1 Spatio-Temporal Variability of Droughts and Terrestrial Water Storage 2 over Lake Chad Basin using Independent Component Analysis

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9 Abstract

10 Lake Chad has recently been perceived to be completely desiccated and almost extinct due
11 to insufficient published ground observations. Given the high spatial variability of rainfall in
12 the region, and the fact that extreme climatic conditions (for example, droughts) could be
13 intensifying in the Lake Chad basin (LCB) due to human activities, a spatio-temporal ap-
14 proach to drought analysis becomes essential. This study employed independent component
15 analysis (ICA), a fourth-order cumulant statistics, to decompose standardised precipitation
16 index (SPI), standardised soil moisture index (SSI), and terrestrial water storage (TWS) de-
17 rived from Gravity Recovery and Climate Experiment (GRACE) into spatial and temporal
18 patterns over the LCB. In addition, this study uses satellite altimetry data to estimate vari-
19 ations in the Lake Chad water levels, and further employs relevant climate teleconnection
20 indices (El-Niño Southern Oscillation-ENSO, Atlantic Multi-decadal Oscillation-AMO, and
21 Atlantic Meridional Mode-AMM) to examine their links to the observed drought temporal
22 patterns over the basin. From the spatio-temporal drought analysis, temporal evolutions of
23 SPI at 12 month aggregation show relatively wet conditions in the last two decades (although
24 with marked alterations) with the 2012 – 2014 period being the wettest. In addition to the
25 improved rainfall conditions during this period, there was a statistically significant increase of
26 0.04 m/yr in altimetry water levels observed over Lake Chad between 2008 and 2014, which
27 confirms a shift in the hydrological conditions of the basin. Observed trend in TWS changes
28 during the 2002 – 2014 period shows a statistically insignificant increase of 3.0 mm/yr at the
29 center of the basin, coinciding with soil moisture deficit indicated by the temporal evolutions
30 of SSI at all monthly accumulations during the 2002 – 2003 and 2009 – 2012 periods. Further,
31 SPI at 3 and 6 month scales indicated fluctuating drought conditions at the extreme south of
32 the basin, coinciding with a statistically insignificant decline in TWS of about 4.5 mm/yr at

the southern catchment of the basin. Finally, correlation analyses indicate that ENSO, AMO, and AMM are associated with extreme rainfall conditions in the basin, with AMO showing the strongest association (statistically significant correlation of 0.55) with SPI 12 month aggregation. Therefore, this study provides a framework that will support drought monitoring in the LCB.

Keywords: TWS, Soil moisture, ICA, SPI, Drought, Rainfall

1. Introduction

Lake Chad Basin (LCB), the world's largest interior drainage basin, covers an approximate area of 2,500,000 km² and supports an estimated 37 million people who depend on its water resources for agriculture, fishing, and other domestic applications (e.g., [Coe and Birkett, 2004](#); [Leblanc et al., 2003](#)). The basin is geographically bounded by latitudes 6°N and 24°N and longitudes 7°W and 24°E (Fig. 1) and is occupied by Lake Chad at the centre, a prominent freshwater body, which largely forms the live wire of the basin's hydrology. The historic and dramatic decline in the spatial extent of the Lake from 24,000 km² in the 1950's to segmented open water pool of approximately 1700 km² (i.e., about 90% decline) in recent times, has been reported (see, e.g., [Wald, 1990](#); [Birkett, 2000](#); [Coe and Foley, 2001](#); [Leblanc et al., 2003](#); [Lemoalle et al., 2012](#)). Lake Chad receives its water supply primarily from the Chari-Logone river, which provides approximately 95% of the total inflows into the southern pool, and also the Komadugu-Yobe River (see Fig. 2), which provides less than 2.5% of water that flows into the northern pool of the Lake ([Birkett, 2000](#); [Coe and Birkett, 2004](#)). In relation to other Lakes in Africa, recent illustration of Lake Chad presupposes a completely desiccated and almost extinct Lake (e.g., [Moore and Williams, 2014](#); [Coe and Foley, 2001](#); [Birkett, 2000](#)). This perception may be partly associated with lack of documented analyses of satellite-based observations ([Lemoalle et al., 2012](#)). Consequently, the drought narrative of the Lake and the entire LCB has been a subject of much less scientific discussion.

A number of studies on Lake Chad's hydrology and the corresponding basin have been carried out. For example, [Coe and Birkett \(2004\)](#) used satellite radar altimetric measurements of water height to estimate river discharge at the Chari/Ouham confluence while [Lemoalle et al. \(2012\)](#) used a hydrological model to reconstruct the past water levels of the Lake and inundated areas from 1973 to 2011 in order to compensate for the lack of hydrological data. [Birkett \(2000\)](#) and [Coe and Foley \(2001\)](#) had earlier reported the combined effects of regional precipitation patterns and the impact of human activities on the desiccation of the Lake while [Okonkwo](#)

et al. (2014) examined the relationship of El-Niño Southern Oscillation (ENSO) with rainfall, river discharge at Chari river, and Lake Chad water level at Kalomand Kindjeria. Leblanc et al. (2003) used Advanced Very High Resolution Radiometer (AVHRR) and Meteosat data in a Geographic Information System (GIS) framework to map the fluctuations of the spatial extent of Lake Chad. But recently, Lopez et al. (2016) studied the quaternary phreatic aquifer of the basin, indicating that there is an association between piezometric levels and sedimentary thickness.

However, from the studies highlighted so far, we find a relatively strong research lacuna in the knowledge of water availability, drought patterns, and spatio-temporal variability of water storage over the LCB. Apart from the effort of Okonkwo et al. (2013), which provided a location-specific information regarding the probability distribution of rainfall and drought in the LCB during the 2002-2011 period, drought studies in the LCB are generally lacking and largely undocumented. Also, with increased human activities (e.g., irrigation schemes) in LCB (e.g., Lemoalle et al., 2012; Coe and Foley, 2001), especially within the precinct of the Lake, one may assume that the water resources of the basin could be more vulnerable, given the significant global drying trends observed in water availability and hydrological regimes in the Sahel region of West Africa (Greve et al., 2014). Furthermore, in the wake of global climate change and perturbations of ocean warming, it is likely that the limited alimentation occasioned by lack of or deficit in precipitation and human activities in the basin might get worse in the future. This may have significant impact on the local economy and the freshwater tributaries (that is, Chari and Logone rivers) that nourishes Lake Chad.

Furthermore, despite the recognised recovery of rainfall in some parts of the Sahel region (see, Nicholson, 2013, and the references therein), the impact of this recovery on the hydrology of Lake Chad and TWS changes over the entire basin are still rather unclear, largely unknown, and undocumented. For instance, in addition to the inconsistent trends between increased rainfall and lake level, Okonkwo et al. (2014) showed that the variability in ENSO could explain only 31% and 13% of variations in Lake Chad water level at Kindjeria and precipitation in the northern LCB, respectively. Notably, the LCB has been ravaged by frequent droughts leading to limited freshwater availability. The reduced alimentation of the basin in terms of freshwater shortage can be seen in the yearly water balance as reported by Odada et al. (2005). They reported that there was an inflow and outflow of 24.68 km³/yr and 24.5 km³/yr, respectively, with evapotranspiration being a major component of the outflow (approximately 23.1 km³/yr) in the basin between 1971 and 1990. Added to this is the drought narrative for the region,

98 which may be highly generalised (that is, in terms of its spatial variability, characteristics, etc.)
99 due to lack of an optimised framework to determine its space-time occurrence. Considering the
100 high spatial variability of rainfall in the region, and the fact that extreme climatic conditions
101 could be intensifying in the basin possibly due to anthropogenic factors (for example, water
102 abstractions for irrigation), a spatio-temporal approach to drought analysis becomes vital.

103 Numerous studies, mostly in the mainstream of satellite hydrology, have shown how multi-
104 satellite data from altimetry, gravimetry, and optical remote sensing platforms can be used
105 to estimate terrestrial water storage (TWS)¹ variations in drainage basins and poorly gauged
106 regions, in addition to estimating water volume variations from surface waters such as lakes
107 and reservoirs (see, e.g., [Tourian et al., 2015](#); [Baup et al., 2014](#); [Duan and Bastiaanssen, 2013a](#)).
108 In particular, the launch of Gravity Recovery and Climate Experiment (GRACE)
109 satellite mission ([Tapley et al., 2004](#)) has enabled hydrologists to validate water storage outputs
110 from hydrological models and also to fully utilize GRACE observations for the inter-annual
111 variations of TWS and water balance studies (see, [Wouters et al., 2014](#), and the references
112 therein). While few hydrological studies that utilized GRACE data in West Africa (see, e.g.,
113 [Ndehedehe et al., 2016a](#); [Grippa et al., 2011](#); [Hinderer et al., 2009](#)) have been reported, some
114 drought studies and extreme rainfall conditions have also been documented in other sub-regions
115 of West Africa (see, e.g., [Ali and Lebel, 2009](#); [Ndehedehe et al., 2016b](#); [Masih et al., 2014](#);
116 [Bader and Latif, 2011](#); [Nicholson et al., 2000](#); [Nicholson, 2013](#), and the references therein).
117 Despite the progress made so far in the use of GRACE data in hydrological studies, for instance,
118 applications in drought and flood estimation (e.g., [Reager et al., 2014](#); [Yirdaw et al., 2008](#)),
119 the potential of GRACE data in monitoring the space-time development of TWS changes and
120 droughts in the LCB are yet to be fully explored.

121 In this study, we capitalize on GRACE observations to estimate the TWS over the LCB,
122 in addition to satellite altimetry-derived water levels and other hydrological variables such as
123 rainfall, and soil moisture to monitor water storage changes and the spatio-temporal character-
124 istics of droughts. Contrary to previous studies that have analysed spatio-temporal drought
125 events in other regions of the world (see, e.g., [Bazrafshan et al., 2014](#); [Santos et al., 2010](#);
126 [Bonaccorso et al., 2003](#)) using principal component analysis (e.g., [Jolliffe, 2002](#)), we employ
127 independent component analysis (ICA, see, e.g., [Cardoso, 1999](#); [Common, 1994](#); [Cardoso and](#)
128 [Souloumiac, 1993](#)), a higher order statistical method to localize drought patterns and time-

¹The sum total of surface waters (i.e., rivers, lakes, and wetlands), soil moisture, canopy, and groundwater.

variable hydrological signals (i.e., TWS). Unlike in the Volta basin where the influence of low frequency climate oscillations on hydrological drought was reported by Ndehedehe et al. (2016b), here, the Lake Chad basin (a semi-arid Sahelian environment) is adopted as a tentative test bed, primarily to demonstrate the use of a fourth-order cumulant statistics such as the ICA to analyze spatio-temporal evolutions of drought indices at different time scales (3, 6, and 12 months aggregation), and to examine the relationship of other climate modes (i.e., ENSO, AMO, and AMM), which were not considered with drought temporal evolutions in the Volta basin. Such analysis is essential not only in understanding drought variability, but also the causes of rainfall variability, which though unclear has been somewhat associated with sea surface temperature anomalies of the nearby Oceans (e.g., Bader and Latif, 2011). For the drought analysis, we used the recently introduced standardised non-parametric univariate and multivariate drought indices (see, Hao and AghaKouchak, 2013, 2014; Farahmand and AghaKouchak, 2015) for the characterisation of different droughts (e.g., meteorological, agricultural, and hydrological) over LCB. The ICA technique was employed to statistically decompose SPI and standardised soil moisture index (SSI) values into spatial and temporal patterns while the multivariate standardised index (MSDI), was used to evaluate the effectiveness of two climate variables (rainfall and soil moisture) in capturing drought properties such as frequency, persistence, and termination. This study specifically aims at (i) localising and characterising spatio-temporal evolutions of drought patterns over the LCB and (ii) identifying spatial variability of TWS changes and the estimation of trends in lake height variations over the LCB.

