

Response:

Dear Reviewers, Thank you so much for your constructive feedback and comments. We have revised the manuscript based on your comments, and we believe that the manuscript is improved due to those changes. Below, we provide point-by-point responses to each of your comments. We have also included any new texts/figures added to manuscript in response to each comment. New texts have been italicized and highlighted in light yellow color.

Reviewer #1

To my understanding, this paper connects dynamical forecasts of soil moisture with regional crop yields over southern Africa statistically, and the results are encouraging since the soil moisture forecast correlates with crop yield quite well with a lead time of a few months. This study is novel and has a solid basis on climate-hydrology forecasting, where NASA Hydrological Forecasting and Analysis System that incorporates seasonal climate prediction and land surface hydrological simulation is implemented over southern Africa, and is evaluated for a number of extreme drought cases including the 2015/16 drought during the super El Nino. Utilizing dynamical hydrological forecasts in agricultural and water resources management sectors is not trivial, and this study push it a step further by smartly combining dynamical and statistical approaches, which provides implications for applications over other regions around the world. The paper is well written and the results are convincing, so I could not comment more while listing only a few minor suggestions below.

Response: Thank you so much for your review and encouraging feedback. Your summary of the study is indeed accurate. Below, we have responded to each of your comments. We believe that the revisions made in response to your comments will improve the quality of the manuscript.

Comment #1:

The abstract could be condensed and reconstructed by placing this southern Africa study in a wider context, where I believe the system has potential to be implemented Globally.

Response: Great suggestion. We have trimmed the abstract and added the following sentence to texts to highlight global implications of this study.

Text added to the abstract:

Finally, since a framework similar to NHyFAS can be used to provide RZSM monitoring and forecasting products over other regions of the globe, this case study also demonstrates potential for supporting food insecurity early warning globally

Text added to the Conclusion:

This study demonstrates the value of the NHyFAS products in supporting food insecurity early warning in the SA region. It is worth mentioning that since NHyFAS currently covers Africa and the Middle East region, the NHyFAS products are applicable for food insecurity early warning in the rest of Africa and the Middle East as well. Based on this study, it is postulated (future research pending) that NHyFAS RZSM products can be particularly effective for those rainfed agriculture regions and seasons which are not known to have strong teleconnection (e.g. with ENSO), as in the SA region. Finally, since the data sets and models used to implement the NHyFAS are available globally, a similar seasonal RZSM monitoring and forecasting framework can be developed at a global scale to support food insecurity early warning in other rainfed regions across the globe.

Comment #2:

Two references regarding the African ensemble drought forecasting (Yuan et al., 2013) and southern Africa 2015/16 severe drought attribution (Yuan et al., 2018) might be relevant. The latter focus on rapid evolving soil moisture drought (i.e., flash drought) over southern Africa, where the anthropogenic climate change intensified southern Africa flash drought, especially during 2016/16 El Nino in the midst of heat waves. So, an effective early warning system is essential for drought mitigation over the region.

References:

Yuan, X., L. Wang, and E. F. Wood, 2018: Anthropogenic intensification of southern African flash droughts as exemplified by the 2015/16 season. Bulletin of the American Meteorological Society, 99, S86-S90, doi:10.1175/BAMS-D-17-007.1

Yuan, X., E. F. Wood, N. W. Chaney, J. Sheffield, J. Kam, M. Liang, and K. Guan, 2013: Probabilistic Seasonal Forecasting of African Drought by Dynamical Models. *Journal of Hydrometeorology*, 14, 1706-1720, doi:10.1175/JHM-D-13-054.1

Response: Thank you for suggesting these articles. Both of them have now been cited.

Comment #3:

L208-209. The authors mentioned that existing systems like FEWS NET and SADC failed to forecast rainfall during 2015/16. I am wondering whether they can compare the latest GEOS5 rainfall prediction, which is a central component in the forecast system proposed in this study, with those predictions from existing systems. This might highlight the advantage of the new system/method.

Response:

Regarding the first sentence, please allow us to clarify that we did not imply that FEWS NET and SADC had failed to forecast rainfall during 2015/16. Please see the corresponding text from the manuscript:

“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”

FEWS NET and SADC were indicating below-normal rainfall in the region during the start of this season, as it was accompanied by one of the strongest El Niño events ever recorded. We argue that RZSM forecasts available on November 1, 2015, (if this system were live back then) would have further substantiated their assessments and actually further supported their concerns, as the Nov. 1 RZSM forecasts indicated that the RSA, which is one of the main producers in the region, was going to experience the strongest level of drought severity.

The reviewer’s point about comparing FEWS NET and SADC’s forecasts with the forecasts from the NHyFAS is fair suggestion. However, a direct comparison between NHyFAS forecasts and FEWS NET and SADC forecasts is not feasible. We have included the following section in the manuscript, in response:

4.1 Comparison with existing drought forecasting systems and approaches:

In this study, we keep the comparison with existing forecasting systems and approaches limited to the comparison of the performance of NHyFAS products with (i) ESP (i.e. climatology)

based RZSM forecasts and (ii) ENSO-based crop yield forecasts, both of which are commonly used approaches for drought forecasting in the region, including by early warning agencies such as FEWS NET. Comparison against both approaches shows clear added value of using the NHyFAS products. We could not compare the performance of the NHyFAS with FEWS NET or SADC's official historical forecasts because:

(i) FEWS NET's official forecast is an outlook of food insecurity conditions ([Funk et al. 2019](https://fews.net/)) (<https://fews.net/>) which is based not only on agroclimatology (i.e., agriculture and climate conditions) but also on market conditions and nutrition and livelihood conditions. The NHyFAS forecasts that are now being used by FEWS NET would fall into the category of agroclimatological conditions. In fact, the goal of the evaluation of the NHyFAS forecasts is to establish whether NHyFAS forecasts can be suitable agroclimatological forecast inputs for FEWS NET to guide the development of food insecurity outlook assessments. Also, FEWS NET Food Insecurity Outlook is partly based on subjective assessments, in some ways similar to the U.S. drought monitor (Svoboda et al., 2002) or U.S. Seasonal Drought Outlook, in addition to quantitative assessments such as agroclimatological forecasts. Finally, FEWS NET's archive of Food Insecurity Outlooks currently extends back only to mid-2011.

(ii) SADC CSC's issues probabilistic seasonal-scale rainfall forecasts. These forecasts are based on multiple models (both statistical and dynamical) as well as subjective expert assessments, which makes comparison with purely quantitative products inappropriate. Additionally, the archive of purely quantitative forecasts from SADC CSC only goes back to 2017.

Finally, the NHyFAS products are intended to be used as an addition to the existing early warning tools of FEWS NET and SADC CSC, which are partners in the efforts described in this study, rather than replacing any of the existing tools."

Comment #4:

Although Figure 4 shows a good relationship between crop yield and predicted soil moisture, it might be useful to use some statistical techniques to convert soil moisture prediction into crop yield prediction. Perhaps the authors could comment on that in the discussion section, if they believe it would be useful for their future development of the forecast system.

Response: Great point. In response to this comment, as well as comments by the Reviewer #2, we have now included an additional analysis in the following section. Shown below (and in the manuscript) are Figure 8 and Table 1, which summarize the results of this section.

3.3 Performance of NHyFAS in providing routine operational crop yield forecasts

Finally, we evaluate the performance of NHyFAS for supporting food insecurity early warning in SA by examining the accuracy of RZSM monitoring and RZSM forecasting products in predicting regional crop yields. We compare the crop yield forecasts made with the RSZM products against both univariate forecasts (using only past observed crop yields) and forecasts made with ENSO. As ENSO is a widely used predictor for precipitation and crop yield forecasts in this region, we examine the added value of using NHyFAS RZSM monitoring and forecasting products above and beyond ENSO. All forecasts are done using ARIMA models described in section 2.6.

Figure 8 shows a comparison between the “observed” reported crop yield (black lines) and the “out-of-sample” (i.e. post-training period) forecasted yield (red lines) produced with a univariate model, and the models using environmental exogenous predictors (i) DJF ENSO, (ii) Feb-RZSM (monitoring) product, (iii) Feb-RZSM (Forecasting product) initialized on Nov. 1., in addition to that univariate model.

The results indicate that: (i) environmental predictors such as ENSO and the NHyFAS products can make crop yield forecasts that are more accurate than those produced using only a univariate approach. When ENSO is used as an additional predictor (in addition to a Univariate

model), the MAE reduces from 0.342 MT/HA to 0.285 MT/HA, a ~17% reduction in error. (ii) Use of the Feb-RZSM monitoring product has an even larger impact, reducing the MAE by about 50%, to 0.174 MT/HA. (iii) Use of the Feb-RZSM forecasting product (initialized on Nov 1) has an impact similar to that of DJF ENSO. Although the MAE is about 6% larger when the forecasting product is used rather than the ENSO predictor, the forecasting product has the significant advantage of being available for about 4 months earlier. For comparison (not shown here) MAE of Feb-RZSM forecasting product (initialized on Nov 1) is slightly smaller (~6%) than the MAE of August-October (ASO)-ENSO (also available in early Nov) and is comparable to the MAE of September-November (SON)-ENSO (available in early December) as a predictor of crop yield forecast.

Table 1 shows the number of times the observed yield is within the 80% confidence interval of the forecasts and the mean spread of the confidence interval. The improvement in performance obtained when the Feb-RZSM monitoring product is used is clear; during 10 of the 11 years in the validation period, the observed yield falls within the 80% confidence interval, whereas this happens in only 7 years when DJF ENSO is used as the additional predictor. The mean spread of the confidence interval associated with the use of the Feb-RZSM monitoring product (0.70 MT/HA) is also the smallest.

Table 1: Performance of “out-of-sample” crop yield forecasting over the validation period of 2008-2018.

