Hydrol. Earth Syst. Sci. Discuss., 11, 3049–3081, 2014
www.hydrol-earth-syst-sci-discuss.net/11/3049/2014/
doi:10.5194/hessd-11-3049-2014

Hydrology and Earth System Sciences
Discussions
Open Access

A seasonal agricultural drought forecast system for food-insecure regions of East Africa

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Received: 21 February 2014 – Accepted: 3 March 2014 – Published: 14 March 2014

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Published by Copernicus Publications on behalf of the European Geosciences Union.

Abstract

The increasing food and water demands of East Africa's growing population are stressing the region's inconsistent water resources and rain-fed agriculture. More accurate seasonal agricultural drought forecasts for this region can inform better water and agricultural management decisions, support optimal allocation of the region's water resources, and mitigate socio-economic losses incurred by droughts and floods. Here we describe the development and implementation of a seasonal agricultural drought forecast system for East Africa (EA) that provides decision support for the Famine Early Warning Systems Network's science team. We evaluate this forecast system for a region of equatorial EA (2° S to 8° N, and 36° to 46° E) for the March-April-May growing season. This domain encompasses one of the most food insecure, climatically variable and socio-economically vulnerable regions in EA, and potentially the world: this region has experienced famine as recently as 2011.

To assess the agricultural outlook for the upcoming season our forecast system simulates soil moisture (SM) scenarios using the Variable Infiltration Capacity (VIC) hydrologic model forced with climate scenarios for the upcoming season. First, to show that the VIC model is appropriate for this application we forced the model with high quality atmospheric observations and found that the resulting SM values were consistent with the Food and Agriculture Organization's (FAO's) Water Requirement Satisfaction Index (WRSI), an index used by FEWS NET to estimate crop yields. Next we tested our forecasting system with hindcast runs (1993–2012). We found that initializing SM forecasts with start-of-season (5 March) SM conditions resulted in useful SM forecast skill (> 0.5 correlation) at 1-month, and in some cases at 3 month lead times. Similarly, when the forecast was initialized with mid-season (i.e. 5 April) SM conditions the skill until the end-of-season improved. This shows that early-season rainfall is critical for end-of-season outcomes. Finally we show that, in terms of forecasting spatial patterns of SM anomalies, the skill of this agricultural drought forecast system is generally

greater (> 0.8 correlation) during drought years. This means that this system might be particularity useful for identifying the events that present the greatest risk to the region.

1 Introduction

The 2011 famine in Horn of Africa was one of the most severe humanitarian disasters of this century. It affected more than 13 million people (Hillier, 2012) and resulted in a disastrous loss of life. According to a FAO and FEWS NET report "excess deaths" (i.e. number of deaths in excess of baseline mortality rate) in southern and central Somalia alone were in between 244 000 to 273 000 (Checchi and Robinson, 2013). The situation was most dire in southern and central Somalia (Mosley, 2012) but spilled over the borders into south-eastern Ethiopia and northern Kenya as well. There is general consensus that improvement of early warning systems and more timely response is needed (Hillier, 2012) to mitigate socio-economic losses of future drought events of this magnitude.

FEWS NET is a program of the United States Agency for International Development (USAID) tasked with providing timely and rigorous early warning and vulnerability information on emerging and evolving food security issues. FEWS NET is active in about 35 of the world's most food-insecure countries including Ethiopia, Kenya and Somalia. Each month FEWS NET's food analysts, working in each of the USAID's focus regions, compile a set of agroclimatic working assumptions for the upcoming season. Meanwhile FEWS NET's hydroclimate scientists review those assumptions with a deeper focus on the climate conditions and revise the assumptions if need be. This process requires compiling available information on soil moisture (SM), rainfall, vegetation health, sea surface temperatures (SSTs) and land temperatures (surface and air) to provide weekly to seasonal climate outlooks for the upcoming season.

Thus far the hydroclimate science team has focused on forecasting rainfall anomalies of the upcoming season. Rainfall, the variable most often associated with water resources in the developing world, has been the focus of real-time monitoring and

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attribution activities (Funk et al., 2005, 2010). Due to this attention, rainfall estimation has also experienced significant technical advances and is the premier input to assess agricultural production and available water resources (Funk et al., 2014). As such, disaster management actions tend to be based on estimates of rainfall anomalies. While seasonal rainfall may be the most accessible indicator of yields, available moisture during the growing season, a variable directly associated with agricultural drought, is dependent on the state of the SM at the beginning of the season as well. Accurate knowledge of the SM state at the time of forecast initialization significantly contributes to the forecast skill of available moisture for up to six months (in some cases) during the forecast period (Koster et al., 2010; Shukla and Lettenmaier, 2011; Shukla et al., 2013). Due to the shortage of real time observed SM measurements, estimates computed using hydrologic models are among the best indicator of antecedent SM conditions and agricultural drought (Keyantash and Dracup, 2002). These same hydrologic models can be driven with climate forecasts for the upcoming season to provide SM forecasts. This additional step, of using forecast rainfall and other meteorological variables to provide a seasonal outlook for plant available water, provides a more nuanced and accurate assessment of agricultural drought conditions than rainfall forecasts alone.

During the October-November-December growing season of 2013, the FEWS NET science team developed and implemented a seasonal agricultural drought forecast system using the Variable Infiltration Capacity (VIC) hydrologic model and NCEP's Climate Forecasts System Version-2 (CFSv2). In this manuscript we describe the development, implementation and evaluation of that seasonal drought forecast system with a focus on the equatorial East Africa (EA) (i.e. southeastern Ethiopia, northern Kenya and southern Ethiopia) as captured in Fig. 1. For evaluation of this system we chose to focus on March-April-May (MAM), which is the primary growing and rainy season as shown by the ratio of MAM and annual precipitation based on the Climate Hazards group InfraRed Precipitation with Station data (CHIRPS) dataset (Funk et al., 2014) (see Sect. 2.2) in Fig. 1. Reliable rainfall forecasts over this region during the rainy season have proven to be a challenge (Nicholson, 2014; Owiti et al., 2008). Furthermore,

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rainfall in MAM season has declined in last two decades (Funk et al., 2008; Lyon and DeWitt, 2012; Williams and Funk, 2011). Although the primary causes of this decline have recently been a matter of debate (Hoell and Funk, 2013a; Lyon and DeWitt, 2012; Tierney et al., 2013), the MAM season will be prone to drought events in the future and continue to pose challenges for water and drought management given increases in population and water demands, and degradation of land in past few decades (Pricope et al., 2013). These facts support a need to improve and develop tools to assist decision makers.