While we provide background information on the spatio-temporal variability of drought patterns in Section 2, further details on the method and the results of the study are presented in Sections 3 and 4, respectively.

2. Spatio-temporal Variability of Drought

The lack of in-situ measurements to assist in hydrological monitoring limits the prospects of a robust, large scale monitoring of major hydrological variables (i.e., rainfall, water levels, groundwater, and river discharge) in the LCB. Standard routine measurements of these hydrological quantities are lacking due to limited gauge stations and deterioration of existing hydrological facilities. Although local measurements from dedicated regional networks such as the African Monsoon Multidisciplinary Analysis-Couplage de l'Atmosphère Tropicale et du Cycle Hydrologique (AMMA-CATCH, Lebel et al., 2009) hydro-meteorological observing sys-

Figure 1: Study area showing Lake Chad, the riparian countries that constitute the Lake Chad basin, and important river networks (blue line) within the basin. Our analysis focuses on the conventional basin area (a subset of the blue polygon), which includes mostly southern and north eastern sections of Niger, Chad, north-eastern Nigeria, northern Cameroon, and most parts of Central African Republic. Maps are adapted from www.worldmap.org and <http://assets.panda.org/img/original/chadmap.gif>. The LCB lies at the south western crossroads of the Sahel and forest savanna, a transition zone between the Sahara Desert and the tropical savanna of West Africa (Okonkwo et al., 2013).

tem have been used in some studies (e.g., Gosset et al., 2013), the AMMA-CATCH networks are highly insufficient for a regional study as they are only available in few countries (i.e., Niger, Mali, and Benin). Further, while most available data cannot be accessed by the public and relevant research institutions as a result of government policies and bureaucracies, political instability in the sub-regions complicates efforts to acquire such data. In addition, incomplete data records and gaps in available data tend to affect proper assessment and monitoring of hydrological conditions in the region.

However, with the plethora of available climate data either in the form of satellite observations or model-generated products, monitoring hydro-climatic conditions is somewhat not difficult. The critical issues have often revolved around the understanding and localisation of these multiple and growing climate signals. For instance, the use of mean standardised precipitation index (SPI, McKee et al., 1993) time series in estimating drought conditions over the Sahel has not been very effective. This is because of the influence of strong spatial variability

Figure 2: The spatial and temporal changes in Lake Chad surface area as shown by Landsat imageries for 1973, 1987, 2003, and 2013. The Chari river, which provides about 95% of the inflow to the Lake is indicated. The blue lines on the map (left) show the river networks within the basin most of which constitute the Chari river system. The present Lake Chad show two segmented pools with the northern pool completely dried up during drought periods (right). Maps and imageries are adapted from (i) www.stud.informatik.uni-frankfurt.de/sfb268/d6/pics/misc/franke2000gr-abb1-gross.gif and (ii) United States geological surveys (<http://earthshots.usgs.gov/earthshots/Lake-Chad-West-Africa>).

174 of rainfall at annual scale and the mean inter-annual climatological gradients across the region
 175 (Ali and Lebel, 2009). Schewe et al. (2013) described the signal problem more succinctly,
 176 indicating that at regional scales, the projections of climate models for instance, in terms
 177 of precipitation patterns and magnitudes, are inconsistent when compared to global average
 178 changes. This unavoidably leads to uncertainties in the attempt to understand the effect of
 179 climate change on water resources at regional scales. In West Africa, Ali and Lebel (2009)
 180 reported that despite the significantly dry season of 2006, working with a rainfall product with
 181 spatial resolution of $0.5^\circ \times 0.5^\circ$ resulted in only 28% of the area being significantly dried while
 182 15% of the Sahel region was significantly wet. They also observed that SPI on a $1^\circ \times 1^\circ$ grid
 183 in the Sahel was not representative of the whole region. Irrespective of the spatial resolution
 184 of the data and differences in climatic zones, drought analysis from a spatio-temporal point of

view can improve our understanding of drought occurrence. One approach to spatio-temporal drought analysis would be the use of a component extraction technique, in particular, principal component analysis (PCA, [Jolliffe, 2002](#)). For example, [Bazrafshan et al. \(2014\)](#) in a recent study reported on the multivariate approach, which uses the PCA of the SPI time series in capturing the temporal variability of drought patterns at different time scales (i.e., 3, 6, and 12 month scale) while [Bonaccorso et al. \(2003\)](#) studied long-term drought variability in Sicily during 1926-1996 period using the PCA technique. Further, using PCA and K-means clustering, [Santos et al. \(2010\)](#) was able to show that the south of Portugal had more frequent cycles of dry events (every 3.6 years) than the northern part where severe to extreme droughts occurred approximately every 13.4 years. Following the strong spatial variability of rainfall in the Sahel region where LCB is located, our approach uses a regionalisation process where the decomposed SPI time series from PCA are rotated towards statistical independence, a process referred to as independent component analysis (e.g., [Aires et al., 2002](#); [Cardoso, 1999](#); [Cardoso and Souloumias, 1993](#)). Our approach differs from the aforementioned studies in that the derived SPI time series, which are based on a non-parametric approach derived from the empirical probability method (see [Farahmand and AghaKouchak, 2015](#); [Hao and AghaKouchak, 2014](#)) are decomposed through a classical rotation of the PCA modes. This is done in a way to enable the localisation and extraction of physically meaningful drought signals that are statistically significant. The use of a regionalization method such as the ICA enables the localization of SPI and standardised soil moisture index (SSI) signals in terms of its spatial variability and temporal evolutions in the basin. This approach is useful in understanding the space-time evolution of extreme rainfall and soil moisture conditions in the basin. For an endorheic basin such as the LCB, which lacks a suitable framework to monitor space-time occurrence of drought, this approach to drought monitoring, when integrated with the analysis of changes in TWS and altimetry derived water levels of Lake Chad, largely supports the assessment of available water resources. We provide more details on the ICA technique in Section 3.

Moreover, in this study, we hypothesized that following the dramatic decline and desiccation of Lake Chad surface area due to strong precipitation deficit of the 1980's (see cumulative rainfall anomalies, Fig. 3), meteorological drought propagates into both agricultural and hydrological droughts with strong impact on the catchment stores (i.e., lakes, rivers, soil water, and aquifers). Several drought studies have associated hydrological drought with precipitation deficit on a longer time scale such as 6, 12, and 24 months (see, e.g., [Li and Rodell, 2015](#);

218 Santos et al., 2010; Vicente-Serrano, 2006; Rouault and Richard, 2003; Hayes et al., 1999; Ko-
 219 muscu, 1999). In sum, we used precipitation and soil moisture data, covering a 35-year period
 220 to quantify drought frequency (how often a drought event occurs) and severity (the intensity
 221 or strength of a drought event) for all drought categories (meteorological, agricultural, and
 hydrological).

Figure 3: Cumulative rainfall anomalies averaged over LCB using the GPCP based precipitation. (a) Monthly cumulative rainfall anomaly over the basin during 1979-2014 period. (b) Annual cumulative rainfall anomaly over the basin during 1979-2014 period.

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223 3. Data and Method

224 3.1. Data

225 3.1.1. GRACE-Derived Terrestrial Water Storage (TWS) Changes

226 Gravity Recovery and Climate Experiment (GRACE, Tapley et al., 2004) Release-05
 227 (RL05) spherical harmonic coefficients from Center for Space Research (CSR) for the period
 228 of April 2002 to October 2014 were used in this study to compute changes in TWS. The CSR
 229 RL05 gravity field solutions, which are truncated at degree and order 60 were retrieved from the
 230 open access files available at <http://icgem.gfz-potsdam.de/ICGEM/shms/monthly/csr-rl05/>.
 231 These spherical harmonic coefficients suffer from signal attenuation and satellite measurement
 232 errors leading to noise in the higher degree coefficients (Landerer and Swenson, 2012; Swenson
 233 and Wahr, 2002). As a first step in the processing, the degree 2 coefficients were replaced with
 234 estimates from satellite laser ranging (Cheng et al., 2013) while the degree 1 coefficients pro-
 235 vided by Swenson et al. (2008) were used. This was necessary since GRACE does not provide

changes in degree 1 coefficients (i.e., C_{10} , C_{11} , and S_{11}), and is also affected by large tide-like aliases in the degree 2 coefficients (i.e., C_{20}). Secondly, after removing the long term mean, DDK2 de-correlation filter (Kusche, 2007) was applied on the GRACE monthly solutions in order to reduce the effect of correlated noise. Practically, non-isotropic filters such as the DDK2 (Kusche, 2007) accommodate better the GRACE error structure when compared to the conventional isotropic Gaussian filter (see, e.g., Werth et al., 2009). We point out briefly that there are no standard filtering procedures as most GRACE users would largely prefer the most convenient and easy-to-implement approaches. However, the filtering process can be significantly improved by using decorrelation filters, which unlike the Gaussian filter, fits better the noise in the data (e.g., Belda et al., 2015). The filtered monthly solutions were then converted to equivalent water heights on a $1^\circ \times 1^\circ$ grid using the approach of Wahr et al. (1998):

$$\Delta W(\phi, \lambda, \xi) = \frac{R\rho_{ave}}{3\rho_w} \sum_{l=0}^{l_{max}} \frac{2l+1}{1+k_l} \sum_{m=-l}^l P_{lm}(\phi, \lambda) \Delta Y_{lm}(\xi) \quad (1)$$

where ΔW is equivalent water height (hereafter TWS) for each month in time (ξ), and where ϕ and λ are the latitudes and longitudes, respectively. R is the mean radius of the Earth (i.e., 6378.137 km), ρ_{ave} is the average density of the Earth (5515 kg/m^3), ρ_w is the average density of water (1000 kg/m^3), k_l is the load Love numbers of degree l , P_{lm} are the normalized spherical harmonic functions of degree l and order m with $l_{max}=60$ and ΔY_{lm} are the normalized complex spherical harmonic coefficients after subtracting the long term mean. Since the effect of the DDK2 filter whose radius coincides with 340 km of the Gaussian filter leads to attenuation of the signal amplitude (e.g., Wouters and Schrama, 2007; Baur et al., 2009), a scaling factor obtained from Global Land Data Assimilation System (GLDAS, Rodell et al., 2004) derived terrestrial water storage content (see details in Section 3.1.7) was computed in a manner similar to Landarer and Swenson (2012). This scaling factor was applied to the GRACE-derived TWS values in order to restore the geophysical signal loss caused by the impact of the DDK2 decorrelation filter. Apparently, the use of GRACE data has progressed in the direction of full scale hydrological applications and water resources monitoring (see Wouters et al., 2014). Thus, accounting for the effect of the filter in the transformed GRACE observations becomes essential as the signal attenuation will become an error in the residual in regional water balance or might serve as a constraint in water budget closure (see Landarer and Swenson, 2012). The rescaled monthly TWS grids had a few random gaps of up to 12 months in between that were filled through interpolation. This is particularly important for the regionalisation process,

267 which requires continuous spatio-temporal data.

