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Changes in temperature and precipitation extremes over the Greater Horn of Africa region from 1961 to 2010

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ABSTRACT: Recent special reports on climate extremes have shown evidences of changes in the patterns of climate extremes at global, regional and local scales. Understanding the characteristics of climate extremes at regional and local levels is critical not only for the development of preparedness and early warning systems, but is also fundamental in the development of any adaptation strategies. There is still very limited knowledge regarding the past, present and future patterns of climate extremes in the Greater Horn of Africa (GHA). This study, which was supported by the World Bank Global Facility for Disaster Reduction and Recovery (WB-GFDRR) and implemented by the World Meteorological Organization, was organized in terms of three workshops with three main objectives; (1) analysis of daily rainfall and temperature extremes for ten countries in the GHA region using observed *in situ* data running from 1971 to 2006, (2) assessing whether the United Kingdom Met-office and Hadley centre Providing REgional Climates for Impact Studies (UK-PRECIS) modelling system can provide realistic representation of the past and present climate extremes as observed by available *in situ* data, and (3) studying the future regional climate extremes under different scenarios to further assess the expected changes in climate extremes. This paper, therefore, uses the outputs of these workshops and also includes post-workshop analyses to assess the changes of climate extremes within the GHA. The results showed a significant decrease in total precipitation in wet days greater than 1 mm and increasing warm extremes, particularly at night, while cold extremes are decreasing. Considering a combination of geophysical models and satellite gravimetry observations from the Gravity Recovery and Climate Experiment (GRACE) mission in the frame of GRACE daily Kalman-smoothing models, for the years 2002 to 2010, we explored a decline in total water storage variations over the GHA.

KEY WORDS climate extremes; Greater Horn of Africa; climate indices; water storage changes; PRECIS model

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1. Introduction

Extreme events not only cause property damage, injury, hunger, loss of life and threaten the existence of some species (see, e.g. Downing, 1991), but also drive changes in natural and human systems much more than average

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climate (Parmesan *et al*., 2000; Peterson and Manton, 2008; Tierney *et al*., 2013). Impacts of extreme climate change and variability lead to human suffering, particularly for the poor as witnessed, for example, during the prevalent droughts and floods in the GHA region (Lyon and DeWitt, 2012). Analysis of changes in extreme climate events, therefore, is important due to the potentially high social, economic and ecological impact of such events (e.g. Bohle *et al*., 1994; Arnell, 2004). Limited availability of long records of daily climate data in some parts of the world, including the GHA, hampers efforts to analyse the impacts of climate change and variability on the frequency and severity of climate extremes (Folland *et al*., 2001). Long records of daily climate data for the GHA region are discussed by Camberlin and Philippon (2002), WMO (2003), Brant *et al*. (2012) and Omondi (2011, 2012a, 2012b). Availability of long term high quality data in the region is hampered by inadequate monitoring networks; gaps in the records; a general decline of number of stations; chronic underfunding; differences in processing and quality control; and differences in data policies (WMO, 2003). It is evident that the GHA countries share pronounced climatic trends (Tierney *et al*., 2013) and variability and are vulnerable to extreme climatic conditions (e.g., Downing, 1991; Schreck and Semazzi, 2004; Anyah and Qiu, 2011 and Omondi *et al*., 2012a, 2012b).

It is increasingly becoming apparent that behind the ongoing research and debate on climate change, many parts of Africa are already witnessing dire consequences of erratic climatic conditions (Shongwe *et al*., 2011; Anyah and Qiu, 2011) that are likely associated with regional climatic changes (Funk *et al*., 2008, 2012). This is expected to pose unprecedented challenges to most African economies that are significantly hinged on a predominantly rain-fed agriculture. Further challenges lie in understanding low frequency multi-decadal and centennial climate variability in the vastness and uniqueness of the complex African terrain and climate systems over eastern Africa (Omondi *et al*., 2012a, 2012b; Tierney *et al*., 2013).

In recent years over the GHA region, particularly in Kenya, Ethiopia and Somali, climate related extremes have been the dominant trigger of natural disasters. The region has recently witnessed frequent episodes of both excessive (e.g. Anyah and Semazzi, 2006; Kijazi and Reason, 2009a; Hastenrath *et al*., 2010; Viste *et al*., 2012) and deficient rainfall (e.g. Hastenrath *et al*., 2007, 2010; Kijazi and Reason, 2009b; Omondi *et al*., 2012a, 2012b). Consequently, there has been an upsurge in interest both from the scientific communities (e.g. van Oldenborgh *et al*., 2005; Omumbo *et al*., 2011) and policy makers to the risk of increased extreme climatic events. A recent climate analysis for East Africa was conducted by Christy and co-authors examining air temperature trends at 60 stations across Kenya (Christy *et al*., 2009). After spatially interpolating the station-based data, the study reports finding a statistically significant upward trend in minimum temperature (Tn) in the Kenyan Highlands region. Omumbo *et al*. (2011) found evidence of a warming trend in observed maximum, minimum and mean temperatures at Kericho during the period 1979–2009 using gold standard meteorological observations. An upward trend of $\approx 0.2\,^{\circ}$C/decade was observed in all three temperature variables ($p < 0.01$). Mean temperature variations in Kericho were associated with large-scale climate variations including tropical SST ($r = 0.50$; $p < 0.01$). Other authors have also studied malaria resurgence using extreme climatic events over the region (e.g. Hay *et al*., 2002; Pascal *et al*., 2006 among others). Analysis of rainfall, minimum and maximum temperatures records showed increasing trends in annual minimum and maximum temperatures from 1951 to 2002 (0.4 and $0.2\,^{\circ}$C/decade, respectively) but little trend in rainfall from 1901 to 1950, 1951 to 2002 and 1901 to 2002 (Conway *et al*., 2004). In analysis of rainfall seasonality index (SI), precipitation concentration index (PCI) and modified Fournier index (MFI), Elagib (2010) found no statistically significant trends in observed rainfall for the hyper-arid region of Sudan during the common data period of 1945–2007.

Some recent studies using Global Climate Models (GCMs) have shown that changes in climate over the region are expected in a global warming scenario (IPCC, 2007; Shongwe *et al*., 2010; Anyah and Qiu, 2011). These are likely to include changes in the intensity, duration, and frequency of droughts and floods, heat waves, etc, and will have serious implications on agriculture, human health, as well as human activities. It is well documented that some parts of the GHA region are perennially prone to droughts and floods (Hastenrath *et al*., 2007; Kijazi and Reason, 2009a, 2009b; Omondi, 2011; Lyon and DeWitt, 2012).

Although there is a lack of long records of daily data for extreme climate change detection, international collaboration is significantly improving the situation, culminating in an analysis (see, e.g. Alexander *et al*., 2006) that provided a near-global perspective on changing climate extremes for the Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report (IPCC, 2007). Yet quantifiable information, describing how weather and climate extremes are changing over the GHA region has been unavailable. In preparation for the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report, a major effort by the Expert Team on Climate Change Detection and Indices (ETCCDI) has been undertaken to analyse how extremes are changing over as much of the world as possible (Alexander *et al*., 2006). This included intensive international collaboration on data exchange and analysis, and, where data were not available, holding regional climate change workshops to generate information on extremes (Alexander *et al*., 2006). This global assessment initiative has greatly benefited from the contributions from a series of workshops (Peterson and Manton, 2008) coordinated by ETCCDI which is jointly sponsored by the WMO Commission for Climatology (CCl), the Joint Commission for Oceanography and Marine Meteorology (JCOMM), as well as

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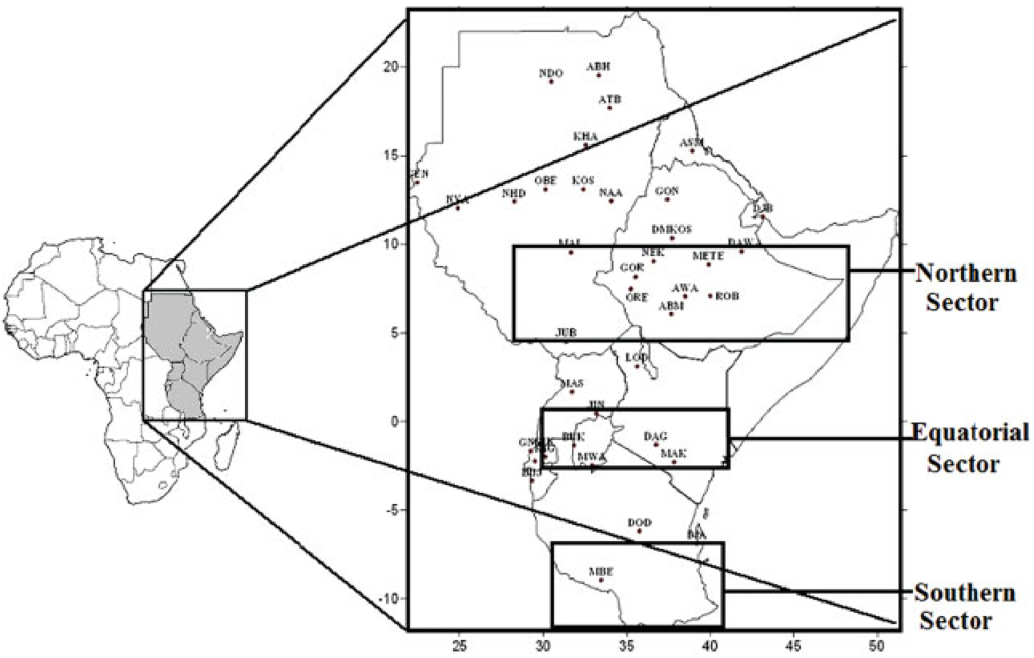

Figure 1. Location of the Greater Horn of Africa region in Africa together with stations used in the study (see Table I for full names, the values of latitude and longitude for each station).

the Research Programme on Climate Variability and Predictability (CLIVAR). The ETCCDI workshops seek to bring participants together from countries within a data sparse region to fill in data gaps and to provide capacity building.

The availability of daily observation data is steadily improving and has led to the development of gridded regional (Haylock *et al*., 2008) and global datasets (Caesar *et al*., 2006). For some areas such as the GHA region where daily data availability is still relatively poor, assembling and research using this data would be useful in decision making and policy formulation on the climate sensitive sectors of the region.

To address the issue of data shortage in GHA, therefore, and in line with global standard practice (e.g. Alexander *et al*., 2006), this study is intended to help fill the data gap in the region by assembling the necessary climate observations. Further, the understanding and use of regional climate downscaling tool known as PRECIS would help GHA countries design adaptation policies and reduce climate associated risks.

This study is divided into four parts namely (1) the assessment of the adequacy of regional climate observations and trends for adaptation purposes, (2) the assessment of the adequacy and reliability of available model based climate projections for adaptation needs, (3) the assessment of the expected changes in climate extremes needed to assist in developing effective adaptation and climate risk management strategies, and (4) the analysis of changes in total water storage for the period 2002–2010 in order to assess recent vulnerability of GHA region to climatic variations. The study is inherently regional in nature since, to be useful, regional climate models need observational support from as wide a region as possible. Climate does not recognize national boundaries, so in order to analyse and validate models, it is necessary to take a regional approach.