In the remainder of this manuscript we describe the approach and data used to implement the agricultural drought forecasts system, its evaluation and future directions.

2 Approach and data

This section describes the approach undertaken to develop the seasonal agricultural drought forecast system. Our approach is similar to other experimental/operational seasonal hydrologic and drought forecast systems such as NCEP's Multimodal Drought Monitoring System (http://www.emc.ncep.noaa.gov/mmb/nldas/drought/), Climate Prediction Center's Land Surface Monitoring and Prediction System (http://www.cpc.ncep.noaa.gov/products/Soilmst_Monitoring/US/Soilmst/Soilmst.shtml), as well as Princeton University's Africa Flood and Drought Monitor (http://stream.princeton.edu/AWCM/WEBPAGE/index.php) (Sheffield et al., 2013). A schematic diagram shown in Fig. 2 summarizes our approach and lists all the data and models used to implement this system.

In following sections we describe in detail the hydrology model (Sect. 2.1), observed atmospheric forcings (Sect. 2.2), and the methodology adopted to build seasonal climate scenarios (Sect. 2.3) and generate seasonal forecasts of SM (Sect. 2.4).

2.1 Hydrologic model and parameters

For this analysis we used the Variable Infiltration Capacity (VIC) model, which is a semi-distributed macroscale hydrology model. The VIC model has been widely used at global scale in many previous studies and has been demonstrated to capture the hydrology of different regimes well (Nijssen et al., 1997, 2001; Maurer et al., 2002; Adam et al., 2007).

The VIC model parameterizes major surface, subsurface, and land–atmosphere hydrometeorological processes (Liang et al., 1994, 1996; Nijssen et al., 1997) and represents the role of sub-grid spatial heterogeneity in SM, elevation bands, and vegetation, on runoff generation. Each grid cell in the VIC model is divided into different vegetation types, each with a characteristic root length, and bare soil. Month varying vegetation parameters include Leaf Area Index (LAI), albedo, minimum stomatal resistance, architectural resistance, roughness length, and displacement length. Actual evapotranspiration in the VIC model is calculated using the Penman–Monteith equation. Total actual evapotranspiration is the sum of canopy evaporation and transpiration from each land cover type (including bare soil), weighted by the coverage fraction for each tile.

The soil profile (i.e. depth) in the VIC model is partitioned into three layers. The first layer has a fixed depth of 10 cm and responds quickly to changes in surface conditions and precipitation. Moisture transfers between the first and second, and second and third soil layers are governed by gravity drainage, with diffusion from the second to the upper layer allowed in unsaturated conditions (Liang et al., 1996). Baseflow is a non-linear function of the moisture content of the third soil-layer (Todini, 1996).

The soil and vegetation parameters used for this study were originally developed for Princeton's Africa Flood and Drought Monitor (http://hydrology.princeton.edu/~nchaney/ADM_ML/), documented in Sheffield et al. (2013) and Chaney et al. (2013). We briefly describe their origin and sources here for the benefit of the reader. Soil texture and bulk density were from Batjes (1997) and the rest of the soil parameters were from Cosby et al. (1984). For a complete list of the soil parameters

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used by the VIC model see: http://www.hydro.washington.edu/Lettenmaier/Models/VIC/Documentation/SoilParam.shtml). In order to insure that the VIC model yields reasonable water balance, the soil parameters were calibrated following the method of Troy et al. (2008); against runoff fields derived by Global Runoff Data Center gauges in Africa. Troy et al. (2008) demonstrated that this approach is sufficiently accurate, computationally efficient and results in reasonable soil parameters for ungagued basins, which makes it particularity attractive for a data sparse region such as Africa. Monthly LAI values used in this study were derived from Myneni et al. (1997), whereas other vegetation parameters were taken from Nijssen et al. (2001b).

2.2 Observed atmospheric forcings

This project used the CHIRPS rainfall product (Funk et al., 2014), which is available from 1981-present. This dataset was developed and is continually updated by the United States Geological Survey (USGS) in collaboration with the Climate Hazards Group of the Department of Geography at the University of California, Santa Barbara. CHIRPS is generated by blending together three different datasets: (1) global 0.05° precipitation climatology (2) time varying grids of satellite based and climate model precipitation estimates, and (3) in situ precipitation observations. This dataset has been compared with other global precipitation datasets such as Global Precipitation Climatology Project (GPCP), and has a high level agreement in our area of interest. See Funk et al. (2014) for further details.

Other meteorological inputs include maximum and minimum daily temperature and wind speed. From 1982–2008 we used the same data as in Princeton's Africa Flood and Drought Monitor described in Chaney et al. (2013) and Sheffield et al. (2006, 2013). From 2009 to present we used Global Ensembles Forecast System (GEFS)'s (Hamill et al., 2013) temperature (daily T_{max} and T_{min}) analysis fields (accessed from: http://www.esrl.noaa.gov/psd/forecasts/reforecast2/download.html). We bias-corrected these data relative to retrospective temperature data (Sheffield et al., 2006) using a quantile-quantile mapping approach for the overlapping climatological

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period of both dataset (i.e. 1985–2008). For the wind speed post 2009 we simply use the climatological monthly mean of wind speed data over 1982–2008. Livneh et al. (2013) demonstrated that using climatological mean value of wind speed has minimal impact on simulated SM.

