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DEEP LEARNING FOR PRECIPITATION RETRIEVALS USING COMBINED MEASUREMENTS FROM GOES-16 AND GOES-18 SATELLITES

Yifan Yang[1], *Haonan Chen*[1], *and Kwo-Sen Kuo*[2]

[1]Colorado State University, Fort Collins, CO; [2]University of Maryland, College Park, MD

ABSTRACT

Geostationary satellite sensors have been widely used for precipitation retrieval, and numerous algorithms have been developed for precipitation retrieval using observations from geostationary satellite sensors. However, using the observations from a single geostationary satellite only offers a certain viewing angle and lacks the observation from a different perspective. In this research, we propose a deep learning (DL) framework for precipitation retrieval by leveraging the combined observations from the duo GOES satellites, namely, GOES-16 and GOES-18, as well as the Digital Elevation Model (DEM) information of the selected study domain. The experimental results show that the precipitation retrieval performance of the proposed framework is superior to the currently operational GOES RRQPE product and provides more accurate satellite-based precipitation retrieval.

1. INTRODUCTION

Satellite sensors have been widely used for precipitation retrieval, and numerous algorithms have been developed for precipitation retrieval using observations from geostationary satellite sensors. The current operational rainfall rate quantitative precipitation estimate (RRQPE) product from the geostationary operational environmental satellite (GOES) offers full disk rainfall rate estimates based on the observations from the advanced baseline imager (ABI) aboard the GOES-R series. However, the performance of this precipitation product still needs to be improved, especially in the western United States where orographic precipitation processes are often undetected by the RRQPE and in mesoscale convective systems (MCSs) that frequent the midwestern United States [1]. A typical example of the DL-based precipitation retrieval framework is the Precipitation Estimation from remotely Sensed information using Artificial Neural Networks (PERSIANN) products [2]. Chen et al. improved satellite-based precipitation retrievals using a deep-learning-based approaches in [3, 4]. Recently, a DL framework for precipitation retrieval using ABI and geostationary lightning mapper (GLM) measurements on the GOES-16 in [5]. The results in [5] show the superiority of the DL-based precipitation retrieval model to the currently operational GOES RRQPE product. However, the framework in [5] overlooked the parallax shift issue of ABI measurement. The parallax effects refer to the fact that the cloud-top features observed by the GOES satellite sensors appear to be displaced away from the satellite subpoint. Thus, it poses a significant challenge when attempting to match the satellite observations with the ground reference for training and testing a robust DL model for precipitation retrieval.

In this research, we propose a DL framework for precipitation retrieval by leveraging the combined observations from the duo GOES satellites, namely, GOES-16 and GOES-18, to address the parallax shift. The differing nadirs of GOES-16 and GOES-18 result in distinct viewing angles over the selected study domain. By combining their observations, we benefit from multi-angle perspectives, providing additional information compared to using observations from a single satellite alone.

2. DATASET AND METHODOLOGY

Aboard the GOES-16 and GOES-18 satellites, the ABI measurement has 16 spectral bands with 10-min temporal resolution and 2-km spatial resolution. 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 temperature 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 GOES-16 GLM data by counting the hourly flashes in a 2-km grid are also utilized. In this research, we also incorporate the Digital Elevation Model (DEM) data from Shuttle Radar Topography Mission (SRTM) with 30 meters spatial resolution [6] to our DL model. Thus, 22 features are applied to the deep learning model. In the preprocessing, the 11 features are partitioned into $29 \times 29 \times 22$ patches with stride size 1 in a similar manner used in [5].

The proposed DL framework is composed of two deep convolutional neural networks (CNNs) that are designed for precipitation detection and quantification as shown in Figure 1. In the input layer, The cloud-top brightness temperatures (BTs), brightness temperature differences (BTDs) from

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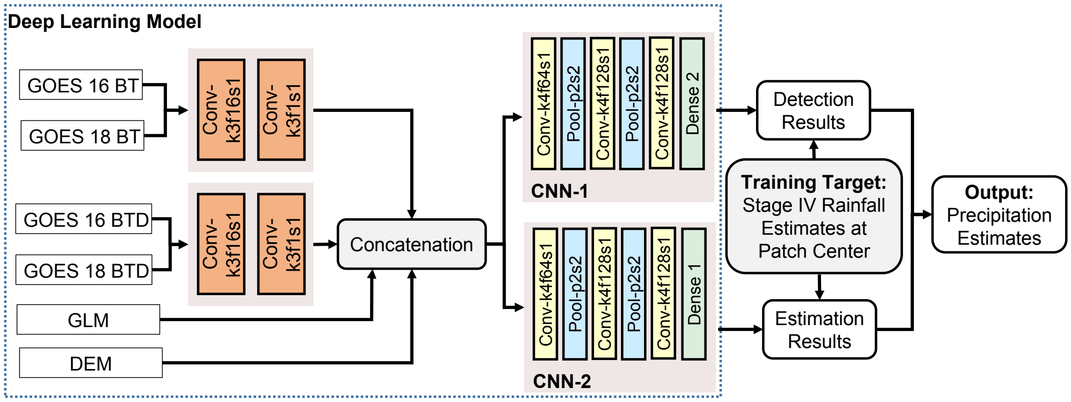

