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Workshop on Precipitation Estimation from LEO Satellites: Retrieval and Applications

A Report of The Virtual NOAA Workshop on Precipitation Estimation using LEO Satellite Information

Center for Hydrometeorology and Remote Sensing,

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Contents

Abbreviations and acronyms

Acronyms	Description
AIRS	Atmospheric Infrared Sounder
ALPW	Advected Layer Precipitable Water
AMSR	Advanced Microwave Scanning Radiometer
AMSU	Advanced Microwave Sounding Unit
AMW	Active Microwave
AOS	Atmospheric Observation System
ATMS	Advanced Technology Microwave Sounder
AVHRR	Advanced Very High Resolution Radiometer
AWC	Aviation Weather Center
AWS	Arctic Weather Satellite
CDRs	Climate Data Records
CGMS	Coordination Group for Meteorological Satellites
CHRS	Center for Hydrometeorology and Remote Sensing
CIMR	Copernicus Imaging Microwave Radiometer
CIMSS	Cooperative Institute for Meteorological Satellite Studies
CIRA	Cooperative Institute for Research in the Atmosphere
CISESS	Cooperative Institute for Satellite Earth System Studies
CMORPH	Climate Prediction Center Morphing
CNN	Convolutional Neural Network
CONUS	Continental United States
CORRA	Combined Radar Radiometer Algorithm
COWVR	Compact Ocean Wind Vector Radiometer
CPC	Climate Prediction Center
CPR	Cloud Profiling Radar
CRTM	Community Radiative Transfer Model
CSPP	Community Satellite Processing Package
DB	Direct Broadcast
DMSP	Defense Meteorological Satellite
DPR	Dual-frequency Precipitation Radar
EarthCARE	Earth Clouds, Aerosols, and Radiation Explorer
EIA	Earth Incidence Angle
EPOCH	Ensemble Prediction of Oceanic Convective Hazards
EPS-SG	EUMETSAT Polar System – Second Generation
ESA	European Space Agency
ESMR	Electronically Scanning Microwave Radiometer.
EUMETSAT	European Organisation for the Exploitation of Meteorological Satellites
GCOM-W	Global Change Observation Mission
GEO	Geostationary Earth-Orbiting
GeoXO	Geostationary Extended Observations

Acronyms	Description
GEWEX	Global Energy and Water Exchanges
GINA	Geographic Information Network of Alaska
GMI	GPM Microwave Imager
GOSAT-GW	Global Observing SATellite for Greenhouse Gases and Water Cycle
GPCP	Global Precipitation Climatology Program
GPM	Global Precipitation Measurement
GPROF	Goddard Profiling Algorithm
GSMaP	Global Satellite Mapping of Precipitation
HISA	Hurricane Structure and Intensity Algorithm
ICI	Ice Cloud Imager
IDSS	Impact-Based Decision Support Services
IMERG	Integrated Multi-satellitE Retrievals for Global Precipitation Measurement
IPWG	International Precipitation Working Group (IPWG)
IR	Infrared
ISCCP-NG	International Satellite Cloud Climatology - Next Generation
JAXA	Japan Aerospace Exploration Agency
JPSS	Joint Polar Satellite System
LEO	Low Earth-Orbiting
MERRA 2	Modern-Era Retrospective Analysis for Research and Applications, Version 2
METOP	Meteorological Operational Satellite
MHS	Microwave Humidity Sounder
MIRS	Microwave Integrated Retrieval System
ML	Machine Learning
MRMS	Multi-Radar Multi-Sensor
MW	Microwave
MWI	Microwave Imager
MWS	Microwave Sounder
NCEI	National Centers for Environmental Information
NESDIS	National Environmental Satellite, Data, and Information Service
NEXRAD	Next Generation Weather Radar
NIDIS	National Integrated Drought Information System
NOAA	National Oceanic and Atmospheric Administration
NWS	National Weather Service
OSSE	Observing System Simulation Experiments
PDF	Probability Density Function
PDIR	PERSIANN-Dynamic Infrared Rain Rate
PERSIANN-CCS	Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks-Cloud Classification System
PIA	Path Integrated Attenuation
PMM	Precipitation Measurement Missions
PMW	Passive Microwave
PQPE	Probabilistic QPE

