NOAA ROSES Semi-Annual Report

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Project Title: Probabilistic Quantitative Precipitation Estimation with Geostationary Satellites

Executive Summary

Progress in precipitation estimation is critical to advance weather and water budget studies and prediction of natural hazards caused by extreme rainfall events from local to global scales. The low latency and high space/time resolution from geostationary satellites (e.g. GOES-16/17, Himawari-8) are essential for monitoring and predicting precipitation processes occurring over short space and time scales and driving hydrometeorological hazards. Hydrometeorological applications require more than just one deterministic precipitation “best estimate” to adequately cope with the intermittent, highly skewed distribution that characterizes precipitation. As geostationary quantitative precipitation estimation (QPE) is currently deterministic, we propose to advance the interpretation of GOES-16/17 observations for hydrometeorological applications with the use of probability as an integral part of QPE. The overarching goal of this research project is to leverage reliable ground-based radar Multi-Radar/Multi-Sensor (MRMS) quantitative precipitation applications to geostationary missions and synergize CONUS-wide GOES-16/17 precipitation enhancement. We will explore the use of GOES-16/17 ABI multiple spectral bands and high space/time resolution through spatial and temporal textures. Probability distributions of precipitation rates will be established using models quantifying the relation between ABI observations and the corresponding “true” precipitation from MRMS. Probabilistic QPE (PQPE) mitigates systematic biases from deterministic retrievals and quantifies uncertainty for hydrologic applications and advances the monitoring of precipitation extremes with remote sensing. It provides the basis for multisensory integration across GOES-16, GOES-17, and MRMS through quantified uncertainties to optimally merge PQPEs. PQPEs can be more readily fused with MRMS ground radar products for seamless precipitation estimation over CONUS, specifically in the western United States where the vantage point of space can complement the degraded weather radar coverage of the NEXRAD network. It opens perspectives for improved estimation of precipitation at multiple scales, hydrological prediction, and risk monitoring.

Progress toward FY20 Milestones and Relevant Findings (with any Figs)

1. GOES-16 – GV-MRMS matchups have been generated at 30-min timescale over Summer 2018 and at 2-min timescale over Summer and Winter 2020;
2. An interpretable machine learning model has been set up for precipitation type classification. Two manuscripts have been submitted;
3. A preliminary machine learning model has been set up for precipitation quantification (see Fig. 1 & 2). A detailed inter-comparison is being performed with SCaMPR across CONUS climate regions;

4. Initial experiments investigate the use of the temporal frequency of GOES-R observations for precipitation detection and quantification using advanced machine learning techniques (e.g., Convolution Neural Networks).

A preliminary Machine Learning (Random Forest) based Precipitation Quantification for GOES-16 ABI has been generated. An example of CONUS precipitation retrieval on August 17, 2018 at 2300UTC is provided in Fig. 1. The RF precipitation estimates are closer to the ground reference (GV-MRMS) than SCaMPR that tends to miss precipitation.