2.3 Seasonal climate scenarios

We generated seasonal scale climate scenarios by using a hybrid dynamical–statistical downscaling approach. We utilized CFSv2 precipitation forecasts for MAM season, initialized in February (ensembles sampled from 11 January through 11 February) (Saha et al., 2013) and a statistical method of forecasting rainfall based on those dynamical forecasts. Note that for generating climate scenarios (and SM scenarios as discussed in Sect. 2.4) as well as hindcast assessment of the agricultural drought forecast system we use only 1993–2012 period; a period over which the teleconnection between MAM rainfall over the study region (Fig. 1) and Indo-pacific SST has been the strongest as reported by Funk et al. (2013). Increase in this sensitivity at least partially can be attributed to the co-occurrence of La Niña events with a strong West Pacific Gradient (WPG) (Hoell and Funk, 2013b).

The steps undertaken to generate seasonal climate scenarios are as follows:

1. Calculate the correlation of the MAM observed rainfall (CHIRPS) averaged for the EA study region (Fig. 1) with CFSv2 precipitation forecasts at each grid cell (within EA, Indo-Pacific domain as shown in Fig. 3) for the 1993–2012 period. The resulting correlation pattern is shown in Fig. 3.

2. Multiply CFSv2 precipitation forecasts for MAM season of each year (1993–2012) by the absolute value of the correlation values (estimated in step 1). The resulting correlation-weighted precipitation effectively discards or puts less weight on the CFSv2 forecasts for those grid cells that demonstrate little correlation with MAM rainfall in the study region.

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3. Perform a pairwise comparison between correlation-weighted precipitation forecasts for the target year (the year for which climate scenarios are to be generated) and each of the other years to estimate a similarity metric. Based on that similarity metric we proportion weights to each year, with the most similar year having the highest weight. This approach is similar to constructed analog approach suggested by Hidalgo et al. (2008) however we do not just use the best analogue years (as in Hidalgo et al., 2008) but also include other years, although at a reduced likelihood, for generating climate scenarios.

4. Use the weights (calculated in previous step) to establish a probability of selection in a bootstrapping approach (following the methods described in Husak et al., 2013) to generate scenarios of daily sequences of precipitation along with maximum and minimum temperature. For example Fig. 4 shows the frequency of years in the available record (1993–2012) being picked in generating climate scenarios for MAM season of the year 2011, which was a drought year. The plot in top panel shows the frequency conditioned to the CFSv2 based weighted probability estimates. The bottom panel shows the frequency if all years were assigned the same probability weights, or an assumption of climatology. Based on our probability estimates year 2011 was most similar to the years 2009, 1999 and 2000, which were all drought years.

2.4 Seasonal hydrologic forecasts

Two sets of hindcasts of SM forecasts were generated by combining the antecedent conditions, one at 5 March and one 5 April (1993–2012), with a suite of climate scenarios (daily precipitation, maximum and minimum temperature, as described in Sect. 2.3) for the remainder of the season. (Note that same climate scenarios were used in both cases). We chose these dates because 5 March is near the start-of-the-season (SOS) and about a week before FEWS NET's seasonal forecast review meeting in March; likewise 5 April is near the middle-of-season (MOS) and about a week before the seasonal forecast review meeting in April. While date of forecast initialization can vary, forecast “timeliness” is important, i.e. earlier forecasts are better. However there can be a trade-off between forecast skill and timeliness (Fig. 5).

As the season progresses, the control of hydrologic initial state over the SM conditions during the rest of the season increases. This results in higher forecast skill, but a late forecast which is less than ideal with respect to timeliness (also illustrated in the results section).

3 Evaluation of agricultural drought forecasts

First we evaluated the suitability of VIC-derived SM for providing agricultural drought assessments across our domain (Fig. 1). Due to the lack of long-term high quality crop yield data in the region, we compared SM values, spatially aggregated over the crop zones only, with the Water Requirement Satisfaction Index (WRSI) (Verdin and Klaver, 2002) for those crop zones. WRSI is a water balance model that has been long used by Food and Agricultural Organization (FAO) as well as FEWS NET scientists to provide crop yield assessment (Senay and Verdin, 2003; Verdin and Klaver, 2002; Verdin et al., 2005). WRSI was calculated using the same precipitation data (i.e. CHIRPS) as VIC's SM. WRSI is approximately equal to the percent of potential evapotranspiration met by available water resources, either rainfall or soil moisture. As such, WRSI values range from 0 to 100, with a value below 50 commonly being associated with crop failure. Because only a limited amount of excess water is retained for the next time interval in the WRSI model, the relationship of seasonal precipitation with WRSI is not entirely linear. For example, WRSI values may be the same for 100% of normal precipitation and 120% of normal precipitation, since both precipitation values meet the required available moisture for crop growth. For this reason we compared standardized anomalies of SM, rainfall and WRSI over the crop zones. As shown in Fig. 6, the spearman rank correlation between rainfall and WRSI is 0.83 and correlation between SM and WRSI is slightly less (0.75). We chose spearman rank correlation value to make sure

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that the correlation value is not sensitive to a few outlier years given the small sample size. Based on this finding we postulate that VIC derived SM is a reasonable indicator of agricultural drought in the focus domain.

Next we assessed the skill of the precipitation and SM forecasts. Our model hindcasts consisted of an ensemble of 30 precipitation and SM scenarios or each year in 1993–2012. We used the ensemble median of the scenarios and correlated this with the observed seasonal outcome. We used the CHIPRS to assess the skill of the precipitation forecasts and SM "observations" generated by forcing VIC model (Sect. 2.1) using observed atmospheric forcings (Sect. 2.2) to assess the skill of the SM forecasts. We do so due to the lack of long-term SM observations for the region.

Figure 7 shows a comparison between spatially aggregated (over the focus domain) MAM seasonal precipitation forecasts made during 1993–2012 and observations (CHIRPS). The value of spearman rank correlation between precipitation forecasts and observations is 0.67.