Acronyms	Description
PR	Precipitation Radars
PSD	Particle Size Distribution
QPE	Quantitative precipitation Estimation
RR	Rain Rate
SCaMPR	Self-Calibrating Multivariate Precipitation Retrieval
SD	Snowfall Detection
SFR	Snowfall Rate
SI	Scattering Index
SIGMETs	Significant Meteorological Information
SPI	Standardized Precipitation Index
SPPs	Satellite Precipitation Products
SSM/I	Special Sensor Microwave/Imager
SSMIS	Special Sensor Microwave Imager/Sounder
TB	Brightness Temperature
TCA	Triple Collocation Analysis
TCs	Tropical Cyclones
TEMPEST	Temporal Experiment for Storms and Tropical Systems
TOVS	TIROS Operational Vertical Sounder
TRMM	Tropical Rainfall Measurement Mission
TROPICS	Time-Resolved Observations of Precipitation Structure and Storm Intensity with a Constellation of Smallsats Mission
VIS	Visible
WFO	Weather Forecast Office
WMO	World Meteorological Organisation
WPC	Weather Prediction Center
WSF-M	Weather System Follow-on Microwave
XGB	eXtreme Gradient Boosting

Executive Summary

Satellite precipitation retrieval provides essential data over regions where in-situ measurements are limited. Low Earth Orbit (LEO) meteorological satellites operated by the National Oceanic and Atmospheric Administration (NOAA), the Japan Aerospace Exploration Agency (JAXA), the European Organization for the Exploitation of Meteorological Satellites (EUMETSAT), and other agencies worldwide have been the primary source of remotely sensed information used in global and regional precipitation estimation algorithms.

Under the guidance of Dr. Satya Kalluri, the Program Scientist for the Joint Polar Satellite System (JPSS) at NOAA's National Environmental Satellite, Data, and Information Service (NESDIS), the Center for Hydrometeorology and Remote Sensing (CHRS) at the University of California, Irvine has been tasked to bring together remote sensing precipitation experts. These experts comprise sensor and algorithm developers and operational data users. The purpose of this effort is to conduct a review of the existing and future requirements of LEO meteorological satellites. By bringing together a diverse range of expertise, the aim is to identify the current and emerging needs in this field for enhanced satellite-based precipitation monitoring and analysis.

The workshop was held on March 1 and 2, 2023. This workshop presents recommendations for addressing various aspects of precipitation sensing from LEO satellites in different areas: **Observation system requirements,** which consider the need for the satellite constellation or other platforms to ensure comprehensive coverage and data collection. **Value/impact studies** are critical for understanding the potential value and impact of the observation system. The workshop demonstrated the benefits and implications of implementing satellite-based precipitation estimation and analysis uncertainty. **Measurement requirements,** which cover measurement criteria, such as the required channels or sensors, should be addressed in the observation system designs. **Data delivery requirements** ensure efficient and effective data delivery. The workshop offers insights into factors like latency and availability that should be considered. **Algorithm development and applications,** which explore various applications by leveraging the observation system's capabilities. The workshop highlights the importance of algorithm development for processing and analyzing the collected data. Considering the above areas, the workshop was organized into four major themes:

- Theme 1: NOAA and international communities' plan on LEO satellites and sensors.
- Theme 2: Precipitation estimation and algorithms from LEO and combined satellite sensors.
- Theme 3: Precipitation estimation and uncertainties.
- Theme 4: Users and applications.

In summary, this workshop offers valuable recommendations to address the requirements and considerations associated with the satellite observation system, specifically emphasizing precipitation sensing. The participants and stakeholders have contributed key insights and recommendations presented in detail after each theme session in this document.

Four primary conclusions emerged overarching the workshop:

- The best precipitation product that NOAA generates now, and that can be improved upon in the future, is from an integrated satellite and surface observation approach; no single observation method can accomplish this on a global scale
- LEO passive MW (PMW) imagers serve as the backbone to the global satellite precipitation observation system, complemented by an expanding number of passive MW sounders. This sensor diversity requires accurate inter-sensor calibration with other similar class sensors, complemented with spaceborne radar and ground-based radars for validation.
- Frequent and low-latency observations are required to fulfill the multitude of NOAA operational responsibilities such as weather, water, climate, and aviation hazards
- Scientific advances are needed to optimize the information content provided by satellite and surface observations; approaches such as AI/ML should continue to be pursued

A summary of the recommendations that emerged from each theme are listed below:

On observation system and data delivery requirements:

- NOAA should actively engage with national and international partners to ensure the continuity and expansion of sensors with precipitation-sensing microwave (MW) capabilities so as to achieve hourly to sub-hourly refresh rate. Such capability is crucial for NOAA operations and the application communities at large.
- Operational users require timely access to low-latency satellite data (one hour or less) for nowcasting and short-term forecasting. NOAA should prioritize the efficient acquisition of sensor data by developing capacities for near-real-time data downlinks through ground stations or expanding the Direct Broadcast networks from both NOAA and partner agencies. This includes the acquisition of legacy sensor data. Sun-synchronous operational MW observations should be augmented with additional asynchronous MW observations and more frequent geostationary full disk infrared (IR) observations.
- Sustaining a joint satellite precipitation radar and conically scanning PMW radiometer reference capability, currently provided by the GPM core spacecraft, is critically essential for the intercalibration of constellation radiometers used in Level-3 global precipitation datasets.

