DROUGHT, CLIMATE AND HYDROLOGICAL CONDITIONS IN AFRICA: AN ASSESSMENT BASED ON THE APPLICATION OF REMOTELY SENSED GEOSPATIAL DATA AND VARIOUS MODELS

THIAN YEW GAN, MARI ITO, STEPHAN HUELSMANN

WORKING PAPER - No.1

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About UNU-FLORES

BACKGROUND

The United Nations University Institute for Integrated Management of Material Fluxes and of Resources (UNU-FLORES) was established in Dresden, Germany in 2012. The institute is supported by the Federal Ministry of Education and Research (BMBF) and the Ministry for Higher Education, Research and the Arts (SMWK) of the Free State of Saxony, Germany. As part of the United Nations University (UNU), the institute helps to build a bridge between the academic world and the United Nations. The UNU was founded in 1973 as an autonomous organ of the UN General Assembly. It encompasses 16 research and training institutes and programmes in 12 countries around the world. UNU as a whole aims to develop sustainable solutions for pressing global problems of human survival and development. Through a problem-oriented and interdisciplinary approach, UNU aims at teaching, applied research and education on a global scale.
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VISION

The Dresden-based institute of UNU-FLORES acts at the forefront of initiatives promoting a nexus approach to the sustainable management of water, soil and waste. UNU-FLORES acts as a think tank for the United Nations and its member states, in particular addressing the needs of developing and emerging countries. As a think tank, UNU-FLORES will be an internationally recognized hub and intellectual focal point promoting integrated management strategies. Additionally, UNU-FLORES will attract high-calibre students for postgraduate study and research programmes in cooperation with other research institutions. The institute will build the capacity of future leaders in the area of environmental resources management and develop innovative concepts for target- and region-specific knowledge transfer.

MISSION

UNU-FLORES develops strategies to resolve pressing challenges in the area of the sustainable use and integrated management of environmental resources such as soil, water and waste. Focusing on the needs of the UN and its member states, particularly the developing and emerging countries, UNU-FLORES engages in research, capacity development, advanced teaching and training as well as dissemination of knowledge. In line with UNU's general mission to promote sustainability, UNU-FLORES also considers impacts of global change on resources management.

THE NEXUS APPROACH

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RESEARCH AREAS

UNU-FLORES aims at a truly integrative and global perspective on resources management, considering interrelated resources in a comprehensive manner. This holds also true for impacts of global change and its nexus to green economy. In all of the following research areas of UNU-FLORES, the institute will cooperate closely with other universities and research institutions in both research and teaching:

- Water inventory and fluxes;
- Soil and land use management;
- Management and treatment of waste;
- Systems and flux analysis;
- Resources quality and quantity; and
- Global change assessment.

EDUCATION AND CAPACITY DEVELOPMENT

UNU-FLORES will engage in the following areas of postgraduate education, capacity development and trainings:

- UNU-FLORES will establish PhD as well as other postgraduate programmes together with its partners, especially with the Technische Universität Dresden (TUD). The programmes will focus on each of the research areas of UNU-FLORES and will include course work according to a pre-defined scheme.

- Additional capacity development and training programmes will focus on the further education of professionals who are working in the area of environmental resources management.

A unique feature of all education activities will be the emphasis on the global dimension of the covered issues. One aspect of this global nature will be international exchange programmes for students and teachers as well as internships with other UNU and UN bodies.

Drought, climate and hydrological conditions in Africa: An assessment based on the application of remotely sensed geospatial data and various models

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Abstract

Improving sustainable access to safe drinking water, one of the Millennium Development Goals established in 2000, has been a challenge in Africa. Global change, such as rapid population growth and climate change, is anticipated to further affect sustainable access to drinking water, public health, agricultural production, and the entire economy, while major droughts in Africa could accelerate water scarcity, land degradation, crop failure and humanitarian crises. Previous studies reveal that Africa has in general seen increases in temperature and decreases in precipitation and streamflow.

Climate and hydrological predictions, based on remotely sensed geospatial data (satellite data) and various models, suggest warming and drying patterns in Africa in the future, although large uncertainties exist in forecasting. Various international and regional efforts for mitigation and adaptation are in progress to deal with droughts and climate change, but their results are yet to come. Based on existing studies, the present paper provides an overview of climate and surface water conditions related to droughts in Africa, an assessment of droughts, climate and hydrological predictions with the application of remotely sensed geospatial data (satellite data) and various models, uncertainties associated with forecasting, the present status of drought preparedness, and recommendations for the preparation for, and management of, possible droughts.

1. Introduction

In 2000, Millennium Development Goals (MDGs) were established to reduce poverty, including MDG7, which aimed at ensuring environmental sustainability and reducing by half the number of people without sustainable access to safe drinking water and improved sanitation. While global progress towards this goal is seen as encouraging, in the sub-Saharan region in Africa, only about 58% of the population has access to safe drinking water; moreover this proportion has not been improved. Three hundred million people, or half of those who have currently access to water in the sub-Saharan region, are projected to be unsure about access to safe drinking water in the future (JMP, 2008). Climate change, including high temperatures, higher water evaporation rates, changed timing and quantities of rainfall that are difficult to predict, and the occurrence of more frequent or more severe droughts, could further deteriorate access to safe drinking water and agricultural production (especially the rainfed farming often practised in Africa) and increase the incidence of disease, affecting public health (Africa Progress Panel, 2012). Further, water is needed not only for domestic, agricultural and industrial uses and other economic activities, but also to sustain ecosystems and biodiversity, which in turn could impact the life of the population. Climate change has been found to increase uncertainty in future climate conditions and water cycles, especially in several regions in Africa where water is already in short supply. In the 5th Coupled Model Intercomparison Project (CMIP5), the Sahel region, western and southern Africa are identified as climate change hotspots (Diffenbaugh and Giorgi, 2012).

Drought is a temporary, extremely dry period over land with limited precipitation, lasting months to years (Dai, 2011) and its occurrence has historically been seen. Several major droughts have recently occurred in Africa, and there were a total of 12 droughts in eastern Africa between 1965 and 1997 (Mwale and Gan, 2005). Droughts could cause water shortage, land degradation, crop failure and humanitarian crisis in Africa. A drought in the Horn of Africa in 2011 affected 10 million people, while droughts in Ethiopia and Sudan in the 1980s each killed several hundred thousand people (Kallis, 2008).

Growing issues of water security, climate and climate change, including droughts, have led to various global and regional efforts, for example, for mitigation (e.g., a reduction in greenhouse gases) and adaptation to adjust to changes in climate. Although international concerted actions to deal with these issues are imperative, the managers of, and the public who are interested in, water resources, agriculture, land use planning and the environment would need to have access to the information that could help understand the present status and prepare for unexpected climate conditions in a timely manner.

This paper provides an overview of climate and surface water conditions related to the occurrence of droughts in Africa, especially the arid and semi-arid regions, the assessment of droughts, climate and hydrological predictions for drought assessment and uncertainties, and the present status and recommendations for the preparation for, and management of, droughts in Africa. The present paper is intended to inform the managers of water resources, agriculture, land use planning and the environment, and those interested in the above areas in Africa and elsewhere, of available information associated with droughts and to assist them in taking timely actions to deal with possible droughts.

2. Overview of climate and surface water conditions in Africa – the basis for drought assessment

Spatial variability

The monitoring of climate and the assessment of hydrological conditions are a fundamental part of characterising droughts and estimating their impact. On the African continent, mean annual precipitation increases from less than 300 mm to over 2000 mm, as spatially moved from the Sahara desert in northern Africa to the south, from the Kalahari Desert in southern Africa to the north, or from the Great Horn of Africa (GHA) to the west, respectively, toward western and central Africa (Figures 1a-1c, based on the precipitation data 1901 –1995 from New et al., 2000). The seasonality of precipitation also varies spatially from December-February; there is a rainy season in southern Africa, except for the Kalahari Desert (Figure 1b), while from June to August there is a rainy season in the Guinean and Sudan regions (Figure 1c).

