https://doi.org/10.5194/nhess-2019-267
Preprint. Discussion started: 19 August 2019

Natural Hazards and Earth System Sciences
Discussions

Improving early warning of drought-driven food insecurity in Southern Africa using operational hydrological monitoring and forecasting products

Shraddhanand Shukla[1], Kristi R. Arsenault[2,3], Abheera Hazra[4,3], Christa Peters-Lidard[3], Randal D. Koster[3], Frank Davenport[1], Tamuka Magadzire[5,1], Chris Funk[6,1], Sujay Kumar[3], Amy McNally[2,5], Augusto Getirana[4,3], Greg Husak[1], Ben Zaitchik[7], Jim Verdin[8,5], Faka Dieudonne Nsadisa[9], Inbal Becker-Reshef[3,4]

[1]University of California, Santa Barbara, California, USA

[2]SAIC, Reston, Virginia, USA

[3]NASA Goddard Space Flight Center, Greenbelt, Maryland, USA

[4]University of Maryland, Maryland, USA

[5]Famine Early Warning Systems Network, Washington D.C., USA

[6]EROS, United States Geological Survey, Sioux Falls, South Dakota, USA

[7]John Hopkins University, Baltimore, Maryland, USA

[8]United States Agency for International Development, Washington D.C., USA

[9]Southern African Development Community Climate Services Center, Botswana

Correspondence to: Shraddhanand Shukla (sshukla@ucsb.edu)

Abstract: The region of southern Africa (SA) has a fragile food economy and is vulnerable to frequent droughts. In 2015-2016, an El Niño-driven drought resulted in major maize production shortfalls, food price increases, and livelihood disruptions that pushed 29 million people into

https://doi.org/10.5194/nhess-2019-267
Preprint. Discussion started: 19 August 2019

Natural Hazards and Earth System Sciences
Discussions
Open Access

severe food insecurity. Interventions to mitigate food insecurity impacts require early warning of droughts —preferably as early as possible before the harvest season (typically, starting in April) and lean season (typically, starting in November). Hydrologic monitoring and forecasting systems provide a unique opportunity to support early warning efforts, since they can provide regular updates on available rootzone soil moisture (RZSM), a critical variable for crop yield, and provide forecasts of RZSM by combining the estimates of antecedent soil moisture conditions with climate forecasts. For SA, this study documents the predictive capabilities of a recently developed NASA Hydrological Forecasting and Analysis System (NHyFAS). The NHyFAS system's ability to forecast and monitor the 2015/16 drought event is evaluated. The system's capacity to explain interannual variations in regional crop yield and identify below-normal crop yield events is also evaluated. Results show that the NHyFAS products would have identified the regional severe drought event, which peaked during December-February of 2015/2016, at least as early as November 1, 2015. Next, it is shown that February RZSM forecasts produced as early as November 1 (4-5 months before the start of harvest and about a year before the start of the next lean season) correlate fairly well with regional crop yields (r=0.49). The February RZSM monitoring product, available in early March, correlates with the regional crop yield with higher skill (r= 0.79). It is also found that when the February RZSM forecast produced on November 1 is indicated to be in the lowest tercile, the detrended regional crop yield is below normal about two-thirds (significance level ~86%) of the time. Furthermore, when the February RZSM monitoring product (available in early March) indicates a lowest tercile value, the crop yield is always below normal, at least over the sample

https://doi.org/10.5194/nhess-2019-267
Preprint. Discussion started: 19 August 2019

Natural Hazards and Earth System Sciences Discussions

years considered. These results indicate that the NHyFAS products can effectively support food insecurity early warning in the SA region.

1 Introduction

Southern Africa (SA) is vulnerable to food insecurity. Climate stressors (e.g. precipitation and temperature) are among the important drivers of food insecurity (Misselhorn 2005; Conway et al. 2015). The primary rainy season in SA spans October to March, which overlaps the main planting season from October to February (Fig. 1 (a)). This period also covers the lean season, when food supplies are typically limited. April-July is typically the main harvest season, when the food reserve is expected to begin replenishing. In several SA countries, with the Republic of South Africa (RSA) being the main exception, typical monthly variability in food prices closely follows this crop cycle, as shown in Fig. 1(b). The prices typically start to rise after the harvest season and reach their peak just before or near the start of the harvest season. This correspondence between the prices and crop cycles highlights the region's climate-related sensitivity to food insecurity. In the case of below-normal crop yield, the food prices rise even more than normal, reducing access to food for the poorest of the population.

The percentage income of wealth shared by the poorest 10% and 20% of the population in several SA countries has not improved significantly over time (not shown here). These portions of the population are likely to be more food insecure in drought years. They already use a relatively higher share of their income on food, and in the case of price rises related to low crop yield, their access to food becomes even more limited.

The 2015-16 drought event (attributed to a strong El Niño) in southern Africa further highlighted its vulnerability to climate-related regional food insecurity (Archer et al., 2017; Funk

https://doi.org/10.5194/nhess-2019-267
Preprint. Discussion started: 19 August 2019

et al., 2018; Pomposi et al., 2018). This event led to a substantial reduction in regional agricultural production —including in the Republic of South Africa (RSA), which is the main crop-producing country in the region—a reduction and rationing of water supplies, a loss of livestock, and an increase in unemployment in the region (SADC, 2016). Throughout the Southern African Development Community (SADC) region in 2015-16, cereal production was down by -10.2% (varying from +61% to -94% in individual member countries) relative to the previous 5-year average (SADC, 2016). Figure 1 (c)-(f) shows a comparison of national retail maize prices (in USD) in several of the SA countries during 2015-16, with the previous 5-year mean prices in those countries. The prices in 2015-16 were substantially higher than the previous 5-year mean. Of particular importance is the price increase in RSA, where, typically, the food prices do not vary much throughout the year due to its general self-sufficiency in food production, as well as its international trade. Consumer Price Index (CPI) for food for RSA also experienced a drastic upward shift during the 2015-16 drought year (not shown here). In fact, based on the CPI data (available from the FAO) the CPI was substantially higher than that of the past 5-year mean during the beginning of the following growing season of 2016-17 including in RSA where typically the CPI remains fairly stable during a year. These price shocks can dramatically impact poor households, who typically spend 60% or more of their income on food. According to the recent World Bank Development Indicator, incomes for the poorest 10% and 20% of households in these countries have remained generally constant underscoring the depth of poverty (not shown). On average, in Malawi, Mozambique, Zimbabwe and South Africa, these individuals subsist on $70, $126, $288, and $716 USD a year, respectively.

https://doi.org/10.5194/nhess-2019-267
Preprint. Discussion started: 19 August 2019

Figure 1(c)-(f) and the income related facts (based on World Bank Development indicator) presented above highlight the severity of food insecurity in a regional drought event like 2015-16. In the 2015-2016 event, food imports from RSA—which is the main producer and exporter of food in the region to the other SA countries—were not enough, and international assistance becomes crucial.

This is why in June 2016, the SADC launched a Regional Humanitarian Appeal stating that approximately 40 million people in the region required humanitarian assistance, at a cost of approximately USD $2.4 billion (Magadzire et al. 2017).