On value/impact studies:

- NOAA should routinely invest in performing sensor impact studies on precipitation products whenever new observation capabilities emerge from domestic, international, and private sector partners. Additionally, such impact studies should be performed before existing observation capabilities are considered for elimination for use by NOAA.
- International Precipitation Working Group (IPWG) is a central platform for the scientific community to collaborate on issues related to precipitation retrievals, supporting the future of

precipitation-oriented missions. NOAA should continue its engagements with IPWG activities to refine existing techniques, develop innovative methodology, and, most importantly, address the challenges in the field.

On measurement requirements:

- It is recommended to use satellite/sensor impact study results to define and specify desired channel requirements, including resolution and polarization for PMW-based rainfall and snowfall retrieval, including window channels near 6, 10, 19, 37, and 89 GHz, together with temperature and water vapor sounding bands near 23, 50, 118, 166, and 183 GHz and higher (**Table 1**).

Table 1. *Recommended channels for PMW-based rainfall and snowfall retrievals*

Frequency (GHz) / Characteristics	10 H/V	19 H/V	23 H/V	31-37 H/V	50-55 H/V	89 H/V	166 H/V	183 H/V
Light rain over land					x	x	x	x
Heavy rain over land	x	x	x	x	x	x	x	x
Light rain over ocean	x	x	x	x	x			
Heavy rain over ocean	x	x	x	x	x	x	x	x
Snowfall detection over land		x	x		x		x	x
Snowfall detection over ocean		x	x	x	x		x	x
Snowfall rate over land		x	x	x	x	x	x	x
Snowfall rate over ocean				x	x	x	x	x

- NOAA should prioritize improving the resolution of MW sounders, as their current coarse resolution limits the accuracy and the applications of MW precipitation products, particularly for extreme precipitation.

On algorithm development and applications:

- Assessing uncertainty using prognostic approaches, employing probabilistic methods, leveraging global radar and ground observations beyond the continental US, and considering robust data-driven techniques (e.g., Machine Learning) are strongly recommended to enhance satellite precipitation estimation.
- Collaboration with the user community is important to define requirements for establishing robust Climate Data Records (CDRs) using precipitation radar reference, considering the long duration of operational PMW satellites extending back to 1987 with the Special Sensor Microwave Imager (SSMI) series.
- Using spaceborne radars for calibrating passive sensors and integrating ground-based observations are essential for diagnosing errors and improving the accuracy of precipitation retrievals. It is advisable to incorporate precipitation parameterizations and "a priori" information from ground observations to mitigate uncertainties in spaceborne radar observations, leading to more accurate and reliable multi-satellite precipitation retrievals.

- To effectively utilize satellite products in hydrological modeling, water resources management, and climate studies, incorporating location-specific error and uncertainty models that account for regional variability, timeframes, precipitation events, and application domains is recommended.

Introduction

Precipitation is the fundamental component of the Earth's hydrological cycle and plays a critical role in understanding global water resources. Accurate precipitation estimation is essential for assessing the current state of water availability and distribution worldwide. Numerous operational agencies, research institutions, and academic organizations provide global and regional satellite-based precipitation data, serving as valuable resources for flood forecasting and managing water resources in remote areas. Comparative analysis of these high-resolution satellite algorithms and products has revealed both their strengths and limitations in retrieving precipitation from satellite-based information. Moreover, those algorithms/data offer variable insights but also come with notable uncertainty, especially when dealing with extreme weather events and complex terrains. Recognizing and addressing these uncertainties is crucial for improving the accuracy and reliability of satellite-based precipitation measurements.

The National Environmental Satellite, Data, and Information Service (NESDIS) is actively exploring innovative technologies and applications of precipitation estimation using microwave imagers to enhance the capability of the JPSS Program and pave the way for future missions. To gather valuable inputs and guidance for future mission planning in precipitation estimation using Low-Earth-Orbiting satellites, the NESDIS JPSS program sponsored a workshop hosted by the Center for Hydrometeorology and Remote Sensing (CHRS) at the University of California Irvine. The workshop brought together expert scientists and participants from various organizations worldwide, creating a collaborative discussion and knowledge exchange platform.

Four major themes were presented and discussed during the virtual workshop held on 1-2 March 2023. These themes encompassed various aspects of NOAA and International Communities' plan for LEO satellites and sensors, precipitation measurements and algorithms utilizing LEO and combined satellite sensors and platforms, precipitation products and uncertainties in real-time and climate data), and users and applications. More than 100 participants worldwide joined in the workshop. The attendees included experts in remote sensing instruments and technologies, developers of precipitation algorithms, and users of precipitation data and their respective applications. The workshop covered various topics, including presenting and discussing operational sensors, algorithms, and products from past, current, and future satellites. Additionally, long-term climate datasets were a subject of focus.

