A DROUGHT MONITORING AND FORECASTING SYSTEM FOR SUB-SAHARA AFRICAN WATER RESOURCES AND FOOD SECURITY

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The development and implementation of a drought monitoring and seasonal hydrological forecast system for sub-Saharan Africa contributes to building capacity through technology and knowledge transfer.

Drought is a naturally occurring climate phenomenon that impacts human and environmental activity globally and can be considered to be one of the costliest and widespread of natural disasters (NCDC 2012; Below et al. 2007). One of the reasons for this is the often large spatial extent and lengthy duration of droughts, sometimes reaching continental scales and lasting for multiple years (Sheffield and Wood 2011). Compared to other natural disasters, this translates into a greater proportion of the population affected. Drought can also be exacerbated by human activities such as deforestation, land use change, and poor management of water resources that feed back to climate and alter the storage of water on the land. In sub-Saharan Africa (SSA), droughts account for less than 20% of natural disasters but account for over 80% of the affected population (UN/ISDR 2009). Much of the continent is dependent on rain-fed agriculture, which makes it particularly susceptible to climate variability. Almost 70% of the labor force is engaged in agricultural work and agriculture contributes to about 25% of average gross domestic product (GDP) across the continent (Dixon et al. 2001). When the direct impacts of drought on agriculture and water resources occur over these large space and time scales there are deleterious effects on food and water security. The impacts are driven by the generally high vulnerability of the local populations

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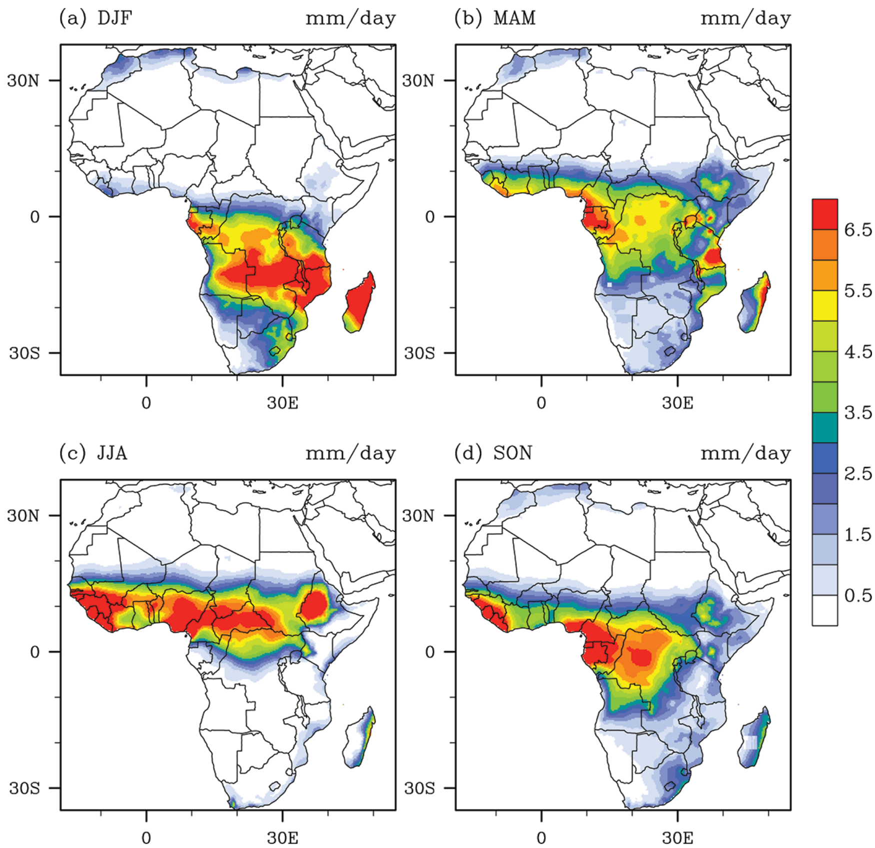

Fig. 1. Seasonal mean precipitation for 1950–2008 for (a) Dec–Feb, (b) Mar–May, (c) Jun–Aug, and (d) Sep–Nov.

and are exacerbated by prevailing local and external economic and political conditions (Haile 2005), which can be associated with development of famine and may be accompanied by the spread of disease. Drought hampers efforts to reach the Millennium Development Goals (MDGs; UN Millennium Project 2005) and is therefore one of the leading impediments to development in SSA (Benson and Clay 1998; Brown et al. 2011). The population of SSA is over 870 million people and is expected to at least double by midcentury. Coupled with expected overall drying with climate change, in particular in southern Africa and parts of West Africa (Sheffield and Wood 2008; Williams and Funk 2011; Seneviratne et al. 2012), there are worrisome implications for water resource sustainability and food security.

Sub-Saharan Africa has suffered from many devastating droughts in recent history. Among some of the most devastating droughts globally during the past 50 years have been the Sahelian droughts of the 1970s and '80s, which drove famine conditions over much of the region and led to an estimated 600,000 deaths (Benson and Clay 1998; Mortimore and Adams 2001) and droughts in 1991/92 in southern Africa (Benson and Clay 1998). Most recently, multiyear droughts across the Horn of Africa (Lyon and DeWitt 2012) led to food shortages across the region and famine conditions in Somalia and northern Kenya (UNOCHR 2011) that have intensified the debate on the role of climate change and how drought will change in the future (Kotir 2011).

Drought in SSA is linked to the high seasonal and interannual variability in rainfall as shown in Figs. 1 and 2. In general, seasonal rainfall higher than 500 mm is required to sustain healthy agriculture, highlighting the tenuous nature of agropastoral livelihoods in many parts of SSA. Rainfall is highly seasonal with well-defined dry seasons across most of the continent. In West Africa, the rainy season is mainly concentrated in July–September with the northward movement of the West African monsoon rains. This is also the case in the Horn of Africa, with some parts (Kenya, northern Tanzania) experiencing two peaks (short and long rains). In southern and East Africa the rainy season is generally from November to April. Variability at interannual and decadal time scales is large (Fig. 2), especially in the transitional regions between semiarid and arid regions, such as the Sahel during the early growing season (June–August). Decadal persistence in wet or dry conditions is one of the greatest problems. Much of this variability is driven by connections to the El Niño–Southern Oscillation (ENSO) as well as to variations in the Atlantic and Indian Ocean (e.g., Rowell 2013).

THE NEED AND POTENTIAL FOR PHYSICALLY BASED DROUGHT MONITORING AND PREDICTION. Monitoring drought development and providing timely seasonal forecasts are essential for drought risk reduction and especially in SSA where livelihoods are closely intertwined with climate variability (Tarhule and Lamb 2003; Amissah-Arthur 2003; Hayes et al. 2004; Hansen et al.

2011; Pozzi et al. 2013). Current approaches in developing countries have generally been limited, in part because of unreliable monitoring networks and lack of access to information and technology that prevents the development of systems locally, as well as generally low institutional capacity and lack of national policy on drought mitigation. In SSA, regional climate outlook forums (RCOFs) were initiated in 1997 and have been the primary mechanism for generating and disseminating seasonal climate forecasts (Ogallo et al. 2008). These operational seasonal climate forecasts are reliant on statistical regressions and provide only a broad-brush view of seasonal rainfall (e.g., tercile probabilities), and are therefore unable to provide detailed information relevant for agricultural adaptation, such as start of the wet season, intraseasonal rainfall, soil moisture, and extreme temperatures (Patt et al. 2007). There is also a reported tendency for the consensus of the forums to hedge on the side of caution when issuing forecasts (Hansen et al. 2011). In several countries, the national meteorological and hydrological agencies extend the RCOF outlooks to provide local interpretation and more detailed impact orientated information to farmers, subsistence communities, and water resources managers. Nevertheless, the skill, resolution, and local relevance of the forecasts generally remain dependent on the RCOF outlooks, which may limit confidence and uptake of the forecasts (e.g., Manatsa et al. 2012).

The wealth of data from satellites and advancements in large-scale hydrological modeling and seasonal climate model predictions have enabled the development of state-of-the-art monitoring and prediction systems in developed regions, such as the United States and Europe, that can help address many of the problems inherent to developing regions. For example, the U.S. Drought Monitor (Svoboda et al. 2002) and the European Drought Observatory (EDO; Vogt et al. 2011) combine bottom-up approaches of merging drought evaluations at national and subnational levels with a top-down approach of providing continental-scale information from meteorological networks, hydrological modeling, and satellite remote sensing. In SSA, elements of these are mirrored by the Famine Early Warning System Network (FEWS-NET) and the Food and Agriculture Organization of the United Nations (FAO) Global Information and Early Warning System on Food and Agriculture (GIEWS). These systems accumulate information from local observers, market reports, and remote sensing on evolving drought and food security conditions and provide outlooks on potential problem areas.

