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Interactive comment

Interactive comment on "Skill of large-scale seasonal drought impact forecasts" *by* Samuel J. Sutanto et al.

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Reply to Referees

We would like to thank the Referee 1 for the comments, recommendation, and valuable suggestions. In this document, we reply to each of the comments. (Px refers to page number x and Laa-bb refers to line numbers aa to bb in the revised manuscript).

1. General Comments: The manuscript submitted showed the efforts devoted to predict drought impacts with lead-times up to 7 months ahead, using the Logistic Regression and Random Forest machine learning approaches. The idea of relating the drought indices to the drought impacts is relatively new and relevant to the journal's scope of understanding the natural hazards and their consequences.

We would like to thank the referee for the acknowledgment of the novelty of our paper.

2. The machine learning approaches adopted are relatively old-fashioned. It would be nice if the authors can provide better justification for the selected approaches over other methods available. Besides, there are some queries on some statements made by the authors to be justified.

We do agree with the referee that the Logistic Regression (LR) and Random Forest (RF) are not new techniques, but have proven value in some studies that linked drought hazards to impacts (e.g., Blauhut et al., 2015; Stagge et al., 2015; Blauhut et al., 2016; Bachmair et al., 2016; Bachmair et al., 2017). Therefore, we decided to use the LR and RF to forecast drought impacts (previous version P2L38-46). However, those studies reconstructed historical conditions and were not used for drought impact forecasting using dynamical weather forecasts, which is the novelty of our paper. The results are promising and can be implemented in the forecast mode. Additional explanation of why we chose the LR and RF was added in the revised manuscript (P2L54-56 and P3L64-68).

3. Abstract: The authors are advised to include more results in the abstract to provide a better overview for the readers.

We would like to thank the referee for his/her suggestion. More results were added in the abstract (P1L3-15).

4. Page 1, Line 3: Kindly revise “with a lead-time of 7 months ahead” to “with lead-times up to 7 months ahead” as the study produces predictions with lead-time of 1-,2-,3-,4-,5-,6- and 7-months ahead, not only 7-month.

The text was revised (P1L3).

5. Page 2, Line 40: Kindly revise “Energy and Industry, Pubic Water Supply” to “Energy and Industry Public Water Supply”.

Unfortunately, we cannot follow up on the suggestion made by the referee to combine

Energy and Industry with Public Water Supply, because they are reported as different impacted sectors in the key paper on the European Drought Impact Inventory, EDII (see Stahl et al., 2016). We would like to keep our study consistent with this.

6.a. Page 2, Line 40 – 46: The literature reviews show that Logistic Regression (LR) and Random Forest (RF) are already well studied in different studies for deriving the link between drought hazard and their impact.

The LR and RF indeed already have been used in previous drought studies (see point 2). However, those studies tried to link the historical drought hazards using the standardized indices, such as SPI and SPEI, to drought impacts using LR and RF. Thus we decided to move one step forward by linking the forecasted drought hazards (SPI, SPEI, and SRI) using dynamical forecasts to drought impacts using the same methods with different combinations of spatial aggregations and impact categories (previous version P2L54-55).

b. May I know why are these two methods selected as the approaches in this study? As there are many other approaches available to be further investigated, such as Artificial Neural Network and etc.

As mentioned above, we selected the LR and RF methods because these were used in previous studies that connected drought hazard to impacts. The use of other methods is foreseen for future study.

c. Besides, the methods compared have different nature LR (Linear) and RF (Nonlinear). Shouldn't we test the data's linearity before adopting either of these methods? As it will be unfair to the LR (RF) if the nature of the data is nonlinear (linear)?

The referee makes a good point here. The input data for the RF and LR are not linear. The drought severity obtained from the standardized indices (i.e. SPI, SPEI, and SRI), i.e. input data, was derived from functions that were developed by fitting the gamma distribution and later were transformed to the normal distribution (previous version P4L122-125). We added text on this topic in the Discussion as to the main advantage of RF method, which can handle non-linear data better (P10L294-298).

d. Recommended recent paper: Drought forecasting: A review of modeling approaches 2007–2017. Journal of Water and Climate Change. 2019.

The suggested paper was added to the revised manuscript (P10L294).

7. Page 2, Line 58: the symbol “box 1” is confusing, kindly revise as “box i" (similar correction for the caption in Figure 1).

The word on page 2 line 58 writes as box l (BOX L) and not i. We are sorry that we created confusion about the letter. We revised the letters using capital (e.g., A, B, C, and so on) (P2L70-74, and throughout the text).

8. Page 3, Line 64: Kindly state the full-form of every abbreviation when it is first used, e.g. SRI-x.

The full form of the standardized indices was already mentioned in the previous paragraph (e.g., previous version P2L34 for SPI and P2L48 for SPEI). We provided the full-form of SRI in the revised manuscript (P2L58). We thank the reviewer for noticing this.

9. Page 5, Line 153: It is stated that the RF is able to avoid overfitting. To my best knowledge, this statement is wrong as RF does overfit although the generalization error does not increase when the tree size increases. Kindly justify how do the authors avoid overfitting in the current study? How significant is the difference if the cross-validation was adopted?

The referee is correct that the RF is not completely able to avoid overfitting. The RF produces randomly numerous independent trees as an ensemble to reduce the chance of overfitting. The text was revised (P6L170).

One possible way to counteract overfitting is by using cross-validation. In our study, we did not do the cross-validation (CV). However, we did OOB (out of bag) performance analysis for the development of our RF model, which is not exactly the same but has connections with CV. We think that the calculation of the OOB error in the model training phase is sufficient to test the performance of the model. We added a remark about cross-validation in the revised manuscript (P6L175-178).

10. Discussion: The RF showed better performance and the authors claimed that it was due to the long memory of RF compared to LR. However, the authors never mention about the linearity of the data. Could it be due to the linear/nonlinear nature of the data? Based on the results available, it seems that nonlinear models are favorable, have the authors compare the performance of RF with other nonlinear models? e.g. ANN, Deep learning, and etc.

The referee has a point about the linearity of the data. Drought indices used as input in the machine learning models are not linear (see point 6 above). We discussed the non-linearity of our data in the revised manuscript (P10L294-298). We did not compare the results with other machine learning models. However, some previous studies concluded that RF produces better performance compared to other Machine Learning approaches (e.g., Boosted regression trees, cubist, decision trees, Hurdle, and logistic regression; Park et al., 2016; Rhee and Im, 2017; Bachmair et al., 2017) (previous version P9L264-266).

11. Supporting information, Figure S2: The y-label of the histogram for Log Regression is wrong, kindly revise. Besides, may I know how do the authors summarize the predictor importance of few counties into one histogram?

We thank the referee for his/her careful reading of our manuscript. The figure was revised accordingly. We plotted the histograms based on the average of the predictor of importance for each county. An explanation was added to the revised Supplementary Material.

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