Background

The conventional method of measuring surface precipitation using in-situ gauges is limited due to their uneven distribution, which fails to adequately capture precipitation variability, particularly in remote and high-altitude areas (Kidd et al., 2017). Ground-based weather radar networks, where available, offer the advantage of estimating precipitation over large areas. However, they still face limitations in complex terrains and coastal regions (Sun et al., 2018; Maddox et al., 2002). In recent decades, meteorological satellites have extended observation capabilities and provided sustained information for high spatiotemporal resolution precipitation estimation (Sorooshian et al., 2000; Houze, 2014; Levizzani et al., 2020a,b). Satellite sensors have been instrumental in developing global-scale precipitation products that effectively map precipitation variabilities and properties. Obtaining high spectral, spatial, and temporal resolution information from satellite sensors is essential to achieve accurate and comprehensive precipitation mapping. These advanced capabilities enable a more detailed and comprehensive understanding of precipitation patterns and dynamics on a global scale. Another critical factor in utilizing precipitation data is the time latency or delay between observation and delivery of precipitation products. Minimizing data latency ensures that decision-makers and stakeholders can access up-to-date and accurate precipitation data for effective decision-making and timely response to weather events.

Various operational agencies, research institutions, and academic organizations have developed high-resolution global and regional satellite-based rainfall products. These products leverage different retrieval algorithms and data sources to provide comprehensive precipitation datasets at both near-real-time and climate scales. Hereafter some examples are listed. Goddard Profiling Algorithm (GPROF): developed by NASA Goddard Space Flight Center. GPROF utilizes PMW observations from LEO satellites to estimate precipitation (GPROF; Kummerow et al., 1996, 2015). Integrated Multi-satellitE Retrievals for Global Precipitation Measurement (IMERG): IMERG is a product developed by NASA's GPM mission; it combines information from multiple satellites, including both LEO and GEO satellites, to provide global precipitation estimates at high spatial-temporal resolution (IMERG; Huffman et al., 2020). Global Satellite Mapping of Precipitation (GSMaP): developed by Japan Aerospace Exploration Agency (JAXA), GSMaP utilizes data from GEO and LEO satellite sensors to generate a global precipitation map (GSMaP; Kubota et al., 2007; Aonashi et al., 2009; Ushio et al., 2009). Climate Prediction Center (CPC) Morphing Technique (CMORPH): CMORPH, developed by the NOAA Climate Prediction Center, uses a morphing technique to enhance the spatial and temporal resolution of the precipitation fields (CMORPH; Joyce et al., 2004). Scattering Index (SI): The SI algorithm utilizes PMW observations and scattering properties of precipitation particles to estimate precipitation (SI; Ferraro & Marks, 1995). Self-Calibrating Multivariate Precipitation Retrieval (SCaMPR): SCaMPR, developed by NESDIS NOAA, combines GEO and LEO precipitation estimates. It employs a self-calibration approach to improve the accuracy of the precipitation retrievals (SCaMPR; Kuligowski, 2002). Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks-Cloud Classification System (PERSIANN-CCS): developed by researchers at UC Irvine, employs artificial neural networks and cloud classification techniques to estimate precipitation from satellite data (PERSIANN-CCS; Hong et al., 2004). PERSIANN-Dynamic Infrared Rain Rate (PDIR): PDIR, also developed by UC Irvine, uses infrared satellite observations, calibrated by LEO PMW-derived precipitation to estimate rainfall rates (PDIR; Nguyen et al., 2020). These are just a few examples of the operational satellite retrieval algorithms available for near-global-scale precipitation estimation. Such algorithms leverage data from LEO and sometimes combine it with data from GEO satellites to provide valuable precipitation information for near-real-time monitoring and climate studies.

Near-real-time precipitation products can be combined with hydrological models to monitor and forecast floods effectively. Moreover, obtaining precipitation estimates at high spatiotemporal resolution is valuable for various applications. In the context of hydropower generation management, accurate and frequent precipitation data enables operators to optimize the operation of reservoirs and dams, considering the inflow of streamflow and making informed decisions regarding energy generation. For agriculture, high-resolution precipitation estimates can contribute to forecasting crop yield. Long-term climate precipitation records can be critical for trend analysis and understanding the effects of climate change. Long-term records provide valuable insights into droughts' spatial and temporal distribution, allowing for the development of strategies to mitigate their impacts and plan appropriate adaptation measures, such as effective water management and drought-resistant crop cultivation.

