Reviewer comments are shown in blue color fonts, and authors' responses are given black color fonts.

This paper examines the use of climate indices to predict a high or low rainfall period. Classification tools are used for this. The results that are obtained are not very impressive, but the authors argue that, for the local farmers and water managers, this will still be of value, which is a fair point. So while the scientific interest of this paper is limited, it has some clear practical value. The paper in its current form suffers from: (i) an insufficiently detailed presentation of the methodology which would not enable a reader, even in principle, to understand how the methods work unless the reader had prior knowledge of them; (ii) a strange organisation of the material so that the presentation of the study area is given under a 'methods' section for instance. This may be because the authors seem to be wedded to organising the paper according to some standard headings: methods, results, discussion, etc. But this is not always helpful and here, as with the obligatory conclusion section which is just a repetition of material just above that section, I would urge the authors to feel free to adapt the structure to their needs.

Response: The objective of this study is to explore the climate teleconnection to dual monsoon and inter monsoon and provide information for water resources managers and water users (farmers and hydropower producers) decisions considering forecasted climate indices. Specifically for our case study of Sri Lanka, presently there is no seasonal precipitation forecast and this information will be informed water resources planning and water users' climate adaptation decisions.

Shortcomings of the paper identified by the reviewers will be rectified as suggested, for the next submission. Response for the detail comments are given below.

Detailed Comments:

1. something missing in this sentence, perhaps 'to' before 'climate variability' (without 'the') (page 1, line 21)

Response: This sentence will be corrected as below:
"Results from these models are not very accurate; however, the patterns recognized are useful input to the water resources management and to the adaptation climate variability of agriculture and energy sectors."

2. It is not clear here whether you are making a methodological point here. It seems that you are identifying two reasons for your methodological approach: (i) the weakness of the linear regression approach when the scatter is large and (ii) the nature of the forecasts available to water managers, which may just be of some broad category of rainfall rather than actual quantities. Based upon these two reasons, you are advocating a method based upon classification models. If that is the case, please spell this out as these are key issues for understanding your chosen approach. (page 2, line 56-61)

Response: Seasonal precipitation is generally forecasted in broad categories. For example, the US National Weather Service forecasts seasonal precipitation as above normal, below normal, and normal (National Oceanic and Atmospheric Administration, 2018). The International Research Institute for Climate and Society also forecasts seasonal precipitation as above, below and near normal (International Research Institute for Climate Society, 2018). We chose to follow a similar approach and present seasonal precipitation prediction in three classes based on ENSO and IOD.

3. Secontion 2 until the middle of page 5 (the start of subsection 2.3) is not about methods. Please choose a more appropriate title for the section, such as 'Hydrometeorology and climatology of the study area'. Subsection 2.3 can then become a section 3 entitled 'Methods'. (page 2-5)

Response: We will reorganize the structure of the paper as suggested, in the final submission.

4. I am not sure why you mention a minimum and a maximum in the table. Given that we have no idea what these might be, I suggest taking out any reference to them (so the first class is just defined for standardised anomalies below -0.5C, and similarly for the third class with standardised anomalies large then 0.5C) (page 5, line 117-118)

Response: The Table was revised as given below. Originally, the terms maximum and minimum referred to the largest observed positive anomaly value and largest negative anomaly value respectively but the reviewer points out that these terms are misleading so they were dropped.

Table 1

Class	Range
below	$X_{S\_ANM} < -0.5$
normal	-0.5 <= X_{S_ANM}<0.5
above	0.5 <= X_{S_ANM}

5. Capital letters are required here: 'Atmospheric' and 'Administration' as well as a comma after the latter word. (page 5, line 122)

Response: Word will be corrected as "National Oceanic and Atmospheric Administration".

6. To make this presentation of the QDA clearer to someone who has, for instance, some idea of Bayesian statistics, but does not know this method, I suggest adding the quadratic discriminant function is therefore proportional to the logarithm of the a posteriori density function of class k conditional upon the value of the observed predictor x: this logarithm is the product of the prior probability of x and the density. (page 6, line 138-145)

Response: A brief outline of the Quadtratic Districriminant Analysis method is given below. We can include this information in the methods part of the paper or possibly in an Appendix to the paper. More information about the methods can be obtained from the references as indicated in the paper.

"The mathematical formulation of QDA can be derived from Bayes theorem assuming that observations from each class are drawn from a Gaussian distribution ((James, Witten, Hastie, & Tibshirani, 2013; Löwe, Madsen, & McSharry, 2016).

The prior probability π_k represents the randomly chosen observation coming from kth class with density function$f_k(x)$. Bayes theorem states that

$$Pr(Y = k|X = x) = -\frac{\pi_k f_k(x)}{\sum_{l=1}^{K} \pi_l f_l(x)} \qquad \text{Eq.(1)}$$

In Eq (1), the posterior probability $Pr(Y = k|X = x)$ indicates that observation $X = x$ belongs to the kth class. For p predictors, the multivariate Gaussian distribution density function is defined for every class k (Eq.(2)).

$$f_k(x) = -\frac{1}{(2\pi)^{p/2}|\sum_k|^{1/2}} \, exp\left(-\frac{1}{2}(x - \mu_k)^T \textstyle\sum_k^{-1}(x - \mu_k\,)\right) \qquad \text{Eq.(2)}$$

In Eq.(2), $\sum_k$ is the covariance matrix and μ_x is the mean vector. The covariance matrix ($\sum_k$) and mean (μ_x) for each class are estimated from the training data set (Eq.(3), Eq.(4)).

$$\mu_k = -\frac{1}{N_k} \sum_{i:y_i=k} x_i \qquad \text{Eq.(3)}$$

$$\textstyle\sum_k = -\frac{1}{(N_k - 1)} \displaystyle\sum_{i:y_i=k} (x_i - \mu_k)^T (x_i - \mu_k) \qquad \text{Eq.(4)}$$

Substituting a Gaussian density function for the kth class (Eq.(2) into Bayes theorem and taking the log values, the quadratic discriminant function is derived (Eq.(5)). Prior probabilities for class k (π_k) is calculated by the frequency of data points of class k in the training data (Eq.(6)). For a total number of N points in the training observations, N_k is the number of observations belong to kth class.

$$\delta_k(x) = -\frac{1}{2}\,(x - \mu_x)^T \textstyle\sum_k^{-1}(x - \mu_x\,) \, + log\,\pi_k \qquad \text{Eq.(5)}$$

$$\pi_k = -\frac{N_k}{N} \qquad \text{Eq.(6)}$$

Covariance, mean and prior probability values are inserted into the discriminant function ($\delta_k(x)$) together with the state variables (Eq.(5)). The corresponding class is selected according to the largest value of the function. The number of parameters to be estimated for the QDA model for k classes and p predictors is $k.p.(p + 1) \,/\, 2$. For this study, the QDA model output is the probability that an observation of a climate category will fall into each of the rainfall classes."

References:

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