Satellite remote sensing is a particularly promising source of information in SSA as it is possible to measure every component of the hydrological cycle at the land surface and the state of natural vegetation and agriculture, often at very high spatial resolution (<1 km) and in near–real time (Tang et al. 2009; Wardlow et al. 2012). Satellite-based retrievals for some variables are well developed (e.g., for precipitation, Huffman et al. 2007, and vegetation, Funk and Brown 2005) and are a promising new source of

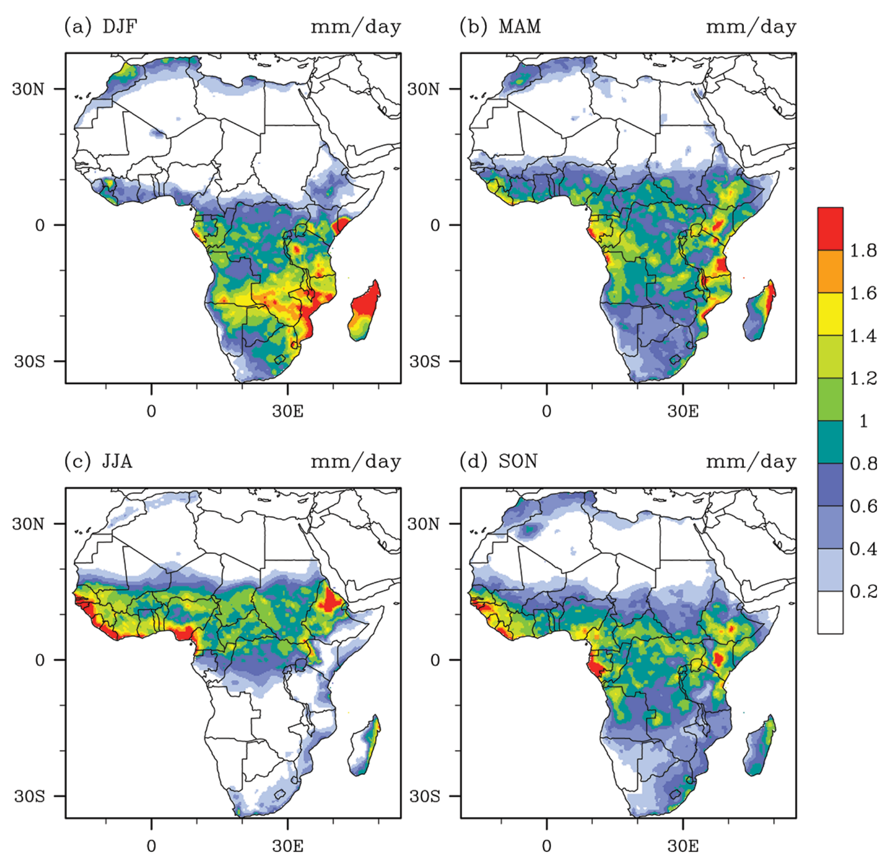

Fig. 2. Seasonal standard deviation of precipitation for 1950–2008 for (a) Dec–Feb, (b) Mar–May, (c) Jun–Aug, and (d) Sep–Nov.

data for other variables (e.g., Gao et al. 2012; Tapley et al. 2004; de Jeu et al. 2008; Vinukollu et al. 2011). Their use in operational drought monitoring is still generally in its infancy, although a substantial body of research literature now exists on the potential for drought monitoring at large scales (e.g., Anderson et al. 2011; Houborg et al. 2012; Mu et al. 2013). The use of satellite remote sensing to augment low density in situ observations has obvious benefits; however, there are several challenges that need to be addressed to realize their potential in the context of drought monitoring. In general, these include the relatively short record lengths of satellite products, changes in satellite sensors that can lead to temporal inhomogeneities, and the indirect nature of the retrievals of physical variables. In particular, errors in individual products, inconsistencies between products, and nonclosure of the water budget imply that they should be used with caution (Sheffield et al. 2009; Gao et al. 2010; Pan et al. 2012a; Armanios and Fisher 2014).

Remote sensing generally provides independent views of different parts of the coupled ecological–hydrological system. However, there is scope to provide a holistic and consistent view of drought by merging remote sensing data with land surface hydrological modeling, either directly via assimilation (e.g., satellite retrievals of soil moisture) or indirectly in the form of input drivers (e.g., precipitation or vegetation). Several studies have shown this potential (Brocca et al. 2010; Milzow et al. 2010; van Dijk and Renzullo 2011; Anderson et al. 2012). Furthermore, land surface hydrological modeling has evolved to a state that models can provide realistic depictions of the water cycle over large scales with acceptable errors when driven by accurate meteorological data and/or merged with remote sensing data. Much of this progress has been derived from regional and global intercomparison studies that have highlighted key model differences and provided mechanistic insights into model behavior and errors (Henderson-Sellers et al. 1993; Mitchell et al. 2004; Guo et al. 2006; Xia et al. 2012), as well as better input data. In particular, availability of real-time satellite precipitation data has enabled the use of hydrological models for flood and drought applications in regions of low-density ground measurements (e.g., Pan et al. 2010; Yilmaz et al. 2010), although currently this approach does not outperform those using just a handful of gauges (e.g., Stisen and Sandholt 2010).

Seasonal hydrological predictions have the potential to provide vital information throughout SSA for a variety of needs including water resources management, agricultural and urban water supply, and flood mitigation. In particular, seasonal forecasts of drought risk can enable farmers to make adaptive choices on crop varieties, labor usage, and technology investments (Hansen et al. 2011). Forecast skill is generally derived from teleconnections with ocean variability—specifically sea surface temperature (SST) anomalies—as well as persistence in the state of the land in terms of soil moisture, snowpack, or streamflow conditions (Shukla et al. 2013). The persistence of SST anomalies forms the basis of climate forecasts either as a predictor in a statistical model or as boundary conditions to dynamic seasonal forecasts using general circulation models (GCMs). For SSA, the main source of predictability is derived from ENSO and its manifestation in SST anomalies in the eastern tropical Pacific Ocean, with drought more likely over West Africa and southern Africa during El Niño events and over East Africa during La Niña events (Camberlin et al. 2001; Smith et al. 2012; Yuan et al. 2013; Rowell 2013), although the spatial footprint of these teleconnections may be limited (Yuan et al. 2013). Forecasts of hydrological variables can also be derived using hydrological models forced by statistical or dynamical precipitation forecasts. More often, operational systems are based on the use of ensemble streamflow prediction (ESP) type forecasts, which sample from the historic climate record and rely mainly on the skill derived from the land surface initial conditions. Operational versions of such systems are generally limited to a few regions around the world—for example, in the United States, Europe, and Australia—and are virtually absent in SSA.

Seasonal climate forecasts from dynamical models have evolved considerably over recent years and are now showing greater skill than statistical forecasts, at least for large-scale climate features such as ENSO (e.g., Jin et al. 2008; Weisheimer et al. 2009; Barnston et al. 2012). They also provide forecasts that are grounded in the physics of weather and climate and therefore can provide objective information on multiple aspects of drought (e.g., precipitation and temperature), in contrast to statistical prediction tools, which are generally limited to single-variable outcomes. The challenge is that precipitation forecasts from these models are generally limited in skill beyond a few weeks because of the inherent chaotic nature of the atmosphere (Lavers et al. 2009; Yuan et al. 2011) and otherwise to regions with strong teleconnections with ENSO at seasonal time scales, and then only for coarse tendencies for drier- or wetter-than-normal conditions. Furthermore, the model spatial resolution (on the order of hundreds of kilometers) is generally too coarse to be useful for hydrological prediction. Nevertheless, continued improvements in dynamical forecasts (Yuan et al. 2011; Pappenberger et al. 2011; Barnston et al. 2012), the development of downscaling and bias correction methodologies for hydrological applications (Luo and Wood 2008; Gobena and Gan 2010), and the focus on improved estimates of initial conditions in lieu of forecast skill (Bierkins and van Beek 2009; Li et al. 2009; Shukla et al. 2013; van Dijk et al. 2013) have provided incentive to develop and test experimental hydrological forecast systems. Despite the high frequency and impacts of drought on SSA populations, and the potential for increased resilience of local populations if monitoring and forecast information can be accessed and utilized, the evaluation and implementation of seasonal hydrological forecasts has been limited to a few regional (e.g., Oettli et al. 2011; Manatsa et al. 2012) and continental studies (e.g., Dutra et al. 2012a; Yuan et al. 2013).

This article presents the development and implementation of an African Drought Monitor (ADM), an advanced real-time drought monitoring and seasonal forecast system for sub-Saharan Africa, which has evolved via collaboration with the United Nations Educational, Scientific and Cultural Organization (UNESCO) International Hydrological Programme (IHP). The IHP supports an international scientific cooperative program in water research, education, and capacity building responding to the growing needs of sustainable development. In 2006, IHP discussed the possibility of developing a demonstration system for SSA that would respond to the needs of UNESCO members, contribute to IHP activities and capacity building, and respond to the drought needs of the Group on Earth Observations (GEO). The initial demonstration system has now matured into an operational framework that merges statistical and dynamical climate predictions, hydrological models, and remote sensing data to provide timely and useful information on drought in SSA. The system has been implemented at regional centers in Niger and Kenya and the article highlights the feedback with local meteorologists and hydrologists who are charged with managing local water resources systems and providing information to farmers.