The presentation is organized as follows; in Section 2, the study area, data used, and the analysis methods are presented. Section 3 presents the results, which are discussed in Section 4. The study is then concluded in Section 5.

2. Data and methods

2.1. The Greater Horn of Africa

At the time of this study, the GHA region comprised of Burundi, Djibouti, Ethiopia, Eritrea, Kenya, Rwanda, Somalia, Sudan, Tanzania and Uganda (Figure 1). But currently, South Sudan that recently ceased and became sovereign state on 9th of July 2011 forms the 11th country in the GHA region. Majority of these countries are classified as least developed where most of the societies survive on less than one dollar per day (UNDP 2004). Its climate may be classified as arid and semi-arid with frequent recurrences of floods and droughts. The recurrences of floods and droughts have been associated with many socio-economic miseries. Furthermore, the region is often faced with serious food insecurity and resource-based conflicts. For example, 2010–2011 has been shown to be the driest period in 60 years with more than 12 million people in need of emergency relief (CRS Report, 2012). Recent assessments (IPCC, 2007) showed that climate change is real and the poor are the most vulnerable due to the already high level of vulnerability and low coping capacity. The vulnerability is amplified by the fact that many of East Africans

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Table I. List of stations (see Figure 1 for their exact location).

No.	Station	STN	Code	Longitude	Latitude	Period
1	ABU HAMAD	ABH	62640	33.3	19.5	1960–2002
2	ARBA MINCH	ABM	63500	37.7	6.1	1986–2007
3	ASMARA	ASM	63021	38.9	15.3	1960–2009
4	ATBARA	ATB	62680	34.0	17.7	1960–2000
5	AWASSA	AWA	63460	38.5	7.1	1971–2007
6	BUJUMBURA	BUJ	64390	29.3	−3.3	1970–2010
7	BUKOBA	BUK	63729	31.8	−1.3	1960–1991
8	GIKONGORO	GIK		30.1	−1.6	1967–2010
9	GISENYI	GNY		29.3	−1.7	1971–2010
10	KAMEMBE	KMBE		28.9	−2.5	1971–2010
11	METE	METE		39.9	8.87	1983–2007
12	NAAMA	NAA		34.08	12.44	1963–2000
13	NAHOUD	NHD		28.26	12.42	1960–2000
14	OBIED	OBE		30.14	13.1	1960–2000
15	ORE	ORE		35.53	8.15	1951–2007
16	DAGORETTI	DAG	63741	36.8	−1.3	1960–1991
17	DAR.I.AIRP.	DIA	63894	39.2	−6.9	1971–2009
18	DEBRE MARCOS	DMKOS	63334	37.7	10.4	1970–2003
19	DIRE DAWA	DDAWA	63471	41.9	9.6	1970–2003
20	DJIBOUTI	DJB	63125	43.2	11.6	1979–2010
21	DODOMA	DOD	63862	35.8	−6.2	1971–2009
22	GENEINA	GEN	62770	22.5	13.5	1960–2001
23	GONDAR	GON	63331	37.4	12.5	1970–2003
24	GORE	GOR	63403	35.6	8.2	1970–2003
25	JINJA	JIN	63682	33.2	0.5	1970–2003
26	JUBA	JUB	62941	31.4	4.5	1960–2000
27	KHARTOUM	KHA	62721	32.6	15.6	1960–2000
28	KIGALI	KIG	64387	30.1	−2.0	1971–2010
29	KOSTI	KOS	62772	32.4	13.1	1960–2000
30	LODWAR	LOD	63612	35.6	3.1	1960–1991
31	MAKINDU	MAK	63766	37.8	−2.3	1960–1991
32	MALAKAL	MAL	62840	31.7	9.6	1960–2000
33	MASINDI	MAS	63654	31.7	1.7	1960–1991
34	MBEYA	MBE	63932	33.5	−8.9	1970–2009
35	MWANZA	MWA	63756	32.9	−2.5	1960–1991
36	NDONGOLA	NDO	62650	30.5	19.2	1960–2000
37	NEKEMTE	NEK	63340	36.6	9.1	1952–2007
38	NYALA	NYA	62790	24.9	12.1	1960–2000
39	ROBE	ROB	63474	40.0	7.1	1983–2007
40	SOMALIA[a]	SOM				

[a]Missing Data.

livelihoods are dependent on farming and livestock; two sectors that are especially sensitive to perturbations in the climate system. Climate change is, therefore, likely to set back development and food production in many of the predominantly agro-based economies of most communities. The GHA countries, like other African countries have short and/or fragmented climate records, often as a result of armed conflict at various times in the last 50 years. In a few cases, the available records are too short to be used for the adequate calculation of climate trends, but they are still valuable in providing a baseline for future analyses, as well as monitoring inter-annual climate variability.

2.2. Station data and quality control

It is important to note that three workshops were organized to aid with the collection of data from the member countries that would hitherto not be possible when organized by an individual country. The workshop participants brought along with them selection of their best quality digitized daily temperature and precipitation series (Figure 2).

Daily observed station data for maximum and minimum temperatures together with precipitation for a total of 73 stations from the ten countries are employed in the analysis (Figure 1 and Table I). These data sets were subjected to quality control and homogeneity of their series using RClimDex software (Peterson *et al*., 1998; Zhang *et al*., 2009). RHtest software was also used to perform homogeneity tests (Aguilar *et al*., 2005, 2009). These packages were downloaded from the ETCCDI website.[1]

Inhomogeneities in all the time series were identified and corrected. Linear trends were identified via a least-squares regression analysis with statistical significance

[1]http://cccma.seos.uvic.ca/ETCCDI/

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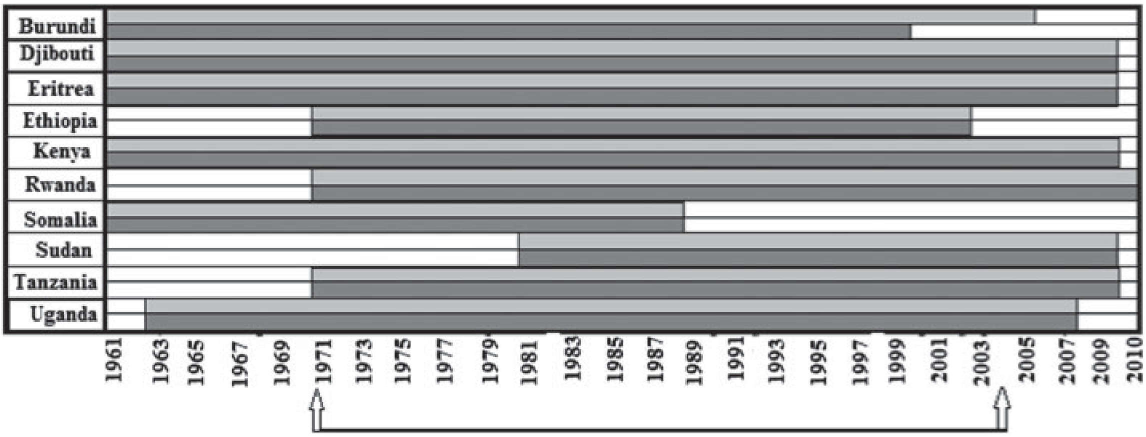

Figure 2. Available data for the time series used in the analysis. White indicates no data; upper box indicate rainfall while the lower one indicates temperature. The arrows show the common years available for all the countries.

assessed using a two-tailed t-test. These 'standard' meteorological observations were compared with spatially interpolated temperature datasets that have been developed for regional or global applications (Omumbo *et al*., 2011). The statistical and visual procedures contained in the RClimDex package were complemented by the required tests, following the guidelines given in Brunet *et al*. (2008). In fact, the tests are focused on the detection of nonsystematic errors usually caused by data processing, which happens most frequently during digitization procedure (Aguilar *et al*., 2005, 2009). Ambiguous values (e.g. negative precipitation or maximum temperature lower than minimum temperature) were identified. Also, the distribution of the precipitation data was visually inspected, as were plots of the temperature and precipitation time series in order to detect outlying values.

In the case of temperature, statistical outliers, identified as daily values outside a threshold of the mean value for that particular day plus/minus four standard deviations were also flagged (see Section 2.4). The suspicious data were validated, set to missing value or corrected on the basis of subjective inspection of partial time series for the adjacent days at the same period with other years and by spatial comparison with those available from close neighbouring stations.

Once the data passed the quality control checks, they were evaluated for homogeneity. The station data underwent homogeneity testing using the RHtest software package (Aguilar *et al*., 2005, 2009), which helps in identifying step changes in a time series by comparing the goodness of fit of a two-phase regression model with that of a linear trend for the entire series (Wang, 2003, 2008a, 2008b). RHtest is used to help identify series break points for further investigations. Selection of data for analysis was based on series length and completeness, quality control and homogeneity (Aguilar *et al*., 2005, 2009). In this study, we used a base period of 1961–1990 and 1971–2000 where most of the station data are available. In some cases such as in Somalia, Sudan and Rwanda; we used a shorter base period; for example, the data supplied for Gikongoro in Rwanda began in 1967, so we used a base period of 1967–1996. To be included in the analysis, time series need to be sampled for at least 30 years and contain fewer than 10% of missing/rejected values. The reference period of 1971–2000 was chosen to maximize the number of stations with available data for calculation of the percentile-based indices. Even with this maximization, only 8 countries with a total 58 of the 73 original stations had long enough homogeneous periods to be included in the analysis, and not all the indices were calculated for all the stations. Figure 1 shows the location of stations and Figure 2 the data availability for these stations.

Of the ten countries that had participants in the workshop, Somalia and Sudan had data time series falling outside the 1971–2000 period (Figure 2). Since many of the stations had data problems prior to 1970, the analysis was limited to the period 1971–2009. For percentile-based indices (e.g. the number of days exceeding the 90th percentile of minimum temperature), the methodology uses bootstrapping for calculating the baseline period values in order to avoid discontinuities in the indices time series at the beginning or end of the base period following the approach by Zhang *et al*. (2005).

The PRECIS modelling system was applied over the region to develop high-resolution climate scenarios. It was driven with initial and lateral boundary conditions using the UK Met Office Hadley Center Regional Climate Model (HadRM3P), which is a high-resolution atmospheric component of the Hadley Centre coupled ocean-atmosphere GCM-HadCM3, with a resolution of 1.875° in longitude and 1.25° in latitude. Details of the Global Climate Models (GCMs) used in verification of the PRECIS Regional Climate Model (RCM) can be obtained in the study of Simon *et al*. (2004).

2.3. Gravity recovery and climate experiment (GRACE)

Global and regional water cycles are related to different phenomena within the Earth system, including variations in atmosphere, hydrosphere, ice cover and land surface in various ways, while ranging from sub-seasonal and

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inter-annual to decadal and secular interactions. These all make it difficult to develop realistic models to simulate or predict water variations.

