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Hydrology and Earth System Sciences
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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.

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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. Note the following conventions: RC = referee comments, AC = author comments (replies)

Referee 1 General response. This is a well-written paper that develops and demonstrates a framework for season-ahead forecasts of an irrigation-relevant index, the CDI. Although there have been other studies examining season-ahead forecasting for the agricultural sector, the significance of this paper is the demonstration of the forecast-

ing of a decision-relevant index, rather than routinely forecasted products, such as precipitation. I recommend the paper for publication, with a few minor revisions for consideration by the authors:

Thank you.

RC1. General comment for Section 4. This section is well written, but is quite dense, making it hard to follow each step. I suggest adding a flow chart detailing the main steps (along with the associated section #), to help the reader follow along.

RC1.a. Related to this point, in section 4.2.1. "Predictor Selection" I was not clear if there was any consideration for having more versus less predictors, especially since these would likely be co-linear; i.e., your best model includes Niño 12 MAM-DJF, Niño 34 MAM-DJF, and ITF. It would seem like these would have similar information, though I recognize that this is a data-driven approach (i.e., is ultimately used in the feature vector in the knn, not linear regression). Was there any penalty calculated in your metrics (i.e., RMSE and RPSS) for including additional predictors?

AC1: We have created the flowchart suggested by the reviewer, outlining the main steps in section 4 and labelling each step with the paper section and subsection numbers in which those steps appear.

The following flowchart is added as Figure 2 in the revised manuscript (see first attachment).

AC1a: The final set of predictors we obtained from the exhaustive search method turned out to be oceanic tele-connections that are from different Âăspatial regions over the equatorial Pacific and Indian Oceans. In this regard, Nino 34 and Nino 12 trends and ITC are not correlated in space, as Nino 34 and Nino 12 are located in unconnected regions of the Pacific, and ITC is a different phenomenon best described as a pathway for warm freshwater to move from the Pacific to the Indian Ocean. However, they may be correlated in time subject to a lag. Âă

The reason that we used all three of the predictors is that we wanted to incorporated all of the spatial features. ÂăWe demonstrate concurrent time correlations across the predictors by showing a scatterplot matrix between any and every two of the three chosen predictors. ÂăThere does not appear to be any significant correlation between Nino 12 MAMMDJF and ITC. There appears to be some degree of correlation between Nino 34 MAMMDJF and ITC. ÂăAlthough Nino 34 and Nino 12 are in disconnected regions of the Pacific, they appear to have some correlation, at least over time. We did not add any penalty to the metrics (RPSS and RMSE). See second attachment for scatterplot matrix alluded to earlier.

RC2. General comment for section 5.1. Your evaluation of the forecasts is effective (e.g., Figure 4, and Tables 1 & 2), especially when you compare with the precip forecasts (Table 3).

RC2.a. Minor comment related to this point: Figure 4 & Line 562. If possible, maybe have a color coding or symbol of the triangles to indicate the directional similarity? And add a legend to that effect? Otherwise this is hard to see. At first glance, I was looking to see if the observation was captured by the IQR.

RC2.b. Table 3 and lines 611. Agreed that it is important to note that your forecasts are tailored to the location, which is quite resource intensive to do for every crop, and every location. I agree that this is where a framework (such as what you have put forth) is helpful, but it may be worth highlighting that there is a rich literature on opportunities and barriers to using seasonal forecasts (see next comment: 3. General comment for section 5.2).

AC2a: We have elected to color-code boxplots corresponding to identical directionality as gray and the boxplots corresponding to dissimilar directionality as white. ÂăA legend to that effect has been included in the plot. Thank you for this suggestion.

Figure 4 in the paper shows this change has been implemented. See third attachment.

AC2b: The literature on opportunities and barriers to using seasonal forecasts is integrated into the manuscript in the relevant section(s). The following paragraph is added as the concluding paragraph of section 5.2.

"An interesting and excellent discussion concerning the usability of such science is found in Dilling and Lemos (2011) and several papers cited therein. ÂăIn the context of that discussion, we find that our forecasting procedure combines the "science push" and "demand pull" approaches to creating scientific usability. ÂăThe impetus for crafting the CDI and, prior to that, independently developing the k-NN algorithm, was scientific. However, the decision to combine them and apply them as we have to seasonal forecasting was made with agricultural stakeholder interests in mind. ÂăAs discussed in Dilling and Lemos (2011), the problem of overcoming informal institutional barriers to availing of such seasonal forecasts, namely the idea that current methods of forecasting through weather and climate prediction centers are the only reliable methods, is one potentially faced by our methodology. ÂăIf this is the case, this is unfortunate, as we feel that our targeted forecasting system is potentially very useful to stakeholders and decision-makers in relevant sectors."