SUB-SAHARAN AFRICAN DROUGHT MONITORING AND SEASONAL FORECASTING SYSTEM. *Overview of approach.* The system estimates drought conditions through a combination of hydrological modeling, satellite remote sensing, and seasonal climate forecasts. It draws from the long legacy of operational and experimental systems in the United States—in particular, the

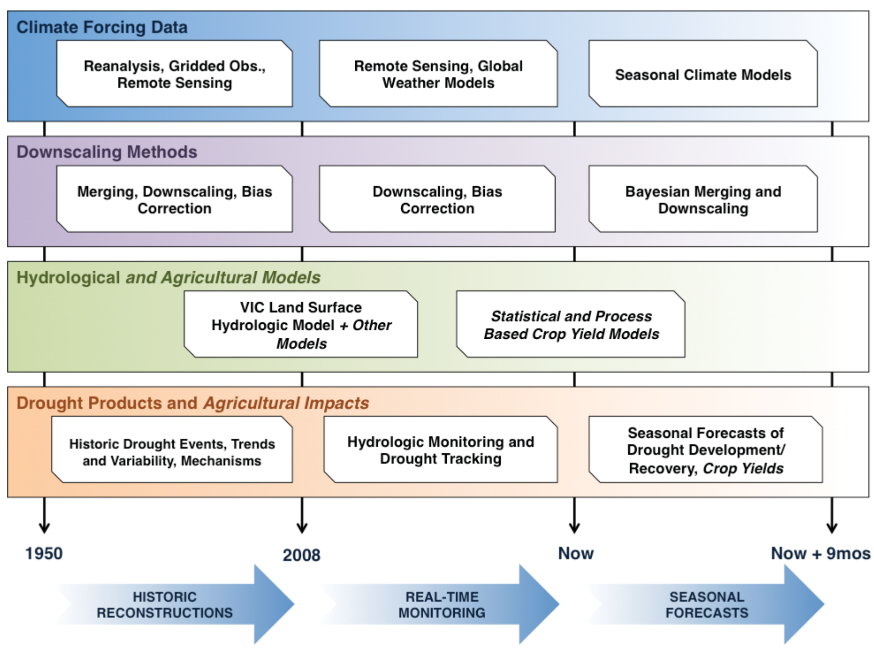

Fig. 3. Flowchart of the African Drought Monitor and Forecast System. The system comprises three parts: 1) Historic reconstructions of the terrestrial hydrological cycle that are derived from simulations of the VIC land surface model forced by a hybrid reanalysis–observational meteorological dataset. The datasets are used for a variety of applications including analysis of historic drought events, estimation of trends and variability, and investigation of drought mechanisms. 2) Real-time monitoring component that updates the model run to 2–3 days from real time forced by bias-corrected and downscaled TMPA satellite precipitation and GFS analysis fields of temperature and wind speed. There is also potential to force other impact models such as crop models. 3) Seasonal hydrological forecast component that uses bias-corrected and downscaled CFSv2 climate forecasts of precipitation and temperature to drive the model and provide ensemble predictions of drought conditions for precipitation, soil moisture, and streamflow. Existing components are shown in normal font and potential future components in italic font.

Princeton drought monitoring and forecasting system (Luo et al. 2007) that was developed within the North American Land Data Assimilation System Phase 2 (NLDAS-2; Xia et al. 2012) and the National Centers for Environmental Prediction (NCEP) Climate Test Bed program. The system consists of three parts (Fig. 3): First, a historic, multidecadal reconstruction of the terrestrial water cycle is obtained by forcing the Variable Infiltration Capacity (VIC) land surface hydrological model (Liang et al. 1996) with a merged reanalysis–observation dataset. This forms the climatology against which current conditions are compared. Second, the real-time monitoring system (2009–present) is driven by remotely sensed precipitation and atmospheric analysis data that track drought conditions in real time. The simulated outputs are augmented by satellite remote sensing of soil moisture and vegetation indices. Third, a seasonal forecast component provides hydrological predictions and derived drought products out to 6 months, based on bias-corrected and downscaled climate model forecasts that are used to drive the VIC model.

Hydrological modeling and data sources. The VIC model is used to predict land surface hydrological fluxes and states. VIC is a semidistributed, grid-based model that represents subgrid variability in land cover, elevation, soil water storage capacity, and storm coverage. The model is run in two simulation modes: retrospectively and in near–real time. The retrospective simulation mode forms a long-term climatology to which current conditions from the real-time mode can be compared. The retrospective simulation covers the period 1950–2008 and is forced by the long-term global meteorological forcing dataset of Sheffield et al. (2006), which merges gridded observational data with satellite remote sensing products and atmospheric reanalysis data. This dataset has been downscaled to 0.25° resolution and is currently being updated based on improved assimilation of station data (Chaney et al. 2014).

The real-time simulation is forced by a combination of precipitation from the Tropical Rainfall Measurement Mission (TRMM) Multisatellite Precipitation Analysis (TMPA; Huffman et al. 2007) and temperature and wind speed from the National Oceanic and Atmospheric Administration (NOAA) NCEP Global Forecast System (GFS). Other required variables (surface solar and longwave radiation, humidity, pressure) are predicted from the precipitation and temperature data using empirical regressions (Bohn et al. 2013). The satellite-based TMPA and GFS data are bias corrected based on climatological differences with the long-term dataset for their overlap period (approximately 2002–08) by matching their empirical cumulative probability distribution functions. We evaluated the robustness of this approach by comparing the historic simulation with a simulation forced by the bias-corrected TMPA data for the overlap period. This showed relative biases of less than 1% in predicted runoff and soil moisture averaged over large river basins such as the Niger and Congo.

Boundary conditions for the model include the land cover map based on Advanced Very High Resolution Radiometer (AVHRR) data (Hansen et al. 2000) and soil type and texture based on the FAO Digital Soil Map of the World (FAO 1995). The model was calibrated against streamflow observations from 966 stations of the Global Runoff Data Center (GRDC) across SSA, filtered for upstream dams. The GRDC stream gauge database over the continent was disaggregated into gridded monthly runoff fields over the entire domain. Following Troy et al. (2008), the VIC model is calibrated at each grid cell against the derived runoff fields between 1970 and 1990 using the shuffled complex evolution algorithm (Duan et al. 1992).

Other data products. The system is flexible enough to incorporate other sources of data including output from other models and remote sensing. Currently, remotely sensed soil moisture and vegetation data are included in the system to complement the modeled information. Data from the Soil Moisture Ocean Salinity (SMOS) L-band upwelling passive microwave sensor are included in the system in the form of a soil moisture index (Kerr et al. 2012). This dataset has been initially evaluated by Al-Bitar et al. (2012) and Pan et al. (2012b) over the United States and by Gruhier et al. (2011) for West Africa, and shows promise for drought monitoring (Sahoo et al. 2011) as a complement to the modeled output, as well as to provide corrections to the satellite rainfall (e.g., Pellarin et al. 2008; Crow et al. 2011) or directly via assimilation (Sahoo et al. 2012).

The system also displays operational retrievals of vegetation stress from visible and microwave sensors drawing from the distinctive and complementary information that each provides about vegetation (Guan et al. 2012). The optical-based vegetation index (VI) product captures the landscape-integrated canopy-level leaf chlorophyll and photosynthetic intensity (Sellers et al. 1992). It is based on a merging of the Global Inventory Modeling and Mapping Studies (GIMMS) normalized difference vegetation index (NDVI) for the historic period (1982–2008) and the Moderate Resolution Imaging Spectroradiometer (MODIS) enhanced vegetation index (EVI) for 2000–present. The passive-microwave-based vegetation optical depth (VOD) product captures the landscape-integrated total water column through the whole canopy (Jones et al. 2012). It is composed of the VOD product of Liu et al. (2011) based on Special Sensor Microwave Imager (SSM/I), TRMM, and Advanced Microwave Scanning Radiometer for Earth Observing System (EOS) (AMSR-E) for 1987–2008 and the AMSR-E-based VOD (Jones and Kimball 2012). A third product based on scatterometer backscatter (dB) captures the landscape-integrated vegetation canopy biomass (depending on the penetration of the wavelength) and top-canopy water content (Jarlan et al. 2002). In our case, we merged the Ku-band dB from Quick Scatterometer (QuickSCAT) (2000–09) and C-band dB from Advanced Scatterometer (ASCAT) (2009–present) using the quantile matching approach. The Ku-band dB only detects the top-canopy information owing to its relatively small wavelength (13 GHz), whereas the C-band dB (6 GHz) penetrates the canopy and captures information about both surface soil moisture and vegetation states (Guan et al. 2013).

Seasonal drought forecasts. The seasonal forecast system is based on climate forecasts from the NCEP Climate Forecast System, version 2 (CFSv2; Saha et al. 2014), which is the second generation system from the CFSv1 (Saha et al. 2006). The CFSv2 improves on the previous version through upgraded physical parameterizations and data assimilation scheme. The precipitation and temperature forecasts from CFSv2 show a significant improvement over CFSv1 (Yuan et al. 2011). Monthly precipitation and temperature at the CFSv2 model scale are bias corrected and downscaled using a Bayesian merging method (Luo et al. 2007, 2008) to 0.25° daily resolution. These data are then used to force the VIC model to generate the hydrologic forecasts.