Mitigation of the most adverse impacts of food insecurity, like the event of 2015-16, requires timely and effective early warning. An effective early warning system has two key attributes (Funk et al., 2019): (1) the ability to provide routine, frequent early warning of drought status and (2) the ability to incorporate both monitoring and forecasting to best account for the conditions until the date of early warning, in combination with the climate outlook for the upcoming season.

A seasonal scale hydrologic forecasting system can potentially effectively support an early warning system, as it can provide updated hydrologic forecasts monthly by accounting for the drought conditions as of the forecast release date and climate outlook over the forecast period (Sheffield et al., 2014; Shukla et al., 2014). However, thus far, the application of seasonal-scale hydrologic forecasts in food insecurity early warning has been limited at best. On the other hand, operational, publicly available, state-of-the-art dynamical climate forecasts have found regular usage in guiding climate outlook, as well as assessments of expected food insecurity. For example, USAID's Famine Early Warning Systems Network (http://fews.net/), G20-Group on

https://doi.org/10.5194/nhess-2019-267
Preprint. Discussion started: 19 August 2019

Earth Observations Global Agricultural Monitoring (GEOGLAM) Crop Monitor for Early Warning, and SADC's Climate Service Center (CSC) all utilize the dynamical climate forecasts as one of their early warning tools. Furthermore, numerous past studies have investigated the predictability of SA climate (Meque and Abiodun, 2014) and examined the skill of diverse approaches in forecasting, particularly of rainfall, as well as streamflow and agricultural production in different parts of this region (Archer et al., 2017; Cane et al., 1994; Diro, 2015; Landman et al., 2001; Landman and Beraki, 2010; Landman and Goddard, 2002; Manatsa et al., 2015; Martin et al., 2000; Sunday et al., 2014; Trambauer et al., 2015; Winsemius et al., 2014). Historically, El Niño-Southern Oscillation (ENSO) has proven to be among the main predictors of this region's climate, with another important predictor being the Southern Indian Ocean Dipole (Hoell et al., 2016, 2017; Hoell and Cheng, 2017).

However, the application of climate-model-driven hydrological forecasts, which, as stated above, derive their skills from the climate forecast skill and initial hydrologic conditions, has been limited. Thus, it can be an effective early warning tool, as operational food insecurity assessment has been limited, with the only other main example being the African Flood and Drought Monitor (Sheffield et al., 2014).

In August 2018, a new NASA Hydrological Forecasting and Analysis System (NHyFAS), an operational seasonal hydrologic forecasting system (Arsenault et al., 2019), was implemented to support the early warning efforts of FEWS NET, building upon existing hydrologic monitoring (McNally et al., 2017). This study evaluates this system in supporting early warning of regional food insecurity in the SA region. The evaluation is conducted by examining the performance of this system (i) for the 2015-16 drought event, which led to

https://doi.org/10.5194/nhess-2019-267
Preprint. Discussion started: 19 August 2019

regional food insecurity, (ii) in explaining regional crop yield variability in the region, and (iii) in identifying below normal crop yield events, which are characteristically associated with overall lower food availability in the region and, hence, food insecurity. Regional crop yield is used as a target variable here, as it is among the main contributors to regional food insecurity. It is hypothesized that if this system can skillfully forecast regional crop yield and identify below normal regional crop yields, it can successfully support the early warning of food insecurity in the region.

As noted above and shown in Fig. 1(a), April-July is typically the main harvest season, when the food reserve is expected to begin replenishing and last through the lean season, which starts in November. Below-normal food availability during this period can lead to food insecurity. Therefore, early warning systems aim to provide outlooks for food insecurity as far in advance of the harvest and lean season as possible. Consequently, this study focuses on using forecasting and monitoring products that are available in November (4-5 months before the start of the harvest and about a year before the start of the next lean season) through March (1-2 months before the start of the harvest and about 8-9 months before the start of the next lean season) to examine their value in supporting early warning of food insecurity in the region.

2 Data and Methodology

2.1 Hydrologic Modeling Framework

The hydrologic monitoring and forecasting products used in this study come from the NHyFAS (Arsenault et al., 2019). Arsenault et al. (2019) describes the system in much detail; we provide below a brief description of the products. To generate hydrological forecasts, we use NASA's Catchment land surface model (CLSM; [(Ducharne et al., 2000; Koster et al., 2000) and

https://doi.org/10.5194/nhess-2019-267
Preprint. Discussion started: 19 August 2019

Natural Hazards and Earth System Sciences
Open Access
Discussions

the Noah Multi-Parameterization (Noah-MP; [(Niu et al., 2011; Yang et al., 2011) land surface model (LSM), which account for changes in soil moisture (e.g., root zone) and groundwater storage, and surface energy and water flux terms. These two LSMs are part of the model suite in the Land Information System (LIS) framework (Kumar et al., 2006)—the primary software system used to produce this study's forecast experiments. Both LSMs were spun-up twice for the period from 1 January, 1981 to 31 December, 2015; then, historical open-loop (OL) runs were generated for January 1981 through 2018. Rootzone SM (RZSM), which is the main hydrologic variable used in this analysis, indicates the soil moisture in the top one meter of the soil profile. The entire depth of the soil profile is different for the two models used in this analysis (typically about 2 m for Noah-MP and about 4 m for CLSM).

2.2 Model Parameters

In the version of CLSM used here, hydrologic and catchment parameters (Ducharne et al., 2000) are based on a high-resolution, global topographic data set (Verdin and Verdin, 1999), and soil texture (Reynolds et al., 2000) and profile parameters are derived from the Second Global Soil Wetness Project (GSWP-2; (Guo and Dirmeyer, 2006) data set and mapped to the catchment tiles. Land cover classes are mapped from the University of Maryland AVHRR data set, and vegetation parameters include, for example, leaf area index (LAI), which are also derived from GSWP-2. Albedo scaling factors are based on Moderate Resolution Imaging Spectroradiometer (MODIS) direct and diffuse visible or near infra-red radiation inputs (Moody et al., 2008).

Noah-MP vegetation parameters include the modified IGBP MODIS-based land cover data set (Friedl et al., 2002), leaf area index, and monthly greenness fraction (Gutman and

https://doi.org/10.5194/nhess-2019-267
Preprint. Discussion started: 19 August 2019

Ignatov, 1998). The soil texture data set is based on Reynolds et al. (2000), and soil parameters are mapped to the varying textures. Monthly global (snow-free) albedo (Csiszar and Gutman, 1999) and a maximum snow albedo parameter field are also employed. Additional details are found in (Niu et al., 2011).

2.3 Input observed forcings and climate forecasts

The spin-up and OL runs used to generate the long-term "observed" climatology of RZSM are driven with NASA's Modern-Era Retrospective analysis for Research and Applications, version 2 (MERRA-2; [(Gelaro et al., 2017) atmospheric fields (e.g., 2m air temperature, humidity). Precipitation forcing comes from the U.S. Geological Survey (USGS)/University of California, Santa Barbara (UCSB) Climate Hazards Center InfraRed Precipitation with Station data set, version 2.0 (CHIRPSv2; [(Funk et al., 2015).