	Univariate model	Univariate model + ENSO	Univariate model + Feb- RZSM (Monitoring)	Univariate model + Feb- RZSM (forecast)
Mean absolute error over the validation period (MT/HA)	0.342	0.285	0.174	0.301
Number of years observed yield is within 95% confidence interval bound	9	10	10	9
Mean spread of 95% confidence interval (MT/HA)	1.64	1.20	1.07	1.20
Number of years observed yield is within 80% confidence interval bound	9	7	10	7
Mean spread of 80% confidence interval (MT/HA)	1.07	0.78	0.70	0.78

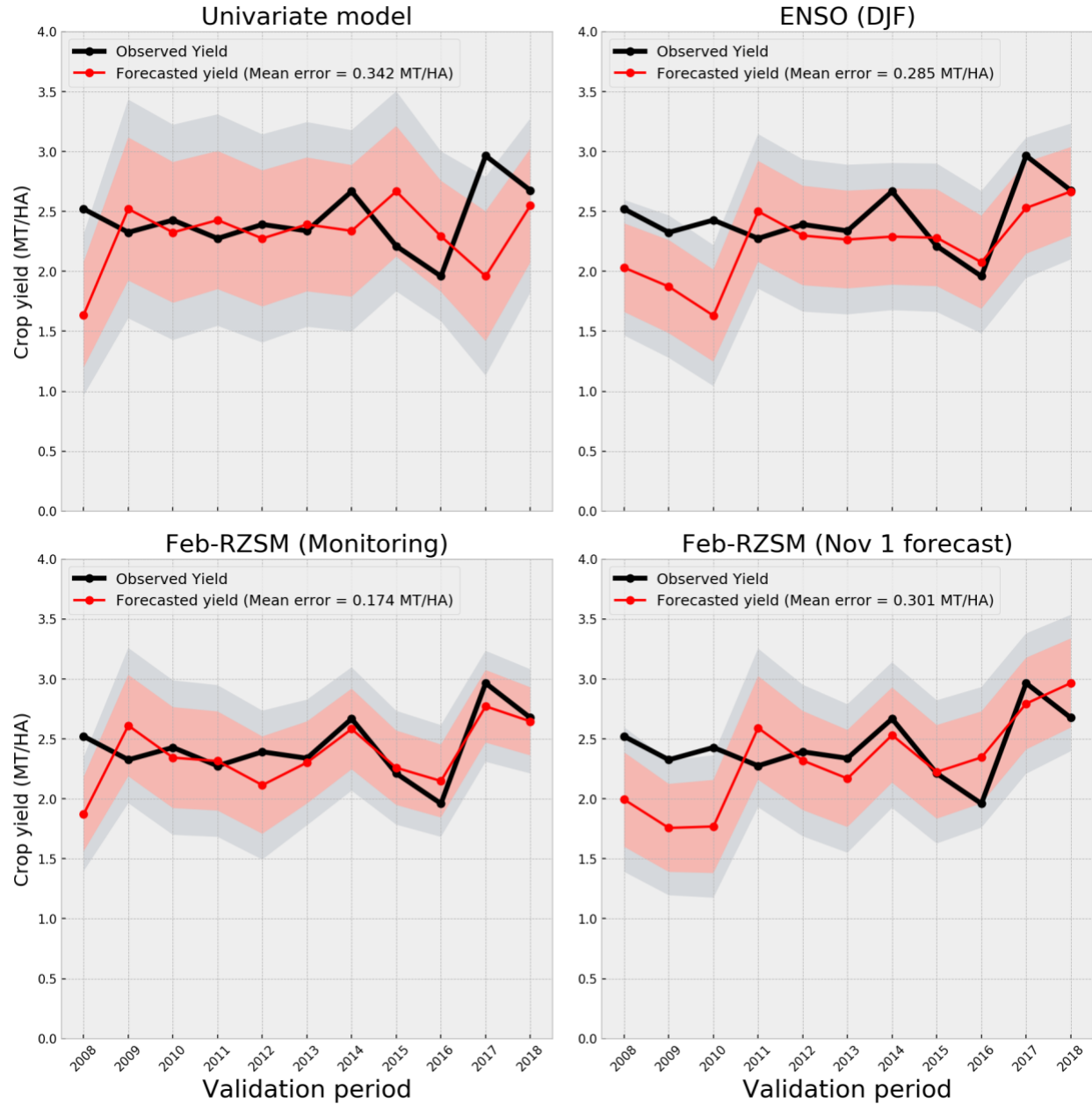


Figure 8: Comparison of the performance of a Univariate model alone, ENSO (DJF), Feb-RZSM monitoring product, Feb-RZSM forecasting product as a predictor in forecasting crop yield of Southern Africa. Pink [gray] shading indicates 80% [95%] confidence interval.

This paper applies a recently developed hydrological forecasting and monitoring system (NHyFAS) to drought early-warning in Southern Africa. This forces a large-scale hydrological model whose parameters depend on global datasets, with 1) observation data and 2) a multi-ensemble forecast. These forcings input in the hydrological model provide monitoring and forecasting hydrological metrics that are then correlated with crop yields to assess their performance as early-warning signals of drought in Southern Africa. Rootzone soil moisture (RZSM) is used as the main hydrological variable for both monitoring and forecasting. With harvest starting in March, authors use monitoring variables available in early Dec, Jan, Feb, Mar (i.e. up to 3-4 months in advance) and monitoring in early Nov and Jan (i.e. up to 4-5 months in advance). Authors test the efficiency of these RZSM products, first on the 2015-16 drought event (with dramatic repercussions on the prices of staple foods) and then on the whole 1982-2018 period (36 years). They show that the proposed forecasting products could have forecast the food availability crisis in Southern Africa in 2015-16 up to 4-5 months before the next harvest starts. They then go on to show that if products are in the lower tercile, there is a high confidence that crop yields will be below average months in advance. Their conclusion is that the proposed products will improve early warning systems of low water-food availability. The paper's results are interesting, very relevant to this journal and timely, at a time when such early-warning systems for drought conditions are viewed as a priority in Africa (see Nature <https://www.nature.com/articles/d41586-019-02760-9>). Yet, the text is marred by unstated assumptions, the lack of comparison with existing early-warning systems, and the absence of rationale to explain the results' performance.

Response: Thank you very much for the review and for your constructive comments. Thank you also for pointing us to the *Nature* article, which we have now cited in the manuscript. Please see our response to your comments below. We hope that these revisions made in response to your comments will further clarify and substantiate the results. In addition, we have reviewed the method and results sections again to clarify our methods as/when needed for improved comprehensibility of the manuscript.

Comment #1

In particular: 1) The work provides evidence that the proposed products correlate with crop yields, but as the authors know, correlation is not causation. Authors should discuss evidence in the literature of what key variables the forecasts pick up (ENSO maybe?), or alternatively, what supplementary work is needed to establish causation, and therefore, credibility for the products they propose.

Response: Thank you for this comment. It is indeed valid. In response to your comment and comment from reviewer #1, we have now included an additional analysis in the manuscript, in the following section. Shown below (and in the manuscript) are Figure 8 and Table 1, which summarize the results of this section.

3.3 Performance of NHyFAS in providing routine operational crop yield forecasts

Finally, we evaluate the performance of NHyFAS for supporting food insecurity early warning in SA by examining the accuracy of RZSM monitoring and RZSM forecasting products in predicting regional crop yields. We compare the crop yield forecasts made with the RSZM products against both univariate forecasts (using only past observed crop yields) and forecasts made with ENSO. As ENSO is a widely used predictor for precipitation and crop yield forecasts in this region, we examine the added value of using NHyFAS RZSM monitoring and forecasting products above and beyond ENSO. All forecasts are done using ARIMA models described in section 2.6.

Figure 8 shows a comparison between the “observed” reported crop yield (black lines) and the “out-of-sample” (i.e. post-training period) forecasted yield (red lines) produced with a univariate model, and the models using environmental exogenous predictors (i) DJF ENSO, (ii) Feb-RZSM (monitoring) product, (iii) Feb-RZSM (Forecasting product) initialized on Nov. 1., in addition to that univariate model.

The results indicate that: (i) environmental predictors such as ENSO and the NHyFAS products can make crop yield forecasts that are more accurate than those produced using only a univariate approach. When ENSO is used as an additional predictor (in addition to a Univariate model), the MAE reduces from 0.342 MT/HA to 0.285 MT/HA, a ~17% reduction in error. (ii) Use of the Feb-RZSM monitoring product has an even larger impact, reducing the MAE by about

50%, to 0.174 MT/HA. (iii) Use of the Feb-RZSM forecasting product (initialized on Nov 1) has an impact similar to that of DJF ENSO. Although the MAE is about 6% larger when the forecasting product is used rather than the ENSO predictor, the forecasting product has the significant advantage of being available for about 4 months earlier. For comparison (not shown here) MAE of Feb-RZSM forecasting product (initialized on Nov 1) is slightly smaller (~6%) than the MAE of August-October (ASO)-ENSO (also available in early Nov) and is comparable to the MAE of September-November (SON)-ENSO (available in early December) as a predictor of crop yield forecast.

Table 1 shows the number of times the observed yield is within the 80% confidence interval of the forecasts and the mean spread of the confidence interval. The improvement in performance obtained when the Feb-RZSM monitoring product is used is clear; during 10 of the 11 years in the validation period, the observed yield falls within the 80% confidence interval, whereas this happens in only 7 years when DJF ENSO is used as the additional predictor. The mean spread of the confidence interval associated with the use of the Feb-RZSM monitoring product (0.70 MT/HA) is also the smallest.

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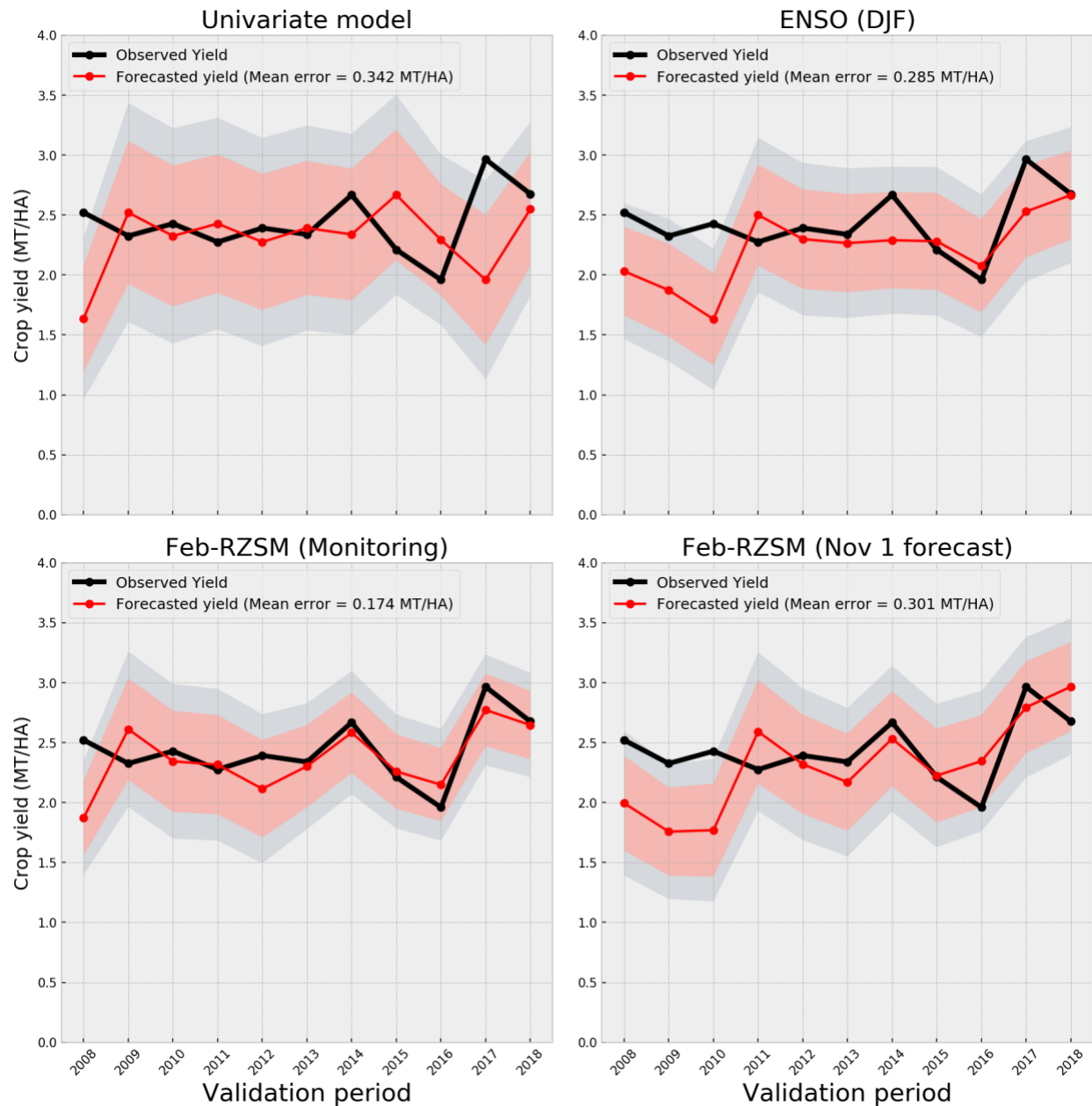