268 3.1.2. Tropical Rainfall Measuring Mission (TRMM) Data

269 Rainfall observations from TRMM 3B43 (Huffman et al., 2007; Kummerow et al., 2000)
270 provide good estimates of rainfall magnitude not detected by other satellite precipitation
271 products. In West Africa for example, Nicholson (2013) had reported that TRMM valida-
272 tion using in-situ data showed zero bias, having a root mean square error (RMSE) of 0.7
273 and 0.9 mm/day for the seasonal and August rainfall, respectively. Specifically, TRMM
274 3B43 version 7, which has a global coverage (i.e., 50°S and 50°N) provides monthly pre-
275 cipitation estimates at a spatial resolution of 0.25° x 0.25° and has been significantly im-
276 proved (e.g., Duan and Bastiaanssen, 2013b). Due to its spatial resolution and bias with
277 in-situ observations, we used TRMM 3B43 to estimate monthly and seasonal rainfall in the
278 LCB. The data covering the period 1998-2013 was used and is available at the National
279 Aerospace and Space Administration (NASA) Goddard Space Flight Center (GSFC) website
280 (<http://disc.gsfc.nasa.gov/datacollection/TRMM3B43-V7.shtml>).

281 3.1.3. Global Precipitation Climatology Project (GPCP)

282 The 2.5° x 2.5° global grids of monthly estimate from GPCP version 2.2 precipitation
283 data set (e.g., Huffman et al., 2009; Adler et al., 2003) is a merged satellite-based product
284 (includes satellite microwave and infrared data) that is adjusted by the use of rain gauge
285 analysis. Unlike Ethiopia and some other countries in East Africa where TRMM is com-
286 pletely inconsistent with GPCP (Paeth et al., 2012), the GPCP rainfall product is highly
287 correlated and consistent with TRMM in the region and is used here for the spatio-temporal
288 analysis of drought in the LCB. The GPCP version 2.2 data, covering the period of 1979-
289 2015, was used since drought analysis using SPI requires data record of at least 30 years.
290 The archived data is distributed through World Data Center and is available for download at
291 <http://lwf.ncdc.noaa.gov/oa/wmo/wdcamet-ncdc.html>.

292 3.1.4. Satellite Altimetry Water Level Variations

293 Lake level height variations computed from TOPEX/POSEIDON (T/P), Jason-1 and
294 Jason-2/OSTM altimetry provided by the United States Department of Agriculture (USDA)
295 was used to study Lake Chad surface water. The data covering the period 1993 to 2015 was
296 downloaded from www.pecad.fas.usda.gov/cropexplorer/globalreservoir and used to analyse
297 water level variations. The time series of USDA monthly lake height variation used for the

study have been smoothed with a median type filter in order to eliminate outliers and reduce high frequency noise. The use of altimetry-based measurements for a data deficient region such as the LCB, as stated by [Coe and Birkett \(2004\)](#), is beneficial since they are continuous and potentially available few days after measurement. That is quite unlike gauge data that are irregular and difficult to acquire due to government policies and bureaucracies.

3.1.5. *Climate Prediction Center (CPC) Soil Moisture*

The monthly CPC soil moisture data version 2 ([Fan and Dool, 2004](#)) with spatial resolution of $0.5^\circ \times 0.5^\circ$ for the period between 1979 to 2014 was used in this study to investigate water availability through standardised soil moisture index (SSI). The data, which is model-based is derived from monthly global rainfall data that uses more than 17000 rain gauges worldwide and monthly global temperature from reanalysis. In addition, the data has been used to extract climate teleconnection patterns such as the El-Niño Southern Oscillation and long term trends ([Fan and Dool, 2004](#)). The data is freely available at NOAA (<http://www.esrl.noaa.gov/psd/data/gridded/data.cpcsoil.html>) for download.

3.1.6. *Climate Indices*

Relevant and well known global climate teleconnections indices such as El-Niño Southern Oscillation (ENSO), Atlantic Multi-decadal Oscillation (AMO), and Atlantic Meridional Mode (AMM) have been associated with precipitation patterns (see, e.g., [Giannini et al., 2003](#); [Nicholson, 2013](#); [Giannini et al., 2013](#); [Paeth et al., 2012](#)), important factors that regulate the formation and persistence of drought events in the Sahel and some countries of West Africa. These indices, covering the period 1979-2014, were used to examine the relationship and possible links of observed temporal evolutions of droughts in LCB with coupled atmosphere-ocean system and perturbations of nearby oceans. We point out briefly that other ENSO indices such as Nino3.4 and Nino4.0 exist but we used Multivariate Enso Index-MEI (hereafter called ENSO) since it comprises six other variables over the Pacific coupled with atmospheric anomalies. The climate indices used in this study can be downloaded from National Oceanic & Atmospheric Administration (NOAA) websites (e.g., <http://www.cpc.ncep.noaa.gov>).

3.1.7. *Global Land Data Assimilation System (GLDAS)*

GLDAS ([Rodell et al., 2004](#)) derived monthly total water storage content (TWSC) at $1^\circ \times 1^\circ$ spatial resolution was used to rescale the GRACE-derived TWS change in order to remedy the signal loss due to filtering. GLDAS is unique because it integrates both satellite

and in-situ data to produce optimal fields of land surface states and fluxes (Rodell et al., 2004). The TWSC was derived from summing all the layers from Noah 2.7.1 land surface model of GLDAS (i.e., all the soil moisture layers including the canopy water storage). This land surface model (i.e., the NOAH component of GLDAS) showed a good agreement with GRACE-derived TWS in West Africa, indicating a coefficient of determination (R^2) of 0.85 (Ndehedehe et al., 2016a). However, the averaged TWSC and GRACE-derived TWS in the LCB showed a relatively stronger agreement (i.e., R^2 of 0.88) with a root mean square error of 19.83 (see Appendix A3, Fig. 17). While it is important to acknowledge that the GLDAS model incorporates soil moisture and plant canopy surface water storage, it does not include surface and groundwater components. However, previous studies have reported a good agreement between GLDAS-TWSC and GRACE-derived TWS at basin scale (e.g., Moore and Williams, 2014). To derive the scale factor, TWSC was filtered using the DDK2 filter similar to GRACE observations. Thereafter, the ratio of the DDK2 filtered TWSC to the unfiltered and synthesised TWSC was used to derive a scale factor. This scale factor, which measures the impact of DDK2 filter on GRACE-observations, was then applied to the gridded TWS values similar to previous studies (see, e.g., Long et al., 2015; Landerer and Swenson, 2012). GLDAS-derived TWSC covering the years 2001-2014 was obtained from the open access file available at <http://grace.jpl.nasa.gov/data/get-data/land-water-content/>.

3.1.8. Sea Surface Temperature (SST)

SST version 2 (Reynolds et al., 2002) data was downloaded from the website (<http://www.esrl.noaa.gov/psd/data/gridded/data.noaa.oisst.v2.html>) of the National Oceanic and Atmospheric Administration (NOAA). The period covered is from 2002 to 2014. The SST averaged of the Atlantic Ocean (30°S–30°N and 70°W–20°E) was used in this study to investigate its relationship with annual cycles of rainfall over the basin.

3.1.9. Satellite Image Analysis

Landsat 7 Enhanced Thematic Mapper plus (ETM+) and Landsat 8 imageries were downloaded from the United States geological surveys website (<http://glovis.usgs.gov/>). The imageries for 2000, 2003, and 2015 in the Lake Chad area were clipped and classified using Iterative Self-Organizing Data Analysis Technique Algorithm (ISoData) technique proposed by Ball and Hall (1965). The method is an unsupervised classification method that uses an iterative clustering algorithm and allows the number of clusters to be dynamically determined. The surface area of the Lake at different epoch was estimated using the classified pixels rep-

resenting water bodies. Estimating the recent surface area is critical to understanding the desiccation story of the basin in recent times. It is also important to evaluate the wet/dry regimes of the basin in the last decade.

3.2. Method

3.2.1. Standardised Drought Indices

Drought phenomenon is usually expressed using standardised indices for example, standardised precipitation index (SPI, [McKee et al., 1993](#)) and standardised runoff index ([Shukla and Wood, 2008](#)) amongst others. The SPI is a very popular drought index. It is normalized so that wetter and drier climates can be represented in a similar way and can be calculated for other water variables and hydrological quantities such as snowpack, reservoir, streamflow, soil moisture, and ground water ([McKee et al., 1993](#)). In this study, we utilised two variables (rainfall and CPC model soil moisture) to implement a non-parametric standardised multivariate drought index in order to compensate for the weakness of single drought index as argued by [Hao and AghaKouchak \(2014\)](#). The mathematical framework of this non-parametric multivariate standardised drought index (MSDI) and other single drought indicators (e.g., SPI and SSI) is fully documented by [Farahmand and AghaKouchak \(2015\)](#). These drought indicators adopt empirical method to determine the marginal probability of precipitation and other variables such as soil moisture, evapotranspiration, and runoff. The MSDI combines two hydrological quantities to derive a composite drought index, which can be described as a multivariate prototype of the popular SPI ([AghaKouchak, 2015](#)). Recently, the MSDI has been shown to be a statistically consistent drought index ([Huang et al., 2015](#)) and is employed here for the first time in the region. The joint distribution of two variables X and Y expressed as ([Hao and AghaKouchak, 2013](#))

$$P(X \leq x, Y \leq y) = p, \quad (2)$$

where p represents the joint probability of any two variable (e.g., rainfall and soil moisture). The joint probability is then used to define the MSDI as

$$MSDI = \phi^{-1}(p) \quad (3)$$

where ϕ^{-1} is the standard normal distribution function. For the bivariate case, the Gringorten plotting position formula (see [Farahmand and AghaKouchak, 2015](#); [Hao and AghaKouchak, 2014](#)) is used to estimate the empirical joint probability. The empirical Gringorten plotting position is expressed as:

$$p(x_k, y_k) = \frac{m_k - 0.44}{n + 0.12}, \quad (4)$$

where n is the number of the observation and m_k is the number of times which the pair (x_i, y_i) occur for $x_i \leq x_k$ and $y_i \leq y_k$ ($1 \leq i \leq n$). Eq. 4 is used in Eq. 3 to compute the MSDI while the standardised precipitation index (SPI) and standardised soil moisture index (SSI) are also estimated using the univariate form of Eq. 4. Thus, we combined averaged GPCP rainfall and soil moisture to derive time series of MSDI, in addition to the single drought indicators across different time scales (i.e., 1, 3, 6, and 12 months). The drought classification and extreme rainfall events used in this study are based on the description of McKee et al. (1993) (Table 1).

As discussed earlier in Section 2, localising drought signals has been a major limitation in drought studies. Hence, the ICA method (see details in Section 3.2.2) was used to decompose the gridded time series of computed SPI and SSI at 3, 6, and 12 month scales into independent modes (i.e., temporal and spatial patterns) where drought/wet signals are localised in terms of their spatial and temporal variations. The statistically significant modes of variability identified in the LCB were analysed further. Essentially, this statistical decomposition of meteorological and land surface state variables (i.e., rainfall and soil moisture) into spatial and temporal patterns allow the extraction of climate teleconnection patterns and other relevant coupled ocean atmosphere patterns that are related to the observed wet and dry periods in the basin. Prior to decomposing gridded rainfall and soil moisture drought indicators into spatial and temporal patterns, the spatially averaged time series of each of the two datasets were used to compute time series of SPI and SSI. That provides the opportunity to compare the results of the two approaches (i.e., the decomposed gridded drought indicators and time series of averaged indicators over the basin). To understand the relationship of climate teleconnection indices with ICA-derived temporal variability of drought patterns, Pearson correlation analysis was applied. The SPI values at 3, 6, and 12 month scales for all first and second ICA modes, were selected for this correlation with global climate teleconnection indices (i.e., AMO, AMM, and MEI). This choice is based on the theoretical assumption that the first and second ICA modes have relatively stronger dominant modes of variability. A student T-test was then used to calculate the significance of the correlation at 95% confidence level.

