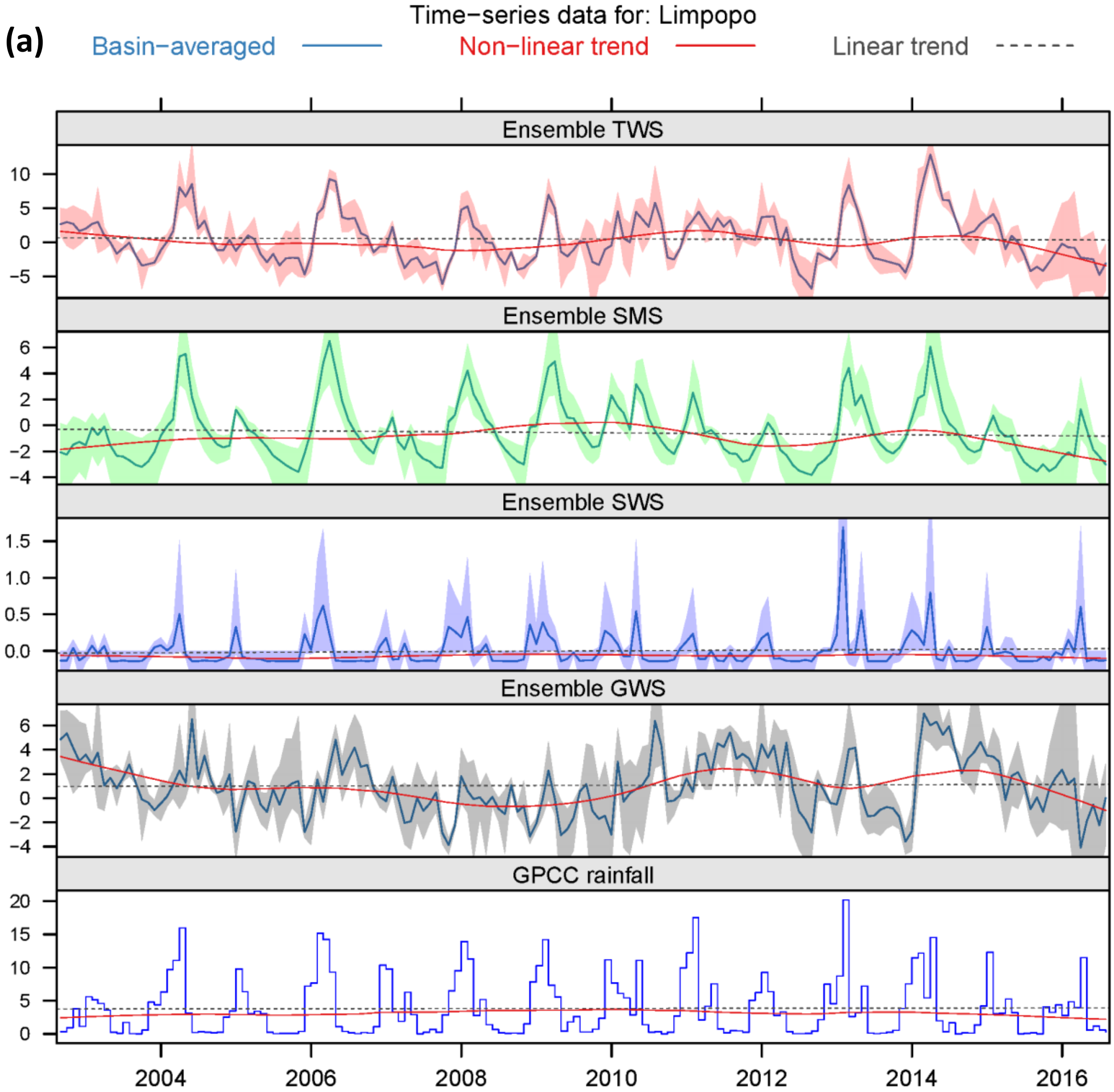


Fig. S1. (a) Climatological precipitation for the October-April season for the period of 1901-2016 (mm month^{-1}). Boxes in Fig. S1(a) show the EASE (small box) and SA (big box) domains used in the IAF analysis (see Section 2.1). The blue and red filled circles denote the piezometer observation locations at Makutapora, Tanzania and Limpopo, South Africa, respectively. (b) Leading mode of interannual October-April variability calculated using the empirical orthogonal function (EOF) analysis of de-trended rainfall of GPCC. (c) Correlation between coefficients of EOF1 (Fig. S1(b)) and global SST (October-April mean) 1901-2016. (d) SST anomalies (K) October-April 2015-16, with respect to 1980-2010 reference period



