Detection of Precipitation Type from Satellite PMW Measurements

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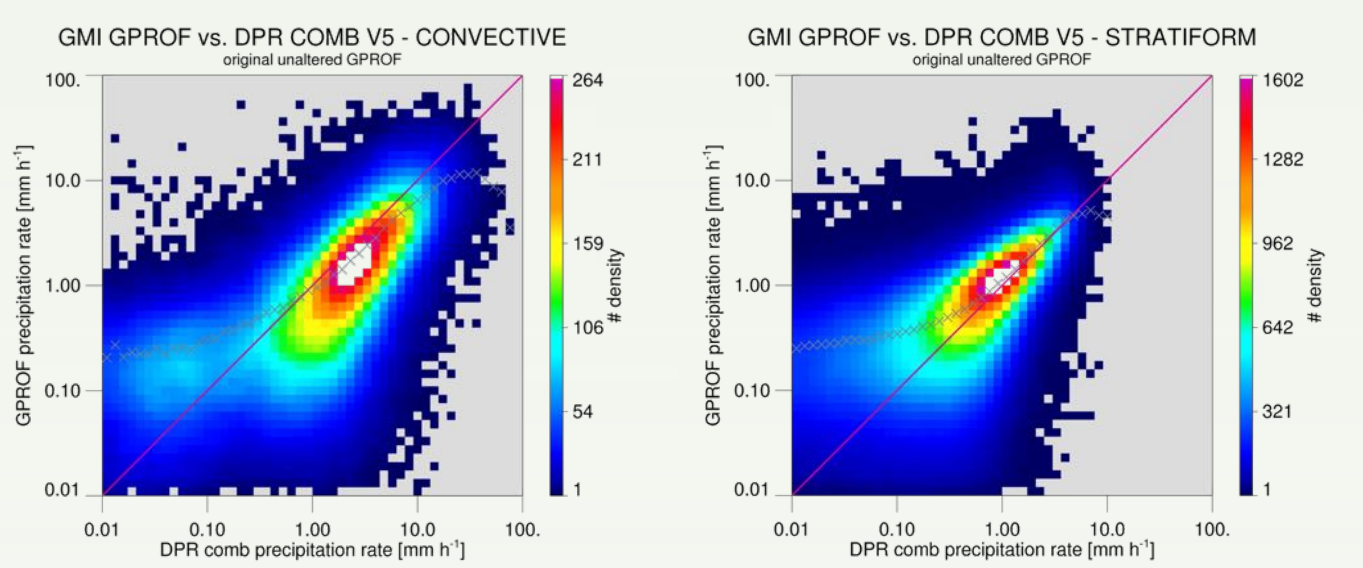
Objectives

A longlisting effort to retrieve precipitation rates form PMW observations resulted in high overall accuracy of GPM precipitation products. However, their consistency across a variety of atmospheric conditions and precipitating regimes is still far from an ideal. The cause is seen in inability of the PMW retrieval to delineate between distinct vertical profiles of precipitable water due to a column-integrated nature of its observation vector. This problem poses a major obstacle in latent heat retrievals while affecting the accuracy of both the overall (Figure 1) and regional precipitation estimates.

The presented study explores a potential that recent advances in computational resources have in retrieving convective fraction of precipitating systems using PMW measurements only.

Passive Microwave (GPROF) Precipitation type bias



Bias: -29 % Correlation: 0.63

Bias: 25 % Correlation: 0.67

Figure 1. GPROF GMI to DPR-combined Level-2 comparison. One year of conditional precipitation rate averaged over GMI FOV and separated into convective (right) and stratiform (left) regime using DPR-combined precipitation type flag.

Methodology and Data

Problem of classifying convective vs. stratiform precipitation is posed as the supervised learning problem given the availability of the data and the ability to prepare and label dataset for the training of the classification algorithm. Specifically, deep learning methods are used to enable the classification from raw satellite channels. In this application of deep learning we use a feedforward neural network (Figure 2) with fully connected architecture [1]. Neural network was developed using TensorFlow API, an open source software library for Machine Learning Intelligence [2].

One year of GPM observations is used to train Deep Neural Network (DNN) model to retrieve two classes of DPR combined precipitation type (convective and stratiform) based on GMI 13-channel brightness temperature (Tb) vector.