The gravity field of the Earth and its temporal variations, measured globally by GRACE (a joint US–German satellite mission launched in March 2002); however, are interrelated to total water storage (TWS) variations of the Earth (Wahr *et al*., 1998). This offers the unique opportunity to detect spatio-temporal variations of water within the Earth system from space (Tapley *et al*., 2004a, 2004b).

The GRACE mission consists of two identical spacecrafts flying approximately 220 km apart in the same near-polar orbit of about 450 km (Tapley *et al*., 2004a, 2004b). The main observable is the distance between the two satellites, measured using a microwave ranging system. Additional tracking information is provided by Global Positioning System (GPS) receivers on board each of the spacecraft and Satellite Laser Ranging (SLR) reflector. On-board accelerometers sense non-conservative forces such as atmospheric drag and solar radiation pressure. Time-variable gravity field solutions are obtained by the exploitation of GRACE observation data over certain time intervals, namely daily to monthly gravity field solutions. The solutions are computed in terms of spherical harmonics (SHs). GRACE time-variable products have been frequently used to study water variations and their relations to climate change, as documented, for example, by Ramillien *et al*. (2004), Awange *et al*. (2008, 2009, 2011), Becker, *et al*. (2010) and Forootan *et al*. (2012).

This study made use of the ITG-GRACE2010 daily solutions (Kurtenbach *et al*., 2009), which are computed up to the SHs of degree and order 40, covering October 2002 to September 2009. For computation of such daily fields, the WaterGAP global hydrology model (WGHM), the atmospheric model European Centre for Medium-Range Weather Forecasts (ECMWF), and the ocean circulation model (OMCT) have been used, within the framework of a Kalman-smoother procedure, to derive the temporal correlations while using GRACE observations as the main information for computation of the gravity models. Details of computations can be found in the study of Kurtenbach (2011).

The priority of using daily solutions for studying water variations when it is compared to those of monthly solutions is that it allows to recover fast gravity field (its equivalent water) variations as detailed as possible with reasonable temporal resolution. For studying TWS variation over the GHA, first, 2588 daily gravity solutions covering October 2002 to September 2009 were downloaded from the official website of the Astronomical Physical und Mathematical Geodesy (APMG) group at Bonn University.[2] These fields were then used to generate the global TWS values according to the approach of Wahr *et al*. (1998) and the boundary of the GHA as it is shown in Figure 1 was extracted from the fields. Finally, spatially averaged TWS along with their corresponding cumulated TWS variations were computed (see Figure 7(b)). Daily GRACE products, in this study, have been used to examine the impact of climate variability on total water storage variations for recent years (2002–2009) when the station data sets were not available. In fact, TWS variability reflected in GRACE data indicates the prolonged impact of decadal climate change over the region. Discussions on the use of GRACE-TWS for drought monitoring, for instance, can be found in the study of Houborg *et al*. (2012).

2.4. Analysis methods

2.4.1. Trend calculation and indices

All stations from different countries were analysed. Trends for individual stations were calculated by adapting Sen's (1968) slope estimator. This method has been applied in other similar works describing extreme indices (Aguilar *et al*., 2005, 2009; Zhang *et al*., 2005; Caesar *et al*., 2010) and also adapted to climatological data by Zhang *et al*. (2000) in a study of annual temperatures over Canada and by Wang and Swail (2001) in their analysis of extreme wave heights over the Northern Hemisphere. Trends are significant at the 5% level when results are ± 1.96 standard deviations from the median trend. We require at least 70% of annual data to be non-missing to calculate a trend and refer to trends as being significant if they are determined to be statistically significant at the 5% level. To avoid biased estimates, station level trends were not calculated for series with excessive missing values.

A total of 27 indices, based upon recommendations of the ETCCDI, were calculated using RClimDex (Caesar *et al*., 2006, 2010). Many of the indices use locally defined thresholds, making it easier to compare results over a wide region. The indices are primarily based on station level thresholds calculated over a base period, such as the 90th percentile of minimum temperature. These thresholds are determined for each day of the year using data from that day and two days on either side of it over the course of the base period. Table II lists the indices presented in this paper while detailed descriptions of the indices and the exact formulae for calculating them are available on the ETCCDI web page.[3]

All the indices are essentially anomalies from the same base period. However, some precipitation indices could potentially be dominated by those stations with the greatest precipitation, as those stations may see precipitation vary from year to year by more than the total annual precipitation at stations with the least total precipitation (Aguilar *et al*., 2009). To determine whether this was the case for the stations analysed, precipitation indices were also calculated by first standardizing the indices (dividing by the index's standard deviation). As a comparison of both approaches revealed similar shape

[2]http://www.igg.uni-bonn.de/apmg/index.php?id = itg-grace2010

[3]http://cccma.seos.uvic.ca/ETCCDI/

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Table II. List of the ETCCDI indices used in this study.

ID	Indicator name	Description	Units
FD*	Frost days	Count of days where TN (daily minimum temperature) < 0 °C	d
SU	Summer days	Count of days where TX (daily maximum temperature) > 25 °C	d
ID	Icing days	Count of days where TX < 0 °C	d
TR	Tropical nights	Count of days where TN > 20 °C	d
GSL*	Growing season length	Annual count of days between first span of at least six days where TG (daily mean temperature) > 5 °C and first span in second half of the year of at least six days where TG < 5 °C.	d
TXx		Monthly maximum value of daily maximum temperature	°C
TNx		Monthly maximum value of daily minimum temperature	°C
TXn		Monthly minimum value of daily maximum temperature	°C
TNn		Monthly minimum value of daily minimum temperature	°C
TN10p	Cold nights	Count of days where TN < 10th percentile	%
TX10p	Cold day-times	Count of days where TX < 10th percentile	%
TN90p*	Warm nights	Count of days where TN > 90th percentile	%
TX90p	Warm day-times	Count of days where TX > 90th percentile	%
WSDI*	Warm spell duration index	Count of days in a span of at least six days where TX > 90th percentile	%
CSDI	Cold spell duration index	Count of days in a span of at least six days where TN > 10th percentile	d
DTR	Diurnal temperature range	Mean difference between TX and TN (°C)	
RX1day	maximum 1-d Precipitation	Highest precipitation amount in 1-d period	mm
RX5day*	Maximum 5-d Precipitation	Highest precipitation amount in 5-d period	mm
SDII*	Simple daily intensity index	Mean precipitation amount on a wet day	mm
R10mm*	Heavy precipitation days	Count of days where RR (daily precipitation amount) ≥ 10 mm	d
R20mm	Very heavy precipitation days	Count of days where RR ≥ 20 mm	d
R_{nn}mm		Count of days where RR ≥ user-defined threshold in mm	d
CDD*	Consecutive dry days	Maximum length of dry spell (RR < 1 mm)	d
CWD	Consecutive wet days	Maximum length of wet spell (RR ≥ 1 mm)	d
R95p TOT*		Precipitation due to very wet days (>95th percentile)	mm
R99pTOT		Precipitation due to extremely wet days (>99th percentile)	mm
PRCPTOT		Total precipitation in wet days (>1 mm)	mm

Full definitions are available from the ETCCDI website http://cccma.seos.uvic.ca/ETCCDI/.

and trends, the standardized indices are not used and the results are provided through the analysis of the simple anomaly series.

2.4.2. *Modelling of extreme rainfall and temperature*

Using the PRECIS regional climate modelling system, this study analyses the distribution of extremes of temperature and precipitation in GHA in the recent past (1961–1990) and in a future (2071–2100) climate under the IPCC SRES A2 and B2 emissions scenarios (IPCC 2007, chapter 19, p. 18). Rainfall and temperature were simulated by PRECIS RCM and compared with observations (in areas in which data are available) for the period 1961–1990. The main task here is to evaluate the simulations of current climate (particularly precipitation) of regional climate model by comparing them with currently available data, and thereby assessing the uncertainty associated with future climate predictions. The UK-Met Office high resolution PRECIS model runs are compared with available data to assess its performance. The model is used to generate future climate projections to demonstrate how they can be used and interpreted at the national level. Emphasis is placed on determining the extremes, trend and the variance explained by each model. The purpose of the simulation of regional climate is to examine and compare statistics relevant to the region in observations extremes and regional circulation model. This further demonstrates value of climate observations and regional models for decision making, to provide advice on model performance and limitations, and to improve capabilities across the region for using climate data records and model projections.

2.4.3. *Temporal independent component analysis of GRACE spatio-temporal total water storage products*

Independent component analysis (ICA) is a higher-order statistical technique, which can be viewed as an extension to the commonly used principle component analysis (PCA) (Forootan and Kusche, 2012, 2013). Using an ICA algorithm, the input data (spatio-temporal observations) are assumed to consist of a linear mixture of unknown source signals, which cannot be directly measured. By incorporating higher order statistical information contained in the data in the decomposition procedure, ICA extracts statistically independent components that reflect spatial and temporal manifestations of physical processes hidden in the data (Lotsch *et al*., 2003; Hannachi *et al*., 2009).

Generally, there are two alternative ways to implement ICA on a temporal sequence of gridded datasets

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Table III. Regional trends in temperature indices.[a]

Index	Guinea	Central Africa	Zimbabwe	Global	Kenya	Ethiopia	Units
Warmest day	**0.14**	**0.25**	0.15	**0.21**	**0.35**	0.11	°C/decade
Warmest night	**0.17**	**0.21**	0.10	**0.30**	0.17	**0.33**	°C/decade
Coldest day	**0.23**	**0.13**	0.00	0.37	0.02	0.10	°C/decade
Coldest night	0.04	**0.23**	0.02	**0.71**	**0.21**	**0.32**	°C/decade
DTR	0.12	0.00	0.11	−0.08	0.22	0.61	°C/decade
Cold Night frequency	−0.21	**−1.71**	**−1.24**	**−1.26**	**−1.10**	**−1.23**	% of days in a year/decade
Cold Day frequency	**−2.15**	**−1.22**	**−1.05**	**−0.62**	**−1.6**	**−1.0**	% of days in a year/decade
Warm night frequency	**1.19**	**3.24**	0.71	**1.58**	**1.44**	**2.14**	% of days in a year/decade
Warm day frequency	**1.56**	**2.87**	**1.86**	**0.89**	**1.07**	0.65	% of days in a year/decade

[a]The trends for the globe area from Alexander *et al*. (2006) and Caesar *et al*. (2010) based on the time period 1955–2003. A trend significant at the 5% level is marked with bold font.

in which either temporally independent components or spatially independent time series can be estimated. The methods are respectively called temporal ICA and spatial ICA (for details see, e.g. Forootan and Kusche, 2012; Forootan *et al*., 2012). This study made use of temporal ICA method, since the scope of the study is to extract the temporal behaviour of TWS changes for the period of October 2002 to September 2009, to further investigate the impacts of rainfall after the long-term study of 1970–2000.