Figure 8a shows the skill of SM forecasts initialized on 5 March (start-of-season) for lead-time of 1 to 3 months. (Where lead-1 is month of March and lead-3 is month of May). The skill shown in these plots is spearman rank correlation between the ensemble median of all 30 SM scenarios for each year and SM values that were simulated by forcing the VIC model with observed forcings (Sect. 2.2). SM forecast skill is generally greater than 0.5 across the most of the region and greater than 0.9 for some parts at 1 month lead. The SM forecast skill dissipates as the time between forecast month and day of forecast initialization increases. This finding about the SM forecast skill is consistent with the results of other studies (Mo et al., 2012; Shukla and Lettenmaier, 2011; Shukla et al., 2013). Nevertheless over part of the focus domain (southeastern parts of Ethiopia, eastern parts of Kenya as well as southern Somalia) the SM forecast skill remains as high as 0.5 for up to three months lead-time. This observation is particularly important in an early warning context, since it implies that over those regions skillful assumptions about the agricultural drought can be made early in the growing season. This lead-time is particularly helpful for FEWS NET food analysts, who can provide advanced warning about potential growing conditions in those regions.

Hydrologic forecast skill is primarily controlled by the initial hydrologic state and the climate forecast skill. Mahanama et al. (2012) proposed use of the κ (kappa) parameter; a simple yet powerful measure to estimate controls of initial hydrologic state and precipitation variability on hydrologic predictability. κ is the ratio of standard deviation of initial total moisture (SM + snow) and standard deviation of total precipitation during the forecast period. In Fig. 8b we show the value of κ for lead times of 1 to 3 months. It can be seen that SM forecast skill is generally higher where the value of the κ parameter is greater than 1, which means that variability of initial SM is greater than precipitation variability. In another words even in the case of low precipitation forecast skill, those places where the κ parameter is greater than 1, useful SM forecast skill can be derived from the knowledge of initial moisture only. Skillful climate forecasts can of course further increase SM forecast skill in those regions.

Similar to Fig. 8a, Fig. 9a shows SM forecast skill but during the forecast period starting on 5 April. Although SM forecast skill dissipates as one moves further from the initial state, one noteworthy observation from this figure is the higher SM forecast skill over second and third month (lead-1 and lead-2 months respectively) of the MAM season. Comparing Lead-2 and Lead-3 forecasts skill in Fig. 8a with Lead-1 and Lead-2 forecast skill in Fig. 9a we see the higher values across the region in Fig. 9a, corresponding to improved EOS information at the beginning of April compared to March. Although (as also mentioned in Sect. 2.4 and illustrated in Fig. 5) middle of season is less than ideal time for providing forecasts of agricultural drought, this is the time when antecedent SM state has larger influence over SM until end-of-season. This also highlights the value of incorporating precipitation during the early part of the season, which is reflected in the initial hydrologic state of the middle-of-season. What this means in practical terms is that in case of delayed onset of rainfall and/or below normal rainfall during the first month of the season, SM at the middle of the season will be below normal and chances of recovery from the SM deficit (or failure of the crop) becomes lower

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(higher) than what they are at the beginning of the season. Again Fig. 9b shows that the higher skill in second and third month (i.e. Lead-1 and lead-2) of the MAM season is due to greater variability in initial SM relative to precipitation variability. Higher levels of skill are more spatially continuous (more number of grid cells with high skill) in this case than when the forecast is initialized at the start of season.

Finally we examine how the SM forecast skill varies among drought vs. normal years. Presumably during drought years contribution of precipitation in SM during the growing season would be less than in normal years giving larger influence to initial SM state. We looked at the correlation of spatial anomaly pattern of ensemble median SM forecasts and observations (Fig. 10). The higher correlations mean the better the forecast is in capturing the spatial variability of SM anomaly pattern. Spatial anomaly pattern correlation is greater than 0.60 for all years (Fig. 10). As indicated by Fig. 10 there is a correlation of −0.62 between spatial anomaly pattern correlation for MAM SM and standardized anomaly of MAM precipitation, which means that spatial anomaly pattern correlation is generally higher (lower) for negative (positive) anomaly of precipitation. In almost all years (except one) the value of spatial anomaly pattern correlation is greater than 0.8 when MAM precipitation anomaly was negative (i.e. meteorological drought years). This finding indicates that during drought years this system does relatively better (than in normal or above normal year) in capturing spatial variability of SM. This could be potentially useful for another event like 2011 MAM (which was a drought year).

4 Discussion

We describe the development and evaluation of a seasonal agricultural drought forecast system for food insecure regions of EA. This is certainly not the first attempt to provide seasonal hydrologic forecasts for EA. Nevertheless it is important for FEWS NET to have an in-house platform to help provide seasonal assessment of agricultural drought conditions and meet the decision making needs of the food analysts. This also

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allows us to test different approaches to generate climate scenarios and estimate initial hydrologic state (approaches that we plan to implement in this system are described in further details in Sect. 5).

Our approach is most similar to Sheffield et al. (2013) and Yuan et al. (2013), used to develop Africa Flood and Drought Monitor as mentioned in Sect. 2. Specifically, we used the same model parameters and temperature and wind forcings. The main differences between our system and theirs are the precipitation forcings (CHIRPS dataset blends in more station data and uses a high resolution background climatology, providing better estimates of precipitation means and variations, resulting in a better hydrologic state) and the approach used for generating seasonal climate scenarios. Besides the Africa Flood and Drought Monitor other approaches have been developed for drought monitoring and forecasting for Africa or EA, in last few years: Rojas et al. (2011) described a drought monitoring approach that utilizes Vegetation Health Index (VHI) from the Advanced Very High Resolution Radiometer (AVHRR) averaged over the crop season. Anderson et al. (2012) suggested an approach that takes advantage of the relative strength of three different methods for obtaining SM estimates. Mwangi et al. (2014) examined the skill of Standardized Precipitation Index (SPI) forecasts based on European Centre for Medium-Range Weather Forecasts (ECMWF).