Fig. 1. The deep learning framework for precipitation retrievals using GOES-16 ABI and GLM and GOES-18 ABI measurements. In the convolutional (Conv-) and pooling (Pool-) layers, k, f, s, and p represent kernel size, number of feature maps, stride size, and pooling size, respectively.

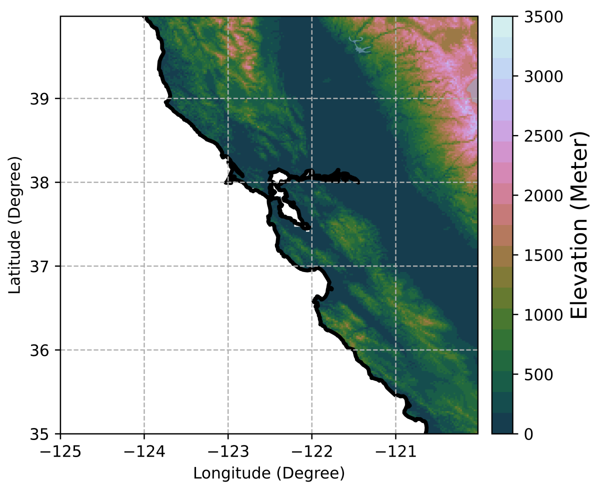

Fig. 2. The DEM information of the selected study domain.

GOES-16 and GOES-18 ABI channels and the lightning flash rate from the GLM measurement on GOES-16 are used as inputs to the DL model. The DL model includes 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 squared error (MSE) 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 this research, the proposed DL model was trained and tested in a region over the western coast of the United States as shown in Figure 2.

The Stage-IV 6-hour precipitation accumulation data from the National Centers for Environmental Prediction (NCEP) are used as target labels to optimize the network parameters. Particularly, the Stage IV estimates at the center of the partitioned patches are used as targets during the training. To accommodate temporal and spatial resolution of the GOES and the Stage IV data, the following pre-processing is also performed: (1) the GOES data are aggregated to 6 hours; (2) the Stage IV rainfall rate data are interpolated from 4 km to 2 km; (3) the DEM information is also down-sampled from 30 m to 2-km.

In the testing phase, the test data (i.e., features) were pre-processed into $29 \times 29 \times 22$ 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 at the center location of this patch will be the estimate at the center location from CNN-2. Otherwise, the rainfall is 0 mm.

3. EXPERIMENT RESULTS

In this research, the data from September to December in 2022 are used for training the designed DL model and the data from January to April in 2023 are used for independent testing. Figure 3 (a), (b), and (c) display an example of 6-hour accumulated precipitation estimates on 12:00 UTC, Jan 9, 2023, from the Stage IV ground reference, the proposed DL-based precipitation retrieval results using the observations from Duo Satellites Precipitation Estimates (DSPE) model, and the operational product on GOES, respectively. The experimental results show that the precipitation retrieval performance of the proposed framework is superior to the currently operational GOES RRQPE product. In addition, the scatter plots for this precipitation retrieval are presented in Figure 4. It can be observed that DSPE outperformed the operational product by having a closer cluster along the diagonal line.

To investigate the precipitation performance at different levels on the testing set, the evaluation metrics were computed based on a number of rainfall thresholds, including Heidke skill score (HSS), critical success index (CSI), probability of detection (POD), false alarm ratio (FAR), mean squared error (MSE), mean absolute error (MAE), normalized mean er-