RC3. General comment for section 5.2. It is useful to provide a discussion of the utility of such forecasts. Targeted forecasts, such as those presented here, can help to increase the utility of the forecasts since they intersect with actual decision contexts (e.g., irrigation needs for particular crops). It would also be worth mentioning (briefly) that there have been studies on developing useable climate information, and mention how this study fits into that bigger picture. Dilling and Lemos (2011) have a good overview of some of the opportunities and barriers to the use of seasonal climate forecast information (but there are other studies), which might be of interest to that end. Dilling, L., & Lemos, M. C. (2011). Creating usable science: Opportunities and constraints for climate knowledge use and their implications for science policy. Global Environmental Change, 21(2), 680–689. http://doi.org/10.1016/j.gloenvcha.2010.11.006

AC3: The literature suggested here (Dilling and ÂăLemos, 2011, etc.) has been reviewed and incorporated in the revised manuscript. More discussion on the utility of these forecasts is also added. ÂăPlease see AC2 for a reference to the change in the manuscript.

Other Minor comments:

RC: Line 208: Any prior studies/experience/justification for this selection?

AC: 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). Here are the references 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.

RC: Next time, please put the captions beneath each figure for ease of reading. AC: We will follow this in the corrected/updated manuscript.

RC: Figure 2 – What is CWSI (plot title)? Also, the x-axis does not seem to line up properly.

AC: The CWSI plot title is a mistake – changed it to CDI. The x-axis label has also been modified to cover the entire horizontal plotting area. ÂăThe revised Figure is shown below (see fourth attachment):

RC: I see the local smoother trends indicating the variability. Did you test to see if there is any monotonic trend over the time series? From the figure it seems like recent

years may be pulling it down towards a negative trend (but perhaps not stat significant). Just curious, as this might be relevant to calculating the anomalies (e.g., line 539, the anomalies being estimated from the 1901-2013 mean).

AC: Mann-Kendall test indicates a likely monotonic decreasing trend, with a p-value of 0.013. Trend analysis typically involves carefully understanding the causes for the trend. We wish to explore these in a later work.

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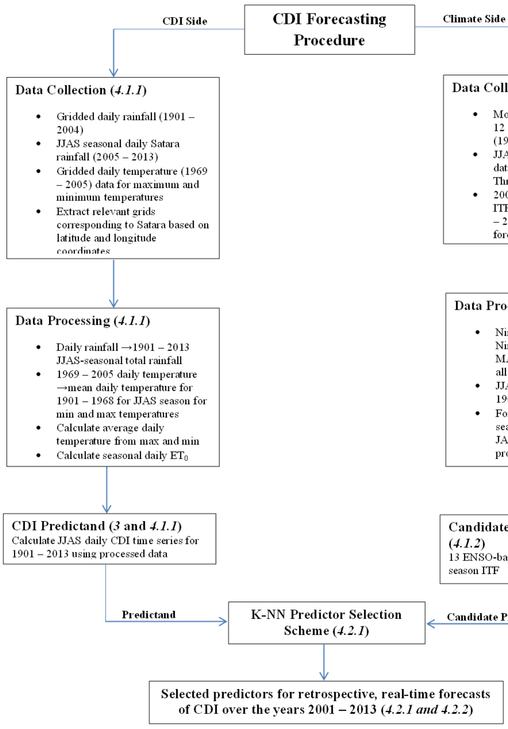
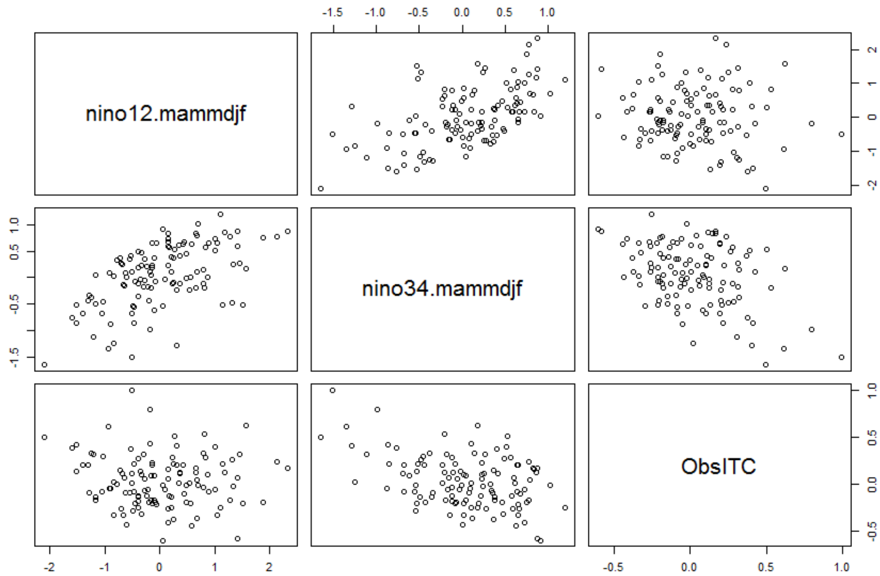