Figure 8: Comparison of the performance of a Univariate model alone, ENSO (DJF), Feb-RZSM monitoring product, Feb-RZSM forecasting product as a predictor in forecasting crop yield of southern Africa. Pink [gray] shading indicates 80% [95%] confidence interval.

Comment #2 and #3:

Other forecasting systems for the area are evoked (Sheffield et al 2014, the African Flood and Drought Monitor (lines 103-104), why not compare results with those obtained with other products? A justification should be provided in the introduction. If forecasting systems are unavailable, authors link food security crises with El Niño. So that's a simple, well-established indicator (the ENSO index) whose predictive power could easily be compared with that of the RZSM-based products.

Response:

Thank you for this important comment. In response to your comment and a comment from reviewer #1, we have added the following two sections to the manuscript.

1. “3.3 Performance of NHyFAS in providing routine operational crop yield forecasts”
This section provides a comparison of crop yield forecast skill based on the NHyFAS products with ENSO. Please also see our response to your comment #1.
2. “4.1 Comparison with existing drought forecasting systems and approaches”

4.1 Comparison with existing drought forecasting systems and approaches:

In this study, we keep the comparison with existing forecasting systems and approaches limited to the comparison of the performance of NHyFAS products with (i) ESP (i.e. climatology) based RZSM forecasts and (ii) ENSO-based crop yield forecasts, both of which are commonly used approaches for drought forecasting in the region, including by early warning agencies such as FEWS NET. Comparison against both approaches shows clear added value of using the NHyFAS products. We could not compare the performance of the NHyFAS with FEWS NET or SADC's official historical forecasts because:

(i) FEWS NET's official forecast is an outlook of food insecurity conditions ([Funk et al. 2019](https://fews.net/)) (<https://fews.net/>) which is based not only on agroclimatology (i.e., agriculture and climate conditions) but also on market conditions and nutrition and livelihood conditions. The NHyFAS forecasts that are now being used by FEWS NET would fall into the category of agroclimatological conditions. In fact, the goal of the evaluation of the NHyFAS forecasts is to establish whether NHyFAS forecasts can be suitable agroclimatological forecast inputs for

FEWS NET to guide the development of food insecurity outlook assessments. Also, FEWS NET Food Insecurity Outlook is partly based on subjective assessments, in some ways similar to the U.S. drought monitor (Svoboda et al., 2002) or U.S. Seasonal Drought Outlook, in addition to quantitative assessments such as agroclimatological forecasts. Finally, FEWS NET's archive of Food Insecurity Outlooks currently extends back only to mid-2011.

(ii) SADC CSC's issues probabilistic seasonal-scale rainfall forecasts. These forecasts are based on multiple models (both statistical and dynamical) as well as subjective expert assessments, which makes comparison with purely quantitative products inappropriate. Additionally, the archive of purely quantitative forecasts from SADC CSC only goes back to 2017.

Finally, the NHyFAS products are intended to be used as an addition to the existing early warning tools of FEWS NET and SADC CSC, which are partners in the efforts described in this study, rather than replacing any of the existing tools.

Finally, regarding the comparison with the Africa Flood and Drought monitor we note that, as accessed on November 22nd, 2019, the Africa Flood and Drought monitor only provides access to seasonal forecasts from April 2018 to September 2018. Additionally, it is also worth noting that the NHyFAS is the only seasonal hydrologic forecasting system for Africa that is based on the The Climate Hazards InfraRed Precipitation with Stations (CHIRPS) (<https://www.nature.com/articles/sdata201566>), which benefits from the satellite era precipitation estimates, as well as greater access to station based precipitation measurements, hence over Africa, is of higher quality. Several past studies have indicated that too. Reliance on a high-quality precipitation data set allows for an improved climatology of simulated hydrologic variables (such as RZSM) and improvement in hydrologic initial conditions (which are a substantial source of skill in any seasonal scale hydrologic forecasting system).

Comment #4

This journal is an interdisciplinary forum around natural hazards such as droughts and not a hydroclimatology outlet, so authors should make their methods more accessible. A figure of the workflow could help, and so could extra explanations along some of the acronyms.

Response: We understand the logic behind this comment. Initially, we had not provided details on the setup of the NHyFAS, as it is described in Arsenault et al. (in review), which is the key paper on this system. However, we have now added the following flowchart to the manuscript. This flowchart provides an overview of the process to get gridded RZSM percentile, and also defines the hydrologic forecast-related acronyms.

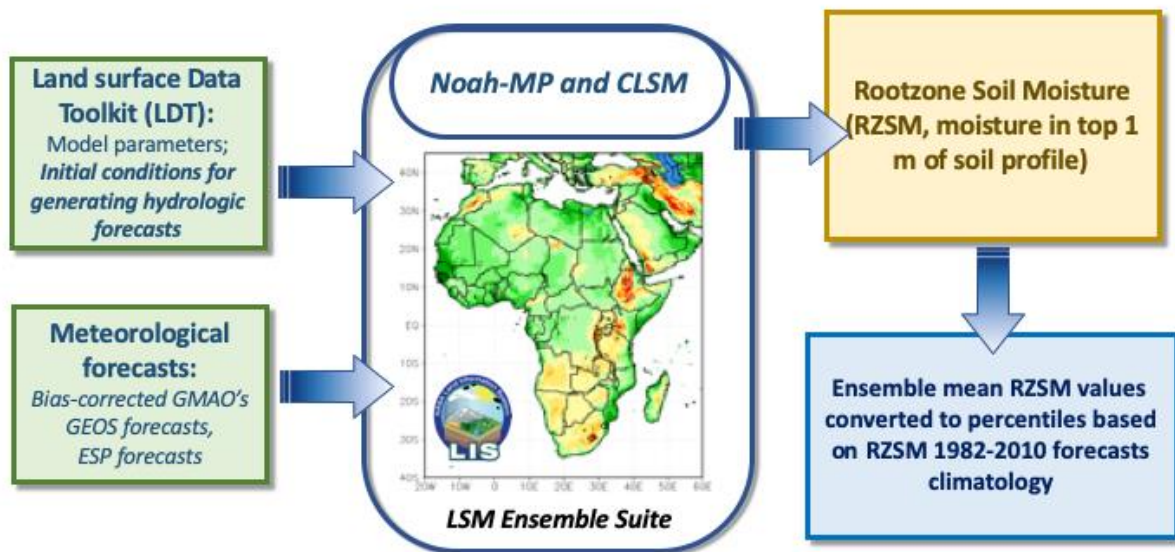


Figure 3: Overview of the NHyFAS implementation to produce RZSM monitoring and forecasting products, as used in this study.

Reference: Arsenault, K.R., Shukla, S., Hazra, A., Getirana, A., McNally, A., Kumar, S.V., Koster, R.D., Peters-Lidard, C.D., Zaitchik, B.F., Badr, H., Jung, H.C., Narapusetty, B., Navari, M., Wang, S., Mocko, D., Funk, C., Harrison, L., Husak, G.J., Adoum, A., Galu, G., Magadzire, T., Roningen, J., Shaw, M., Eylander, J., Bergaoui, K., McDonnell, R.A., and Verdin, J.P., 2019, The NASA hydrological forecast system for food and water security applications. Bulletin of the American Meteorological Society, In review. water security applications. Bulletin of the American Meteorological Society (in review)

Comment #5

Likewise, justifications for the selection of the key variable (RZSM) or of the forecast ensemble, among others, should be provided to help the paper to be understandable by a larger audience.

Response: Good point. We have now added the following text in the manuscript, in section 2.4:

The performance of the NHyFAS system is evaluated mainly through its RZSM monitoring (generated from OL) and forecasting products. RZSM indicates the soil moisture in the top one meter of the soil profile. Typically, the length of the roots of crops such as maize (main crop in the region of SA) is close to one meter, hence the choice of RZSM as the key forecast variable. Moreover, 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; hence RZSM also allows for a consistent way to merge soil moisture products from both models.

Comment #6

I would advise a careful, rigorous revision accounting for the remarks above and where at the minimum, the products' performance should be compared with that of ENSO. If the products work mainly because the forecast ensemble picks up the state of the ENSO index, is there added value to that work.

Response: Please see our response to your comments #2 and #3, which addresses this comment as well.

Comment #7

There is no mention of model/ code / processed data availability for this study: all data sources are the raw data that was used into NHyFAS.

Response: Good point. We have included the following text in the acknowledgements:

GEOS forecast data sets are generated and supported by NASA's Global Modeling and Assimilation Office (GMAO). Model source code can be found at NASA's Land Information System's GitHub repository (<https://lis.gsfc.nasa.gov/news/latest-lis-code-now-available-github>). Model parameters are available through email request. The daily CHIRPS precipitation data can be found here (ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/global_daily/netcdf/p25/). MERRA-2 reanalysis-based atmospheric forcings can be found through NASA's GES DISC archive (<https://disc.gsfc.nasa.gov/datasets?keywords=%22MERRA-2%22&page=1&source=Models%2FAnalyses%20MERRA-2>). NHyFAS forecasts, in the form of maps, can be found here <https://lis.gsfc.nasa.gov/projects/nhyfas>. As of now, NHyFAS forecast

data sets are not publicly accessible. Please note that bias-corrected seasonal forecasts and hydrologic forecasts (e.g., RZSM) data are currently not available for public access. We anticipate though that those forecasts will eventually be available for public access from NASA web-services, similar to other NASA and FEWS NET supported land data assimilation (FLDAS) outputs.