Hydrological and drought products. A suite of drought indices is produced by the system (Table 1) that reflects different aspects of drought. The standardized precipitation index (SPI; McKee et al. 1993) is the World Meteorological Organization (WMO) ratified index for meteorological drought. The current SPI – n value is calculated by considering data from the current and $n - 1$ preceding months. The forecasted SPI – n values are calculated in the same way and may contain historic data depending on the forecast lead time and value of n (Quan et al. 2012; Yoon et al. 2012; Yuan and Wood 2013). The antecedent historic data can be considered as information from initial conditions in the same way as other drought indices based on land surface hydrological variables, such as soil moisture. The soil moisture index is based on the percentile index of

Table 1. Drought indices represented in the African Drought Monitor and their attributes.

Index	Data source	Drought type	Attributes
SPI	Bias-corrected TMPA (2009–present), hybrid observational/reanalysis (1950–2008)	Meteorological drought	0.25°, SPI-1, -3, -6, -12
VIC soil moisture index	VIC land surface model (1950–present)	Agricultural drought	0.25°, daily
SMOS soil moisture index	SMOS retrievals (2010–present)	Agricultural drought (top 5 cm of soil)	0.25°, daily
NDVI, EVI	GIMMS NDVI (1982–2008), MODIS EVI (2000–present)	Ecological drought (optical based)	8 km/0.5°, bimonthly/daily
VOD index	SSM/I, TRMM, AMSR-E VOD (1987–2008); AMSR-E VOD (2000–present)	Ecological drought (passive microwave)	0.25°, daily
dB index	QuickSCAT (1999–2009), ASCAT (2009–present)	Ecological–hydrological drought (active microwave)	0.25°, 2/4 days
Streamflow percentiles	VIC land surface model (1950–present)	Hydrological drought	822 streamflow gauges, daily/monthly
Cumulative streamflow deficit	VIC land surface model (1950–present)	Hydrological drought	822 streamflow gauges, daily/monthly

Sheffield et al. (2004) developed for the continental United States and previously applied regionally (e.g., Wang et al. 2011) and globally (e.g., Sheffield et al. 2009). The index is calculated by determining the percentile of the daily average of relative soil moisture at each grid cell with respect to its empirical cumulative probability distribution function provided by the historical simulations (1950–2008). The cumulative streamflow index represents the volume deficit below the median flow (Tallaksen and van Lanen 2005, 53–96) and is calculated at 822 streamflow gauging points across SSA. The vegetation indices are based on the visible and microwave data products and are calculated as percentiles—similar to the soil moisture. Each of the indices represents a normalized representation of the variable that is calculated relative to the long-term climatology from the retrospective simulation. The approximately 60-yr climatology is long enough to contain several extreme drought events, such as those of the 1970s and 1980s in the Sahel and in the 1990s in southern Africa, and therefore provides a robust climatology. Extending the dataset to the earlier part of the instrumental record would include more extreme events but this is only possible for some regions with adequate station density. The drought indices (and all hydrological variables and meteorological forcings) are available for the entire record between 1950 and real time.

Web interface. A key element of the system is the provision of an intuitive and easy to use web interface to allow users to view the predictions and extract data for further analysis. Figure 4 shows a snapshot of the interface showing recent soil moisture conditions. The interface is based on Google Maps, which provides the geographical information system (GIS) capabilities for panning and zooming and overlaying other geographic layers, such as political boundaries, towns and cities, and satellite land cover imagery. The system features a simple and intuitive user interface that allows the user to access different hydrological and drought products as spatial maps. The user can display current conditions or animate a series of maps to show evolving conditions. Streamflow

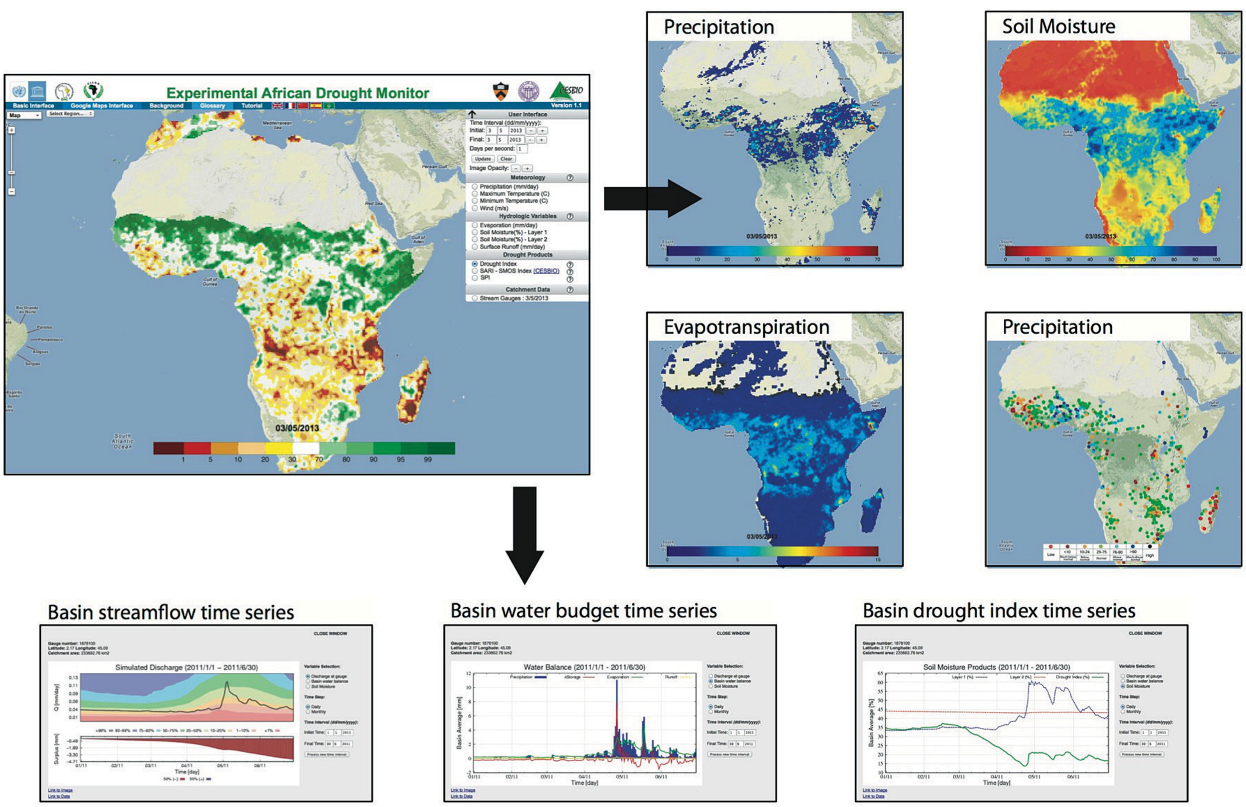

Fig. 4. The African Drought Monitor web interface (http://hydrology.princeton.edu/adm) enables users to access the system's input and output data interactively. Google Maps is used to display the spatial information in an efficient and intuitive manner. (top right) The user can visualize and animate the temporal evolution of the drought-related hydrologic variables over the continent and (bottom) select among the stream gauges monitored in the system to display the time series of the evolution of basin averaged water balance variables and drought products. The user can also readily download the data.

drought can also be displayed for the 822 gauges that correspond to the GRDC network and FAO reservoir database. These gauges were chosen to coincide with actual gauging locations that are or were active. Other locations can be added where necessary at gauged or ungauged locations. The user can also drill down to examine the water budget and drought indices averaged over the upstream river basin by clicking on a stream gauge (see Fig. 4). Given the large spatial domain and potential diversity of users, the system also features multilingual support, currently for English, French, Arabic, Mandarin, and Spanish. The interface can be accessed at http://hydrology.princeton.edu/adm. The drought indices output by the system are also provided as an Open Geospatial compliant web service that can be picked up by other organizations to produce, for example, blended drought indicators such as provided by the U.S. Drought Monitor. Currently, the soil moisture drought index is served to the NOAA National Climatic Data Center to provide coverage for the African continent for the Global Drought Monitor Portal (Heim and Brewer 2012).

Fig. 5. (a) A training session at the first workshop in Jan 2012 at the AGRHYMET center in Niamey, Niger, in which participants from national meteorological and hydrological agencies and river basin management authorities were trained in the use of the system. (b) Participants from the second workshop in June 2012 at the ICPAC center in Nairobi, Kenya.