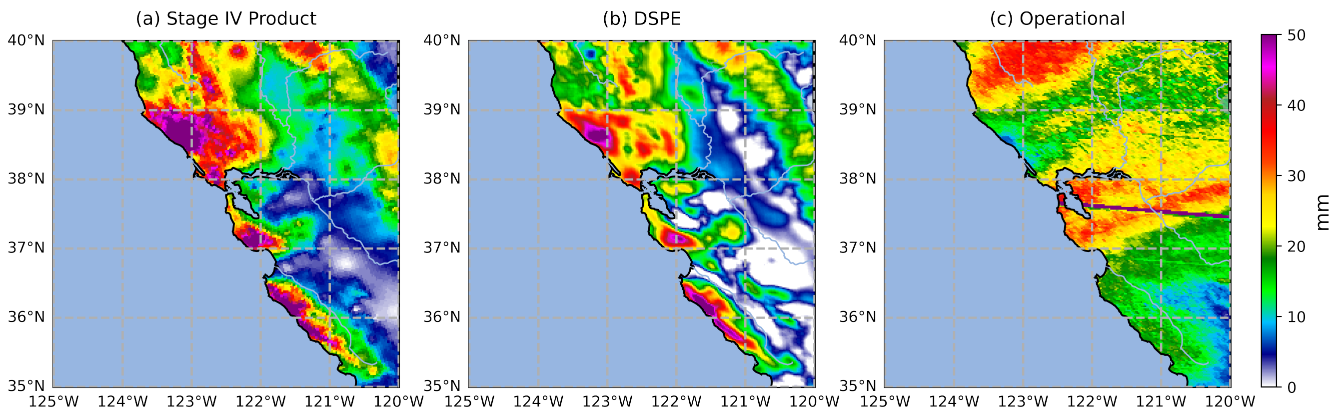

Fig. 3. Example of 6-hour accumulated precipitation estimates on 12:00 UTC, Jan 9, 2023 from: (a) Stave IV ground reference (b) DSPE model; (c) operational GOES-16 RRQPE product. The light blue color indicates the ocean areas.

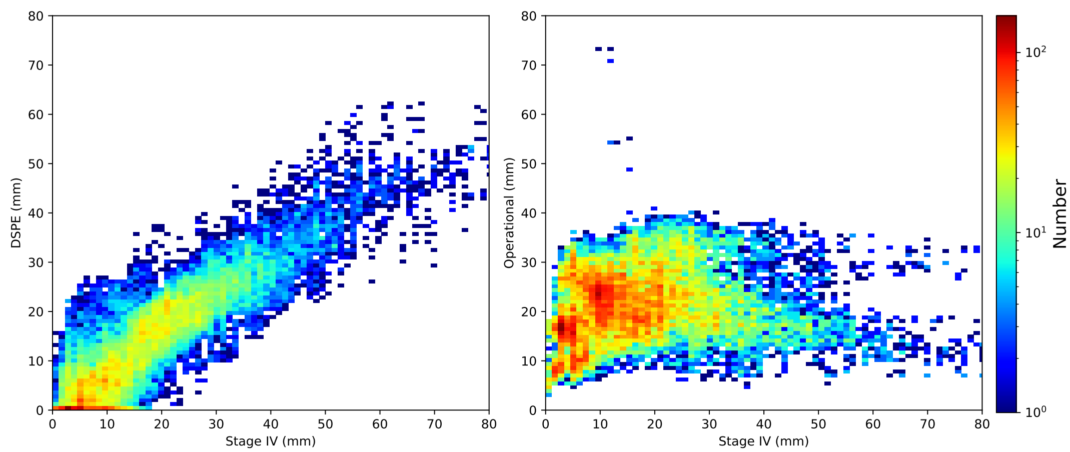

Fig. 4. Scatter plots of DSPE vs. Stage IV (left) and Operational GOES-16 RRQPE vs. Stage IV (right).

ror (NME), and normalized mean absolute error (NMAE). At each threshold, we determine the grid pixel indices where the ground-based Stage IV product exceeds the threshold value. We subsequently calculate the eight categories of evaluation metrics based on the predicted rainfall and the ground-based Stage IV product exclusively for these selected pixel indices. These metrics versus thresholds were plotted in Fig. 5. It can be seen from Fig. 5 that the proposed DSPE approach produced higher skill scores and lower errors compared to the operational GOES-16 RRQPE product, especially for strong precipitation.

One may notice that the proposed DL model was trained based on autumn data while tested on winter/spring data. This introduced the rain stationality effect. In this research, although we neglect the rain stationality effect, leading to some performance deficiencies (such as the under-estimation over the valley region of the study domain), the proposed DL model still outperformed the operational product and provided promising precipitation distribution.

4. SUMMARY

In this research, we propose a DL framework for precipitation retrieval by using the duo GOES satellites to address the parallax shift. The experimental results show that the precipitation retrieval performance of the proposed framework is superior to the currently operational GOES RRQPE product and provides more accurate satellite-based precipitation retrieval. Future work will focus on investigating the potential noise and inaccuracy introduced when we interpolate the Stage IV data from 4 km to 2 km spatial resolution. In addition, we will evaluate the generalization performance of the proposed DL model over regions such as mountains and oceans where ground-based radars are not available or reliable.

