Probabilistic Precipitation Estimates from GOES-R for Hydrological Applications

Shruti Upadhyaya[1], Pierre-Emmanuel Kirstetter[2,3,4,5], Jonathan Gourley[5]

[1] Cooperative Institute for Mesoscale Meteorological Studies, Norman, Oklahoma; [2] School of Meteorology, University of Oklahoma, Norman, Oklahoma
[3] School of Civil Engineering and Environmental Science, University of Oklahoma, Norman, Oklahoma; [4] Advanced Radar Research Center, University of Oklahoma, Norman, Oklahoma
[5] NOAA/National Severe Storms Laboratory, Norman, Oklahoma

Email: shruti.a.upadhyaya-1@ou.edu, pierre.kirstetter@noaa.gov, bob.kuligowski@noaa.gov, jj.gourley@noaa.gov

1. Introduction

Goal: To derive unified, consistent, accurate and fine-resolution precipitation rates over the Conterminous U.S., by leveraging GOES-R satellite observations and ground-radar based precipitation product from the Multi-Radar/Multi-Sensor (MRMS) system.

Specific Objective: To investigate the potential for improving precipitation estimation using multi-spectral data from the GOES-R satellite w.r.t. deterministic retrieval algorithms such as SCaMPR (Kuligowski et al. 2016).

Advanced Baseline Imager (ABI) on GOES-R satellite: Views Earth with three times more spectral channels (16), four times the resolution (~ 2km), and five times faster scanning (5min across Conterminous U.S.) compared to its predecessor IMAGER on GOES 12-15.

Challenge: To effectively mine GOES-R "big data" observations for precipitation and document relations between multi-spectral ABI observations and MRMS surface precipitation estimates. `

2. Self-Calibrating Multivariate Precipitation Retrieval (SCaMPR) : NOAA's Operational Precipitation Algorithm for GOES-R satellite (Kuligowski et al. 2016)

I. SCaMPR Predictors derived from GOES-R

*T6.19 (WV)	T8.5-T7.34 (IR-WV)
S=0.568-(Tmin,11.2) (Texture)	T11.2-T7.34 (IR-WV)
Tavg,11.2-Tmin,11.2-S (Texture)	T8.5-T11.2 (IR-IR)
T7.34-T6.19 (WV-WV)	T11.2-T12.3 (IR-IR)

IR: Infrared spectral band **WV:** Water Vapor absorption band

***T6.19:** Brightness temperature observed in the ABI band at wavelength 6.19µm

Tavg,11.2: Average value of T11.2 across 5x5 pixel

Tmin,11.2: Minimum T11.2 over the closest six neighboring pixels

II. Stages in SCaMPR

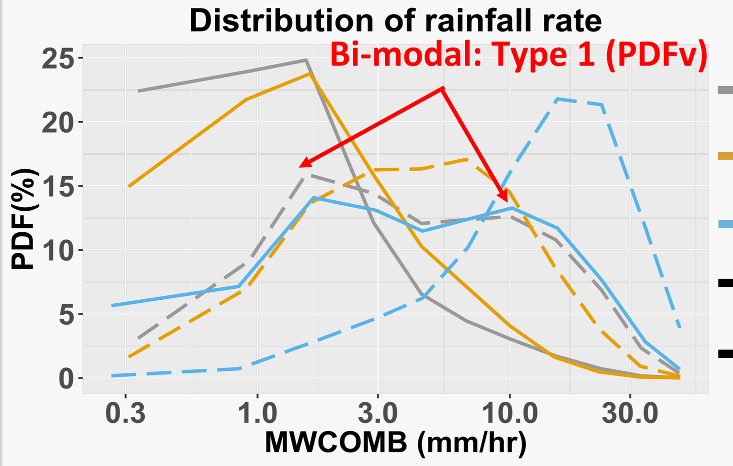
- Cloud Type **Classification** (Deterministic) → **Type 1 (Ice Cloud):** T7.34<T11.2 and T8.5-T11.2<-0.3; **Type 2 (Water Cloud):** T7.34<T11.2 and T8.5-T11.2≥-0.3; **Type 3 (cold-top convective cloud):** T7.34≥T11.2
- Rain/No-Rain **Detection** (Deterministic) → Using Discriminant Analysis
- Precipitation **Quantification** (Deterministic) → Using Multiple Linear Regression
- Post Processing → E.g. Bias Correction, Relative Humidity Correction