Once available precipitation type flags are used to rebuild and subset an a priori database for GMI instrument in GPROF retrieval. An independent 12-month period is used to test the performance of the new, precipitation-type-enhanced, GPROF algorithm.

GPM products:
- GMI brightness temperatures (GPM_BASEGPMGMI_XCAL - V05) – training dataset
- DPR combined precipitation type (training dataset) and precipitation rates (GPM_2BCMB)
- GPROF GMI precipitation (application): PPS GPROF V5 (GPM_2AGPROFGPMGMI)

MRMS data:
- Quantitative precipitation estimates
- Precipitation type

Machine Learning approach and DNN model

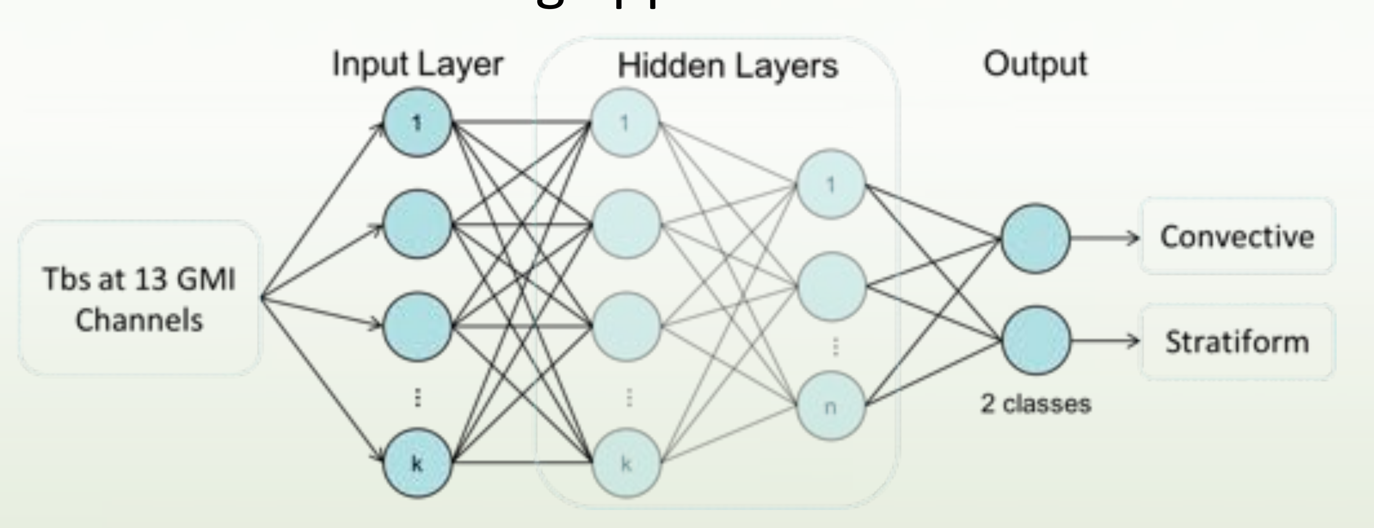


Figure 2. The architecture of neural network uses Tb fields observed at 13 GMI channels to provide input features. This is fed into fully connected hidden layers. The two precipitation classes are given by two output neurons.