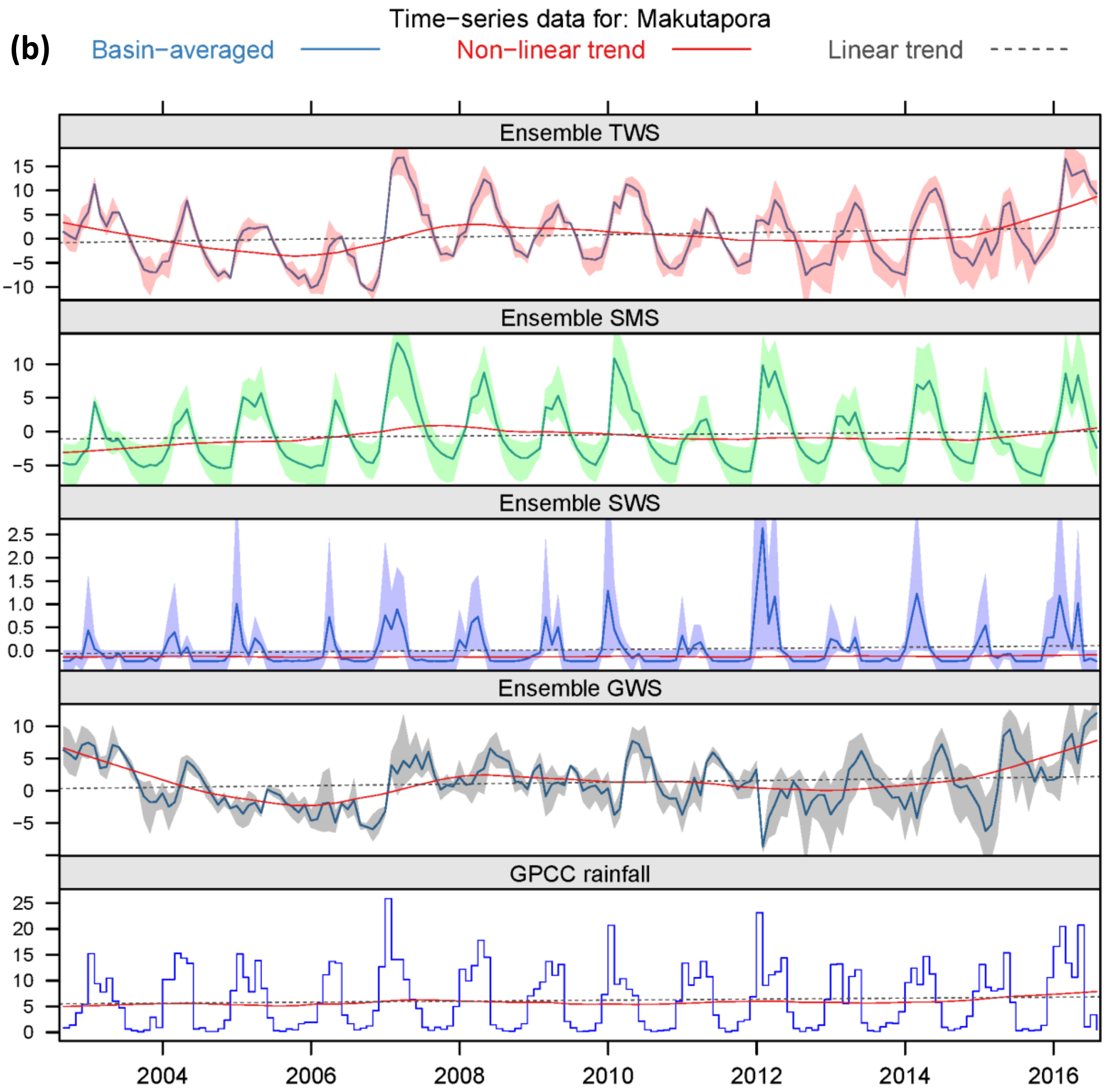


Fig. S2: Time series of monthly estimates of anomalies in the individual components of water balance (lines) and the associated uncertainty range (shaded). From top to bottom TWS from GRACE; SMS and SWS both from LSMs; the residual GWS; observed GPCC rainfall, (all in cm) at (a) Limpopo, and (b) Makutapora.