Table 1: Drought classification and extreme rainfall/soil moisture events based on McKee et al. (1993) classification system.

Description	Threshold
Extreme wet	+2.0 and above
Very wet	+1.5 to +1.99
Moderately wet	+1.0 to +1.49
Near normal	-0.99 to +0.99
Moderate drought	-1.0 to -1.49
Severe drought	-1.5 to -1.99
Extreme drought	-2.0 or less

3.2.2. Independent Component Analysis (ICA)

The ICA (see, e.g., Ziehe, 2005; Cardoso and Souloumiac, 1993; Cardoso, 1991; Common, 1994; Cardoso, 1999) technique (see further details in Appendix A2) was used to decompose a data matrix $\mathbf{X}$, into spatial maps $\mathbf{M}$, and temporal patterns $\mathbf{T}$, as:

$$\mathbf{X}_{SPI/SSI/TWS}(x, y, t) = \mathbf{T}\mathbf{M}, \quad (5)$$

where (x, y) are grid locations, t is the time in months. $\mathbf{T}$ is unit-less since it has been normalised using its standard deviation while the corresponding spatial patterns $\mathbf{M}$, have been scaled using the standard deviation of its independent components (i.e., $\mathbf{T}$). In this study, we used the JADE (see further details in Appendix A2) algorithm (available at <http://perso.telecom-paristech.fr/cardoso/Algo/Jade/jadeR.m>) to decompose standardised drought indicators (i.e., the gridded SPI and SSI data) and GRACE-derived TWS into spatial maps and temporal patterns. Each ICA mode (a pair of the independent components and spatial patterns) of variability is a combination of the temporal and spatial patterns and are usually interpreted together (i.e., the unit-less temporal evolution is multiplied with the spatial pattern in order to obtain the actual values of SPI, SSI, and TWS).

3.2.3. Trends and Correlation Analysis

The trends in observed temporal evolutions of TWS and Lake Chad water level variations were estimated using the least squares method. Further, we examined the relationship of climate teleconnections with observed temporal SPI patterns (i.e., at 3, 6, and 12 months aggregation) using the linear correlation coefficient (r). The significance of observed correlations

437 were tested at 95% confidence level using the Student-t distribution test as

$$t = r \sqrt{\frac{n-2}{1-r^2}}, \quad (6)$$

where n is the total number of given observations for the data.

Figure 4: Averaged monthly rainfall over Lake Chad basin and annual cycles of TRMM-based precipitation and sea surface temperature (SST). (a) Time series of spatially averaged rainfall over Lake Chad basin using GPCP version 2.2 (1979 – 2013) and TRMM 3B43 based precipitation (1998 – 2013) (b) Long term mean annual cycle of rainfall over Lake Chad basin using TRMM 3B43 based precipitation and annual cycle of SST data averaged over the Atlantic Ocean (30°S–30°N and 70°W–20°E).

438

439 4. Results and Discussions

440 4.1. Seasonal Rainfall Patterns over the Lake Chad Basin (LCB)

441 TRMM 3B43 version 7 precipitation product was used for the seasonal analysis and long
 442 term annual cycle while the GPCP version 2.2 precipitation data was used for the drought
 443 analysis because of its duration (35 years). A 35-year data meets the criteria for SPI since a
 444 30-year data or less shortens the sample size and undermines the confidence in its usage (e.g.,
 445 Svoboda et al., 2012). Comparing the TRMM and GPCP based precipitation products, the
 446 spatially averaged GPCP product was consistent (indicated a linear correlation of 0.99) with
 447 the spatially averaged TRMM product. This near-perfect correlation is expected since TRMM
 448 is adjusted by rain gauge observations, most of which are included in the GPCP datasets.
 449 Despite the differences in the spatial resolutions of these two precipitation products, their
 450 strong agreement over the LCB can be useful in future studies to characterise uncertainties in

water budget analysis. Although no notable trend is observed in the spatially averaged rainfall over the basin, we observe a recent pronounced maximum peak in 2012 that is similar to other extreme wet years, for example, 1988, 1994, 1999, 2003, and 2006 (Fig. 4a). The lowest annual rainfall peak observed in 1984 (Fig. 4a) is consistent with the well known drought that ravaged the African continent during the 1982-1984 period (e.g., Masih et al., 2014). The annual cycle of precipitation over LCB indicates a peak in August while the seasonality of SST shows an opposite phase with rainfall (Fig. 4b). Most parts of the LCB lies in the Sahel region, and the impact of SST variability on rainfall has been reported (Mohino et al., 2011; Paeth et al., 2012; Lebel and Ali, 2009). Rainfall decline in the coastal West African countries has been associated with cold SST along the Atlantic and warm SST in the eastern tropical Pacific while decadal rainfall trends in the Sahel is assumed to be influenced by a combination of multiple low-frequency SST signals (e.g., Rodriguez-Fonseca et al., 2011).

Moreover, the seasonal analysis show that maximum rainfall (temporal variations) comes between July and September with a maximum averaged rainfall of about 150 mm while other seasons have less than a 100 mm of rainfall (Fig. 5, right). The spatial distribution of rainfall indicates a maximum of about 250 mm of rainfall towards the southern part of the basin and more than 300 mm outside the conventional basin area (Fig. 5, left). Comparatively, the GPCP version 2 seasonal rainfall patterns over the basin also show similar temporal and spatial patterns with the July-September period indicating relatively low pronounced amplitudes of rainfall (e.g., 1983 – 1984, 1987, etc.) in the temporal variations due to extreme drought conditions (see Appendix A1, Fig. 16). Generally, the July-September rainfall (i.e., using the GPCP data) in the basin is the dominant rainfall as the most pronounced maximum peaks correspond to those of Fig. 5. Overall, the seasonal rainfall patterns over the basin, clearly show the dichotomy between the northern section (having low rainfall) and the southern band (which receives more rainfall especially between July and September) (Fig. 5). This seasonal picture of rainfall in the basin is crucial as it has the capacity to enhance the assessment of the basin's hydrology. The knowledge of the basin's climatology, in terms of seasonal rainfall can enhance our interpretation of the standardised drought indices.

4.2. Drought Characteristics Over the Lake Chad Basin (LCB)

4.2.1. Time Series of Standardised Drought Indicators

The standardised drought indicators (i.e., SPI, SSI, and MSDI) for the LCB were computed at 1, 3, 6, and 12 month cumulations using spatially averaged GPCP and CPC soil moisture

Figure 5: Seasonal rainfall analysis for Lake Chad Basin (5.5°N - 24.5°N and 5.5°E - 24.5°E) using TRMM satellite data for the period 1998 – 2013. Spatial patterns (left) and temporal patterns (right) are averaged over the geographical boundary describing the spatial extent of Lake Chad basin used in this study. The inset (i.e., the solid black line) is the conventional basin boundary.

483 data over the basin. Results show that shorter time scales (e.g., 1 and 3 month cumulations)
 484 have high drought frequencies (Fig. 6a-b). The frequency reduces with increase of time scales
 485 (e.g., 6 and 12 month cumulations) (Fig. 6c-d). According to Komuscu (1999), this kind of
 486 relationship implies that the index responds more slowly as the time scales increases. Con-
 487 sistent decrease in SPI and MSDI values were observed from 1979 to 1985 (Fig. 6) but with
 488 recovery in 1984 at 3 and 6 months scale. The strong decline of SPI and MSDI within this
 489 period coincides with the hydrological drought record of the basin, which showed a dramatic
 490 loss of 15138 km^2 in the surface area of Lake Chad (see, Alfa et al., 2008). The MSDI and
 491 SSI show drought persistence in 1990/1991 at all scales (Fig. 6a-d); 1998 at 3 and 6 months
 492 (Fig. 6b-c); and 2009 at 6 and 12 months (Fig. 6c-d). The drought years as indicated in the

493 standardised drought indicators are generally consistent with observed decline in the northern
 494 pool of the Lake as previously reported by Lemoalle et al. (2012). In addition, the observed
 495 wet (e.g., 1988 and 1994) and dry (e.g., 1983 – 1985) years (Fig. 6) are consistent with the
 496 records of observed water levels at Kindjéria (i.e., at the northern section of LCB) as reported
 497 in a previous study by Lemoalle et al. (2012). They noted that the northern pool gets flooded
 498 during extreme wet periods and completely dry for several years due to incessant drought con-
 ditions. Similar patterns in the behaviour of surface waters (e.g., Lakes) vis-à-vis drought and

Figure 6: Time series of standardised drought indicators (i.e., SPI, SSI, and MSDI) for Lake Chad basin using averaged GPCP and CPC soil moisture data covering the period 1979 – 2013 (i.e., over the basin). The MSDI is derived through the combination of GPCP based precipitation and CPC based soil moisture data. These standardised drought indicators are based on empirical probability, different from the gamma distribution function used in the SPI case of McKee et al. (1993).

499
 500 wet periods in the region have been reported (e.g., Bekoe and Logah, 2013; Lemoalle et al.,
 501 2012). Also, previous studies have associated the decline in the surface area of the lake to
 502 human activities (e.g., water use for irrigation) and the impact of climate variability (see, e.g.,
 503 Coe and Foley, 2001; Gbuyiro et al., 2001). Some of the drought cases identified in the study
 504 (i.e., using averaged SPI) are somewhat generalised and appear not to be very massive (i.e., in

terms of severity). But the cases are significant enough to impact negatively on the agrarian system and food security conditions of the basin where agriculture is predominantly rain-fed.

Furthermore, extreme wet conditions in 1987/1988 (all through the year), and 1994/1995 show strong persistence in wetness by SSI (Fig. 6a-d). On the contrary, SPI and MSDI showed drought conditions in 1987 while in 1995 they indicated that the wet conditions actually ended, unlike SSI, which indicated that the severe wet conditions that started in late 1994 persisted even till 1996 (Fig. 6b-d). This inconsistency is probably caused by intense rainfall occurring within few months while the remaining months of the year are consistently dry. The SPI values (i.e., at 1 and 3 months cumulation) tend to be very high during the 2003 – 2013 period (Fig. 6a-b), and are consistent with the findings of Okonkwo et al. (2013) whose report showed increase in SPI values between 2002 and 2011 in the basin. However, the SSI and MSDI show longer drought durations in late 2004 (Fig. 6a-b) and 2005 (Fig. 6c-d). In the drought assessment done so far using the three standardised indicators over the LCB, recent conditions of wetness in late 2010 and 2012/2013 captured by SPI, SSI, and MSDI (Fig. 6a-d) appear to be a dramatic deviation from the long string of frequent drought conditions observed in the basin (note that at 12 month cumulation period, only SPI indicated wet condition in 2010 while SSI and MSDI showed a recovery from drought condition). This period (i.e., between 2010 and 2013), which also coincides with increased water level in Lake Chad as shown in Section 4, is largely consistent with the spatially averaged rainfall over the basin within the same period (Fig. 4a). Further, as the accumulation period increases (i.e., for SPI), soil moisture conditions tend to respond slowly to extreme wet conditions of SPI. It seems that the extreme wet condition was not sufficient enough to cushion the deficit conditions of soil moisture in the basin. For instance, when we evaluate SPI (i.e., 12 month scale) values of 1991, 2006 – 2007 and 2012 – 2013 periods against SSI and MSDI (i.e., 12 month scale) values during the same period, the inconsistencies are rather obvious. SPI indicates extreme wet conditions during those periods (1991/1992 and 2006 – 2007) while MSDI and SSI show extreme drought (1991 and 2006 – 2007) and normal conditions (2011 – 2013 period) as against the extreme wet condition indicated by the SPI (2012 – 2013 period) (Fig. 6). Soil moisture deficits have been related to antecedent conditions, evaporation, seepage to groundwater, evapotranspiration, and runoff (e.g., Loon, 2015). According to Birkett (2000), Lake Chad loses about 80% of water through evaporation due to low humidity and high temperatures. Considering the fact that the basin is located in a semi-arid Sahelian environment, these factors and others (e.g., soil characteristics) may account for the observed inconsistencies between SPI and SSI. In

subsequent sections we show results of the statistical decomposition of SPI and SSI signals into spatial and temporal patterns using the ICA technique.