Retrieving Precipitation Type

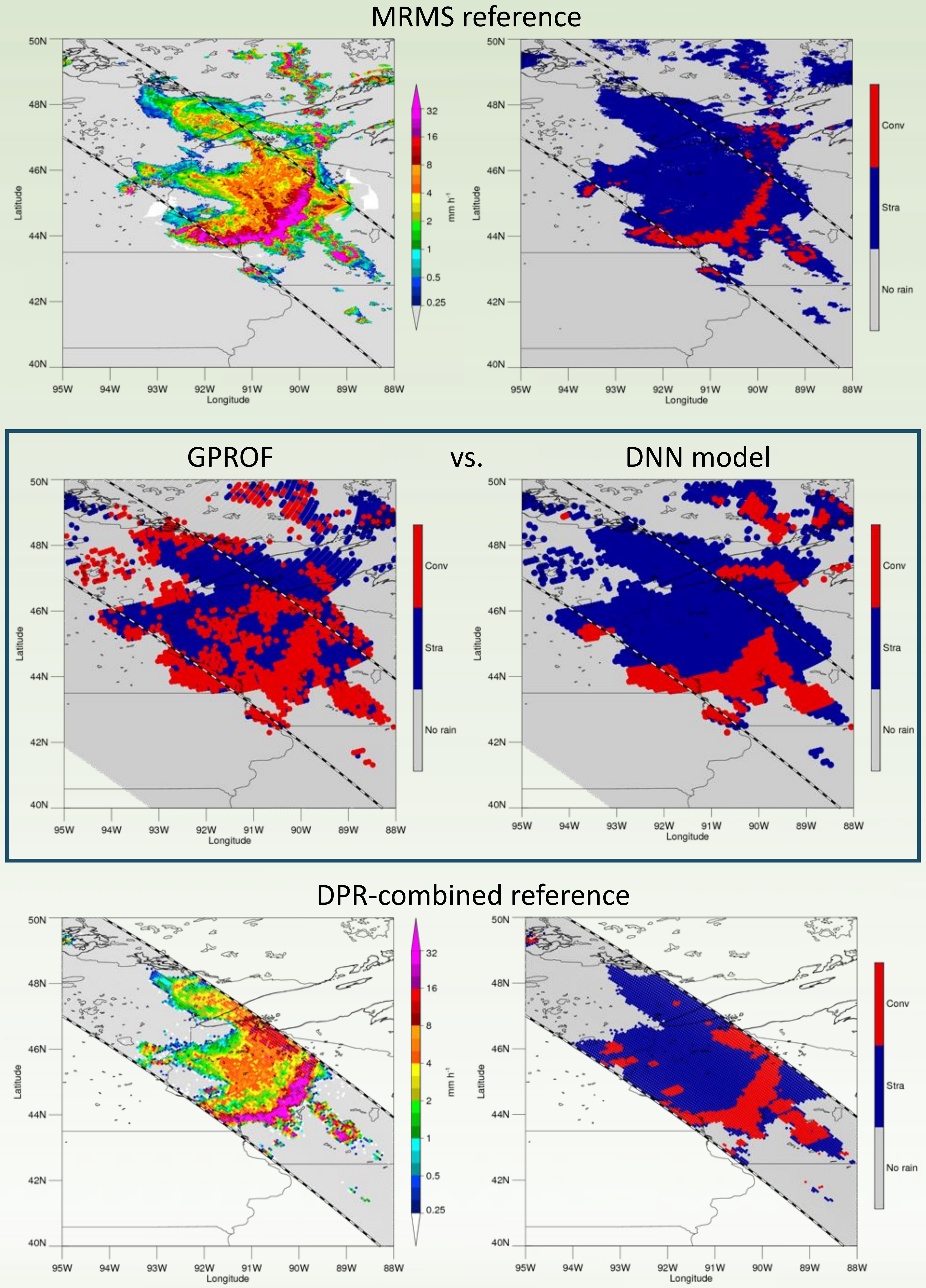
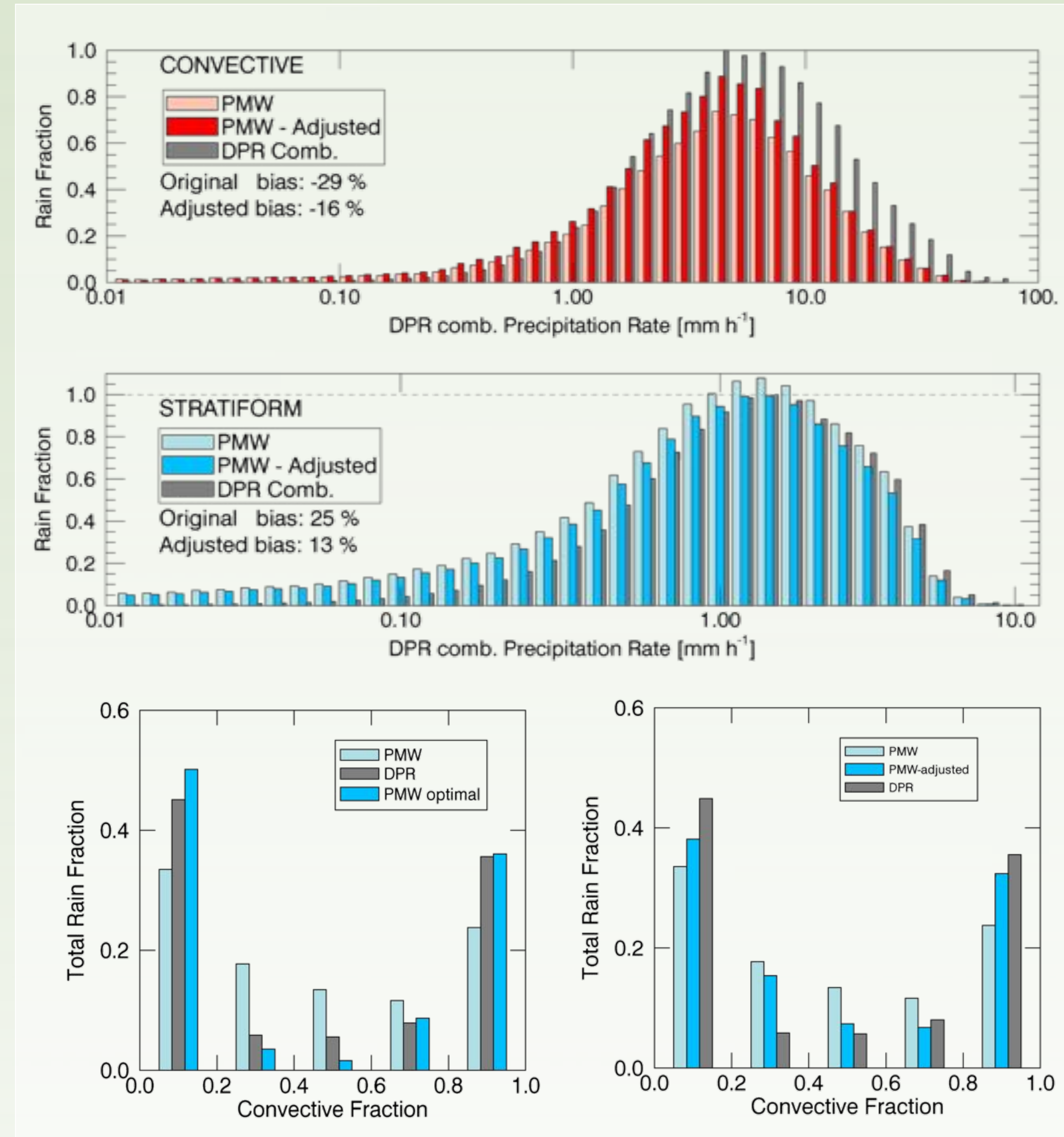