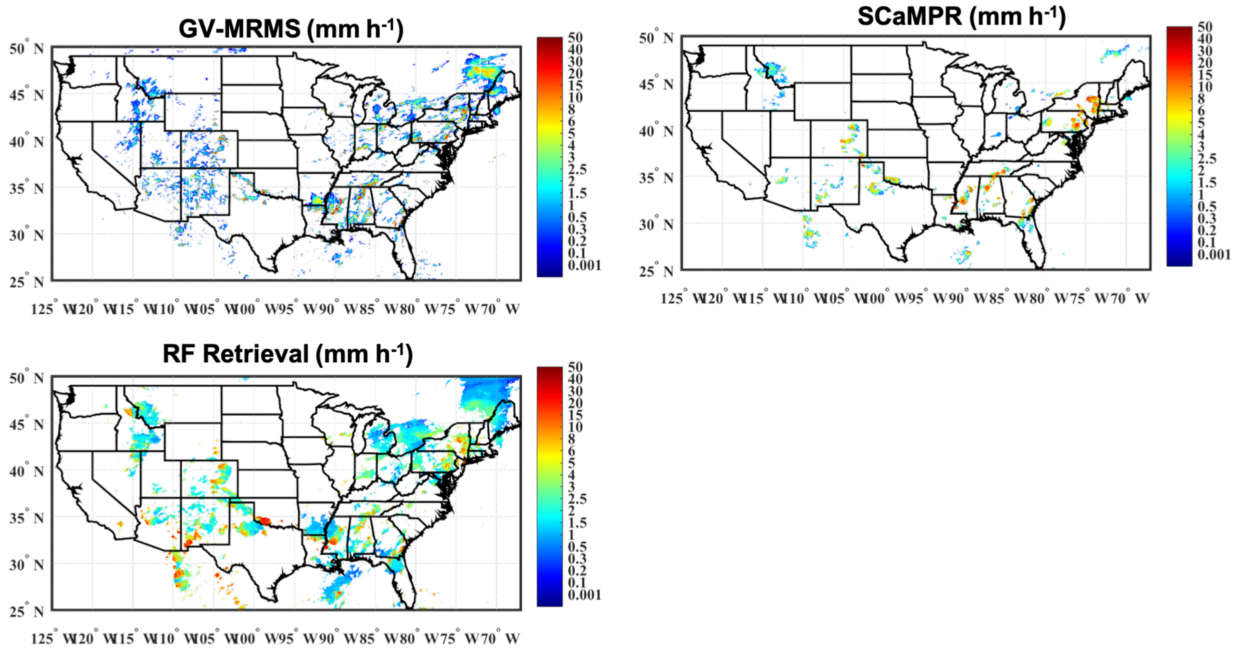

Figure 1: Precipitation estimates from (top left) the GV-MRMS independent radar-gauge reference, (top right) SCaMPR using GOES-16 observations, and (bottom left) the Random Forest retrieval using GOES-16 observations.

A preliminary statistical comparison with the GV-MRMS independent surface reference confirms the advantages of the Random Forest retrieval (RF) w.r.t. operational algorithms such as SCaMPR and PERSIANN-CCS. The RF estimates show lower overall bias (7.62%) than SCaMPR and PERSIANN-CCS (-13.9% and 12%, respectively; see table below). RF estimates also show significantly higher correlation (0.45) than SCaMPR and PERSIANN-CCS (0.28 and 0.17, respectively).

	POD	CC	RMSE	Rbias (%)
RF* (Random Forest)	0.99	0.45	5.21	7.62
SCaMPR	0.46	0.28	5.82	-13.9
PERSIANN-CCS	0.50	0.17	6.62	12.03

*RF: Developed precipitation retrieval algorithm using Random Forest (RF)

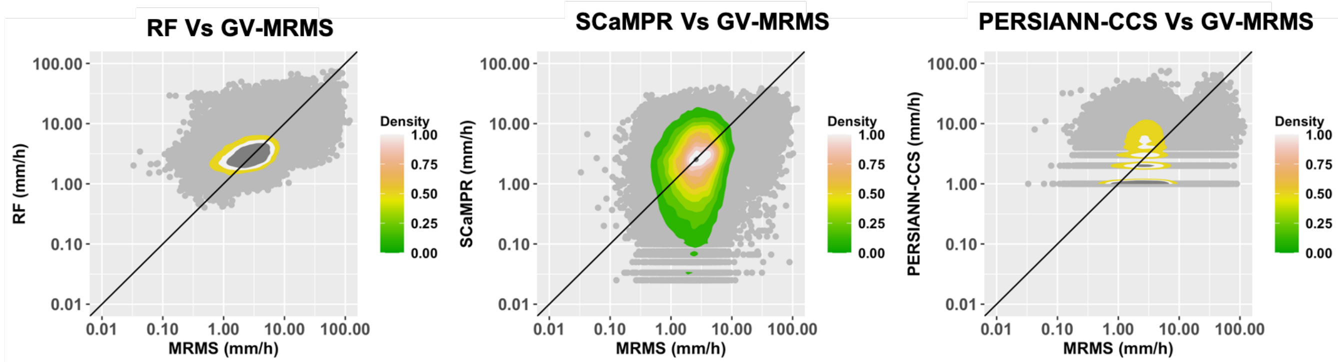

Figure 2: (top) Quantification scores between SCaMPR, PERSIANN-CCS, the RF retrievals with respect to the independent GV-MRMS reference; (bottom) density scatterplots between the GV-MRMS reference and the three satellite-based retrievals: (left) RF, (center) SCaMPR and (right) PERSIANN-CCS.

An intercomparison analysis is underway across various climate regions of the U.S.

Manuscripts under Review:

- Upadhyaya, S., P.E. Kirstetter, R. Kuligowski, J.J. Gourley, & H. Grams (2021). Classifying precipitation from GEO Satellite Observations: Prognostic Model. *Submitted to the Quarterly Journal of the Royal Meteorological Society*.
- Upadhyaya, S., P.E. Kirstetter, R. Kuligowski, & M. Searls (2021). Classifying precipitation from GEO Satellite Observations: Diagnostic Model. *Submitted to the Quarterly Journal of the Royal Meteorological Society.*

Plans for Next Reporting Period

1. Build GV-MRMS-GOES17 matchup datasets;
2. Build preliminary probabilistic precipitation retrievals for GOES-16;
3. Submit two manuscripts:

- Upadhyaya, S. and P.E. Kirstetter (2021). A New Era of Geostationary Satellites: Towards the next generation of space-based precipitation estimation (Under Preparation)
- Upadhyaya, S., P.E. Kirstetter, R. Kuligowski, J.J. Gourley (2021). Quantifying precipitation from GOES-16 Satellite Observations (Under Preparation)