Some detailed comments:

Comment #8

Abstract: it should be made clear in there that the RZSM products are derived from the new NHyFAS. It reads like that they are not.

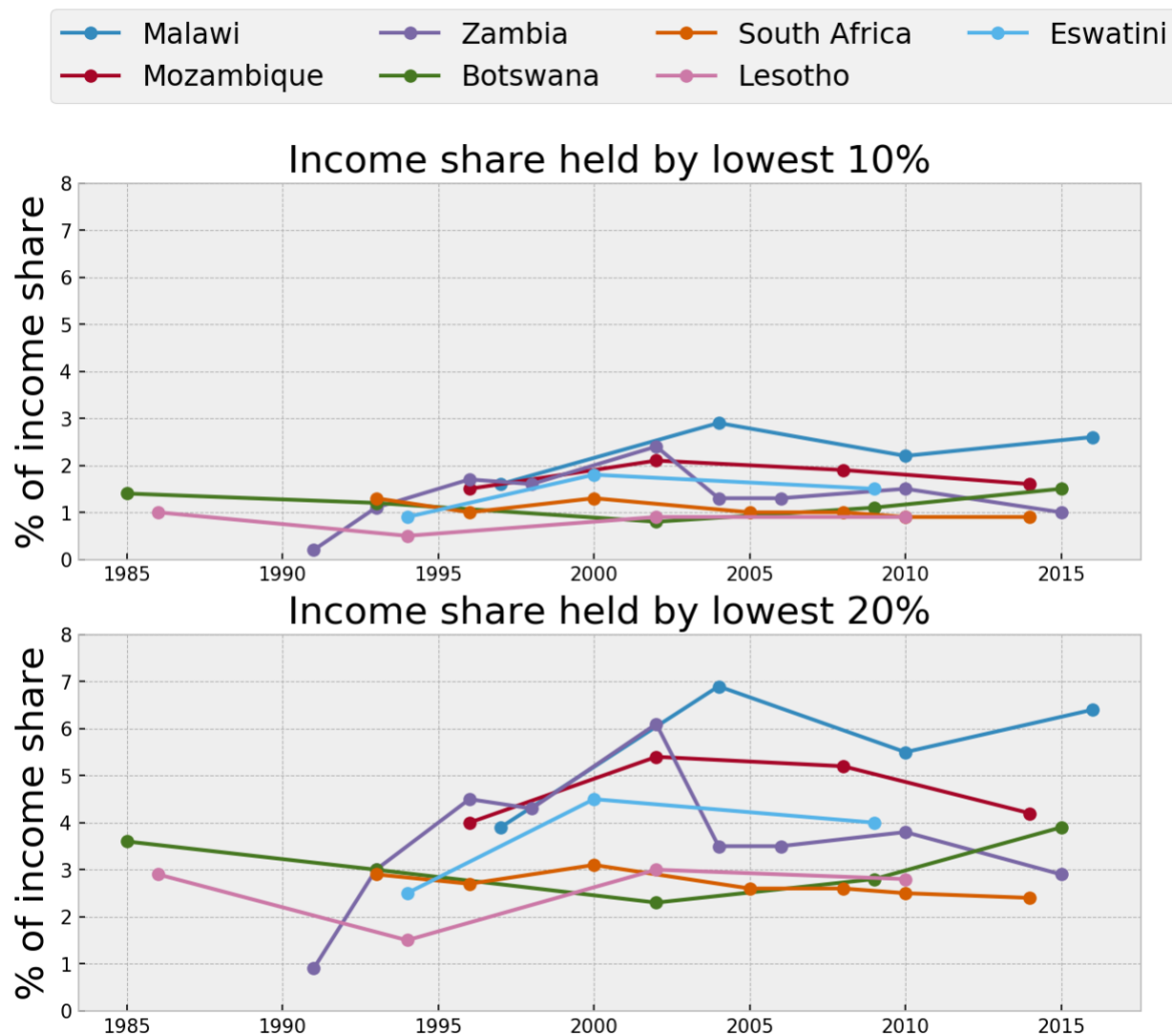
Response: Done. We have included the following sentence in the abstract:

“For SA, this study documents the predictive capabilities of RZSM products from a recently developed NASA Hydrological Forecasting and Analysis System (NHyFAS).”

Comment #9

lines 39-43: authors aren’t obligated to show a graph (also that is helpful) but they should cite references.

Response: We have added the following figure, as Figure 2, showing that the percentage of income held by the bottom 10% and 20% of the population has not changed significantly in the region.



Comment #10

Line 137: the choice of RZSM as a hydrologic variable of interest makes sense but a rationale should be provided for it being the main (or indeed only) variable of interest in this study. What justifies not using other variables.

Response: Please see our response to your comment #5.

Comment #11

Figure 3, and commentary lines 230-250: this seems needlessly confusing. My understanding is that Fig 3 shows the correlation of crop yield with three monitoring-based products whereas the text touts the superiority of the forecasting-based product on all three as early as November. The

latter, as well as one of the three monitoring products, includes RZSM, and the distinction is not always clear on first read.

Besides, back-and-forth with Figure 4 doesn't make the reading easy either. Could it be a good idea to 1) include the forecasting-based product on Figure 3 to provide a striking visual of why the proposed product is better, and 2) separate comment on Figure 3 from that of Figure 4.

Response: We apologize for the confusion. We have now revised the text discussing the results of Figure 3 and 4 (now Figure 5 and 6) to the following:

First, we show in Figure 5 how detrended crop yield correlates (from early November to early March) with the monthly RZSM monitoring product relative to how it correlates with 3-monthly seasonal precipitation and air temperature. The results indicate that the monthly RZSM monitoring product generally correlates better with detrended crop yield than with the seasonal precipitation or air temperature, with the correlation reaching its peak by early March, when the Feb-RZSM monitoring product and December-February precipitation and temperature are available. Feb-RZSM still shows higher correlation than seasonal precipitation and temperature; however, the difference in correlation is not statistically significant.

Next, the correlation between detrended crop yield and February RZSM forecasts (based on ESP method and bias-corrected GEOS forecasts) initialized on November 1 (Fig. 6a) and January 1 (Fig. 6b) is analyzed. The correlation of the yield with GEOS-based February RZSM forecasts initialized on November 1 is 0.49, which is substantially higher than that of ESP-based RZSM forecasts (0.16), clearly demonstrating the added value of using GEOS-based climate forecasts. Similarly, the correlation of yield with the GEOS-based February RZSM forecasts initialized on January 1 is 0.45, higher than that of the ESP-based forecasts (0.30) at that time of the year. Moreover, the correlation of detrended crop yield with GEOS-based February RZSM forecasts initialized on November 1 (0.49) and January 1 (0.45) is higher than that with the RZSM monitoring product (Figure 5) at those times of the year (<0.1 in early November and

<0.4 in early January). Again, this highlights the value of using forecasts of Feb-RZSM through early January in supporting food insecurity early warning. Figure 6c shows that Feb-RZSM monitoring product, which is available in early March, has the highest correlation of 0.79 with the detrended crop yield.

Comment #12

Line 266: why the lower tercile? Please justify

Response: We have now added the following text in the manuscript.

We use the lower tercile values of RZSM monitoring and forecasting products to focus on the drought years as indicated by those products. Because SA is a mostly rainfed region, the crop yield is generally below normal during drought years, as indicated in several recent events (2014-15, 2015-16, 2018-19).

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

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Abstract:

Commented [1]: Abstract is trimmed in response to Reviewer #1, comment #1.

The region of southern Africa (SA) has a fragile food economy and is vulnerable to frequent droughts. 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 RZSM products from a recently developed NASA Hydrological Forecasting and Analysis System (NHyFAS). Results

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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 during 1982-2016, February RZSM forecasts [monitoring product] available in early November [early March] have a correlation of 0.49 [0.79] with the detrended regional crop yield. It is also found that when the February RZSM forecast [monitoring product] available in early November [early March] is indicated to be in the lowest tercile, the detrended regional crop yield is below normal about two-thirds of the time [always], at least over the sample years considered. Additionally, it is shown that February RZSM forecast [monitoring product] can provide “out-of-sample” crop yield forecasts with comparable [substantially better with 40% reduction in mean error] skill to December-February ENSO. These results indicate that the NHyFAS products can effectively support food insecurity early warning in the SA region. Finally, since a framework similar to NHyFAS can be used to provide RZSM monitoring and

22 forecasting products over other regions of the globe, this case study also demonstrates potential
23 for supporting food insecurity early warning globally.

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1 Introduction

Southern Africa (SA) is vulnerable to food insecurity. Droughts driven by climate stressors (e.g. precipitation and temperature) are among the important drivers of food insecurity (Misselhorn 2005; Conway et al. 2015). Moreover, anthropogenic climate change is shown to increase the likelihood of climate-driven flash droughts (Yuan et al., 2018). The primary rainy season in SA spans from 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 from the prior year's harvest become 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 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 SA further highlighted its vulnerability to climate-related regional food insecurity (Archer et al., 2017; Funk et al., 2018; Pomposi et al., 2018). This event led to a substantial reduction in regional agricultural production

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47 —including in the RSA, which is the main crop-producing country in the region—a reduction
48 and rationing of water supplies, a loss of livestock, and an increase in unemployment in the
49 region, and it pushed 29 million people into severe food insecurity (SADC, 2016). Throughout
50 the Southern African Development Community (SADC) region in 2015-16, cereal production
51 was down by -10.2% (varying from +61% to -94% in individual member countries) relative to
52 the previous 5-year average (SADC, 2016). Figure 1 (c)-(f) shows a comparison of national retail
53 maize prices (in USD) in several of the SA countries during 2015-16, with the previous 5-year
54 mean prices in those countries. The prices in 2015-16 were substantially higher than the previous
55 5-year mean. Of particular importance is the price increase in RSA, where, typically, the food
56 prices do not vary much throughout the year due to its general self-sufficiency in food
57 production, as well as its international trade. Consumer Price Index (CPI) for food for the RSA
58 also experienced a drastic upward shift during the 2015-16 drought year (not shown here). In
59 fact, based on the CPI data (available from the FAO), the CPI was substantially higher than that
60 of the past 5-year mean during the beginning of the following growing season of 2016-17,
61 including in the RSA where typically the CPI remains fairly stable during a year. These price
62 shocks can dramatically impact poor households, which typically spend 60% or more of their
63 income on food. According to the recent World Development Indicator ([World Bank 2016](#)),
64 incomes for the poorest 10% and 20% of households in these countries have remained generally
65 constant, underscoring the depth of poverty (Figure 2). On average, in Malawi, Mozambique,
66 Zimbabwe, and South Africa, these individuals subsist on USD 70, 126, 288, and 716 a year,
67 respectively.

