MiRS Precipitation Estimation from LEO Observations at NOAA: Performance, Requirements, Challenges and Opportunities

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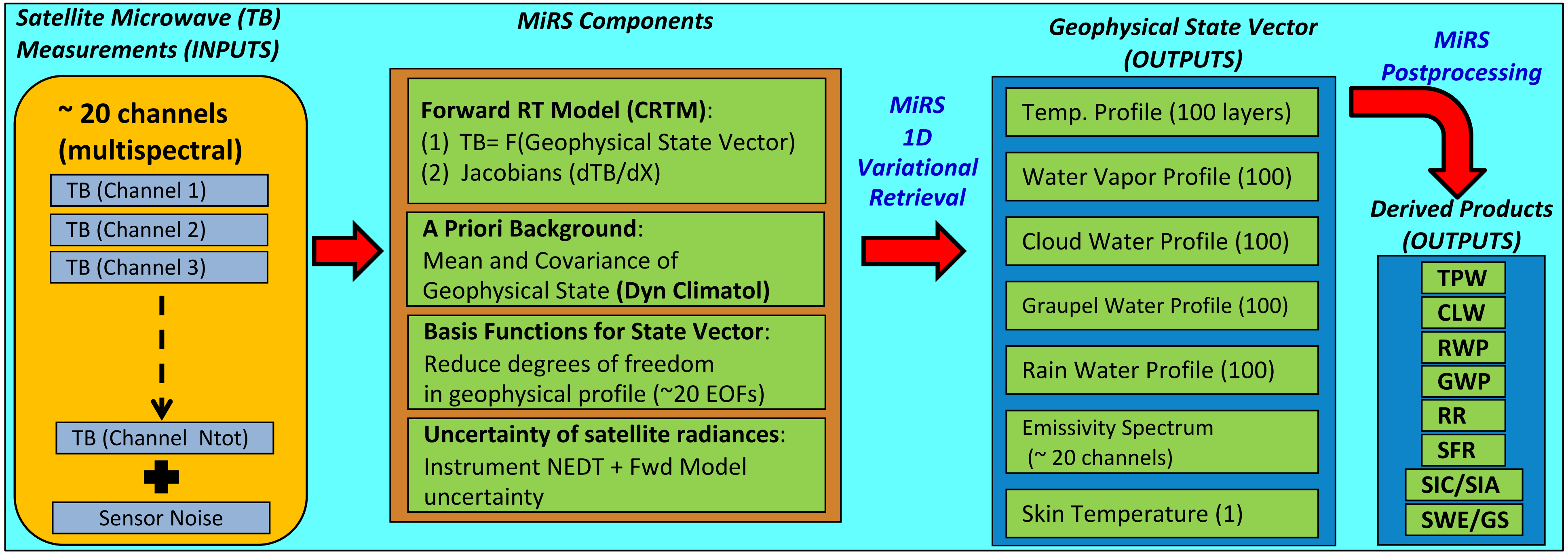
Algorithm Overview



- MW Only, Variational Approach: Find the "most likely" atm/sfc state that: (1) best matches the satellite measurements, and (2) is still close to an a priori estimate of the atm/sfc conditions.
- **Same core software runs on all satellites/sensors; facilitates science improvements and extension to new sensors.**
- Can run on SNPP, N20, N21/ATMS, N18, N19, MetopA, MetopB, MetopC F17, F18, GPM/GMI, Megha-Tropics/SAPHIR (experimentally on TRMM, AMSR2, TROPICS).
- V11.9 delivered in 2022, transition to operations in early 2023.

Requirements and Validation Results: NOAA-20 and SNPP ATMS

- Official reference is Stage-IV
- Stratified by surface type, but requirement is for land only
- Requirements from JPSS-REQ-1004
- All requirements are met except some individual cases for False Alarm Rate

Attribute	Threshold	Validated
Geographic coverage	Global (non-frozen surfaces)	See table/figs
Vertical Coverage	Surface	
Horizontal Cell Size	15 km at nadir	
Mapping Uncertainty	N/A (reflects SDR characteristics)	
Measurement Range	N/A	
Measurement Accuracy	See table	
Measurement Precision	See table	

Data Collected: Fall 2018, Winter 2018-19, Spring 2019, Summer 2019

Meets requirements except some cases (blue)
Meets requirements (green)

Reference: Stage IV
Values in () indicates NPP

Product	SFC	EDR Attribute	MiRS	Requirement
RR (mm/h)	Land	Accuracy (bias) (mm/h)	0.02 ~ 0.05 (0.02 ~ 0.05)	0.1
		Precision (std dev) (mm/h)	0.5 ~ 0.8 (0.5 ~ 0.8)	1.0
		Probability of Detection (%)	66 ~ 80 (67 ~ 80)	50
		False Alarm Rate (%)	4.9 ~ 7.0 (4.8 ~ 6.3)	5
		Heidke Skill Score	0.44 ~ 0.51 (0.47 ~ 0.52)	0.3

