EGU General Assembly 2024

EGU24-17446, updated on 13 Jun 2024
https://doi.org/10.5194/egusphere-egu24-17446
EGU General Assembly 2024

Aggregations of parametrizations and machine learning for gravity wave momentum flux reconstruction

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In this talk, we pursue the investigation of the relation between the large-scale flows and observed gravity wave momentum fluxes (GWMFs), starting from parameterizations and machine learning as two alternatives for predicting the gravity wave momentum fluxes in the lowermost tropical stratosphere. We investigate how much aggregation methods may allow to further improve on both alternatives, and what complementarity there may be between them. Observed gravity wave momentum fluxes are obtained from superpressure balloons during the Strateole 2 mission. The parameterizations come from the different climate models involved in the QBOi project, that have been compared to balloon measurements in Lott et al. (2023). The other predicted features are three tree-based ensemble machine learning algorithms, trained on part of the Strateole 2 dataset. Three groups of aggregations are performed: aggregation among machine learning models, aggregation among parametrizations, and the aggregation between parametrizations and machine learning models. For the methodology, three aggregation methods are employed; two methods treat predictions from different models (parametrizations or machine learning) as features or information to be aggregated, while the remaining one uses both, inputs and predictions provided by those models.

The outcomes indicate that, despite struggling to estimate GWMFs individually, the collective information from various parametrizations proves valuable, particularly when combined with the large-scale flow variables. Additionally, the performance of the aggregation methods is sensitive to the choice of balloons. When the description of large-scale flows aligns well with the target GWMFs (balloon 2 and 8), all aggregation methods perform just as well as machine learning or the best-case scenario of parametrizations. Interestingly, there are also a few cases where machine learning and parametrizations perform poorly (correlation less than 0.2), yet their predictions, combined with large-scale information, can significantly elevate their performances more than 2 times (correlation larger than 0.5) in the aggregation methods (balloon 5). This suggests that existing parameterizations and machine learning approaches trained on observations have a complementarity that remains to be exploited. The present study was entirely offline, with no issue about the costs of computation. For practical applications, further investigation will be required to narrow down on the specific elements of parameterizations that are most informative.