Figure 7: ICA-derived spatio-temporal SPI patterns of LCB using 3-month gridded SPI values. The SPI values are computed using GPCP rainfall product for the period 1979 – 2014. Localised spatial SPI patterns (right) corresponds to the temporal evolutions (left). The actual SPI values to be used for drought classification are jointly derived from the spatial and temporal SPI patterns. The green solid line is drought threshold.

539

540 4.2.2. Spatio-temporal Analysis of Drought Patterns for SPI

541 Unlike Section 4.2.1, where the spatially averaged values of rainfall and soil moisture over
 542 LCB were used to compute the standardised indicators (e.g., SPI and MSDI), here, we use,
 543 the gridded values of rainfall and soil moisture to compute standardised indicators, which were
 544 subsequently decomposed into temporal and spatial patterns using the ICA technique. The
 545 spatial patterns are localised signals (i.e., spatial maps indicating the direction of wet/drought
 546 conditions) that show spatial variability of rainfall conditions corresponding to the temporal
 547 evolutions. The classification scales (e.g., extremely wet, moderately dry, severely dry, ex-
 548 tremely dry) for the SPI values (see, e.g., Hayes et al., 1999; McKee et al., 1993) are jointly
 549 derived from each ICA mode (i.e., a combination of the spatial and temporal patterns).
 550 The spatio-temporal SPI patterns were computed for three different time scales (3, 6, and 12
 551 months). In Section 4.2.1, we showed drought index at 1 month scale (i.e., in the temporal

Table 2: Correlation coefficients between temporal evolutions of SPI (i.e., 3, 6, and 12 months SPI scales) derived from the ICA process and global climate teleconnection indices. Correlation values in bold are significant at $\alpha = 5\%$ confidence level.

SPI Scale	Independent Components	AMO	AMM	ENSO
3 month	1	0.31	0.30	-0.18
	2	-0.13	-0.21	0.07
6 month	1	0.38	0.38	-0.22
	2	-0.45	-0.33	0.18
12 month	1	0.55	0.38	-0.34
	2	0.36	0.08	-0.07

Figure 8: ICA-derived spatio-temporal SPI patterns of LCB using 6-month gridded SPI values. The SPI values are computed using GPCP rainfall product for the period 1979 – 2014. Localised spatial SPI patterns (right) corresponds to the temporal evolutions (left). The actual SPI values to be used for drought classification are jointly derived from the spatial and temporal SPI patterns. The green solid line is drought threshold.

drought patterns), however, in this section we choose these intermediate and long term scales (3, 6, and 12 months) for the spatio-temporal drought variability since they fit in well with

Figure 9: ICA-derived spatio-temporal SPI patterns of LCB using 12-month gridded SPI values. The SPI values are computed using GPCP rainfall product for the period 1979 – 2014. Localised spatial SPI patterns (right) corresponds to the temporal evolutions (left). The actual SPI values to be used for drought classification are jointly derived from the spatial and temporal SPI patterns. The green solid line is drought threshold.

agricultural and hydrological drought monitoring as indicated earlier in Section 2.

When comparing the temporal evolutions of SPI for 3 and 6 month time scales, a number of similar characteristics are observed. Declining SPI values from 1980 up to 1984 and extreme drought in 1984 are observed (Figs. 7 and 8) in the central part of the conventional basin. Also there is a change in drought frequency as the time scale changes. In Fig. 9, drought frequency is reduced when compared to Figs. 7 and 8 where drought frequencies are high. However, drought persistence is higher on longer time scales than short aggregation windows (see, Figs. 7-9). This is not to suggest that all cases of longer drought duration are usually related to the aggregation window. SPI aggregated over longer time scales (e.g., 12 and 24 months) are sometimes used in monitoring hydrological droughts (see e.g., Ndehedehe et al., 2016b; Li and Rodell, 2015; Lloyd-Hughes, 2012; Santos et al., 2010). But the propagation processes from meteorological to hydrological drought conditions may take some time depending on the soil surface conditions, which creates a lagged response (see IC1, Figs. 7-9). At all monthly SPI scales, we observed relatively strong drought spatial patterns towards the north and centre

of the conventional basin area and the entire basin at large. Even though we do not observe strong spatial drought patterns directly over Lake Chad, the southern part of the basin where the lake receives $\sim 95\%$ of its alimentation via the Chari-Logone river experienced drought at 3 and 6 month scales (IC2 and IC4 of Figs. 7 and 8, respectively), that is, when the SPI values are jointly considered or interpreted together from the spatial and temporal patterns. From their temporal evolutions (i.e., IC2 and IC4 of Figs. 7 and 8 respectively), specific years such as 1984, 1990, 1992/1993, 1996, 2000, 2002, and 2010 indicate similar drought characteristics, which we attribute to strong deficit in rainfall in those years. Still on the conventional basin area, the corresponding temporal evolution of drought spatial patterns at 12-month scale (i.e., hydrological drought) indicates extreme drought conditions, which began in 1983 and persisted till 1985 (IC1, Fig. 9). Similar temporal pattern is also observed in the section of the basin that

Figure 10: Influence of global climate teleconnection indices (i.e., 1979 – 2014) on temporal evolutions of hydrological droughts (i.e., 12 month SPI). The temporal drought pattern of ICA mode 1 shown in Fig. 9 are correlated with AMO (top), AMM (middle), and MEI (bottom).

belongs to Niger (IC4, Fig. 9). IC2 and IC3 of Fig. 9 show SPI signals in Libya and northern Chad respectively. Apart from the extreme wet conditions of 1988, 1994, and 1998-1999 in some parts of the LCB (IC1 and IC4, Fig. 9), which was also reported by Nicholson et al. (2000), the period between late 1995 and 1997 indicates drought persistence with extreme dry

583 conditions in 1996/1997 at northern Chad (IC3, Fig. 9). We point out briefly that while IC1
 584 of Fig. 9 (i.e., Central Chad) showed extreme wet conditions in the 1988/1989 period, IC2 of
 585 Fig. 9 (i.e., Libya) indicated a drought condition in 1998 with recovery in 1999. As a result,
 586 Libya was more or less climatically stable (i.e., when compared to 1994, 2006, and 2012).
 587 While the conventional basin area was relatively wet during 2001 – 2014 period (though with
 588 fluctuating SPI values) (IC1 of Fig. 9), drought conditions in the last decade (2001, 2009, and
 589 late 2013 – 2014) in Libya (IC2, Fig. 9) and southern Niger (IC4, Fig. 9) demonstrate the
 590 importance of a spatio-temporal approach to drought analyses. Apart from the SPI signal
 591 in Libya, recent wet conditions in 2010-2013 seems to be prevalent in the basin (IC1, IC3-
 592 IC4, Fig. 9) with the conventional basin area indicating mostly wet conditions since 1999
 593 (IC1, Fig. 9). The observed wet and dry periods from our localised drought signals, which we
 594 attribute partly to the impacts of La-Niña and El-Niño, respectively in the region are consistent
 595 with the findings of [Nicholson et al. \(2000\)](#) on the trends of rainfall conditions in West Africa.
 596 They identified 1988, 1994, and 1998 as the wettest years since the late 1960's (i.e., besides the
 597 pre-1980 period) while drier conditions prevailed in other areas of West Africa. In addition to
 598 these wet periods of 1988, 1994, and late 1998-2000 (IC1, Fig. 9), which are usually referred to
 599 as the rainfall recovery period in the Sahel (see, e.g., [Nicholson, 2013](#); [Nicholson et al., 2000](#)),
 600 strong positive deviations in normal rainfall in 2012, which may be the combined influence of
 601 climate teleconnections (i.e., ENSO, AMM, and AMO as discussed further in the later part of
 602 the study) in the region are observed at all scales (see IC1-IC4, Figs. 7-9). Specifically, the 1998
 603 and 1999 wet periods as observed in this study are consistent with the periods of high Chari
 604 flows, which led to flooding and loss of agricultural land within the southern basin (see [Birkett,](#)
 605 [2000](#)). Moreover, for all monthly cumulations, we observed a relatively strong declining SPI
 606 values between 1980 and 1984 over the region (IC1-IC4, Figs. 7-9), which are consistent with
 607 well known and acknowledged extreme drought conditions of 1983 – 1984 in Africa (e.g., [Masih](#)
 608 [et al., 2014](#)). Likewise, a relatively stronger decline of SPI values are observed between 1980
 609 and 1991/1992 mostly at Niger (i.e. IC3, Fig. 8) and Chad (i.e. IC3, Fig. 9). These extreme
 610 drought periods especially those occurring during 1982 – 1984 period (see e.g., IC1 and IC4
 611 of Fig. 9) have been attributed to the synergy between the abnormally warm Indian Ocean
 612 SST and that of the eastern Atlantic, which suppressed rainfall in the Sahel due to large scale
 613 subsidence in the troposphere (see, e.g., [Bader and Latif, 2011](#); [Giannini et al., 2003](#)). The
 614 Lake Chad basin had experienced prominent alterations in hydro-meteorological conditions
 615 in the past decades, which eventually led to widespread drought and sometimes flood in the

616 region. From the analysis of other ICA-derived modes of drought variability in this study (not
 617 shown), either for rainfall or soil moisture (Section 4.2.3), extreme wet and drought conditions
 were also observed in the extreme southern and northern part of the basin.

Figure 11: ICA-derived spatio-temporal SSI patterns of LCB using 3-month gridded SSI values. SSI values are computed using CPC model soil moisture product for the period 1979 – 2013. Localised spatial SSI patterns (right) corresponds to the temporal evolutions (left). The actual SSI values to be used for drought classification are jointly derived from the spatial and temporal SSI patterns. The green solid line is drought threshold.

618

619 Furthermore, we explored the relationship between SPI and global climate teleconnection
 620 indices that have been associated with rainfall variability and drought conditions in the Sahel.
 621 Results (Table 2) show that at 12 month SPI scale, AMO has a significant positive correlation
 622 of 0.55 with the first ICA mode of Fig. 9. In Fig. 10, we show the relationship of ICA-
 623 decomposed 12-month gridded SPI (i.e. IC1) with climate indices (i.e., AMO, ENSO, and
 624 AMM). We observe that the hydrological character vis-a-vis extreme rainfall conditions (e.g.,
 625 droughts) of LCB could also be as a result of the influence of AMO. Our linear correlation result
 626 (Table 2) agrees with the findings of Diatta and Fink (2014), that pointed out the influence of
 627 AMO on rainfall conditions in the Sahel. They reported positive linear correlations (0.28 and
 628 0.29) of AMO with West African Monsoon rainfall variability in two Sahel regions. Aligning
 629 with our perceived influence of AMO, Rodriguez-Fonseca et al. (2011) also reported on the
 630 impact of AMO on rainfall variability in the region. Still on the first independent mode of SPI

631 12 month scale (i.e., IC1 of Fig. 9), AMM showed positive correlations of 0.30, 0.38, and 0.38
632 with SPI at 3, 6, and 12 month cumulations, respectively (Table 2). The observed positive
633 linear correlation of AMM with temporal evolutions of wet/dry periods in the first mode (i.e.,
634 IC1 of Fig. 9), which is along the Sahel strip, is also consistent with the results reported
635 by Diatta and Fink (2014). The study reported a similar relationship of AMM with Sahel
636 rainfall variability. On the other hand, ENSO showed negative correlations of -0.22 and -0.34
637 with 6 and 12 month SPI cumulations, respectively (Table 2). For ENSO, a similar negative
638 relationship with Lake Chad water level variability was reported by Okonkwo et al. (2014).
639 Overall, the observed relationships between these climate teleconnections and SPI temporal
640 evolutions are statistically significant at 95% confidence level. The associations of AMM at 6
641 and 12 month scales and the relationship of ENSO and AMO with SPI temporal evolutions,
642 gives us the impression that the observed wet and dry periods in this study are probably also
influenced by multiple forcing mechanisms.