This report provides a summary of the workshop, which brought together participants from diverse disciplines, including remote sensing experts, precipitation algorithm developers, weather forecasting experts, and water resources management users. The workshop encompassed presentations and panel discussions, covering four major themes:

- **Theme 1:** Exploration of current and future missions, sensors, and challenges associated with NOAA and International agencies' LEO satellites and programs.
- **Theme 2** Discussion of satellite-based precipitation algorithms and datasets derived from PMW imagers and sounders on LEO satellites. Experts from operational agencies and academic institutions were invited to present and discuss the current and near-future PMW constellation and sensors utilized for satellite-based precipitation. Additionally, the use of GEO satellite sensors and algorithms to enhance temporal sampling by combining multiple satellite estimations and products was discussed.
- **Theme 3:** Presentation and discussion on quantifying the uncertainties of the products at short-term and climatological scales, as well as addressing time latency for user applications.
- **Theme 4:** Focus on NOAA operational users and applications since the data products and services are critical for societal applications, including the private weather forecasting industry.

This report summarizes the key outcomes of the workshop, providing practical recommendations for NOAA's future meteorological satellite operations and observations relevant to precipitation.

Theme 1: NOAA and International Communities' Plan on LEO Satellites and Sensors

NOAA operates one of the three primary LEO baseline satellites through the NOAA satellite series in the afternoon orbit, nominally at 1330 Local Standard Time (LST). This includes NOAA's Joint Polar Satellite System (JPSS) Advanced Technology Microwave Sounder (ATMS) PMW sensor. Through partnerships with national and international agencies, NOAA obtains near-real-time data at approximately 4-hourly temporal sampling, including those from PMW sensors such as the Global Change Observation Mission (GCOM-W), Advanced Microwave Scanning Radiometer (AMSR)-2 and Meteorological Operational Satellite (METOP) Advanced Microwave Sounding Unit (AMSU)/Microwave Humidity Sounder (MHS) sensors. By maintaining the operation of legacy satellites (even if in degraded sensor operation), including those from the Defense Meteorological Satellite Program (DMSP) Special Sensor Microwave Imager/Sounder (SSMIS), more frequent observations of precipitation systems can be maintained and approach the needs of the precipitation community. Challenges exist in obtaining all these measurements in real-time through existing ground station configurations.

Over the next several years, EUMETSAT and JAXA will introduce advanced PMW observations on next-generation satellites. These are urgently needed to maintain and enhance the observation of precipitation systems. Additionally, emerging small satellites, such as those in demonstration mode from NASA programs, offer the potential to complement the baseline satellite configuration. Also, plans from commercial satellite ventures provide additional temporal and spatial coverage that NOAA can exploit.

Satellite Global Precipitation Measurement: The Story So Far

Precipitation detection and quantification are challenging and vary tremendously over regions and requirements. Local short time scale data are essential for small river basins, while global time-averaged data is needed to monitor the Earth's climate system. Detecting the various forms of precipitation is also necessary – drizzle, snow, mixed phase – depending on climate regimes. All these considerations must be accounted for when determining the optimal observing system, which includes ground measurements (gauges, radars) and satellite systems (visible (VIS), infrared (IR), and microwave (MW) portions of the electromagnetic spectrum). A review of available sensors and measurement techniques is presented in **Table 2**. The existing precipitation products exhibit a range of attributes due to the temporal and spatial characteristics associated with each observation method. In this theme, which emphasizes satellite observations, a more comprehensive examination of these measurement techniques was undertaken to gain deeper insights.

Table 2. *A summary of observation methods and their attributes for precipitation (Source: Chris Kidd).*

Instrument	Temporal	Spatial	Notes
Gauges: accumulation	**Variable**	**Point**	**Temporal scale depends upon frequency of observation**
Gauges: Tipping Bucket	**Quantised**	**Point**	**Quantisation of bucket (0.1, 0.2 mm or 1/100'') and data logger**
Disdrometers	Instantaneous	Point	Individual drop measurements
Micro rain radar	Instantaneous	Point	Vertical profile up to 256 levels/10 s sampling
Weather radar	**Instantaneous**	**Radial**	**Radial measurements of dBZ converted to Cartesian grid**
Microwave links	Instantaneous	Linear	Line of sight measurements along the length of the link
Visible imagery	Instantaneous	1-4 km	Intermittent (LEO) 15 min sampling (GEO)
Infrared imagery	**Instantaneous**	**1-4 km**	**Intermittent (LEO) 15 min sampling (GEO)**
Passive Microwave Imagers	**Column**	**5-25 km**	**Intermittent sampling (LEO)** **Resolution = frequency dependent**
Passive Microwave Sounders	**Column**	**16-48 km**	**Intermittent sampling (LEO)** **Resolution = frequency/scan position dependent**
Active Microwave (radar)	Instantaneous	5 km	c.80 vertical levels; Limited intermittent sampling (LEO)

