Hydrol. Earth Syst. Sci. Discuss.,
https://doi.org/10.5194/hess-2018-183-AC3, 2018

Hydrology and Earth System Sciences
Discussions

Interactive comment on "Season-Ahead Forecasting of Water Storage and Irrigation Requirements – An Application to the Southwest Monsoon in India" *by* Arun Ravindranath et al.

Arun Ravindranath et al.

arunravi86@gmail.com

Received and published: 14 July 2018

We thank the three referees for their valuable comments. Here are our point-by-point responses. Some comments that had similar concerns were grouped together for the response. ÂăNote the following convention: RC = referee comments, AC = author comments (replies).

Referee 3

The manuscript presents a framework for the season ahead forecasting for water requirements in India using cumulative deficit index. The manuscript raises an important

topic, however, has a few relevant but unanswered questions. The major comments are as following:

RC1) Authors use the coarse resolution (1 deg) precipitation data for the period of 1901 - 2004 while high-resolution data can be more appropriate for this study. High-resolution and updated precipitation data are available at 0.25 deg for the 1901-2015 period (Pai et al. 2014). Moreover, air temperature data have been obtained from NCAR. Precipitation and temperature during the monsoon season have co-variability. Therefore, authors should use both precipitation and temperature data from India Meteorology Department (IMD).

AC1: The 0.25 degree rainfall data is not available to us at this point. We have tried to get it, but were not successful. Hence, we used the dataset we had from our previous studies. Moreover, the original citation of NCAR for temperature was done by mistake. For this work, we in fact used the temperature data from IMD. We corrected this in the revised manuscript.

RC2) It is not clear to me that why the forecast was done only for 2001-2013 period? To ensure the robustness of the forecast, retrospective evaluation for a long-period (at least 30-years) is required.

AC2: The forecast model was run over the years 1901 - 2013, but the results are only displayed for the final 13 years. ÂăThis is due to the fact that the model-forecasted ITF runs only from 2001 - 2013 and the model-forecasted Nino 34 JJAS (concurrent season Nino 34 index) runs only from 2002 - 2013. ÂăThe first 100 years (1901 - 2000) of data are used to train the model and the remaining years (2001 - 2013) are forecasted for CDI in the following way: 1901 - 2000 data for climate and CDI are used to generate a probabilistic forecast of CDI for 2001, then 1901 - 2001 data is used to generate a probabilistic forecast of CDI for 2002, and so on up until 2013. ÂăThe model-generated estimates of ITF and Nino 34 JJAS (both indices are for the concurrent JJAS season) are used for the year being forecasted, whereas observations are used in the nearest neighbors training scheme. This is updated in this manner for each successive year. So the limitation of model-generated ITF and Nino 34 JJAS values is the limiting factor here. ÂăHowever, we have used observations for ITF and Nino 34 JJAS to generate forecasts for the years 1976 - 2000 and augmented this with the 2001 - 2013 forecasts. The table attached as supplementary PDF material summarizes the results of this longer-term evaluation. We observed 24/38 hit rate (63% hits), 9/38 false alarm rate (24% false alarms) and 5/38 miss rate (13% miss), as reported in the final row of the table (see supplementary material 1). We added this summary in the revised manuscript, in section 5.1 end. ÂăThis proves robustness of the forecasting system developed in this paper.

The sentences added to the manuscript (end of 5.1) are

"To conclude, we used observations for ITF and Nino 34 JJAS to generate CDI forecasts for the years 1976 - 2000 and augmented these forecasts with the 2001 - 2013 CDI forecasts depicted in Figure 5. ÂăRunning the forecasts for a longer period of time, which in this case is 38 years, ensures robustness of the procedure. ÂăThe hit/false alarm/miss rates resulting from this extended retrospective, adaptive forecast are 24/38 hits, 9/38 false alarms and 5/38 misses, respectively. ÂăHence, we are observing 63% hits, which indicates a fairly good, robust forecasting procedure for an informative crop water stress index."

RC3) Crop water stress has been estimated using cumulative deficit index (CDI). CDI is the difference between rainfall and crop water requirement (based on PET). This raises a major concern as CDI completely ignores the role of soil moisture persistence. If I am not mistaken, this issue has to be addressed in the revised manuscript.

AC3: CDI is a storage metric (surrogate for the amount of water that should be kept in storage in order to satisfy crop water requirement for the growing season given seasonal rainfall conditions). ÂăCDI is, in this sense, essentially a measure of soil moisture deficit. Crop water demand incorporates the temperature and crop coefficient,

which in turn represents crop water use at various stage of growth. ÂăThe precipitation is multiplied by the fraction of usable water by the crop. This multiplier implicitly takes soil moisture into account. In our still unpublished work (Troy et al. 20xx), we find comparable results with a simple bucket style water balance model that included soil moisture as a storage layer with specified porosity and allows for lag responses. To keep the index simple and with minimum amount of data, we derived this cumulative deficit index.

