BAMS Article

The NASA Hydrological Forecast System for Food and Water Security Applications

Kristi R. Arsenault, Shraddhanand Shukla, Abheera Hazra, Augusto Getirana, Amy McNally, Sujay V. Kumar, Randal D. Koster, Christa D. Peters-Lidard, Benjamin F. Zaitchik, Hamada Badr, Hahn Chul Jung, Bala Narapusetty, Mahdi Navari, Shugong Wang, David M. Mocko, Chris Funk, Laura Harrison, Gregory J. Husak, Alkhalil Adoum, Gideon Galu, Tamuka Magadzire, Jeanne Roningen, Michael Shaw, John Eylander, Karim Bergaoui, Rachael A. McDonnell, and James P. Verdin

ABSTRACT: Many regions in Africa and the Middle East are vulnerable to drought and to water and food insecurity, motivating agency efforts such as the U.S. Agency for International Development's (USAID) Famine Early Warning Systems Network (FEWS NET) to provide early warning of drought events in the region. Each year these warnings guide life-saving assistance that reaches millions of people. A new NASA multimodel, remote sensing–based hydrological forecasting and analysis system, NHyFAS, has been developed to support such efforts by improving the FEWS NET's current early warning capabilities. NHyFAS derives its skill from two sources: (i) accurate initial conditions, as produced by an offline land modeling system through the application and/or assimilation of various satellite data (precipitation, soil moisture, and terrestrial water storage), and (ii) meteorological forcing data during the forecast period as produced by a state-of-the-art ocean–land–atmosphere forecast system. The land modeling framework used is the Land Information System (LIS), which employs a suite of land surface models, allowing multimodel ensembles and multiple data assimilation strategies to better estimate land surface conditions. An evaluation of NHyFAS shows that its 1–5-month hindcasts successfully capture known historic drought events, and it has improved skill over benchmark-type hindcasts. The system also benefits from strong collaboration with end-user partners in Africa and the Middle East, who provide insights on strategies to formulate and communicate early warning indicators to water and food security communities. The additional lead time provided by this system will increase the speed, accuracy, and efficacy of humanitarian disaster relief, helping to save lives and livelihoods.

https://doi.org/10.1175/BAMS-D-18-0264.1
Corresponding author: Kristi R. Arsenault, kristi.r.arsenault@nasa.gov
In final form 7 November 2019

AFFILIATIONS: **Arsenault, Wang, and Mocko**—NASA Goddard Space Flight Center, Greenbelt, Maryland, and Science Applications International Corporation, Reston, Virginia; **Shukla**—Climate Hazards Center, University of California, Santa Barbara, Santa Barbara, California; **Hazra and Getirana**—NASA Goddard Space Flight Center, Greenbelt, and Earth System Science Interdisciplinary Center, University of Maryland, College Park, College Park, Maryland; **McNally**—NASA Goddard Space Flight Center, Greenbelt, Maryland, and Science Applications International Corporation, Reston, Virginia, and Office of Food for Peace, U.S. Agency for International Development, Washington, D.C.; **Kumar, Koster, and Peters-Lidard**—NASA Goddard Space Flight Center, Greenbelt, Maryland; **Zaitchik and Badr**—Department of Earth and Planetary Sciences, The Johns Hopkins University, Baltimore, Maryland; **Jung**—NASA Goddard Space Flight Center, Greenbelt, and Science Systems and Applications, Inc., Lanham, Maryland; **Narapusetty**—INNOVIM, NOAA/Climate Prediction Center, College Park, Maryland; **Navari**—Earth System Science Interdisciplinary Center, University of Maryland, College Park, College Park, Maryland; **Funk**—Center for Earth Resources Observations and Science, U.S. Geological Survey, Sioux Fall, South Dakota, and Climate Hazards Center, University of California, Santa Barbara, Santa Barbara, California; **Harrison and Husak**—Climate Hazards Center, University of California, Santa Barbara, Santa Barbara, California; **Adoum**—Famine Early Warning Systems Network, Niamey, Niger, and Climate Hazards Center, University of California, Santa Barbara, Santa Barbara, California; **Galu**—Famine Early Warning Systems Network, Nairobi, Kenya, and Climate Hazards Center, University of California, Santa Barbara, Santa Barbara, California; **Magadzire**—Famine Early Warning Systems Network, Gaborone, Botswana, and Climate Hazards Center, University of California, Santa Barbara, Santa Barbara, California; **Roningen**—New Hampshire Department of Information Technology, Concord, and Cold Regions Research and Engineering Laboratory, Engineer Research and Development Center, U.S. Army Corps of Engineers, Hanover, New Hampshire; **Shaw and Eylander**—Cold Regions Research and Engineering Laboratory, Engineer Research and Development Center, U.S. Army Corps of Engineers, Hanover, New Hampshire; **Bergaoui**—International Center for Biosaline Agriculture, Dubai, United Arab Emirates, and National Institute of Meteorology, Tunis, Tunisia; **McDonnell**—International Water Management Institute, Rome, Italy; **Verdin**—Office of Food for Peace, U.S. Agency for International Development, Washington, D.C.

Many regions around the globe are susceptible to recurring drought conditions that can cause socioeconomic losses, environmental degradation, displacement, or loss of life. Failure to adequately prepare for and respond to droughts has increased the number of food-insecure people since 2015 (UN 2018). In drought-vulnerable parts of Africa and the Middle East, these events contribute to significant food and water insecurity, undermining political stability and advances made in poverty reduction (Vörösmarty et al. 2005). According to the global Emergency Events Database (CRED 2019), since 2015, Africa has experienced 21 droughts, affecting 50 million people. To support early warning efforts and mitigate adverse impacts of food and water insecurity, a recent National Aeronautics and Space Administration (NASA) supported effort, known as the Forecasting for Africa and the Middle East (FAME) project, partnered with U.S. Agency for International Development's (USAID) Famine Early Warning Systems Network (FEWS NET; Verdin et al. 2005; Funk et al. 2019) and other agencies and universities to develop a hydrologic forecasting system. This new NASA hydrological forecast and analysis system (NHyFAS) makes use of NASA's satellite, data assimilation, and modeling capabilities, as well as regional expertise from partners. Here we describe the development, evaluation, implementation, and transition from research to operations of this system. Examples are provided of the system's application to drought forecasts in southern Africa and to forecasting flood risk in Kenya.

The NHyFAS hydrologic forecasting system has three novel attributes: (i) the application of advanced observational and reanalysis-based datasets; (ii) seasonal hydrological forecasts initialized with remotely sensed data; and (iii) a partnership with FEWS NET to facilitate the move to operations as well as into monitoring schemes for food, water, and energy security. NHyFAS also includes a flexible framework to support additional operational features, such as different climate seasonal forecast datasets and even medium-range to subseasonal forecasts. To help with integration of NHyFAS outputs into operations, FEWS NET partners are being trained on the products and are providing feedback through collaborative discussions.

NASA has a long history of contributing to early warning systems (McNally et al. 2019a), beginning with the use of remotely sensed datasets, such as the normalized difference vegetation index (NDVI; e.g., Tucker and Sellers 1986; Anyamba and Tucker 2012), and more recently with the development of the FEWS NET Land Data Assimilation System (FLDAS; McNally et al. 2017). FLDAS combines observational precipitation with atmospheric reanalysis to drive advanced land surface models (LSMs) for both long-term and near-real-time monitoring of hydrological conditions contributing to drought. This accordingly provides FEWS NET with spatial and temporal estimates of drought indicators with relevance to water and food availability (e.g., through declined crop production), livestock, and livelihoods. FEWS NET has a high-priority demand for hydrologic monitoring and forecasting products to support food security outlooks (e.g., Funk et al. 2019; McNally et al. 2019a).

While routine hydrologic monitoring is a powerful tool for early warning, reliance on monitoring alone limits the timeliness of early warning efforts. Past research has shown the potential for seasonal-scale hydrologic forecasts (e.g., Wood et al. 2002; Luo and Wood 2007, 2008; Sheffield et al. 2014; Shukla et al. 2014) to extend the lead time at which early warning of droughts and resulting food security events can be provided. Given this potential, FEWS NET has made hydrologic forecasts a high priority, leading to the development of the forecasting system described herein. This forecasting effort benefits from a close relationship between the NASA Global Modeling and Assimilation Office (GMAO) and the NASA Land Information System (LIS) team, the former providing state-of-the-art dynamical seasonal forecasts and the latter translating those forecasts into hydrologic forecasts with a state-of-the-art land surface modeling system.

For successful transition of research to operations, engagement with end-users and regional expertise are essential. For NHyFAS, FEWS NET's regional experts in Africa and the Middle East are receiving guidance about the products to help facilitate their use in operational applications. Due to a paucity of in situ data to support system development and evaluation in these regions (e.g., Getirana et al. 2015; James et al. 2018), the close relationship with FEWS NET experts helps with verifying current local conditions when observations are not available. This can be particularly useful for identifying system accuracy in forecasting extreme events. In addition to facilitate uptake by FEWS NET monitoring experts, the inputs for the model were selected from those that are already in the FEWS NET data streams. An example of this is that NHyFAS is driven with the Climate Hazards Infrared Precipitation with Stations (CHIRPS; Funk et al. 2015) rainfall product, which is widely used for estimating precipitation over the FEWS NET regions. A number of studies have compared CHIRPS to stations and other satellite-based estimates, with CHIRPS performing favorably over many spatial and temporal domains (e.g., Funk et al. 2015; Jung et al. 2017; Dinku et al. 2018).

Importantly, the development of NHyFAS, described herein, entailed a significant amount of basic research given that the full suite of available data and analysis tools used in the system is relatively new and is not being utilized in current operational efforts. One of the key advancements provided by the new operational system is the ingestion, through data assimilation, of satellite data for improved hydrological-state initialization, which is critical for useful hydrological forecasts. Another advancement over existing systems in Africa is that NHyFAS supports a multimodel approach. Several studies have shown the added skill of multimodel ensembles over individual models, especially in terms of soil moisture (e.g., Guo et al. 2007; Xia et al. 2014), streamflow (e.g., Sharma et al. 2019), and drought detection (e.g., Wang et al. 2009; Mo et al. 2011). This work presents a new multi-LSM seasonal forecast system that uses NASA's models, satellite data, and tools and is set up specifically for continental Africa and the Middle East. Through data assimilation and a multimodel approach we are able to provide a variety of forecasted hydrological variables, including soil moisture (SM), terrestrial water storage (TWS), streamflow, and drought indices for end-user partners such as the FEWS NET community.

The basis for providing skillful seasonal hydrologic forecasts

Seasonal forecasts have been produced and evaluated for different regions in Africa (e.g., Yuan et al. 2013), with various studies focusing on meteorological drought (e.g., Dutra et al. 2013), agricultural drought (e.g., Shukla et al. 2014), crop yields (e.g., Sultan et al. 2010), and hydrological resources (e.g., Trambauer et al. 2015; Seibert et al. 2017). Current operational efforts that produce seasonal dynamical forecasts of temperature and precipitation include NOAA's North American Multi-Model Ensemble (NMME; Kirtman et al. 2014). NASA SERVIR ClimateSERV downscaled NMME forecasts are provided for different continental (e.g., Africa) and oceanic (e.g., Indian Ocean) regions (https://climateserv.servirglobal.net; Flores Cordova et al. 2012). Also, the Global Flood Awareness System (GloFAS; Emerton et al. 2018) provides routine, global 30-day and seasonal flood forecasts using land surface and calibrated hydrological routing models.

More specific to Africa, operational drought forecasts include application of subseasonal to seasonal meteorological forecasts via NOAA (Thiaw and Kumar 2015), FEWS NET, and formerly the Drought Early Warning and Forecasting in Africa (i.e., DEWFORA; Dutra et al. 2014a,b), which provided forecasted meteorological drought estimates [i.e., standardized precipitation index (SPI)]. For hydrological forecasts, Yuan et al. (2013) and Sheffield et al. (2014) developed an Africa-wide hydrological seasonal forecast system as part of the Princeton University African Flood and Drought Monitor (AFDM; Sheffield et al. 2014), which in the past was driven using NOAA's Climate Forecast System, version 2 (CFSv2; Saha et al. 2014) but is currently using the Canadian Centre for Climate Modeling and Analysis Coupled Climate Model (Merryfield et al. 2013). However, there still remains a lack of operationally based, drought-focused seasonal forecast systems for the African continent and the Middle East that routinely support food and water security (Wolski et al. 2017).