TRANSITION TO AFRICAN REGIONAL CENTERS. In 2012, the system was transitioned and tested for operational usage by African collaborators at workshops held in two regional centers in SSA. The goals of the workshops were to understand user needs for drought information, current capabilities of regional centers and national agencies for providing climate and hydrological information, and training and feedback on the system, including design and implementation of regional validation plans. The drought monitor software and data were installed on center servers and hydrological scientists and professionals were trained in the operational running of the system and interpretation of the data output. Feedback was also solicited from scientists and managers from national hydrological, meteorological, and agriculture agencies and services. The first workshop was held in January 2012 at the Centre Regional de Formation et d'Application en Agrométéorologie et Hydrologie Opérationnelle (AGRHYMET) regional center in Niamey, Niger (Fig. 5a), which provides information and training in support of improved agricultural production and food security for Commité Permanent Inter-Etats de Lutte contre la Sécheresse dans le Sahel (CILSS) member countries of Burkina Faso, Cape Verde, Chad, Gambia, Guinea Bissau, Mali, Mauritania, Niger, and Senegal. Feedback from this workshop was vital to understand the utility of the system, from the point of view of users from the meteorological and hydrological communities who saw the potential of the historic and real-time data at ungauged locations and from the point of view of managers who saw the potential of the system for decision making. A key lesson learned was that providing a working system was essential to show the potential for management and research, but one that could then be tailored to local user needs and was validated to ensure confidence in the data and uptake of the information. Feedback from participants also highlighted the pressing need for a predictive component for water resources and agricultural planning and hazard mitigation. The second workshop was held in June 2012 at the Intergovernmental Authority on Development (IGAD) Climate Prediction and Applications Center (ICPAC) in Nairobi, Kenya (Fig. 5b), which disseminates information to countries within the greater Horn of Africa (Djibouti, Eritrea, Ethiopia, Kenya, Rwanda, South Sudan, Sudan, Somalia, Tanzania, and Uganda). Both workshops developed a validation plan as an outcome, the results of which are shown below for the ICPAC workshop.

A third workshop took place at AGRYHMET in late 2013 with the goals of strengthening capacity and long-term sustainability in use of the system and, in particular, the seasonal forecasting component that was developed since and in response to the first workshop in January 2012. User needs focused on the point of view of women and youth who are generally underrepresented but particularly vulnerable to drought impacts, with the goal of mainstreaming their engagement in understanding user needs and developing drought policies. Policy makers were invited to discuss drought management issues through plans and policy recommendations, including the kinds of institutional settings that are required. The workshop also focused on user needs and alternative information pathways for dissemination of data, and revisited validation and operational aspects of the system.

VALIDATION AND RESULTS. *Overview of performance of the VIC model.* Figure 6 shows a summary of large-scale evaluations of the bias-corrected satellite precipitation and the VIC model output against available observational and other model-based data. Evaluations at this scale provide confidence in the overall approach of using satellite-based products and hydrological models as surrogates for ground measurements of hydrological variables. The lynchpin of the system is the accuracy of the satellite precipitation. Improvements in the TMPA product have led to several updates in its real-time and historical research products (e.g., Zhou et al. 2014), and the real-time product is now calibrated based on climatological evaluations against monthly gauge analyses. Sylla et al. (2012) evaluated the TMPA (3B42 V6) dataset for Africa and showed that the large-scale patterns of precipitation were similar to observational estimates from Global Precipitation Climatology Project (GPCP) and FEWS products but there were considerable differences between all datasets in terms of daily higher-order statistics, such as extreme rainfall and the duration between rain events. Of particular importance is the latter, which the TMPA overestimates and this is corrected for in the system based on the historical-gauge-based climatology. Figures 6a–c show that, in general, the real-time TMPA (3B42RT V6) are biased high annually compared to our long-term observational dataset, despite the calibration. The bias is corrected for at monthly scale to ensure consistency between the historic and real-time predictions.

Figures 6d–f show an evaluation of the VIC output for simulated streamflow against 624 station time series from the GRDC database. The figure highlights the scarcity of readily available data for many parts of the continent and especially in humid regions of central Africa and the drier greater Horn of Africa. The uncalibrated model shows large errors in terms of the Nash–Sutcliffe efficiency (NSE; Nash and Sutcliffe 1970), especially in Cameroon and Gabon, with negative values indicating that the model does not perform better than the mean. The median NSE values increase after calibration from −0.04 to 0.93 and the mean from −0.54 to 0.66. In particular, the model simulations are improved across West Africa and East Africa, but stations in drier regions such as the Horn of Africa and southwestern Africa show little improvement. The spatial distribution of the calibrated parameters generally reflects climate gradients for parameters that control baseflow and infiltration, but with random structure in the other parameters that reflects the many degrees of freedom in the calibration process.

The model output was also evaluated for consistency against satellite-based evapotranspiration and land water storage change (Figs. 6g–l). Evapotranspiration is from the RS-PM algorithm with the surface resistance parameterization of Mu et al. (2007) as implemented by Vinukollu et al. (2012). This algorithm uses the same Penman–Monteith approach as the VIC model to estimate potential evaporation but differs in its representation of surface resistances, which are based on relationships with humidity and temperature. The evapotranspiration is compared for the annual mean over 1997–2006 and shows similar spatial distribution and magnitudes but with large (>1 mm day^{-1}) negative differences in West Africa and the Ethiopian highlands and positive differences in parts of the northern Congo. A lack of observational-based estimates of evapotranspiration (except for a handful of flux measurement towers) means that the validation of the model simulation is difficult. The change in seasonal water storage is from the Gravity Recovery and Climate Experiment (GRACE) satellite and is calculated as the difference in the maximum and minimum seasonal water storage averaged over 2003–11. The comparison shows consistency between the datasets, given the differences in representative scale (GRACE represents variations on scales of about 500 km) and physical quantities represented (GRACE represents total water storage, including surface water, soil moisture, and groundwater; VIC represents soil moisture only). The VIC data tend to underestimate the seasonal change across north-central and central Africa, which may be a reflection of the current lack of groundwater representation in the model as north-central Africa has relatively shallow groundwater tables (MacDonald et al. 2012), current lack of representation of inland water bodies and wetlands, or uncertainties in rainfall, particularly over central Africa.

User driven validation: Example for greater Horn of Africa. Driven by feedback from the workshops and the need to evaluate the system for potential use in specific regions, a validation plan was developed that centered on hydrological validation at gauging sites of interest. National representatives were eager to understand the utility of the system, in particular for providing predictions at ungauged or no longer reporting locations. It was

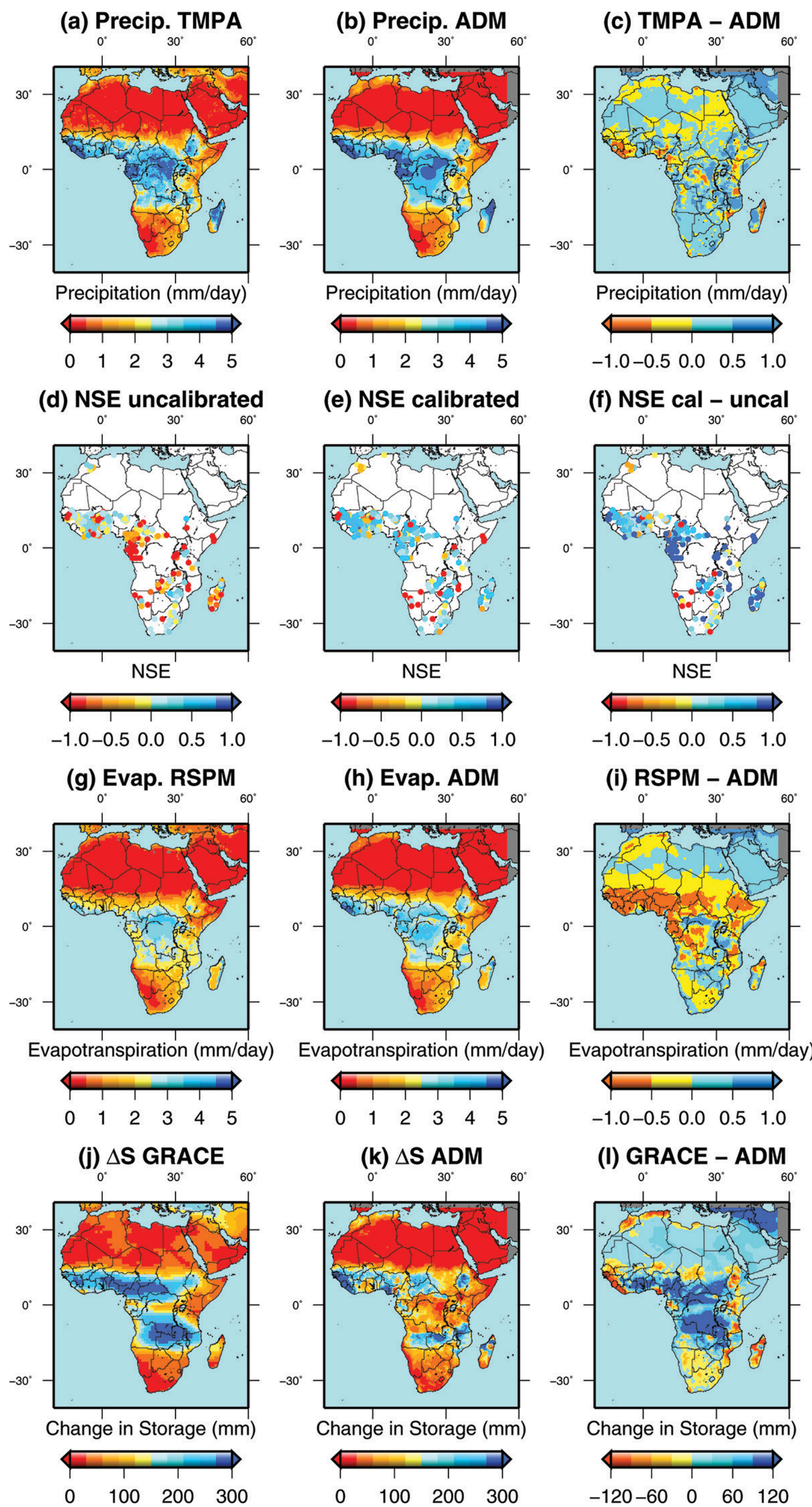

FIG. 6. Evaluation of VIC model input and output data. Annual mean precipitation (mm day^{-1}) for 2003–08 for (a) the TMPA 3B42RT V6 satellite product, (b) the long-term (1948–2008) historic ADM data, and (c) and their difference (TMPA minus ADM). Monthly Nash–Sutcliffe efficiency values of the VIC-simulated streamflow with respect to available historic GRDC observations for (d) the uncalibrated model, (e) the calibrated model, and (f) their difference (calibrated minus uncalibrated). Annual mean evapotranspiration (mm day^{-1}) for 1997–2006 for (g) the RS-PM satellite product of Vinukollu et al. (2012), (h) VIC, and (i) their difference (VIC minus RS-PM). The seasonal range in water storage (Δ*S*; mm) for 2003–11 for (j) GRACE Jet Propulsion Laboratory (JPL) rel5, (k) VIC, and (l) their difference (GRACE minus VIC).