Figure 12: ICA-derived spatio-temporal SSI patterns of LCB using 6-month gridded SSI values. SSI values are computed using CPC model soil moisture product for the period 1979 – 2013. Localised spatial SSI patterns (right) corresponds to the temporal evolutions (left). The actual SSI values to be used for drought classification are jointly derived from the spatial and temporal SSI patterns. The green solid line is drought threshold.

643

644 4.2.3. Spatio-temporal Analysis of Drought Patterns for SSI

645 Apart from precipitation, society usually depends upon usable water from various sources,
646 such as soil moisture, streamflow, lakes, and reservoir storage for agriculture, ecosystem func-
647 tioning, domestic, and industrial purposes. Consequently, most drought impacts can also be
648 related to soil water drought (i.e., agricultural drought) and hydrological drought (abnor-
649 mally low water levels, in lakes, reservoir levels, and groundwater). Previous drought studies
650 have related hydrological and agricultural droughts with precipitation deficits on shorter and
651 longer time scales such as 3, 6, 12, and 24 months cumulations (see, e.g., [Li and Rodell, 2015](#);
652 [Lloyd-Hughes, 2012](#); [Hayes et al., 1999](#); [Komuscu, 1999](#)). But the use of soil moisture in quan-
653 tifying drought episodes that may be useful in hydrological applications and in understanding
654 the propagation process of rainfall deficit to hydrological drought (i.e., through soil moisture
655 deficit) are not known in the LCB. Hence, in order to investigate the spatio-temporal vari-
656 ability of agricultural and hydrological droughts, similar to the SPI concept of [McKee et al.](#)
657 ([1993](#)), the CPC soil moisture product was used to derive the SSI. Results indicate that sim-
658 ilar to the SPI (see Section [4.2.2](#)), the 1983/1984 drought is captured here at all monthly
659 scales in the basin (Figs. [11-13](#)). Generally, while there seem not to be differences in drought
660 frequency and persistence at all monthly scales, extreme wet years of 1988, 1994, 1998, and
661 2012 are consistent with results in Section [4.2.1](#). Apparently, at all monthly SSI accumulation
662 scales, the central part of the conventional basin where the Lake is located (i.e., Lake Chad,
663 Njamena and environs), show declining SSI values between 2008 and 2012, with extreme and
664 severe drought conditions in 2011 and the early part of 2012, respectively (see IC3, Fig. [11](#)
665 and IC2 of Figs. [12-13](#)). Although the later part of 2012 in the central part of the conventional
666 basin area shows drought recovery (e.g., IC2, Fig. [12](#)), the inconsistency between the tempo-
667 ral evolutions of SSI and SPI in 2012 in this part of the basin is a contrasting hydrological
668 situation that needs to be considered. This hydrological situation is attributed to a number
669 of factors. First, in the previous years, drought persisted between 2010 and early 2012 with
670 extreme drought condition observed in 2011 (see IC3, Fig. [11](#) and IC2 of Figs. [12-13](#)), hence,
671 the apparent soil moisture deficit even during periods of improved rainfall. Second, the rainfall
672 must have been hyped-up due to its intensity in few months (e.g., July and August) while the
673 remaining months of the year remained dry leading to observed drought condition. Third, it
674 could be that the strong amplitude of rainfall in 2012 (see Fig. [4](#)) and the wet conditions
675 observed from the spatio-temporal analysis of SPI (Figs. [7-9](#)) was not significant enough to
676 be reflected in soil water storage. Another argument in this regard could be that the previous

677 drought condition (e.g., 2009 and 2011) of the basin was quite overwhelming (IC1, Figs. 7 and
678 8). While Birkett (2000) had previously reported that about 80% of the lake's water is lost
679 through evaporation, the tremendous loss of water in the basin through evapotranspiration
680 process as further reiterated by Odada et al. (2005) could play a major role in the hydrological
681 situation observed. In addition to all of these considerations, the surface characteristics of
682 the soil (e.g., geological patterns) and local hydrodynamic behaviour (e.g., Descroix et al.,
683 2009) of the region can create temporary soil water shortage conditions leading to observed
inconsistencies between SPI and SSI signals. Moreover, model soil moisture products driven

Figure 13: ICA-derived spatio-temporal SSI patterns of LCB using 12-month gridded SSI values. SSI values are computed using CPC model soil moisture product for the period 1979 – 2013. Localised spatial SSI patterns (right) corresponds to the temporal evolutions (left). The actual SSI values to be used for drought classification are jointly derived from the spatial and temporal SSI patterns. The green solid line is drought threshold.

684

685 by observed meteorological forcing may show some limitations. They are inconsistent during
686 extreme wet and dry conditions and tend to show limited skills in regions with strong annual
687 rainfall cycle (Dirmeyer et al., 2004). Nevertheless, consistent with our arguments, Dirmeyer
688 et al. (2004) indicated that the variability in model soil moisture products may not completely
689 follow the variability in rainfall as a result of the surface characteristics of the soil.

690 In other drought events of the basin, extreme drought condition is observed on the southeast

part of the conventional basin during the periods of 1984 – 1985, 1996 – 1997, and 2000 – 2003 (IC4, Figs. 11-13). Also, this period (2000 – 2003) shows one of the period with the longest drought duration (i.e., soil moisture deficit, IC4 of Figs. 11-13) in the study and is consistent with the observed well pronounced negative water levels shown in Section 4.3. Note that this southeastern part of the conventional basin is also made up of tributaries that flows into the Chari-Logone river system. Hence, the observed extreme drought for the periods of 1984–1985, 1996–1997, and 2000–2003 as indicated in IC4 of Figs. 11-13 are specific examples of severe water shortage with grave agricultural and domestic consequence in the Lake and the conventional basin. Further, longer drought duration in recent times, is observed in the part of the basin that belongs to Niger between 2008 and early part of 2010 (see IC1, Figs. 11-13). This generally leads us to the understanding that the hydrological footprint of LCB in recent times (e.g., 2008 – 2012), indicates reduced alimentation and water deficit. It is likely that the loss of soil water storage in the basin could be the result of huge evapotranspiration and insufficient rainfall during the previous years. Although other environmental conditions such as increased surface temperature in the basin may intensify the soil moisture deficit conditions, SPI temporal evolutions (i.e., at 3 and 6 months aggregation) showed drought conditions in 2009, 2011, and early 2012 (IC1 of Figs. 7 and 8), coinciding with the soil moisture deficits during 2009 – 2012 period (IC3 of Fig. 11 and IC2 of Figs. 12 and 13). To further consolidate on these findings, the results of TWS regionalisation is presented in the next section.

4.3. Dynamics in Land Water Storage over the Lake Chad Basin

From the statistical decomposition of TWS changes over the LCB, four significant modes of variability were identified. The ICA approach generally, shows a relatively better performance in exploring the spatial dynamics of variability in GRACE-derived TWS changes compared to PCA, which was recently employed in analysing TWS and rainfall over West Africa by Ndehedehe et al. (2016a). The four modes of TWS variability (IC1-IC4, Fig. 14) analysed indicate a total variability of 67.6% with the first mode explaining 27.6% variability while IC2, IC3, and IC4 explained 16.2%, 13.6%, and 10.2%, respectively. IC1 (Fig. 14) is a strong hydrological signal emanating from the Benue river drainage basin (i.e., north-east Nigeria, as can be seen in the corresponding spatial pattern), which is made up of freshwater tributaries that also flows into LCB (cf. Fig. 1, left). This signal is mostly outside the conventional basin area but surface waters (i.e., rivers) from north-east Nigeria also provides nourishment to the LCB. From the temporal patterns (IC1, Fig. 14), a statistically significant increase of 12 ± 4.0

Figure 14: The independent components (right) of GRACE-derived TWS (2002 – 2014) over LCB corresponding to spatial patterns (left), which are scaled using the standard deviation of the computed independent components. These independent components are unitless since they have been standardised using their standard deviations.

723 mm/yr between 2002 and 2014, which is attributed to rainfall is observed. IC2 (Fig. 14) is
 724 TWS variability in the southern sector of the basin where $\sim 95\%$ of LCB's nourishment takes
 725 its origin. It is basically the TWS change in the southern catchment of the basin where average
 726 monthly rainfall between July and September could be up to 300 mm (cf. Fig. 5, left). TWS
 727 in this southern catchment indicates a statistically insignificant decline of 4.5 mm/yr (IC2,
 728 Fig. 14). This decline may be the result of marked fluctuations in precipitation patterns as the
 729 SPI indicates frequent drought conditions with relatively short durations during the 2002–2014
 730 period (IC2 and IC4 of Figs. 7 and 8). IC3 (Fig. 14) is the hydrological signal from Nigeria,

the Kainji reservoir area to be specific. The statistically significant increase of 22 ± 4.0 mm/yr can be attributed to water ponding in the Kainji reservoir and probably increase in rainfall within the period. Lastly, the statistically insignificant increase of 3.0 mm/yr in the central part of the conventional basin area, as observed in IC4 (Fig. 14), coincides with the water deficit conditions discussed in Section 4.2.3.