Hindcasts of RZSM are generated by forcing the hydrologic models with NASA's Goddard Earth Observing System (GEOS) Atmosphere-Ocean General Circulation Model, version 5 (GEOS; [(Borovikov et al., 2017)]) Seasonal-to-Interannual Forecast System. The eleven ensemble members of version 1 of this forecast system that were used in the North American Multi-Model Ensemble (NMME) project are used in the forecast portion of this study. To make the GEOS forecasted meteorology consistent with the meteorology underlying the OL initial conditions, we Bias-Corrected and Spatially Downscaled (BCSD; [(Wood et al., 2002)]) the GEOS forecasts using the MERRA-2 and CHIRPS data sets. The BCSD-GEOS forecast files are then ingested into LIS to drive the LSMs and generate the dynamical hydrological forecasts. The BCSD-GEOS hindcasts are initialized on November 1st (near the start of the planting

https://doi.org/10.5194/nhess-2019-267
Preprint. Discussion started: 19 August 2019

Natural Hazards and Earth System Sciences
Open Access
EGU
Discussions

season) and January 1st (middle of the planting season) and are run for each 6-month forecast period from 1982-83 to 2017-18.

Hindcasts of RZSM are also generated using the Ensemble Streamflow Prediction (ESP) method (Day 1985; Shukla et al. 2013), where the models are forced with resampled climatology of observed forcings (forcings that are used to drive the OL simulation). The hindcasts generated using the ESP method derive their skills from the initial hydrologic conditions only.

2.4 RZSM Monitoring and forecasting products

The performance of the NHyFAS system is evaluated through its RZSM monitoring (generated from OL) and forecasting products. Both products are generated at 0.25 X 0.25 degree spatial resolution and daily temporal resolution. Daily values are averaged over a month to get monthly values. The monthly values of the monitoring product are converted to percentiles relative to OL climatology over 1982-2010, and monthly values of the ensemble mean forecasting products (GEOS and ESP based) are converted into percentiles relative to the (ensemble mean) climatology over 1982-2010 of the respective hindcast runs. In both cases, empirical distribution taken from the climatology is considered to convert values to percentiles. Once gridded percentile values are generated they are spatially aggregated over the SA region (as shown in Fig. 2) to get RZSM monitoring and forecasting products over the SA region.

2.5 Regional Crop Yield

The regional crop yield is calculated using country-level crop production and area harvested reports. These reports come from the United States Department of Agriculture's Foreign Agricultural Service's Production Supply and Distribution (PSD) database. To compile this database, USDA relies on several sources, including official country statistics, reports from

https://doi.org/10.5194/nhess-2019-267
Preprint. Discussion started: 19 August 2019

agricultural attaches at U.S. embassies, data from international organizations, publications from individual countries, and information from traders both inside and outside of the target countries. For this study, we focus only on maize, as it is the main crop in the region and the key crop for food security. To get regional crop yield from country-level crop yield, we first converted country-level yield into production using the harvested area (provided by the PSD), added the total production, and then divided it by the sum of the harvested area in all SA countries in our focus domain. The regional crop yield is detrended for the purposes of this study to reduce the effect of any long-term changes (e.g. technological changes) on the crop yield.

3. Results

3.1 Performance of NHyFAS during the 2015-16 drought event

As highlighted in section 1, the 2015-16 drought event in SA is among the most severe in terms of drought severity and food insecurity impacts in the last few decades. Therefore, we begin the evaluation of the suitability of NHyFAS in supporting food insecurity early warning in the SA region by examining how this system would have performed during the 2015-16 event. Although the NHyFAS operationally provides the seasonal forecasts every month, for the purpose of this study, we focus on the forecast initialized on November 1 (near the start of the planting season) and January 1 (near the middle of the growing season) of 2015-16 event. Figure 2 shows the RZSM forecasts for the growing season made on November 1st of 2015. By this time in the season, both FEWS NET and SADC had provided early warning of poor rainfall performance in the region (Magadzire et al. 2017). The NHyFAS RZSM forecasts would have provided further evidence of a looming unprecedented drought in the region. These forecasts would have also indicated that RSA, which is the most important country for the region's food production, was going to be within the epicenter of this drought event. These forecasts, in turn, could potentially have triggered appropriate actions earlier by the early warning agencies as well as the decision-makers (e.g., national governments and international relief agencies).

Later in the season as the observed precipitation data became available, RZSM monitoring products would have provided refined estimates of the spatial extent and severity of drought in the region. Figure 2 (bottom panel) shows the RZSM monitoring product available after each of the months of November 2015 through February 2016. This monitoring product would have provided additional proof of the drought occurrence in the region and shown that RSA was within the epicenter of this drought. It is important to state that even the monitoring product can be effectively used as a predictor of food insecurity events as they are available before the typical start of the harvest season (in April) and the lean season (in November).

3.2 Performance of NHyFAS in supporting food insecurity early warning

Next, we investigate the long-term performance of NHyFAS in supporting food insecurity early warning by examining how well forecasting and monitoring products available from this system can explain historical variability in regional crop yield of the SA region and in particular, help identify below-normal regional yield events. Regional crop yield is calculated by adding the yearly productions from the SA countries, then dividing it by the yearly total harvested area. The regional crop yield is then detrended to remove the effect of any long-term changes (such as technological changes) on the regional yield.

For this analysis, we make use of the February RZSM forecasts initialized on November 1 and January 1, and February RZSM monitoring product (available in early March), as February RZSM historically has the highest correlation with the detrended crop yield, as highlighted in

https://doi.org/10.5194/nhess-2019-267
Preprint. Discussion started: 19 August 2019

Fig. 3. This figure also indicates that February RZSM has higher correlation with detrended crop yield than December-February (DJF) seasonal precipitation and air temperature however the difference in correlation is not statistically significant.

Figure 4 (a & b) show the interannual covariability of February RZSM forecasts (based on ESP method and bias-corrected GEOS forecasts) initialized on November 1 and January 1, respectively, with the detrended regional crop yield. The correlation between GEOS-based February RZSM forecasts initialized on November 1 is 0.49, which is higher than the correlation based on monitoring products at this point in the season (Fig. 3). This indicates that a more skillful (than the monitoring product) early warning of regional crop yield can be potentially made as early as on November 1, about 4-5 months before the harvest season starts (around April) and about a year before the next lean season (around November) starts. The correlation value remains similar (0.45) even when the forecast is initialized on January 1; however, the correlation value is still higher than what can be achieved using the monitoring product at this point in the season (Fig. 3). Furthermore, the correlation values of GEOS-based RZSM forecasts is higher than ESP-based RZSM forecasts. ESP-based RZSM forecasts derive their skill from the initial hydrologic conditions only, whereas GEOS-based RZSM forecasts derive their skill from the climate forecasts as well. Hence, the source of additional skill of GEOS-based RZSM forecasts is the climate forecasts.

Figure 4 (c) shows the covariability of the February RZSM monitoring product with the detrended regional yield. The correlation value with the regional crop yield increases to 0.79 and is substantially higher relative to when RZSM forecasting products are used (Fig. 4a and b). February RZSM monitoring product is available in early March, so a high correlation of the

Natural Hazards and Earth System Sciences
Open Access
EGU
Discussions

regional crop yield with that product potentially means that early warning of regional crop yield can be made with a high skill, about 1-2 months before the harvest season starts (around April) and about 8-9 months before the next lean season (around the next November) starts. This is likely to strengthen FEWS NET's current food insecurity early warning efforts in the region.