III. Study Area and Dataset

- **Reference data:**
  - **SCaMPR:** CPC combined microwave (MWCOMB) dataset (Joyce et al. 2004) derived from satellite passive microwave sensors at 30min and 8km resolution
  - **Proposed: Multi-Radar/Multi-Sensor (MRMS) precipitation product at native ABI resolution**
- **Study Period:** Summer 2018
- **Study Area:** Conterminous United States (CONUS)

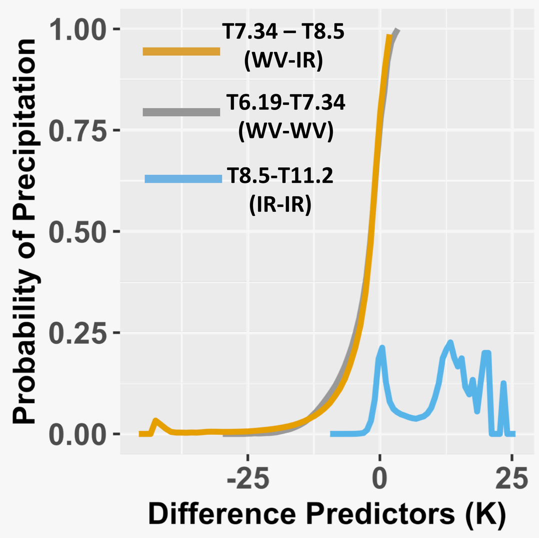
3. Challenges at different stages of SCaMPR

I. Classification



PDFc: Probability distribution by occurrence
PDFv: Probability distribution by volume

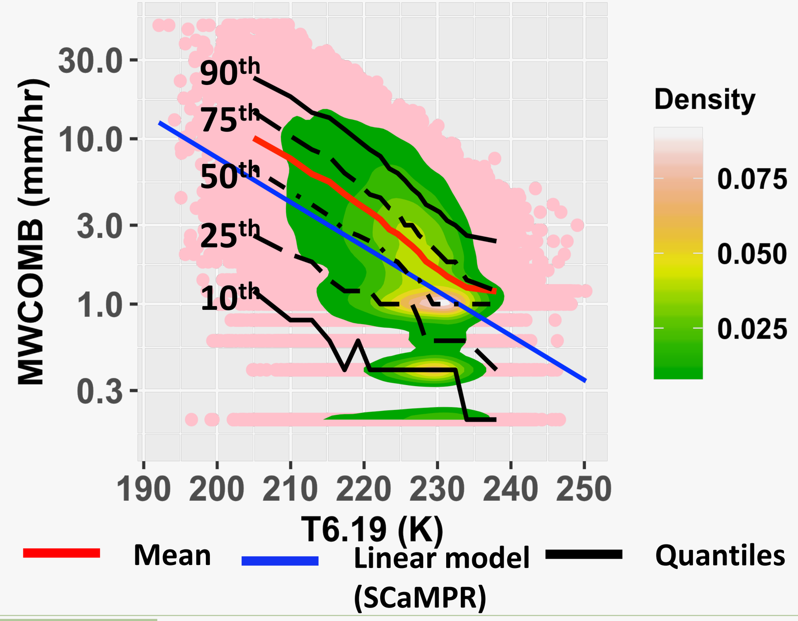
II. Detection



Challenge:
- Bi-modal distribution suggests two different cloud populations in the Type 1 class of SCaMPR
- SCaMPR deterministic detection of precipitation and choice of channels questioned by Probability of Precipitation

Proposed Solution: Explore more indices such as all possible difference and textures along with better reference to aid the classification (Section 4-II)

III. Quantification



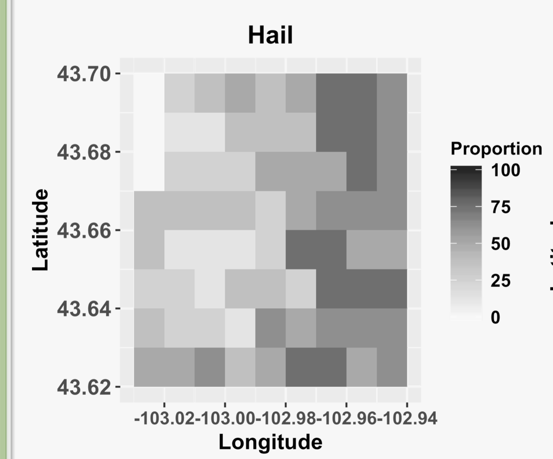
Challenge:
Precipitation retrieval requires more than just one deterministic "best estimate" and linear relation