The hydrological condition of the LCB has not been a one-sided narrative of desiccation and decline in surface water extent as two inter-decadal wet/dry cycles have been observed in the altimetry time series (Fig. 15). Essentially, the cumulative rainfall anomalies in Fig. 3 and the increase of 0.04 ± 0.03 m/yr (statistically significant at 95% confidence level) in the satellite altimetry derived water levels of Lake Chad during the 2008 – 2014 period (see, Fig. 15) suggest wetter conditions given the endemic droughts that ravaged the basin in the past. Such circumstance (increased altimetry water levels of Lake Chad or wet conditions around the Lake area), which occasionally leads to flood in the basin can also be attributed to high flows from the Chari river catchment, a major source of the Lake’s nourishment. During such periods (i.e., high flow) as noted by Coe and Birkett (2004), the marshlands and areas around the shores of Lake Chad get flooded and may lead to crop damage while the dry years lead to reduced yields in both fishing and farming. Such fluctuating hydrological conditions are largely caused by extreme rainfall conditions and can be seen in the Lake’s temporal and spatial patterns (see Fig. 2). For instance, in 1987 when the SPI time series over the basin all indicated severe and extreme drought conditions at all monthly aggregations (see Fig. 6a-d and Figs. 7-9), the northern pool completely disappeared leaving behind debris and dunes (Fig. 2, right). Further, Lemoalle et al. (2012) reported the occasional flooding and drying of the Lake (mostly the northern pool) and associated them with inter-annual rainfall conditions in the basin (especially the southern part of the basin). The satellite image analysis of Lake Chad in recent decade indicates a loss of about 573 km² in surface area between 2000 and 2015 while an estimated loss of 249 km² between 2000 and 2003 was observed. Using NOAA’s Advanced Very High Resolution Radiometer (AVHRR) images, Birkett (2000) estimated the Lake’s areal extent as $1,385 \pm 25$ km² in 2000 while Coe and Foley (2001) reported an area less than 1,350 km² in 2001 as the active area of the Lake. This further emphasizes the continuous shrinking of the Lake even during a relatively short period of time. Our surface area estimation of the Lake in those years (i.e., 2000 (~ 1576 km²), 2003 (~ 1326 km²), and 2015 (~ 1003 km²)) was treated cautiously as they only followed the outline of the southern pool (cf. Fig. 2). There are indications that the lake is still receding though with possibilities

of reverting back to the *Small Lake Chad* during increased rainfall, a period when the northern pool is partially inundated with Chari river discharge falling between 470 and 1080 m³/s (see, Lemoalle et al., 2012). Given the rising trend in cumulative rainfall anomalies during the 2012 – 2014 period (Fig. 3a) and trends in lake water level (Fig. 15), the likelihood of such possibilities in recent times (2008 – 2014) is apparent. However, the observed insignificant trends in TWS of the Lake Chad area (IC2 and IC4 of Fig. 14) and the soil moisture deficit conditions (see Section 4.2.3) make us to be cautiously optimistic about such tendencies. This is because soil moisture deficit decreases recharge to groundwater, leading to groundwater deficit and severe hydrological drought (Loon, 2015). But given that the Lake surface extent and inundation areas are related to wet periods in the basin, the rising trend in cumulative annual rainfall anomalies (Fig. 3 b) and the wet periods observed in the conventional basin area (see Section 4.2) may be deviations in the hydro-meteorological patterns of the region that could improve agriculture and strengthen socio-economic activities within the basin. Notably, the slow desiccation of the Lake has been largely perceived as the combined effect of changes in regional precipitation patterns and anthropogenic influence (e.g., Birkett, 2000; Coe and Foley, 2001). The improved rainfall conditions in recent times as observed in the SPI and cumulative rainfall anomalies, could be a simple return to near-normal hydrological conditions in the Lake Chad area. As indicated in Fig. 3, the recent rainfall trends over the basin, which is also apparent in the recent (2008 – 2014) altimetry time series (Fig. 15) over the Lake, may reverse the drought narrative of the basin. This assumption may imply a possible resurgence of the normal Lake, in the absence of any further severe marked alteration of the current hydro-meteorological patterns of the basin. This position contrasts with the perceptions of Moore and Williams (2014) regarding the present Lake Chad, who based on an earlier report (i.e., Coe and Foley, 2001) concluded that the Lake had completely disappeared.

Figure 15: Trends in Lake Chad water level variation derived from satellite altimetry data for the period 1993-2015.

787

788 4.4. Lake Chad Water Resources: Synopsis and Policy Options

789 The desiccation and decline in the surface area of Lake Chad has been largely attributed
790 to impacts of climate variability and human activities (see, e.g., [Coe and Foley, 2001](#); [Birkett,](#)
791 [2000](#)). As highlighted previously in Section 1, Lake Chad receives its nourishment from $\sim 95\%$
792 of discharge from the Chari/Logone river network in the southern part of the basin and $\sim 2.5\%$
793 of discharge from the Komadougou-Yobe river system in Nigeria. According to [Coe and Birkett](#)
794 [\(2004\)](#), the Chari/Logone river discharge, which is measured at N'Djamena (see Fig. 1) and
795 the discharge from Komadougou-Yobe river system and precipitation over the lake surface are
796 balanced by seepage to groundwater, evaporation, and inter-annual storage. Considering the
797 importance of the two river systems that nourishes Lake Chad, the inter-annual variations of
798 water storage from these two drainage systems can be used to predict and determine water
799 storage changes in the Lake. Let us recall that IC2 and IC4 of Fig. 14 are TWS signals from
800 the Chari/Logone river system. Observed TWS trend in the Chari/Logone drainage system
801 indicates a decline of 4.5 ± 3.0 mm/yr and an increase of 3.0 ± 2.0 mm/yr for IC2 and IC4
802 of Fig. 14, respectively. Also within the Chari/Logone drainage system (see IC3, Fig. 11 and
803 IC2, Figs. 12 and 13), soil moisture deficit and hydrological drought (i.e., at 3, 6, 12 month
804 scales) have been observed between 2010 and 2012. Given these hydrological situations in the
805 LCB, one may assume that the potential for further desiccation and reduced alimentation are
806 likely in the years to come. In a recent study, [Greve et al. \(2014\)](#) observed that the Sahel
807 region (i.e., region where the basin is located) is actually leaning towards aridity. The dry
808 gets dryer paradigm as observed in the study ([Greve et al., 2014](#)), was largely attributed to
809 significant drying trends in water availability and changes in large-scale circulation patterns.

810 Further, when trends in the variations of Lake Chad water levels are considered, the increase
811 of 0.09 ± 0.03 m/yr and 0.04 ± 0.03 m/yr in 1993 – 1998 and 2008 – 2014, respectively might
812 be insignificant when compared to the decline of 0.09 ± 0.03 m/yr in 1999 – 2003 (Fig. 15).
813 This is because the hibernation period in the Lake (2002 – 2007, Fig. 15) where a great deal of
814 less pronounced annual amplitudes in water levels are observed may rescind the effect of the
815 previous increase in the Lake's height (1993 – 1998), leading to a hypothetical water deficit
816 (especially with the human disturbance of the Lake). We make this assumption because the
817 impact of extreme drought conditions of previous years are known to have negative effects on
818 surface waters even after an improved rainfall condition in the present (see, e.g., [Bekoe and](#)
819 [Logah, 2013](#)). For example, the relatively strong and consistent negative anomalies, observed
820 in water levels all through the period between 2004 and 2005 coincides with observed extreme

drought conditions in the conventional basin area within the same period (see, IC4 of Fig. 9; IC1-IC2 of Fig. 11; IC1 and IC3 of Fig. 12 and ; IC1 of Fig. 13). In the same vein, the increase of ~ 0.04 m/yr between 2008 and 2014, when related to the current surface extent of the Lake, which stands at ~ 1002 km^2 gives an increase of ~ 0.04 km^3 /yr of water in the Lake. This amount of water is relatively small when compared to $33km^3$ /yr of water that flowed from the Central African Republic to the LCB in the 1970's and ~ 17 km^3 /yr in the 1980's (FAO, 1997). This comparison could be useful in assessing lake water level trends and the impact of climate variability and human influence on the Lake. Moreover, dam construction and increasing irrigation activities in the 1980's contributed a great deal to the desiccation of Lake Chad, putting the water requirements of the basin at 12.525 km^3 /yr (FAO, 1997). If human activities in the basin intensify, the resurgence of the Lake may be far away than expected, given that about 21 km^3 /yr of water is expected to permanently maintain the *Normal* Lake Chad as it was in the 1960's (Lemoalle et al., 2012). Going by the observed trends in TWS changes (see Section 4.3), much of the conventional basin, which is under the mandate of Lake Chad Basin commission, is somewhat stable in terms of freshwater availability. Although soil moisture indicated deficit (see Section 4.2.3) during 2009 – 2013 period, in the event that the observed improved rainfall conditions (Section 4.2.2) of the basin persist, the hydrological condition may be altered significantly, leading to freshwater availability. We acknowledge the limitation of our study owing to the lack of in-situ river discharge data, especially for the Chari river system. However, the observed trends in TWS changes and altimetry-derived water levels, which depends largely on the river flow from the Chari river system, provides us with a clue regarding recent hydrologic conditions of the Chari river system. This is particularly true because, Coe and Birkett (2004) demonstrated the possibility of using radar altimetry to predict discharge at N'Djamena and the Lake stage within the permanent waters of the Lake bed (i.e., the Lake Chad).

Lake Chad, which is shared by four riparian countries (Nigeria, Chad, Cameroon, and Central African Republic) has suffered huge desiccation and decline in the last three decades due to decrease in rainfall and extreme hydrological drought conditions. But the corresponding basin has been a hub of huge loss of bio-diversity and extreme climate conditions with severe consequences on freshwater availability. In addition, large irrigation schemes and other forms of human activities (e.g., Lemoalle et al., 2012; Coe and Foley, 2001) also profoundly contributed to the much pressure on the basin's water resources, leading to freshwater deficit. These resulted in the hypothetical decision of transferring water from the Congo basin to

support the LCB (see, e.g., [Lemoalle et al., 2012](#); [Inogwabini et al., 2006](#)). While the use of legislation to ensure sustainable practices and long-term conservation of the basin’s water resources is essential, we suggest that the ground water resources and aquifer storage be investigated. This can be achieved in future studies by using scientific methods such as the combination of GRACE observations, in-situ data, and outputs from hydrological models. Seepages, infiltration, evapotranspiration, and the effect of the Lake on local recycling of precipitation will have to be fully understood in order to address the challenging physical, and hydrological conditions of the basin. Our approach in drought monitoring and TWS analysis can be employed in inter-basin water transfer projects. For instance, understanding the space-time evolutions of extreme rainfall conditions and changes in TWS of the Congo basin could be useful in managing a hypothetical water transfer to the LCB. This will complement technological, institutional, and other policy solutions in water resources planning. While it is important to investigate the ground water resources of the basin using robust scientific methods as proposed, our contribution provides a general framework for drought monitoring and the understanding of changes in TWS of the region and other parts of the world. For the LCB, the findings of this study can assist and support improved legislation and policies tailored towards the regulation of unsustainable practices. Furthermore, as outlined in [Vassolo \(2012\)](#), few steps have been taken by the Lake Chad Basin commission to strengthen the trans-boundary water resources of the region. They include (i) the adoption of United Nations draft resolutions for trans-boundary aquifers as a basic document that will support groundwater management and (ii) the planned adoption of a Water Charter for the basin to enable the regulation of shared management of water resources and ecosystems. As indicated in the groundwater need assessment of [Vassolo \(2012\)](#), trans-boundary surface water has not been extensively studied since the establishment of the Lake Chad Basin Commission, leading to poor understanding of the trans-boundary groundwater resources. Hence, multi-satellites, especially satellite gravimetric approaches using GRACE observations and outputs from hydrological models can be adopted to monitor the groundwater resources of the basin in future studies.

5. Conclusions

In this study, we used independent component analysis (ICA), a fourth-order cumulant statistics to characterise and localise space-time evolutions of drought patterns over the LCB. Satellite altimetry data was employed to analyse Lake Chad water level variations while nor-

malised time series of climate teleconnection indices were used to examine the association of SPI temporal evolutions with coupled atmosphere-ocean system. In addition to the drought signature that have been identified, the LCB has also been used primarily as a tentative test bed to demonstrate the spatio-temporal variability of drought. Also, trends and spatial variability of TWS changes in LCB were investigated. The results in this study are summarised as follows:

1. We observed some unusual deviation from the long string of drought conditions observed in the basin as the time series of SPI values between late 2010 and early 2013 are indicative of wet conditions. These wet conditions are attributed to recent increase in rainfall over the basin and is also consistent with recent increase in Lake Chad water levels. However, from the spatio-temporal drought analysis and trends in TWS changes the southern part of the basin, which provides $\sim 95\%$ of the total input to the basin's surface water indicates a deficit, as the SSI between late 2009 and 2012 shows drought conditions at 6 and 12 month cumulations.

2. The time series of SSI and MSDI are inconsistent with extreme positive SPI values (wet conditions) at 12 month aggregation as they both indicate extreme drought conditions and in some cases near-normal conditions. For the SSI, this may be the effect of previous drought conditions, high evaporation due to low humidity and high temperatures, and seepage to groundwater amongst others.