3. Results

3.1. Trends in temperature indices

Trends for the temperature indices for some selected countries are shown in Table III in comparison to global and other regional indices. The two countries, that is, Ethiopia and Kenya are used for comparison purposes since their data coverage is relatively good and trends calculated include similar window period of 1971–2003. The warm extremes are increasing while cold extremes decreasing, thus these series clearly indicate significant warming. Individual stations show most spatial coherence in the TN90p index, that is, frequency of nights warmer than the 90th percentile. Nearly half of the available stations indicate a significant increase in this index over the period 1971–2004. Sample time series for the percentile-based temperature indices are shown in Figure 3 for Asmara in Eritrea. The frequencies of warm days and nights, relative to the base period 1961–1990, increased strongly between 1961 and 1990, with a large increase in the number of nights per year exceeding the 90th percentile threshold. There were also large reductions in the frequency of cold nights and cold days over the 49 years. The warmest day and night of the year is warming at a rate approximately comparable to the global average.

In general, over the entire region, the frequency of warm days and warm nights has increased, and the frequency of cold days and cold nights has decreased. This agrees with the results from other studies that have analysed these trends across different parts of the world (Griffiths *et al*., 2005; Klein Tank *et al*., 2006; Choi *et al*., 2009; Caesar *et al*., 2010). However, the results for the absolute temperature indices (TXx, TNx, etc.) defined for the entire region are sensitive to the large variability in these indices across the region. The percentile indices (e.g. TN90p) are more robust across large regions because they account for the influence of local climate effects. There has been a significant increase in the absolute annual maximum of both daily maximum and minimum temperatures, again in common with the global picture (Griffiths *et al*., 2005; Klein Tank *et al*., 2006; Choi *et al*., 2009; Caesar *et al*., 2010). The coldest day and night of the year is warming slower than the global average, although planetary trend for the coldest day is not significant.

3.2. Trends in precipitation indices

The map in Figure 4(b) depicts total precipitation in wet days (>1 mm) (PRCPTOT), and is an example indicating relative lack of spatial coherence for precipitation in the region. The number of stations with significant negative or positive trends is low. Sample graphs of trends, calculated for various precipitation indices are shown in Figures 4(a), 5(a) and (b), while Table IV compares similar trends at regional and global scales (Alexander *et al*. 2006, Caesar *et al*., 2010) at similar window period. Western Lake Victoria, southern Sudan and western Ethiopia generally show significant decreases in total precipitation (e.g. see Figure 4(b)). For Asmara (Figure 4(a)) and Djibouti (Figure not shown), there are sharp drops in the total annual precipitation time series around 2000–2010. Likely associated with the decrease in total precipitation, the length of the maximum number of consecutive dry days is increasing in Asmara and Djibouti, while the length of the maximum number of consecutive wet days shows a significant decrease (figure not shown). The Simple Daily Intensity Index (SDII), which takes into account the number of days with rainfall greater than or equal to 1 mm shows no significant changes. In general, decreasing trend in total precipitation in wet days (>1 mm) is observed in the north western sector (western Ethiopia and southern Sudan), and equatorial sector around Lake Victoria, while much of Ethiopia had significant positive increase (Figure 4(b)). The precipitation due to very wet days greater than 95th percentile (R95p) index (Figure 5(a)) indicate that the annual amount of precipitation contributed on days

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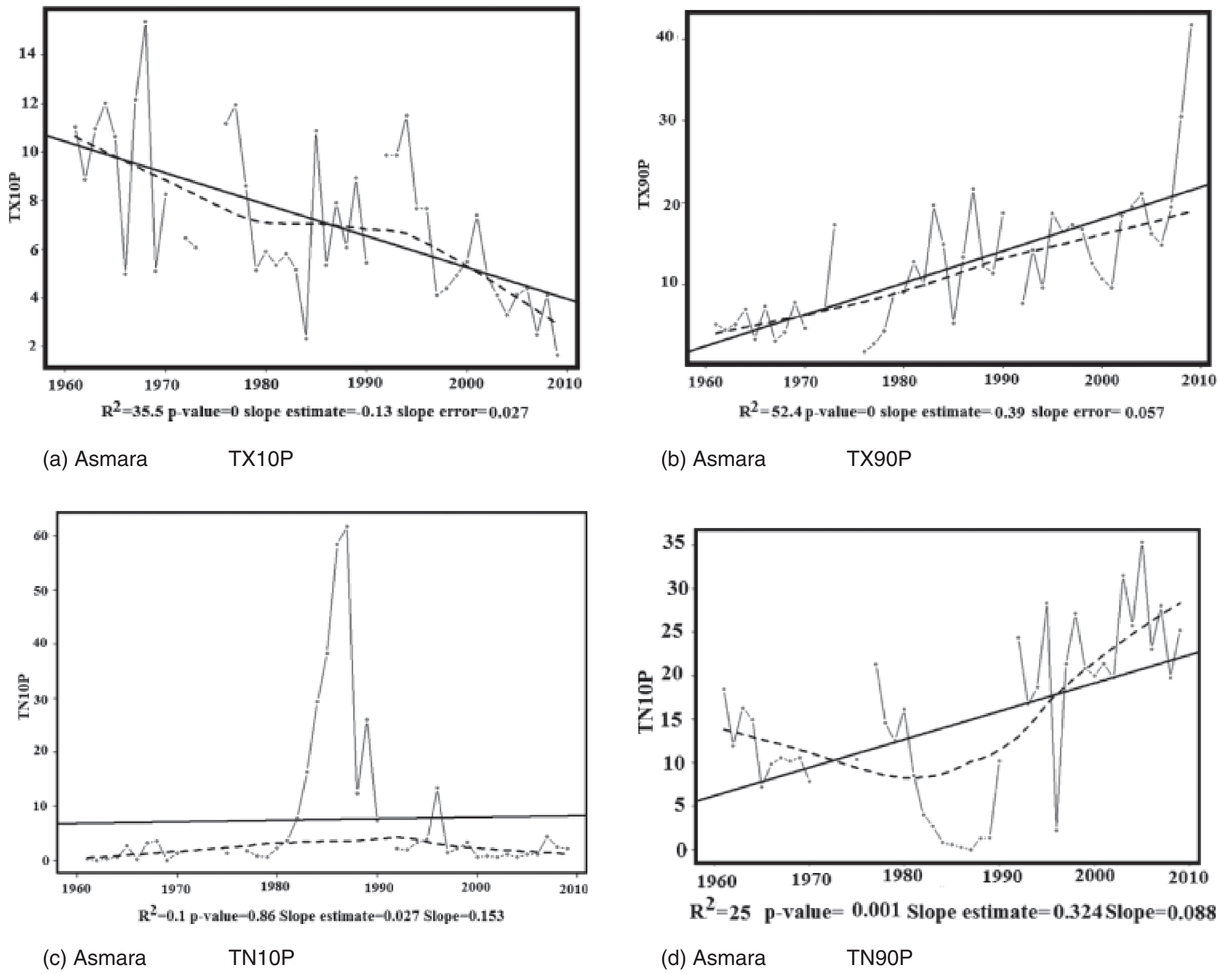

Figure 3. Time series 1971–2010 for (a) cold days, (b) warm days, (c) cold nights and (d) warm nights (units: %). Bold line indicates ordinary least squares fit for Asmara, Eritrea.

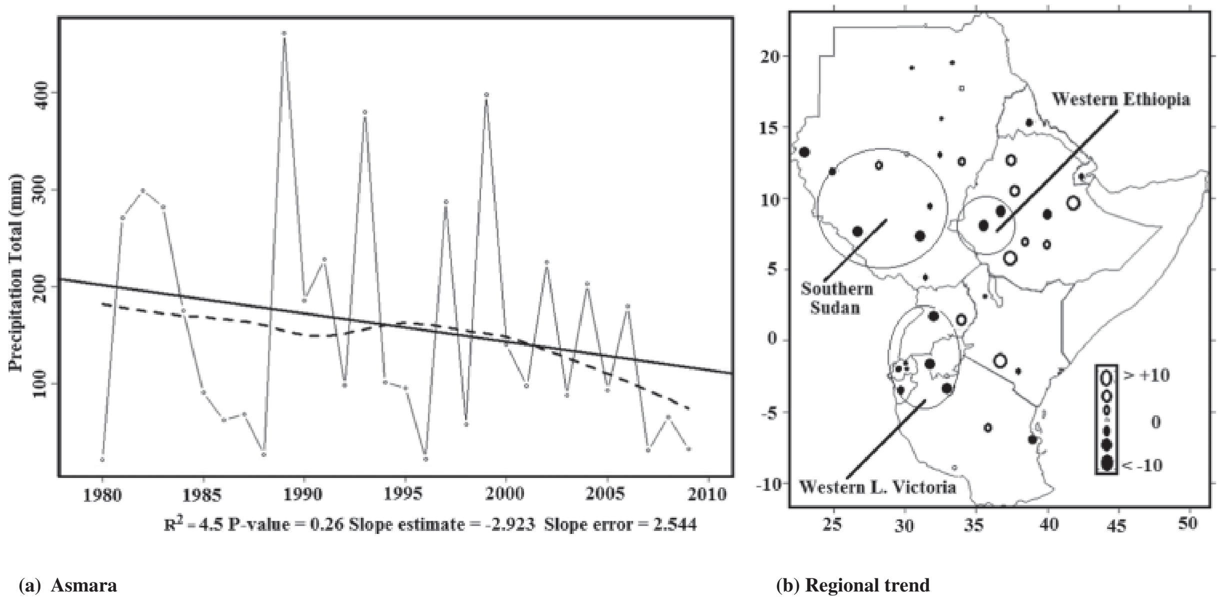

Figure 4. Precipitation total (PRCPTOT). Individual station's time series and regional trend (a) Individual time series 1980–2010 for Asmara in Eritrea, (b) regionally averaged station trends. Positive (negative) trends are shown in red (blue) circles. Large (small) circles indicate significant (insignificant) trends.