Proposed Solution:
Probabilistic Quantitative Precipitation Estimation (PQPE)(Kirstetter et al. 2018) (Section 4-III)

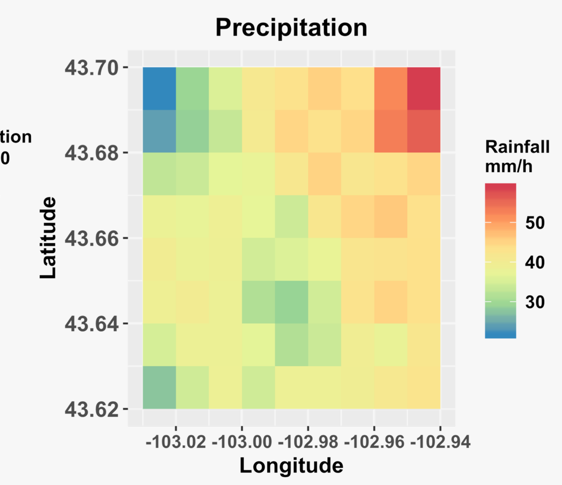
4. Proposed Algorithm: Preliminary Results

I. Better Reference

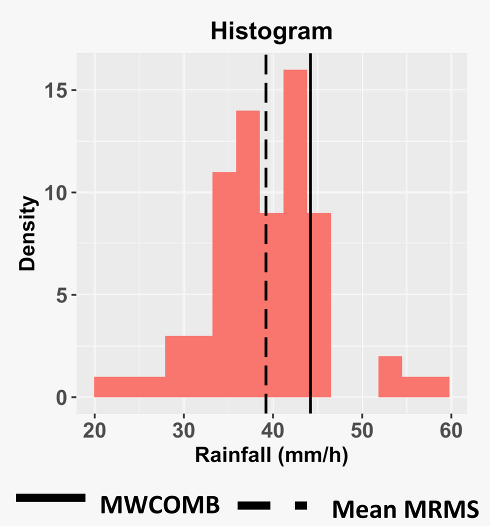
- To explore the potential of high resolution, low latency, and more spectral bands from ABI, a reference better than MWCOMB is required;
- High resolution, more physically based precipitation rates and types retrieved from MRMS are ideal to effectively mine data from GOES-R for precipitation retrieval



Proportion of Hail from MRMS in 30min window of MWCOMB

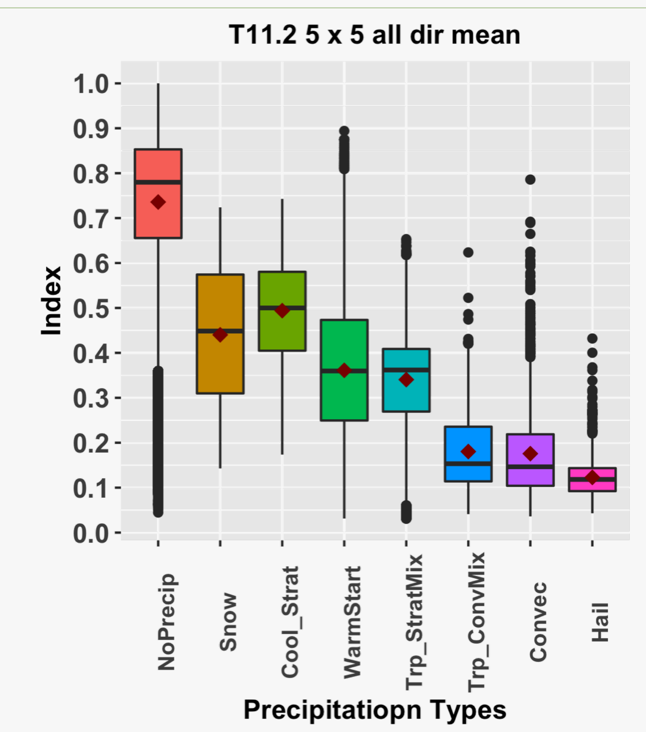


Date: 2018-07-22 04:00:00 UTC



II. Detection and Classification

- More channel combination and textures are derived: total 480 indices ;
- A Random Forest based Machine Learning (ML) algorithm is developed