Next, we examine how well the forecasting and monitoring RZSM products do in providing early warning of below-normal crop yield events. This criterion for performance evaluation is of particular significance for food insecurity early warning in the region, as below-normal crop yield events are the ones which generally lead to food insecurity. To investigate this, we calculate the probability of below-normal crop yield events when either February RZSM forecasting products (initialized on November 1 and January 1), and RZSM monitoring product for the month of November (available in early December) through the month of February (available in early March) were in the lower tercile. In this case, below-normal regional crop yield events are the events that lie in the bottom 18 (i.e. bottom half) when detrended crop yields for the 36 years is ranked in ascending order. Similarly, lower terciles of RZSM products are the values that are in the bottom 12 (i.e. bottom tercile) of the RZSM products when ranked in ascending order. In the case of RZSM, the ranked climatology is different for each of the forecasting products and the monitoring products for each month.

Figure 5 shows the fraction of years with below-normal crop yield when February RZSM forecasts (made on November 1 or January 1) were in the lower tercile (shown by blue color bars) or when monthly RZSM monitoring products (shown by green color bars) were in the lower tercile. These results indicate that as early as November 1, if the February RZSM is being forecasted to be in the lower tercile, then there is about ~66% probability of the regional crop

https://doi.org/10.5194/nhess-2019-267
Preprint. Discussion started: 19 August 2019

yield being below normal (statistically significant at 86% confidence level). This would be 4-5 months before the start of the harvest season and about one year before the start of the next lean season. The inferred probability value increases to ~83% when the February RZSM forecasts, initialized in January, are in the lower tercile (statistically significant >95% confidence level). Finally, by early March, by the time monitoring of February of RZSM is available, the inferred probability increases to 100% (statistically significant >95% confidence level). In other words, over 1982-2016, whenever the February RZSM for the SA region was in the lowest tercile, the crop yield in the following season had been below normal (based on detrended yield). This would be 1-2 months before the start of the harvest season and about 8-9 months before the start of the next lean season.

Of course, the estimation of these probabilities is necessarily limited by the small sample sizes examined; the actual probability of low crop yield based on low February RZSM, for example, while apparently high, is not a full 100%. Nevertheless, these results provide, overall, further evidence of the suitability of the forecasting and monitoring products from the NHyFAS in supporting early warning of food insecurity in the region.

4 Discussion

This study makes a case for the application of NHyFAS's RZSM forecasting and monitoring products in supporting the early warning of food insecurity in SA. It has been shown that the successful early warning of crop yield, and especially below-normal crop yield years, can be issued based on these products, which would offer significant implications for the region's food security. Here, it is assumed that when the SA region faces a production shortfall, the regional food insecurity is likely to rise. This was certainly the case during the 2015-16 El Niño—which was the last major food insecurity event in the region. However, this narrow

https://doi.org/10.5194/nhess-2019-267
Preprint. Discussion started: 19 August 2019

Natural Hazards and Earth System Sciences
Open Access
Discussions

assumption ignores other important factors that may lead to or further worsen food insecurity in the region, such as inadequate agricultural inputs, price shocks (which can be global in nature), rise in population, conflict, limited livelihood options, stocks, etc. Nonetheless, the direct relationship of crop yield with the interannual variability in available moisture makes RZSM an important variable for food security monitoring. It is of keen interest to early warning systems like FEWS NET, which is presently the primary end user of the NHyFAS**.** Crop yield early warning based on the NHyFAS products are also directly relevant to international collaborative efforts like the GEOGLAM initiative and, particularly, to the Crop Monitor for Early Warning, which provides monthly assessments of crop conditions for the countries most vulnerable to food insecurity. Such assessments are key to helping reduce uncertainty of crop prospects as the growing season progresses, and provide critical evidence for informing food security decisions by humanitarian organizations and governments alike.

It is also worth mentioning here that crop yield reports can be influenced by external factors (for example, reporting issues related to methods) other than long-term agricultural, technology-driven changes and climate interannual variability. The effect of these factors on the regional crop yield of course cannot be discounted by the detrending method employed in this study.

Finally, the results of this study are also likely affected by the use of only one dynamical climate forecast model for driving the seasonal hydrologic system. Adding forecasts from more climate and hydrologic models would likely enhance the skill of the system. The choice of one dynamical system was made mostly for operational purposes, since GEOS archived and

https://doi.org/10.5194/nhess-2019-267
Preprint. Discussion started: 19 August 2019

Natural Hazards and Earth System Sciences
Open Access
Discussions

real-time forecasts include all atmospheric forcing variables needed to drive such LSMs, and are available routinely to facilitate operational production of hydrologic forecasts.

5 Conclusions

The region of SA witnessed several food insecurity events in the last few decades. Mitigation of food insecurity impact requires timely and effective interventions by national, regional, and international agencies. To support those interventions, early warning of food insecurity is needed. In this study, we investigate the suitability of the operational RZSM products produced by a recently developed NASA seasonal scale hydrologic forecasting system, NHyFAS, in supporting food insecurity early warning in this region.

The key findings of this study are: (i) the NHyFAS products would have identified the regional severe 2015-2016 drought event (which peaked in December-February) at least as early as November 1st of 2015; (ii) February RZSM forecasts produced as early as November 1 (4-5 months before the start of harvest, and about one year before the start of the next lean season) can explain the interannual variability in regional crop yield production with moderate skill (correlation 0.49); (iii) use of dynamical climate forecasts adds to the skill (relative to the skill coming from the initial hydrologic conditions alone) of February RZSM forecasts in predicting regional crop yield; (iv) the February RZSM monitoring product, available in early March (1-2 months before the start of harvest and 8-9 months before the start of the next lean season) can explain the variability in regional crop yield with high skill (correlation of 0.79); (v) when the February RZSM forecast (initialized on November 1) is found to be in the lowest tercile, the subsequent detrended regional crop yield is below normal about 66% of the time (statistical significance level ~86%), and likewise, when the February RZSM monitoring product is in the

https://doi.org/10.5194/nhess-2019-267
Preprint. Discussion started: 19 August 2019

lowest tercile, the subsequent crop yield, for the sampling period considered, is always below-normal (statistical significance level >95%)

The NHyFAS products described here began being generated in August 2018 for operational applications by FEWS NET. Each month, FEWS NET's regional scientists (located in eastern, western and southern Africa) review the latest products ahead of the FEWS NET's monthly climate discussions (Funk et al. 2019). The products are used to support or revise the assumptions of climate and hydrologic conditions for the upcoming season. The updated assumptions are then passed on to food analysts for the region in order to help inform needed relief actions. The forecasting products are currently available via https://lis.gsfc.nasa.gov/projects/fame.

https://doi.org/10.5194/nhess-2019-267
Preprint. Discussion started: 19 August 2019

Author contribution:

SS led the design of the analysis, conducted the analysis and wrote the manuscript and generated figures. KA, CL, CF and FD contributed to the design of the analysis. KA and AH conducted the model simulations. RK and CL reviewed the article and proposed substantial changes. CL and GH are PIs of projects supporting this work. TM, JV, AM, AH fasciliate real-time application of the products. Rest of the co-authors reviewed the article and provided their input/edits.