5 Summary, conclusions and future directions

We described the development and implementation of a seasonal hydrologic forecast system that is being used by FEWS NET scientists to provide seasonal assessment of agricultural production for food-insecure regions of EA. This system combines satellite, station and model analysis observations, state-of-the-art hydrologic model (Variable Infiltration Capacity) and a hybrid approach (combining dynamical CFSv2 forecasts with statistical forecasting) for seasonal climate scenarios building. Our primary findings are as follows:

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1. VIC model derived SM values over the crop zones of the focus domain aligns well with end-of-season WRSI, which is an FAO indicator that's often used for providing crop yield assessments.

2. The hybrid approach that utilizes dynamical CFSv2 precipitation forecasts over EA and Indo Pacific Ocean to statistically forecast rainfall over the focus domain is skillful (correlation = 0.67 for MAM precipitation forecasts initialized in February)

3. Contribution from the antecedent SM state to SM forecast skill during rest of the season could be most useful in the middle of the season. SM forecasts initialized at the beginning of the season are most skillful across the domain at 1 month lead. Forecast skill during second and third months of the season increases when the SM forecast was initialized with updated initial hydrologic state and same climate scenarios as the one used at the time of the start of the season.

4. Spatial anomaly pattern correlation between SM forecast and observations are generally higher (> 0.8) for drought years indicating the value of this system during drought events, which is the primary focus of FEWS NET.

As mentioned before this seasonal agricultural drought forecast system is already being used to provide scientific assessment of seasonal agricultural outlook. However we acknowledge that a lot can be done to further improve this system to better meet the decision-making needs of the food analysts. Three primary avenues of improvements in this system are:

1. Improvement in the estimation of initial hydrologic state
Depending on how they partition precipitation into evapotranspiration and runoff, and their different water holding capacity different hydrologic models may have differences in SM sensitivity to precipitation variability. These differences may lead to discrepancies among the model based SM drought estimates (Crow et al., 2012; Wang et al., 2010). Therefore we plan to transfer this agricultural drought forecast system to NASA's FEWS NET Land Data Assimilation System: an instance

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of NASA's Land Information System (LIS) (Kumar et al., 2006) that includes hydrologic and soil water balance models such as NOAH (Ek et al., 2003; Schaake et al., 1996) and WRSI (Verdin and Klaver, 2002; Verdin et al., 2005) in addition to VIC and will include other land surface models such as CATCHMENT model (Koster et al., 2000) in near future.

Besides using a multimodel framework for seasonal agricultural drought forecasting another promising approach that we plan to test is data assimilation. Previous works have shown the usability of data assimilation in improving estimates of SM and snow state in large scale hydrologic model (Andreadis and Lettenmaier, 2006; Kumar et al., 2008) leading to a higher hydrologic forecast skill.

2. Improvement in climate scenario building process
For the current version of the seasonal agricultural drought forecast system we only use dynamical seasonal climate forecasts from CFSv2. However NCEP's National Multi-model Ensemble system (NMME, http://www.cpc.ncep.noaa.gov/products/NMME/) includes five other models aside from CFSv2. Recent studies have demonstrated the value of using multimodel ensembles of seasonal forecasts relative to using just one of the models (Hagedorn et al., 2005; Kirtman et al., 2013; Lavers et al., 2009). Therefore we plan to use NMME model ensembles to generate climate scenarios.

We also aim to test other statistical forecasting methods to improve the skill of climate scenarios. One of those methods is recently suggested by Nicholson (2014), who found that atmospheric variables, when used as predictors, can provide higher rainfall forecast skill in Greater Horn of Africa than other surface variables such as sea surface temperature (SST) and sea level pressure (SLP).

3. Improvement in presentation of the forecasts
Primary goal of this seasonal agricultural drought forecast system is to assist USAID's Food Analysts with their decision making process. Hence it is imperative for us to provide forecasts in a manner that is easily understandable by the decision

makers and still includes key information about the forecast (such as probabilities of a region being both wet or dry in an upcoming season). We recognize that this is a slow and iterative process however through this unique position of working directly with the food analysts we have the perfect opportunity to translate science into action.

Acknowledgements. This research was supported by the Postdocs Applying Climate Expertise (PACE) Fellowship Program, partially funded by the NOAA Climate Program Office and administered by the UCAR Visiting Scientist Programs. Additional support for this work was provided by the USAID's FEWS NET (USGS award #G09AC00001) and NOAA Technical Transitions grant NA11OAR4310151. The authors would like to thank Diego Pedreros (USGS/UCSB) for his work on generating WRSI data.

Finally we also like to extend our thanks to Justin Sheffield, Nate Chaney and others at Terrestrial Hydrology Research Group in the Department of Civil and Environmental Engineering at Princeton University for their work on developing forcing and model parameter datasets and kindly sharing them with us.

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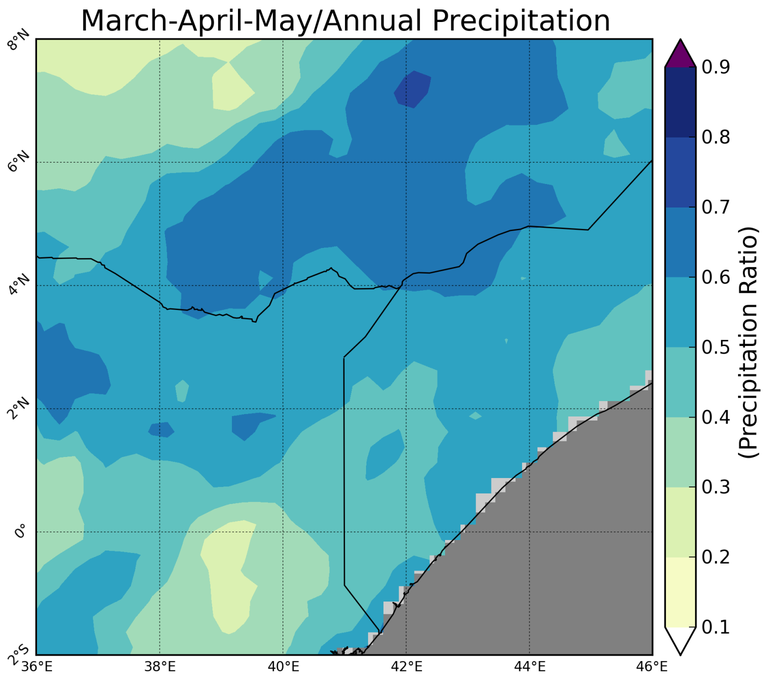

Fig. 1. Ratio of March-April-May (MAM) precipitation with the annual precipitation (calculated using CHIRPS) over the focus domain that expands over parts of Ethiopia, Kenya and Somalia. This region was the epicenter of the 2011 humanitarian disaster.