Troy, T, J., N Devineni and U.Lall, (20xx), A system out of balance: (Un)sustainable water resources in India's breadbasket, to be submitted to Hydrology and Earth System Sciences.

RC4) How does CDI account for pre-season soil moisture?

AC4: The CDI is based on a storage estimation algorithm (sequent peak method) which assumes that the reservoir is full at the beginning or has the potential to fill up in a few cycles. In our application, one can make a similar assumption that farmers wait for a couple of pre-monsoon rainfall events to fill up the soil store before planting, basic irrigation and tilling. In this regard, the farmer starts with reasonably full storage and the CDI will estimate the irrigation water required through the season to sustain a healthy crop.

RC5) If possible, authors should test the validity of CDI using soil moisture data. Authors may use soil moisture available from global land data assimilation system (GLDAS).

AC5: There is a statistically significant correlation between average soil moisture and CDI. ÂăGLDAS soil moisture data for surface soil moisture (SM_S), root zone soil moisture (SM_RZ) and profile soil moisture (SM_P) is obtained. ÂăThe data ran from 1948 - 2014, whereas our CDI data runs from 1901 - 2013. The GLDAS data for each of the three soil moisture types was on the daily resolution. ÂăWe calculated JJAS seasonal averages for each of SM_S, SM_RZ AND SM_P for the years 1948 - 2014, and then correlated these three average time series with CDI. The correlation values were -0.31, -0.33 and -0.28 for the correlation of CDI with SM_S, SM_RZ and SM_P, respectively. ÂăThese are statistically significant, and indicate that CDI is a sufficiently good measure for crop water deficit and takes into account some degree of soil moisture deficit (note the negative sign of the correlation values). We also calculated JJAS seasonal maxima (i.e. for each JJAS season in the years 1948 - 2014, we took the maximum value of soil moisture) and correlated these maxima with CDI. ÂăFor SM_S, its correlation with CDI is -0.42; for SM_RZ, its correlation with CDI is -0.45; and for SM_P, its correlation with CDI is -0.37. These indicate a strong relationship between soil moisture, particularly root zone which is the most appropriate comparison, and CDI. For the future, it is possible to include soil moisture (most likely root zone) as a second variable to CDI in a multivariate forecasting system.

RC6) It is not clear to me that why did authors select the potato crop and not rice and wheat? For their analysis. The approach should be evaluated for other crops and the other regions as well.

AC6: In this paper, we were focused on presenting the forecasting system, which includes a non-linear, non-parametric algorithm (kNN) that gives a measure of uncertainty in its forecasts and a hydrologic index that fairly assesses crop water stress. ÂăThe purpose of the paper was not to extend this system to more crops and locations, which may be beyond the scope of what is required to demonstrate the procedure. However, extending this analysis to other regions and crops is an excellent idea, and we would be very interested in working with the referee on such a project. We did look at some predictors that could be used for predicting deficit in rice. The map below shows the field correlations with global SSTa. The identified predictors for rice are similar to the ones identified for Potatoes. Hence, we can use these predictors to forecast rice deficit in the same spirit. ÂăThis is shown in the attached graph (first attachment).

RC7) The estimation of daily reference crop ET estimation is based on only maximum and minimum temperature and does not include radiation and wind. Therefore, uncer-

tainty in ET estimation should be evaluated.

AC7: We agree that we had a constrained method. ÂăTemperature and precipitation data were all that were available, so we constructed a form of CDI that fairly evaluates crop water stress yet does so with minimal, easy-to-obtain inputs. ÂăPlease see Etienne et al. (2016) for a form of CDI that incorporates Penman-Monteith instead of Hargreaves method for estimating crop water requirement.

Etienne, E., Devineni, N., Khanbilvardi, R., Lall, U., (2016). Development of a Demand Sensitive Drought Index and its Application for Agriculture over the Conterminous United States. Journal of Hydrology, 534, 219–229. doi: http://dx.doi.org/10.1016/j.jhydrol.2015.12.060

Minor comments

RC1) The organization of the manuscript should be improved. There are many long paragraphs that should be shortened.

AC1: We shortened or separated some of the longer paragraphs.

RC2) Lines 122-129 should be removed.