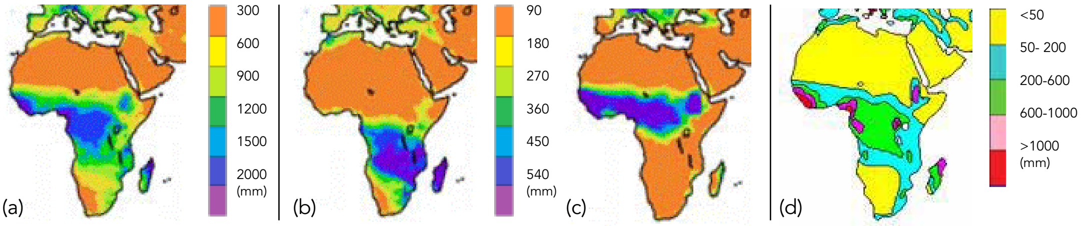

Figure 1 (a) annual, (b) precipitation (December-February), (c) precipitation (June-July), and (d) annual surface runoff in Africa. Figures 1a–1c are based on precipitation data 1901–1995 from New et al., 2000; Figure 1d is adapted from UNEP (1995).

The annual surface streamflow (Figure 1d) shows a similar spatial pattern as that of the annual precipitation. In arid northern and southern Africa, both the annual streamflow and the runoff coefficients (the ratio of annual streamflow to precipitation) are low (less than 50 mm/year and mostly less than 0.2, respectively). In relatively humid central Africa, the annual streamflow ranges from several hundred to more than a thousand millimetres, and the runoff coefficients are generally greater than 0.3 and occasionally over 0.5. Based on the spatial patterns of annual precipitation and streamflow in Africa, northern Africa, the GHA region and southern Africa are considered to be drier than other parts of Africa. Precipitation and streamflow of major rivers in western Africa, GHA, and southern Africa is summarised in Table 1.

Region	River Basin	Country	Area (km²)	Annual	Annual Runoff Km³/year (mm/year)
Western Africa	Upper Niger	Guinea/Ivory Coast/ Mali	147,000	250 - northeast 1750 – southwest	46.4 (315)
	Volta	Transboundary	400,000	200 – north 2,000 – south	38.7 (100)
Greater Horn Of Africa (GHA)	Awash	Ethiopia	110,000	1,000	4.6 (40)
	Blue Nile	Ethiopia/Sudan	317,000	1800 – Upper 520 – lower	48.3 (150)
	Kagera	Transboundary	59,800	1000	7.5 (125)
	Juba Shaballe	Ethiopia/Somalia	280,860	796	3.6 (13)
	Awash	Ethiopia	110,000	200 (low) 1400-1800 (high)	4.6 (40)
Southern Africa	Limpopo	Transboundary	412,940	530	4.8 – 5.2 (12)
	Zambezi	Transboundary	1,390,000	956	108 (80)
	Okavango	Transboundary	530,000	609	14.9 (30)

Table 1 Selected River Basins in western Africa, Greater Horn of Africa (GHA), and southern Africa. The information was compiled from various sources.

Temporal variability

The observed data from 1950 to 2008 show that surface air temperature increased and precipitation decreased, except for northern Africa and the GHA region where precipitation marginally increased (Figure 2; Dai, 2011). Decreasing trends in precipitation have been also reported in western Africa from 1900 to 2005 (7.5% which was statistically significant at <1%) and in the 1980s in southern and eastern Africa, based on the Global Historical Climatology Network (GHCN) data (Figures 2 and 3; Trenberth et al., 2007). Precipitation was also estimated to decrease for the period from 2001 to 2010, based on gridded one degree rain gauge data for the period 1951-2000 (Figure 3d; WHO, 2013).

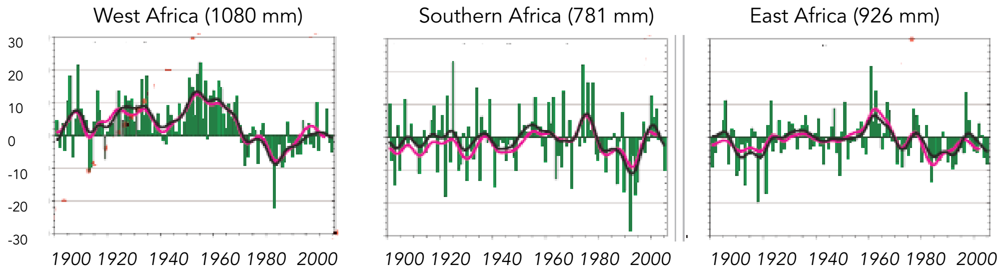

Figure 2 1900-2005 Annual precipitation time series of GHCN for (a) West Africa, (b) Southern Africa, and (c) East Africa (modified from Trenberth et al., 2007).

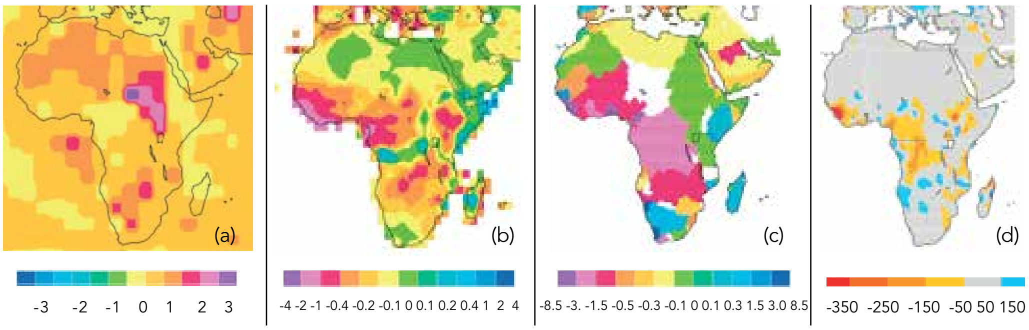

Figure 3 Trend maps for 1950-2008, observed annual (a) surface air temperature (oC/50 yrs) (HadCRUT3: www.cru.uea.ac.uk/cru/data/data/temperature/), (b) precipitation (mm/day/50yrs), (c) runoff from streamflow records (mm/day/50 yrs) (modified from Dai, 2011); and (d) trend map for 2001-2010 decadal precipitation anomalies (mm/yr) derived from gridded 1° raingauge data over the 1951–2000 base period (WMO, 2013).

A study which estimated monthly streamflow for the world's 900 large ocean-reaching rivers from 1948 to 2004 reported that the streamflow in African rivers showed decreasing trends (Dai et al, 2009). This study used both observed monthly streamflow data and streamflow values simulated by a land surface model, the Community Land Model, version 3 (CLM3). The mean annual streamflow decreased by about 4 km^3/yr^2 in the Congo River (1270 km^3/yr) and by about 0.5 km^3/yr^2 in the Niger River (180 km^3/yr). These results suggest that during 56 years (1948–2004), streamflow decreased by about 200 km^3 in the Congo River and by about 30 km^3 in the Niger River, or decreased by about 15% in these two rivers. The decreases in streamflow in African rivers would add a further stress to already limited freshwater resources in the continent.

The decreasing rates of streamflow were found to be larger than those of precipitation, especially in central and southern Africa, due to an increase in evaporation caused by an increase in temperature (Figures 2b and 2c) (Dai, 2011).

3. Identification of present and past droughts in Africa - conventional approaches

For the assessment of droughts that occurred during the past few years to the past few decades, measured data may be available. The marked declines in measured rainfall and streamflow in western Africa since the early 1970s indicate persistent droughts in the region. The declines in rainfall and streamflow in the region have been primarily attributed to changing Atlantic sea surface temperatures (SST) (Lamb and Peppler, 1992) and warming in the Indian Ocean, which enhances subsidence over West Africa (Lu, 2009).