Competing interests:

The authors declare that they have no conflict of interest.

Acknowledgements:

Support for this study comes from NASA Grant NNX15AL46G and the US Geological Survey (USGS) cooperative agreement #G09AC000001. Crop yield, production, and consumption data were obtained from USDA FAS's PSD: https://apps.fas.usda.gov/psdonline/app/index.html#/app/home. Average price data were obtained from FAO's FAO STATS database http://www.fao.org/faostat/en/#home. World Bank Development Indicators were downloaded from https://data.worldbank.org/indicator/. GEOS forecast data sets are generated and supported by NASA's Global Modeling and Assimilation Office (GMAO). High-performance computing resources were provided by the NASA Center for Climate Simulation (NCCS) in Greenbelt, MD. The authors thank Climate Hazards Center's technical writer Juliet Way-Henthorne for providing professional editing.

Natural Hazards and Earth System Sciences
Discussions
Open Access

References

Archer, E., Landman, W. A., Tadross, M. A., Malherbe, J., Weepener, H., Maluleke, P. and Marumbwa, F. M.: Understanding the evolution of the 2014–2016 summer rainfall seasons in southern Africa: Key lessons, Climate Risk Management, 16, 22–28, 2017.

Arsenault, K., Shukla, S., Hazra, A., Getirana, A., McNally, A., Kumar, S., Koster, R., Zaitchik, B., Badr, H., Jung, H. C., Narapusetty, B., Navari, M., Wang, S., Mocko, S., Funk, C., Harrison, L., Husak, G., Verdin, J. V., and Peters-Lidard, C. C.: A NASA modeling and remote-sensing based hydrological forecast system for food and water security applications. Bulletin of the American Meteorological Society (in review)

Borovikov, A., Cullather, R., Kovach, R., Marshak, J., Vernieres, G., Vikhliaev, Y., Zhao, B. and Li, Z.: GEOS-5 seasonal forecast system, Clim. Dyn., doi:10.1007/s00382-017-3835-2, 2017.

Cane, M. A., Eshel, G. and Buckland, R. W.: Forecasting Zimbabwean maize yield using eastern equatorial Pacific sea surface temperature, Nature, 370(6486), 204–205, 1994.

Csiszar, I. and Gutman, G.: Mapping global land surface albedo from NOAA AVHRR, Journal of Geophysical Research: Atmospheres, 104(D6), 6215–6228, doi:10.1029/1998jd200090, 1999.

Diro, G. T.: Skill and economic benefits of dynamical downscaling of ECMWF ENSEMBLE seasonal forecast over southern Africa with RegCM4, Int. J. Climatol., 36(2), 675–688, 2015.

Ducharne, A., Koster, R. D., Suarez, M. J., Stieglitz, M. and Kumar, P.: A catchment-based approach to modeling land surface processes in a general circulation model: 2. Parameter estimation and model demonstration, J. Geophys. Res. D: Atmos., 105(D20), 24823–24838, 2000.

FAO, 2019: FAOSTAT Database. FAO. Rome, Italy. http://www.fao.org/publications/en Accessed on July 1, 2019

Friedl, M. A., McIver, D. K., Hodges, J. C. F., Zhang, X. Y., Muchoney, D., Strahler, A. H., Woodcock, C. E., Gopal, S., Schneider, A., Cooper, A., Baccini, A., Gao, F. and Schaaf, C.: Global land cover mapping from MODIS: algorithms and early results, Remote Sensing of Environment, 83(1-2), 287–302, doi:10.1016/s0034-4257(02)00078-0, 2002.

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A. and Michaelsen, J.: The climate hazards infrared precipitation with stations--a new environmental record for monitoring extremes, Sci Data, 2, 150066, 2015.

Funk, C., Davenport, F., Harrison, L., Magadzire, T., Galu, G., Artan, G. A., Shukla, S., Korecha, D., Indeje, M., Pomposi, C., Macharia, D., Husak, G. and Nsadisa, F. D.: Anthropogenic Enhancement of Moderate-to-Strong El Niño Events Likely Contributed to Drought and Poor Harvests in Southern Africa During 2016, Bull. Am. Meteorol. Soc., 99(1), S91–S96, 2018.

Funk, C., Shukla, S., Thiaw, W. M., Rowland, J., Hoell, A., McNally, A., Husak, G., Novella, N., Budde, M., Peters-Lidard, C., Adoum, A., Galu, G., Korecha, D., Magadzire, T., Rodriguez, M., Robjhon, M., Bekele, E., Arsenault, K., Peterson, P., Harrison, L., Fuhrman, S., Davenport, F., Landsfeld, M., Pedreros, D., Jacob, J. P., Reynolds, C., Becker-Reshef, I. and Verdin, J.: Recognizing the Famine Early Warning Systems Network (FEWS NET): Over 30 Years of Drought Early Warning Science Advances and Partnerships Promoting Global Food Security, Bulletin of the American Meteorological Society, doi:10.1175/bams-d-17-0233.1, 2019.

Gelaro, R., McCarty, W., Suárez, M. J., Todling, R., Molod, A., Takacs, L., Randles, C. A., Darmenov, A., Bosilovich, M. G., Reichle, R., Wargan, K., Coy, L., Cullather, R., Draper, C., Akella, S., Buchard, V., Conaty, A., Da Silva, A. M., Gu, W., Kim, G., Koster, R., Lucchesi, R., Merkova, D., Nielsen, J. E., Partyka, G., Pawson, S., Putman, W., Rienecker, M., Schubert, S. D., Sienkiewicz, M. and Zhao, A. B.: The Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2), J. Climate, 30, 5419–5454, 2017.

Guo, Z. and Dirmeyer, P. A.: Evaluation of the Second Global Soil Wetness Project soil moisture simulations: 1. Intermodel comparison, Journal of Geophysical Research, 111(D22), doi:10.1029/2006jd007233, 2006.

Gutman, G. and Ignatov, A.: The derivation of the green vegetation fraction from NOAA/AVHRR data for use in numerical weather prediction models, International Journal of Remote Sensing, 19(8), 1533–1543, doi:10.1080/014311698215333,1998.

Hoell, A. and Cheng, L.: Austral summer Southern Africa precipitation extremes forced by the El Niño-Southern oscillation and the subtropical Indian Ocean dipole, Clim. Dyn., 50(9-10), 3219–3236, 2017.

Hoell, A., Funk, C., Zinke, J. and Harrison, L.: Modulation of the Southern Africa precipitation response to the El Niño Southern Oscillation by the subtropical Indian Ocean Dipole, Clim. Dyn., 48(7-8), 2529–2540, 2016.

Hoell, A., Gaughan, A. E., Shukla, S. and Magadzire, T.: The Hydrologic Effects of Synchronous El Niño–Southern Oscillation and Subtropical Indian Ocean Dipole Events over Southern Africa, J. Hydrometeorol., 18(9), 2407–2424, 2017.

