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Exploring cirrus cloud microphysical properties using explainable machine learning

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Cirrus cloud microphysics and their interactions with aerosols remain one of the largest uncertainties in global climate models and climate change projections. The uncertainty originates from the high spatio-temporal variability and their non-linear dependence on meteorological drivers like temperature, updraft velocities, and aerosol environment. We combine ten years of CALIPSO/CloudSat satellite observations of cirrus clouds with ERA5 and MERRA-2 reanalysis data of meteorological and aerosol variables to create a spatial data cube. Lagrangian back trajectories are calculated for each cirrus cloud observation to add a temporal dimension to the data cube. We then train a gradient boosted tree machine learning (ML) model to predict vertically resolved cirrus cloud microphysical properties (i.e. observed ice crystal number concentration and ice water content). The explainable machine learning method of SHAP values is applied to assess the impact of individual cirrus drivers as well as combinations of drivers on cirrus cloud microphysical properties in varying meteorological conditions. In addition, we analyze how the impact of the drivers differs regionally, vertically, and temporally.

We find that the tree-based ML model is able to create a good mapping between cirrus drivers and microphysical properties (R^2 ~0.75) and the SHAP value analysis provides detailed insights in how different drivers impact the prediction of the microphysical cirrus cloud properties. These findings can be used to improve global climate model parameterizations of cirrus cloud formation in future works. Our approach is a good example for exploring unsolved scientific questions using explainable machine learning and feeding back insights to the domain science.