For droughts that occurred before the measurement of necessary parameters (e.g., precipitation), other approaches have been employed. Multi-century tree-ring records, consisting of 13 Cedrus atlantica and Pinus halepensis chronologies, were analysed to reconstruct a drought index, the Palmer Drought Severity Index (PDSI) (the PDSI is computed using precipitation and surface temperature values; for PDSI, see further below) (Touchan et al., 2008). The reconstructed PDSI suggests a strong signal for warm-season drought (May–August) in Tunisia and Algeria for the period AD 1456–2002. Based on these results, the most recent drought (1999–2002) is considered to be the worst since the mid-15th century. This is consistent with the result of the simulation by general circulation models (GCMs) of the Intergovernmental Panel on Climate Change (IPCC). Touchan et al. (2011) report that droughts in northwestern Africa were negatively correlated and those in northeastern Africa were positively correlated with selected sectors of the winter (December to February) Kaplan Sea Surface Temperature Anomaly (SSTA;1857 to 2003) in the Atlantic, Indian and Pacific oceans.

Lake sediments also provide valuable information on past climate variations. Based on the correspondence between the oxygen isotopic ($\delta^{18}O$) signature of carbonate preserved in the uppermost sediment record of Lake Bosumtwi in Ghana on one hand and the recorded precipitation (1920–2004) at a neighbouring climate station on the other, the $\delta^{18}O$ values of the lake sediment were used as a proxy of past precipitation before the 20th century (Shanahan et al., 2009). Isotopic data, together with geomorphic and geochemical information, from the sediment of Lake Bosumtwi were analysed to reconstruct natural variability in the African monsoon over the past three millennia. Tree-ring data were also used to reconstruct the Atlantic Multidecadal Oscillation (AMO). A cross-wavelet coherence analysis between the summer West African Monsoon (WAM) and the reconstructed Atlantic Multidecadal Oscillation shows that WAM and AMO have been related for the past 400 years (Figure 4). These results suggest that the severe droughts during the past multiple decades correspond to the characteristics of the monsoon. Further, recent severe droughts are not found to be anomalous when analysis is conducted for the past three millennia (Shanahan et al., 2009).

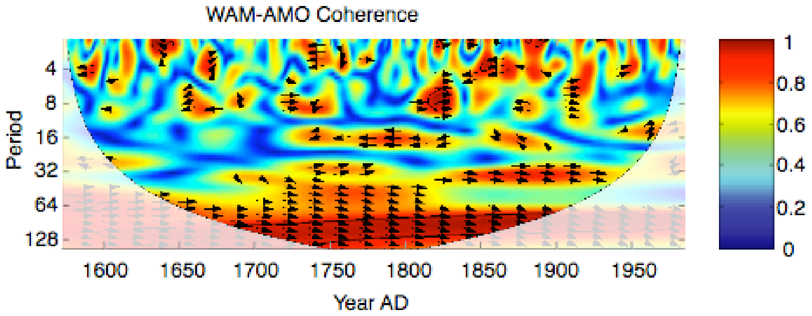

Figure 4 Cross wavelet coherence between the summer WAM and a tree ring reconstructed AMO for the past 400 years (taken from Shanahan et al., 2009).

4. Drought types and indicators

Droughts can be classified into four types: meteorological, agricultural, hydrological, and socio-economic droughts, in which the first three types are treated as physical phenomena, while the last type is measured in socio-economic systems (Wilhite and Glantz, 1985). Drought indicators are used to assess droughts which have different spatial scales, severities and durations. Various drought indices have been reported for each type of drought (Dai, 2011). It is important that drought indices are clear and suggestive, so that they can be easily understood and help take appropriate measures for prevention or minimisation of damages or risks. Meteorological drought is defined as a period when the actual moisture supply at a location consistently falls below the climatically appropriate moisture supply. Meteorological drought indices, such as the Standardised Precipitation Index (SPI) (McKee et al., 1993) and the Bhalme-Mooley Index (BMI) (Bhalme and Mooley, 1979), are computed using precipitation as the primary variable. The SPI can be applied to different time scales, and has thus been frequently used. But an exclusive use of precipitation data as the input has posed a limitation. Some other drought indices, such as the Palmer Drought Severity Index (PDSI) (Palmer, 1965) and the Standardised Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010), overcome the above limitation by incorporating surface air temperature data, and account for the effect of evaporation, moisture supply and runoff. The original PDSI can however be used only on a fixed temporal scale, while hydroclimatic variables may respond to droughts over a wide range of time scales. Several indices have been proposed by improving the original PDSI, including the self-calibrating PDSI (sc-PDSI), a version modified for Canadian Prairies, and PDSI with a Penman-Monteith (pm) evaporation model, among others (Gobena and Gan, 2013; Dai, 2011).

Agricultural drought pertains to a soil moisture supply that fails to meet the water requirement of a crop at a particular time. Agricultural drought indices are often based on soil moisture content estimated by hydrologic models or field observations, such as the computed soil moisture (CSM; Huanug et al., 1996) or the crop moisture index (CMI) that takes into account annual precipitation and annual potential evapotranspiration (Palmer, 1968). The CMI ranges from -1 to +1 in dry to wet climates (Willmott and Feddema, 1992). For example, median CMI of about -0.80 in Africa, compared to the global median CMI values ranging from -0.10 to -0.25, suggests that Africa is relatively dry and in water scarcity (Vörösmarty et al., 2005). The decreases in the top-1 m soil moisture from 1948 to 2004 in many parts of Africa, especially in western and southern Africa by up to 20 mm, (Figure 2c; modified from Dai, 2011) suggest a potential decline in crop yield. The decreases in top soil moisture were simulated by the Community Land Model Version 3 (CLM3) land surface scheme. Remotely sensed geospatial data has facilitated access to the information on land processes, especially vegetation dynamics, and thus the effects of drought on vegetation and the detection and assessment of agricultural droughts. Geospatial analysis and vegetation indices are discussed in more detail below.

Hydrological drought refers to deficiency in surface and subsurface water supplies (Wilhite and Glantz, 1985). Hydrological drought indices are often based on basin streamflow data, such as the Standardised Streamflow Index (SSI) (Vicente-Serrano et al., 2011). Since measured streamflow data of many African rivers are often either incomplete or difficult to obtain, necessary hydrologic data are estimated using hydrological models. A comparison of annual surface streamflow in Africa from 1901–1995 (Figure 1d) with the projected changes in annual stream flow from 1980–1999 to 2080–2099 under the Special Report on Emissions Scenarios (SRES) A1B suggests drier conditions in the arid northern and southern Africa by the late 21st century. On the other hand, the relatively wet central Africa may become slightly wetter or remain unchanged.

Socio-economic drought occurs when water supply cannot meet the demand for an economic good, such as water for domestic, agricultural and industrial uses, grain or fish for food, and hydroelectric power, due to the weather (US National Drought Mitigation Center, 2013). Alternatively, a socio-economic drought can be said to occur when the shortage of water supply starts to affect health, the well-being and quality of life of the population. It is beyond the scope of this paper to further discuss this drought type.

In addition to the four types of drought based on the widely accepted classification above, Misha and Singh (2010) suggest groundwater drought as an additional type. Groundwater drought is defined as a decreased groundwater level, decreased or depleted groundwater storage, low recharge or low discharge. Groundwater drought occurs following a decrease in precipitation, soil moisture and recharge or an increase in groundwater abstraction. Groundwater drought is a physical phenomenon, similar to meteorological, agricultural and hydrological droughts, but could be directly caused by a human factor, that is, an excessive abstraction of groundwater. The indicators to quantify groundwater storage, recharge or discharge could be used as drought indices for groundwater drought (Mischa and Singh, 2010). Various drought indices reported for different types of droughts are summarised by Dai (2011), and Misha and Singh (2010).