68 Figure 1(c)-(f) and the income-related facts (based on World Bank Development
69 Indicator) presented above highlight the severity of food insecurity in a regional drought event

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70 like 2015-16. In the 2015-2016 event, food imports from the RSA—which is the main producer
71 and exporter of food in the region to the other SA countries—were not enough, and international
72 assistance became crucial. This is why in June 2016, the SADC launched a Regional
73 Humanitarian Appeal stating that approximately 40 million people in the region required
74 humanitarian assistance, at a cost of approximately USD 2.4 billion (Magadzire et al. 2017).

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

81 A seasonal-scale hydrologic forecasting system can potentially support an early warning
82 system, as it can provide updated hydrologic forecasts on a monthly basis by accounting for the
83 drought conditions as of the forecast release date and climate outlook over the forecast period
84 (Sheffield et al., 2014; Shukla et al., 2014; Yuan et al., 2013). However, thus far, the application
85 of seasonal-scale hydrologic forecasts in food insecurity early warning has been limited at best,
86 with the only other main example being the African Flood and Drought Monitor (Sheffield et al.,
87 2014).

88 On the other hand, operational, publicly available, state-of-the-art dynamical climate
89 forecasts have found regular usage in guiding climate outlooks, as well as assessments of
90 expected food insecurity. For example, USAID's Famine Early Warning Systems Network
91 (<http://fews.net/>), G20-Group on Earth Observations Global Agricultural Monitoring
92 (GEOGLAM) Crop Monitor for Early Warning, and SADC's Climate Service Center (CSC) all

93 utilize the dynamical climate forecasts as one of their early warning tools. Furthermore,
94 numerous past studies have investigated the predictability of SA climate (Meque and Abiodun,
95 2014) and examined the skill of diverse approaches in forecasting, particularly of rainfall, as well
96 as streamflow and agricultural production in different parts of this region (Archer et al., 2017;
97 Cane et al., 1994; Diro, 2015; Landman et al., 2001; Landman and Beraki, 2010; Landman and
98 Goddard, 2002; Manatsa et al., 2015; Martin et al., 2000; Sunday et al., 2014; Trambauer et al.,
99 2015; Winsemius et al., 2014). Historically, El Niño-Southern Oscillation (ENSO) has proven to
100 be among the main predictors of this region's climate, with another important predictor being the
101 Southern Indian Ocean Dipole (Hoell et al., 2016, 2017; Hoell and Cheng, 2017).

102 In August 2018, a new NASA Hydrological Forecasting and Analysis System
103 (NHyFAS), an operational seasonal hydrologic forecasting system (Arsenault et al., 2020), was
104 implemented to support the early warning efforts of FEWS NET, building upon existing
105 hydrologic monitoring (McNally et al., 2017). This study evaluates this system's ability to
106 support early warning of regional food insecurity in the SA region. The evaluation is conducted
107 by examining the performance of this system (i) for the 2015-16 drought event, which led to
108 regional food insecurity, (ii) in explaining regional crop yield variability in the region, and (iii) in
109 identifying below-normal crop yield events, which are characteristically associated with overall
110 lower food availability in the region and, hence, food insecurity. Regional crop yield is used as a
111 target variable here, as it is among the main contributors to regional food insecurity. It is
112 hypothesized that if this system can skillfully forecast regional crop yield and identify below-
113 normal regional crop yields, it can successfully support the early warning of food insecurity in
114 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

The hydrologic monitoring and forecasting products used in this study come from the NHyFAS (Fig. 3) (Arsenault et al., 2020). Figure 3 shows an overview of the implementation of the NHyFAS for the purpose of this study. Because Arsenault et al. (2020) already describes the system in detail, we simply provide here a brief description of the hydrologic models (section 2.1), the model parameters (section 2.2), the input observed forcings and climate forecasts (section 2.3), and the RZSM monitoring and forecasting products (section 2.4) used in the present study. The reported crop yield data used in this study are described in section 2.5.

2.1 Hydrologic Modeling Framework

To generate hydrological forecasts, we use NASA's Catchment land surface model (CLSM; (Ducharne et al., 2000; Koster et al., 2000) and the Noah Multi-Parameterization (Noah-MP; (Niu et al., 2011; Yang et al., 2011) land surface model (LSM), which compute changes in soil moisture (e.g., root zone) and groundwater storage in response to computed surface energy and water fluxes. These two LSMs are part of the model suite in the Land Information System

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(LIS) framework (Kumar et al., 2006)—the primary software system used to produce this study’s forecast experiments. Both LSMs were spun-up using two cycles of forcing 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, represents 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 is 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 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).

161 **2.3 Input observed forcings and climate forecasts**

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

168 Hindcasts of RZSM are generated by forcing the hydrologic models with NASA’s
169 Goddard Earth Observing System (GEOS) Atmosphere-Ocean General Circulation Model,
170 version 5 (GEOS; [Borovikov et al., 2017]) Seasonal-to-Interannual Forecast System. The eleven
171 ensemble members of version 1 of this forecast system that were used in the North American
172 Multi-Model Ensemble (NMME) project are used in the forecast portion of this study. To make
173 the GEOS forecasted meteorology consistent with the meteorology underlying the OL initial
174 conditions, we Bias-Corrected and Spatially Downscaled (BCSD; [Wood et al., 2002]) the
175 GEOS forecasts using the MERRA-2 and CHIRPS data sets. The BCSD-GEOS forecast files are
176 then ingested into LIS to drive the LSMs and generate the dynamical hydrological forecasts. The
177 BCSD-GEOS hindcasts are initialized on November 1st (near the start of the planting season)
178 and January 1st (middle of the planting season) of each year in 1982-83 to 2017-18. Each
179 hindcast is run for 6 months.

180 Hindcasts of RZSM are also generated using the Ensemble Streamflow Prediction (ESP)
181 method (Day 1985; Shukla et al. 2013), where the models are forced with resampled observed
182 forcings (forcings that are used to drive the OL simulation) taken from 1982-2010 period. 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 mainly through its RZSM monitoring (generated from OL) and forecasting products. RZSM indicates the soil moisture in the top one meter of the soil profile. Typically, the length of the roots of crops such as maize (main crop in the region of SA) is close to one meter, hence the choice of RZSM as the key forecast variable. Moreover, 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; hence RZSM also allows for a consistent way to merge soil moisture products from both models.

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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 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

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

215

216 **2.6 Out-of-sample crop yield forecasting**

217 We also evaluate the NHyFAS RZSM monitoring and forecasting products' performance
 218 in supporting food insecurity early warning in SA through a series of out-of-sample crop
 219 forecasting experiments. Specifically, we compare the accuracy of crop yield forecasts made
 220 with NHyFAS products against univariate yield forecasts (using only the past yields) and yield
 221 forecasts made with ENSO, a widely used predictor for crop yield in this region. This evaluation
 222 has a direct implication on the usage of NHyFAS products for operational purposes, as crop yield
 223 forecasts are a common tool in food security analysis and response (Davenport et al., 2019).

224 Our baseline model is a univariate (no exogenous predictors) Autoregressive Integrated
 225 Moving Average (ARIMA) model,

$$226 \quad y'_t = \phi_1 y'_{t-1} + \dots + \phi_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \dots + \theta_q \varepsilon_{t-q} + \varepsilon_t, \quad (1)$$

227 Where y_t is the time series of observed yields (and the ` indicates potential differencing of the
 228 time series), p is the order of lags, ϕ are the autoregressive parameters, q is the order of moving

averages, θ are the moving average parameters, and ϵ are forecast errors from the prior periods. ARIMA(p,d,q) models are standard and frequently used methods for time series analysis and forecasting (Hyndman and Athanasopoulos, 2018; Hyndman and Khandakar, 2007). As discussed above, we compare the forecast performance of univariate ARIMA models eq.[1], with ARIMA models that also include environmental exogenous predictors, which, in this case, are (i) DJF ENSO (ii) February RZSM monitoring product and (iii) February RZSM forecast initialized on Nov. 1, during the growing season preceding harvested yields in year t (e.g. 1982/83 DJF used for 1983 yield). All models are fit using the `auto.arima()` function from the forecast package in the R software language.

We use the period of 1983-2007 (25 years) as a training period and then provide “out-of-sample” forecasts of crop yield starting in 2008. The training period always spans through the year before the target forecast year. For example, the model fit over 1983-2008 is used to forecast yields in 2009, and the model fit over 1983-2009 is used to forecast yield in 2010, and so on. We repeat this exercise through 2018 and record the one-step-ahead prediction error in each iteration. In this way, we emulate the forecasting process that food security analysts in the region go through during every year prior to harvest.

245

246 **3. Results**

247 **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.

252 Although the NHyFAS operationally provides the seasonal forecasts every month, for the
253 purpose of this study, we focus on the forecast initialized on November 1 (near the start of the
254 planting season) and January 1 (near the middle of the growing season) of 2015-16 event. Figure
255 4 shows the RZSM forecasts for the growing season made on November 1, 2015. By this time in
256 the season, both FEWS NET and SADC had provided early warning of poor rainfall
257 performance in the region (Magadzire et al, 2017). The NHyFAS RZSM forecasts would have
258 provided further evidence of a looming unprecedented drought in the region. These forecasts
259 would have also indicated that RSA, which is the most important country for the region's food
260 production, was going to be within the epicenter of this drought event. These forecasts, in turn,
261 could potentially have triggered earlier appropriate actions by the early warning agencies, as well
262 as the decision-makers (e.g., national governments and international relief agencies).

263 Later in the season, as the observed precipitation data became available, RZSM
264 monitoring products would have provided refined estimates of the spatial extent and severity of
265 drought in the region. Figure 4 (bottom panel) shows the RZSM monitoring product available
266 after each of the months of November 2015 through February 2016. This monitoring product
267 would have provided additional proof of the drought occurrence in the region, and shown that
268 RSA was within the epicenter of this drought. It is important to state that even the monitoring
269 product can be effectively used as a predictor of food insecurity events, as they are available
270 before the typical start of the harvest season (in April) and the lean season (in November).

271 **3.2 Performance of NHyFAS in supporting food insecurity early warning**

272 Next, we investigate the long-term performance of NHyFAS in supporting food
273 insecurity early warning by examining how well forecasting and monitoring products available
274 from this system can explain historical variability in regional crop yield of the SA region and in

275 particular, help identify below-normal regional yield events. Regional crop yield is calculated by
276 adding the yearly productions from the SA countries, then dividing it by the yearly total
277 harvested area. The regional crop yield is then detrended to remove the effect of any long-term
278 changes (such as technological changes) on the regional yield.