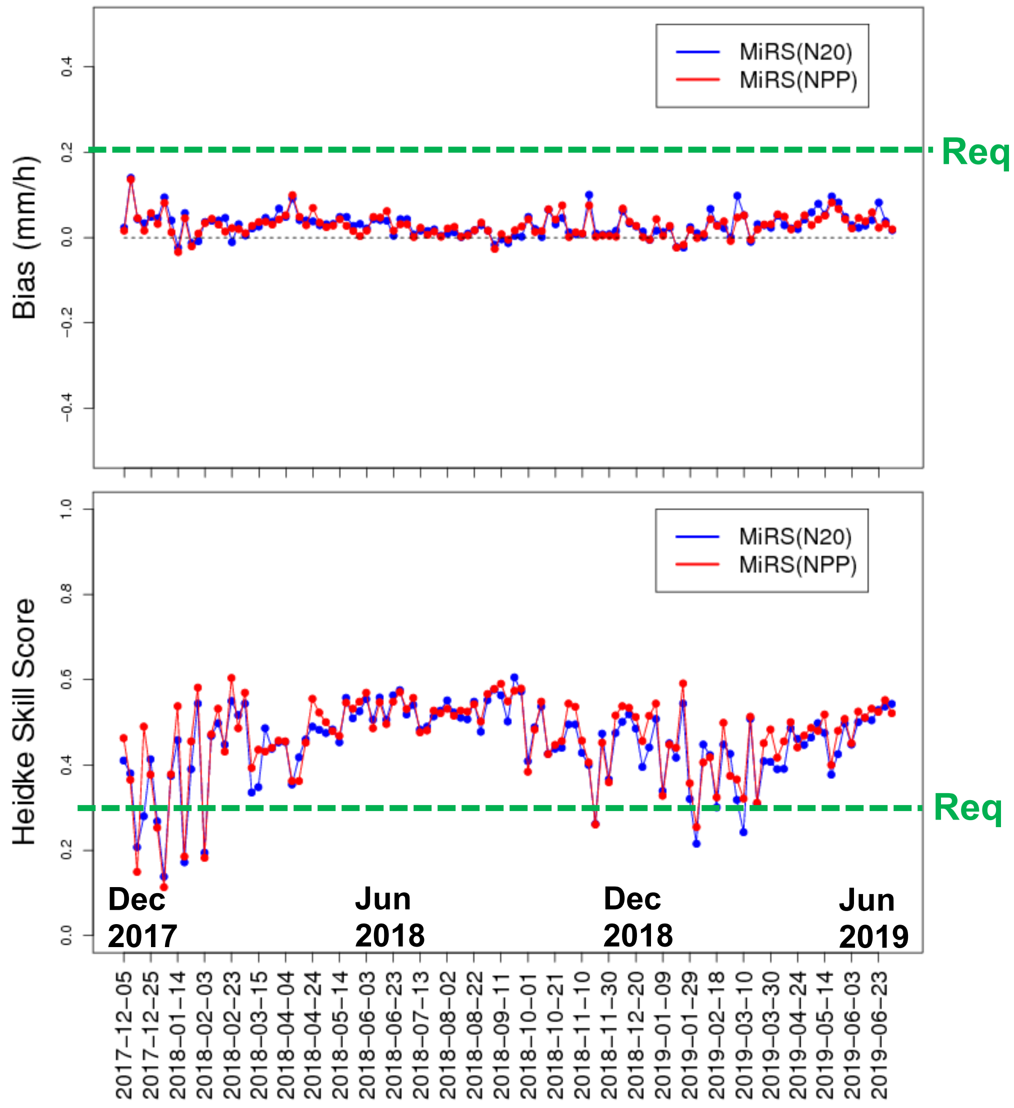
Product	SFC	EDR Attribute	MiRS	Requirement
RR (mm/h)	Ocean	Accuracy (bias) (mm/h)	0.02 ~ 0.08 (0.03 ~ 0.08)	0.1
		Precision (std dev) (mm/h)	0.62 ~ 0.95 (0.64 ~ 0.92)	1.0
		Probability of Detection (%)	75 ~ 80 (74 ~ 80)	50
		False Alarm Rate (%)	3.3 ~ 5.7 (3.2 ~ 5.5)	5
		Heidke Skill Score	0.47 ~ 0.61 (0.50 ~ 0.61)	0.3

Collocation details:

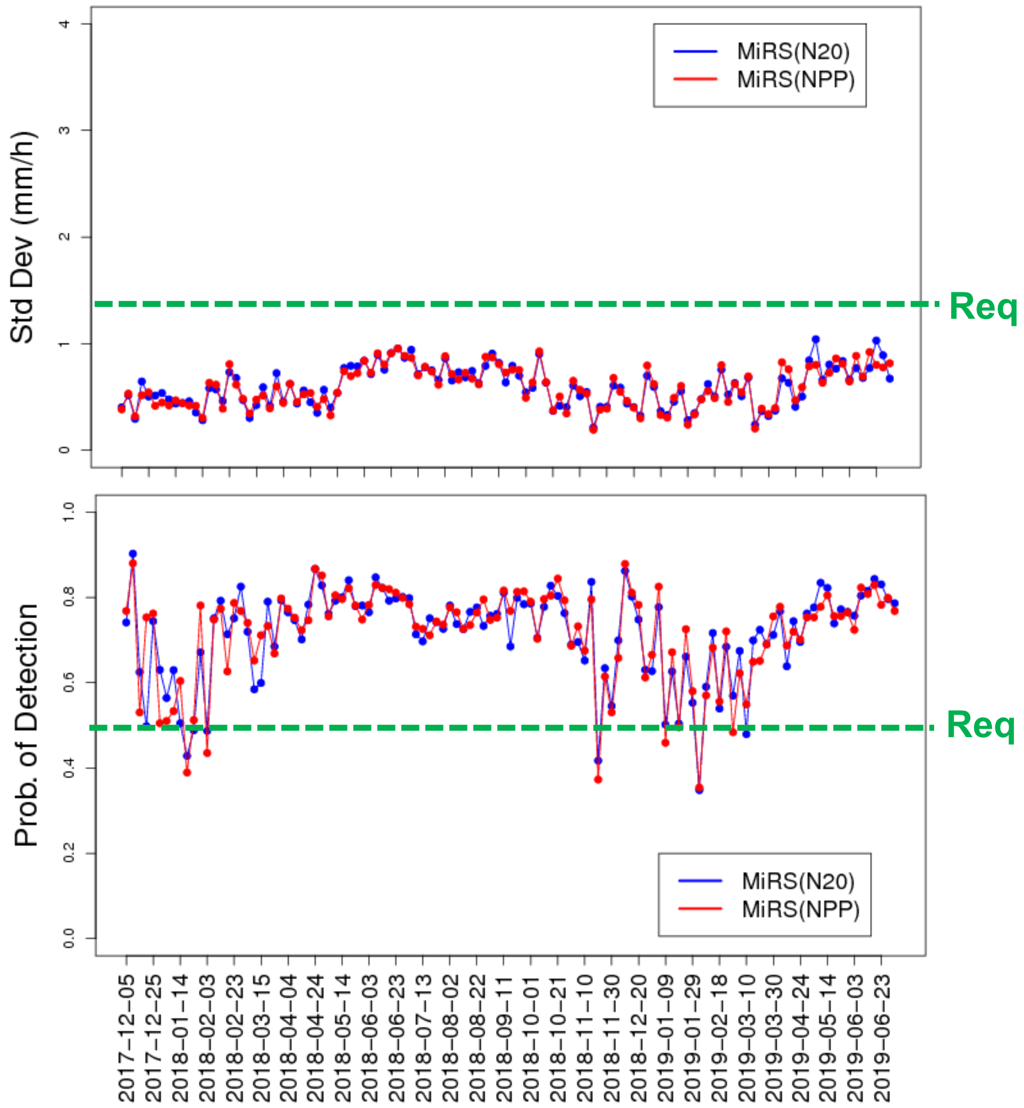
- Stage-IV:
  - NOAA NCEP Multisensor (radar + gauges) Precipitation Estimator (MPE) analyses, hourly over CONUS and adjacent near ocean, spatial resolution is 4 km.
  - Collocation spatial radius: ~4.55 km, average Stage-IV values within the range.
  - Collocation time window: ± 30 minutes.
- MRMS :
  - Multi-Radar Multi-Sensor (MRMS) Quantitative Precipitation Estimation (QPE), in situ gauge corrected radar QPE, hourly over CONUS and adjacent near ocean, spatial resolution 0.01 degree.
  - Collocation spatial radius: FOV size, average grid values fall within each FOV.
  - Collocation time window: ± 30 minutes