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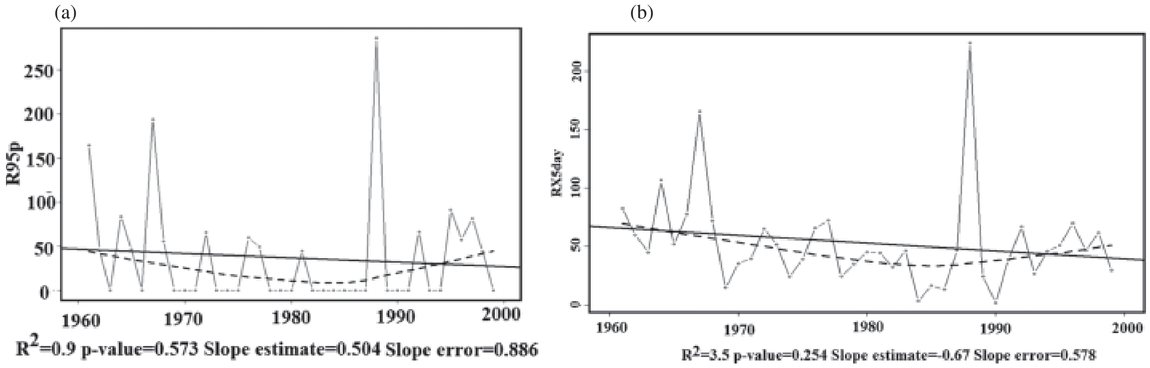
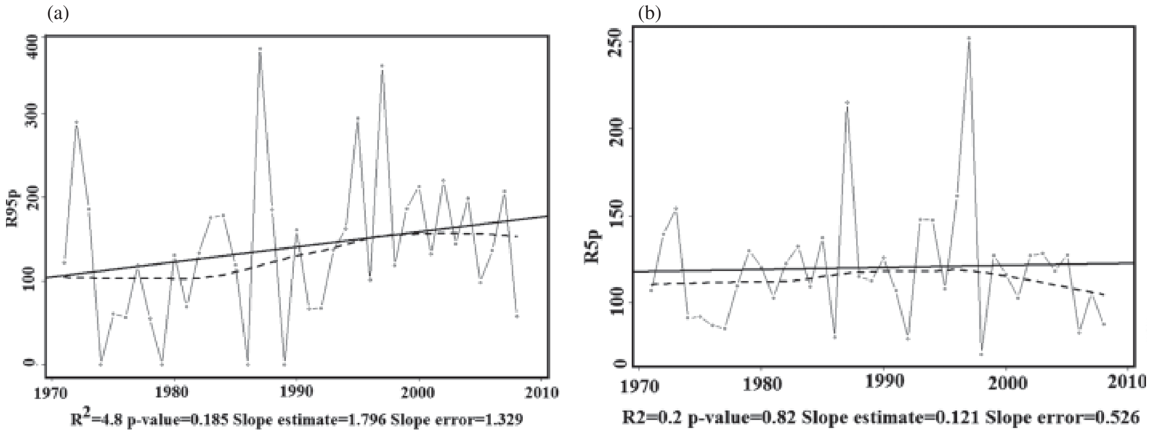


Khartoum R95p

Khartoum RX5day

Figure 5. Time series 1961–2000 for (a) contribution from very wet days (R95p, units: mm) and (b) annual maximum 5-d precipitation amounts (RX5day, units: mm) for Khartoum. Bold lines indicate ordinary least squares fit.



Dodoma R95p

Dodoma RX5day

Figure 6. Time series 1970–2010 for (a) contribution from very wet days (R95p, units: mm) and (b) annual maximum 5-d precipitation amounts (RX5day, units: mm) for Dodoma. Bold lines indicate ordinary least squares fit.

exceeding the long-term 95th percentile has decreased from about 50 mm to around 30 mm in Khartoum, but this change is non-significant (Figure 5(a)). The highest precipitation amount in 5-d period or maximum 5-d precipitation (RX5day) index (Figure 5(b)) depicts significant reduction over the 40-year period.

Similar time series of R95p for the southern sector is represented by Dodoma (Figure 6(a)). There are increases in R95p over the southern sector, a marginal decrease over the equatorial sector, and a decrease over the northern sub-region. Between them, only the change within the southern sector is statistically significant.

Table IV lists the regional trends for the precipitation indices and also the global trends. The same problems exist with defining some of the precipitation indices across the whole region that applied to the absolute temperature indices, and indices defined relative to a local climatology (e.g. percentile based) are preferable for comparing across such a large region.

Compared to the temperature indices, there are fewer significant trends in the precipitation indices. In contrast to the other sub-regions, the northern sector has decreasing trends in all precipitation indices, apart from the consecutive dry day index, suggesting a consistent change towards drier conditions. However, it must be emphasized that these trends are non-significant. Over the region as a whole, the precipitation trends are mixed (Funk *et al*., 2008, 2012). This does not parallel the global results of Caesar *et al*. (2010) indicating consistent trends towards wetter conditions across nearly all of the indices, although it should be noted that analysis was for a different time period (1971–2005) and had only limited coverage of the tropics.

3.3. Relationship between precipitation and TWS changes

Regarding the precipitation results, it was clear that the overall precipitation over the GHA is declining. To support the precipitation results of the last 7 years of the study (2002–2009), we used daily TWS products as described in Section 2.3. The goal was to see whether the total water availability of the region is affected by climate variations or not. As a matter of fact, TWS tells quite more sophisticated story of water variations over the study region by providing information on daily precipitation minus evaporation minus run-off over the region. Our results of spatially averaged TWS over the GHA (Figure 7) show that TWS declined between 2002

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Table IV. Regional and global trends in precipitation Indices for the period 1971–2005.

Index	Indian Ocean	Himalayas	Indo-Pacific	Global	Northern sector	Equatorial sector	Southern sector	Units
PRCPTOT	**81.84**	**41.77**	−2.86	5.91	−2.92	−0.85	10.3	mm/decade
SDII	**1.05**	**1.55**	**0.25**	0.05	−0.81	−0.89	−0.13	mm/d/decade
CDD	0.66	2.61	−1.01	**−1.19**	0.37	0.32	0.45	d/decade
CWD	0.10	−0.24	−0.13	**−0.07**	−0.05	−0.50	−0.07	d/decade
RX1day	1.12	1.70	−1.12	0.26	0.48	−0.33	−0.72	mm/decade
RX5day	5.96	16.39	0.90	**0.73**	0.67	−0.67	0.12	mm/decade
R10mm	2.09	0.00	−0.14	**0.03**	−0.29	−0.28	0.35	d/decade
R20mm	1.26	0.53	−0.04	0.06	−0.01	−0.04	0.14	d/decade
R95p	22.66	**82.30**	12.24	**4.68**	12.9	−0.50	1.79	mm/decade
R99p	−12.61	32.39	4.98	**3.38**	51.1	−2.30	8.05	mm/decade

Note that global trends were calculated from Alexander *et al*. (2006) together with Caesar *et al*. (2010) data and referred to the period 1971–2003. Trends significant at the 5% level are shown in bold font.

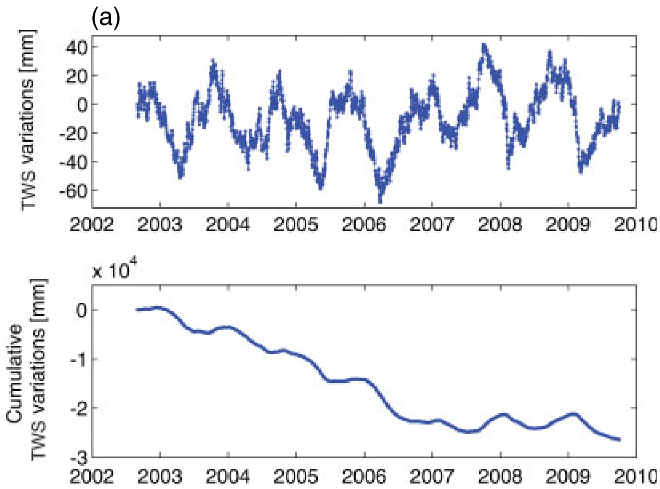

Figure 7. (a, top) Spatially averaged total water storage (TWS) variations over the GHA, derived from daily Kalman-smoother GRACE products, (a, bottom) Accumulated TWS changes over the GHA. (b) Implementing the temporal ICA method over 2588 d of TWS maps over the GHA, computed from Kalman-smoother daily GRACE products provided by the APMG group at Bonn University. Independent patterns are ordered according to the variance they represent. One can reconstruct each mode of TWS variability by multiplying the spatial patterns with their corresponding temporal components.

and 2007. An increase in TWS in 2007 is associated with the El Niño southern oscillation phenomenon, which usually brings rainfall to most parts of the region (Janowiak, 1988; Ogallo *et al*., 1988; Indeje *et al*., 2000; Mutemi, 2003). This has been followed again by a decline in TWS variations over the GHA up to the end of the study period. The cumulative TWS over the study period supports the results of precipitation (e.g., Figure 4(a)), showing that the total water availability has decreased over the GHA during the last 7 years of the study (see Figure 7(b), bottom).

Applying the ICA method on GRACE-TWS data over the GHA shows that the first ICA mode (IC1) extracts 75% of variability in TWS changes. The spatial pattern of IC1 shows a dipole spatial structure with respect to the Equator. The temporal pattern of IC1 shows a dominant annual water cycle over the study area. The second ICA mode (IC2) corresponds to 15% of the variance, while the temporal pattern shows a summation of a long-term trend and an inter-annual variability. Considering the spatial pattern, therefore, a declining rate for the regions of the Lake Victoria Basin and the surrounding lakes were found. The declining pattern of TWS is also extended up to the south of Sudan (c.f., Figure 4(b)). In contrast, over the tropical regions as well as Ethiopia a slight increase of TWS during 2002–2010 is seen (c.f., Figure 4(b)). The spatial and temporal patterns of IC2, therefore, confirm the results of precipitation, which was derived for the long-term period during 1970–2000.

3.4. Modelling precipitation extremes

PRECIS Regional Climate Model (RCM) analysed correctly and reproduced the mean seasonal and annual cycles of precipitation for the period 1961–1990 over the southern (Figure 8(a)), northern (Figure 8(b)) and equatorial (Figure 8(c)) sectors. The mean surface temperature climatology for all the four seasons of the region, that is, March–May (MAM), June–August (JJA), October–December (OND) and December–February (DJF) are spatially and temporally (Figure 8(d)) simulated for the baseline period of 1961–1990 compared with the observed Climate Research Unit (CRU) data (gridded data based on the set aggregated to the RCM