279 First, we show in Figure 5 how detrended crop yield correlates (from early November to
280 early March) with the monthly RZSM monitoring product relative to how it correlates with 3-
281 monthly seasonal precipitation and air temperature. The results indicate that the monthly RZSM
282 monitoring product generally correlates better with detrended crop yield than with the seasonal
283 precipitation or air temperature, with the correlation reaching its peak by early March, when the
284 Feb-RZSM monitoring product and December-February precipitation and temperature are
285 available. Feb-RZSM still shows higher correlation than seasonal precipitation and temperature;
286 however, the difference in correlation is not statistically significant.

287 Next, the correlation between detrended crop yield and February RZSM forecasts (based
288 on ESP method and bias-corrected GEOS forecasts) initialized on November 1 (Fig. 6a) and
289 January 1 (Fig. 6b) is analyzed. The correlation of the yield with GEOS-based February RZSM
290 forecasts initialized on November 1 is 0.49, which is substantially higher than that of ESP-based
291 RZSM forecasts (0.16), clearly demonstrating the added value of using GEOS-based climate
292 forecasts. Similarly, the correlation of yield with the GEOS-based February RZSM forecasts
293 initialized on January 1 is 0.45, higher than that of the ESP-based forecasts (0.30) at that time of
294 the year. Moreover, the correlation of detrended crop yield with GEOS-based February RZSM
295 forecasts initialized on November 1 (0.49) and January 1 (0.45) is higher than that with the
296 RZSM monitoring product (Figure 5) at those times of the year (<0.1 in early November and
297 <0.4 in early January). Again, this highlights the value of using forecasts of Feb-RZSM through

298 early January in supporting food insecurity early warning. Figure 6c shows that Feb-RZSM
299 monitoring product, which is available in early March, has the highest correlation of 0.79 with
300 the detrended crop yield.

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301 Next, we examine how well the forecasting and monitoring RZSM products do in
302 providing early warning of below-normal crop yield events. This criterion for performance
303 evaluation is of particular significance for food insecurity early warning in the region, as below-
304 normal crop yield events are the ones that generally lead to food insecurity. In this case, below-
305 normal regional crop yield events are the events that lie in the bottom 18 (i.e. bottom half) when
306 detrended crop yields for the 36 years are ranked in ascending order.

307 We calculate the probability of below-normal crop yield events when either the February
308 RZSM forecast (initialized on November 1 and January 1) or the RZSM monitoring product for
309 the month of November (available in early December) through the month of February (available
310 in early March) is in the lowest tercile. RZSM products in this tercile are those lying in the
311 bottom 12 of the RZSM products when ranked in ascending order. In the case of RZSM, the
312 ranked climatology is different for each of the forecasting products and the monitoring products
313 for each month. We use the lower tercile values of RZSM monitoring and forecasting products to
314 focus on the drought years as indicated by those products. Because SA is a mostly rainfed region,
315 the crop yield is generally below normal during drought years, as indicated in several recent
316 events (2014-15, 2015-16, 2018-19).

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317 Figure 7 shows the fraction of years with below-normal crop yield when February RZSM
318 forecasts (made on November 1 or January 1) were in the lower tercile (shown by blue color
319 bars) or when monthly RZSM monitoring products (shown by green color bars) were in the
320 lower tercile. These results indicate that as early as November 1, if the February RZSM is being

321 forecasted to be in the lower tercile, then there is about ~66% probability of the regional crop
322 yield being below normal (statistically significant at 86% confidence level). This would be 4-5
323 months before the start of the harvest season, and about one year before the start of the next lean
324 season. The inferred probability value increases to ~83% when the February RZSM forecasts,
325 initialized in January, are in the lower tercile (statistically significant >95% confidence level).
326 Finally, by early March, when the February RZSM monitoring product is available, the inferred
327 probability increases to 100% (statistically significant >95% confidence level). In other words,
328 over 1982-2016, whenever the February RZSM monitoring product for the SA region was in the
329 lowest tercile, the crop yield in the following season had been below normal (based on detrended
330 yield). This would be 1-2 months before the start of the harvest season, and about 8-9 months
331 before the start of the next lean season.

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

337

338 **3.3 Performance of NHyFAS in providing routine operational crop yield forecasts**

339 Finally, we evaluate the performance of NHyFAS for supporting food insecurity early
340 warning in SA by examining the accuracy of RZSM monitoring and RZSM forecasting products
341 in predicting regional crop yields. We compare the crop yield forecasts made with the RSZM
342 products against both univariate forecasts (using only past observed crop yields) and forecasts
343 made with ENSO. As ENSO is a widely used predictor for precipitation and crop yield forecasts

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344 in this region, we examine the added value of using NHyFAS RZSM monitoring and forecasting
345 products above and beyond ENSO. All forecasts are done using ARIMA models described in
346 section 2.6.

347 Figure 8 shows a comparison between the “observed” reported crop yield (black lines)
348 and the “out-of-sample” (i.e. post-training period) forecasted yield (red lines) produced with a
349 univariate model, and the models using environmental exogenous predictors (i) DJF ENSO, (ii)
350 Feb-RZSM (monitoring) product, (iii) Feb-RZSM (Forecasting product) initialized on Nov. 1., in
351 addition to that univariate model.

352 The results indicate that: (i) environmental predictors such as ENSO and the NHyFAS products
353 can make crop yield forecasts that are more accurate than those produced using only a univariate
354 approach. When ENSO is used as an additional predictor (in addition to a Univariate model), the
355 MAE reduces from 0.342 MT/HA to 0.285 MT/HA, a ~17% reduction in error. (ii) Use of the
356 Feb-RZSM monitoring product has an even larger impact, reducing the MAE by about 50%, to
357 0.174 MT/HA. (iii) Use of the Feb-RZSM forecasting product (initialized on Nov 1) has an
358 impact similar to that of DJF ENSO. Although the MAE is about 6% larger when the forecasting
359 product is used rather than the ENSO predictor, the forecasting product has the significant
360 advantage of being available for about 4 months earlier. For comparison (not shown here) MAE
361 of Feb-RZSM forecasting product (initialized on Nov 1) is slightly smaller (~6%) than the MAE
362 of August-October (ASO)-ENSO (also available in early Nov) and is comparable to the MAE of
363 September-November (SON)-ENSO (available in early December) as a predictor of crop yield
364 forecast.

365 Table 1 shows the number of times the observed yield is within the 80% confidence
366 interval of the forecasts and the mean spread of the confidence interval. The improvement in

367 performance obtained when the Feb-RZSM monitoring product is used is clear; during 10 of the
368 11 years in the validation period, the observed yield falls within the 80% confidence interval,
369 whereas this happens in only 7 years when DJF ENSO is used as the additional predictor. The
370 mean spread of the confidence interval associated with the use of the Feb-RZSM monitoring
371 product (0.70 MT/HA) is also the smallest.

372 **4 Discussion**

373

374 This study makes a case for the application of NHyFAS's RZSM forecasting and
375 monitoring products in supporting the early warning of food insecurity in SA. It has been shown
376 that the successful early warning of crop yield, and especially below-normal crop yield years,
377 can be issued based on these products. In this section, we address a few important caveats.

379 **4.1 Comparison with existing drought forecasting systems and approaches:**

380 In this study, we keep the comparison with existing forecasting systems and approaches
381 limited to the comparison of the performance of NHyFAS products with (i) ESP (i.e.
382 climatology) based RZSM forecasts and (ii) ENSO-based crop yield forecasts, both of which are
383 commonly used approaches for drought forecasting in the region, including by early warning
384 agencies such as FEWS NET. Comparison against both approaches shows clear added value of
385 using the NHyFAS products. We could not compare the performance of the NHyFAS with
386 FEWS NET or SADC's official historical forecasts because:
387 (i) FEWS NET's official forecast is an outlook of food insecurity conditions ([Funk et al. 2019](#))
388 (<https://fews.net/>) which is based not only on agroclimatology (i.e., agriculture and climate
389 conditions) but also on market conditions and nutrition and livelihood conditions. The NHyFAS
390 forecasts that are now being used by FEWS NET would fall into the category of

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391 agroclimatological conditions. In fact, the goal of the evaluation of the NHyFAS forecasts is to
392 establish whether NHyFAS forecasts can be suitable agroclimatological forecast inputs for
393 FEWS NET to guide the development of food insecurity outlook assessments. Also, FEWS NET
394 Food Insecurity Outlook is partly based on subjective assessments, in some ways similar to the
395 U.S. drought monitor (Svoboda et al., 2002) or U.S. Seasonal Drought Outlook, in addition to
396 quantitative assessments such as agroclimatological forecasts. Finally, FEWS NET's archive of
397 Food Insecurity Outlooks currently extends back only to mid-2011.

398 (ii) SADC CSC's issues probabilistic seasonal-scale rainfall forecasts. These forecasts are based
399 on multiple models (both statistical and dynamical) as well as subjective expert assessments,
400 which makes comparison with purely quantitative products inappropriate. Additionally, the
401 archive of purely quantitative forecasts from SADC CSC only goes back to 2017.

402 Finally, the NHyFAS products are intended to be used as an addition to the existing early
403 warning tools of FEWS NET and SADC CSC, which are partners in the efforts described in this
404 study, rather than replacing any of the existing tools.

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406 **4.2 Influence of crop yield on regional food insecurity and issues in crop yield reports**

407 In this study, it is assumed that when the SA region faces a production shortfall, the
408 regional food insecurity is likely to rise. This was certainly the case during the 2015-16 El Niño,
409 the most recent major food insecurity event in the region (SADC 2016). However, this
410 assumption ignores other important factors that may lead to or further worsen food insecurity in
411 the region, such as inadequate agricultural inputs, price shocks (which can be global in nature),
412 rise in population, conflict, limited livelihood options, stocks, etc. Nonetheless, the direct
413 relationship of crop yield with the interannual variability in available moisture makes RZSM an

414 important variable for food security monitoring and thus, it is of keen interest to early warning
415 systems like FEWS NET, which is presently the primary end user of the NHyFAS. Crop yield
416 early warning based on the NHyFAS products are also directly relevant to international
417 collaborative efforts like the GEOGLAM initiative ([Becker-Reshef et al. 2018; Becker-Reshef et](#)
418 [al. 2019](#)) and, particularly, to the Crop Monitor for Early Warning (<https://cropmonitor.org/>),
419 which provides monthly assessments of crop conditions for the countries most vulnerable to food
420 insecurity. Such assessments are key to reducing the uncertainty of crop prospects as the growing
421 season progresses, and to providing critical evidence for informing food security decisions by
422 humanitarian organizations and governments alike.

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

427 **4.3 Reliance on single climate model forecasts:**

428 Finally, the results of this study are also likely affected by the use of only one dynamical
429 climate forecast model for driving the seasonal hydrologic forecasting system. Adding forecasts
430 from more climate and hydrologic models would likely enhance the skill of the system ([Kirtman](#)
431 [et al. 2014; Krishnamurti et al. 1999](#)). The choice of one dynamical system was made mostly for
432 logistical purposes, since GEOS archived and real-time forecasts include all atmospheric forcing
433 variables needed to drive such LSMs, and are available through NASA-GSFC routinely, to
434 facilitate operational production of NHyFAS forecasts.