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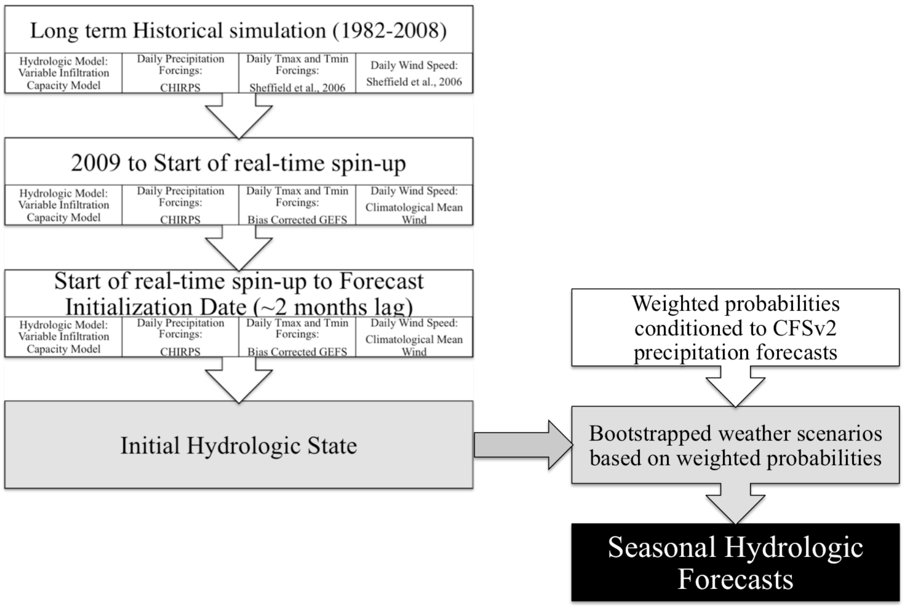

Fig. 2. Schematic diagram summarizing the approach, data and models used for the development and implementation of current version of Seasonal Agricultural Drought Forecast system.

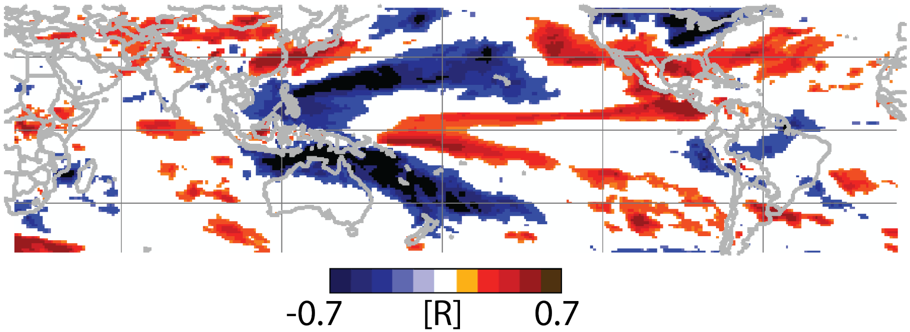

Fig. 3. Spatial pattern of correlation between CFSv2 precipitation forecasts for MAM season (initialized in February) and observed MAM rainfall (CHIRPS) in the focus domain. Correlation values have been masked for significance (values $r < |0.35|$ have been screened).

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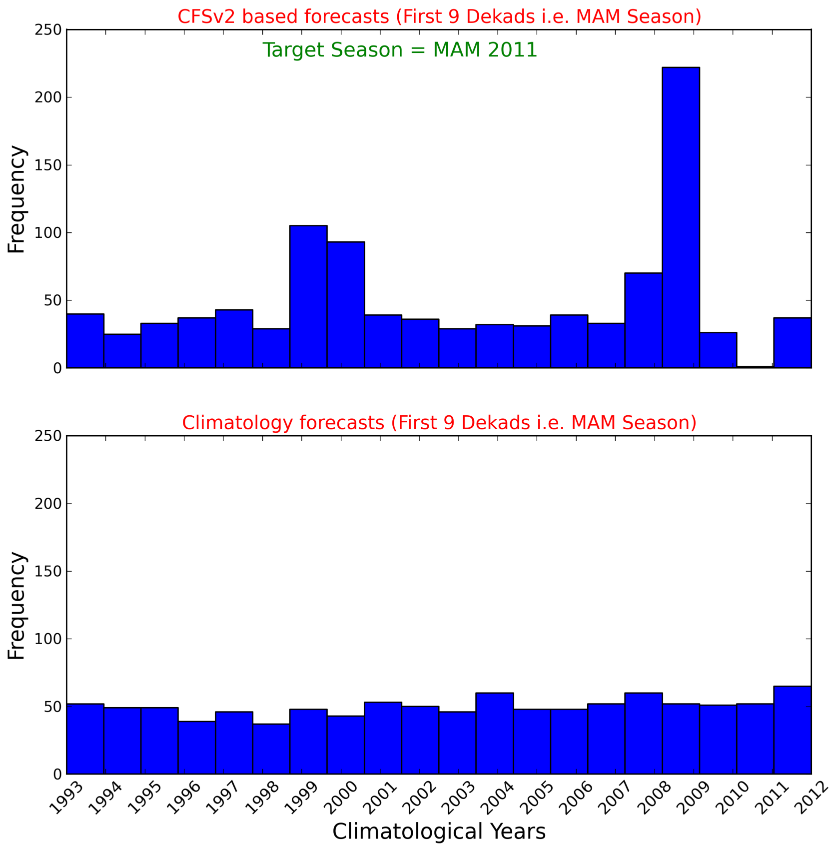

Fig. 4. Frequency of picking each climatological years for generating 30 climate scenarios for MAM season of the year 2011. Top panel shows the frequency resulted from conditioning bootstrapping process to CFSv2 based weighted probabilities and the bottom panel shows the same but for climatogical forecasts where each years were assigned the same probability.