The ability to forecast extreme hydrological events, such as drought, is naturally constrained by the limited skill of general circulation model (GCM) forecasts, especially of precipitation at seasonal time scales (e.g., Li et al. 2008; Lavers et al. 2009; Narapusetty et al. 2018). Errors in such forecasts can be mitigated somewhat through the use of multimodel forecast ensembles (e.g., Krishnamurti et al. 2000), and this can translate to improved drought or flood potential forecast skill (e.g., Shukla et al. 2019). There are, however, fundamental limits to the forecast skill that can be attained (NRC 2010).

Seasonal hydrological forecasts are also influenced by initial hydrological conditions (IHCs), which relate to model states such as soil moisture (e.g., Maurer and Lettenmaier 2003; Shukla and Lettenmaier 2011) and snow water equivalent (e.g., Mahanama et al. 2012). Impacts of the IHCs on hydrological forecasts can vary depending on geographical location and season (e.g., Li et al. 2009) and on how extreme the IHCs are (e.g., Wood et al. 2002). Improving the IHCs can potentially increase the skill of drought forecasts (e.g., Shukla et al. 2013).

Several studies have explored assimilating remotely sensed measurements, such as snow and soil moisture, into LSMs to improve hydrological forecast initial conditions (e.g., DeChant and Moradkhani 2011; Liu et al. 2015; Lin et al. 2016). However, one IHC state that is relatively unexplored in the context of drought and flood potential forecasts is terrestrial water storage (TWS), which is particularly relevant for the hydrological prediction of groundwater (Wanders et al. 2019), especially for large river basins (Yossef et al. 2013). Reager et al. (2014) demonstrated the potential of using remotely sensed TWS estimates from NASA's Gravity Recovery and Climate Experiment (GRACE) satellites for flood prediction in select U.S. river basins. Also, Lin et al. (2016) noted that assimilated GRACE TWS used as IHCs improved seasonal temperature predictions in higher latitudes. Thus, assimilating GRACE TWS into state-of-the-art LSMs with groundwater representation may also better capture initial groundwater conditions for forecasting drought conditions.

The Hydrological Forecast System

Background. Starting in 2015, scientists at NASA's Goddard Space Flight Center (GSFC); University of California, Santa Barbara (UCSB); University of Maryland (UMD), The Johns Hopkins University (JHU); U.S. Geological Survey (USGS); U.S. Army Corps of Engineers (USACE); and other international partners have supported a NASA-funded project referred to as Forecasting for Africa and the Middle East (FAME). That project was aimed at developing the early warning system, NHyFAS, to support proactive drought management efforts that could help mitigate related socioeconomic losses (e.g., from decreased food production) in areas such as Africa. This new forecast system would help to build on the main FEWS NET hydrologic monitoring system, FLDAS (McNally et al. 2017), by incorporating additional LSMs, satellite-based observations, data assimilation methods, and seasonal-scale forecasts from NASA's state-of-the-art seasonal forecast system [the Goddard Earth Observing System (GEOS) forecast system; Borovikov et al. 2019], which is a model member of the NMME seasonal forecast suite. NHyFAS features several data assimilation-based methods and a variety of satellite-based observations (soil moisture and TWS) that can be used to improve the system's IHCs. The overall system enhances FEWS NET's early warning capabilities by enabling regional experts to visualize the potential hydrologic impacts of forecasted precipitation. Components of the system also support other efforts, such as SERVIR's West Africa LDAS and Hindu Kush–Himalaya subseasonal to seasonal forecast system.

Figure 1 describes the overall workflow of NHyFAS and illustrates the multiple seasonal forecast components supported, including bias-corrected and spatially downscaled (BCSD) seasonal forecasted meteorological variables from the GMAO's GEOS model, ensemble streamflow prediction (ESP) forecast methods, and forecast initial conditions derived from historic and data assimilation–based simulations. This system utilizes satellite-based data along with well-known data assimilation methods, including the ensemble Kalman filter (EnKF) and the ensemble Kalman smoother (EnKS). New output fields are also provided by NHyFAS, including

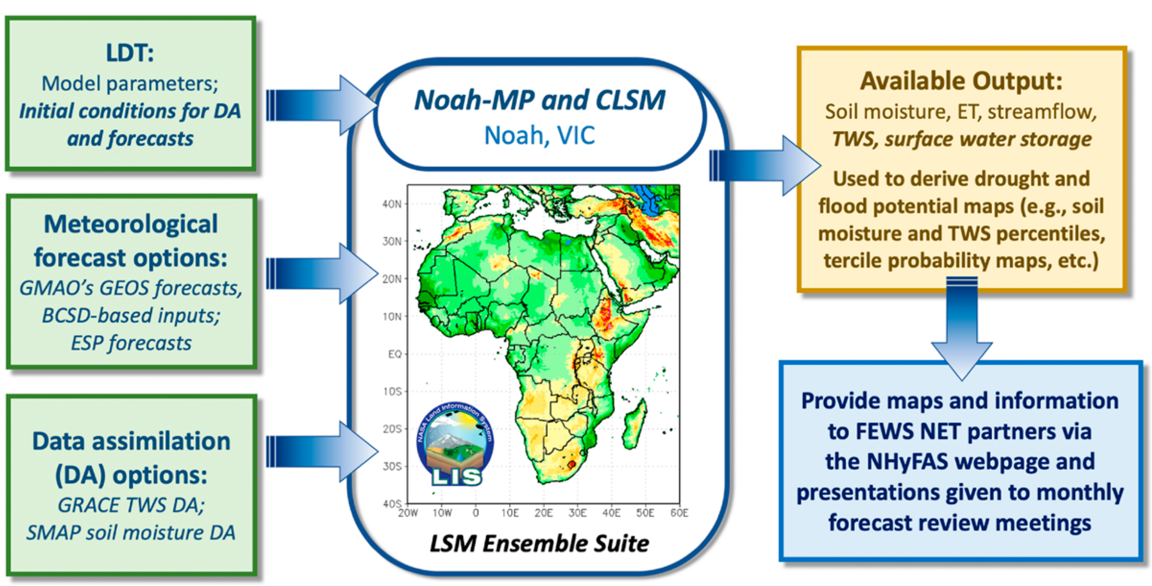

Fig. 1. Diagram highlighting the new hydrological forecast system elements, which include additional models, forecast features, data assimilation, and model outputs, helping to extend FLDAS monitoring support. Italicized words indicate newer features.

TWS generated by the two additional LSMs and surface water storage (SWS) as generated by a comprehensive routing scheme. Finally, examples of the product maps that are generated and provided to the FEWS NET partners are highlighted in the final box.

NASA land surface modeling tools. NHyFAS expands upon the FLDAS modeling framework, which used two LSMs [Noah (Ek et al. 2003) and the Variable Infiltration Capacity model (Liang et al. 1994)] to derive 30+ years of historic records and near-real-time hydrological and drought-related products (McNally et al. 2017; McNally et al. 2019b). For NHyFAS, we utilize two additional LSMs, each of which has representative groundwater schemes: Noah with multiparameterizations (Noah-MP; Niu et al. 2011) and NASA's Catchment LSM (CLSM; Koster et al. 2000). The overarching land modeling software framework is the Land Information System (LIS; Kumar et al. 2006; Peters-Lidard et al. 2007), a flexible framework that can be customized by users for their needs but also expanded to meet growing needs. NHyFAS serves as an instance of LIS. LIS also includes several of the LSMs mentioned above plus many others; it thus allows multimodel ensemble and multiple data assimilation strategies to better address land surface conditions such as drought. The LIS framework includes a wide array of available inputs via the Land Data Toolkit (LDT; Arsenault et al. 2018), and it provides multiple evaluation and drought metrics via the Land Verification Toolkit (LVT; Kumar et al. 2012). LIS also supports river routing schemes such as the Hydrological Modeling and Analysis Platform (HyMAP; Getirana et al. 2012, 2017a).

Meteorological and seasonal forecast input datasets. The LSMs in NHyFAS are used to generate historic simulations that span almost 40 years. This 40-yr period of record is critical for drought assessments. These simulations, also referred to as the open-loop (OL), use precipitation inputs from UCSB/USGS CHIRPS, version 2.0 (CHIRPS; Funk et al. 2015), and other meteorological inputs from NASA's Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-2; Bosilovich et al. 2016; Gelaro et al. 2017). Note that for monitoring and for producing forecast initial conditions, we use CHIRPS-prelim (Funk et al. 2015), since the reduced (3-day) latency of this product allows us to update the models closer to real time. The final CHIRPS product, at present, has about a 2-week latency. We use a 6-hourly CHIRPS product available from UCSB for the Africa continent domain. For the daily CHIRPS-prelim data, LDT is used to temporally downscale the daily data, making use of a dataset with higher temporal resolution (e.g., hourly MERRA-2 precipitation), as described in Arsenault et al. (2018). MERRA-2 data have about a 10-day latency, which is sufficient for seasonal climate forecast initialization and monitoring.

The meteorological forcing for the land models during the forecast period are derived from seasonal forecasts produced by the GMAO (Borovikov et al. 2019). We use these data since the GMAO system provides the full complement of required inputs (e.g., temperature, radiation, winds), whereas the NMME database only offers monthly precipitation and temperature. The GMAO seasonal forecasts consist of 10 ensemble members for real-time applications and various ensemble sizes for the hindcast period. For NHyFAS, the forecasts are bias-corrected and spatially downscaled (BCSD) using the MERRA-2 reference height forcing fields and CHIRPS for the precipitation, following the method outlined in Wood et al. (2004). The modification of the forecasts via the BCSD method has been evaluated and verified across most of Africa for NHyFAS.

To benchmark the impact of the GMAO meteorological forecasts and to provide additional hydrological forecast ensembles, a simple ESP type approach (Twedt et al. 1977; Day 1985; Yuan et al. 2015) is supported in LIS, arising from a climatology-based forecast method (e.g., Li et al. 2009; Yossef et al. 2017). The skill of the hydrological ESP forecast is derived solely from the IHCs. LIS generates the ensemble of ESP forecast members by using individual years from the historical MERRA-2 and CHIRPS meteorological data; thus, the 1982–2017 MERRA-2 data holdings allow us to produce 36 ESP ensemble members for a given forecast year. The realistic IHCs are derived from the individual LSMs' historic OL runs. NHyFAS-based real-time ESP forecasts are also generated for Africa as a whole.

Model setup and historical experiments. As in FLDAS, the CLSM and Noah-MP models used in NHyFAS were each spun up with two cycles of MERRA-2/CHIRPS forcing, with each cycle covering 1981–2016. We subsequently ran the land models for different Africa focus regions (e.g., southern Africa) and the entire continent at a 0.25° × 0.25° spatial resolution and 15-min model time step from 1981 to close to the present day.

Use of NASA satellite data for evaluation and assimilation. NASA's wide array of satellite-based products can be used to help evaluate the model forecasts in areas, like Africa, with limited surface observations. Also, assimilating such satellite data into the models prior to a forecast should improve IHCs and thus forecast skill. For NHyFAS, we use LIS's data assimilation framework that includes well-known assimilation methods (e.g., ensemble Kalman filter) to make optimal use of the satellite data.

For soil moisture data assimilation, LIS is able to assimilate several different soil moisture datasets, including NASA's Soil Moisture Active Passive (SMAP) satellite products (Kumar et al. 2019). SMAP has produced, since its launch in early 2015, estimates of surface soil moisture down to 5-cm depth at least once every 3 days (Entekhabi et al. 2014) and available within a few days of overpass time (O'Neill et al. 2018). SMAP also supports a range of applications, including drought monitoring (e.g., Mishra et al. 2017), crop growth (e.g., Sazib et al. 2018), and many other applications (Brown et al. 2013). Thus, as part of NHyFAS, we can assimilate SMAP data to enhance the modeling states and forecast initial conditions, using EnKF (e.g., Reichle et al. 2002; Kumar et al. 2019) and related bias correction methods (e.g., Reichle and Koster 2004).