3. Drought analysis with SPI shows that drought persistence is higher on a longer time scale while on short time scales drought becomes more frequent. Generally, while there seem not to be differences in drought frequency and persistence at all monthly scales for SSI spatio-temporal analysis, extreme wet years as identified in the study (e.g., 1988, 1994, and 1998) are consistent with results of spatio-temporal drought analysis for SPI.

4. Apart from the droughts of the 1980's, the spatio-temporal analysis of SPI at 3 and 6 month scales indicated fluctuating drought conditions with relatively short duration in the last two decades in the extreme southern part of the basin. These drought conditions coincide with the observed decline in TWS (though statistically insignificant at 95% confidence level) around the precinct of the southern part of the basin. On the contrary, the trend in TWS changes during the 2002 – 2014 period shows an insignificant increase at the center of the basin, coinciding with soil moisture deficit indicated by the temporal evolutions of SSI at all monthly accumulations during the 2002 – 2003 and 2009 – 2012 periods. It is unclear if this could be a temporary soil water shortage condition due to surface and hydraulic characteristics of the soil, seepages or increased evapotranspiration and surface temperature over the basin.

919 This can be clarified further in future studies by integrating GRACE-derived TWS and other
920 soil moisture data to investigate the groundwater resources of the basin. Overall, the ICA
921 approach to drought analysis demonstrates the spatio-temporal variability of drought, which
922 largely may depend on the local climatic or meteorological conditions.

923 5. Also, while the ICA method shows a common hydrological drought period, which lasted
924 for about two years (i.e., 1982 – 1984) in the basin, other areas within the conventional basin
925 have been affected by both agricultural and hydrological droughts at different time periods.

926 6. Apart from the negative correlation of ENSO with 12 month SPI, our results show
927 that at 12 month SPI scale, AMO and AMM have statistically significant positive correlations
928 of 0.55 and 0.38, respectively with the first ICA mode of Fig. 9. This indicates that the
929 hydrological character in relation to extreme rainfall conditions (e.g., droughts) in LCB could
930 also be influenced by these climate teleconnection modes.

931 7. In addition to improved rainfall conditions during 2010 and early 2013 period, two inter-
932 decadal wet/dry cycles have been observed in the altimetry time series. Generally, our SPI,
933 satellite altimetry, and TWS results within the precincts of the conventional basin indicate
934 relatively wet conditions in the last decade as opposed to soil moisture deficits around the
935 vicinity of the Lake. Our contribution provides a framework for drought monitoring that
936 can assist and support management decisions, legislation, and policies tailored towards water
937 resources and agriculture.

Figure 16: Seasonal rainfall analysis for Lake Chad Basin (5.5°N - 24.5°N and 5.5°E - 24.5°E) using GPCP based precipitation for the period 1979-2014. Spatial patterns (left) and temporal patterns (right) are averaged over the geographical boundary describing the spatial extent of Lake Chad basin used in this study. The insert (i.e., the solid black line) is the conventional basin boundary.

939 Appendix A2: Further description of the ICA Technique

940 ICA is a higher order statistical technique that decomposes multivariate data into statis-
 941 tically independent signals (see, e.g., [Cardoso and Souloumiac, 1993](#); [Cardoso, 1999](#)). The
 942 method, which is usually referred to as blind source separation in signal processing (e.g., [Car-](#)
 943 [doso, 1999](#)), explores the unknown dynamics of a system through the rotation of the classical
 944 empirical orthogonal functions ([Aires et al., 2002](#)). ICA has emerged as a better alternative to
 945 principal component analysis (PCA, e.g., [Jolliffe, 2002](#)), an extraction method that is used to
 946 reduce the dimension of large multivariate data. Though mathematically simple and a useful
 947 tool in terms of information compression, however, the capability of PCA to extract individual
 948 modes of variability that are physically meaningful is limited, hence the quest for higher order
 949 statistical method such as the ICA. In our case, the strong spatial variability of rainfall in the
 950 Sahel region at annual scale constrains the effectiveness of SPI in drought analysis. Hence,
 951 decomposing SPI time series using ICA will localise the space-time drought patterns in the
 952 region. Localising SPI and SSI signals in LCB will provide a better understanding as to the
 953 drivers of hydro-climatic variability in the region. To this end, as a first step in our analysis,
 954 the PCA method, was employed to identify statistically significant dominant modes of vari-
 955 ability in the data (i.e the computed gridded SPI and SSI values and GRACE-derived TWS).
 956 The significant PCA modes (i.e., a combination of the principal components and empirical
 957 orthogonal functions) were identified as

$$\mathbf{P}_i = \mathbf{e}_{ij}\mathbf{x}_j, \quad (7)$$

958 where $\mathbf{P}_i$ are linear combinations of $\mathbf{x}$ and $\mathbf{e}_{ij}$ are the set of empirical orthogonal functions
 959 (EOFs). Projecting the data $\mathbf{x}$ onto the EOFs we obtain the principal components (PCs) $\mathbf{P}_i$,
 960 which can be expressed as

$$\begin{aligned} P_{i,1} &= e_{11}\mathbf{x}_1 + e_{12}\mathbf{x}_2 + e_{13}\mathbf{x}_3 + \dots + e_{1k}\mathbf{x}_{i,k} \\ P_{i,2} &= e_{21}\mathbf{x}_1 + e_{22}\mathbf{x}_2 + e_{23}\mathbf{x}_3 + \dots + e_{2k}\mathbf{x}_{i,k} \\ &\dots \\ P_{i,k} &= e_{k1}\mathbf{x}_1 + e_{k2}\mathbf{x}_2 + e_{k3}\mathbf{x}_3 + \dots + e_{kk}\mathbf{x}_{i,k} \end{aligned} \quad i = 1, \dots, n \quad (8)$$

961 $\mathbf{e}_{ij}$ is determined such that $P_{i,1}$ are the new uncorrelated variables and the expression of the
 962 original data in the new coordinate system. $P_{i,1}$ explains the highest variance of the multi-
 963 variate data $\mathbf{x}$ while $P_{i,2}$ up to $P_{i,k}$ explain the possible amount of the remaining variance.
 964 The EOF's are spatially orthonormal while the PC's are orthogonal and linearly independent.

965 The next step was to rotate these dominant patterns (i.e., the statistically significant modes),
 966 which are uncorrelated towards statistical independence using the Joint Approximate Diago-
 967 nalisation of Eigen matrices (JADE) algorithm described in [Cardoso and Souloumiac \(1993\)](#).
 968 The JADE approach exploits the fourth order cumulants of the data matrix rather than the
 969 moments ([Cardoso, 1999](#)). The cumulants are formed through the PCA process and diago-
 970 nalised in order to find a rotation matrix that solves the optimization problem ([Cardoso and](#)
 971 [Souloumiac, 1993](#)). ICA decomposes the time series of data matrix $x_i(t)$, which consist of a
 972 mixing matrix A and a number of statistically independent source signals $s_j(t)$ where t is the
 973 time index. This can be expressed as ([Ziehe, 2005](#))

$$x_i(t) = \sum A_{ij}s_j(t), \quad (i = 1, \dots, n, \quad j = 1, \dots, m) \quad (9)$$

974 x_i in Eq. 9 is the mixing model and can be represented as a matrix as

$$\mathbf{X} = \mathbf{A}\mathbf{S}, \quad (10)$$

975 where the entries of the data matrix $\mathbf{X}$ are samples of the $x_i(t)$ given in Eq. 9, the $n \times m$
 976 matrix $\mathbf{A}$ has elements $A_{i,j}$ and $\mathbf{S}$, the source signals. Essentially, ICA aims at recovering
 977 the set of source signals $\mathbf{S}$ completely from the observed data matrix or the mixed signal $\mathbf{X}$,
 978 by estimating either the mixing matrix $\mathbf{A}$ or its inverse $\mathbf{A}_T = \mathbf{A}^{-1}$. Overall, the ICA problem
 979 consist in *factoring* (i.e solving the optimisation problem) the observed signals in data matrix
 980 $\mathbf{X}$ into the mixing matrix $\mathbf{A}$ and the source signals matrix $\mathbf{S}$. The *factoring* problem is not
 981 uniquely determined and as such many solutions exist that solves the problem (see [Ziehe,](#)
 982 [2005](#)). Most ICA methods are based on maximum-likelihood estimation, maximization of the
 983 output entropy or minimization of mutual information between the outputs, which is equivalent
 984 to the minimization of the *Kullback-Leibler* divergence between the joint and the product of
 985 the marginal distributions of the outputs (see more details in [Ziehe, 2005](#)). However, on
 986 grounds of numerical and computational efficiency, our approach uses the joint diagonalisation
 987 of the fourth order cumulant matrices (see, [Cardoso and Souloumiac, 1993](#)). The cumulant-
 988 based method exploits the remote properties of the signals, which include non-Gaussianity,
 989 non-stationarity, and spectral non-Flatness (e.g., [Ziehe, 2005](#)). Cumulants are empirically
 990 computed from higher-order moments, which are estimated from the data. From the Joint
 991 Approximate Diagonalisation of Eigen matrices (JADE) approach ([Cardoso, 1999](#); [Cardoso](#)
 992 [and Souloumiac, 1993](#)), this fourth-order cumulant tensor provides the suitable matrices to be

993 diagonalized, which are non-gaussian (see, e.g., [Cardoso, 1999](#); [Ziehe, 2005](#)):

$$\mathbf{C}_{i,j}(\mathbf{M}) = \sum cum(x_i, x_j, x_u, x_v) \mathbf{M}_{u,v}, \quad (11)$$

994 such that $\mathbf{M}$ is an arbitrary matrix. After the eigen decomposition of the centered covariance
 995 matrix x , which is aimed at reducing the dimension of the original data, the JADE algorithm
 996 performs an approximate joint diagonalisation of the set of eigen matrices of the cumulant
 997 tensor with an orthogonal transformation, which comprises a sequence of plane rotations (see,
 998 e.g., [Ziehe, 2005](#); [Cardoso and Souloumiac, 1993](#)). This cumulant-based methods have been
 999 exhaustively described in the pioneering works of [Cardoso and Souloumiac \(1993\)](#), [Common](#)
 1000 [\(1994\)](#), and [Cardoso \(1999\)](#). For further details on numerical steps and mathematical formu-
 1001 lations, we refer interested readers to relevant literatures on the subject (see, e.g., [Forootan](#)
 1002 [and Kusche, 2012](#); [Theis et al., 2005](#); [Ziehe, 2005](#); [Cardoso and Souloumiac, 1993](#); [Cardoso,](#)
 1003 [1991](#); [Common, 1994](#); [Cardoso, 1999](#)). While ICA has been previously used to filter and an-
 1004 alyze the hydrological signals in GRACE data (see, e.g., [Boergens et al., 2014](#); [Forootan and](#)
 1005 [Kusche, 2012](#); [Frappart et al., 2010, 2011](#)), the current study employed ICA for the statistical
 1006 decomposition of SPI, SSI, and TWS signals over the Lake Chad basin.

1007 **Appendix A3: Comparison of GLDAS TWSC and GRACE-derived TWS over**
1008 **Lake Chad Basin**

Figure 17: Comparison between GRACE-derived TWS and GLDAS-derived terrestrial water storage content (TWSC). Top: Time series of GRACE-derived TWS (2002-2014) and GLDAS-TWSC for the period during 2001-2014 averaged over the Lake Chad basin. Bottom: Regression fit on GRACE TWS and GLDAS TWSC over Lake Chad basin for the common time period (i.e., 2002-2014).

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