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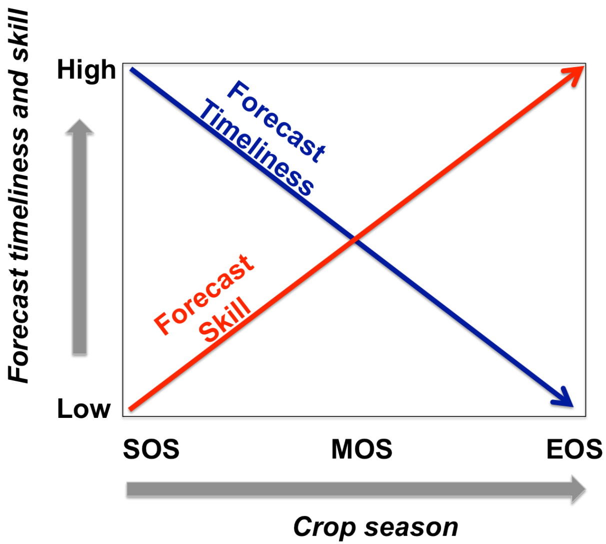

Fig. 5. Schematic diagram showing variability of forecast timeliness and skill during a crop season. Forecast timeliness decreases as the season progress whereas forecast skill increases (SOS: Start of season, MOS: Middle of season, EOS: End of season).

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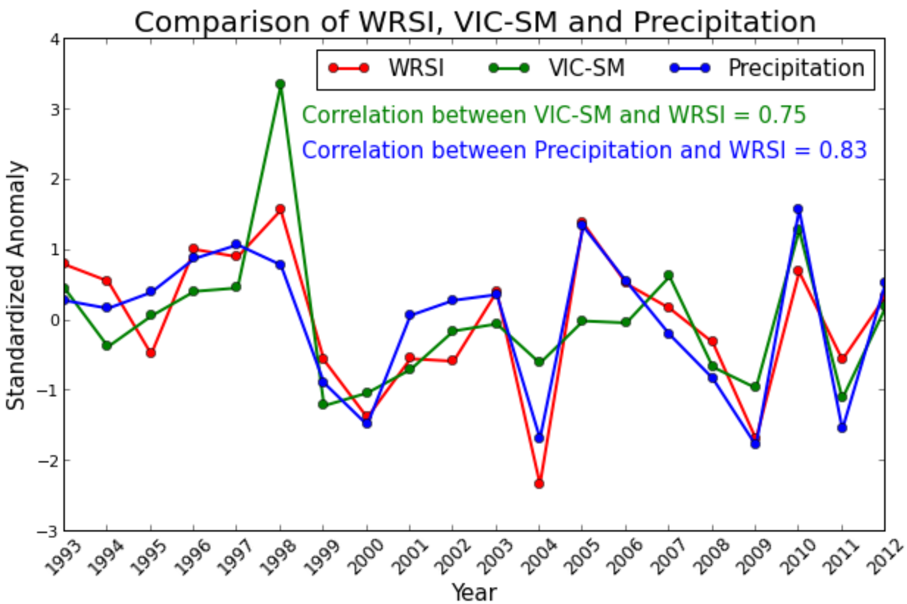

Fig. 6. Comparison of MAM precipitation, VIC-soil moisture (VIC-SM) and End-of-Season Water Requirement Satisfaction Index (WRSI) for crop zones in the focus domain for each year between 1993–2012.

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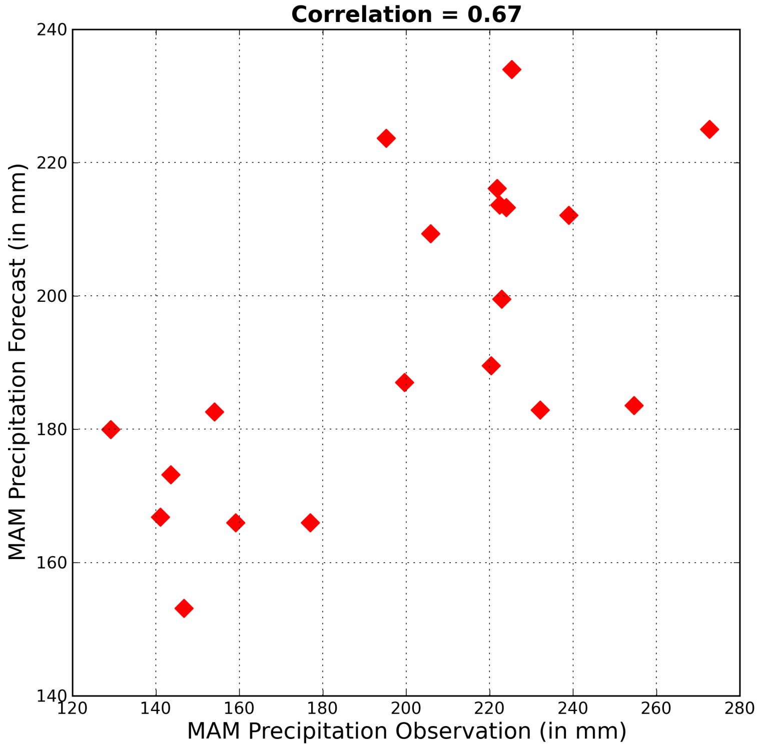

Fig. 7. Comparison of ensemble median MAM precipitation forecasts and observations (CHIPRS) spatially aggregated over the focus domain.