LIS also supports the assimilation of TWS anomaly estimates from NASA's twin-based GRACE satellite (which was decommissioned in late 2017) and, currently, the GRACE follow-on (GRACE-FO) mission, which both measure changes in the gravity field largely related to variability and movement in land and water mass. Different groups, such as the University of Texas Center for Space Research (CSR) and the Jet Propulsion Laboratory (JPL), generate different products, including the latest mass concentration, or mascon products (e.g., Save et al. 2016; Wiese et al. 2016), which provide better TWS signal and reduced errors relative to earlier spherical harmonics–based products (e.g., Rowlands et al. 2010; Save et al. 2012; Scanlon et al. 2016).

The only current monitoring system that includes TWS drought estimates is the U.S. Drought Monitor (USDM) through the assimilation of GRACE TWS measurements into NASA's CLSM (Houborg et al. 2012). For NHyFAS, we assimilate GRACE TWS with a focus on the African continent and on forecast initial conditions, using the EnKS method described in Zaitchik et al. (2008) and Kumar et al. (2016).

End-to-end system description. The end-to-end system of NHyFAS is depicted in the Fig. 2 flow diagram. The model parameters, initial conditions, and satellite-based observational data processing are supported by LDT. Using LIS, the LSMs, along with the HyMAP routing scheme, are driven offline (not coupled to an atmospheric model) by observed and modeled atmospheric fields to produce the long-term, historic OL simulations (from 1981 to the present). The OL simulations are then used to initialize the data assimilation (DA) and forecast simulations. Also, the OL simulations are used as the basis for calculating hydrological extreme metrics, for example, soil moisture percentiles for agricultural drought. Satellite

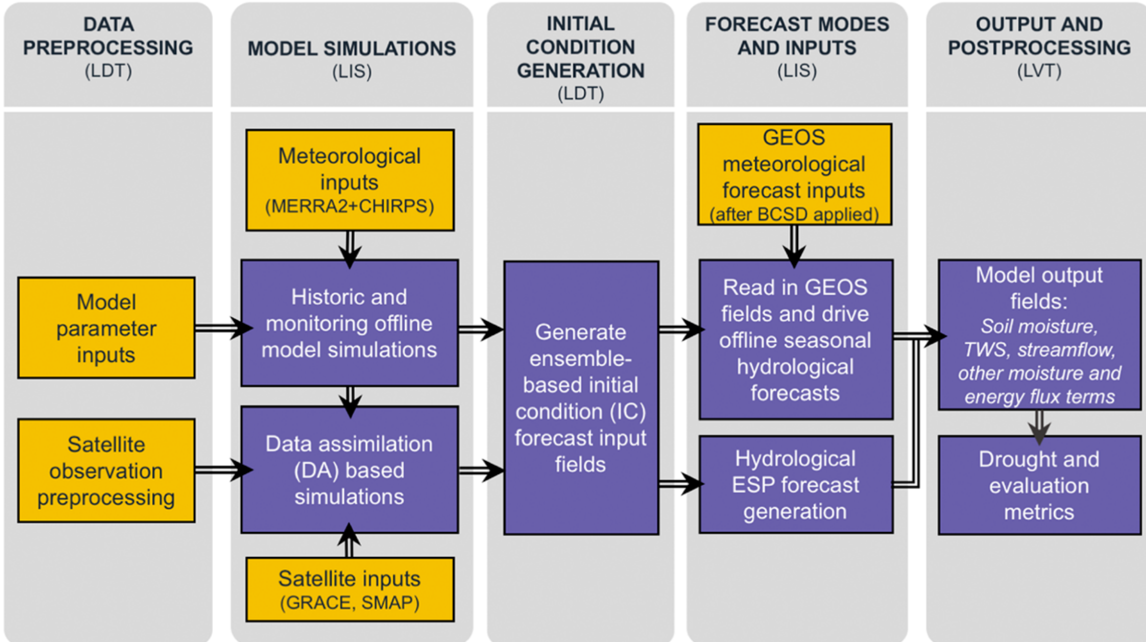

Fig. 2. The main NHyFAS flowchart of system components and data inputs. Yellow-highlighted boxes indicate the inputs to the various parts of the system, and the purple-highlighted boxes represent the different system components and outputs derived.

datasets such as GRACE TWS are assimilated via LIS to produce a blended analysis, one that should improve over the model or observations alone. These simulations are then processed to initialize the offline LSM forecast runs. A set of scripts is used to perform the BCSD step on the GCM-based meteorological forecasts, which are then ingested by LIS. The ESP forecasts are directly generated by LIS through the application of the MERRA2 and CHIRPS historical meteorological forcing datasets.

The LSMs in LIS produce estimates of terrestrial water and energy budget terms, including water fluxes (e.g., evapotranspiration, or ET) and storage (e.g., soil moisture). HyMAP produces streamflow, surface water extent, and storage in both rivers and floodplains, as well as several other stream-based dynamics and storage terms. LVT and other scripts use these output fields to generate different drought metrics, including SPI (McKee et al. 1993), soil moisture percentiles, and hydrological indices such as standardized runoff index (SRI; Shukla and Wood 2008). LVT also evaluates NHyFAS products against independent datasets (e.g., in situ soil moisture, satellite datasets) and produces various skill metrics (e.g., anomaly correlations, root-mean-square error).

Results and skill assessment

Capturing agricultural and hydrological drought events using TWS. CLSM and Noah-MP can capture changes in the various components of TWS, including groundwater, the soil moisture profile, snow, canopy water, and surface water storage (Getirana et al. 2017b). Of particular relevance to drought monitoring and forecasting is the fact that deeper moisture (e.g., groundwater) tends to show more persistence than soil moisture nearer the surface (e.g., Geruo et al. 2017), which reflects the slow-moving nature of agricultural drought.

To see how well the models recreate the overall spatiotemporal variability of past drought events in terms of TWS, we combined the two models' TWS fields and determined the areas in southern Africa for which the simulated TWS (for November–March, 1982/83–2015/16) exceeded different drought severity thresholds. Figure 3 presents the time series of monthly areal percentages for five TWS drought percentile categories and for six different southern

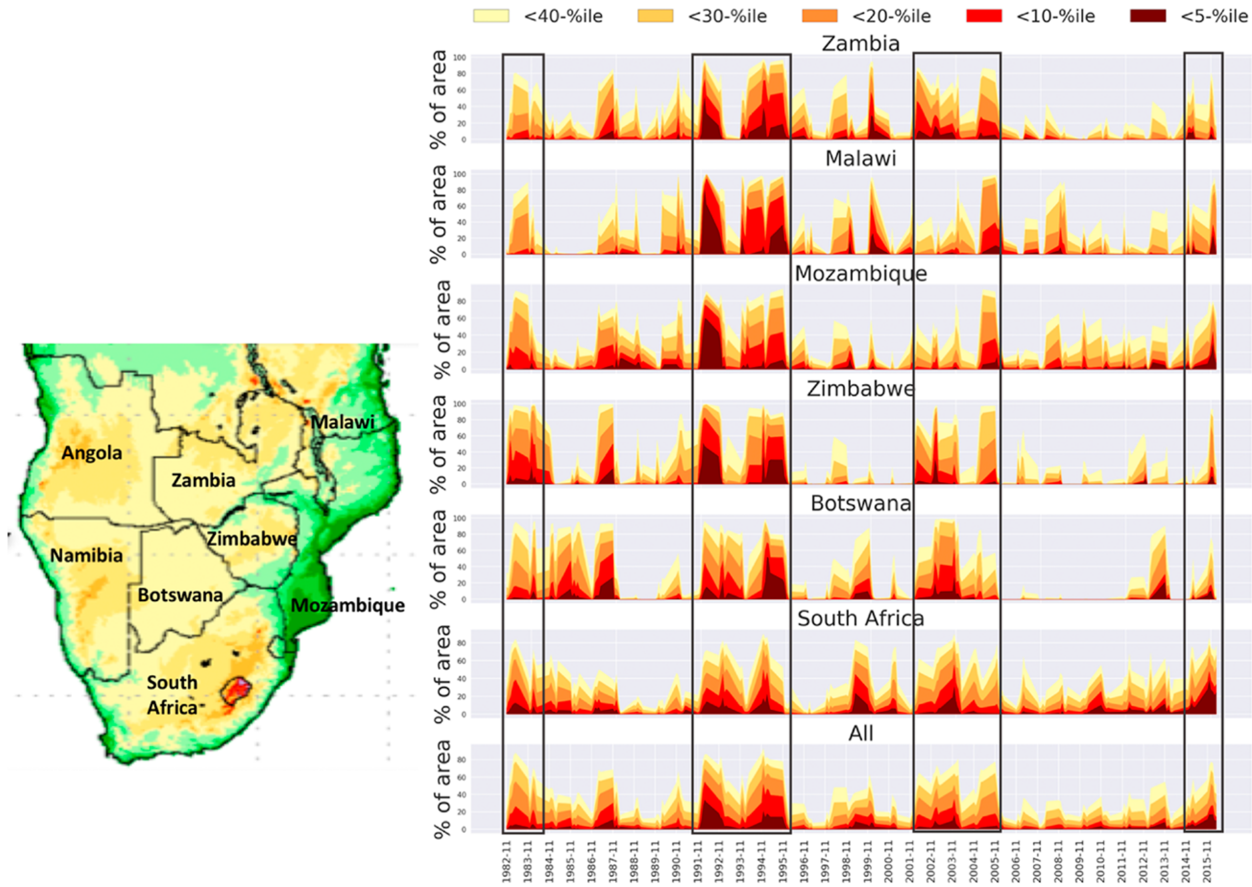

Fig. 3. Time series of percentages of area for each TWS drought percentile category and for each labeled country in southern Africa. Combined CLSM and Noah-MP based TWS are provided for different drought severity thresholds (e.g., 10th percentile) for November–March of each year from 1982/83 to 2015/16. Major drought years are highlighted with thin black boxes, and they include 1982–83, 1991–92, 1994–95, 2001–03, 2004–05, and 2015–16.

Africa countries (highlighted in the map in the lower left of the figure), along with the results for the full domain. Several drought periods, including several confirmed extreme events (e.g., 1982–83, 1994–95, 2004–05, and the more recent 2015–16 event; Pomposi et al. 2018), stand out clearly in the simulation results. The 1991–92 and 1994–95 drought events suggest severe dry conditions in the groundwater and soil moisture storage terms, with almost 60% to 80% of Zambia, Malawi, Mozambique, and Zimbabwe under the most extreme category of drought (e.g., Rouault and Richard 2005; Masih et al. 2014).

Skill of seasonal hydrological forecasts and contributions of initial conditions. Since few datasets are available in most African regions to evaluate NHyFAS forecasts, output from the OL historic runs are used as "truth," following the approach used in previous studies (e.g., Mo et al. 2012; Sheffield et al. 2014; Yuan et al. 2015). Additional validation data are derived from independent satellite-based products (e.g., SMAP soil moisture or satellite-based vegetation index products, like NDVI) as well as from available in situ streamflow observations.

Figure 4 presents the drought prediction skill of NHyFAS in relation to ESP and randomized forecasts. Following the models' drought detection ability highlighted in Fig. 3, the verification target is the percentage of area in different years (from the OL runs) for which TWS lies below two severity thresholds: the 5th and 20th percentiles of TWS (Figs. 4b,d and 4a,c, respectively). Forecast skill is measured as the RMSE of the forecasted percentage of area (for the combined Noah-MP and CLSM models) under the given level of drought severity. All forecasts were initialized on 1 November with states from the OL runs. The randomized forecasts are derived from reshuffled open-loop run data, using a Monte Carlo resampling approach.

The results are presented in such a way as to isolate, through differencing, the contributions of the initial conditions and the meteorological forecasts to the obtained skill. The top row effectively shows the impact of the initial conditions (Figs. 4a,b)—it shows the RMSE of the ESP hydrological forecasts, which derive skill solely from the initialized states, minus that associated with completely randomized forecasts (i.e., forecasts with zero skill, by construction). Red coloring indicates that skill is indeed obtained from the IHCs. For many regions, this skill improvement is shown to extend several months into the forecast. It must be kept in mind, however, that results in the top row may partially reflect the use of the OL runs as the validation data, given that the OL runs and the forecasts were produced using the same land surface models.

