COMMENTS FOR THE AUTHOR:

Response to Reviewer 1

We would like to thank the reviewer for his/her helpful comments. Thank you. All of your comments have been taken into consideration, and the paper was modified accordingly. Please find below our responses.

Comment 1: Section 2.5:

- It would be beneficial to provide a detailed explanation of the Neural Network parameters and the architecture of the NN-SARIMAX model to help readers easily and clearly understand the structure of the neural network.

Answer: A detailed description of the neural network architecture and its associated parameters was added to Section 2.4.1. This description clarifies the structure of the neural network employed within the NLPCA framework, including its role in processing CHIRPS precipitation data and its integration into the SARIMAX modeling approach as an exogenous variable, thereby enhancing model transparency and reproducibility.

Comment 2: Section 3.2.1

- It is stated that two non-linear principal components (explaining 92.5% and 7.4% of the variance, respectively) were selected out of a total of 81 components, collectively explaining 99.9% of the variance. However, this approach may lead to overfitting, as it effectively considers nearly the entire variation unless the model is validated through cross-validation or other model selection criteria (e.g., AIC, BIC, etc.) to determine the optimal number of components. Therefore, it should be clearly explained how potential overfitting was assessed and mitigated.

Answer: Potential overfitting associated with the selection of NLPCs was explicitly assessed and mitigated by implementing a data-splitting strategy within the NLPCA framework. The dataset was divided into independent training, validation, and testing subsets.

- It is also unclear why only the first two principal components account for 99.9% of the variance, while the remaining 79 components contribute only 0.1%. This large discrepancy warrants further clarification.

Answer: The apparent concentration of variance in the first two nonlinear principal components arises from the use of a nonlinear PCA (NLPCA) approach implemented through an autoencoder-based neural network. Unlike linear PCA, NLPCA does not decompose variance through orthogonal eigenvectors but instead learns a low-dimensional nonlinear manifold that captures the dominant structure of the data.

Although the input consists of 81 CHIRPS grid cells, these variables exhibit strong spatial coherence. As a result, the majority of the precipitation variability can be effectively represented by two latent nonlinear components (NLPC1 and NLPC2), which together explain 100% of the reconstructed variance, while the remaining components account for negligible residual variability.

Comment 3: Section 2.4.3:

- The approach used to address multicollinearity is generally sound and viable. However, there is no clear evidence indicating that the multicollinearity issue has been fully resolved, such as through recalculating the Variance Inflation Factor (VIF) after the iterative removal of collinear and less important predictors. Many of the retained variables still exhibit extremely high VIF values (e.g., NINO4 = 29,126; NINO12 = 2,492; NP = 17,705; TNA = ∞; and TSA = ∞). It remains unclear whether multicollinearity persists among these nine predictors or not.

Answer: The assessment of multicollinearity was strengthened by applying a more stringent variable-selection procedure. Following the iterative removal of collinear and less influential predictors, the VIF was recalculated for the final set of retained meteorological variables. This additional step confirmed that multicollinearity was effectively reduced. See in the section 3.2.3.

We thank the reviewer for the thorough evaluation, constructive comments, and helpful recommendations. We have carefully addressed all observations and hope that the revisions adequately strengthen the manuscript. We would be pleased to have the opportunity for the revised version to be re-evaluated.