agreed at the workshops that more detailed evaluations at existing sites would be necessary to understand utility. Figure 7 shows results from the validation exercise for sites in the greater Horn of Africa region for which data were supplied by participating national hydrological agencies at the ICPAC workshop. These sites were chosen because of the available data and key locations for supporting decision making in the various countries. None of these sites are available in the GRDC database and so did not contribute to model calibration. The sites represent a mixture of basin sizes from 100 to 150,000 km^2. The sites therefore provide a stringent test of the system for sites of particular interest to users. The results are mixed as expected given the low density of rain gauge data and the reliance on satellite precipitation since 2009 but are encouraging for most of the sites in terms of the depiction of a range of flows (mean daily flows, 3-day peak values, and 7-day low flows) and the maintenance in the level of skill into the real-time period. However, some of the sites appear to be highly regulated by natural wetlands/lakes (e.g., the Kapiri site in Uganda that sits between two lakes) or potential water withdrawals. Overall, there is a tendency to overpredict the different flow types in the larger/wetter basins and underpredict in the smaller basins. The high bias suggests one or more problems related to the modeling framework, including overestimation by the bias-corrected satellite precipitation, underestimation of evapotranspiration potentially due to upstream wetlands and lakes that are not modeled (also leading to a lack of attenuation of flows), and lack of representation of anthropogenic impacts, such as water withdrawals. Accounting for withdrawals is challenging without direct information on withdrawals and irrigation, and current information is generally limited to national statistics. However, simple bias adjustment or even modeling of withdrawals could be implemented to better represent these local conditions.

Seasonal forecast evaluations. The skill of the CFSv2-forced hydrological forecasts have been evaluated by Yuan et al. (2013) who analyzed a 26-yr (1982–2007) set of seasonal hydrological hindcasts. They found that probabilistic drought forecasts of the 6-month SPI and soil moisture percentiles performed better than climatology over drier regions out to 3–5 months, with SPI6 generally more skillful than soil moisture, except at the beginning of the rainy season in western and southern Africa because of the strength of the seasonal cycle. Similar results were found by Dutra et al. (2012a) based on evaluations of the European Centre for Medium-Range Weather Forecasts (ECMWF) seasonal forecast system of SPI over selected African river basins, but that skill generally increased with longer time scales of SPI. Figure 8 summarizes the skill of the CFSv2 driven hydrological forecasts for the start of wet season for three regions in terms of Brier skill scores (BSS) for 1-, 2-, and 3-month forecasts of soil moisture from the beginning of the wet season. A BSS value of one indicates a perfect forecast and zero indicates no skill relative to a climatological forecast. The scores are very high in parts of the regions that experience a later onset of the wet season (e.g., in the northern Sahel), but are overall modest for lead-1 forecasts (Brier skill scores < 0.6). At lead times of 2 and 3 months, the scores drop to less than 0.4 and less than zero in some areas, indicating that the forecasts are worse than climatology. Examination of the time series of regional skill shows larger variability from year to year at longer lead times (not shown) and hints that slightly higher skill is associated with ENSO: for East Africa during La Niña events and for southern Africa during El Niño events.

CASE STUDY OF THE 2010/11 HORN OF AFRICA DROUGHT. The Horn of Africa (HoA) drought during 2010/11 caused devastating human impacts across the region, in particular affecting southern Somalia, where an estimated 250,000 deaths were associated with severe food insecurity and declared famine conditions, with over half of the deaths to children less than 5 years old (FAO/FEWSNET 2013). Although the famine was a result of many factors, including the ongoing conflict and political insecurity in the region (Maxwell and Fitzpatrick 2012), the drought played a major role. Figure 9 shows the output from the ADM for 2010/11 for precipitation (expressed as SPI3) and soil moisture, vegetation, and streamflow, expressed as percentile indices. The SPI3 shows the decline into drought conditions with the failure of the short rains of the Deyr season at the end of 2010 (October–December) that was associated with the La Niña of 2010/11 (Dutra et al. 2012b; Lyon and DeWitt 2012). The long rains of the Gu season (April–June) of 2011 compounded the 2010 short-rains failure but were not as bad. Peak drought conditions were reached in about June 2011. The soil moisture and vegetation indices follow the decline in precipitation but with lagged response as the drought signal propagates through the system. The EVI shows the quickest response of the vegetation indices followed by the VOD and dB indices. The peak spatial extent covered much of the region, from central Kenya up through southern Somalia and into southeastern Ethiopia, with most of the southeastern part of the region in drought conditions below the 20th percentile. The streamflow time series for the Shebelle River (Fig. 9) indicates the local effect of the drought on one of southern Somalia's main rivers, which is an important source of water for irrigation and pastoral communities.