5 Conclusions

The region of SA witnessed several severe 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) in predicting regional crop yield through the prediction of February RZSM; (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 lowest tercile, the subsequent crop yield is (for a limited set of samples considered) always below normal (statistical significance level >95%); (vi) the February RZSM monitoring product can provide “out-of-sample” crop yield forecasts with higher skill than DJF ENSO (38%

458 reduction in mean error relative to DJF ENSO), whereas the February RZSM forecasting
459 product, available in early November, can provide crop yield forecasts with comparable skill
460 (~6% increase in mean error relative to DJF ENSO).

461 The NHyFAS products described here were first generated in August 2018 for
462 operational applications by FEWS NET. As described in much detail in Funk et al., (2019), each
463 month, FEWS NET's regional scientists (located in eastern, western, and southern Africa)
464 review the latest products ahead of the FEWS NET's monthly climate discussions. The NHyFAS
465 products, in addition to other early warning tools, are used to support or revise the assumptions
466 of climate and hydrologic conditions in the upcoming season. The updated assumptions are then
467 passed on to food analysts for the region in order to help inform needed relief actions. This study
468 demonstrates the value of the NHyFAS products in supporting food insecurity early warning in
469 the SA region. It is worth mentioning that since NHyFAS currently covers Africa and the Middle
470 East region, the NHyFAS products are applicable for food insecurity early warning in the rest of
471 Africa and the Middle East as well. Based on this study, it is postulated (future research pending)
472 that NHyFAS RZSM products can be particularly effective for those rainfed agriculture regions
473 and seasons which are not known to have strong teleconnection (e.g. with ENSO), as in the SA
474 region. Finally, since the data sets and models used to implelement the NHyFAS are available
475 globally, a similar seasonal RZSM monitoring and forecasting framework can be developed at a
476 global scale to support food insecurity early warning in other rainfed regions across the globe.

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483 Author contribution: SS led the design of the analysis, conducted the analysis, and wrote the
484 manuscript and generated figures. KA, CPL, CF, and FD contributed to the design of the
485 analysis. FD contributed to the analysis as well. KA and AH conducted the model simulations.
486 RK and CPL reviewed the article and proposed substantial changes. CPL and GH are PIs of
487 projects supporting this work. TM, JV, AM, AH facilitate real-time application of the products.
488 The other co-authors reviewed the article and provided their input/edits.

489 **Competing interests:**

490 The authors declare that they have no conflict of interest.

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519 Office (GMAO). Model source code can be found at NASA's Land Information System's
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521 parameters are available through email request. The daily CHIRPS precipitation data can be
522 found here (ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/global_daily/netcdf/p25/).
523 MERRA-2 reanalysis-based atmospheric forcings can be found through NASA's GES DISC
524 archive ([https://disc.gsfc.nasa.gov/datasets?keywords=%22MERRA-](https://disc.gsfc.nasa.gov/datasets?keywords=%22MERRA-2%22&page=1&source=Models%2FAnalyses%20MERRA-2)
525 [2%22&page=1&source=Models%2FAnalyses%20MERRA-2](https://disc.gsfc.nasa.gov/datasets?keywords=%22MERRA-2%22&page=1&source=Models%2FAnalyses%20MERRA-2)). NHyFAS forecasts, in the form
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721 Table 1: Performance of ‘out-of-sample’ crop yield forecasting over the validation period of

722 2008-2018.

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	Univariate model	Univariate model + ENSO	Univariate model + Feb- RZSM (Monitoring)	Univariate model + Feb- RZSM (forecast)
Mean absolute error over the validation period (MT/HA)	0.342	0.285	0.174	0.301
Number of years observed yield is within 95% confidence interval bound	9	10	10	9
Mean spread of 95% confidence interval (MT/HA)	1.64	1.20	1.07	1.20
Number of years observed yield is within 80% confidence interval bound	9	7	10	7
Mean spread of 80% confidence interval (MT/HA)	1.07	0.78	0.70	0.78

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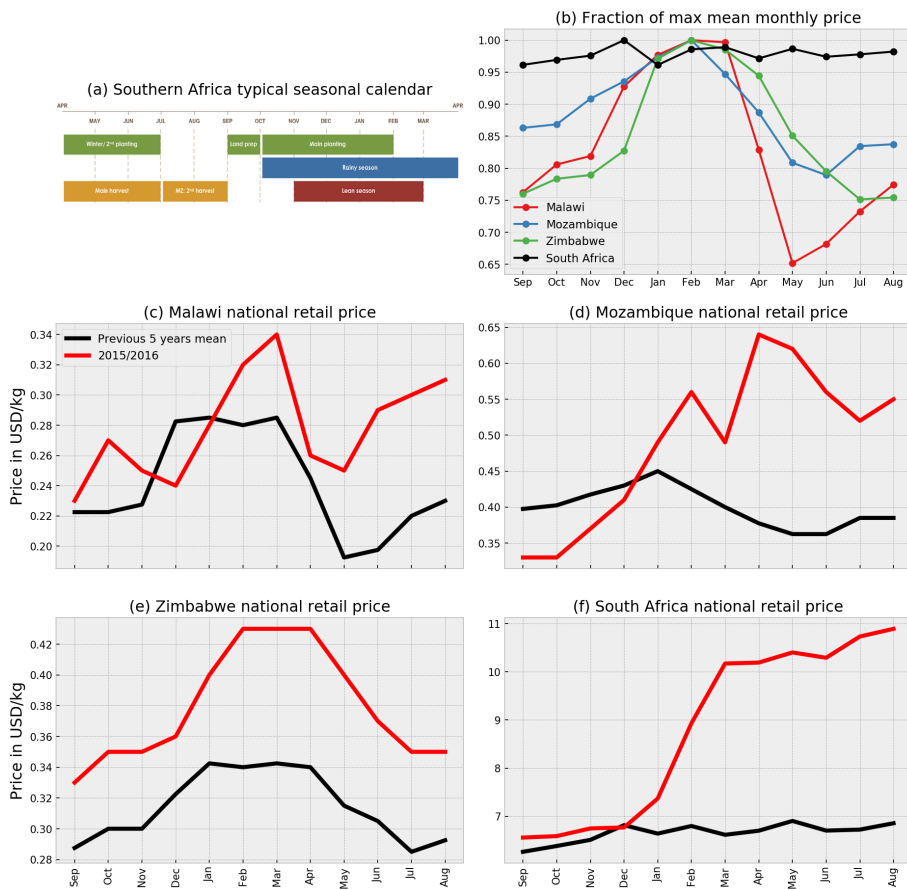


Figure 1: (a) Schematic representation of a typical seasonal calendar for the southern Africa region. (taken from: <http://fews.net/southern-africa>) (b) Monthly climatology of maize prices in SA countries. The monthly mean prices are normalized relative to the maximum mean monthly price for a given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

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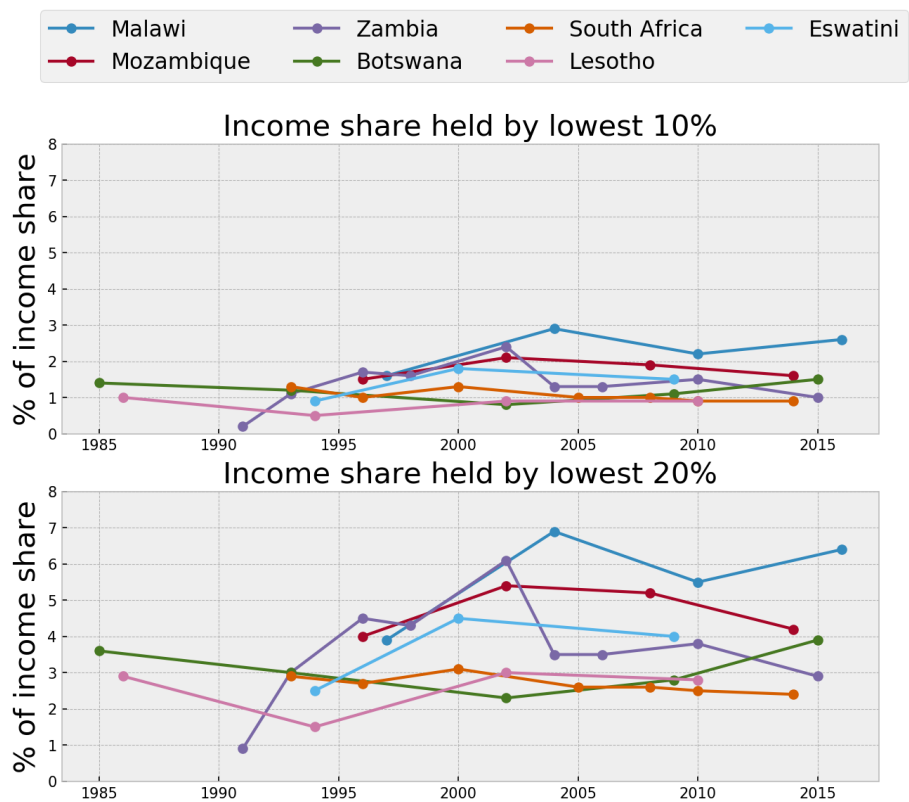


Figure 2: Percentage of income share held by lowest 10% and 20% income population in the Southern Africa countries. (Data Source: the World Bank's World Development Indicators)

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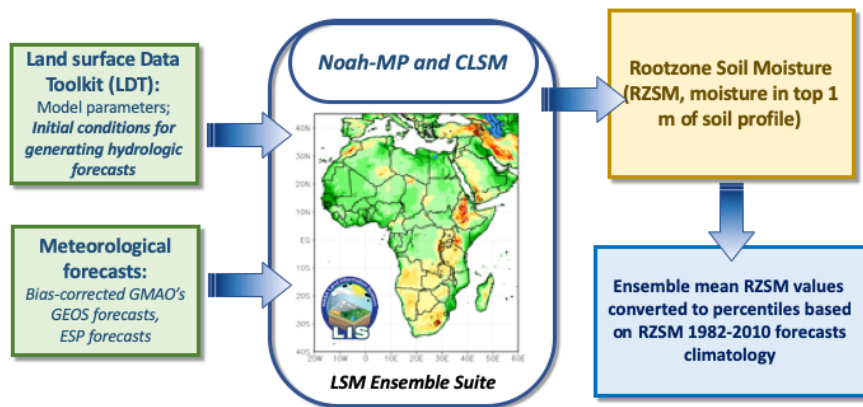
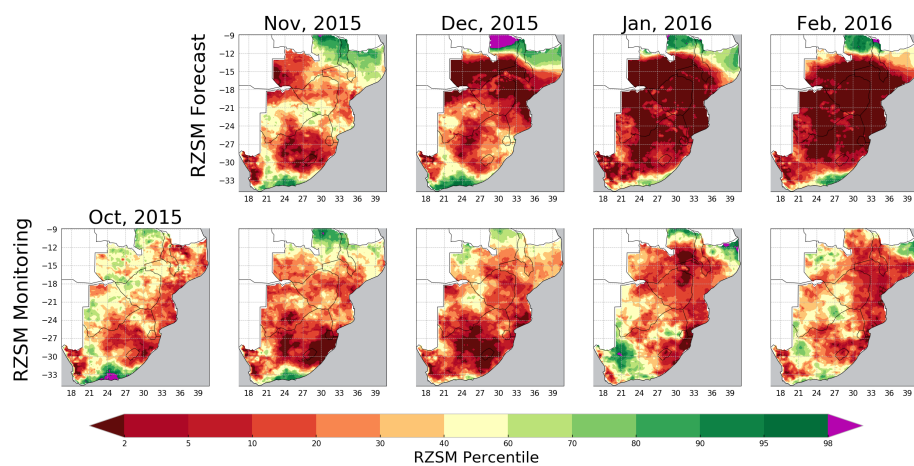


Figure 3: Overview of the NHyFAS implementation to produce RZSM monitoring and forecasting products, as used in this study.