Several LEO and GEO satellites and sensors exist. GEO offers continuous temporal coverage but is restricted to VIS and IR sensors which indirectly measure precipitation from cloud properties (Kidd & Levizzani, 2011). On the other hand, satellite PMW instruments date back to 1968 onboard NASA research satellites, with usable data starting around 1972 with the first Electronically Scanning Microwave Radiometer (ESMR). The first Special Sensor Microwave/Imager (SSM/I) was placed into operation in 1987 and began the most widely used period of record for PMW, see **Figure 1**. PMW are one the most direct remote sensing tools for precipitation estimation because they penetrate cloud tops and sense raindrops and ice associated with precipitation. That set the stage for two precipitation-focused missions, which included both PMW and active MW (AMW) radars: the Tropical Rainfall Measurement Mission (TRMM) in 1997 and the GPM mission in 2014 (Simpson et al., 1988; Hou et al., 2014). Both TRMM and GPM have become the cornerstones of precipitation science. At the time of the workshop, the most readily available PMW sensors are: GPM Microwave Imager (GMI), AMSR2, MHS, ATMS, and SSMIS. Altogether, these offer a mean revisit time of 3 hours 90% of the time. Ultimately, an ideal observing system combines the best attributes of all available measurements – gauges, ground radars, and all satellite observations. There are several widely used merged products in existence today.

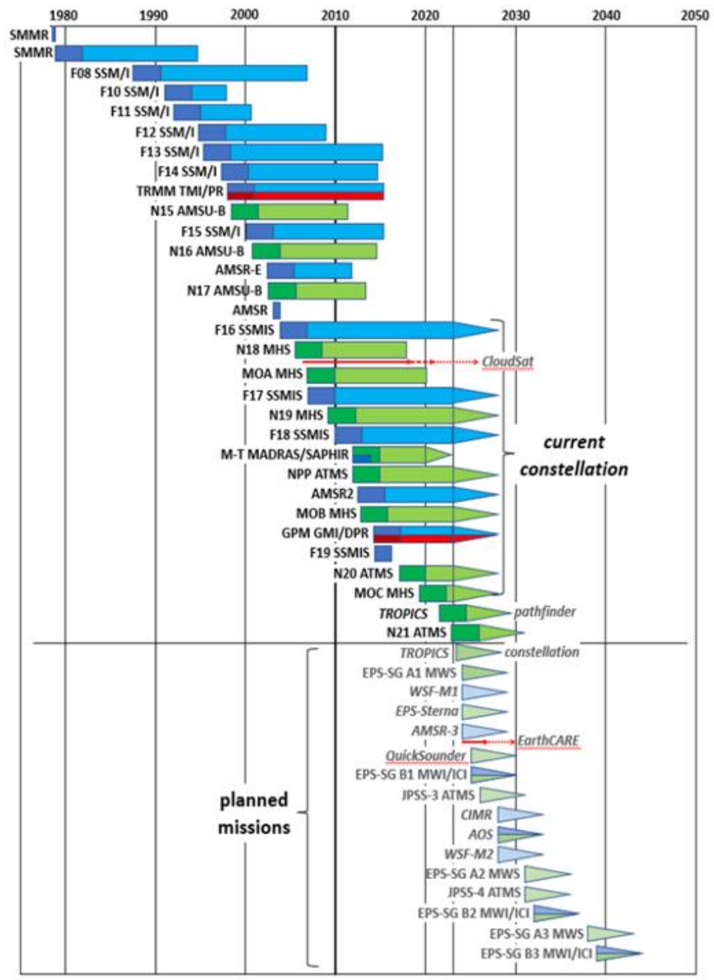


Figure 1. *History of microwave imagers, past, present, and future (Source: Chris Kidd).*

To address one of the workshop's objectives, ideal PMW channels on future sensors should be identified for NOAA to consider. A single-channel PMW sensor would not be adequate, yet, excluding a few channels from current sensor configurations would not diminish their utility. There are a host of future sensors that are coming from international partners, along with the increasing potential of Cube Satellites (e.g., the Time-Resolved Observations of Precipitation structure and storm Intensity with a Constellation of Smallsats (TROPICS) mission). These will be described in more detail later in Theme 1. A future constellation should include a set of “baseline” satellites in LEO with high-class sensors. Other attributes should include sampling at time and space scales that resolve the natural variability of precipitation. Continuing low-inclination satellite sensors, like GMI, is critical to serving as the primary calibrator to the overall constellation. Cube Satellites/Small Satellites may play an increasingly important role to the constellation; however, there are questions about their availability, if launched by the commercial sector, as well as cost, latency, and replenishment.