CDI Forecasting Procedure
CDI Side
Climate Side
Data Collection (4.1.1)
Gridded daily rainfall (1901 – 2004)
JJAS seasonal daily Satara rainfall (2005 – 2013)
Gridded daily temperature (1969 – 2005) data for maximum and minimum temperatures
Extract relevant grids corresponding to Satara based on latitude and longitude coordinates
Data Collection (4.1.2)
Monthly Niño 3, Niño 4, Niño 12 and Niño 34 SST index data (1901 – 2013)
JJAS eastern Indian Ocean SST data (ITF --- Indonesian Throughflow) for 1901 – 2013
2001 – 2013 model-generated ITF forecasts/estimates for 2001 – 2013 retrospective CDI forecasts
Data Processing (4.1.1)
Daily rainfall →1901 – 2013 JJAS-seasonal total rainfall
1969 – 2005 daily temperature →mean daily temperature for 1901 – 1968 for JJAS season for min and max temperatures
Calculate average daily temperature from max and min
Calculate seasonal daily ET0
Data Processing (4.1.2)
Niño 3, Niño 4, Niño 12 and Niño 34 raw →DJF, MAM and MAM-DJF seasonal averages for all four indices over 1901 – 2013
JJAS Niño 34 observations from 1901 – 2013
For 2002 – 2013: JJA Niño 34 seasonal average projections and JAS Niño 34 seasonal average projections
CDI Predictand (3 and 4.1.1)
Calculate JJAS daily CDI time series for 1901 – 2013 using processed data
Candidate Climate Predictors (4.1.2)
13 ENSO-based indices and concurrent season ITF
Predictand
Candidate Predictors
K-NN Predictor Selection Scheme (4.2.1)
Selected predictors for retrospective, real-time forecasts of CDI over the years 2001 – 2013 (4.2.1 and 4.2.2)

Fig. 1.



nino12.mammdjf
nino34.mammdjf
ObsITC

Fig. 2.

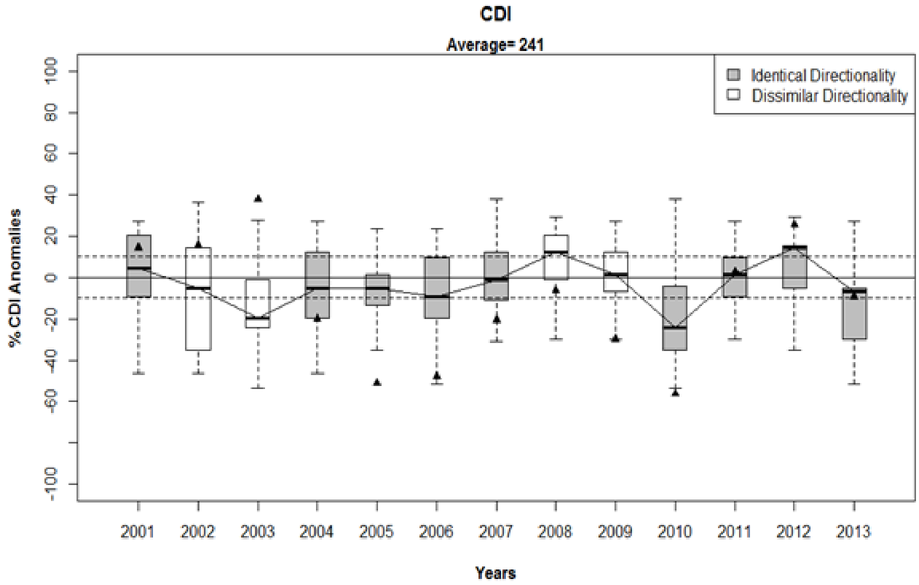

CDI
Average= 241
Identical Directionality
Dissimilar Directionality
% CDI Anomalies
100
80
60
40
20
0
-20
-40
-60
-100
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
Years

Fig. 3.

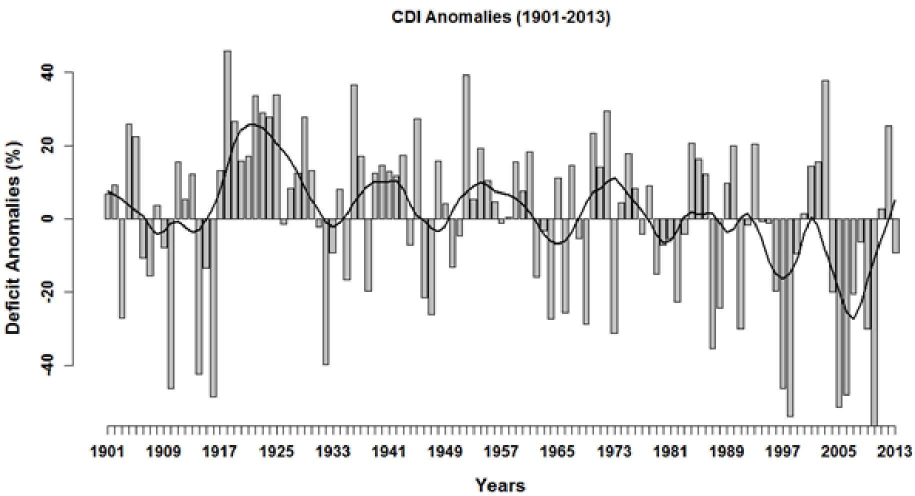

CDI Anomalies (1901-2013)
Deficit Anomalies (%)
40
20
0
-20
-40
1901
1909
1917
1925
1933
1941
1949
1957
1965
1973
1981
1989
1997
2005
2013
Years

Fig. 4.