Example: Texture from ABI Spectral channel 11.2µm distribution across different MRMS precipitation types

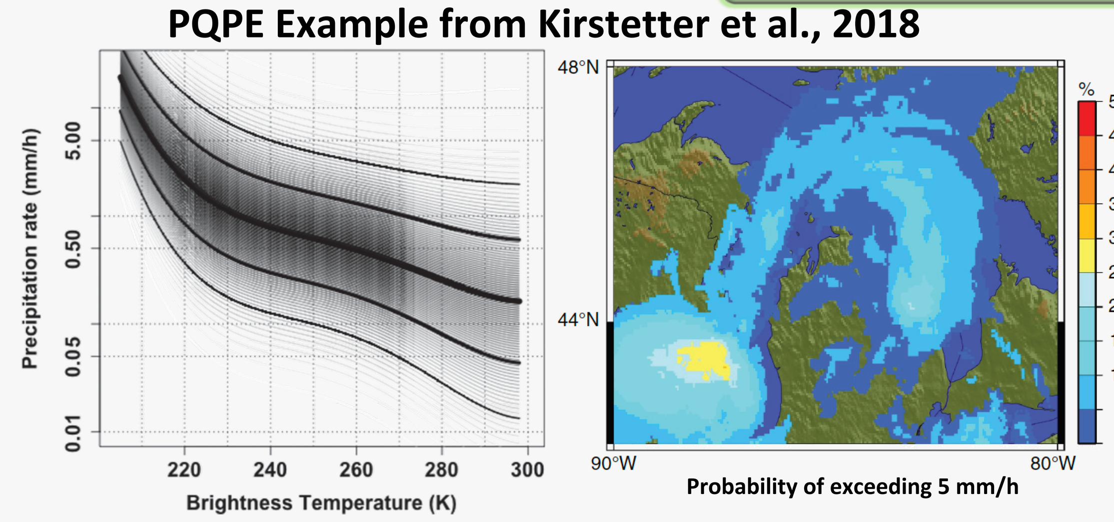
Initial Classification and Detection results

Precipitation Type	Probability of Detection
No-Precipitation	96%
Hail	94%
Convective	69%
Tropical Convective/Mix	83%
Warm Stratiform	50%
Cool Stratiform	91%
Tropical Stratiform Mix	70%
Snow	87%

Overall Accuracy: 80%

III. Quantification: Probabilistic Quantitative Precipitation Estimation (PQPE)

PQPE Example from Kirstetter et al., 2018



Initial Quantification Results with PQPE and its comparison with MWCOMB and SCaMPR

Statistics	MWCOMB	SCaMPR	PQPE(GOES-R)
Correlation Coefficient	0.41	0.32	0.49
Root Mean Square Error (mm/h)	5.63	4.95	4.1
Bias (mm/h)	+1.10	-0.78	+0.12
Mean Relative Error (%)	+41.5 (Overestimation)	-28.8 (Underestimation)	+3.6 (Unbiased)

5. Conclusions and Perspectives

- Challenge: the potential of high-resolution ABI data remains underutilized due to consideration of coarser scale data as reference ➔ solution: to address this issue, we are utilizing high resolution and accurate precipitation estimates from MRMS.
- Challenge: satellite precipitation has been deterministically computed despite the under-constrained relation between the satellite sensor measurements to precipitation rate. ➔ solution: preliminary results on new satellite precipitation approaches which focuses on probabilistic quantification of precipitation (Kirstetter et al. 2018) show promising results with unbiased estimates.
- Challenge: Effective utilization of high resolution (Spatial, Temporal and Spectral) GOES-R observations ➔ solution: results confirm the usefulness of GOES-R infrared and water vapor absorption bands, as well as newly derived indices for precipitation detection, classification and quantification.
- Challenge: simple unsupervised techniques are currently being used for precipitation classification ➔ solution: The detection and classification results using ML approach guided by better reference highlights the potential of GOES-R satellite observations in identifying precipitation types from ground radar i.e. MRMS system

Important References

- Kirstetter, P. E., Karbalaee, N., Hsu, K., & Hong, Y. (2018). Probabilistic precipitation rate estimates with space-based infrared sensors. Quarterly Journal of the Royal Meteorological Society, 144, 191-205.
- Kuligowski, R. J., Li, Y., Hao, Y., & Zhang, Y. (2016). Improvements to the goes-r rainfall rate algorithm. Journal of Hydrometeorology, 17(6), 1693-1704.

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