5. Geospatial analysis and Remotely Sensed Vegetation Indices

Remotely sensed data (satellite data) have become available not only with high temporal and spatial resolutions, but also at low cost. As a result, geospatial data of Earth Observation System (EOS) and climate and other related dynamic model simulation have been more and more widely used to monitor climate and characterise droughts on a regional scale and for an extended time period. Remote sensing is an indispensable tool to capture information on vegetation distribution and types and its hydrological, biophysical and structural properties, such as leaf area index (LAI), green leaf biomass, and net primary production (NPP). These parameters are used to estimate agricultural productivity and its changes, and are thus suitable for assessing agricultural droughts. Remote sensing is particularly useful in, for example, some parts of Africa, where climate, hydrologic and environmental data are limited. Vegetation indices are empirical measures of vegetation activity on the land surface (Solano, et al., 2010). Satellite data used for observing vegetation cover and its properties include those with high spatial resolution (LANDSAT) to high temporal resolution Earth Observation (EO) data (those of National Oceanic and Atmospheric Administration / Advanced Very High Resolution Radiometer (NOAA-AVHRR)). The data of the Normalised Difference Vegetation Index (NDVI) from NOAA-AVHRR are available with 1 x 1 km spatial resolution since 1982; the Moderate Resolution Imaging Spectroradiometer (MODIS) database (250 x 250 m resolution) since 2000; spectral data of MERIS (Medium Resolution Imaging Spectrometer Instrument) of the ENVISAT mission of the European Spatial Agency (ESA) (260 x 300 m resolution) since 2002; and remote sensing data of LANDSAT with high-spatial resolution (30m), but low temporal resolution (about 16 days) since 1972. Synthetic aperture radar (SAR) data have been also collected by satellite active microwave sensors such as ERS2 of the European Space Agency (ESA), ASAR of ENVISAT, and Radarsat 2 of the Canadian Space Agency (CSA) and presently, the data with resolutions of about 10 cm (airborne systems) or a few mm (wideband with modulation) are available.

NDVI from NOAA-AVHRR has been shown to correlate well with LAI and photosynthetic activity (and thus NPP), and rainfall in arid and semi-arid regions (Nicholson et al., 1998). Enhanced Vegetation Index (EVI) of the MODIS sensor is another vegetation index that is highly responsive to LAI and canopy structural variations. EVI is less likely to saturate than NDVI in high biomass regions, less sensitive to residual aerosol contaminations (Potter et al., 2012). Strong relationships were also found between eight-day EVI or NDVI obtained from MODIS on one hand and eight-day sums of eddy-covariance gross primary production (GPP) in a sparse savanna in Sudan on the other hand, where water is the limiting factor in plant growth. The relationship between EVI and GPP was slightly better than the relationship between NDVI and GPP (Sjöström et al.,2009). These results suggest that primary production could be inferred from NDVI and EVI.

The correlation between NDVI and primary production has been used to estimate, for example, a possible vegetation recovery (1982–1999) in the Sahel region due to increased rainfall after a drought period in the 1980s (Eklundh and Olsson, 2003) and phenological changes in the Sudan and Guinean and Sahel regions reflecting the growing season in the post-1980's (Figure 5; Heumann et al., 2007). The spectral properties of satellite data acquired by optical or synthetic aperture radar (SAR) sensors are also related to LAI, gross primary production (GPP) (Jahan and Gan, 2009), dry matter production (Sjöström et al., 2009), surface soil moisture and other hydrological variables that are important for crop growth (Biftu and Gan, 1999; Nasreen and Gan, 2013).

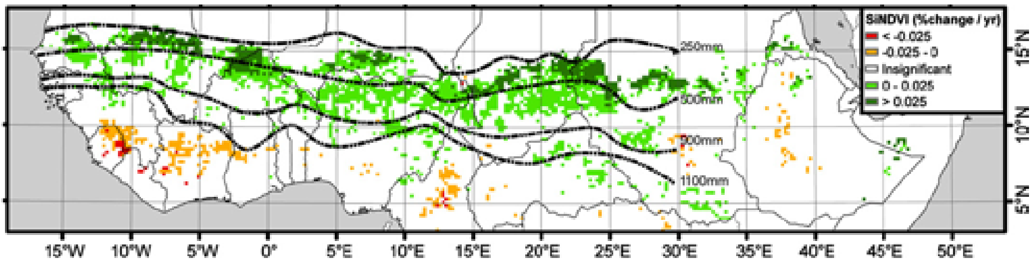

Figure 5 Significant trends of seasonally integrated NDVI (SiNDVI) detected in the Sahel with a mean annual rainfall (mAR) of 250–500mm, in Sudan with a mAR of 500–1100 mm, and in the Guinean region with a mAR of > 1100mm/year (from Heumann et al, 2007).

Based on vegetation indices or the relationships between NDVI and agricultural productivity, the relationships of vegetation indices or NDVI with drought indices, such as SPI, SPEI, Soil Moisture Index (SMI; Sheffield et al., 2004) and PDSI, would suggest the effects of droughts on vegetation and agricultural productivity. For example, the strong correlation between SPEI and NDVI suggests that the Sahel region and eastern and southern Africa are highly vulnerable to drought (Vicento-Serrano et al., 2012).

The application of satellite data for agricultural productivity still requires careful analysis and evaluation. The last decade (2000 to 2010) has been the warmest decade since the start of the instrumental record in 1850 (WMO, 2013). As a result, global terrestrial NPP would have continued to increase, in line with what was observed between 1982 and 1999. But large-scale droughts are found to have suppressed NPP in the Southern Hemisphere and NPP decreased by about 0.55 petagrams of carbon from 2000 to 2009 on a global scale (Zhao and Running, 2010).

Similarly, regional droughts were found to hinder regional NPP by up to about -20 gC/m²/yr in southern Africa and to a lesser degree in western Africa and GHA, as water availability plays a major role in plant growth, especially in grasslands and croplands (Figure 6). Besides the relationship with total precipitation during the growing season, NPP was strongly correlated with PDSI.

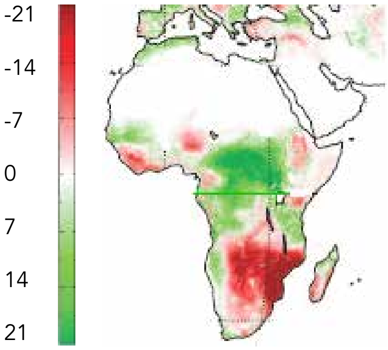

Figure 6 Terrestrial NPP linear trends from 2000 through 2009 (modified from Zhao and Running, 2010)

6. Droughts: complex phenomena – the atmosphere-land surface interactions

As described above, droughts could be assessed by drought indices computed based on physical and other parameters. Droughts are as yet complex phenomena, highly driven by climate and hydrologic regimes, but also affected by the interactions between the atmosphere and the land surface (Koter et al., 2004). The interactions between the atmosphere and the land surface are compounded by human activities, such as deforestation, the over-exploitation of land and other agricultural practices (e.g., intensive agriculture, overgrazing), because deforestation and undesirable agricultural practices could cause land degradation and the advancement of desert (desertification), which in turn could reduce vegetation, increasing surface albedo, decreasing rainfall and/or causing or intensifying droughts (Nicholson et al., 1998). Since an increase in atmospheric carbon dioxide (CO2) is normally modulated by terrestrial carbon sinks on land surfaces, deforestation, land degradation and desertification which affect terrestrial carbon sinks are found to contribute to climatic change (Zhao et al., 2001), possibly influencing the occurrence of droughts.

The analysis of surface air temperature in Africa shows that there is an agreement between the observed surface air temperature for the period 1906–2005 relative to the average of the 1906–1950 values (black-coloured line in Figure 7a) on one hand and the modelled changes, the 5–95% range of 58 simulations from 14 climate models on the other hand, when both natural (e.g., solar and volcanic activities) and anthropogenic factors (e.g., deforestation, increased atmospheric concentrations of greenhouse gases and increased concentrations of aerosols due to human activities) that could increase temperature are considered in the simulation (pink-colour shaded band in Figure 4a).

Both the observed and the simulated values have increased since the 1970s (Figure 7a; modified from IPCC, 2007). In contrast, when only natural factors that could increase temperature are taken into account, the 5–95% range of 19 simulations from five climate models does not show such an increase in surface air temperature (blue-coloured shaded band in Figure 7a). These results suggest the importance of the contribution of anthropogenic factors in the increases in surface air temperature. Coupled with the decreasing patterns in precipitation and streamflow as describe above, anthropogenic factors may be directly or indirectly related to the drying conditions. The drying in central, western and southern Africa during the last 60 years was also supported by a study on the spatial patterns of the leading Empirical Orthogonal Function (EOF) of the monthly PDSI computed for a period from 1900 to 2008 as well as by a study that applied the CLM3 with observed climate data and the National Center for Environmental Prediction/the National Center for Atmospheric Research (NCEP/NCAR) reanalysis for the period from 1950 to 2008. In the latter study, soil moisture patterns were simulated (Figure 8; Dai, et al., 2011), using decreased observed precipitation and streamflow (Figure 2).

