Reviewer #2

Review of "Regionally optimized fire parameterizations using feed-forward neural networks" by Ham et al.

General comments: In this paper, the authors argue that a deep learning technique, namely feed-forward neural networks (FFNN) has a high skill in predicting the fire radiative power (FRP) in comparison to the traditional fire weather index (FWI) and a linear regression model. The FFNN model is trained with the meteorological variables of 2-m relative humidity (RH2m), precipitation, 2-m temperature, and windspeed). The authors propose that the FFNN-based technique can be a better fire parameterization for the weather models. Overall, this is an interesting manuscript. However, I have some concerns that the authors must address before accepting the manuscript. My concerns are listed below.

Specific comments:

1. The manuscript seems to be written as a letter, with only four figures in the main manuscript. I don't think that ESD has a restriction on the number of figures in the main manuscript. So, consider moving some of the supplementary information to the main manuscript. The model architecture needs to be shown in the main manuscript.

: Thank you very much for the suggestion. We agree to the reviewer's comment that some of figures are worthwhile to be moved to main manuscript. We moved 3 Supplementary Figures (model architecture, time-series analysis, LRP result) to the main texts.

2. The training and validation functions are not shown. It is important to show the training and validation curves to see if the model does overfit/underfit. Overall, the methods need more clarity.

: Thank you for pointing this out. We agree with the reviewer's comment that the decrease in both the training and validation loss should be demonstrated that the FFNNs is properly setup. Figure B-1 shows the training and validation loss with respect to the epoch in three specific locations. Total numer of epochs for the traininng is set to 1,000, and early stopping is applied (Raskutti et al., 2014), once the validation loss is not decreased for 100 epoches. It is clearly demonstrated that both the training and validation loss is gradually decreased with the increased epoch; indicating that the FFNNs are successfully formulated. We added Figure B-1, and the related texts as Supplementary Fig. 1 and Line 159-163 of the revised manuscript.

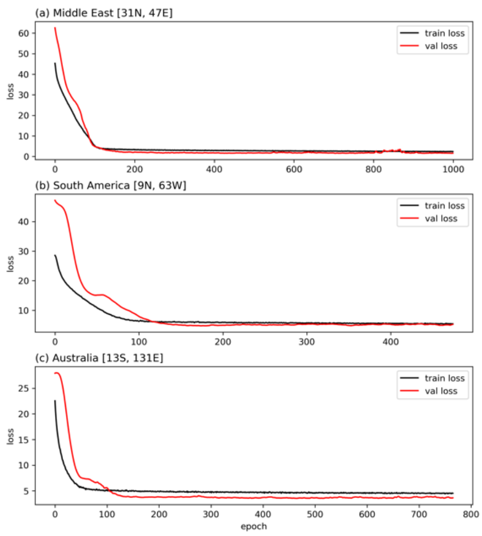

Figure B-1. Training (black) and validation loss (red) with respect to the epoch at the grid point in (a) the middle East (centered at 31°N, 47°E), (b) South America (centered at 9°N, 63°W), and (c) Australia (centered at 13°S, 131°E).

3.The authors compare FFNN with a linear regression model. Why not compare it against an existing parameterization scheme?

: We fully understand the reviewer's question. Actually, we already well followed reviewer's comment as the FWI is one of widely-used parameterizations worldwide, and, our FFNNs is compared to the FWI-based forecasts. Applying the linear regression to the FWI value is just to match the variability between FWI index and the FRP. In other words, we compared the parameterization quality seeking the nonlinearity between the meteorological variable and the FRP in the widely-used meteorology-based fire intensity estimation algorithm (i.e., FWI algorithm) to that seeking the nonlinearity using the neural network weights and the nonlinear activations.

To avoid the confusion by using the terminology of the 'linear regression', we modified the term 'FWI-based linear regression model' to 'FWI-based model' throughout the revised manuscript, and the brief description about the FWI-based model is also modified in the revised manuscript as follows.

Line 128-134 : "A FRP-estimation model based on the FWI was established as a baseline. The FWI is obtained from the daily averages of T2m, RH2m, WS10m, and PRCP, and .... To match the systematic amplitude differences between the FWI and FRP using the different units, a linear regression coefficient of the FRP with respect to the FWI, which was separately calculated for each grid point, is multiplied to produce the FWI-based model."

4. I find the following paper relevant for this study. Zhang et al. (2021) https://doi.org/10.1016/j.ecolind.2021.107735.

: Thank you for the related reference. It has common research interest with ours, but after reading it carefully, we found there are several different points between theirs and ours. 1) their model is to classify the occurrence of the fire, therefore, their model output is simply either 0 (non-fire) or 1 (fire). 2) they did not compare their results with currently used parameterization scheme. 3) they did not provide physical explanations for the improvement in their model. We noted this point with the reference in Line 79-88 of the revised manuscript as follows.

Line 79-88 : "Recently, artificial neutral networks (ANN) have received extensive attention and continue to expand to various application fields. The traditional ANN model with shallow neural networks such as multilayer perceptrons, and convolutional neural networks has been applied to predict the fire probability over the regional domain (Satir et al., 2016), or parameterize the fire occurrence (Zhang et al., 2021) from the meteorological variables. Despite previous literature demonstrating promising accuracy in estimating or predicting fire characteristics, the development of globally applicable ANN-based parameterization is still in its early stages. This is primarily due to the regional idiosyncrasies in the relationships between meteorological variables and fire activity, posing challenges for establishing global implementation."

References

Raskutti, G., Wainwright, M. J., & Yu, B. (2014). Early stopping and non-parametric regression: an optimal data-dependent stopping rule. *The Journal of Machine Learning Research*, *15*(1), 335-366.