Koster, R. D., Suarez, M. J., Ducharne, A., Stieglitz, M. and Kumar, P.: A catchment-based approach to modeling land surface processes in a general circulation model: 1. Model structure, J. Geophys. Res. D: Atmos., 105(D20), 24809–24822, 2000.

https://doi.org/10.5194/nhess-2019-267
Preprint. Discussion started: 19 August 2019

Kumar, S., Peterslidard, C., Tian, Y., Houser, P., Geiger, J., Olden, S., Lighty, L., Eastman, J., Doty, B. and Dirmeyer, P.: Land information system: An interoperable framework for high resolution land surface modeling, Environmental Modelling & Software, 21(10), 1402–1415, 2006.

Landman, W. A. and Beraki, A.: Multi-model forecast skill for mid-summer rainfall over southern Africa, Int. J. Climatol., 32(2), 303–314, 2010.

Landman, W. A. and Goddard, L.: Statistical Recalibration of GCM Forecasts over Southern Africa Using Model Output Statistics, J. Clim., 15(15), 2038–2055, 2002.

Landman, W. A., Mason, S. J., Tyson, P. D. and Tennant, W. J.: Retro-active skill of multi-tiered forecasts of summer rainfall over southern Africa, Int. J. Climatol., 21(1), 1–19, 2001.

Manatsa, D., Mushore, T. and Lenouo, A.: Improved predictability of droughts over southern Africa using the standardized precipitation evapotranspiration index and ENSO, Theor. Appl. Climatol., 127(1-2), 259–274, 2015.

Martin, R. V., Washington, R. and Downing, T. E.: Seasonal Maize Forecasting for South Africa and Zimbabwe Derived from an Agroclimatological Model, J. Appl. Meteorol., 39(9), 1473–1479, 2000.

Meque, A. and Abiodun, B. J.: Simulating the link between ENSO and summer drought in Southern Africa using regional climate models, Clim. Dyn., 44(7-8), 1881–1900, 2014.

Moody, E. G., King, M. D., Schaaf, C. B. and Platnick, S.: MODIS-Derived Spatially Complete Surface Albedo Products: Spatial and Temporal Pixel Distribution and Zonal Averages, Journal of Applied Meteorology and Climatology, 47(11), 2879–2894, doi:10.1175/2008jamc1795.1, 2008.

Niu, G.-Y., Yang, Z.-L., Mitchell, K. E., Chen, F., Ek, M. B., Barlage, M., Kumar, A., Manning, K., Niyogi, D., Rosero, E., Tewari, M. and Xia, Y.: The community Noah land surface model with multiparameterization options (Noah-MP): 1. Model description and evaluation with local-scale measurements, J. Geophys. Res., 116(D12), doi:10.1029/2010jd015139, 2011.

Pomposi, C., Funk, C., Shukla, S., Harrison, L. and Magadzire, T.: Distinguishing southern Africa precipitation response by strength of El Niño events and implications for decision-making, Environ. Res. Lett., 13(7), 074015, 2018.

Reynolds, C. A., Jackson, T. J. and Rawls, W. J.: Estimating soil water-holding capacities by linking the Food and Agriculture Organization Soil map of the world with global pedon databases and continuous pedotransfer functions, Water Resources Research, 36(12), 3653–3662, doi:10.1029/2000wr900130, 2000.

SADC: SADC Regional Vulnerability Assessment and Analysis Synthesis Report 2016: State of Food Insecurity and Vulnerability in the Southern African Development Community : Compiled from the National Vulnerability Assessment Committee (NVAC) Reports Presented at the Regional Vulnerability Assessment and Analysis (RVAA) Annual Dissemination Forum on 6-10 June 2016 in Pretoria, Republic of South Africa., 2016.

Sheffield, J., Wood, E. F., Chaney, N., Guan, K., Sadri, S., Yuan, X., Olang, L., Amani, A., Ali, A., Demuth, S. and Ogallo, L.: A Drought Monitoring and Forecasting System for Sub-Sahara African Water Resources and Food Security, Bull. Am. Meteorol. Soc., 95(6), 861–882, 2014.

Shukla, S., McNally, A., Husak, G. and Funk, C.: A seasonal agricultural drought forecast system for food-insecure regions of East Africa, Hydrology and Earth System Sciences Discussions, 11(3), 3049–3081, doi:10.5194/hessd-11-3049-2014, 2014.

Sunday, R. K. M., Masih, I., Werner, M. and van der Zaag, P.: Streamflow forecasting for operational water management in the Incomati River Basin, Southern Africa, Physics and Chemistry of the Earth, Parts A/B/C, 72-75, 1–12, 2014.

Trambauer, P., Werner, M., Winsemius, H. C., Maskey, S., Dutra, E. and Uhlenbrook, S.: Hydrological drought forecasting and skill assessment for the Limpopo River basin, southern Africa, Hydrol. Earth Syst. Sci., 19(4), 1695–1711, 2015.

Verdin, K. L. and Verdin, J. P.: A topological system for delineation and codification of the Earth's river basins, Journal of Hydrology, 218(1-2), 1–12, doi:10.1016/s0022-1694(99)00011-6, 1999.

Winsemius, H. C., Dutra, E., Engelbrecht, F. A., Van Garderen, E. A., Wetterhall, F., Pappenberger, F. and Werner, M. G. F.: The potential value of seasonal forecasts in a changing climate in southern Africa, Hydrol. Earth Syst. Sci., 18(4), 1525–1538, 2014.

Wood, A. W., Maurer, E. P. and Kumar, A., and Lettenmaier, D. P: Long-range experimental hydrologic forecasting for the eastern United States, J. Geophys. Res., 107(D20), doi:10.1029/2001jd000659, 2002.

Yang, Z.-L., Niu, G.-Y., Mitchell, K. E., Chen, F., Ek, M. B., Barlage, M., Longuevergne, L., Manning, K., Niyogi, D., Tewari, M. and Xia, Y.: The community Noah land surface model with multiparameterization options (Noah-MP): 2. Evaluation over global river basins, J. Geophys. Res., 116(D12), doi:10.1029/2010jd015140, 2011.

https://doi.org/10.5194/nhess-2019-267
Preprint. Discussion started: 19 August 2019

