Precipitation Retrieval Using ABI and GLM Measurements on the GOES-R Series.

Yifan Yang, Haonan Chen, and Kyle A. Hilburn
Colorado State University, Fort Collins, CO

***Abstract*—Accurate detection and estimation of precipitation using satellite sensors is a challenging problem due to the limitations on spatio-temporal sampling of the measurements, as well as those of the parametric retrieval algorithms. In this research, we propose a machine learning framework for precipitation retrieval using observations from the Advanced Baseline Imager (ABI) and Geostationary Lightning Mapper (GLM) on GOES-R satellite series. In particular, a hybrid convolutional neural network (CNN) model is designed for precipitation detection and estimation using ABI multi-channel cloud-top brightness temperatures and the GLM lightning flash rate. The precipitation estimates from a ground-based multi-radar multi-sensor (MRMS) system are used as target labels in the training phase. Experimental results showed that the proposed framework has better performance comparing to the available operational precipitation products.**

I. Introduction

Machine learning (ML) has been used for precipitation retrievals based on satellite data over two decades. Typical examples include the Precipitation Estimation from remotely Sensed information using Artificial Neural Networks (PERSIANN) products [1]. However, almost all the ML-based precipitation retrieval algorithms previously developed were using shallow artificial neural networks [1]–[3]. In recent years, deep learning is emerging as a powerful tool for feature extraction and pattern recognition. As such, this research focuses on designing deep learning models for accurate precipitation detection and estimation using Geostationary Operational Environmental Satellites (GOES) data.

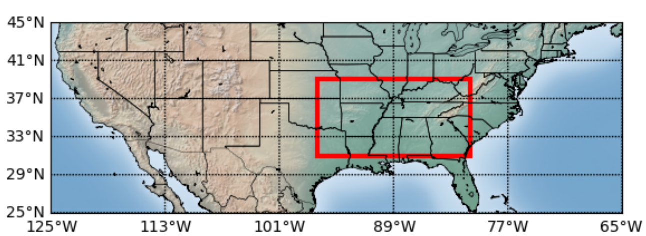

Fig. 1: Study domain (red rectangular) in the southeast United States.

Aboard the GOES-R satellite series, the Advanced Baseline Imager (ABI) has 16 spectral bands [4]. The spectral bands sensitive to water vapor are specifically used for this problem, including the brightness temperatures (BTs) from bands 8, 10, 11, 14, and 15, as well as brightness temperatures differences (BTDs) between band 10 and 8, band 11 and 10, band 14 and 10, band 11 and 14, and band 14 and 15. In addition, the hourly flash rates calculated from the Geostationary Lightning Mapper (GLM) data by counting the hourly flashes is also utilized. Thus, 11 features are applied to the deep learning models. In the following, the deep learning model structure and experimental results in a region over southeast U.S. (rectangular area in Fig. 1) are detailed.

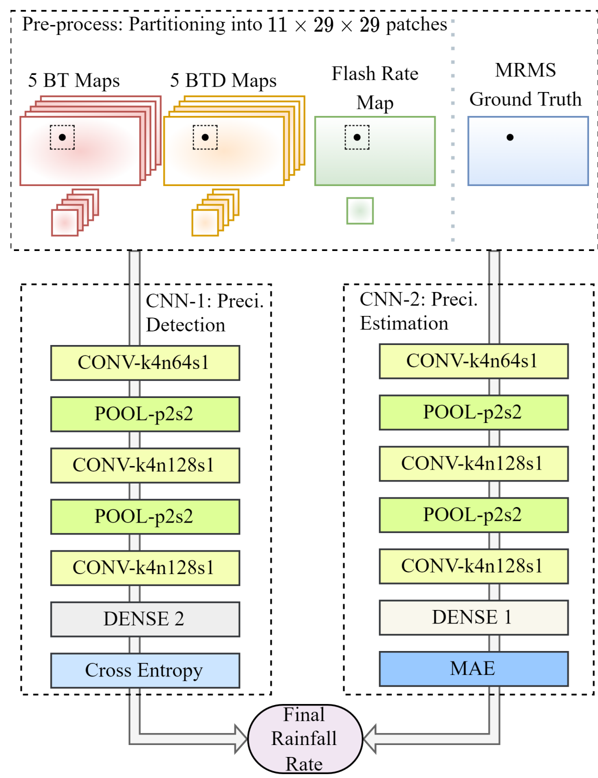

Fig. 2: The deep learning framework for satellite retrievals of precipitation. k, n, s, and p represent kernel size, number of feature maps, stride size and pooling size, respectively. The final rainfall rates are determined by fusing detection results from CNN-1 and estimated rainfall rates from CNN-2.

II. Methodology

In the pre-processing, the 11 features are partitioned into $11 \times 29 \times 29$ patches with stride size 1. The detection and estimation labels are devised based on the precipitation estimates from a ground-based MRMS system [5]. In particular, MRMS estimates at the center of the partitioned patches are used as targets during the training. Both the satellite data and MRMS estimates are aggregated to hourly scales in training the deep learning model. Fig. 2 details the deep learning framework, including a detection CNN module (CNN-1) and an estimation CNN module (CNN-2) both of which can capture spatial and temporal features of precipitation from the muti-channel satellite observations. In the detection model (CNN-1), the cross entropy loss is calculated in the training, whereas the mean absolute error (MAE) loss is used in the estimation model (CNN-2). Both CNNs use ReLU as activation function at each neuron, and the learning rate is set as 1e-5. In the testing phase, the test data (i.e., features) were pre-processed into $11 \times 29 \times 29$ patches similar to the training data and then applied to trained CNN models. The final precipitation retrievals can easily be derived by combining the results from the two models. Specifically, if precipitation is detected by CNN-1 in a patch, then the rainfall rate at the center location of this patch will be the estimate at the center location from CNN-2. Otherwise, the rainfall rate is 0 mm/h.