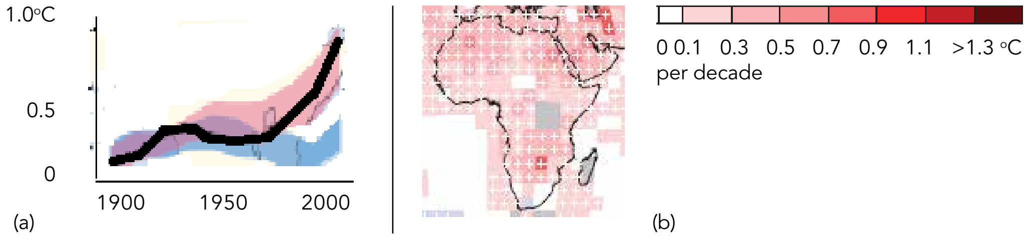

Figure 7 (a) Trends of surface air temperature anomaly (°C) in Africa where the black line is the observed 1906–2005 changes in surface temperature relative to the 1906–1950 average; blue shaded bands show: the 5–95% range for 19 simulations from five climate models using only natural forcings (solar activity and volcanoes); and pink shaded bands show the 5–95% range for 58 simulations from 14 climate models using both natural and anthropogenic forcings (modified from IPCC, 2007); and (b) linear trends of annual temperatures for the period from 1979 to 2005 (°C per decade) based on the Global Historical Climatology Network (GHCN) data set. The areas in grey have insufficient data to produce reliable trends. The minimum number of years needed to calculate a trend value is 18 years. An annual value is available if there are 10 valid monthly temperature anomaly values. The trends significant at the 5% level are indicated by white + marks (modified from Trenberth et al., 2007).

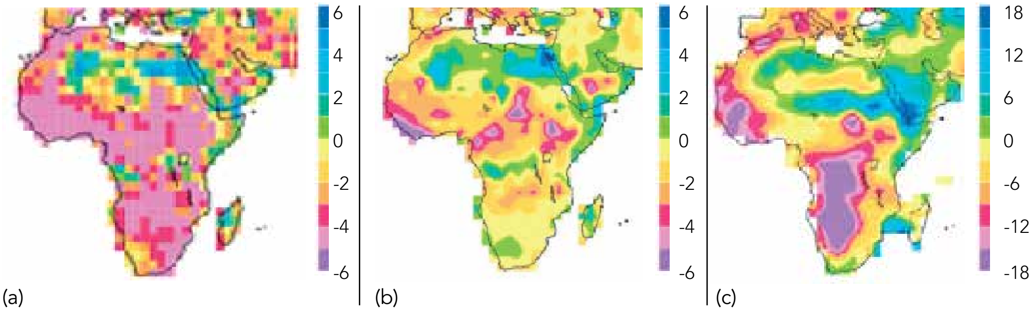

Figure 8 (a) Spatial pattern of the leading EOF of monthly 1900–2008 PDSI (normalised by its standard deviation prior to the EOF analysis) where red (blue) areas represent a drying (wetting) trend, (b) 1950–2008 annual trends (change/50 years) in self-calibrated PDSI based on the Penman-Monteith PET (scPDSI-pm), and (c) 1948–2004 trend in top-1 m soil moisture (mm/50 years) simulated by the CLM3 land surface scheme forced by observation-based atmospheric forcing (modified from Dai, 2011).

7. The influences of climate anomalies such as El Niño Southern Oscillation (ENSO) and Madden Julien Oscillation (MJO)

El Niño Southern Oscillation (ENSO) is anomalous and extensive warming (El Niño) and cooling (La Niña) of the surface waters of the central and eastern tropical Pacific Ocean. Such warming and cooling could affect the circulation of the atmosphere and weather patterns. For example, in the ENSO years, it tends to be drier during the kiremt rainy season (June – September) in Ethiopia (Degefu, 1987). However, the effects of ENSO on rainfall in eastern Africa were found to differ between regions and seasons, and the effects of El Niño were stronger than, and opposite of, those of La Niña, according to a harmonic analysis (a type of generalisation analysis) of the ENSO composites of the six-month standardised precipitation index (SPI) and rainfall anomalies for 1900–1996 (Ntale and Gan, 2004). Among the five regions that showed unique effects of ENSO in eastern Africa, northeastern and southern Tanzanian regions seem to have had the most consistent ENSO responses. Southern Tanzania had a positive response to La Niña and a negative one to El Niño from January to June in the post-ENSO year. Southern Uganda and the most part of the Lake Victoria Basin region exhibit positive responses to ENSO from November to January. The boxplots of the six-month SPI in northeastern and southern Tanzanian regions show differences in the distribution of six-month SPI between ENSO and non-ENSO affected seasons (Figure 9; Ntale and Gan, 2004).

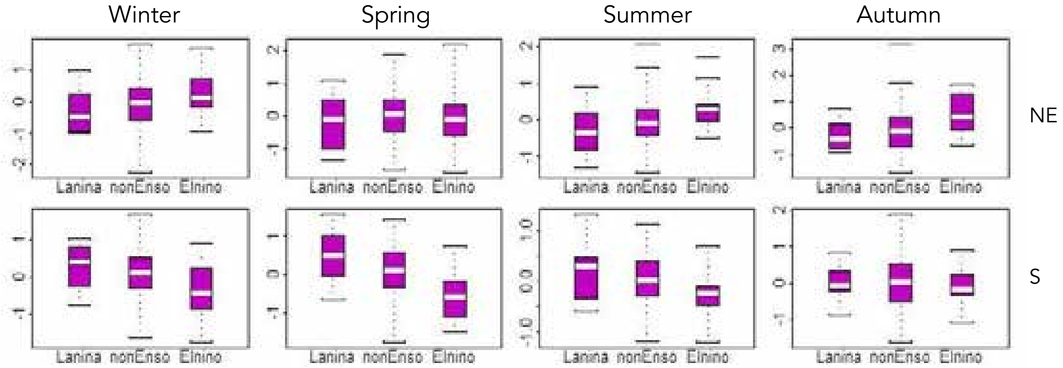

Figure 9 Boxplots of six-month SPI (Standardised Precipitation Index) for El Niño, La Niña and non-ENSO periods in northeastern (NE: the upper plots) and southern Tanzania (S: the lower plots) in eastern Africa. In the box plots, the middle line represents the median and the top and bottom lines the 75th & 25th percentiles of SPI, respectively (modified from Ntale and Gan, 2004).

Another study using a harmonic analysis suggests that southern Africa (south of 15oS) was drier between the October of the year when El Niño started and the April of the following year, while the equatorial eastern Africa (Kenya, Uganda, Rwanda, Burundi and Tanzania) was wetter during the period (Ropelewski and Halpert, 1987). The highly dry condition in response to the ENSO was also suggested for the Sahel region, based on the negative SPEI values computed for the El Niño years (Vicente-Serrano et al., 2012). In addition to the ENSO, or more importantly El Niño, which would bring about a drier condition, the Madden

Julien Oscillation (MJO) has been found to trigger atmospheric convection and moisture flux anomalies in southern Africa and affect the intraseasonal rainfall distribution (Pohl et al., 1998). The MJO, which is also called the 30–60 day or 40–50 day oscillation, is the main inter-annual fluctuation accounting for weather variations in the tropical regions as well as in other areas (Geets and Wheeler, 1998).