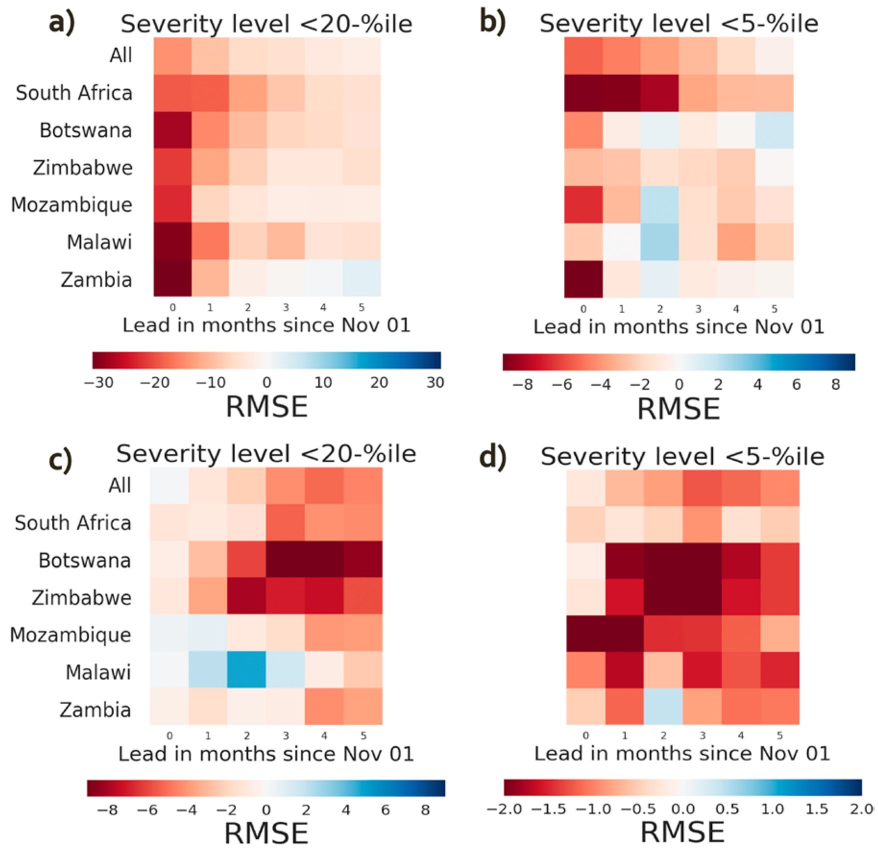

Fig. 4. Differences in RMSE for forecasting percentage area in drought (a),(b) between ESP and randomized forecasts and (c),(d) between the GEOS and ESP forecasts are shown for two drought severity thresholds: (a),(c) 20th and (b),(d) 5th percentiles of TWS. The TWS (for the combined Noah-MP and CLSM) forecasted percentage of area is presented for the different countries in southern Africa and over different lead months for the 1 Nov forecast. Red shows improvement over ESP, and blue shows degradation of skill relative to ESP.

The bottom row (Figs. 4c,d), which shows the RMSE of the full NHyFAS forecasts minus that of the ESP forecasts, isolates the skill derived from the meteorological forecasts (in this analysis, using version 1 of the GEOS system) and is accordingly more objective. Overall, the positive differences greatly outweigh the negative ones, indicating that the meteorological forecasts do provide true skill at seasonal leads, especially indicated for Botswana and Zambia (note the different color bar scale relative to the top row). The contributions from the meteorological forecasts are often larger later in the forecasts, that is, at a lead of 3–5 months. These results also help identify some sources of uncertainty in the system, related to the initial conditions (top row) and meteorological forcing (bottom row). Other uncertainty can relate to the model parameters and physics (not explored in this case).

The skill and performance of the NHyFAS forecasts are also evaluated with other metrics, including ranked correlation (R_{rank}) and equitable threat score (ETS). Figure 5 presents, for the first 5 months of both the bias-corrected GEOS (version 1) and ESP forecast runs initialized on 1 November, the correlation skill (Fig. 5a) and ETS (Fig. 5b) for the lowest tercile or below-normal events (<33rd percentile) for total-column soil moisture. The evaluated hindcast years cover the period 1982–2016. The correlation is calculated between the ensemble mean of the forecast anomaly and the corresponding OL field. The ETS metric is the fraction of "hits" occurring for a given event category (again, with the OL data representing truth) after adjusting for the number of hits that would be expected to occur simply by random chance

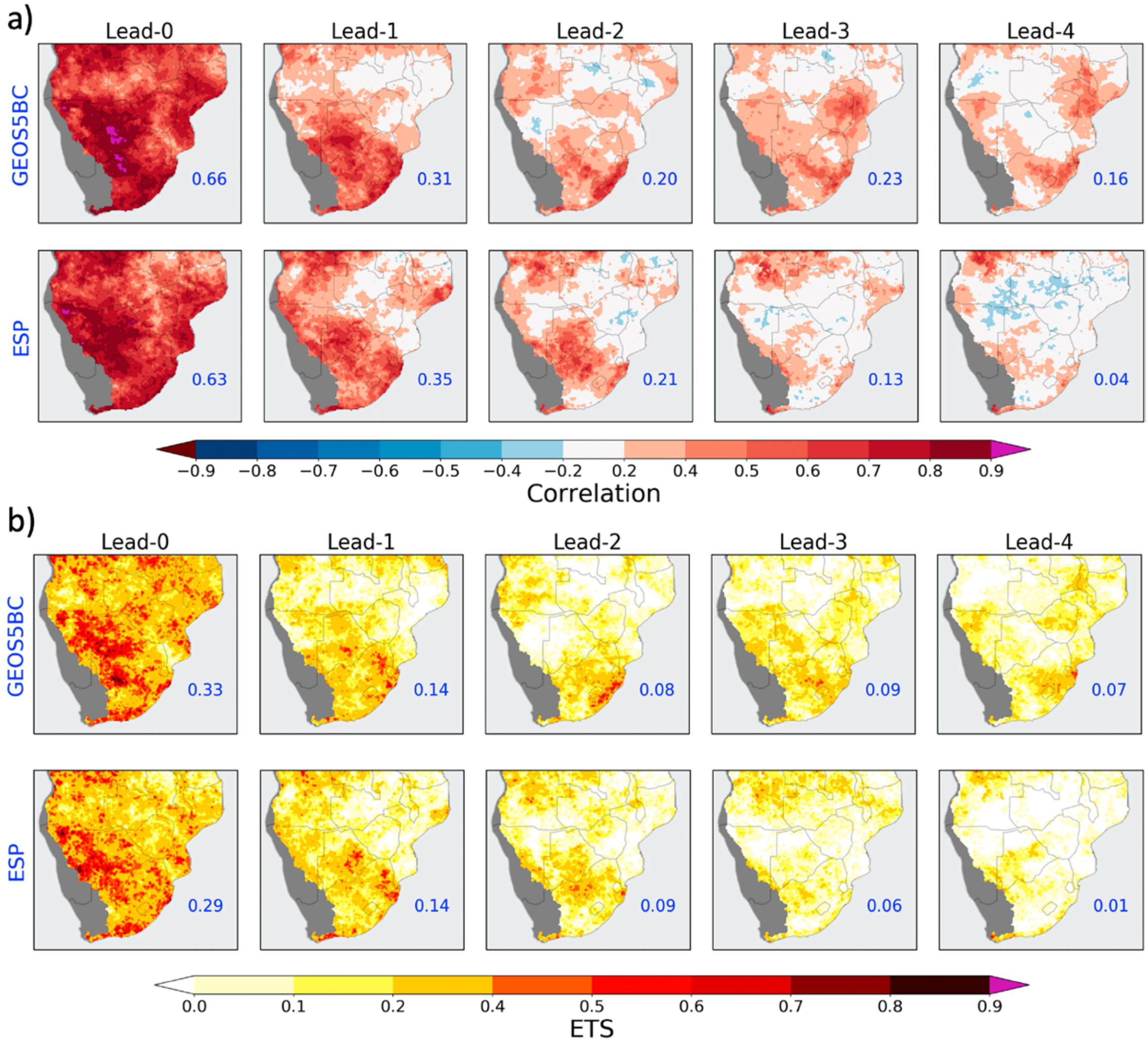

Fig. 5. Comparison of the bias-corrected GEOS with the ESP for 1 November initialized forecasts involving the two LSMs. Skill is shown in terms of (a) ranked correlation and (b) ETS for below-normal events (<33rd percentile), with respect to the OL historic simulations. Areas that receive less than 50 mm of total precipitation during the first three months of the season are masked out (shaded in gray) to allow us to focus mainly on the rainy season of the forecast period. Overall averaged skill values are shown in the lower-right corner of each panel.

(Shukla et al. 2019). Correlation and ETS values are higher for the bias-corrected GEOS forecasts in the first lead month (November) and again in lead months 3 and 4 (February and March), which may reflect the ability of GEOS to capture teleconnection influences on meteorological forcing, such as from El Niño–Southern Oscillation (ENSO; Borovikov et al. 2017). Also, overall averaged skill values are shown in the lower-right corner of each panel.

Figure 6 shows the spatially averaged skill (correlation and ETS) at lead 0–5 months for forecasts initialized on 1 March, 1 July, and 1 November, over the Africa entire domain (after screening for climatologically dry regions as in Fig. 5). The results show that the useful level of skill (>0.25 correlation and 0.1 ETS) exists through lead 3 months. The skill also tends to dissipate sharply after the first month, which highlights the need of at least monthly updates of these forecasts for informing decision-makers.

NHyFAS forecasts also have the potential to provide flood risk early warning. Figure 7 shows results for an extreme rainy period that resulted in several major floods throughout East Africa from March to May of 2018, causing loss of crops, displacement of several thousands of persons, and numerous casualties, especially in Kenya and southern Somalia. Shown on

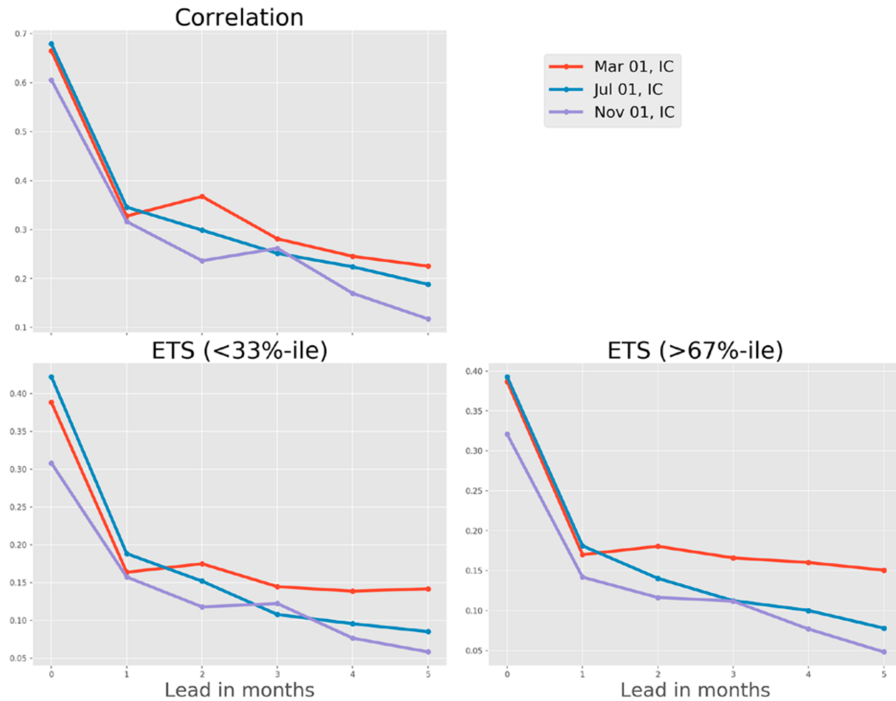

Fig. 6. Spatially averaged skill at lead 0–5 months for forecasts initialized on 1 March, 1 July, and 1 November, over the entire Africa domain (after screening for climatologically dry regions as in Fig. 5). (top left) Correlation, (bottom left) the ETS lower tercile, and (bottom right) ETS upper tercile of the GEOS-based forecasts are calculated against the OL as reference.

