A machine learning approach for faster and more accurate precipitation retrievals

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A novel method for the estimation of surface precipitation using passive observations from the GPM constellation is proposed. The method, which makes use of quantile regression neural networks (QRNNs), is shown to provide a more accurate representation of retrieval uncertainties, high processing speed and simplifies the integration of ancillary data into the retrieval. With that, it overcomes limitations of traditionally used methods, such as Monte Carlo integration as well as standard usage of machine learning.

The bulk of precipitation estimates provided by the Global Precipitation Measurement mission (GPM) is based on passive microwave observations. These data are produced by the GPROF algorithm, which applies a Bayesian approach denoted as Monte Carlo integration (MCI). In this work, we investigate the potential of using QRNNs as an alternative to MCI by assessing the performance of both methods using identical input databases.

The methods agree well regarding point estimates, but QRNN provides better estimates of the retrieval uncertainty at the same time as reducing processing times by an order of magnitude. As QRNN gives more precise uncertainty estimates than MCI, it gives an improved basis for further processing of the data, such as identification of extreme precipitation and areal integration.

Results so far indicate that a single network can handle all data from a sensor, which is in contrast to MCI where observations over oceans and different land types have to be treated separately. Moreover, the flexibility of the machine-learning approach opens up opportunities for further improvements of the retrieval: ancillary information can be easily incorporated and QRNN can be applied on multiple footprints, to make better use of spatial information. The effects of these improvements are investigated on independent validation data from ground-based precipitation radars.

QRNN is here shown to be a highly interesting alternative for GPROF, but being a general approach it should be of equally high interest for other precipitation and clouds retrievals.

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