Time Series: N20 and NPP vs. Stage-IV
Dec 2017 – Jun 2019 (5-day averages over CONUS)

N20/NPP Stage IV Collocation (Land)



N20/NPP Stage IV Collocation (Land)

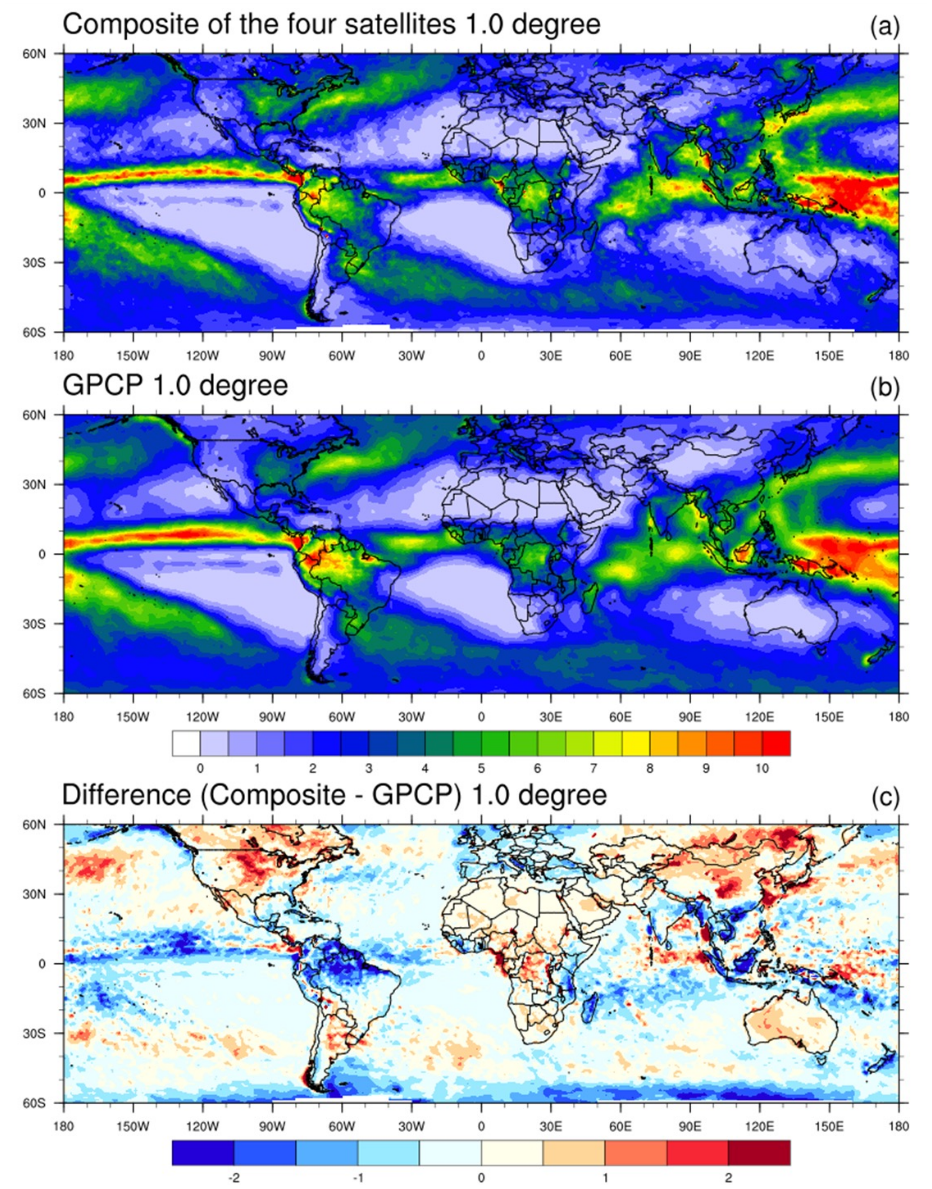


Comparison of 2019 Annual Daily Precipitation Rate: MiRS Composite and GPCP

- MiRS composite based on SNPP, N20, MetopB, MetopC.

- Good qualitative agreement.

- Tendency for MiRS > GPCP over N. America and Asia. (Light precipitation?)