AC2: We prefer to keep lines 122 - 129 (of original submission); this is in keeping with HESS style and serves as a standard roadmap of the paper that people put at the end of introductions. ÂăHence, we will keep the following sentences at the end of the introduction to the paper:

"In section 2, we present a survey of the existing forecasting systems in monsoonal climates and their skill and limitations. In section 3, we discuss the background and scientific basis of CDI, including its explicit formulation and governing equations. ÂăIn section 4, we get into a thorough description of the case study and all steps involved, including background information relating to the case study and location, data collection and processing, a complete description of the forecasting model, methods and predictor selection scheme. ÂăSection 5 presents the results of the forecast, a discussion of these results and their implications, and a comparison of our results with those of IMD. Finally, section 6 summarizes and concludes the paper."

RC3) Lines 146– correlation values should be in two digits after the decimal.

AC3: We have rounded the correlation values on line 146 to two significant figures as suggested by the referee. ÂăThis was found in line 146 of the original submitted manuscript, and is now revised to the following:

"Highest skill, as measured by the correlation coefficient between observed and model-predicted SPI series, occurred at shorter lead times, with correlation values between 0.80 and Âă0.93 depending on which SPI series was forecasted."

RC4) Lines 133-178: long paragraph

AC4: We tried to shorten this.

RC5) Line 195: CDI will mostly overestimate the demand as it does not consider soil moisture persistence?

AC5: We may have overestimation of demand in a strict crop-water modeling sense, however, the partitioning of rainfall has an implicit soil moisture accounting.

RC6) Line 208: What is the basis of effective rainfall with alpha =0.7?

AC 6: We have used alpha = 0.7 in our previous studies of water stress in India [Devineni et al. 2013]. The selection was based on discussions with local agricultural experts from India and some corroborative tests for similar rainfall and temperature conditions in the USA [Devineni et al. 2015]. The reference was added in section 3 to the sentence declaring the value of alpha = 0.7, as shown below:

"In our study, we set ÂăÂă= 0.7 (Devineni et al, 2013)."

Devineni, N., Perveen, S., & Lall, U. (2013). Assessing chronic and climate-induced water risk through spatially distributed cumulative deficit measures: A new picture

of water sustainability in India. Water Resources Research, 49(4), 2135–2145. doi:10.1002/wrcr.20184

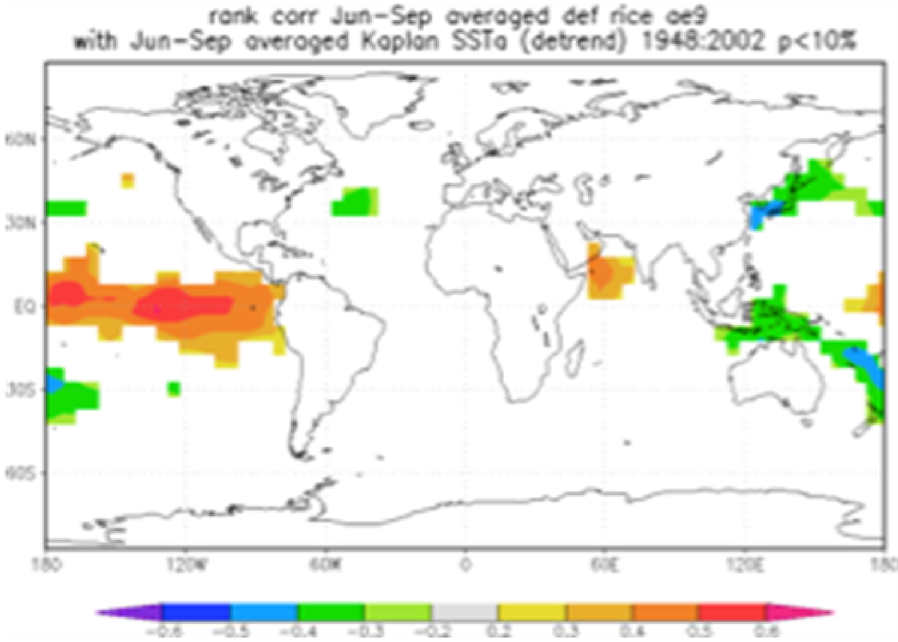
Devineni, N., Lall, U., Etienne, E., Shi, D., & Xi, C. (2015). America's water risk: Current demand and climate variability. Geophysical Research Letters, 1–9. doi:10.1002/2015GL063487.

RC7) Quality of figures can be improved.

AC7: We tried our best to have better quality.

Please also note the supplement to this comment:
https://www.hydrol-earth-syst-sci-discuss.net/hess-2018-183/hess-2018-183-AC3-supplement.pdf

Interactive comment on Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-183, 2018.



rank corr Jun-Sep averaged def rice ae9
with Jun-Sep averaged Kaplan SSTa (detrend) 1948:2002 p<10%
60N
30N
EQ
30S
60S
180
120W
60W
0
60E
120E
180
-0.6
-0.5
-0.4
-0.3
-0.2
0.2
0.3
0.4
0.5
0.6

Fig. 1.