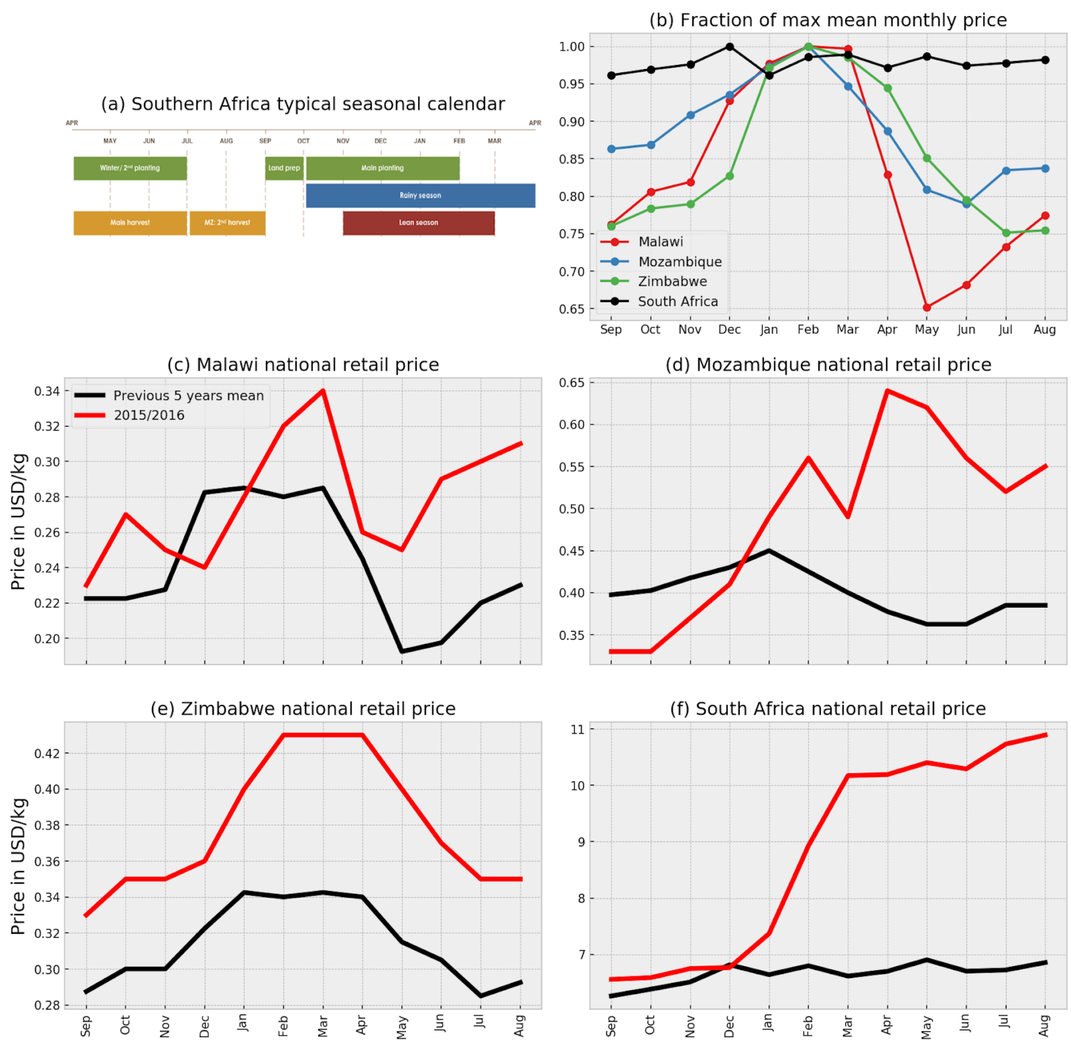

Figure 1: (a) Schematic representation of a typical seasonal calendar for the southern Africa region. (taken from: http://fews.net/southern-africa) (b) Monthly climatology of maize prices in SA countries. The monthly mean prices are normalized relative to the maximum mean monthly price for a given country, as the actual values of the mean monthly prices are different for different countries. Comparison of mean monthly maize

https://doi.org/10.5194/nhess-2019-267
Preprint. Discussion started: 19 August 2019

prices for (c) Malawi (d) Mozambique (e) Zimbabwe (f) South Africa, during the 2015-16 event (red line) with the previous 5-year mean prices (black line). The price data is available from FAOSTAT (FAO 2019).

https://doi.org/10.5194/nhess-2019-267
Preprint. Discussion started: 19 August 2019

Natural Hazards and Earth System Sciences
Discussions

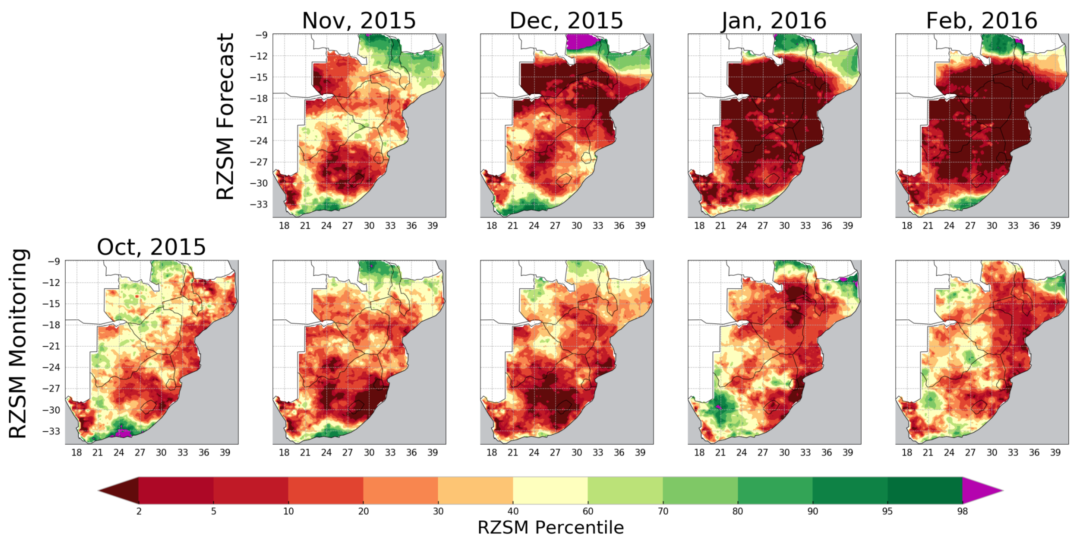

Figure 2: Forecast (top panel) and Monitoring of Rootzone soil moisture (RZSM) percentiles for the months of November 2015 through February 2016. October 2015 conditions reflect forecast initialized on November 1, 2015. The RZSM monitoring product for a given month is available during the early part of the following month. The historical climatology (1982-2010) was used to calculate percentile.

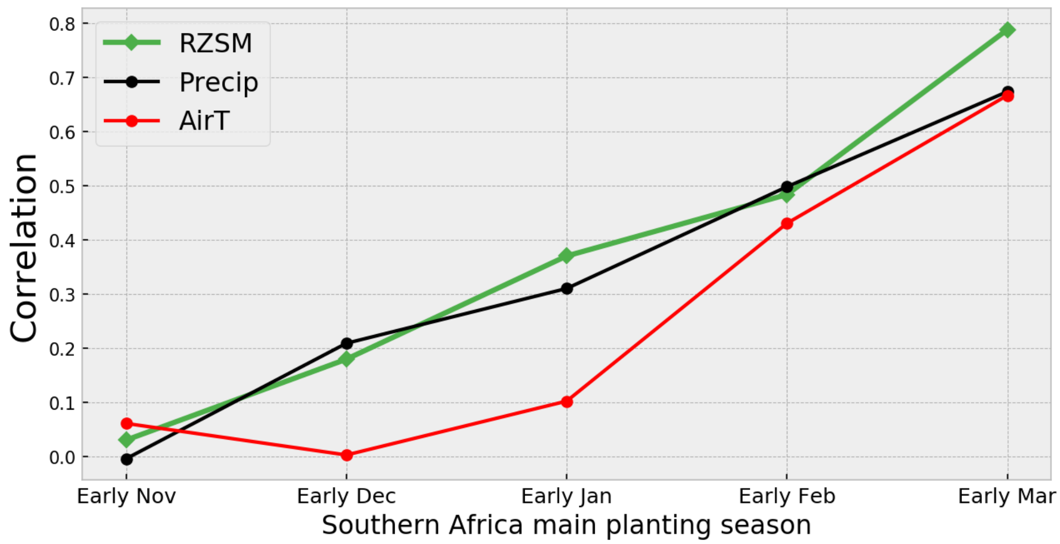

Figure 3: Variability of the correlation between the 3-month seasonal precipitation, 3-month seasonal air temperature (AirT), and monthly RZSM monitoring product with the detrended crop yield. This result highlights that RZSM is potentially a better predictor of crop yield than seasonal precipitation and AirT; also, the skill is the highest in early March when DJF seasonal precipitation, AirT, and February RZSM monitoring products are available.