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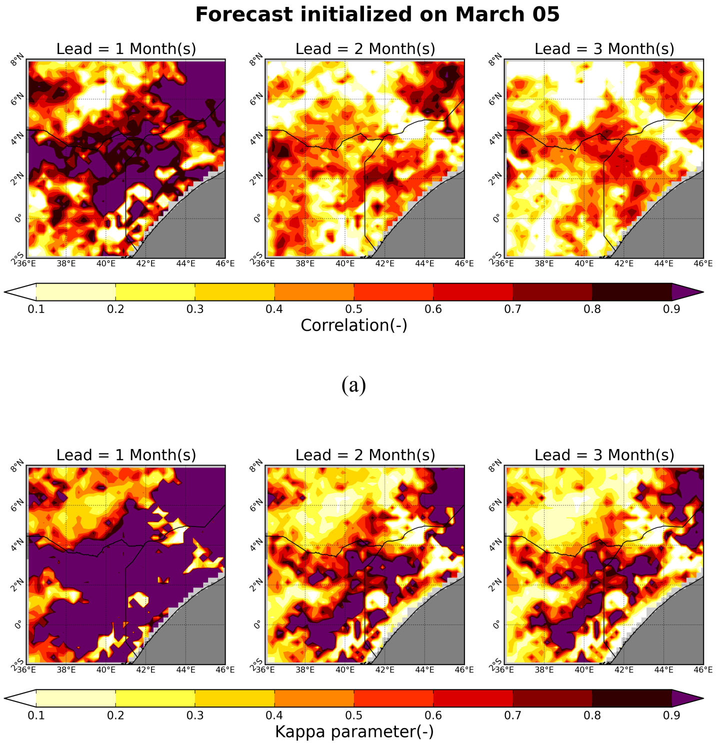

(a)

(b)

Fig. 8. (a) Skill of soil moisture forecasts (i.e. correlation between ensemble median of soil moisture forecasts and observations) initialized on March 04 (start of the season) and **(b)** value of κ parameter (i.e. ratio of standard deviation of initial total moisture and standard deviation of total precipitation during the forecast period) indicating the controls on hydrologic predictability during the forecast period. Greater than 1, κ parameter value indicates greater control of initial moisture on the hydrologic predictability and vice versa.

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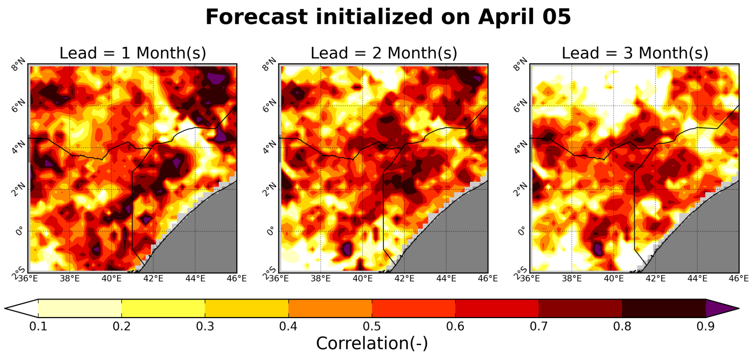
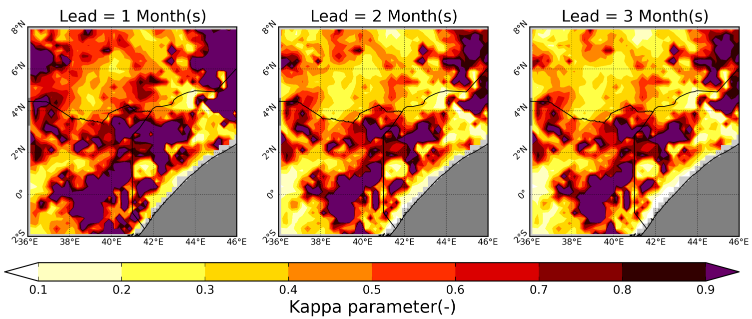


(a)



(b)

Fig. 9. Same as in Fig. 8 but for forecasts initialized on 5 April (middle-of-season).

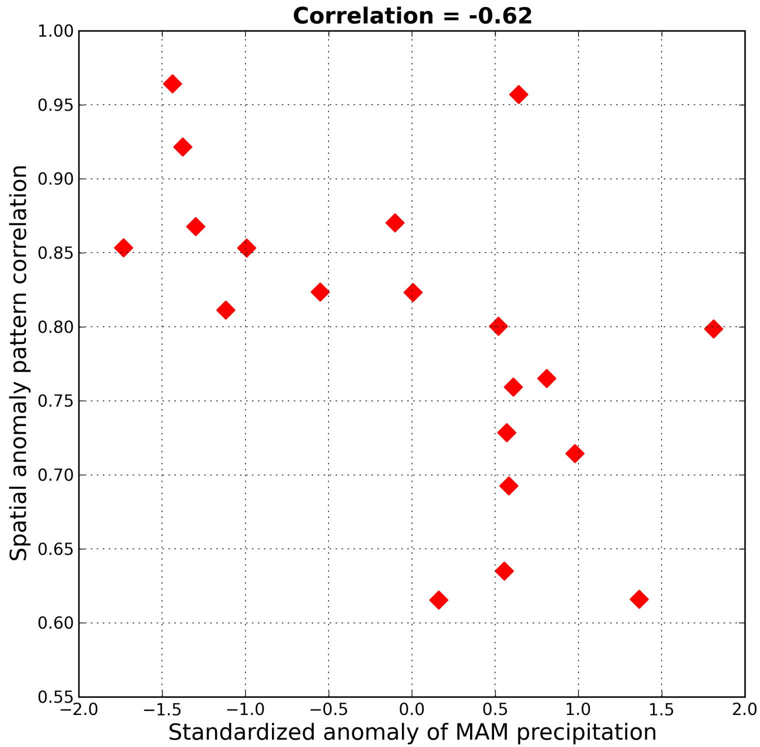


Fig. 10. Comparison between spatial anomaly pattern correlation (between MAM mean soil moisture forecast initialized at the start of season and observation) and standardized anomaly of MAM precipitation. This plot indicates that spatial anomaly pattern correlation is generally higher (> 0.8) during drought years (when standardized anomaly of MAM precipitation is < 0).

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