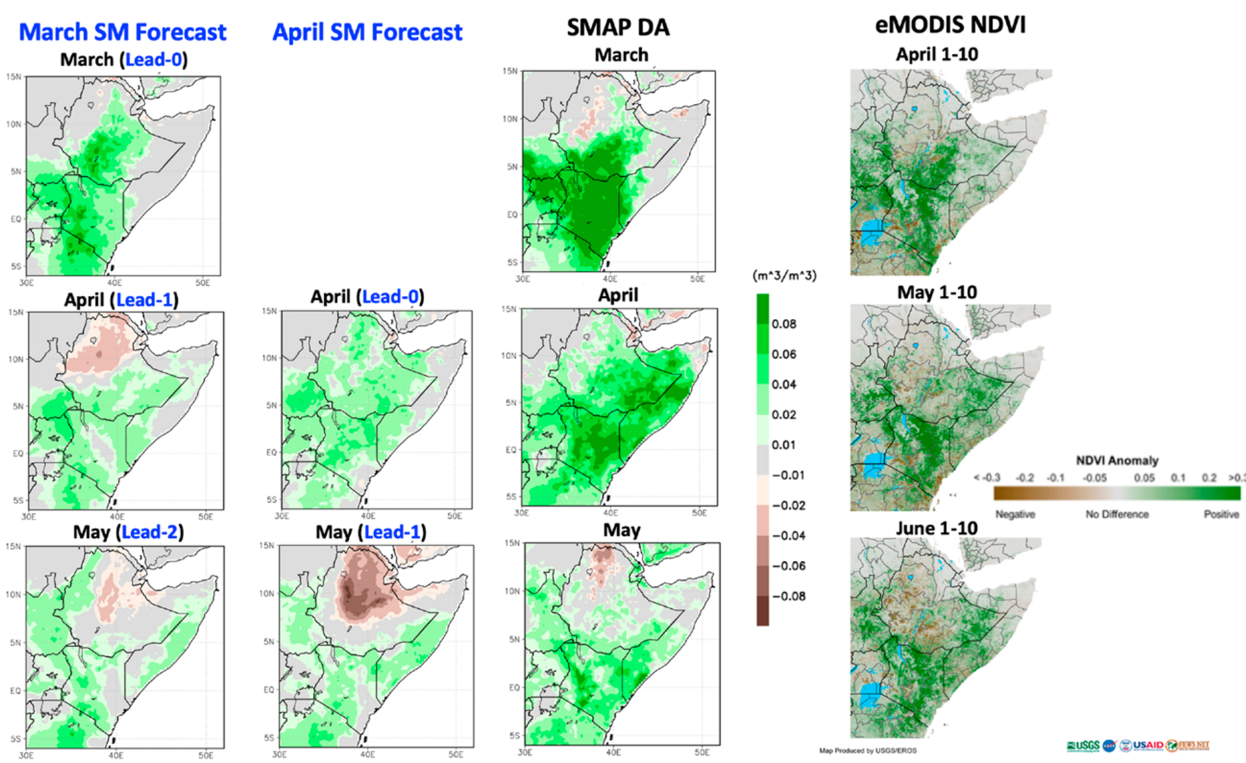

Fig. 7. The East African rainy season from March to May of 2018 experienced several flooding events, especially in Kenya and southern Somalia. The top-layer soil moisture anomalies from the Noah-MP GEOS-V2 forecast lead months, initialized on (first column) 1 March and (second column) 1 April , are compared against (third column) the monthly Noah-MP SMAP DA soil moisture (SM) anomalies and (fourth column) the eMODIS NDVI anomaly estimates from the subsequent month's first 10 days (or dekad). The GEOS forecasts are initialized with SMAP DA soil moisture states. All anomaly panels are calculated and shown as the anomaly relative to the median, based on the period 2003–17 due to availability of the eMODIS NDVI product.

the left are monthly anomalies (relative to 2003–17 median) of the top-layer soil moisture from NHyFAS forecasts, initialized on 1 March (first column) and on 1 April (second column). These particular forecasts used the Noah-MP model with SMAP data built into the IHCs through data assimilation. These forecast results are compared against the corresponding (nonforecast) Noah-MP results produced with SMAP data assimilation (third column) and against eMODIS NDVI (Swets et al. 1999) anomaly estimates (fourth column), which represent the subsequent month's first 10 days, to account for the time lag of vegetation growth relative to changes in soil moisture (e.g., Bolten and Crow 2012). The two forecasts capture much of the region's anomalous wet conditions over parts of Kenya and Ethiopia for April and into May. The drier conditions seen during May over northern Ethiopia with either forecast start date are also seen in the verification panels (third and fourth columns). This example shows that the forecast information could have provided advanced warning of higher-than-normal soil moisture conditions (and also higher-than-normal surface runoff conditions, not shown) in parts of East Africa, as well as the drying trends over northern Ethiopia by at least 1 lead month. Similar lead time skill was reported by Shukla et al. (2019) for this region and season in their seasonal forecast skill assessment.

Data assimilation in NHyFAS has the potential to improve forecasts. GRACE TWS assimilation has been shown to improve overall groundwater storages and drought metrics (e.g., Kumar et al. 2016; Li et al. 2019), especially in areas with high interannual precipitation variability. Earlier studies have shown how TWS, with its high persistence, can contribute to, for example, streamflow forecasts (Yossef et al. 2013; Reager et al. 2014; Getirana et al. 2020). The example in Fig. 8 highlights the impact of assimilated GRACE TWS on the forecast of the 2004–05 drought event in southern Africa. The top row in the figure shows CLSM with assimilation of GRACE TWS data (GRACE DA), showing drought conditions over this region. The middle row shows

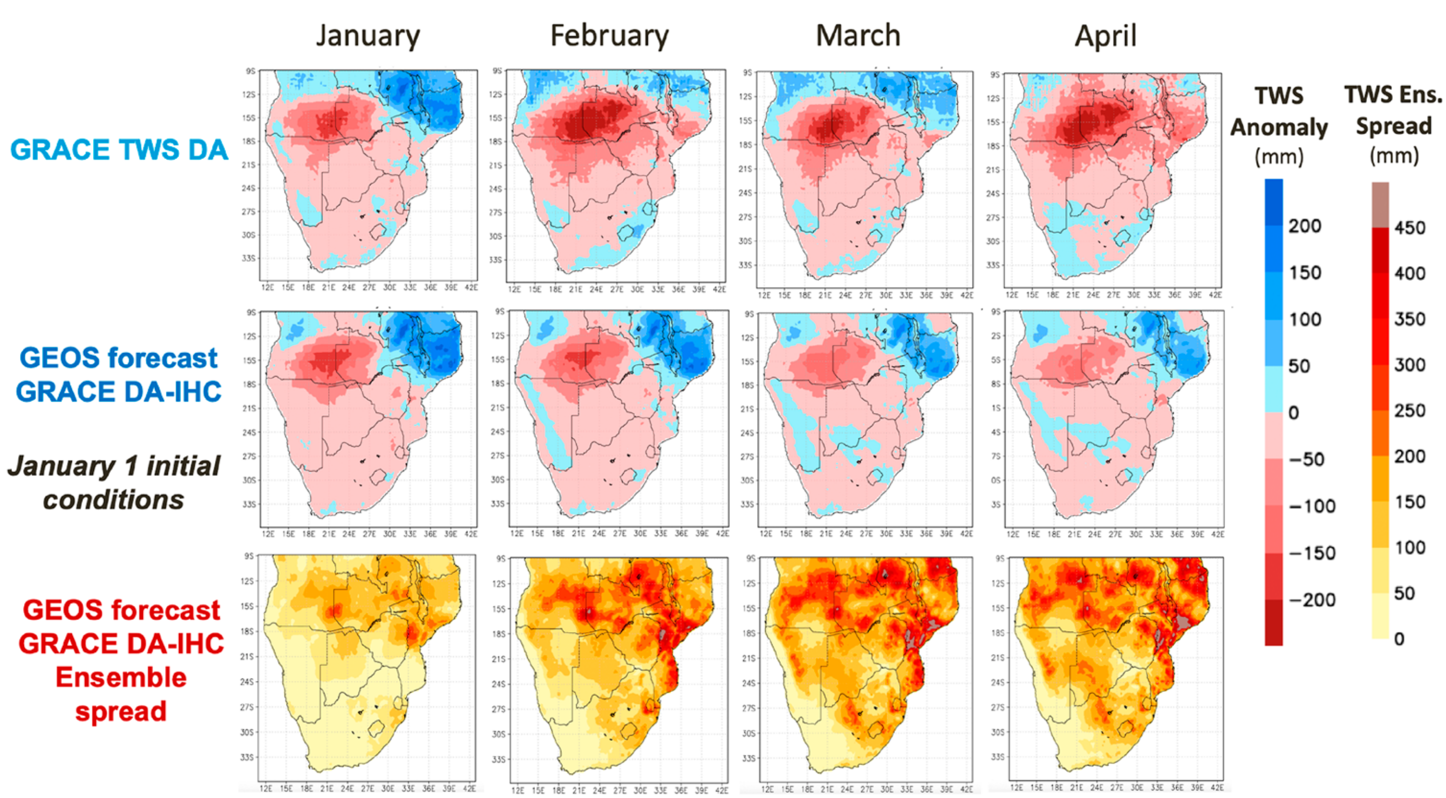

Fig. 8. TWS anomaly comparison is shown for the 2005 southern Africa drought for (top) the CLSM-based GRACE DA simulation with (middle) the GEOS hydrological forecasts, initialized with the GRACE DA hydrological state conditions on 1 January 2005. (bottom) The ensemble spread (difference between maximum and minimum ensemble members) of the GEOS-based TWS forecasts (from the middle row) for each lead month. The anomalies are calculated from a 2003–16 mean.

results from NHyFAS forecasts initialized on 1 January 2005, using the initial conditions taken from the GRACE DA simulation. The bottom row highlights the ensemble spread (differences in the maximum and minimum of the forecast ensemble members) for each lead month of the middle row. The TWS anomalies are calculated from a 2003–16 mean, which encompasses the main GRACE satellite data record. The GRACE DA–based initialization retains the TWS drought conditions over Angola and Zambia into March (lead month 2). The assimilation of the GRACE TWS anomaly data impacts the deeper soil moisture reservoir, and the anomaly is able to persist in the forecast period.

Operational application of drought and flood potential forecasts to support USAID's Famine Early Warning Systems Network Team

Effective humanitarian responses are typically motivated by staged alerts before, during, and after a growing season (Funk et al. 2019). This allows time to plan and implement effective assistance. FEWS NET's monthly food security outlook (FSO; Magadzire et al. 2017) process brings together African, Central American, and U.S. scientists who routinely monitor large-scale climate conditions and forecasts as well as on-the-ground conditions. On a monthly basis, the FSO process involves reviewing and revising a set of agroclimatological working assumptions that are used by FEWS NET food security analysts to develop scenarios of crop production and food insecurity for current and upcoming seasons (Magadzire et al. 2017; Funk et al. 2019). A team of FEWS NET regional scientists then use the monitoring and forecast products to comprehensively evaluate the statements about most likely seasonal precipitation performance. The team provides support using a convergence of evidence approach that incorporates precipitation forecasts ranging from several days to 8 months lead time, current state of conditions, and their working local knowledge of the regions. After a technical discussion, a summary and final revised assumptions are presented back to the food security analysts.

To help support the monthly FSO process, NHyFAS has been set up to target the needs and product delivery timeframe for FEWS NET regional scientists, providing forecasts prior to the time they review the agroclimatology assumptions. These hydrologic forecasts aid the current movement toward more detailed assumptions for crop and rangeland performance associated with recent and forecast weather conditions. We have routinely delivered hydrological forecasts that show agricultural drought and extreme moisture states, such as soil moisture percentiles and anomalies ahead of the monthly forecast review meetings. Figure 9a shows an example from the routine NHyFAS root-zone soil moisture percentile product, with July initial conditions (top-left plot) and combined Noah-MP+CLSM soil moisture seasonal forecasts (20 members in total, 10 for each model) for 1 August 2018 forecast. Regional plots are also provided for the primary African FEWS NET regions. The routine forecast products can be found at https://lis.gsfc.nasa.gov/projects/nhyfas. Probabilistic forecast maps have also been generated to include additional forecast types, like ESP, to isolate the forecast skill stemming from the initial conditions.

The FEWS NET regional scientists have been using the seasonal hydrological forecasts since August 2018. Figure 9b showcases a real example wherein FEWS NET's East Africa FSO science team utilized the September 2018 hydrological forecast to confirm other precipitation-based forecasts (left panel) and the FLDAS monitor's soil moisture rank conditions from August (right panel), which showed preexisting wet soil conditions that contributed to an elevated flood risk in Sudan. This information was used to update one of the agroclimatology assumptions for the region, which was then provided to the food analysts.