https://doi.org/10.5194/nhess-2019-267
Preprint. Discussion started: 19 August 2019

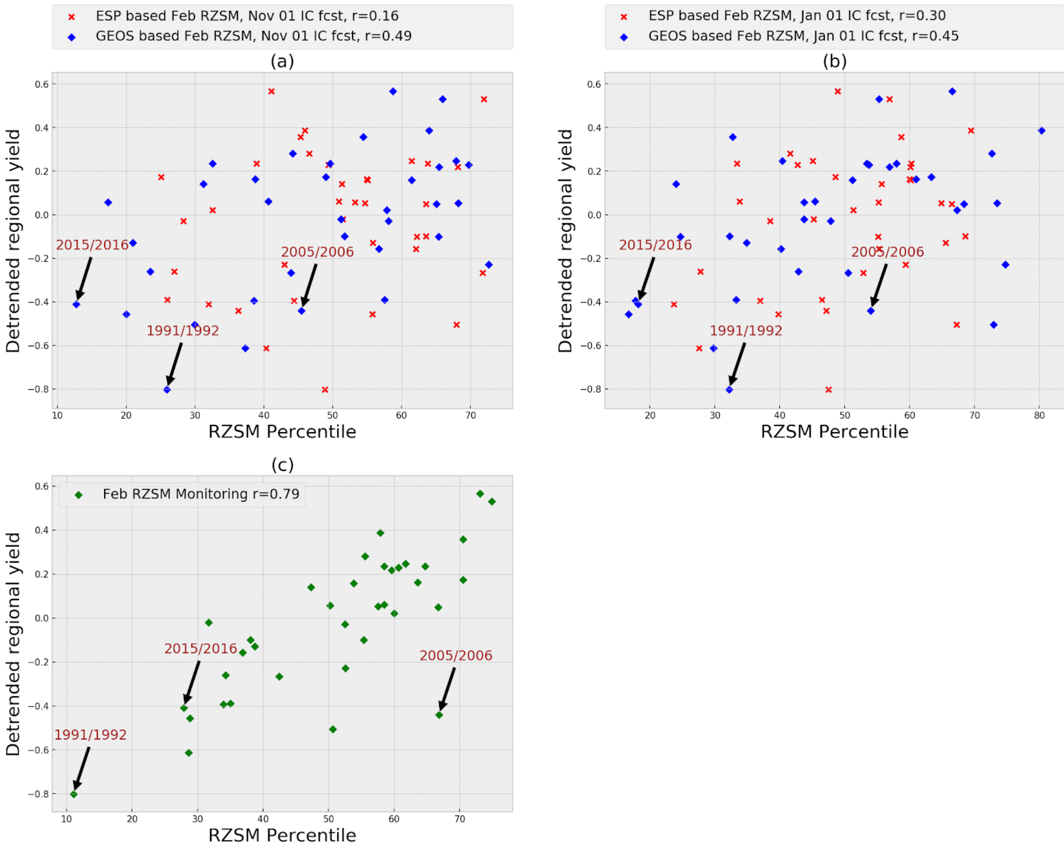

Figure 4: Covariability of (a) February RZSM forecasts (initialized on November 1) generated using ESP method and bias-corrected GEOS forecasts, (b) February RZSM forecasts (initialized on January 1) generated using ESP method and bias-corrected GEOS forecasts, and (c) the February RZSM monitoring product (available in early March), with detrended regional yield in southern Africa.

https://doi.org/10.5194/nhess-2019-267
Preprint. Discussion started: 19 August 2019

Natural Hazards and Earth System Sciences
Open Access
EGU
Discussions

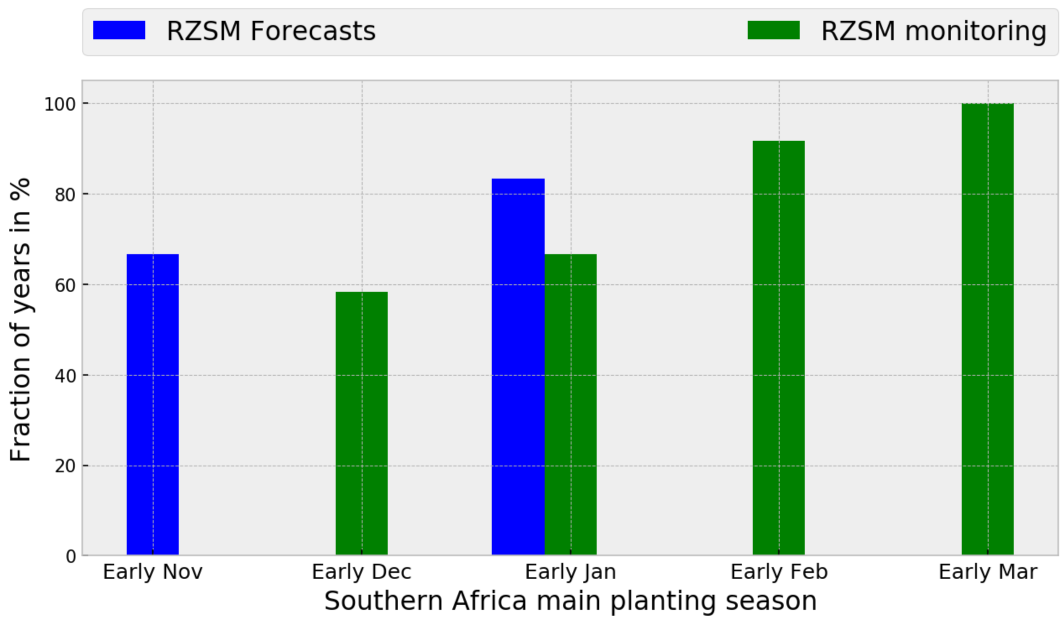

Figure 5: Fraction of years with below-normal regional crop yield (based on the rank of detrended crop yield) given that the corresponding RZSM forecasts (initialized on November 1 and January 1) and RZSM monitoring product (available in early March) were in the lowest tercile (based on the rank of the RZSM climatology). Note that the Nov 1 [Jan 1] RZSM forecasts-based probability of ~66% [~83%] is statistically significant at the ~86% [~95%] confidence level.