Enhancing MiRS ATMS Precipitation Estimates using Machine Learning

Shuyan Liu[1], Yong-Keun Lee[1], Wei Wang[1], John X. Yang[1], Xingming Liang[1], Huan Meng[2]

[1]Cooperative Institute for Satellite Earth System Studies, Earth System Science Interdisciplinary Center, 5825 University Research Court, College Park, MD 20740, USA

[2]National Oceanic and Atmospheric Administration, National Environmental Satellite Data Information Service, Center for Satellite Applications and Research, 5830 University Research Court, College Park, MD 20740, USA

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Abstract

This study integrates machine learning (ML) techniques into the Microwave Integrated Retrieval System (MiRS) to enhance precipitation estimates derived from the Advanced Technology Microwave Sounder (ATMS). ATMS observes microwave radiation across 22 channels, enabling penetration through clouds and retrieval of key atmospheric variables such as temperature and hydrometeor profiles. ATMS is currently onboard the Suomi National Polar-orbiting Partnership (SNPP), NOAA-20, and NOAA-21 satellites.

MiRS is a physics-based retrieval algorithm that produces vertically resolved profiles of temperature, water vapor, cloud liquid water, rain water, and graupel water. In this work, a convolutional U-Net architecture is applied using MiRS-retrieved hydrometeor variables as input features to predict surface precipitation rate. The model is trained using hourly precipitation estimates from the operational Multi-Radar/Multi-Sensor (MRMS) system over the contiguous United States (CONUS).

Results demonstrate substantial improvements in precipitation retrieval performance relative to baseline MiRS estimates. When compared with a fully connected Multi-Layer Perceptron (MLP), the U-Net consistently outperforms the MLP across all evaluated metrics. The MLP, which relies solely on local input features, tends to overcorrect MiRS precipitation overestimates, resulting in a net underestimation and limited overall improvement. In contrast, the U-Net effectively leverages spatial context to correct regional biases, reducing overestimation in the central United States while mitigating dry biases in the Southeast.

The best-performing U-Net model increased the spatial correlation coefficient of accumulated precipitation from 0.75 to 0.89 and reduced the absolute mean bias percentage from 11.95% to 6.33% for 2022. These results highlight the importance of model architecture and input feature selection in capturing meaningful physical and statistical relationships, particularly spatial and regional dependencies, for improving microwave-based precipitation retrievals.