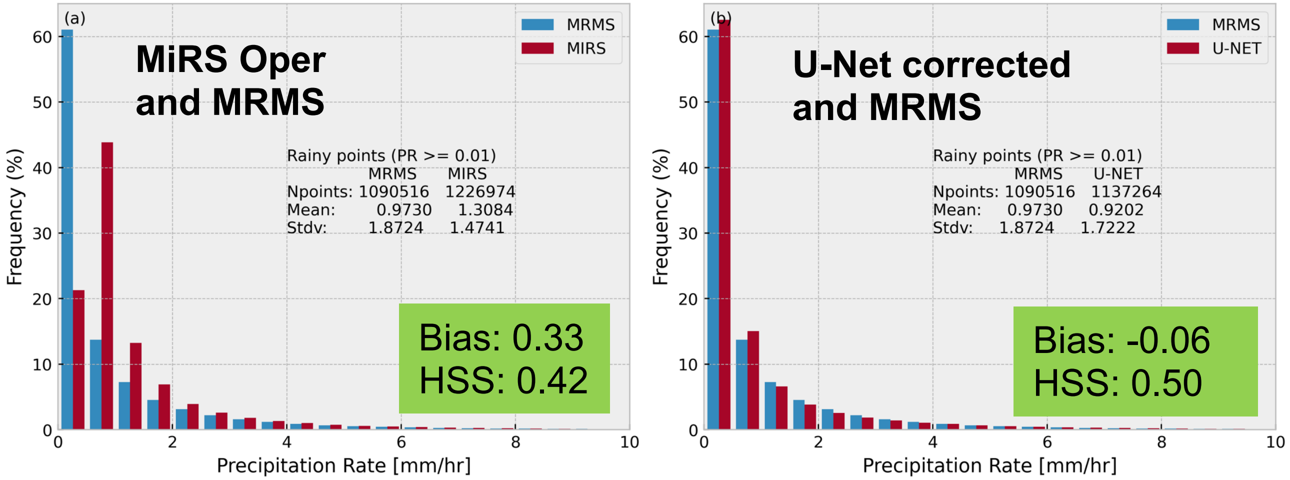


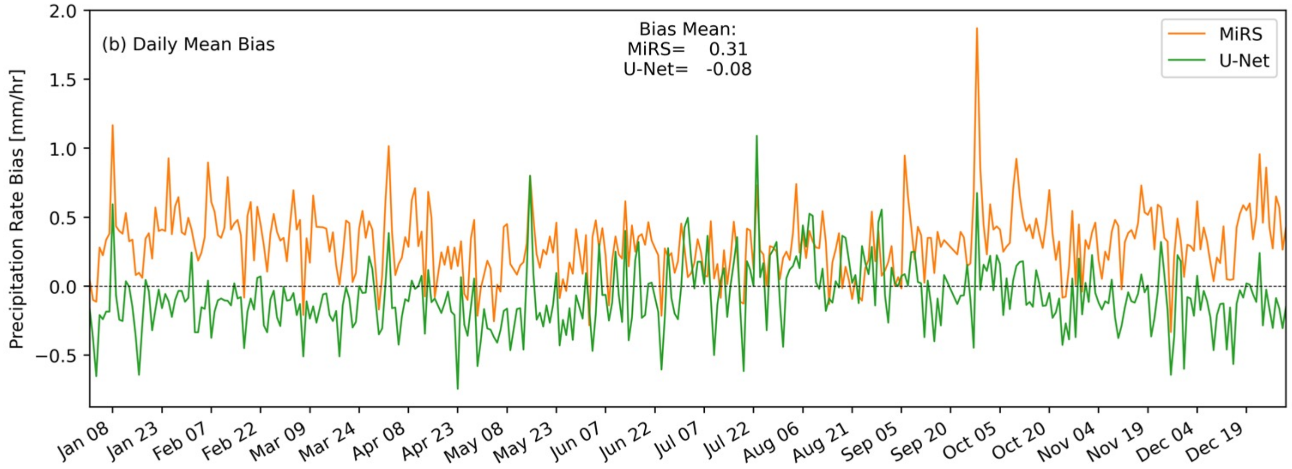
Ref: *Liu, et al., 2020: The NOAA Microwave Integrated Retrieval System (MiRS): Validation of Precipitation from Multiple Polar-Orbiting Satellites. JSTARS.*

Machine Learning: U-Net to correct MiRS precipitation

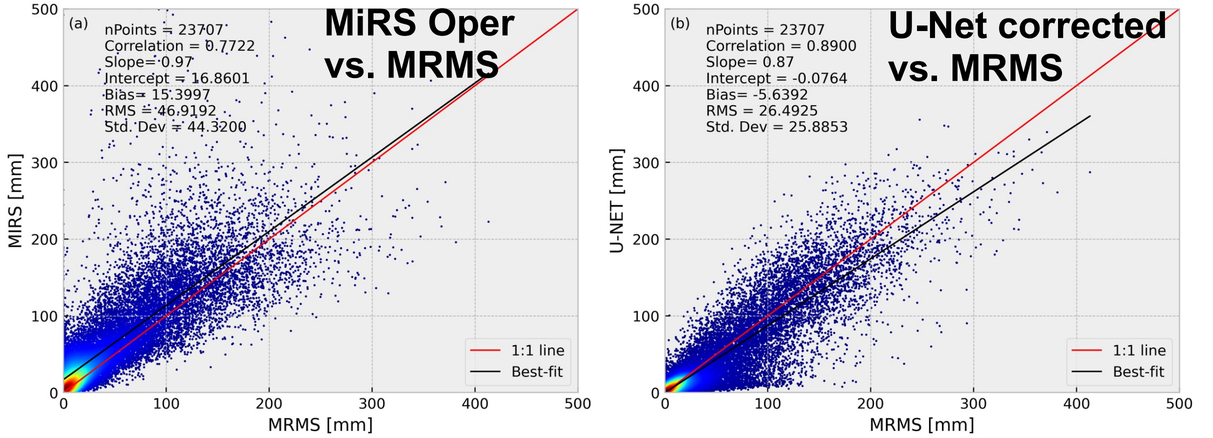
- Explosion in ML/AI applications driven by increasing availability of software tools (e.g. TensorFlow) and processing resources (GPUs).
- U-Net: type of CNN originally developed for biomedical image classification.
- One year (2021) of collocated MiRS N20 and MRMS data used to train U-Net. Tested on independent data in 2022.