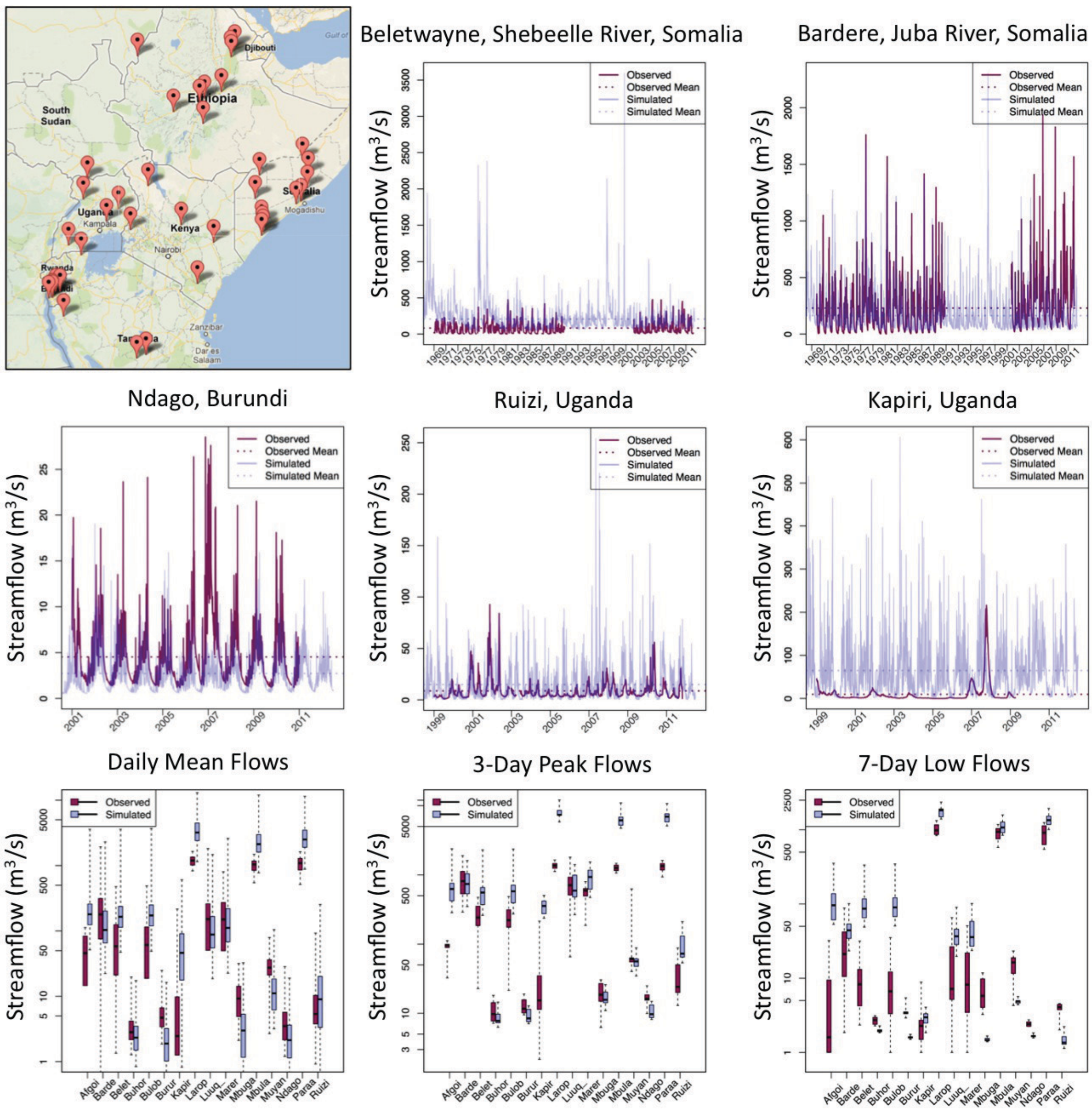

Fig. 7. An example of streamflow validation over the greater Horn of Africa region for a diverse set of basins. (top left) Location of validation sites selected by participants from national hydrological agencies at the ICPAC workshop in 2012. (top)–(middle) Examples of time series of simulated streamflow discharge from the ADM compared to available observations. The Beledweyne site is on the Shebeelle River in south-central Somalia, which is an area of intensive irrigation. The Bardera site is on the Juba River in southern Somalia, which is an important agricultural area. Note the lack of observational data during the peak of the Somali civil war in the 1990s. The Ndago site is in a small catchment in southwestern Burundi. The Ruizi site is in southwestern Uganda and may be subject to water abstractions. The Kapiri site in eastern Uganda is in a wetland area between two lakes. (bottom) Summary comparisons for 16 sites in Somalia, Uganda, and Burundi for (left) mean flows, (middle) 3-day peak flows, and (bottom) 7-day low flows. The median (horizontal line), interquartile range (box), and range (whiskers) are shown for the observations and ADM predictions.

Figure 10 shows the 6-month hydrological forecasts for 10 ensemble members initialized on two dates: September 2010 (September–February) and February 2011 (February–July). The forecasts, using procedures described earlier, are shown in terms of the area averaged soil moisture percentiles and the area in drought calculated for the main drought region (5°–12°N, 40°–52°E), which is also the same region used by Dutra et al. (2012b). The area in drought is calculated using a drought threshold of the 20th percentile of soil moisture. The September 2010 forecasts indicate good skill in reproducing the decline in soil moisture over the 6 months of the forecast but underpredict the drought in latter months (December 2010–February 2011). Furthermore, the spread across ensemble members is relatively small. The February 2011 forecasts also do well for the first 2 months (February–March 2011), showing an increase in drought but then fail to show the continuation to the peak in April–June, with large spread among ensemble members. Dutra et al. (2012b) showed similar results in terms of precipitation using the ECMWF seasonal forecast system.

CHALLENGES AND FUTURE DIRECTIONS. Given the tremendous impact of drought in sub-Saharan Africa, where the growing population is mostly dependent on rain-fed agriculture, the development and implementation of the ADM system has the potential to build capacity through technology and knowledge transfer. The feasibility of the system and its capability to monitor and forecast over large scales and at high resolution has been made possible with the advent of mature remote sensing data products and advances in land surface modeling and seasonal dynamical forecasting, albeit subject to errors in the predictions as discussed previously. In particular, remote sensing is capable

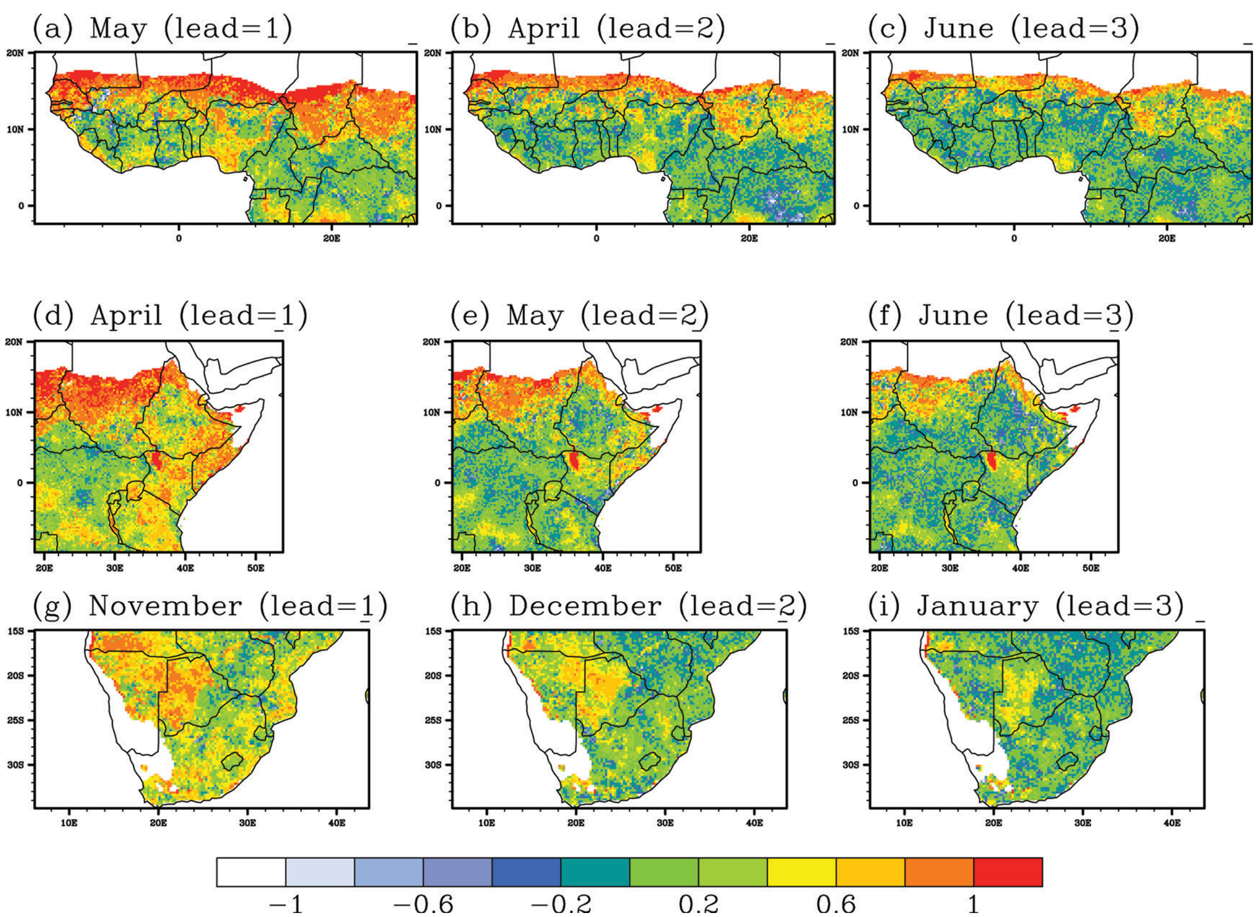

Fig. 8. Brier skill score for 1-, 2-, and 3-month forecasts of soil moisture for (a–c) West Africa (forecast date = 15 Apr), (d–f) East Africa (forecast date = 15 Mar), and (g–i) Southern Africa (forecast date = 15 Oct). The forecasts are from VIC model–simulated soil moisture forced by bias-corrected and downscaled CFSv2 climate forecasts and evaluated relative to the VIC observation-forced historic simulation. The reference forecast is the soil moisture climatology from the offline simulation.

of overcoming sparse in situ monitoring and differences in data availability across political boundaries that have historically hindered monitoring of regional phenomena, such as drought.

The system shows encouraging performance at large scale when compared to other estimates of the land water cycle but notable errors when compared to local measurements. This is to be expected given the low density of monitoring networks, the high spatial and temporal variability of precipitation, and the heterogeneity of the land surface, as well as human influences, such as water and land management. Currently, the system does not simulate surface water bodies, such as lakes and wetlands, although these are features of the VIC model. Inclusion of these would be relatively straightforward and could potentially help improve performance at, for example, the stream gauging sites shown in the validation that are controlled by upstream wetlands and lakes. The system also does not account for human influences on water, such as reservoirs, river withdrawals, and irrigation applications and return flows. Simple representations of these activities have been implemented in large-scale models (e.g., Haddeland et al. 2007), but further research is required to determine the best way to implement these in the system, given the spatial diversity of practices and the low availability of estimates of water use. Continued collaboration with local partners is essential for conveying the current limitations of the system to users and the implications for decision making and for making progress toward addressing these limitations through integration of local knowledge and information about water use.