JAXA’s PMW Imagers and Cloud/Precipitation Radars

JAXA has a long legacy of PMW and AMW sensors that have significantly contributed to the precipitation community (**Figure 2**). These include the AMSR PMW (starting in 2002) and TRMM/GPM AMW sensors (Precipitation Radars (PR), Dual-frequency Precipitation Radar (DPR), the former starting in 1998). JAXA plans to continue enhancing these capabilities in the next-generation precipitation radar mission expected to be launched around 2028-2029 (Kidd et al., 2021).

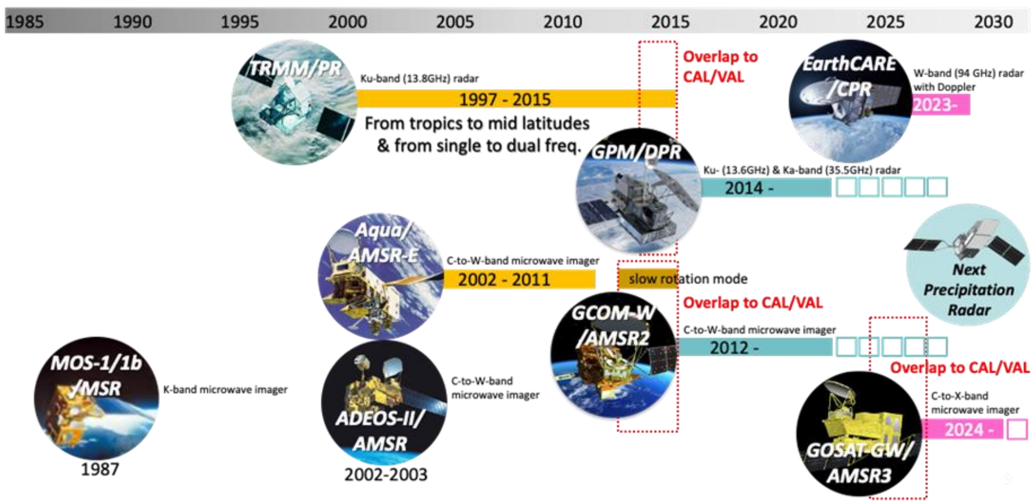


Figure 2. *Precipitation-related missions in Japan (Source: Misako Kachi and Takuji Kubota)*

AMSR3 will be launched on the Global Observing SATellite for Greenhouse Gases and Water cycle (GOSAT-GW) satellite in the 2024-25 timeframe and is expected to have at least one year of overlap with AMSR2 for calibration purposes. AMSR3 will have channels similar to AMSR2's but will also include additional high-frequency channels at 165 and 183 GHz sensitive to cold-season precipitation (details of sensor specifications as shown in **Table 3**). GOSAT-GW will maintain the 1330 equatorial crossing time, as is the case with GCOM-W. Due to a lower orbit of GOSAT-GW, global coverage will take longer than that of GCOM-GW AMSR2. AMW sensors (PR and DPR) can provide the 3D structure of global precipitation. The current data record is more than 20 years long. Over this period, major changes in the calibration of the radar retrievals led to the consistent long-term data record we have today. These calibration efforts did affect global precipitation maps from several merged precipitation products.

Table 3. *AMSR3 sensor specifications. Channels indicated in boldface text are additions for AMSR3 or changes from AMSR2 (Source: Misako Kachi and Takuji Kubota).*

Center frequency [GHz]	Polarization	Bandwidth [MHz]	NEDT (1σ)	Beamwidth (spatial resolution)
6.925—7.3	H/V	350	< 0.34 K	1.8° (34km x 58km)
10.25	**H/V**	**500**	**< 0.34 K**	**1.2° (22km x 39km)**
10.65	H/V	100	< 0.70 K	1.2° (22km x 39km)
18.7	H/V	200	< 0.70 K	0.65° (12km x 21km)

Center frequency [GHz]	Polarization	Bandwidth [MHz]	NEDT (1σ)	Beamwidth (spatial resolution)
23.8	H/V	400	< 0.60 K	0.75° (14km x 24km)
36.42	H/V	**840**	< 0.70 K	0.35° (7km x 11km)
89.0 A/B	H/V	3000	< 1.20 K	0.15° (3km x 5km)
165.5	**V**	**4000**	**< 1.50 K**	**AZ=0.23°/ EL=0.30° (4km x 9km)**
183.31±7	**V**	**2000×2**	**< 1.50 K**	**AZ=0.23°/ EL=0.27° (4km x 8km)**
183.31±3	**V**	**2000×2**	**< 1.50 K**	**AZ=0.23°/ EL=0.27° (4km x 8km)**