MiRS operational and U-Net corrected (Jan-Dec 2022)



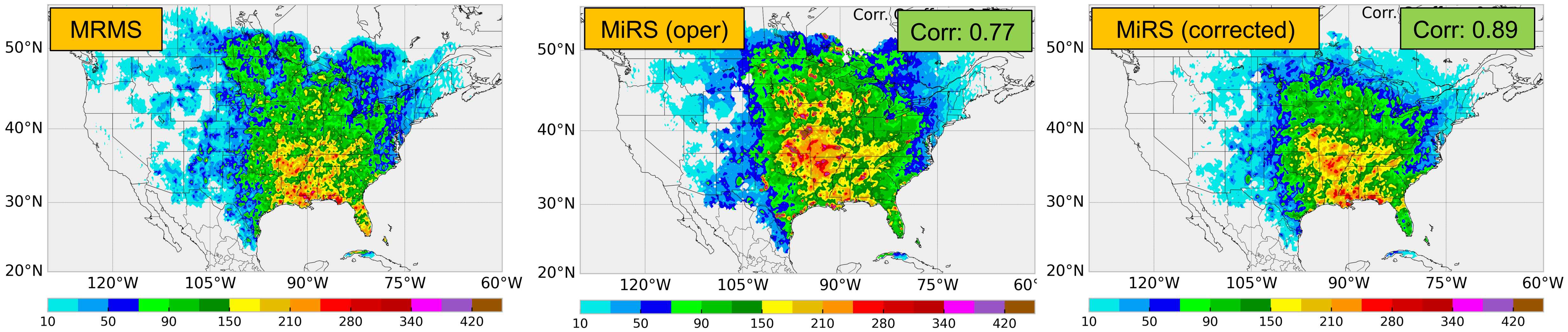


MiRS operational and U-Net corrected accumulated (Jan-Dec 2022)

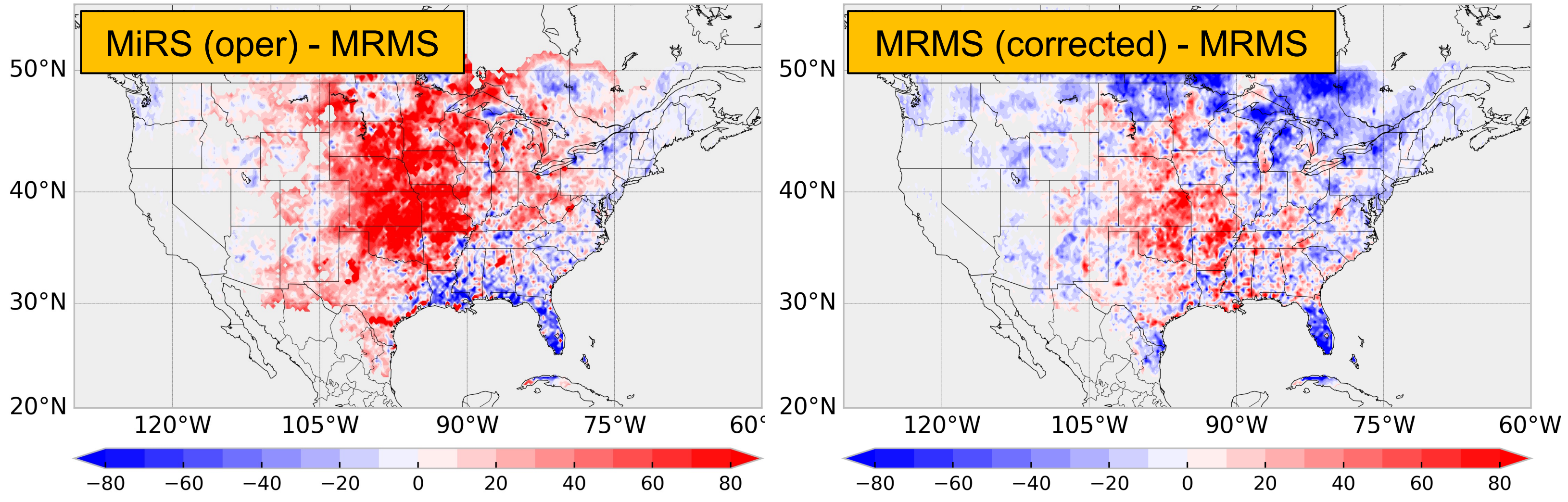


Ref: *Liu et al., 2023: Use of a U-Net Architecture to Improve Microwave Integrated Retrieval System (MiRS) Precipitation Rates, Submitted to TGRS.*

Machine Learning: U-Net to correct MiRS precipitation



2022 Accumulated Precipitation



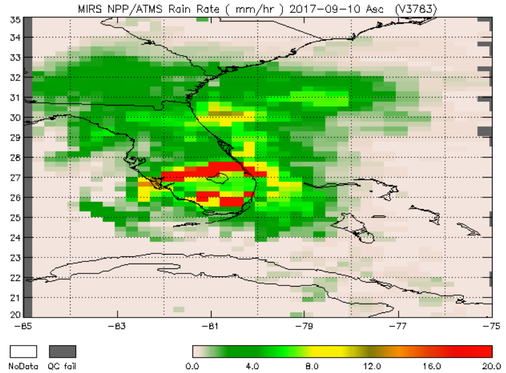
- Generalizability of model to other regions/surface types to be tested.

