Reviewer #1:

General comment:

This paper is concerned with constructing GNSS RO-based climatologies by machine learning (ML) method, and proposes three kinds of approaches: Bayesian Interpolation (BI), a feed-forward neural network (Multilayer Perceptrons, MLPs), and the combination of BI and ML (BI &ML) where the ML is applied to BI residuals. Applications of these methods to real and simulated COSMIC-2 RO data indicate that, the maps of refractivity produced by the MLPs better match the true maps than those by BI, and BI & ML yields the best GNSS RO refractivity maps. The methods are novel and the results exhibit the potential for producing GNSS RO climatologies.

Dear reviewer, thank you very much for taking the time to review our work, we appreciate your input. Below, you can find our answers to all your comments.

specific comments:

“BI & ML” is about learning on residuals, which is a key strategy suggested by the authors. I think it is better to provide some reviews for learning on residuals in the introduction.

We cite the following papers that focus on learning on residuals:

[1] Wang, JX., Wu, JL., Xiao, H. "Physics-informed machine learning approach for reconstructing Reynolds stress modeling discrepancies based on DNS data" Phys Rev Fluids, 2 (3) (2017), Article 034603

[2] Gou, J.; Rösch, C.; Shehaj, E.; Chen, K.; Kiani Shahvandi, M.; Soja, B.; Rothacher, M. "Modeling the Differences between Ultra-Rapid and Final Orbit Products of GPS Satellites Using Machine-Learning Approaches." *Remote Sens.* **2023**, *15*, 5585. https://doi.org/10.3390/rs15235585

[3] Kiani Shahvandi, M., Dill, R., Dobslaw, H., Kehm, A., Bloßfeld, M., Schartner, M., et al. (2023). "Geophysically informed machine learning for improving rapid estimation and short-term prediction of Earth orientation parameters." Journal of Geophysical Research: Solid Earth, 128, e2023JB026720. https://doi.org/10.1029/2023JB026720.

In the paper, at the end of the introduction, we add the following paragraph: 'Several studies have also applied ML to model residuals of observations, computed as a difference between a model not based on ML and target observations. The most typical cases originate from using physical models for prediction and training an ML model to predict the residual part. For example, (Wang, et al. 2017) showed that ML could be used to model the difference between a superior model which is computationally expensive and a simple model, to predict the component of the total stress tensor in a fluid. Similarly, (Gou, et al. 2023) applied several ML and deep learning (DL) algorithms to model the differences between GNSS final orbit products and ultra-rapid orbit products. Therefore, their ML model could help overcome the limitations of simplified physics-based orbit propagators by training on residuals. (Kiani Shahvandi, et al. 2023) used a method based on NNs named ResLearner to calibrate the rapid Earth Orientation Parameters (EOPs) with respect to the final EOPs in a residual manner. In this work, we also propose a loosely coupled combination of ML and BI, in which we first apply BI to the observations, and then we train the ML model on the BI residuals. '

technical corrections :

For the convenience of readers, Figure 3, Figure 4, Table 1 and Table 2 had better be indicated for COSMIC -2 RO data.

Thank you for pointing this out. This will be properly indicated in the final version of the manuscript.