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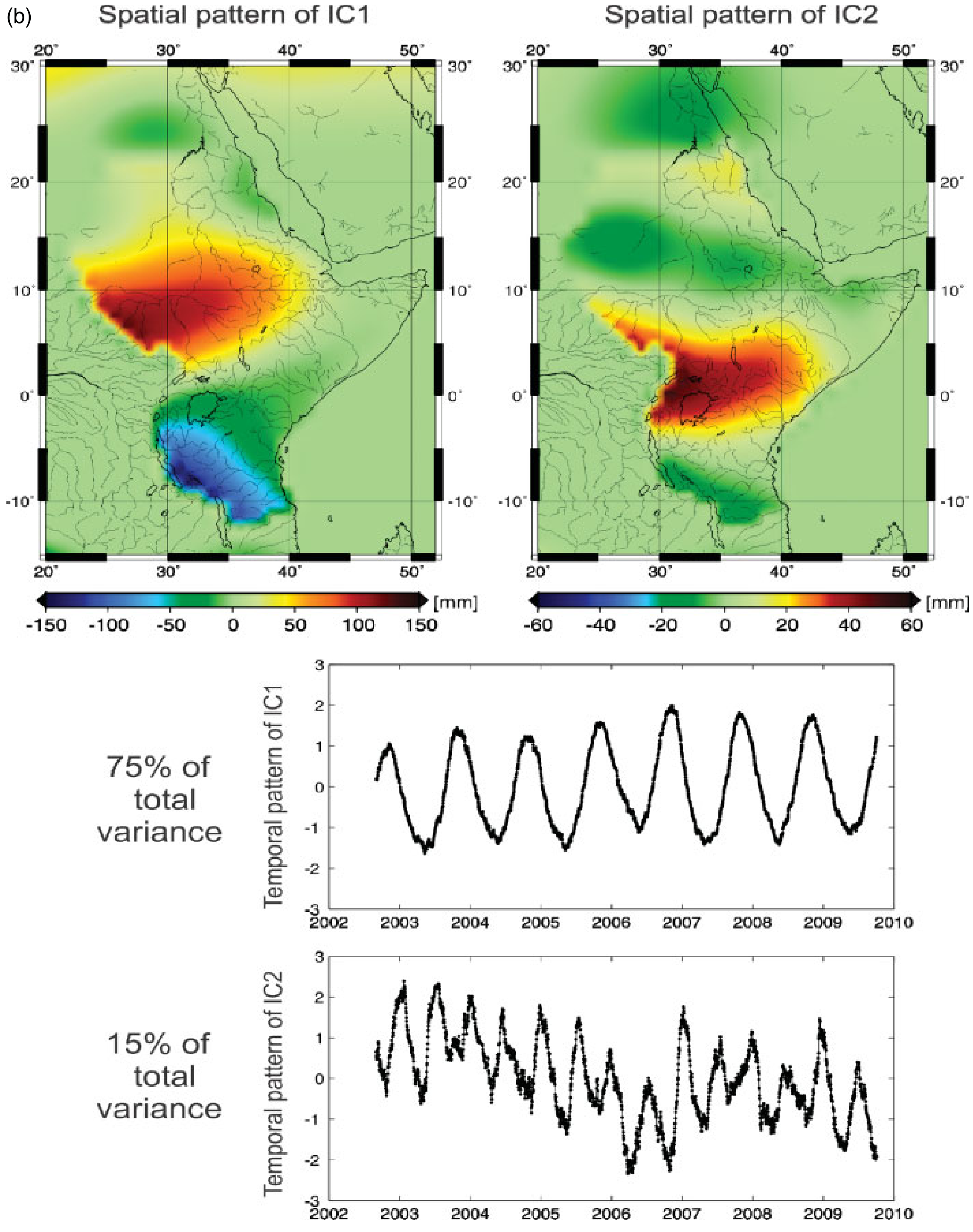

Figure 7. *(Continued).*

grid). The results show that, compared to CRU, the model underestimates rainfall over most parts of eastern highlands during OND while over the central sector (around Lake Victoria area) and southern sector of the region, the model overestimates rainfall (Figure 8(a)). On the contrary, over northern sector, the model produces the observed rainfall reasonably well (Figure not shown). It is thus evident that the simulated rainfall by the PRECIS model is fairly consistent with the observed values over most parts of the study area. Results from the inter-annual variability of PRECIS simulated surface air temperature showed that during JJA season, some sections of the region recorded the lowest temperature and the warmest temperatures during the DJF season (Figure 8(b)). The model results agree reasonably well with the observed patterns in terms of the spatial location of the extreme maximum temperatures.

The trends calculated for projected precipitation indices for the period 2010–2040 are shown in Figure 9. Only central Uganda represented by Mbarara, Masindi

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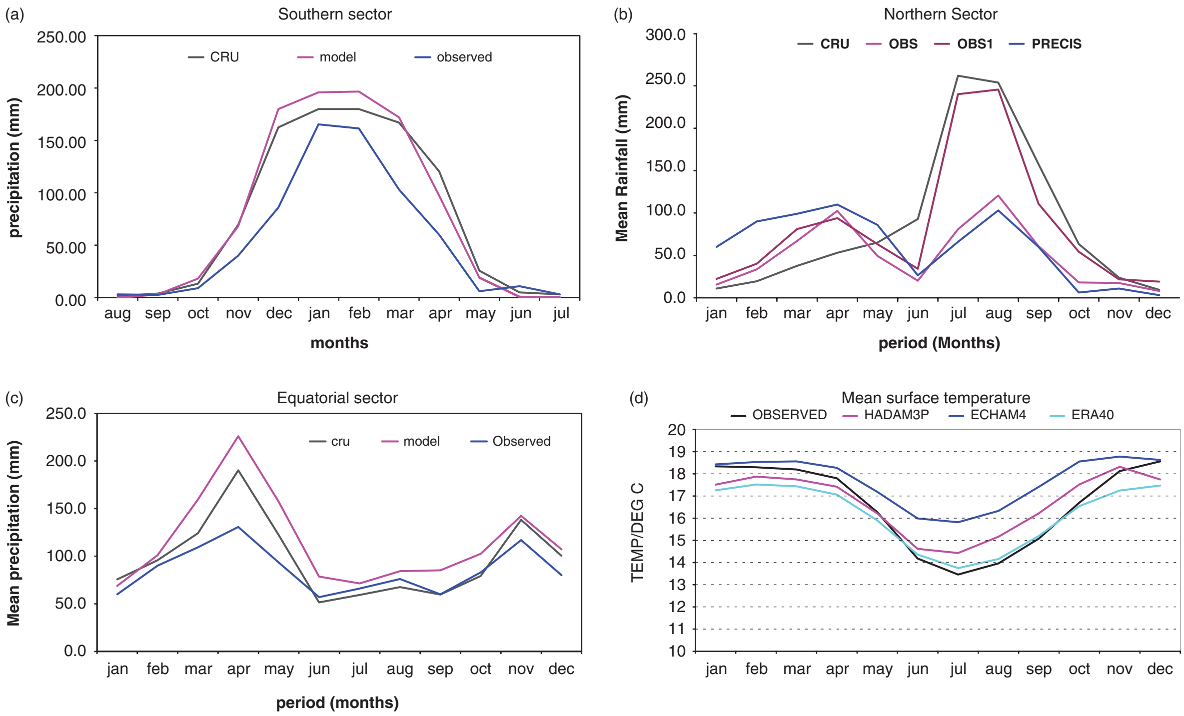

Figure 8. Simulated and observed mean climate cycles for some stations located in various sectors of the region.

and Jinja show significant increases in total precipitation. Sample time series for Gulu is shown by Figure 9(a) and regional projected trends in Figure 9(b). Total annual rainfall (PRCPTOT) showed a decreasing trend for many of the stations over Sudan except for the Khartoum that had significant positive trend. Generally, consecutive wet days (CWD) showed a decreasing trend while the consecutive dry days (CDD) showed an increasing trend. While temperature indices vary from station to station, the dominant features seem to be an increasing trend in the number of cold nights (TN10p) with a decreasing trend in the number of warm nights (TN90p). Time series for projected Total Rainfall (PRCPTOT) over Rwanda, where three stations (Kigali, Kamembe and Gikongoro) were analysed showed evidence of decreasing trends in rainfall. Results show general increasing trend in Consecutive Dry Days (CDD) and decreasing trend for Consecutive Wet Days (CWD) for Gikongoro.

4. Discussion

A set of daily station observations from countries in the GHA region were for the first time compiled and analysed to enable assessment of changes in climate extremes over the region. Most stations showed decrease of total precipitation in wet days greater than 1 mm (PRCPTOT) as well as heavy rainy days (R10mm), maximum 1-d precipitation (Rx1day), maximum 5-d precipitation (Rx5day), heavy precipitation days (R10mm) and warm spell duration (WSDI). Index for warm days (Tx90P) showed increasing trend, while the index for cool days (TX10P) showed decreasing trend. The TXn index (monthly minimum value of daily maximum temperature) showed an increasing trend in most parts of the region. The TNx index (monthly maximum value of daily minimum temperature) showed an increasing trend over most parts of the region, and more significantly in the north-eastern and southern sectors of the region; indicating that there is a general increasing trend of warm nights for most of the stations in the region. Increasing trend in warm nights is indicative of significant night time warming.

Thus, increasing trends for warm nights were the most spatially coherent index consistent with the results of other regional workshops (Klein Tank *et al*., 2006, Choi *et al*., 2009) and the global analysis (Alexander *et al*., 2006, Caesar *et al*., 2010). Less spatial coherence trends in precipitation indices across the region and fewer trends that are locally significant when compared with the temperature indices are observed. In the few cases where statistically significant trends in precipitation indices are identified for regions and sub-regions, there is generally a trend towards wetter conditions consistent with the global results of Alexander *et al*. (2006).

5. Conclusion

The study aimed at:

(i) Assessing the adequacy of regional climate observations and trends for adaptation purposes. In this regard, the study found that there is inadequate *in situ* data for an individual country analysis but provided sufficient ground for regional level

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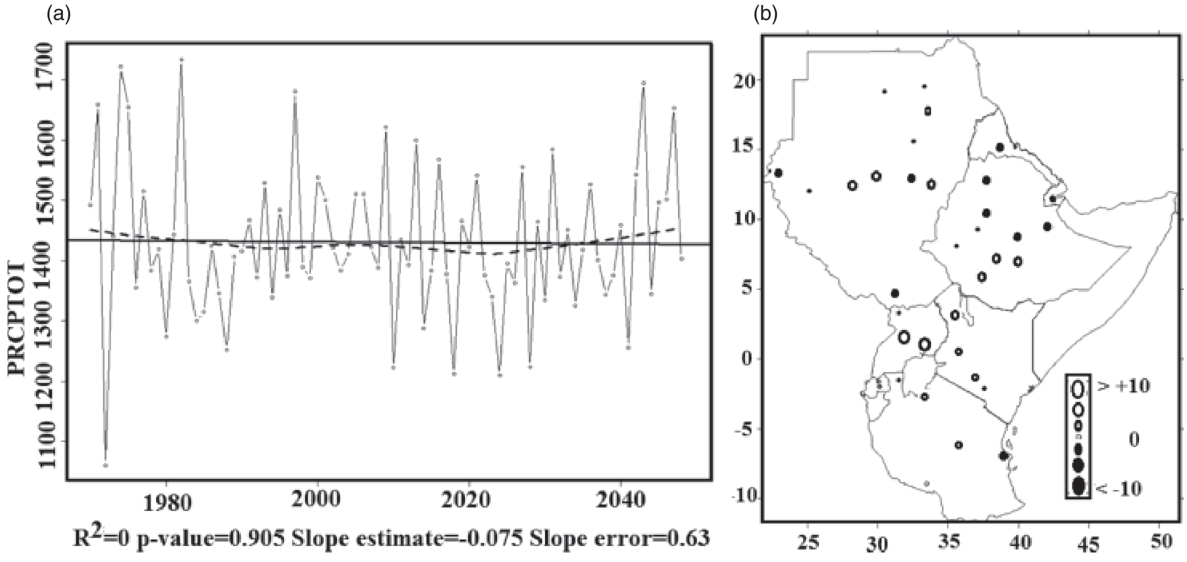

Gulu

Projected regional trend

Figure 9. Projected Precipitation Total (PRCPTOT). Individual station time series and regional trend (a) Individual time series 2010–2040 for Gulu in Uganda, (b) Regionally averaged station trends. Positive (negative) trends are shown in red (blue) circles. Large (small) circles indicate significant (non-significant) trends.

climate analysis. The results further showed increasing/decreasing trend in warm/cold extremes. Furthermore, frequencies of warm days and nights increased strongly, with a large increase in the number of nights per year exceeding the 90th percentile threshold between 1961 and 1990. On the contrary, precipitation patterns are mixed with fewer significant trends except significant decrease in total precipitation in wet days greater than 1 mm across the whole region.