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Figure 4: Forecast (top panel) and Monitoring of Rootzone soil moisture (RZSM) percentiles for the months of November 2015 through February 2016. October 2015 conditions reflect the state of RZSM during the month preceding the forecast initialization 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.

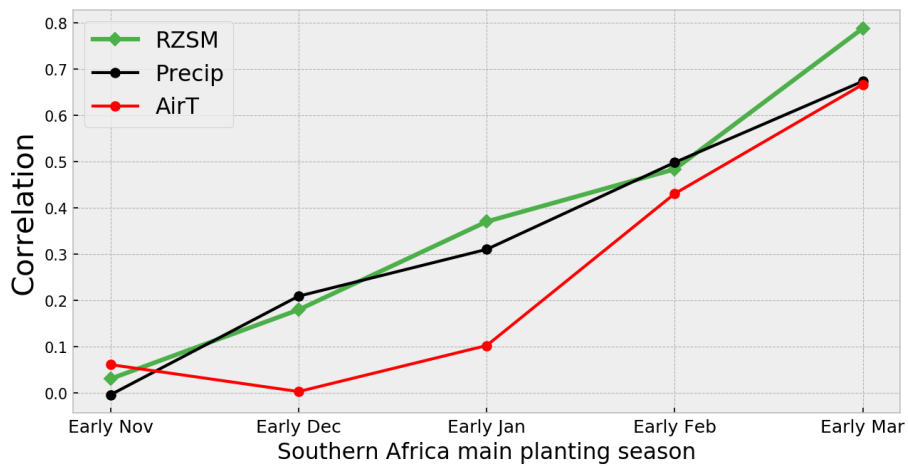


Figure 5: Variability of the correlation between the 3-month seasonal precipitation, 3-month seasonal air temperature (AirT), and monthly RZSM monitoring product with the detrended crop yield. This result highlights that RZSM is potentially a better predictor of crop yield than seasonal precipitation and AirT; also, the skill is the highest in early March when DJF seasonal precipitation, AirT, and February RZSM monitoring products are available.

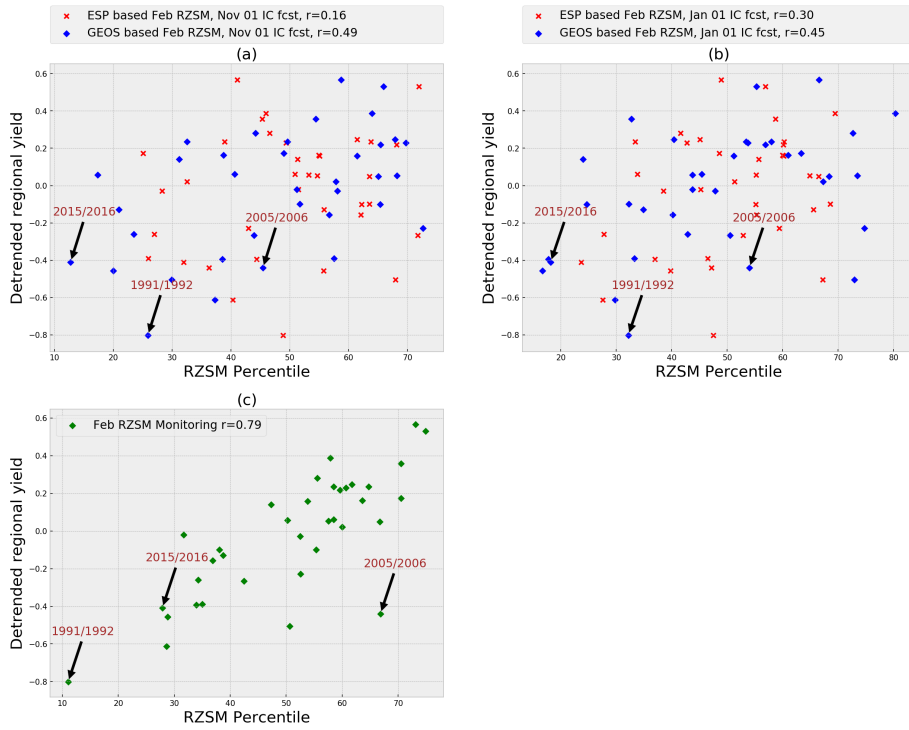


Figure 6: Covariability of detrended regional yield in southern Africa with: (a) February RZSM forecasts (initialized on November 1) generated using ESP method and bias-corrected GEOS forecasts, (b) February RZSM forecasts (initialized on January 1) generated using ESP method and bias-corrected GEOS forecasts, and (c) the February RZSM monitoring product (available in early March).

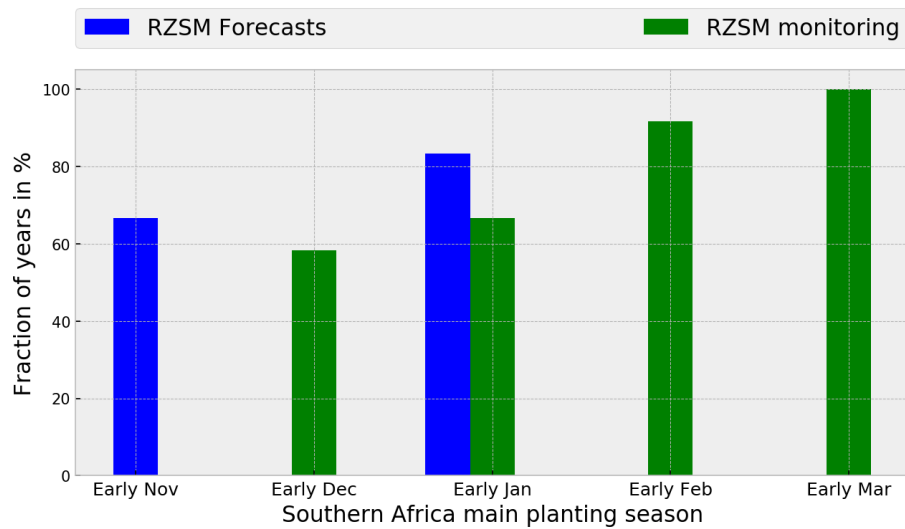


Figure 7: Fraction of years with below-normal regional crop yield (based on the rank of detrended crop yield) given that the corresponding RZSM forecasts (initialized on November 1 and January 1) and RZSM monitoring product (available in early March) were in the lowest tercile (based on the rank of the 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.

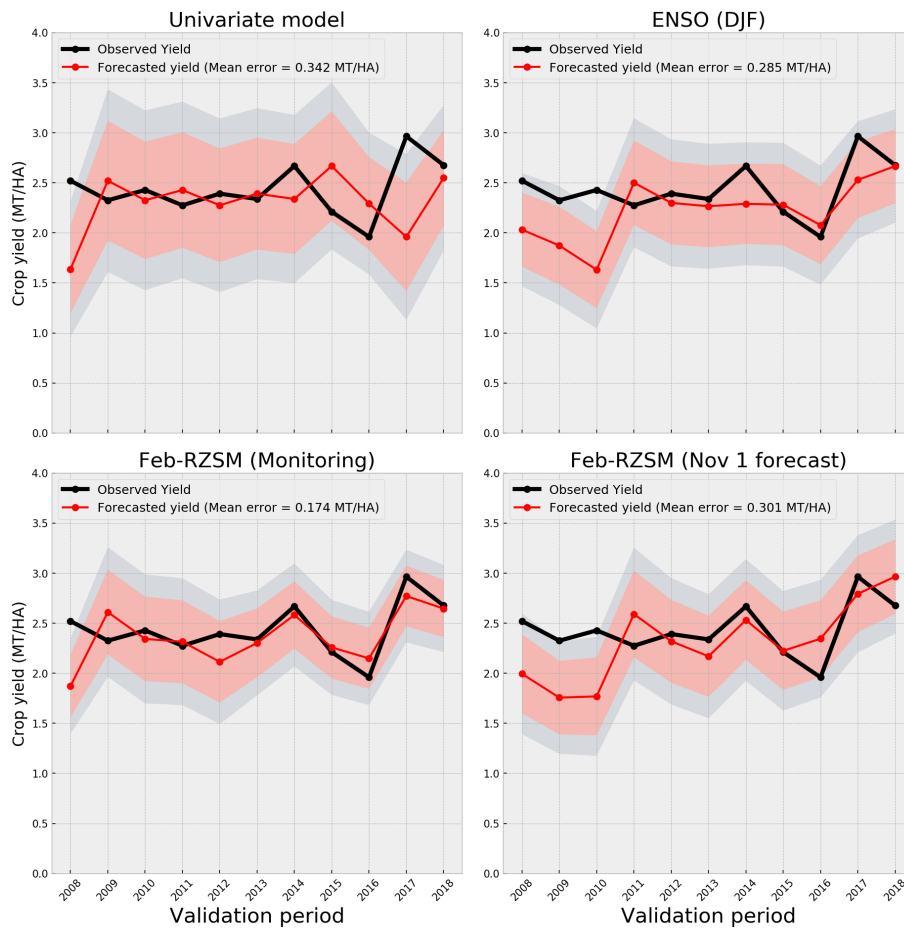


Figure 8: Comparison of the performance of a Univariate model alone, ENSO (DJF), Feb-RZSM monitoring product, Feb-RZSM forecasting product as a predictor in forecasting crop yield of Southern Africa. Pink [gray] shading indicates 80% [95%] confidence interval.