8. Climate and hydrological predictions and uncertainties

To predict droughts and assess their impacts in an accurate manner, it is desirable that climate and hydrological predictions have minimum uncertainties. Uncertainties associated with climate and hydrological predictions stem from, for example, limitations in climate, hydrologic or carbon cycle models themselves, errors or uncertainties in initial conditions (Kirtman and Min, 2009) and errors due to numerical rounding. Hydrological models are normally operated based on future climate conditions estimated by empirically adjusting historical climate series with information from the simulations by GCMs. Large uncertainties exist in the projections based on the simulations by GCMs of changes in streamflow and soil moisture as well as precipitation, among others. This is because an important part of the simulation results vary significantly among different climate models, as found in the fourth assessment reports of the IPCC as well as in the fifth report to be published (e.g., Kharin et al., 2013), and elsewhere (e.g., Teng et al., 2012). The fifth Assessment Report of the IPCC will show that uncertainty exists in the simulation by different climate models, the Coupled Model Intercomparison Project Phase 5 (CMIP5) models with new scenarios called Representative Concentration Pathways (RCP; http://www.wmo.int/pages/themes/climate/emission_scenarios.php; e.g., RCP2.6, RCP4,5, RCP6.0, and RCP8.5) (Sillmann et al., 2013a, b). The simulations by CMIP5 models of several indices, including consecutive dry days (CDD; the length of the longest period of consecutive dry days in a year ending in that same year), which is essentially a meteorological drought index; total wet day precipitation (PRCPTOT); heavy precipitation days (R10 mm; the number of days with daily precipitation > 10mm); the annual maximum of daily maximum temperatures of each month (TXx); and the warm spell duration index (WSDI; the daily maximum temperature in intervals of six or more consecutive days which is greater than TX90 (daily maximum temperature on the 90th percentile centred on a five-day window for 1961–1990), suggest that the projections are not always consistent for the above indices calculated for the Sahel region (Sillmann et al., 2013b). Further, Wang (2005) reported that the uncertainty in the prediction using GCMs of changes in soil moisture is even larger than that of precipitation or temperature.

The use of regional climate models (RCMs) in lieu of GCMs is considered to reduce uncertainty. Some examples of the use of RCMs for studies in Africa include the use of a high resolution RCM (Tadross et al., 2005) and that of a variable-resolution global, conformal-cubic atmospheric model (CCAM) of the Commonwealth Scientific and Industrial Research Organisation (CSIRO) as a RCM (Engelbrecht et al., 2009; 2012). Many hydrologic forecasts are inherently statistical in nature. The uncertainty in the data used to run hydrological models is not epistemic (i.e., systematic), but aleatory (i.e., statistical) uncertainty, which is passed to estimated streamflow (Vrugt et al., 2008). Uncertainty in forecasts can be also classified into conditional and unconditional uncertainty. For example, the knowledge of current conditions reduces uncertainty of relatively short-term forecasts, allowing for the estimation of conditional uncertainty. When a forecast is made for a long-distance future, the influence of current conditions is minimised, leaving the unconditional uncertainty. A classical approach could estimate unconditional uncertainty in a climate forecast by presenting the range of forecasts simulated by multiple climate models.

Uncertainty in hydrological predictions has indeed been examined for some basins in Africa (e.g., Kapangaziwiri et al., 2012). However, a probability analysis would need to be applied based on the multivariate, non-stationary extreme value theory which would be suitable for dealing with climate data. It is because climate data are not stationary, as statistical properties (e.g., the mean, variance and autocorrelation structure) could change over time. Time series data of hydrological characteristics (or drought characteristics) could be analysed using a General Extreme Value or a Generalised Pareto distribution to obtain the probability of the occurrence of hydrological events (or droughts) at selected study sites. The results of the analysis of the time series data could be summarised as maps on distributed drought magnitude and duration at the selected sites.

9. Future climate patterns and preparedness

Despite large uncertainties in climate predictions, as described above, the projections by the GCMs of the IPCC suggest that Africa will be warmer and drier (e.g., Kharin et al., 2013; Sillmann et al., 2013b), thus likely to experience more frequent or more severe drought events in the future. The multi-model projections for mean changes from 1980–1999 to 2080–2099 for the Special Report on Emission Scenarios (SRES) A1B climate change scenarios of the IPCC show that northern and southern Africa will have decreased precipitation, evaporation, streamflow and soil moisture (Figure 10; the IPCC fourth assessment report, 2007). Precipitation is found to be a key parameter affecting evaporation and streamflow, but not necessarily soil moisture in the same direction. Soil moisture could be reduced even if precipitation increased (Figures 10c and 10d). A possible explanation is the occurrence of more intensive storms, but fewer light to moderate rain events, which could increase the runoff coefficient and potential evapotranspiration (PET), thereby decreasing soil moisture and increasing land aridity. Alternatively, an increased downward longwave radiation from increased atmospheric water vapour could warm up the land surface, increasing PET or atmospheric demand for water vapor. To meet this atmospheric demand, the land would become drier. The new scenarios of the IPCC's Coupled Model Intercomparison Project Phase 5 (CMIP5), which are called Representative Concentration Pathways (RCP), including RCP2.6, RCP4.5, RCP6.0 and RCP8.5, are available for climate change studies [http://www.wmo.int/pages/themes/climate/emission_scenarios.php]. The CMIP5 models have in general higher grid resolutions and larger numbers of vertical layers and are more comprehensive than CMIP3 models. Similar to the results from the projections by CMIP3, the projections based on the CMIP5 suggest that northern and southern African regions become drier.

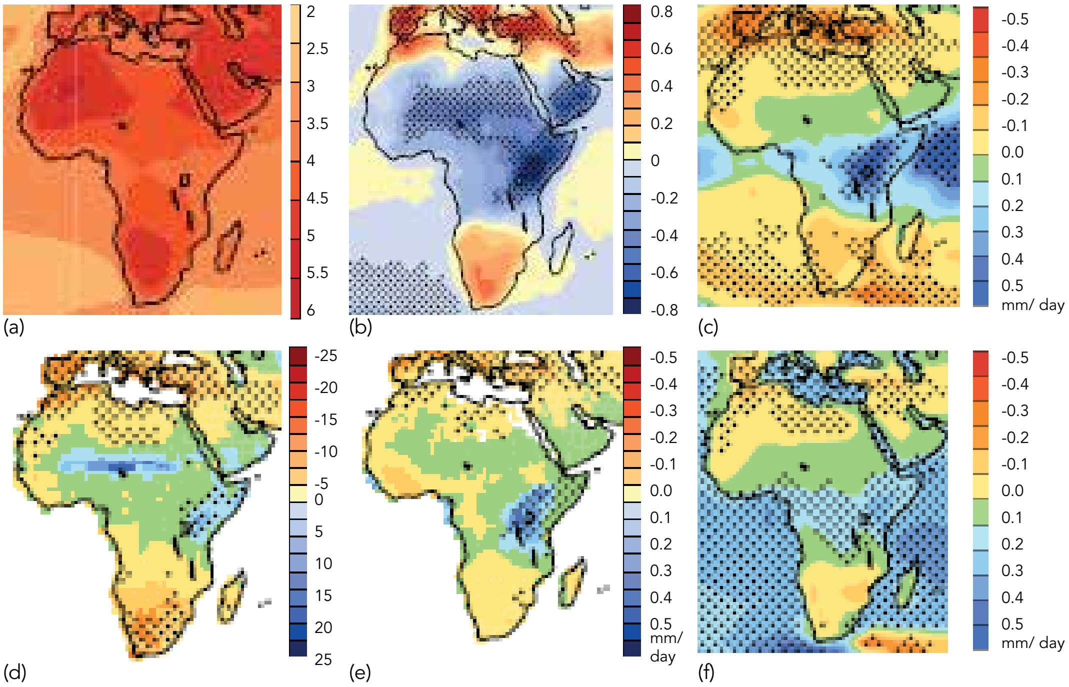

Figure 10 Multi-model mean changes from 1980–1999 to 2080–2099 under the SRES A1B scenario in annual (a) mean surface air temperature change (°C), (b) diurnal temperature range (°C), (c) precipitation (mm/day), (d) soil moisture (%), (e) Runoff (mm/day), and (f) evaporation (mm/day) (modified from Meehl et al., 2007).