(ii) Assessing the adequacy and reliability of available model based climate projections for adaptation needs. To this end, the study found that the simulated climate is fairly consistent with the observed values over most parts of the study area.

(iii) Assessing the expected changes in climate extremes needed to assist in developing effective adaptation and climate risk management strategies. Here, the study established that, generally, the model projected decreasing/increasing trend in consecutive wet/dry days with variations in temperature indices from one station to another. The dominant features in the region seem to be an increasing trend in the number of cold nights with a decreasing trend in the number of warm nights. Increasing trends for warm nights were the most spatially coherent index consistent with the results of other regions of the globe.

(iv) Assessing changes in the total water storage for the period 2002–2010. Here, the study established a decline in total water availability over the GHA region during the last 7 years.

Our findings, therefore, showed that increasing trends in both night and day temperatures had the most spatially coherent indices. The model simulates well the spatial distribution of extreme temperature and rainfall events when compared with present climate observations, with temperature simulation being more realistic across the region. Overall, the future occurrence of warm days and nights are projected to be more frequent in the entire GHA, while the occurrence of cold night events is likely to decrease. The overall precipitation in the region decreased between 2002 and 2007 from the TWS products.

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References

Aguilar E, Peterson TC, Ramírez Obando P, Frutos R, Retana JA, Solera M, Soley J, González García I, Araujo RM, Rosa Santos A, Valle VE, Brunet M, Aguilar L, lvarez LA, Bautista M, Castañón C, Herrera L, Ruano E, Sinay JJ, Sánchez E, Hernández Oviedo GI, Obed F, Salgado JE, Vázquez JL, Baca M, Gutiérrez M, Centella C, Espinosa J, Martínez D, Olmedo B, Ojeda Espinoza CE, Núñez R, Haylock M, Benavides H, Mayorga R. 2005. Changes in precipitation and temperature extremes in Central America and northern South America, 1961–2003. *Journal of Geophysical Research* **110**: D23107. DOI: 10.1029/2005JD006119.

Aguilar E, Aziz Barry A, Brunet M, Ekang L, Fernandes A, Massoukina M, Mbah J, Mhanda A, do Nascimento DJ, Peterson TC, Thamba Umba O, Tomou M, Zhang X. 2009. Changes in temperature and precipitation extremes in western central Africa, Guinea Conakry, and Zimbabwe, 1955–2006. *Journal of Geophysical Research* **114**: D02115. DOI: 10.1029/2008JD011010.

Alexander LV, Zhang X, Peterson TC, Caesar J, Gleason B, Tank AMGK, Haylock M, Collins D, Trewin B, Rahimzadeh F, Tagipour A, Kumar KR, Revadekar J, Griffiths G, Vincent L, Stephenson DB, Burn J, Aguilar E, Brunet M, Taylor M, New M, Zhai P, Rusticucci M, Vazquez-Aguirre JL. 2006. Global observed changes in daily climate extremes of temperature and precipitation. *Journal of Geophysical Research* **111**: D05109. DOI: 10.1029/2005JD006290.

Anyah RO, Qiu W. 2011. Characteristic 20th and 21st century precipitation and temperature patterns and changes over the Greater Horn of Africa. *International Journal of Climatology* **32**: 347–363. DOI: 10.1002/joc.2270.

Anyah RO, Semazzi FH. 2006. Climate variability over the Greater Horn of Africa based on NCAR AGCM ensemble. *Theoretical and Applied Climatology* **86**: 39–62.

Arnell NW. 2004. Climate change and global water resources: SRES emissions and socio-economic scenarios. *Global Environmental Change* **14**(1): 31–52. DOI: 10.1016/j.gloenvcha.2003.10.006.

Awange J, Sharifi M, Ogonda G, Wickert J, Grafarend E, Omulo M. 2008. The falling Lake Victoria water level: GRACE, TRIMM and CHAMP satellite analysis of the lake basin. *Water Resource Management* **22**(7): 775–796. DOI: 10.1007/s11269-007-9191.

Awange J, Sharifi M, Baur O, Keller W, Featherstone W, Kuhn M. 2009. GRACE hydrological monitoring of Australia: Current limitations and future prospects. *Journal of Spatial Science* **54**(1): 23–36. DOI: 10.1080/14498596.2009.9635164.

Awange J, Fleming KM, Kuhn M, Featherstone WE, Heck B, Anjasmara I. 2011. On the suitability of the $4^\circ \times 4^\circ$ GRACE mascon solutions for remote sensing Australian hydrology. *Remote Sensing of Environment* **115**(3): 864–875. DOI: 10.1016/j.rse.2010.11.014.

Becker M, Llovel W, Cazenave A, Günter A, Crétaux J-F. 2010. Recent hydrological behavior of the East African great lakes region inferred from GRACE, satellite altimetry and rainfall observations. *Comptes Rendus Geoscience* **342**(3): 223–233. DOI: 10.1016/j.crte.2009.12.010.

Bohle HG, Downing TE, Watts MJ. 1994. Climate change and social vulnerability: toward a sociology and geography of food insecurity. *Global Environmental Change* **4**(1): 37–48. DOI: 10.1016/0959-3780(94)90020-5.

Brant L, Ileana B, George N, Leila K, Carvalho MV, Gabriel B, Senay DA, Leroux S, Funk C. 2012. Seasonality of African Precipitation from 1996 to 2009. *Journal of Climate* **25**(12): 4304–4322. DOI: 10.1175/JCLI-D-11-00157.1.

Brunet M, Saladié O, Jones P, Aguilar E, Moberg A, Lister D, Walther A, Almarza C. 2008. A case-study/guidance on the development of long-term daily adjusted temperature datasets, WCDMP-66, World Meteorol. Org., Geneva, 46 pp.

Caesar J, Alexander L, Vose R. 2006. Large-scale changes in observed daily maximum and minimum temperatures—creation and analysis of a new gridded dataset. *Journal of Geophysical Research* **111**: D05101. DOI: 10.1029/2005JD006280.

Caesar JA, Alexander LV, Trewin B, Tsering K, Sorany L, Vuniyayawa V, Keosavang N, Shimana A, Htay MM, Karmacharya J, Jayasinghearachchi DA, Sakkamart J, Soares E, Hung LT, Thuong LT, Hue CT, Dung NTT, Hung PV, Cuong HD, Cuong NM, Sirabaha S. 2010. Changes in temperature and precipitation extremes over the Indo-Pacific region from 1971 to 2005. *International Journal of Climatology* **31**(6): 791–801. DOI: 10.1002/joc.2118.

Camberlin P, Philippon N. 2002. The East African March-May rainy season, its teleconnections and predictability over the 1968–1997 period. *Journal of Climate* **15**: 1002–1019.

Choi G, Collins D, Ren G, Trewin B, Baldi M, Fukuda Y, Afzaal M, Pianmana T, Gomboluudev P, Huong PT, Lias N, Kwon WT, Boo KO, Cha YM, Zhou Y. 2009. Changes in means and extreme events of temperature and precipitation in the Asia-Pacific Network region, 1955–2007. *International Journal of Climatology* **29**: 1906–1925.

Christy JR, Norris WB, McNider RT. 2009. Surface temperature variations in East Africa and possible causes. *Journal of Climate* **2009**(22): 3342–3356.

Conway D, Mould C, Bewket W. 2004. Over one century of rainfall and temperature observations in Addis Ababa, Ethiopia. *International Journal of Climatology* **24**: 77–91.

CRS Report. 2012. Congressional Research Service report on Horn of Africa: The Humanitarian Crisis and International Response, http://www.fas.org/sgp/crs/row/R42046.pdf.

Downing TE. 1991. Vulnerability to hunger in Africa: a climate change perspective. *Global Environmental Change* **1**(5): 365–380. DOI: 10.1016/0959-3780(91)90003-C.

Elagib NA. 2010. Changing rainfall, seasonality and erosivity in the hyper-arid zone of Sudan. *Land Degradation & Development* **22**(6): 505–512. DOI: 10.1002/ldr.1023.

Folland CK, Karl TR, Christy JR, Clarke RA, Gruza GV, Jouzel J, Mann ME, Oerlemans J, Salinger MJ, Wang SW. 2001. Observed climate variability and change. In *Climate Change 2001. The Scientific Basis—Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press: New York; 99–181.

Forootan E, Kusche J. 2012. Separation of global time-variable gravity signals into maximally independent components. *Journal of Geodesy* **86**(7): 477–497. DOI: 10.1007/s00190-011-0532-5.

Forootan E, Kusche J. 2013. Separation of deterministic signals, using independent component analysis (ICA). *Studia Geophysica et Geodaetica* **57**(1): 17–26. DOI: 10.1007/s11200-012-0718-1.

Forootan E, Awange J, Kusche J, Heck B, Eicker A. 2012. Independent patterns of water mass anomalies over Australia from satellite data and models. *Journal of Remote Sensing of Environment* **124**: 427–443. DOI: 10.1016/j.rse.2012.05.023.

Funk C, Dettinger MD, Michaelsen JC, Verdin JP, Brown ME, Barlow M, Hoell A. 2008. Warming of the Indian Ocean threatens eastern and southern African food security but could be mitigated by agricultural development. *Proceedings of the National Academy of Sciences* **105**(32): 11081–11086.

Funk C, Michaelsen J, Marshall MT. 2012. Mapping recent decadal climate variations in precipitation and temperature across Eastern Africa and the Sahel. In *Remote Sensing of Drought: Innovative Monitoring Approaches*, Wardlow BD, Anderson MC, Verdin JP (eds). Taylor and Francis, CRC Press: Boca Raton, FL.

Griffiths GM, Chambers LE, Haylock MR, Manton MJ, Nicholls N, Baek HJ, Choi Y, Della Marta PM, Gosai A, Iga N, Lata R, Laurent V, Maitrepierre L, Nakamigawa H, Ouprasitwong N, Solofa D, Tahani L, Thuy DT, Tibig L, Trewin B, Vediapan K, Zhai P. 2005. Change in mean temperature as a predictor of extreme temperature change in the Asia-Pacific region. *International Journal of Climatology* **25**: 1301–1330.

Hannachi A, Unkel S, Trendafilov NT, Jolliffe IT. 2009. Independent component analysis of climate data: a new look at EOF rotation. *Journal of Climate* **22**: 2797–2812. DOI: 10.1175/2008JCLI2571.1.