Ref: *Liu et al., 2023: Use of a U-Net Architecture to Improve Microwave Integrated Retrieval System (MiRS) Precipitation Rates, Submitted to TGRS.*

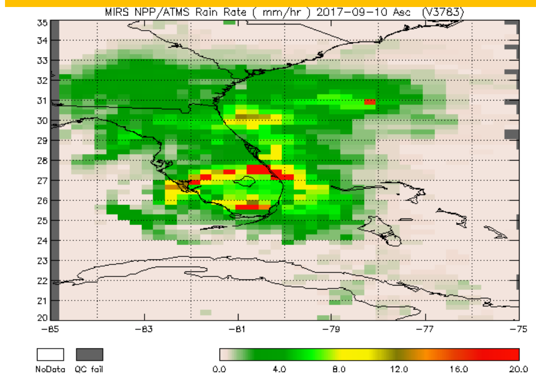
Impact of hydrometeor size assumption: Hurricane Irma (2017-09-10)

- MiRS uses CRTM 2.1.1. for RT model and Jacobians.
- Uncertainty related to hydrometeor microphysics assumptions:
  - Scattering theory (CRTM 2.1.1 assumes spherical shapes (Mie) for both liquid and frozen particles).
  - Particle distribution: size, (shape, orientation)

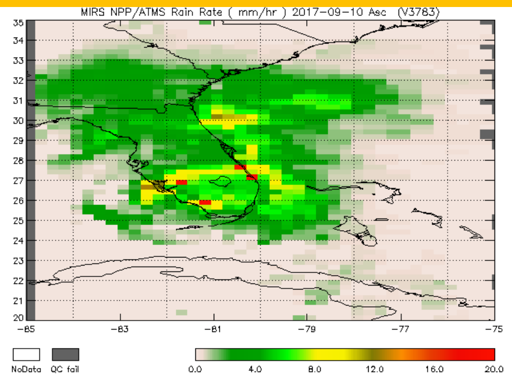
Oper (Reff=500 µm)