Considering the projected climate conditions in Africa in the near future, African countries in general, and the countries that are thought to be more vulnerable to drought in particular, are recommended to urgently prepare and implement drought mitigation and adaptation measures and promote capacity building at the national and regional levels. A comprehensive drought preparedness and management plan was developed by Wilhite et al. (2000) for the United States to provide risk assessment, early warning, monitoring and mitigation. This 10-step drought planning process includes: [1] establishment of a drought task force; [2] setting of and agreement on the purpose and objectives of the drought preparedness plan; [3] stakeholder participation and conflict resolution; [4] resource inventory and the identification of groups at risk; [5] preparation of the drought preparedness plan; [6] identification of research needs and resolution of institutional gaps; [7] integration of science and policy; [8] publicity for the drought preparedness plan and awareness building for the public; [9] development of education programmes; and [10] evaluation and revision of the drought preparedness plan. This plan, which incorporates technical and management perspectives, could serve as a basis for a drought preparedness and management plan in Africa and elsewhere. However, a comprehensive drought plan can be effectively prepared and implemented only if a reliable weather forecast is available which preferably covers several months ahead, real-time or near-time remotely sensed data are accessible, and the public can obtain drought and other weather-related information with ease, for example, through modern information technology, such as the internet and social media (e.g., Twitter, etc.).

10. Meteorological/Hydrological Drought Early Warning Systems

An Early Warning System (EWSs) is to enable individuals, communities and organisations at risk to prepare and take prompt and appropriate action by providing timely and meaningful information for risk reduction and mitigation (UNEP, 2012). With the occurrence of increasing hydrological extreme events and the presence of growing uncertainties associated with future climate, effective EWSs are needed more greatly today than ever before (Loboda et al., 2012). A short-term EWS is built to respond to a seasonal forecast, a medium-term EWS is designed for monitoring and annual services and a long-term EWS aims to reinforce national security. All types of drought in principle arise from meteorological drought or precipitation deficiency, and meteorological forecasting systems are more developed than hydrological forecasting systems. But for a comprehensive assessment of current conditions and future predictions and the dissemination of appropriate information in a timely manner, an EWS needs to incorporate various data and information, including climate, hydrological and agricultural parameters (e.g., precipitation, streamflow, lake levels, groundwater levels, and soil moisture) (UNDP, 2012).

The EWSs in the world include, for example: the US Drought Monitor (http://droughtmonitor.uni.edu/; a partnership between the National Drought Mitigation Center at Nebraska-Lincoln, USA, the US Department of Agriculture, and the US National Oceanic and Atmospheric Administration, which uses multiple indicators); Beijing Climate Center (BCC), the Food and Agriculture Organization (FAO)-Global Information and Early Warning System (GIEWS), which provides information on food and agriculture, and Benfield Hazard Research Centre (a multidisciplinary academic hazard research centre which covers geological and meteorological hazards, seasonal forecasting and disaster studies and management). The World Meteorological Organization, with its international partners and the National Meteorological and Hydrological Services (NMHSs) of its 188 members, works to integrate the early warning systems into emergency management and response. Two American-based drought monitoring programs for Africa include: [a] the African Drought Monitor operated by Land Surface Hydrology Group at Princeton University in cooperation with the UNESCO-International Hydrology Programme, a monitoring system comprising historical reconstruction of data and a real-time monitoring system and [b] the US Agency for International Development (USAID) Famine Early Warning Systems Network

(FEWSNET) operated by the US Geological Survey (USGS), an information system designed to identify problems that could lead to famine or food-insecure conditions in sub-Saharan Africa, among others (http://earlywarning.usgs.gov/adds/).

Regional EWSs in Africa include: Regional Early Warning Centre of the Southern African Development Community (SADC), the West African Permanent Interstate Committee on Drought Control in the Sahel (Le Comité permanent Inter-Etats de Lutte contre la Sécheresse dans le Sahel; CILSS), the Ethiopian early warning system with the Ethiopian National Meteorological Agency as a key organisation, the Intergovernmental Authority on Development (IGAD) Climate Prediction and Applications Centre (ICPAC) for the GHA region, serving Eritrea, Djibouti, Somalia, Ethiopia, Kenya, Tanzania, Sudan, Uganda, Rwanda and Burundi.

Considering that EWSs have not been established in some parts of the world (India, Turkey, Iran, Iraq, Colombia, parts of Spain, parts of France, parts of Sweden, parts of Poland, parts of Thailand, parts of China, parts of Australia) (UNEP, 2012), the extent of coverage in Africa is significant. However, development and improvement will need to be continued so as to obtain and compile more adequate data and information, promote data sharing among various governmental agencies and research institutions and deliver timely and appropriate information to the people who would be most affected.

11. Adaptive capacity and adaptive capacity indicator (ACI)

Adaptive capacity is the ability or potential of people and places to respond to climate variability and change in an appropriate manner (Adger, 2007). To design an effective programme for capacity building to deal with droughts and extreme weather conditions, since the susceptibility of people and places can be compared over time and space (Adger et al., 2004), an adaptive capacity indicator (ACI) could be developed to evaluate the preparedness of people and places and the appropriateness of response measures. Adaptive capacity may have several components including, for example: physical capacity (e.g., total water available to key users), collective social capacity (e.g., the capacity to help the population without access to safe water and the proportion of the population below the poverty line), and economic capacity (e.g., the agriculture part of Gross Domestic Product (GDP) and GDP per capita) as well as natural capital at a selected site or region. An ACI could be calculated by taking the following steps: (a) to select a relevant variable in each component; (b) to normalise the variable based on a selected common baseline in each component; (c) to calculate an ACI in each component; and (c) to calculate an ACI as the weighted average of the components.

Based on the AIC, if crop and livestock farming is a vital part of the economy, as seen in the GHA region, medium-term adaptive measures for a crop and livestock farming economy include : [1] the maintenance and restoration of land fertility and soil organic matters through natural compost, land resting, planting native plants, and zero-tillage farming; [2] efficient irrigation systems; and [3] the application of crop varieties that are resistant to drought and use water more efficiently. Additional measures may include: [4] the development and improvement of production technologies; [5] the diversification of crop and animal commodities; and [6] afforestation and reforestation. For some selected agricultural sites, satellite data in general, LANDSAT-thematic mapper (TM) data in particular, could be used to evaluate land productivity (i.e., the vegetation indices of LANDSAT-TM). Based on a map developed to show land productivity (e.g., low, medium and high productivities), the optimal usage of fertiliser and water could be recommended to maximise crop yield. A satellite map that presents crop residues can also be used to improve soil health. A long-term approach for capacity building for the preparedness and management of drought events would need to be extended to the development of a sustainable economic base at a selected site or region. Long-term strategies would include: building appropriate infrastructure, support for the interactions between the governments and farmers, diversification of dry-land commodities, and access to market opportunities and insurance policies, among others.

Some international programmes for assessing and reducing the impact of droughts in Africa include: the Millennium Development Goals (http://www.undp.org/mdg/basics.shtml); European Commission Humanitarian Aid programme (ECHO); WASCAL (West African Science Service Centre for Climate Change and Adapted Land Use) on climate change and land use issues in West Africa sponsored by Germany; the Drought Early Warning And FORecasting to Strengthen Preparedness and Adaptation to Droughts in Africa (DEWFORA) initiative; and the FAO on food and agriculture, among others.

12. Recommendations for the preparation and management for droughts in Africa

Recommendations for preparation for and management of possible droughts include: improving the understanding of past and present droughts; improving predictions of climate conditions, which could lead to improved hydrological predictions; and establishing, and improving, the network coverage of early warning systems and adaptive capacity development to reach the most needed.

[A] The creation of regional maps of drought episodes for Africa for preparation and management.