Performance of the system is also highly reliant on the accuracy of the meteorological data. There

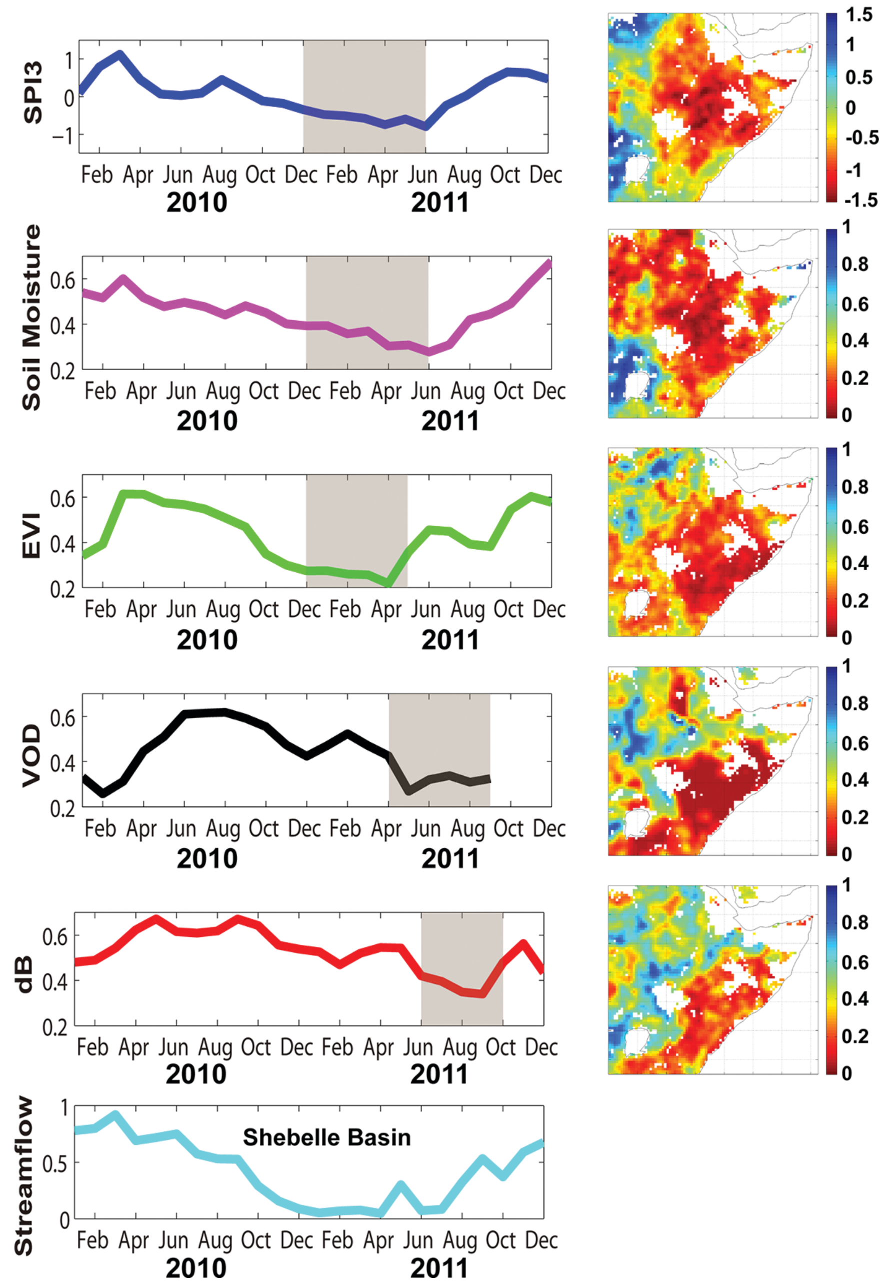

Fig. 9. The evolution of the 2010/11 drought over the Horn of Africa. (left) Time series of drought indices averaged over the HoA region (5°S–15°N, 30°–52°E) and (right) maps of drought indices at the height of the drought as indicated by the gray shading in the time series. (bottom) The time series of simulated streamflow at the Agfoi gauging station on the Shebelle River (upstream area = 107,336 km²), which flows from the Ethiopian highlands and is one of the two main rivers (along with the Jubba River) in southern Somalia. All indices except SPI3 are calculated as percentiles.

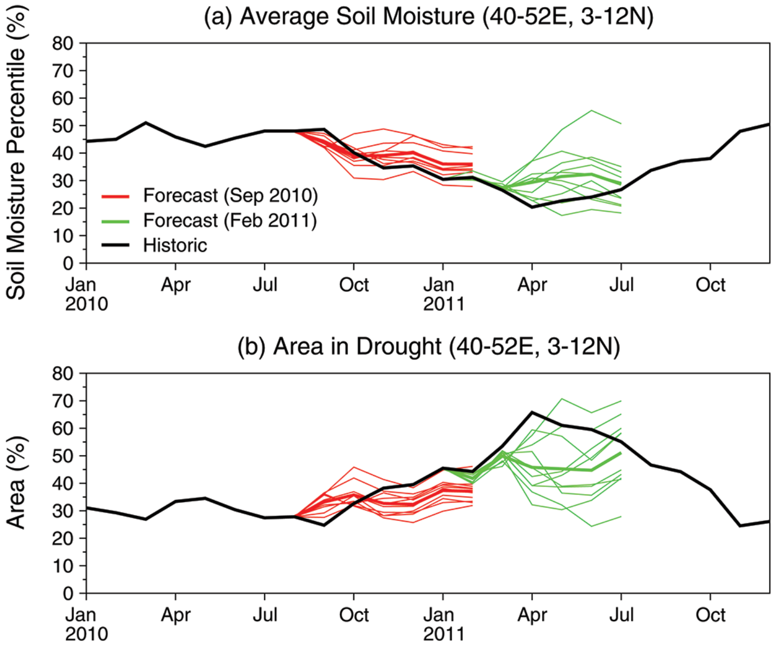

Fig. 10. Seasonal hydrological forecasts of the 2010/11 Horn of Africa drought. (a) Soil moisture percentile averaged over the main drought region (3°–12°N, 40°–52°E) from the historic VIC simulation, Sep 2010 forecast, and Feb 2011 forecast. (b) Percentage area in drought based on a drought threshold of the 20th percentile of soil moisture for the historic simulation and the two forecasts. The forecasts are shown for 10 ensemble members and the ensemble mean (thick lines).

is scope to enhance the accuracy of both the long-term data and real-time satellite-based data by merging with data from regional/national station databases (Chaney et al. 2014), other gauge/remote sensing analyses (e.g., FEWS), and with assimilation of remotely sensed soil moisture as a surrogate for on-the-ground rainfall where gauge data are unavailable (Pellarin et al. 2013). These enhancements will filter down into the seasonal forecasting component for which much of the skill in the first month is dependent on the initial conditions, which can also be improved through real-time assimilation of remotely sensed soil moisture and lake/river levels.

The seasonal hydrological forecasts show encouraging skill in the first 1–3 months depending on the region and season but are inherently limited by the chaotic nature of the atmosphere. Nevertheless, the case study of the 2010/11 Horn of Africa drought exemplifies the potential that large-scale teleconnections such as ENSO can provide extended and useful forecasts out to several months. The forecast system can be enhanced through use of climate forecasts from multiple models (both dynamical and statistical), drawing from strengths in each one, as has been demonstrated in other applications (e.g., Luo et al. 2007), as well as the potentially higher forecast skill conditional on climate states such as ENSO. Of particular importance is that the hydrological predictions provide information on quantities, such as soil moisture and streamflow, and at spatial and temporal resolutions, that are relevant to end users. We are currently adding an agricultural model to the forecast system, which, when merged with the real-time vegetation indices, can provide crop yield forecasts.

Implementation of the system at regional centers in Niger and Kenya has highlighted the potential to augment existing capability in regions with established monitoring networks and provide the only source of information in areas lacking observations. It is important to recognize, however, that the sustainability of the system is highly dependent on the capacity of scientists and professionals who are charged with maintaining and running the system and interpreting and disseminating the real-time updates and forecasts. It was therefore important to identify key personnel at regional centers and national agencies and work with established researchers at affiliated universities while at the same time training new young scientists and professionals. Experience has shown that ongoing collaborations through workshops, exchanges, and educational activities provide the best means of sustained usage and further development of tailored regional systems. In this spirit, the system is open source and free to use to encourage opportunities for further implementation, development, and collaboration, and this is happening with ongoing validation activities for countries within the ICPAC and AGRHYMET regions. Direct funding for the development and implementation of the ADM was based solely on travel support and modest initial development funding from UNESCO IHP but leveraged other funding that supported the development of general methodologies for forecasting and modeling. Sustained funding is required to keep momentum going, train each new wave of scientists and professionals, and facilitate long-term collaborations with African universities and training centers to build long-term capacity in research and development.

The application of hydrological and climate research into transferable technology with minimal overhead has been made possible with the development of the ADM and has the potential to help reduce the impacts of drought across sub-Saharan Africa. Realizing this potential, however, requires overcoming the many barriers that hinder the uptake and utility of output from the system, especially for local farming and pastoral communities. These barriers relate to the relevancy of the information to end users, the robustness of forecasts, and the communication and interpretation of information (Roncoli 2006; Patt et al. 2007), especially given the current errors and uncertainties in the information from the ADM at local scales. Beneficial outcomes have been demonstrated in a few studies at local scales whereby changes in behavior based on forecast information brought about modest improvements in livelihoods; however, the complexity of socio-economic contexts ensures that the benefits are difficult to reap (e.g., Ingram et al. 2002; Luseno et al. 2003; Ziervogel and Calder 2003; Ziervogel et al. 2010; Roncoli et al. 2011). The potential at larger scales has yet to be realized (Tarhule and Lamb 2003; Patt et al. 2007; Webster and Jian 2011; Webster 2013) and requires concerted efforts to bridge the gap between the wealth of physical climate, water, and agricultural information and on-the-ground improvements in water and food security.

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