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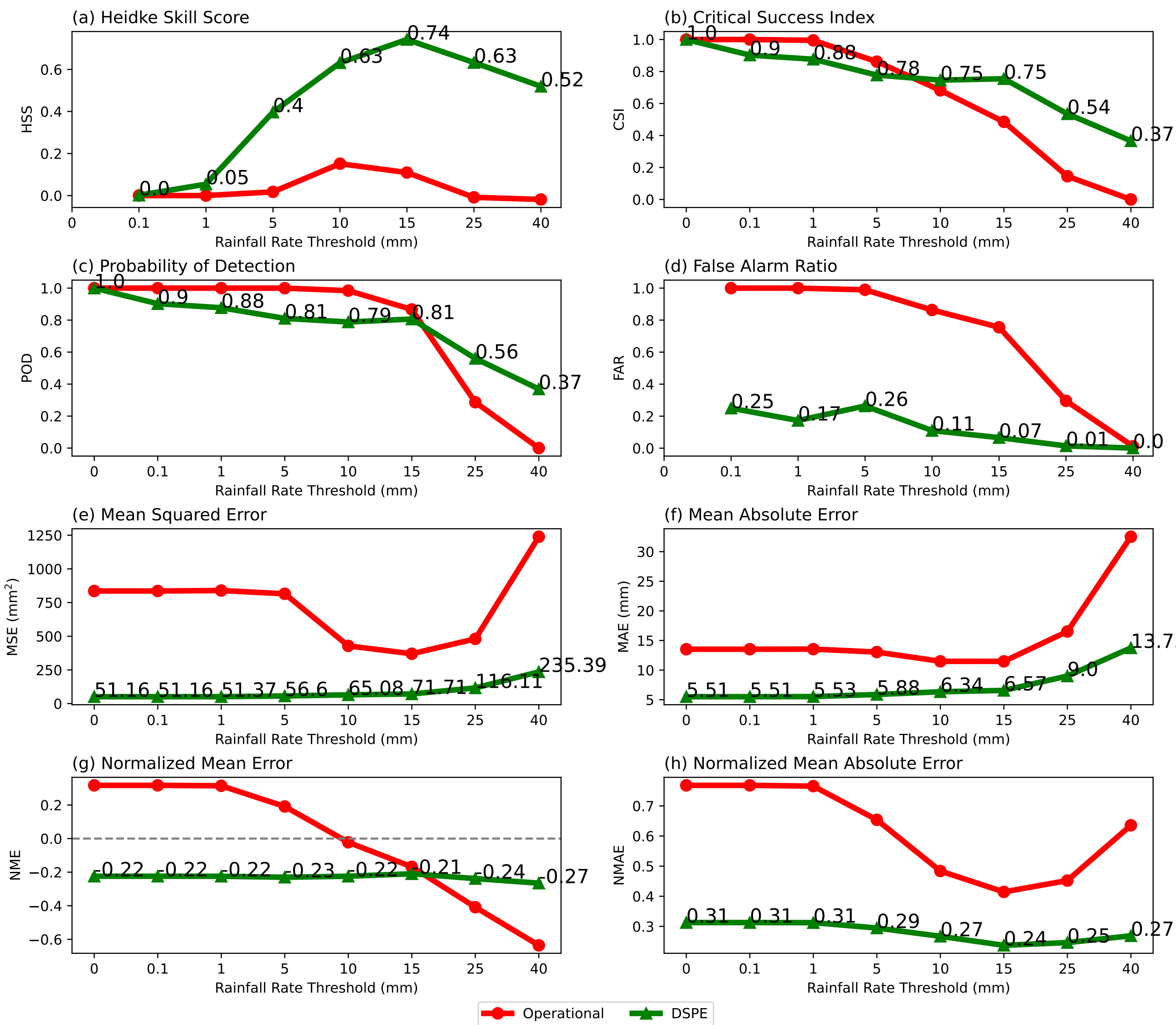

Fig. 5. The quantitative evaluation scores of the operational GOES-16 RRQPE product and DSPE. The evaluation scores are calculated for 6-hour rainfall accumulations based on all the test data, using different thresholds: (a) HSS, (b) CSI, (c) POD, (d) FAR, (e) MSE, (f) MAE, (g) NME, (h) NMAE. The evaluation scores of the DSPE are marked along the green curves.

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