Thank you to the authors for thoroughly addressing the comments. However, further emphasis on the study's contribution to the community would strengthen the manuscript.

1. The authors acknowledge the comment regarding the ultimate goal of developing an ML parameterization trained from superparameterization or cloud-resolved models. An ML parameterization offers two potential advantages: first, it can help reduce uncertainty. Second, it can reduce the computational cost compared to running superparameterization or high-resolution models directly. However, this study presents an ML model as a surrogate for an existing microphysics scheme rather than training it on high-fidelity data, which cannot reduce uncertainty. In order to highlight the contribution, the authors could present the computational efficiency. To better evaluate the ability to reduce costs, the authors could estimate the computational requirements of superparameterization or high-resolution runs to directly compare against the ML model performance. This would strengthen the case for ML as a lower-cost alternative to traditional parameterization approaches.

2. This study presents a novel multi-task ML approach for both trigger function classification and tendency regression. This multi-faceted application of ML could be emphasized as another key contribution of the work. Previous studies have applied ML either to trigger function classification alone (Zhang et al., 2021) or tendencies regression independently (Brenowitz & Bretherton, 2019; Rasp et al., 2018; Wang et al., 2022). As the authors point out that "models based only on regression can yield inconsistent tendencies, resulting in conflicting indications for convection triggering at specific grid points. In contrast, models that rely exclusively on classification are also deficient, as they do not generate the necessary tendencies for the CP scheme". To further validate this assertion, ablation experiments removing each individual task (i.e. classification-only vs regression-only models) could demonstrate the benefits of the proposed multi-task framework. Such an analysis would help substantiate the value of the multi-faceted ML approach over single-task baselines, strengthening the novel aspects highlighted in this work.

Ref:

Brenowitz, N. D., & Bretherton, C. S. (2019). Spatially extended tests of a neural network parametrization trained by coarse-graining. Journal of Advances in Modeling Earth Systems, 11(8), 2728–2744. https://doi.org/10.1029/2019ms001711

Rasp, S., Pritchard, M. S., & Gentine, P. (2018). Deep learning to represent subgrid processes in climate models. Proceedings of the National Academy of Sciences, 115(39), 9684–9689. https://doi.org/10.1073/pnas.1810286115

Wang, X., Han, Y., Xue, W., Yang, G., & Zhang, G. J. (2022). Stable climate simulations using a realistic general circulation model with neural network parameterizations for atmospheric moist physics and radiation processes. Geoscientific Model Development, 15(9), 3923–3940. https://doi.org/10.5194/gmd-15-3923-2022

Zhang, T., Lin, W., Vogelmann, A. M., Zhang, M., Xie, S., Qin, Y., & Golaz, J.-C. (2021). Improving Convection Trigger Functions in Deep Convective Parameterization Schemes Using Machine Learning. Journal of Advances in Modeling Earth Systems, 13(5), e2020MS002365. https://doi.org/10.1029/2020MS002365