Interactive comment on “Identifying ENSO Influences on Rainfall with Classification Models: Implications for Water Resource Management of Sri Lanka” by Thushara De Silva M. and George Hornberger

Thushara De Silva M. and George Hornberger
thushara.k.de.silva@vanderbilt.edu

Received and published: 18 July 2018

Thank you for very valuable comments. Clarification for discussion points are given below.

1. How to justify the selection of range of precipitation when grouping the rainfall into three classes? Grouping of rainfall into three classes is based on our assumptions of water resources management. We assumed water managers would consider rainfall between -0.5xStandard Deviation (SD) and 0.5xSD as average rain and other two ends
as dry and wet. Selection of three rainfall classes are not motivated by statistical considerations. 2. When you choose the predictors, what is the rationality in choosing the Multivariate ENSO Index (MEI) and the Indian Ocean Dipole (IOD)? As you illustrate later, the prediction performance of the trained algorithm is not very good. May I interpret the poor performance is caused by the selection of non-informative predictors? If yes, should you consider using more informative indicators as the input of the model instead of MEI and IOD? There are several climate indices representing El-Nino-Southern Oscillation (ENSO), Indian Ocean Dipole (IOD), Pacific decadal oscillation (PDO) and Atlantic multi-decadal mode oscillation (AMO). We explore teleconnections using several climate indices representing ENSO phenomena such as MEI, NINO 4, NINO 3.4 and NINO3, and found out that MEI is a suitable index. Exploring several indices and literature survey, we selected MEI and DMI to represent ENSO and IOD for climate teleconnection of rainfall of Sri Lanka. 3. Is there any possibility to give the confidence level when making the prediction? You should also demonstrate the correlation between IOD, EMI and the quantity of interest. Correlation between IOD, DMI and seasonal rainfall demonstrate that negative correlation for three rainfall seasons (NEM, FIM and SIM) and positive correlation for SIM. Rainfall classification models identified with QDA, Classification tree and random forest also agree with this. Accuracy level of the models are shown in the Table 2, Table 3, Table 4, Table A.2-6.

4. With the prediction from the trained model, how will it facilitate the decision making in the water infrastructure management? Considering the prediction performance of the trained model, what is the risk the decision maker must carry on when making the decision? Is there any possible means to reduce the risk involved in decision making? In our study, Mahaweli and Kelani river basin main water users are potable water, hydropower and agricultural systems. Water managers' decisions are informed for the water allocation for these two sectors. For example, if drought is forecasted, hydropower production can be reduced to store the water for potable water and agriculture to reduce the damages during drought. During that period, it is possible to do the maintenance of Hydropower plant machineries. Farmers can select less water inten-
sive crops instead of high water intensive crops. Water managers are informed about the accuracy level of models, hence flexibility of emergency plans are available as the usual practice. Quantification of the risk decision maker must carry is not our scope of the study. However, updates of short term weather forecasts and emergency plans will be reduced the risk. Presently, no seasonal ahead forecast about the extremely low rainfalls is available, and this study assists to water managers for preparation of climate variability. 5. It will be better if you can highlight the contributions you have made in this paper with several bullets. This will help readers to quickly grasp the highlights in your paper. Thank you, we will consider the possibility with the manuscript format of journal.