For this FEWS NET FSO process, NHyFAS provides a new operational resource for potential hydrologic and agricultural impact assessment. Since it merges recent precipitation and hydrological forecasts, it is uniquely suited for midseason outlooks for hydrologic drought as well as more positive outcomes, such as if sufficient soil moisture conditions are likely to persist and support normal or good crop production (Shukla et al., 2020). Furthermore, NHyFAS can directly assimilate GRACE TWS and SMAP soil moisture data, completely new sources of information for FEWS NET. Its modeling framework provides objective predictions of water supply and availability—outputs that can be directly validated and used in many

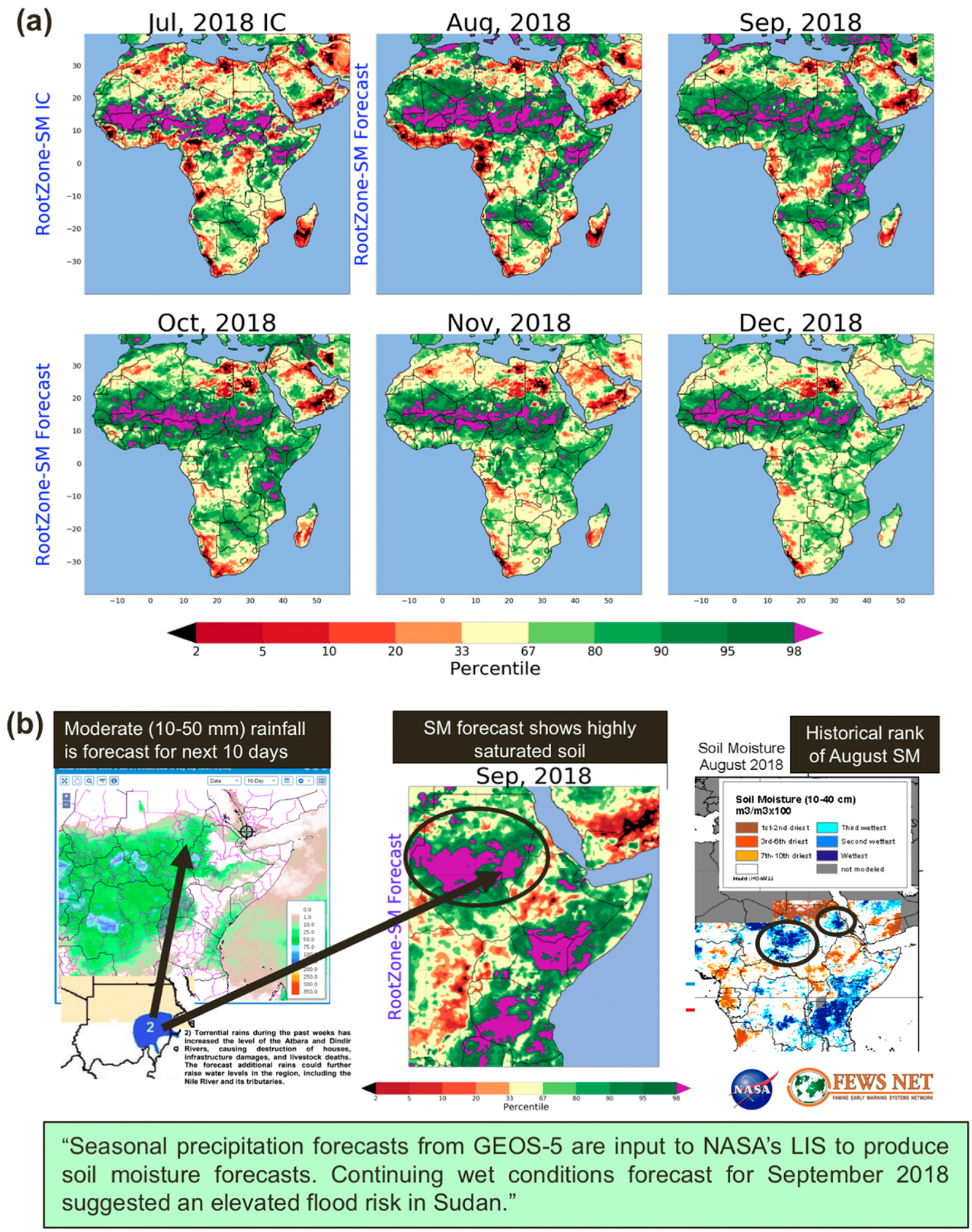

Fig. 9. (a) Example of routine NASA seasonal hydrologic forecast root-zone soil moisture percentile product, with (top left) July initial conditions and combined Noah-MP + CLSM soil moisture GEOS-V2 seasonal forecasts (20 members in total, 10 for each model) for the August 2018 forecast. (b) Real example case where FEWS NET regional scientists utilized the September forecast month to confirm other precipitation-based forecast and preexisting wet soil conditions, contributing to an elevated flood risk in Sudan.

applications and models, such as those used for estimating crop production, water stress, and water storage for hydropower. Continued synergy between FEWS NET partners and international collaborators will continue to explore these applications and how NHyFAS may augment existing resources for policy-makers in the region.

Summary and future directions

As the need for improved monitoring and prediction of water and food insecurity risks grows, the demands for more enhanced data networks and modeling systems to support these needs also grow. Unfortunately, such development is made challenging by the fact that available data networks are in decline in several regions of the world, especially in Africa and the Middle East.

To help address these needs, NASA over the years has provided several satellite- and model-based monitoring and forecast products that are available in near–real time over areas with little data availability. Here we describe a new operational early warning drought and hydrological system that utilizes several of these NASA modeling and data capabilities. Integrated into a full end-to-end system, this seasonal hydrological forecast system, NHyFAS, has been designed to support the early warning efforts through its provision of hydrological and agricultural drought monitoring and forecasts for USAID's FEWS NET and partners. NHyFAS provides FEWS NET regional scientists with important new information to help them better respond to food and water security outlooks and needs, and in turn the regional scientists provide feedback that can help improve NHyFAS. Different examples of the system's application in Africa were provided here to demonstrate its ability to detect and forecast major hydrological extremes. Different skill metrics show how well the system performs at different lead months for parts of southern Africa, especially when compared to benchmark forecasts, like ensemble streamflow prediction, and different drought periods. Also, example use cases were presented that demonstrated the system's ability for flood potential prediction in Eastern Africa and drought in southern Africa. NHyFAS products have been demonstrated as well to effectively support food insecurity early warning in the southern Africa region (Shukla et al., 2020).

Future plans for the system include the use of meteorological forecasts from additional seasonal forecasting systems, such as including other NMME forecast models. The current suite of LSMs can be expanded to take further advantage of the benefits of multimodel analyses. Also, NHyFAS can include more routine assimilation of the different satellite-based products, like SMAP soil moisture, and the latest GRACE follow-on TWS products. Currently, NHyFAS makes precipitation and soil moisture–based forecast products routinely available to the community; it has plans, however, to also provide additional products, such as streamflow, TWS, ET, and other diagnostics useful to end-users (e.g., water stress indices). These, along with other drought and flood-based products, will continue to provide support for USAID's FEWS NET as well as for other ongoing early warning systems and agencies' needs.

Acknowledgments. This work was supported by the NASA Earth Science Applications: Water Resources program, award 13-WATER13-0010 (PI: Peters-Lidard), and the FEWS NET's NASA PAPA Water Availability Monitoring Activity. We also acknowledge support to A. McNally from the NASA Harvest Consortium (NASA Applied Sciences Grant No. 80NSSC17K0625). Computing resources have been provided by NASA's Center for Climate Simulation (NCCS). We would like to acknowledge the many partners that were part of this effort, including from FEWS NET, USAID, ICBA, IWMI, USACE, and USGS, and others who helped provide valuable feedback to this paper, including Dr. Grey Nearing and three anonymous reviewers. We want to especially thank NASA's Global Modeling and Assimilation Office (GMAO) for their ongoing support of the MERRA-2 and GEOS datasets, Pete Peterson and the UCSB/CHC team for the CHIRPS dataset, the LIS team, and the multitude of teams supporting the land model development.

References

Anyamba, A., and C. J. Tucker, 2012: Historical perspectives on AVHRR NDVI and vegetation drought monitoring. *Remote Sensing of Drought: Innovative Monitoring Approaches*, B. D. Wardlow, M. C. Anderson, and J. P. Verdin, Eds., CRC Press, 23–49.

Arsenault, K. R., and Coauthors, 2018: The Land surface Data Toolkit (LDT v7.2)—A data fusion environment for land data assimilation systems. *Geosci. Model Dev.*, **11**, 3605–3621, https://doi.org/10.5194/gmd-11-3605-2018.

Bolten, J. D., and W. T. Crow, 2012: Improved prediction of quasi-global vegetation conditions using remotely-sensed surface soil moisture. *Geophys. Res. Lett.*, **39**, L19406, https://doi.org/10.1029/2012GL053470.

Borovikov, A., R. Cullather, R. Kovach, J. Marshak, G. Vernieres, Y. Vikhliaev, B. Zhao, and Z. Li, 2019: GEOS-5 seasonal forecast system. *Climate Dyn.*, **53**, 7335–7361, https://doi.org/10.1007/S00382-017-3835-2.

Bosilovich, M. G., R. Lucchesi, and M. Suarez, 2016: MERRA-2: File specification. GMAO Office Note 9 (version 1.1), 73 pp., https://gmao.gsfc.nasa.gov/pubs/docs/Bosilovich785.pdf.

Brown, M. E., V. Escobar, S. Moran, D. Entekhabi, P. E. O'Neill, E. G. Njoku, B. Doorn, and J. K. Entin, 2013: NASA's Soil Moisture Active Passive (SMAP) mission and opportunities for applications users. *Bull. Amer. Meteor. Soc.*, **94**, 1125–1128, https://doi.org/10.1175/BAMS-D-11-00049.1.

CRED, 2019: Emergency Events Database (EM-DAT). Centre for Research on the Epidemiology of Disasters, accessed 5 April 2019, www.emdat.be/emdat_db/.

Day, G., 1985: Extended streamflow forecasting using NWSRFS. *J. Water Resour. Plann. Manage.*, **111**, 157–170, https://doi.org/10.1061/(ASCE)0733-9496(1985)111:2(157).

DeChant, C. M., and H. Moradkhani, 2011: Improving the characterization of initial condition for ensemble streamflow prediction using data assimilation. *Hydrol. Earth Syst. Sci.*, **15**, 3399–3410, https://doi.org/10.5194/hess-15-3399-2011.

Dinku, T., C. Funk, P. Peterson, R. Maidment, T. Tadesse, H. Gadain, and P. Ceccato, 2018: Validation of the CHIRPS satellite rainfall estimates over eastern Africa. *Quart. J. Roy. Meteor. Soc.*, **144**, 292–312, https://doi.org/10.1002/qj.3244.

Dutra, E., F. Di Giuseppe, F. Wetterhall, and F. Pappenberger, 2013: Seasonal forecasts of droughts in African basins using the standardized precipitation index. *Hydrol. Earth Syst. Sci.*, **17**, 2359–2373, https://doi.org/10.5194/hess-17-2359-2013.

——, F. Wetterhall, F. Di Giuseppe, G. Naumann, P. Barbosa, J. Vogt, W. Pozzi, and F. Pappenberger, 2014a: Global meteorological drought—Part I: Probabilistic monitoring. *Hydrol. Earth Syst. Sci.*, **18**, 2657–2667, https://doi.org/10.5194/hess-18-2657-2014.

——, and Coauthors, 2014b: Global meteorological drought—Part II: Seasonal forecasts. *Hydrol. Earth Syst. Sci.*, **18**, 2669–2678, https://doi.org/10.5194/hess-18-2669-2014.

Ek, M. B., K. E. Mitchell, Y. Lin, E. Rogers, P. Grunmann, V. Koren, G. Gayno, and J. D. Tarpley, 2003: Implementation of Noah land surface model advances in the National Centers for Environmental Prediction operational mesoscale Eta model. *J. Geophys. Res.*, **108**, 8851, https://doi.org/10.1029/2002JD003296.

Emerton, R., and Coauthors, 2018: Developing a global operational seasonal hydro-meteorological forecasting system: GloFAS-seasonal v1.0. *Geosci. Model Dev.*, **11**, 3327–3346, https://doi.org/10.5194/gmd-11-3327-2018.