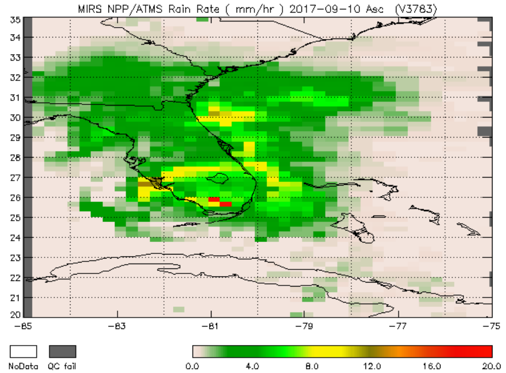
RW= 600 µm, GW= 500 µm



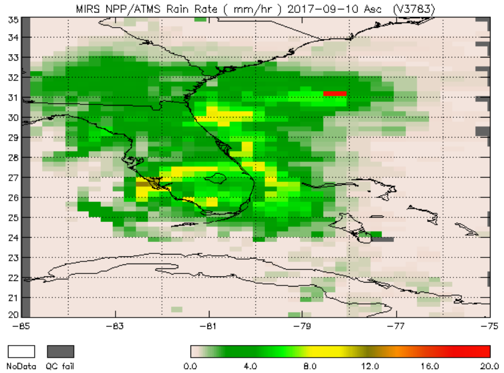
RW= 600 µm, GW= 600 µm



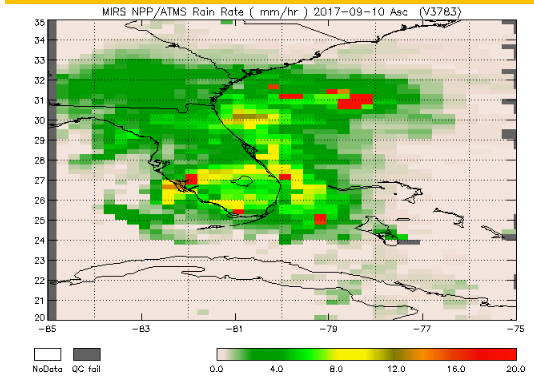
RW= 650 µm, GW= 650 µm



RW= 700 µm, GW= 700 µm



RW= 750 µm, GW= 500 µm

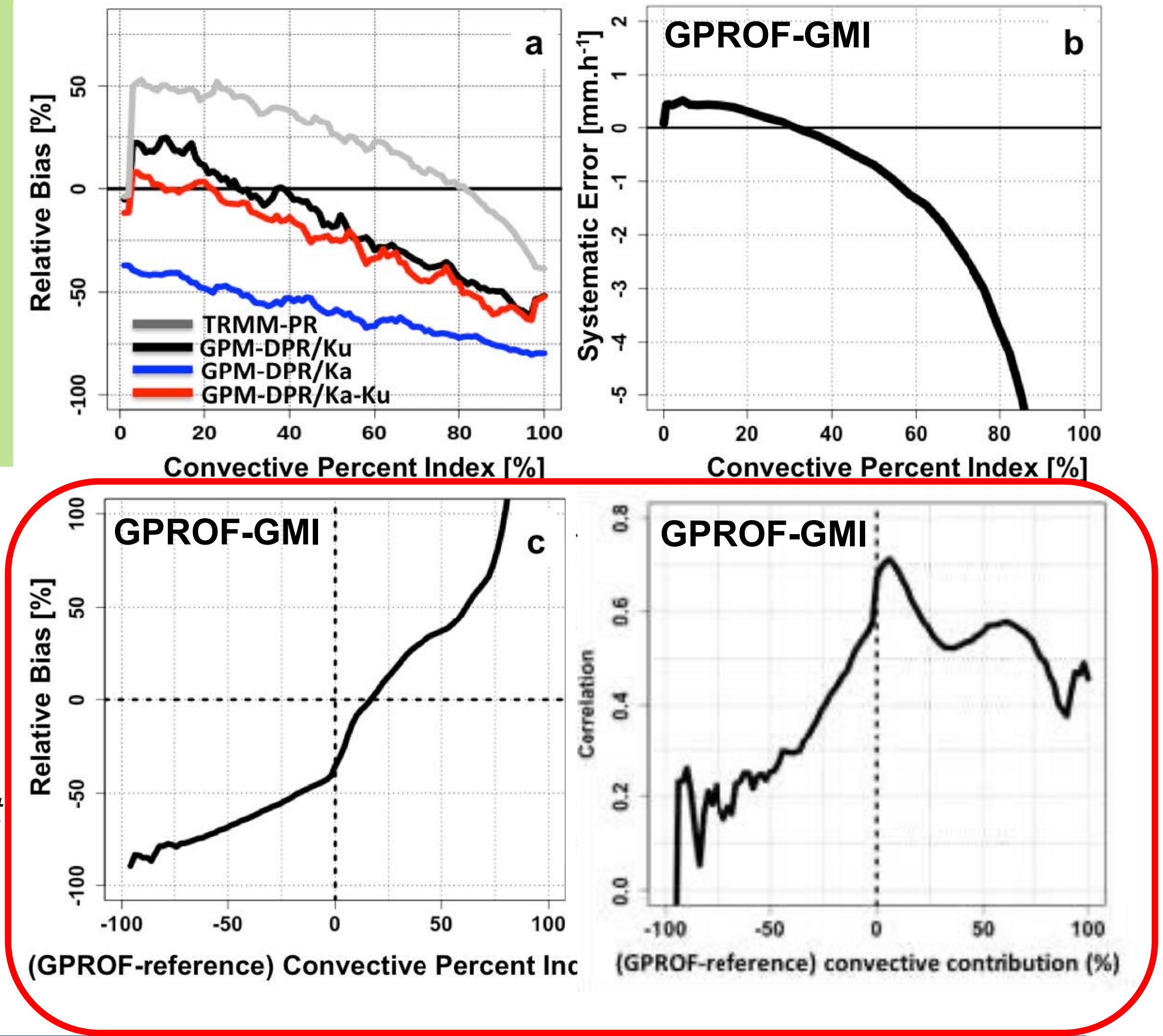


- MiRS assumes effective radius of 500 µm for all scenes.
- In extreme events, this is probably suboptimal.
- Possible approaches:
  - Extend CRTM to output particle size Jacobians and include in retrieval state vector.
  - Preclassification of each FOV to infer particle size and specify in CRTM.
  - Upcoming CRTM 3.0 will have new scattering tables (using DDA).

Precipitation type

- Precipitation type (e.g. convective/stratiform) linked to different microphysical processes, atmospheric dynamics/stability, hydrometeor distributions.
- Algorithm performance dependent on dominant precipitation type.
- Errors in classified type can propagate to precipitation estimates.

Algorithm performance using MRMS as reference



- Retrieval errors minimized when FOV convective percentage agrees with ground reference (MRMS)

Ref:

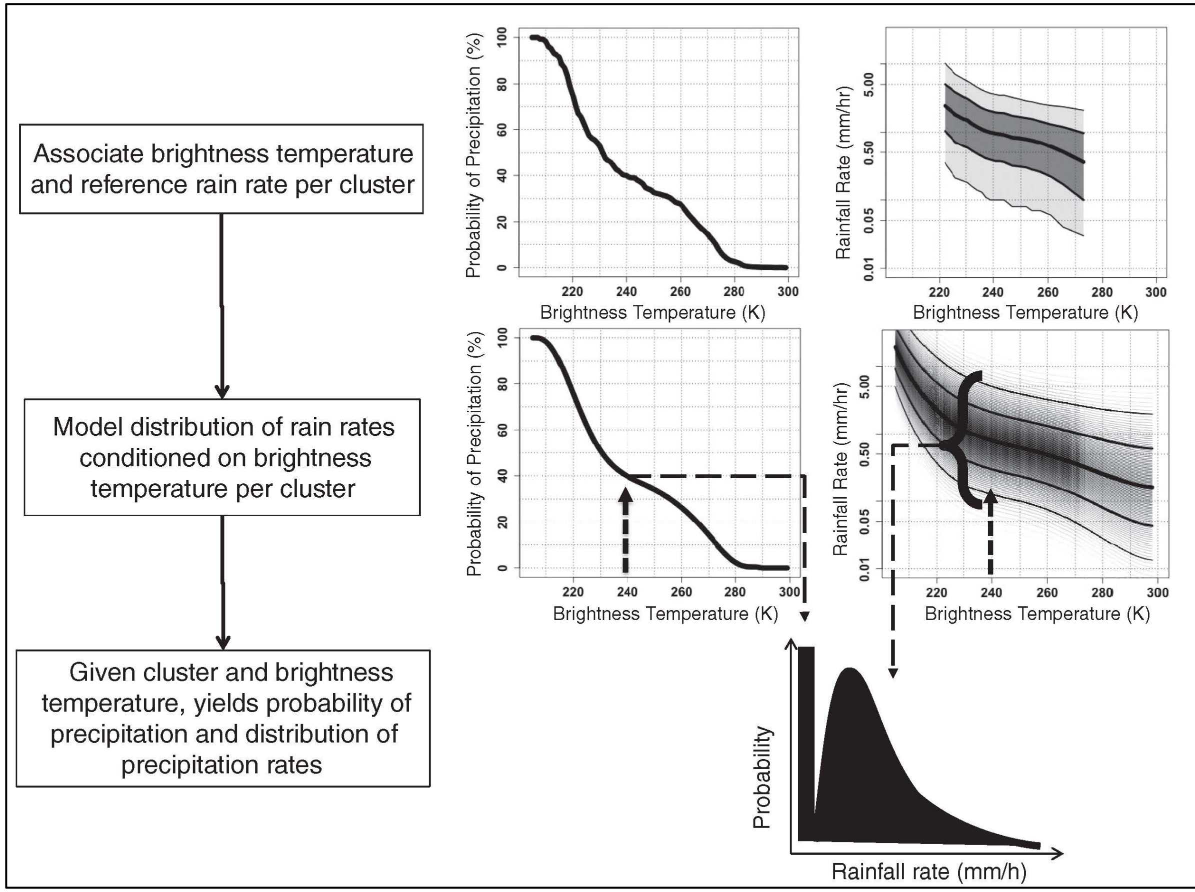
Kirstetter, The Joint IPWG/GEWEX Precipitation Assessment. WCRP Report 2/2021, World Climate Research Programme (WCRP)

Kirstetter et al, 2020: Integrated Multi-satellite Evaluation for the Global Precipitation Measurement: Impact of Precipitation Types on Spaceborne Precipitation Estimation, Satellite Precipitation Measurement, Vol. 2.