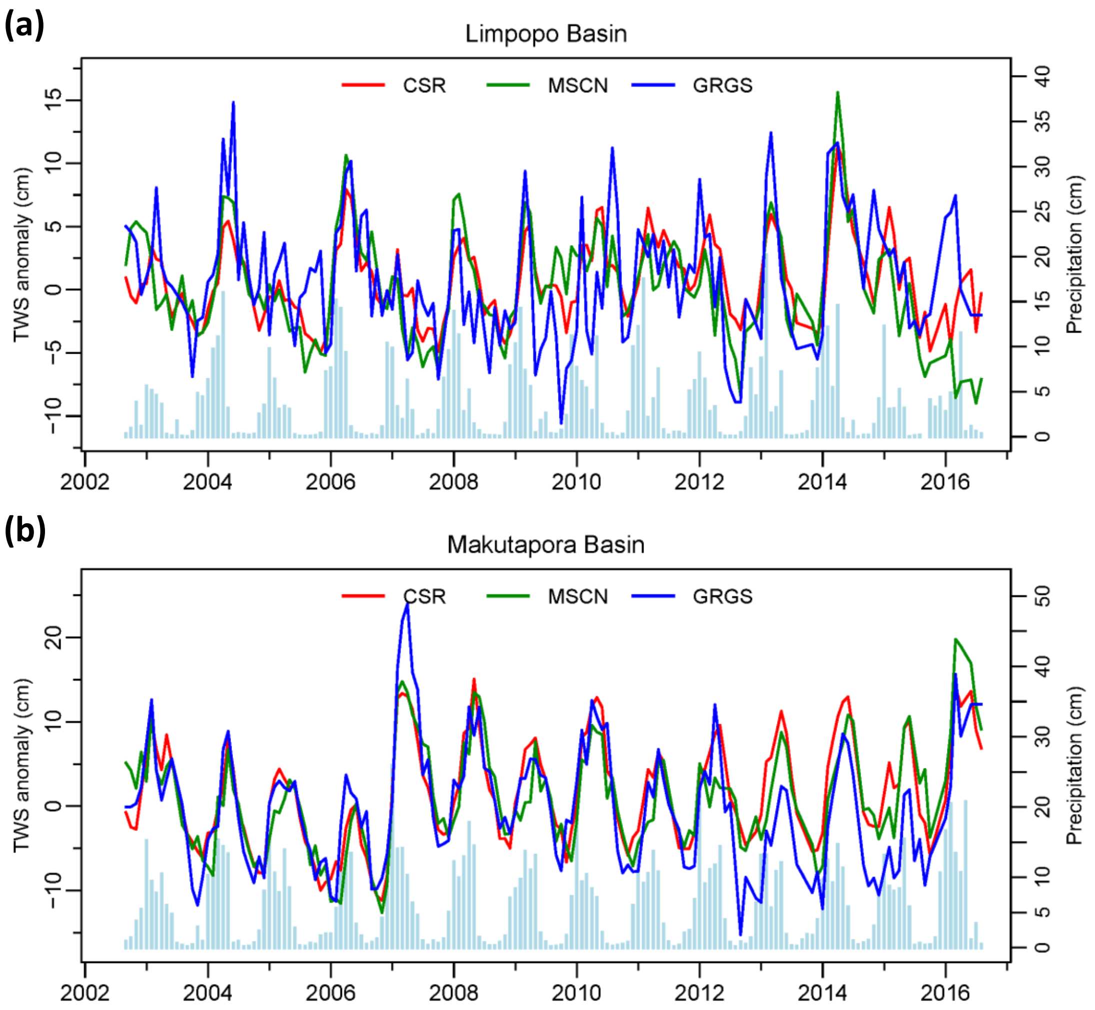


Fig. S3: (a) Time series of estimates of monthly ΔTWS anomaly (cm) at Limpopo from August 2002 to July 2016 (averaged over an area approximately ~120 000 km^2) derived from the three individual GRACE retrievals of CSR (red), JPL-Mascons (green) and GRGS (blue). Monthly rainfall (from GPCP product, cm) shown as bars. (b) As (a) but for Makutapora.

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