Entekhabi, D., and Coauthors, 2014: SMAP Handbook Soil Moisture Active Passive: Mapping soil moisture and freeze/thaw from space. JPL CL14-2285, JPL Publ. 400-1567, Jet Propulsion Laboratory, 180 pp., https://smap.jpl.nasa.gov/system/internal_resources/details/original/178_SMAP_Handbook_FINAL_1_JULY_2014_Web.pdf.

Flores Cordova, A. I., E. R. Anderson, D. Irwin, and E. A. Cherrington, 2012: Contributions of SERVIR in promoting the use of space data in climate change and disaster management. *Proc. 63rd Int. Astronautical Congress*, Naples, Italy, International Astronautical Federation, IAC-12-E3.2.3 x14456, https://iafastro.directory/iac/archive/browse/IAC-12/E3/2/14456/.

Funk, C., and Coauthors, 2015: The climate hazards infrared precipitation with stations—A new environmental record for monitoring extremes. *Sci. Data*, **2**, 150066, https://doi.org/10.1038/sdata.2015.66.

——, and Coauthors, 2019: Recognizing the Famine Early Warning Systems Network (FEWS NET): Over 30 years of drought early warning science advances and partnerships promoting global food security. *Bull. Amer. Meteor. Soc.*, **100**, 1011–1027, https://doi.org/10.1175/BAMS-D-17-0233.1.

Gelaro, R., and Coauthors, 2017: The Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-2). *J. Climate*, **30**, 5419–5454, https://doi.org/10.1175/JCLI-D-16-0758.1.

Geruo, A., I. Velicogna, J. S. Kimball, J. Du, Y. Kim, A. Colliander, and E. Njoku, 2017: Satellite-observed changes in vegetation sensitivities to surface soil moisture and total water storage variations since the 2011 Texas drought. *Environ. Res. Lett.*, **12**, 054006, https://doi.org/10.1088/1748-9326/aa6965.

Getirana, A., A. McNally, J. Roningen, B. Zaitchik, K. Arsenault, H. C. Jung, and C. Peters-Lidard, 2015: Forecasting water availability in data sparse and heavily managed catchments in Africa and the Middle East. *GEWEX News*, Vol. 27, No. 4, International GEWEX Project Office, Silver Spring, MD, 8–11, www.gewex.org/gewex-content/files_mf/1447702455Nov2015GEWEXNewsletter.pdf.

——, C. Peters-Lidard, M. Rodell, and P. D. Bates, 2017a: Trade-off between cost and accuracy in large-scale surface water dynamic modelling. *Water Resour. Res.*, **53**, 4942–4955, https://doi.org/10.1002/2017WR020519.

——, S. Kumar, M. Girotto, and M. Rodell, 2017b: Rivers and floodplains as key components of global terrestrial water storage variability. *Geophys. Res. Lett.*, **44**, 10 359–10 368, https://doi.org/10.1002/2017GL074684.

——, A. Boone, D. Yamazaki, B. Decharme, F. Papa, and N. Mognard, 2012: The Hydrological Modeling and Analysis Platform (HyMAP): Evaluation in the Amazon basin. *J. Hydrometeor.*, **13**, 1641–1665, https://doi.org/10.1175/JHM-D-12-021.1.

——, H. C. Jung, K. R. Arsenault, S. Shukla, S. V. Kumar, C. D. Peters-Lidard, I. Maigari, and B. Mamane, 2020: Satellite gravimetry improves seasonal streamflow forecast initialization in Africa. *Water Resour. Res.*, **56**, e2019WR026259, https://doi.org/10.1029/2019WR026259.

Guo, Z., P. A. Dirmeyer, X. Gao, and M. Zhao, 2007: Improving the quality of simulated soil moisture with a multi-model ensemble approach. *Quart. J. Roy. Meteor. Soc.*, **133**, 731–747, https://doi.org/10.1002/qj.48.

Houborg, R., M. Rodell, B. Li, R. Reichle, and B. Zaitchik, 2012: Drought indicators based on model-assimilated Gravity Recovery and Climate Experiment (GRACE) terrestrial water storage observations. *Water Resour. Res.*, **48**, W07525, https://doi.org/10.1029/2011WR011291.

James, R., and Coauthors, 2018: Evaluating climate models with an African lens. *Bull. Amer. Meteor. Soc.*, **99**, 313–336, https://doi.org/10.1175/BAMS-D-16-0090.1.

Jung, H. C., A. Getirana, F. Policelli, A. McNally, K. R. Arsenault, S. Kumar, T. Tadesse, and C. D. Peters-Lidard, 2017: Upper Blue Nile basin water budget from a multi-model perspective. *J. Hydrol.*, **555**, 535–546, https://doi.org/10.1016/j.jhydrol.2017.10.040.

Kirtman, B., and Coauthors, 2014: The North American Multi-Model Ensemble: Phase-1 seasonal-to-interannual prediction; Phase-2 toward developing intraseasonal prediction. *Bull. Amer. Meteor. Soc.*, **95**, 585–601, https://doi.org/10.1175/BAMS-D-12-00050.1.

Koster, R. D., M. J. Suarez, A. Ducharne, M. Stieglitz, and P. Kumar, 2000: A catchment based approach to modeling land surface processes in a general circulation model: 1. Model structure. *J. Geophys. Res.*, **105**, 24 809–24 822, https://doi.org/10.1029/2000JD900327.

Krishnamurti, T. N., C. M. Kishtawal, Z. Zhang, T. LaRow, D. Bachiochi, E. Williford, S. Gadgil, and S. Surendran, 2000: Multimodel ensemble forecasts for weather and seasonal climate. *J. Climate*, **13**, 4196–4216, https://doi.org/10.1175/1520-0442(2000)013<4196:MEFFWA>2.0.CO;2.

Kumar, S., and Coauthors, 2006: Land information system: An interoperable framework for high resolution land surface modeling. *Environ. Modell. Software*, **21**, 1402–1415, https://doi.org/10.1016/j.envsoft.2005.07.004.

——, C. D. Peters-Lidard, J. Santanello, K. Harrison, Y. Liu, and M. Shaw, 2012: Land surface Verification Toolkit (LVT) - A generalized framework for land surface model evaluation. *Geosci. Model Dev.*, **5**, 869–886, https://doi.org/10.5194/gmd-5-869-2012.

——, and Coauthors, 2016: Assimilation of gridded GRACE terrestrial water storage estimates in the North American land data assimilation system. *J. Hydrometeor.*, **17**, 1951–1972, https://doi.org/10.1175/JHM-D-15-0157.1.

——, M. Jasinski, D. Mocko, M. Rodell, J. Borak, B. Li, H. Kato Beaudoing, and C. D. Peters-Lidard, 2019: NCA-LDAS land analysis: Development and performance of a multisensor, multivariate land data assimilation system for the National Climate Assessment. *J. Hydrometeor.*, **20**, 1571–1593, https://doi.org/10.1175/JHM-D-17-0125.1.

Lavers, D., L. Luo, and E. F. Wood, 2009: A multiple model assessment of seasonal climate forecast skill for applications. *Geophys. Res. Lett.*, **36**, L23711, https://doi.org/10.1029/2009GL041365.

Li, B., and Coauthors, 2019: Global GRACE data assimilation for groundwater and drought monitoring: Advances and challenges. *Water Resour. Res.*, **55**, 7564–7586, https://doi.org/10.1029/2018WR024618.

Li, H., L. Luo, E. F. Wood, and J. Schaake, 2009: The role of initial conditions and forcing uncertainties in seasonal hydrologic forecasting. *J. Geophys. Res.*, **114**, D04114, https://doi.org/10.1029/2008JD010969.

Li, S., L. Goddard, and D. G. DeWitt, 2008: Predictive skill of AGCM seasonal climate forecasts subject to different SST prediction methodologies. *J. Climate*, **21**, 2169–2186, https://doi.org/10.1175/2007JCLI1660.1.

Liang, X., D. P. Lettenmaier, E. F. Wood, and S. J. Burges, 1994: A simple hydrologically based model of land surface water and energy fluxes for general circulation models. *J. Geophys. Res.*, **99**, 14 415–14 428, https://doi.org/10.1029/94JD00483.

Lin, P., J. Wei, Z.-L. Yang, Y. Zhang, and K. Zhang, 2016: Snow data assimilation-constrained land initialization improves seasonal temperature prediction. *Geophys. Res. Lett.*, **43**, 11 423–11 432, https://doi.org/10.1002/2016GL070966.

Liu, Y., C. D. Peters-Lidard, S. V. Kumar, K. R. Arsenault, and D. M. Mocko, 2015: Blending satellite-based snow depth products with in situ observations for streamflow predictions in the Upper Colorado River Basin. *Water Resour. Res.*, **51**, 1182–1202, https://doi.org/10.1002/2014WR016606.

Luo, L., and E. F. Wood, 2007: Monitoring and predicting the 2007 U.S. drought. *Geophys. Res. Lett.*, **34**, L22702, https://doi.org/10.1029/2007GL031673.

——, and ——, 2008: Use of Bayesian merging techniques in a multimodel seasonal hydrologic ensemble prediction system for the eastern United States. *J. Hydrometeor.*, **9**, 866–884, https://doi.org/10.1175/2008JHM980.1.

Magadzire, T., G. Galu, and J. Verdin, 2017: How climate forecasts strengthen food security. *WMO Bull.*, **66** (2), https://public.wmo.int/en/resources/bulletin/how-climate-forecasts-strengthen-food-security.

Mahanama, S., B. Livneh, R. Koster, D. Lettenmaier, and R. Reichle, 2012: Soil moisture, snow, and seasonal streamflow forecasts in the United States. *J. Hydrometeor.*, **13**, 189–203, https://doi.org/10.1175/JHM-D-11-046.1.

Masih, I., S. Maskey, F. E. F. Mussaì, and P. Trambauer, 2014: A review of droughts on the African continent: A geospatial and long-term perspective. *Hydrol. Earth Syst. Sci.*, **18**, 3635–3649, https://doi.org/10.5194/hess-18-3635-2014.

Maurer, E. P., and D. P. Lettenmaier, 2003: Predictability of seasonal runoff in the Mississippi River basin. *J. Geophys. Res.*, **108**, 8607, https://doi.org/10.1029/2002JD002555.

McKee, T. B., N. J. Doesken, and J. Kleist, 1993: The relationship of drought frequency and duration of time scales. Preprints, *Eighth Conf. on Applied Climatology*, Anaheim, CA, Amer. Meteor. Soc., 179–184.

McNally, A., and Coauthors, 2017: A land data assimilation system for sub-Saharan Africa food and water security applications. *Sci. Data*, **4**, 170 012, https://doi.org/10.1038/sdata.2017.12.

——, and Coauthors, 2019a: Hydrologic and agricultural earth observations and modeling for the water-food Nexus. *Front. Environ. Sci.*, **7**, 23, https://doi.org/10.3389/FENVS.2019.00023.

——, and Coauthors, 2019b: Acute water-scarcity monitoring for Africa. *Water*, **11**, 1968, https://doi.org/10.3390/w11101968.

Merryfield, W. J., and Coauthors, 2013: The Canadian seasonal to interannual prediction system. Part I: Models and initialization. *Mon. Wea. Rev.*, **141**, 2910–2945, https://doi.org/10.1175/MWR-D-12-00216.1.

Mishra, A., T. Vu, A. V. Veettil, and D. Entekhabi, 2017: Drought monitoring with Soil Moisture Active Passive (SMAP) measurements. *J. Hydrol.*, **552**, 620–632, https://doi.org/10.1016/j.jhydrol.2017.07.033.

Mo, K. C., L. N. Long, Y. Xia, S. K. Yang, J. E. Schemm, and M. B. Ek, 2011: Drought indices based on the climate forecast system reanalysis and ensemble NLDAS. *J. Hydrometeor.*, **12**, 181–205, https://doi.org/10.1175/2010JHM1310.1.

——, S. Shukla, D. P. Lettenmaier, and L.-C. Chen, 2012: Do Climate Forecast System (CFSv2) forecasts improve seasonal soil moisture prediction? *Geophys. Res. Lett.*, **39**, L23703, https://doi.org/10.1029/2012GL053598.

Narapusetty, B., D. Collins, R. Murtugudde, J. Gottschalck, and C. Peters-Lidard, 2018: Bias correction to improve the skill of summer precipitation forecasts over contiguous United States by the North American multi-model ensemble system. *Atmos. Sci. Lett.*, **19**, e818, https://doi.org/10.1002/asl.818.