III. Experimental Results and Discussion

The data from May to September in 2019 are used for training the designed deep learning model and the data from May to September in 2020 are used for independent testing. The precipitation detection performance of the deep learning model and the operational GOES-16 product is evaluated in terms of Heidke skill score (HSS), critical success index (CSI), probability of detection (POD), and false alarm rate (FAR), and the results are presented in Table I. The impact of the GLM data on the detection performance is also illustrated in Table I. It can be observed that the precipitation detection was improved with GLM data based on the higher HSS, CSI, and POD.

Figure 3 shows an example of the deep learning-based precipitation estimates for the test date of May 19, 2020. The ground reference and the operational GOES-16 product are also shown in Fig. 3. Overall, it can be seen that the deep learning -based approach outperformed the operational products in terms of both precipitation detection and estimation. These results reveal the potential of deep learning models for satellite remote sensing and precipitation estimation. Future work will focus on larger scale demonstration of the proposed model, especially the generalized application over regions such as mountains and oceans where ground-based radars are not available or reliable.

TABLE I: Precipitation Detection Test Results.

Metrics	CNN w/ GLM	CNN w/o GLM	GOES-16 RRQPE
Test Acc.	90.39%	86.62%	49.44%
HSS	0.73	0.73	0.18
CSI	0.88	0.79	0.35
POD	0.94	0.90	0.35
FAR	0.04	0.08	0.03

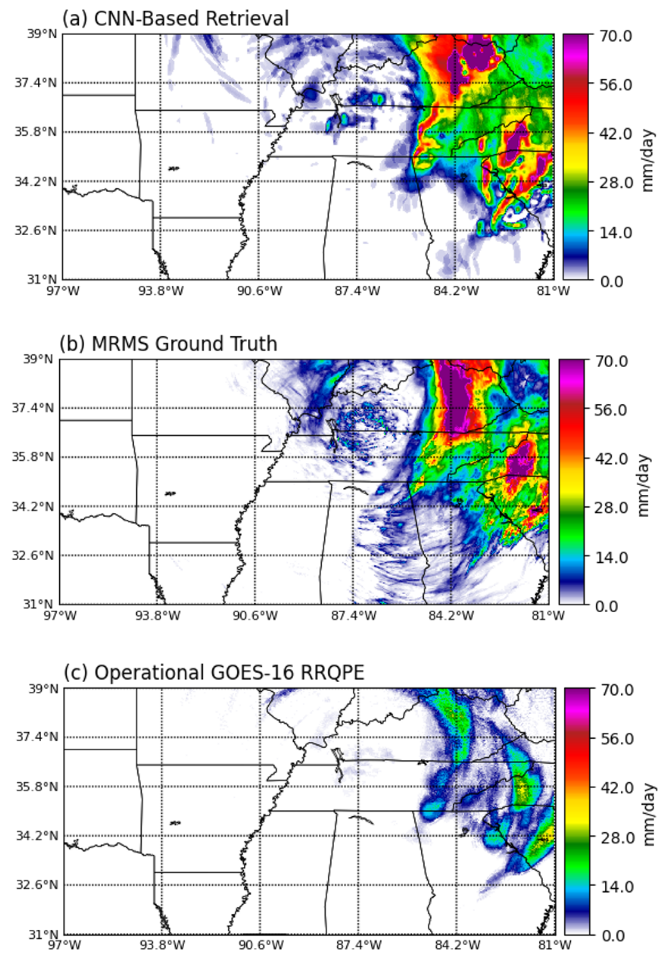

Fig. 3: Daily precipitation retrieval results on May 19, 2020: (a) retrievals from the design CNN model; (b) ground-based MRMS product; (c) operational GOES-16 product.

References

[1] P. Nguyen, M. Ombadi, S. Sorooshian, K. Hsu, A. AghaKouchak, D. Braithwaite, H. Ashouri, and A. R. Thorstensen, "The persiann family of global satellite precipitation data: A review and evaluation of products," *Hydrology and Earth System Sciences*, vol. 22, no. 11, pp. 5801–5816, 2018.

[2] H. Chen, V. Chandrasekar, R. Cifelli, and P. Xie, "A machine learning system for precipitation estimation using satellite and ground radar network observations," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 58, no. 2, pp. 982–994, 2020.

[3] H. Chen, V. Chandrasekar, H. Tan, and R. Cifelli, "Rainfall estimation from ground radar and trmm precipitation radar using hybrid deep neural networks," *Geophysical Research Letters*, vol. 46, no. 17-18, pp. 10 669–10 678, 2019.

[4] S. J. Goodman, T. J. Schmit, J. Daniels, and R. J. Redmon, *The GOES-R series: a new generation of geostationary environmental satellites*. Elsevier, 2019.

[5] J. Zhang, K. Howard, C. Langston, B. Kaney, Y. Qi, L. Tang, H. Grams, Y. Wang, S. Cocks, S. Martinaitis *et al.*, "Multi-radar multi-sensor (mrms) quantitative precipitation estimation: Initial operating capabilities," *Bulletin of the American Meteorological Society*, vol. 97, no. 4, pp. 621–638, 2016.