The probability, magnitude (intensity) and duration of a storm event occurring at a given site can be estimated by the classical approach using the intensity-duration-frequency (IDF) curves developed from historical climate data for the specific site. Similarly, the magnitude, duration and frequency of a drought episode can be estimated at a given site, using classical probability theory (Kuo et al., 2013; Stedinger et al., 1993). The probabilities of drought episodes (magnitude and duration) are obtained using a general extreme value (GEV) probability distribution (PD) or generalised Pareto distribution (Vicente-Serrano and Begueria, 2003) with parameters derived by the probability-weighted moment (PWM) (Hosking, 1986). Regional maps/models of drought episodes (magnitude/duration/frequency) can then be developed based on the estimation of droughts, to aid in the prediction of the extent of possible damages due to the estimated drought. Some examples of the assessment of droughts in Africa include: the Preview Global Risk Data Platform by the United Nations Environment Programme (UNEP) (http://preview.grid.unep.ch/), and a report by the DEWFORA (2012) which summarises the droughts of the Limpopo Basin, the Nile Basin the Ethiopian Plateau, the Niger Basin, and Zimbabwe since the 1960s. Since climate variations and their potential impacts are not stationary, the application of non-stationary analysis methods would be more appropriate for the assessment of droughts and their impacts, as found in a study by Huang et al. (1998).

[B] Improved predictions of climate and hydrological conditions.

[B1] The use of a multi-model ensemble-based system to account for uncertainties associated with climate predictions.

The presence of uncertainties is inevitable in climate and hydrological predictions and the uncertainties associated with climate predictions could be passed to hydrological predictions. As described above, the use of multi-model ensemble-based systems in climate predictions would be able to account in part for the uncertainties in drought and hydrological forecasting. For example, a joint European project, the Development of a European Multimodel Ensemble Prediction System for Seasonal to Interannual Prediction (DEMETER) developed an ensemble-based system with 7 GCMs and the European Community Mid-Weather Forecast (ECMWF) Centre maintains a seasonal climate forecast in Africa (ecmwf.int/products/forecasts/d/charts/seasonal/forecast/) up to four months in advance (Palmer et al., 2004). The US National Centers for Environmental Prediction (NCEP)'s Climate Prediction Center (CPC) makes available meteorological forecasts in Africa. However, careful treatment of data would be still needed, as, for example, while an eight-month prediction of winter SST for the NINO-3.4 area (5oS-5oN; 170oW-120oW) in the Tropical Pacific presents an anomaly correlation of about 0.85, the NCEP-Climate Forecast System (CFS)'s seasonal forecast for precipitation shows major biases in the Tropics.

[B2] The use of regional circulation models (RCMs) to create more accurate climate predictions in selected sites in Africa.

A large uncertainty exists in the predictions based on GCMs of seasonal climate conditions at selected sites in Africa and the use of RCMs is considered to reduce some uncertainty. For more accurate predictions of seasonal climate conditions in African sites, several RCMs could be used, which include the Fifth-Generation Penn State/NCAR Mesoscale Model (MM5) (Dudhia et al., 2004), the Weather Research and Forecasting model (WRF) (Warner, 2011; Skamarock et al., 2005) and those in an ensemble framework which could downscale the seasonal climate projections by GCMs, such as DEMETER (Palmer et al., 2004), among others. However, the downscaling of the projections by GCMs would require several steps of intensive work, including the pre-processing and re-computing of input data (e.g., surface winds, temperature, sea surface temperature SST, sea level pressure SLP, geopotential height, relative humidity, etc.) for the RCMs, the determination of optimal resolution, the adjustment of the RCMs (e.g., cumulus parameterisations, explicit moisture schemes, etc.), followed by a final modification according to climate regimes, major storm types, and land use and terrain characteristics of the selected sites. The obtained RCMs would need to be tested for the selected sites.

[B3] The connection of RCMs with empirical/statistical models driven by real-time patterns of climate anomalies, such as ENSO, and the incorporation of seasonal rainfall variability in climate predictions in selected sites in Africa.

To further reduce uncertainty in the predictions by RCMs in some parts of Africa, the connection with empirical/statistical models that are driven by real-time drought indicators and/or SST of the Indian and possibly the Atlantic oceans has been found to be effective. The applications have been reported for predictions, for example, in eastern Africa (Ntale and Gan, 2003), central-southern Africa (Mwale et al., 2004), and southern Africa (Mwale and Gan, 2007). The information on the patterns of climate anomalies, such as those of the North Atlantic Oscillation (NAO), Arctic Oscillation (AO), El Niño Southern Oscillation (ENSO), and Indian Ocean Dipole (IOD), when these climate anomalies are active, could highly improve the predictive ability of the models. A further improvement in the predictions could be made by incorporating the information on seasonal rainfall variability into the empirical/statistical models in selected sites.

[B4] The incorporation of information on the atmosphere–land surface interactions in climate predictions.

Some land surface–atmosphere feedback mechanisms have been found to contribute to extreme climate conditions (e.g., Fischer et al., 2007). The land surface conditions and their changes could influence climate through, for example, changes in available sensible and latent heat fluxes or available water, including evaporation, transpiration, streamflow and infiltration. Since there are a variety of land surface conditions in Africa, information on the atmosphere–land surface interactions could improve forecasting, especially seasonal climate predictions.

[B5] The improvement in collection and synthesis of relevant climate and hydrological data and information.

The climate and hydrological predictions and the preparation for, and management of, possible droughts and extreme weather conditions require relevant climate and hydrological data and information that are collected, compiled and synthesised in an appropriate manner. Improvements in information technology, access to the World Wide Web and the Internet in particular, have greatly facilitated the collection of relevant data and information. Some of the climate and hydrological data and information sources useful for climate and hydrological predictions for Africa are summarised in Table 2.

[C] The establishment of and improvement in the network coverage of early warning systems and the improvement and continuous effort in adaptive capacity development.

Many regions in Africa have been covered by EWSs and various international, regional and national programmes assist in adaptive capacity development. However, more areas would need to be covered by EWSs, more adequate data and information obtained and compiled, data sharing among various governmental agencies and research institutions promoted, and necessary information be delivered to those actually and potentially affected in a timely manner. Adaptive capacity development is in principle the establishment of a society with appropriate technologies, a sustainable economic basis and the human capacity to make full use of available resources. The effort for adaptive capacity development would need to be extended beyond the duration of the programmes, and be continued and further developed to build robust systems.

Table 2 Possible Sources of Data for Africa

Data Type	Sources
Global reanalysis data	ERA-40* and ERA-interim (ECMWF#), JRA-25 (JMA/CRIEPI), MERRA (NASA GMO), CFSR (NCEP), NCEP-R1 (NCEP/NCAR), NCEP-R2 (NCEP/DOE), 20CRv2 (NOAA/ESRL PSD), and Princeton University. Zhang et al. (2012) recommended 20CRv2 for SA.
Gridded precipitation	CRU TS3.1 of University of East Anglia (Mitchell and Jones 2005); GPCP of NASA/GSFC, GEWEX
Monthly streamflow	Global historical monthly data for world's 925 largest ocean-reaching rivers by NCAR (www.cgd.ucar.edu/cas/catalog/)
PDSI, SPI, SPEI	Princeton University, IRI of Columbia University, ETH of Zurich; SPEI (Standardized Precipitation Evapotranspiration Index) dataset for Africa is available from Begueria et al. (2010).
WorldClim http://www.worldclim.org/ Hijmans et al. (2005)	A global database (1950-2000) of climate surfaces at 30 arc-second resolution, compiled from monthly climate measured at weather stations, using the Thin Plate Smoothing Spline algorithm that yielded climate surfaces for monthly temperatures & total monthly precipitation. It contains data from Global Historical Climate Network Dataset (GHCN), WMO Climatological Normals (CLINO), & FAOCLIM global climate database
Earth systems science (ESS)	ESS data are produced from models, weather prediction, remote sensing, and GIS with well documented protocols, to monitor inland waters and to assess water stress problems.
Global Runoff Data Centre	River discharge observations.
NOAA and NASA, USA CRU	Optical sensors of NOAA-AVHRR, MODIS and ASTER of EOS AM-1, NASA to map land vegetation with NDVI, fPAR, GPP, NPP, and LAI data
European Space Agency-ESA CCI/WACMOS	Soil moisture from SAR data of Envisat, ERS1 & ERS2, TerraSAR-X; Active-passive microwave data of SMMR, SSM/I, TMI, AMSR-E, ASCAT

Note:* = References for reanalysis data are given in Zhang et al. (2012); # = Organization

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