Niu, G.-Y., and Coauthors, 2011: The community Noah land surface model with multiparameterization options (Noah-MP): 1. Model description and evaluation with local-scale measurements. *J. Geophys. Res.*, **116**, D12109, https://doi.org/10.1029/2010JD015139.

NRC, 2010: *Assessment of Intraseasonal to Interannual Climate Prediction and Predictability.* National Academies Press, 192 pp.

O'Neill, P. E., E. G. Njoku, T. J. Jackson, S. Chan, and R. Bindlish, 2018: SMAP algorithm theoretical basis document: Level 2 & 3 soil moisture (passive) data products. SMAP Project JPL D-66480, Jet Propulsion Laboratory, 82 pp., https://smap.jpl.nasa.gov/system/internal_resources/details/original/484_L2_SM_P_ATBD_rev_D_Jun2018.pdf.

Peters-Lidard, C. D., and Coauthors, 2007: High-performance Earth system modeling with NASA/GSFC's land information system. *Innov. Syst. Software Eng.*, **3**, 157–165, https://doi.org/10.1007/s11334-007-0028-x.

Pomposi, C., C. Funk, S. Shukla, and T. Magadzire, 2018: Distinguishing southern Africa precipitation response by strength of El Niño events and implications for decision-making. *Environ. Res. Lett.*, **13**, 074 015, https://doi.org/10.1088/1748-9326/aacc4c.

Reager, J. T., B. F. Thomas, and J. S. Famiglietti, 2014: River basin flood potential inferred using GRACE gravity observations at several months lead time. *Nat. Geosci.*, **7**, 588–592, https://doi.org/10.1038/ngeo2203.

Reichle, R., and R. Koster, 2004: Bias reduction in short records of satellite soil moisture. *Geophys. Res. Lett.*, **31**, L19501, https://doi.org/10.1029/2004GL020938.

——, D. B. McLaughlin, and D. Entekhabi, 2002: Hydrologic data assimilation with the ensemble Kalman filter. *Mon. Wea. Rev.*, **130**, 103–114, https://doi.org/10.1175/1520-0493(2002)130<0103:HDAWTE>2.0.CO;2.

Rouault, M., and Y. Richard, 2005: Intensity and spatial extent of droughts in southern Africa. *Geophys. Res. Lett.*, **32**, L15702, https://doi.org/10.1029/2005GL022436.

Rowlands, D. D., S. B. Luthcke, J. J. McCarthy, S. M. Klosko, D. S. Chinn, F. G. Lemoine, J.-P. Boy, and T. J. Sabaka, 2010: Global mass flux solutions from GRACE: A comparison of parameter estimation strategies—Mass concentrations versus Stokes coefficients. *J. Geophys. Res.*, **115**, B01403, https://doi.org/10.1029/2009JB006546.

Saha, S., and Coauthors, 2014: The NCEP Climate Forecast System version 2. *J. Climate*, **27**, 2185–2208, https://doi.org/10.1175/JCLI-D-12-00823.1.

Save, H., S. Bettadpur, and B. D. Tapley, 2012: Reducing errors in the GRACE gravity solutions using regularization. *J. Geod.*, **86**, 695–711, https://doi.org/10.1007/s00190-012-0548-5.

——, ——, and ——, 2016: High-resolution CSR GRACE RL05 mascons. *J. Geophys. Res. Solid Earth*, **121**, 7547–7569, https://doi.org/10.1002/2016JB013007.

Sazib, N., I. Mladenova, and J. Bolten, 2018: Leveraging the Google Earth Engine for drought assessment using global soil moisture data. *Remote Sens.*, **10**, 1265, https://doi.org/10.3390/rs10081265.

Scanlon, B. R., Z. Zhang, H. Save, D. N. Wiese, F. W. Landerer, D. Long, L. Longuevergne, and J. Chen, 2016: Global evaluation of new GRACE mascon products for hydrologic applications. *Water Resour. Res.*, **52**, 9412–9429, https://doi.org/10.1002/2016WR019494.

Seibert, M., B. Merz, and H. Apel, 2017: Seasonal forecasting of hydrological drought in the Limpopo Basin: A comparison of statistical methods. *Hydrol. Earth Syst. Sci.*, **21**, 1611–1629, https://doi.org/10.5194/hess-21-1611-2017.

Sharma, S., R. Siddique, S. Reed, P. Ahnert, and A. Mejia, 2019: Hydrological model diversity enhances streamflow forecast skill at short- to medium-range timescales. *Water Resour. Res.*, **55**, 1510–1530, https://doi.org/10.1029/2018WR023197.

Sheffield, J., and Coauthors, 2014: A drought monitoring and forecasting system for sub-Sahara African water resources and food security. *Bull. Amer. Meteor. Soc.*, **95**, 861–882, https://doi.org/10.1175/BAMS-D-12-00124.1.

Shukla, S., and A. W. Wood, 2008: Use of a standardized runoff index for characterizing hydrologic drought. *Geophys. Res. Lett.*, **35**, L02405, https://doi.org/10.1029/2007GL032487.

——, and D. P. Lettenmaier, 2011: Seasonal hydrologic prediction in the United States: Understanding the role of initial hydrologic conditions and seasonal climate forecast skill. *Hydrol. Earth Syst. Sci.*, **15**, 3529–3538, https://doi.org/10.5194/hess-15-3529-2011.

——, J. Sheffield, E. F. Wood, and D. P. Lettenmaier, 2013: On the sources of global land surface hydrologic predictability. *Hydrol. Earth Syst. Sci.*, **17**, 2781–2796, https://doi.org/10.5194/hess-17-2781-2013.

——, A. McNally, G. Husak, and C. Funk, 2014: A seasonal agricultural drought forecast system for food-insecure regions of East Africa. *Hydrol. Earth Syst. Sci.*, **18**, 3907–3921, https://doi.org/10.5194/hess-18-3907-2014.

——, J. Roberts, A. Hoell, C. C. Funk, F. Robertson, and B. Kirtman, 2019: Assessing North American Multimodel Ensemble (NMME) seasonal forecast skill to assist in the early warning of anomalous hydrometeorological events over East Africa. *Climate Dyn.,* **53,** 7411–7427, https://doi.org/10.1007/S00382-016-3296-Z.

——, and Coauthors, 2020: Improving early warning of drought-driven food insecurity in southern Africa using operational hydrological monitoring and forecasting products. *Nat. Hazards Earth Syst. Sci.*, **20**, 1187–1201, https://doi.org/10.5194/nhess-20-1187-2020.

Sultan, B., B. Barbier, J. Fortilus, S. M. Mbaye, and G. Leclerc, 2010: Estimating the potential economic value of seasonal forecasts in West Africa: A long-term ex-ante assessment in Senegal. *Wea. Climate Soc.*, **2**, 69–87, https://doi.org/10.1175/2009WCAS1022.1.

Swets, D. L., B. C. Reed, J. D. Rowland, and S. E. Marko, 1999: A weighted least-squares approach to temporal NDVI smoothing. *Proc. 1999 ASPRS Annual Conference: From Image to Information*, Portland, OR, ASPRS, 526–536.

Thiaw, W. M., and V. B. Kumar, 2015: NOAA's African desk: Twenty years of developing capacity in weather and climate forecasting in Africa. *Bull. Amer. Meteor. Soc.*, **96**, 737–753, https://doi.org/10.1175/BAMS-D-13-00274.1.

Trambauer, P., M. Werner, H. C. Winsemius, S. Maskey, E. Dutra, and S. Uhlenbrook, 2015: Hydrological drought forecasting and skill assessment for the Limpopo River basin, southern Africa. *Hydrol. Earth Syst. Sci.*, **19**, 1695–1711, https://doi.org/10.5194/hess-19-1695-2015.

Tucker, C. J., and P. J. Sellers, 1986: Satellite remote sensing of primary production. *Int. J. Remote Sens.*, **7**, 1395–1416, https://doi.org/10.1080/01431168608948944.

Twedt, T. M., J. C. Schaake Jr., and E. L. Peck, 1977: National Weather Service extended streamflow prediction. *Proc. 45th Annual Western Snow Conference*, Albuquerque, NM, Western Snow Conference, 52–57.

United Nations, 2018: *The State of Food Security and Nutrition in the World 2018: Building Climate Resilience for Food Security and Nutrition*. FAO, 181 pp.

Verdin, J., C. Funk, G. Senay, and R. Choularton, 2005: Climate science and famine early warning. *Philos. Trans. Roy. Soc. London*, **360B**, 2155–2168, https://doi.org/10.1098/rstb.2005.1754.

Vörösmarty, C. J., E. M. Douglas, P. A. Green, and C. Revenga, 2005: Geospatial indicators of emerging water stress: An application to Africa. *AMBIO: J. Hum. Environ.*, **34**, 230–236, https://doi.org/10.1579/0044-7447-34.3.230.

Wanders, N., S. Thober, R. Kumar, M. Pan, J. Sheffield, L. Samaniego, and E. F. Wood, 2019: Development and evaluation of a pan-European multimodel seasonal hydrological forecasting system. *J. Hydrometeor.*, **20**, 99–115, https://doi.org/10.1175/JHM-D-18-0040.1.

Wang, A., T. J. Bohn, S. P. Mahanama, R. D. Koster, and D. P. Lettenmaier, 2009: Multimodel ensemble reconstruction of drought over the continental United States. *J. Climate*, **22**, 2694–2712, https://doi.org/10.1175/2008JCLI2586.1.

Wiese, D. N., F. W. Landerer, and M. M. Watkins, 2016: Quantifying and reducing leakage errors in the JPL RL05M GRACE mascon solution. *Water Resour. Res.*, **52**, 7490–7502, https://doi.org/10.1002/2016WR019344.

Wolski, P., C. Lennard, C. Jack, and M. Tadross, 2017: Seasonal hydrological forecasting—Current state of play. *Water Wheel*, **16**, 30–33.

Wood, A. W., E. P. Maurer, A. Kumar, and D. P. Lettenmaier, 2002: Long-range experimental hydrological forecasting for the eastern United States. *J. Geophys. Res.*, **107**, 4429, https://doi.org/10.1029/2001JD000659.

——, L. R. Leung, V. Sridhar, and D. P. Lettenmaier, 2004: Hydrologic implications of dynamical and statistical approaches to downscaling climate model outputs. *Climatic Change*, **62**, 189–216, https://doi.org/10.1023/B:CLIM.0000013685.99609.9e.

Xia, Y., J. Sheffield, M. B. Ek, J. Dong, N. Chaney, H. Wei, J. Meng, and E. F. Wood, 2014: Evaluation of multi-model simulated soil moisture in NLDAS-2. *J. Hydrol.*, **512**, 107–125, https://doi.org/10.1016/j.jhydrol.2014.02.027.

Yossef, N. C., H. Winsemius, A. Weerts, R. van Beek, and M. F. P. Bierkens, 2013: Skill of a global seasonal streamflow forecasting system, relative roles of initial conditions and meteorological forcing. *Water Resour. Res.*, **49**, 4687–4699, https://doi.org/10.1002/wrcr.20350.

——, R. van Beek, A. Weerts, H. Winsemius, and M. F. P. Bierkens, 2017: Skill of a global forecasting system in seasonal ensemble streamflow prediction. *Hydrol. Earth Syst. Sci.*, **21**, 4103–4114, https://doi.org/10.5194/hess-21-4103-2017.

Yuan, X., E. Wood, N. Chaney, J. Sheffield, J. Kam, M. Liang, and K. Guan, 2013: Probabilistic seasonal forecasting of African drought by dynamical models. *J. Hydrometeor.*, **14**, 1706–1720, https://doi.org/10.1175/JHM-D-13-054.1.

——, J. K. Roundy, E. F. Wood, and J. Sheffield, 2015: Seasonal forecasting of global hydrologic extremes: System development and evaluation over GEWEX basins. *Bull. Amer. Meteor. Soc.*, **96**, 1895–1912, https://doi.org/10.1175/BAMS-D-14-00003.1.

Zaitchik, B. F., M. Rodell, and R. H. Reichle, 2008: Assimilation of GRACE terrestrial water storage data into a land surface model: Results for the Mississippi River basin. *J. Hydrometeor.*, **9**, 535–548, https://doi.org/10.1175/2007JHM951.1.