Other Challenges

- Precipitation over snow/ice and surface type characterization.
  - Leverage existing precip over snow datasets (e.g. engage with GPM team) to train a preclassification scheme; Adjust 1DVAR constraints.
- Uncertainty estimation:
  - Provision of uncertainty estimates would help users: how to weight multiple estimates in blended products (e.g. CMORPH, IMERG), provide level of confidence for users.
- Frozen precipitation (microphysics, surface characteristics).
- (Inter)calibration.

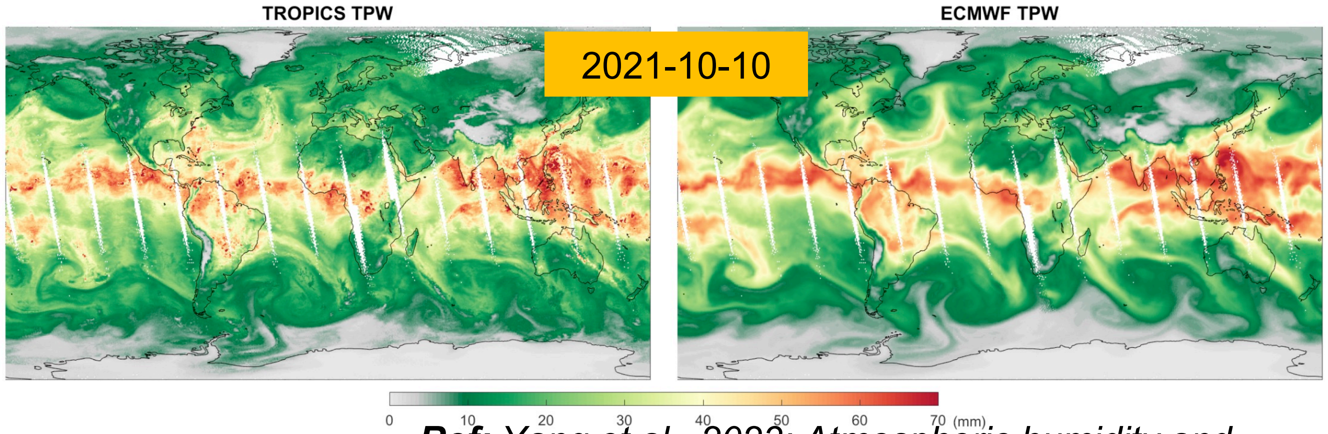
IR Application: POP and PDF estimation within PERSIANN clustering scheme



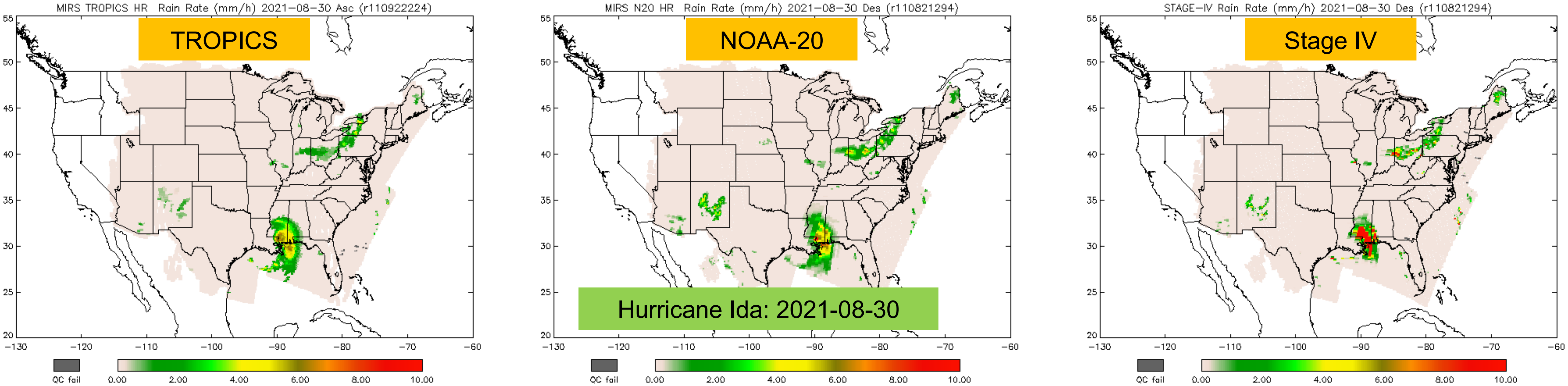
Ref: *Kirstetter et al. 2015: Probabilistic precipitation rate estimates with space-based infrared sensors. QJRMS.*

Potential Opportunities: SmallSats and Future Operational Sensors (e.g. TROPICS)

- MiRS extended to TROPICS TMS data (collaboration with TROPICS science team).
- NOAA QuickSounder/EDU (2025-2026)
- MiRS planned for EPS-SG/MWS (Q1 2025)
- Other opportunities:
  - TEMPEST-D (INCUS, 2026)
  - tomorrow.io (active PR constellation > 2025)
  - EPS-SG/MWI+ICI (Q4 2025)



***Ref:** Yang et al., 2023: Atmospheric humidity and temperature sounding from the CubeSat TROPICS mission: Early performance evaluation with MiRS. Remote Sensing of Environment*



Questions

- What is NOAA’s strategy to leverage increasing deployment of SmallSats (also EPS-SG/ICI)? Pathfinder/demonstration missions vs. operational systems. (NOAA/OSAAP)
  - Space based precipitation radars? (e.g. planned tomorrow.io constellation).
  - Cal/val process (shorter lifecycles) and data processing infrastructure (e.g. bandwidth).
  - Funding? (MiRS has a small team and multiple satellites/products to monitor/validate). Currently, funding weighted toward traditional large payloads.