Hastenrath S, Polzin D, Mutai C. 2007. Diagnosing the 2005 drought in equatorial East Africa. *Journal of Climate* **29**: 4628–4637.

Hastenrath S, Polzin D, Mutai C. 2010. Diagnosing the droughts and floods in equatorial East Africa during boreal autumn 2005–08. *Journal of Climate* **23**: 813–817.

Hay SI, Rogers DJ, Randolph SE, Stern DI, Cox J, Shanks GD, Snow RW. 2002. Hot topic or hot air? Climate change and malaria resurgence in East African highlands. *Trends in Parasitology* **18**: 530–534.

Haylock MR, Hofstra N, Klein Tank AMG, Klok EJ, Jones PD, New M. 2008. A European daily high-resolution gridded data set of surface temperature and precipitation for 1950–2006. *Journal of Geophysical Research* **113**: D20119. DOI: 10.1029/2008JD010201.

Houborg R, Rodell M, Li B, Reichle R, Zaitchik BF. 2012. Drought indicators based on model-assimilated Gravity Recovery and Climate Experiment (GRACE) terrestrial water storage observations. *Water Resources Research* **48**(7). DOI: 10.1029/2011WR011291.

Indeje M, Semazzi FHM, Ogallo LJ. 2000. ENSO signals in East African rainfall and their prediction potentials. *International Journal of Climatology* **20**: 19–46.

IPCC. 2007. Climate change 2007: the physical science basis. In *Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Solomon S, Qin D, Manning M, Chen Z, Marquis M, Averyt KB, Tignor M, Miller HL (eds). Cambridge University Press: Cambridge, NY.

Janowiak J. 1988. An investigation of interannual rainfall variability in Africa. *Journal of Climate* **1**: 240–255.

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Kijazi AL, Reason CJC. 2009a. Analysis of the 2006 floods over northern Tanzania. *International Journal of Climatology* **29**: 955–970.

Kijazi AL, Reason CJC. 2009b. Analysis of the 1998 to 2005 drought over the northeastern highlands of Tanzania. *Climate Research* **38**: 209–223.

Klein Tank AMG, Peterson TC, Quadir DA, Dorji S, Zou X, Tang H, Santhosh K, Joshi UR, Jaswal AK, Kolli RK, Sikder A, Deshpande NR, Revadekar JV, Yeleuova K, Vandasheva S, Faleyeva M, Gomboluudev P, Budhathoki KP, Hussain A, Afzaal M, Chandrapala L, Anvar H, Amanmurad D, Asanova VS, Jones PD, New MG, Spektorman T. 2006. Changes in daily temperature and precipitation extremes in central and south Asia. *Journal of Geophysical Research-Atmospheres* **111**(D16105). DOI: 10.1029/2005JD006316.

Kurtenbach E. 2011. *Entwicklung eines Kalman-Filters zur Bestimmung kurzzeitiger Variationen des Erdschwerefeldes aus Daten der Satellitenmission GRACE*. PhD dissertation, Bonn University, Germany.

Kurtenbach E, Mayer-Gürr T, Eicker A. 2009. Deriving daily snapshots of the Earth's gravity field from GRACE L1B data using Kalman filtering. *Geophysical Research Letters* **36**: L17102. DOI: 10.1029/2009GL039564.

Lotsch A, Friedl MA, Pinzón J. 2003. Spatio–Temporal Deconvolution of NDVI Image Sequences Using Independent Component Analysis. *IEEE Transactions on Geoscience and Remote Sensing* **41**(12).

Lyon B, DeWitt DG. 2012. A recent and abrupt decline in the East African long rains. *Geophysical Research Letters* **39**(2): L02702. DOI: 10.L029/2011GL050337.

Mutemi JN. 2003. *Climate Anomalies Over Eastern Africa Associated with Various ENSO Evolution Phases*. PhD thesis, University of Nairobi, Kenya.

Ogallo LJ, Janowiak JE, Halpert MS. 1988. Teleconnection between seasonal rainfall over Eastern Africa and Global Sea surface temperature anomalies. *Journal of the Meteorological Society of Japan* **66**: 807–822.

van Oldenborgh GJ, Philip SY, Collins M. 2005. El Niño in a changing climate: a multi-model study. *Ocean Science* **1**: 81–95.

Omondi PA. 2011. Agricultural drought indices. In *Proceedings of an Expert Meeting*, 2–4 June, 2010, Murcia, Spain, WMO, AGM-11WMO/TD No. 1572, WAOB-2011, 106–112.

Omondi P, Awange JL, Ogallo LA, Okoola RA, Forootan E. 2012a. Decadal rainfall variability modes in observed rainfall records over East Africa and their relations to historical sea surface temperature changes. *Journal of Hydrology* **464–465**: 140–156. DOI: 10.1016/j.jhydrol.2012.07.003.

Omondi P, Ogallo LA, Anyah R, Muthama JM, Ininda J. 2012b. Linkagesbetween global sea surface temperatures and decadal rainfall variability over Eastern Africa region. *International Journal of Climatology* **33**(8): 2082–2104. DOI: 10.1002/joc.3578.

Omumbo JA, Lyon B, Samuel MW, Connor SJ, Madeleine CT. 2011. Raised temperatures over the Kericho tea estates: revisiting the climate in the East African highlands malaria debate *Malaria Journal* **10**: 12, http://www.malariajournal.com/content/10/1/12.

Parmesan C, Root TL, Willig MR. 2000. Impacts of extreme weather and climate on terrestrial biota. *Bulletin of the American Meteorological Society* **81**: 443–450. DOI: 10.1175/1520-0477(2000)081<0443:IOEWAC>2.3.CO;2.

Pascal M, Ahumada JA, Chaves LF, Rodo X, Bouma M. 2006. Malaria resurgence in the East African highlands: temperature trends revisited. *PNAS* **103**(15): 5829–5834. DOI: 10.1073/pnas.0508929103.

Peterson TC, Manton MJ. 2008. Monitoring changes in climate extremes: a tale of international collaboration. *Bulletin of the American Meteorological Society* **89**: 1266–1271.

Peterson TC, Easterling DR, Karl TR, Groisman P, Nicholls N, Plummer N, Torok S, Auer I, Bohm R, Gullett D, Vincent L, Heino R, Tuomenvirta H, Mestre O, Szentimrey T, Salinger J, Førland EJ, Hanssen-Bauer I, Alexandersson H, Jones P, Parker D. 1998. Homogeneity adjustments of in situ atmospheric climate data: a review. *International Journal of Climatology* **18**: 1493–1517.

Ramillien G, Cazenave A, Brunau O. 2004. Global time variations of hydrological signals from GRACE satellite gravimetry. *Geophysical Journal International* **158**(3): 813–826. DOI: 10.1111/j.1365-246X.2004.02328.x.

Schreck CJ, Semazzi FHM. 2004. Variability of the recent climate of eastern Africa. *International Journal of Climatology* **24**: 681–701.

Sen PK. 1968. Estimates of regression coefficient based on Kendalls Tau. *Journal of the American Statistical Association* **63**: 1379–1389. DOI: 10.2307/2285891.

Shongwe ME, van Oldenborgh GJ, van den Hurk BJJM, van Aalst MK. 2010. Projected changes in mean and extreme precipitation in Africa under global warming. Part II: East Africa. *Journal of Climate* **22**: 3819–3837.

Shongwe ME, van Oldenborgh GJ, van den Hurk B, van Aalst M. 2011. Projected changes in mean and extreme precipitation in Africa under global warming. Part II: East Africa. *Journal of Climate* **24**: 3718–3733.

Simon W, Hassell D, Hein D, Jones R, Taylor R. 2004. *Installing and Using the Hadley Centre Regional Climate Modelling System, PRECIS, Version 1.1*. Exeter: Met Office Hadley Centre.

Tapley B, Bettadpur S, Ries J, Thompson P, Watkins M. 2004a. GRACE measurements of mass variability in the Earth system. *Science* **305**: 503–505. DOI: 10.1126/science.1099192.

Tapley B, Bettadpur S, Watkins M, Reigber C. 2004b. The gravity recovery and climate experiment: mission overview and early results. *Geophysical Research Letters* **31**: L09607. DOI: 10.1029/2004GL019920.

Tierney JE, Smerdon JE, Anchukaitis KJ, Seager R. 2013. Multidecadal variability in East African hydroclimate controlled by the Indian Ocean. *Nature (London)* **493**(7432): 389–392.

UNDP. 2004. *Disasters for Least Developed Countries*.

Viste E, Korecha D, Sorteberg A. 2012. Recent drought and precipitation tendencies in Ethiopia. *Theoretical and Applied Climatology* **112**(3–4): 535–551.

Wahr J, Molenaar M, Bryan F. 1998. Time variability of the Earth's gravity field: hydrological and oceanic effects and their possible detection using GRACE. *Journal of Geophysical Research* **103**(B12): 30205–30229. DOI: 10.1029/98JB02844.

Wang XL. 2003. Comments on "Detection of undocumented change points: a revision of the two-phase regression model". *Journal of Climate* **16**: 3383–3385.

Wang XLL. 2008a. Accounting for autocorrelation in detecting mean shifts in climate data series using the penalized maximal t or F test. *Journal of Applied Meteorology and Climatology* **47**: 2423–2444. DOI: 10.1175/2008JAMC1741.1.

Wang XLL. 2008b. Penalized maximal F test for detecting undocumented mean shift without trend change. *Journal of Atmospheric and Oceanic Technology* **25**: 368–384. DOI: 10.1175/2007JTECHA982.1.

Wang XL, Swail VR. 2001. Changes of extreme wave heights in Northern Hemisphere oceans and related atmospheric circulation regimes. *Journal of Climate* **14**: 2204–2221. DOI: 10.1175/1520-0442(2001)014<2204:COEWHI>2.0.CO;2.

WMO. 2003. Report of the GCOS/GTOS/HWRP Expert Meeting on Hydrological Data for Global Studies, WMO/TD–No. 1156.

Zhang XB, Vincent LA, Hogg WD, Niitso A. 2000. Temperature and precipitation trends in Canada during the 20th century. *Atmosphere-Ocean* **38**: 395–429.

Zhang X, Aguilar E, Sensoy S, Melkonyan H, Tagiyeva U, Ahmed N, Kutaladze N, Rahimzadeh F, Taghipour A, Hantosh TH, Albert P, Semawi M, Ali MK, Al-Shabibi SHM, Al-Oulan Z, Taha Zatari T, Al Dean Khelet IK, Hamoud S, Ramazan Sagir R, Demircan M, Eken M, Adiguzel M, Lisa Alexander L, Peterson TC, Wallis T. 2005. Trends in Middle East climate extreme indices from 1950 to 2003. *Journal of Geophysical Research* **110**: D22104. DOI: 10.1029/2005JD006181.

Zhang X, Zwiers FW, Hegerl G. 2009. The influences of data precision on the calculation of temperature percentile indices. *International Journal of Climatology* **29**: 321–327. DOI: 10.1002/joc.1738.

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