Figure 3. A squall line over Midwest (MN & WI), July 13th 2015. MRMS (top); GPROF and DNN (middle); DPR-combined (bottom)

Results

One 12-month independent period of GMI observations (Tbs) is used to retrieve precipitation type over land surfaces globally. Serving as a reference, collocated DPR-combined product has suggested an overall accuracy in assigning convective/stratiform flag to GMI FOV of 85%. By class, the accuracy is split into 98% for stratiform and 39% for convective. Similar results are seen for over ocean surface.

Overall Effect on GPROF



LAND	Bias [%]		Correlation Coeff.		
	Conv.	Stra.	Conv.	Stra.	All
GPROF V5	-28.66	25.09	0.637	0.674	0.589
GPROF w/DNN	-15.67	13.71	0.652	0.689	0.614

Summary

The potential of deep machine learning approach in retrieving precipitation type from passive microwave observations is tested using GMI and DPR-combined GPM products. A relatively simple fully connected neural network model, trained on collocated DPR-combined precipitation type flag and GMI 13-channel Tb vector, suggests significant improvement in detection skill when compared to the existing GPROF scheme [3].

Seen as a potential solution for regime-driven bias in PMW precipitation retrievals [4], the model is implemented in GPROF V5 to allow Bayesian scheme subset the a priori information and eliminate database entries of non-relevant precipitation type. This led to reduction of precipitation type bias by a factor of 2 while convective and stratiform rain distributions have approached that of DPR-combined product across entire convective fraction range.

References and Acknowledgments

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