JAXA's primary global precipitation product is the GSMaP. It combines multiple PMW sensors, including AMSR, and GEO IR, to deliver hourly, 0.1-degree gridded products at various data latencies, including real-time (GSMaP NOW). It uses AMW sensors, TRMM/PR, and GPM/DPR as references and to develop databases for the PMW retrievals. Looking towards the future, JAXA has started discussions and studies on future PMW sensors, or AMSR3 follow-on, that include additional channels (e.g., submillimeter wave) and/or advanced observation capabilities requested from users. Additionally, the European Space Agency (ESA)-JAXA joint Earth Clouds, Aerosols and Radiation Explorer (EarthCARE) mission will be launched in 2024, and it will have a JAXA-developed Cloud Profiling Radar (CPR), allowing for light rain and snow retrieval. JAXA is also planning to develop the next-generation precipitation radar (a Ku-band Doppler Radar) that may be part of the NASA Atmospheric Observation System (AOS) currently being planned.

EUMETSAT Status/Plans for EPS-SG MWI/MWS, CIMR, EPS Sterna

The EUMETSAT Polar System – Second Generation (EPS-SG) is a follow-on mission of the current Metop and will fly in the mid-morning orbit. Unlike Metop, EPS-SG will consist of two satellites, A and B, operating in tandem (Mattioli et al., 2020; **Table 4**). The Microwave Sounder (MWS) sensor will replace the AMSU-A/MHS system and host 24 channels with FOV sizes ranging from 17 to 40 km, with frequencies covering the 23 to 229 GHz range. The Microwave Imager (MWI) and Ice Cloud Imager (ICI) conically scanning PMW imagers are new capabilities at EUMETSAT. The MWI will have 18 frequencies (26 channels) ranging from 19 to 183 GHz; ICI will have 16 frequencies (18 channels) ranging from 183 to 664 GHz. The ICI may be able to provide info on the shape of hydrometeors. The cross-scan sampling is high for both sensors (e.g., MWI will have ~1400 FOVs across the scan line). The MWS, MWI, and ICI are in synergy with other missions and will contribute to the GPM mission. The first satellites are expected to launch in 2024-2025. The ESA Copernicus Imaging Microwave Radiometer (CIMR) is of interest to the precipitation community. The CIMR is a conically scanning MW fully polarimetric radiometer to fly on a dawn-dusk orbit. This will ensure coordination with EPS-SG 1B (MWI is one of its payload sensors) in the Polar Regions, allowing for synergy. It will provide 95% of global coverage daily and operate in the frequency range of 1.4 GHz to 36 GHz. Of interest to the satellite precipitation community is the 5 km resolution of the 36 GHz channels, which is two times finer than the 10 km resolution of the MWI 89 GHz channels. CIMR is expected to be launched no earlier than 2028.

Table 4. *Comparison of Metop and EPS-SG sensors (Source: Christophe Accadia).*

Metop Payload	Metop-SG Payload	Metop-SG Satellite
Infrared Atmospheric Sounding Interferometer (IASI)	Infrared Atmospheric Sounding Interferometer – New Generation (IASI-NG)	A
Advanced Very High Resolution Radiometer (AVHRR)	Visible-Infrared Imager (METimage)	A
Advanced Microwave Sounding Unit A (AMSU-A1/A2), Microwave Humidity Sounder (MHS)	Microwave Sounder (MWS)	A
Global Ozone Monitoring Experiment 2 (GOME-2)	UV-VIS-NIR-SWIR Sounder (Sentinel-5)	A
Advanced Scatterometer (ASCAT)	Scatterometer (SCA)	B
Global Navigation Satellite System Receiver for Atmospheric Sounding (GRAS)	Radio Occultation (RO)	A and B
-	Microwave Imager (MWI)	B
-	Sub-mm wave Ice Cloud Imager (ICI)	B
-	Multi-viewing, -channel, -polarisation Imager (3MI)	A

Furthermore, EUMETSAT is exploring the possibilities offered by small satellites by preparing a program proposal called EPS Sterna to be proposed to its Member States. It builds upon ESA's Arctic Weather Satellite (AWS) – a small MW-sounding satellite to be launched in 2024. AWS will serve as an in-orbit demonstration for EPS Sterna. If approved, EPS-Sterna will complement and expand the EPS-SG and JPSS constellation in line with the EUMETSAT Strategy and the World Meteorological Organisation (WMO) guidelines. Sterna will have observation channels from 50 to 325 GHz to support National Weather Service (NWS) and nowcasting activities (especially over polar regions). Sterna alone should provide 90% global coverage every 3-5 hours, improving to 2.3-3.5 hours if Sterna, EPS-SG, and JPSS are used together (**Figure 3**).

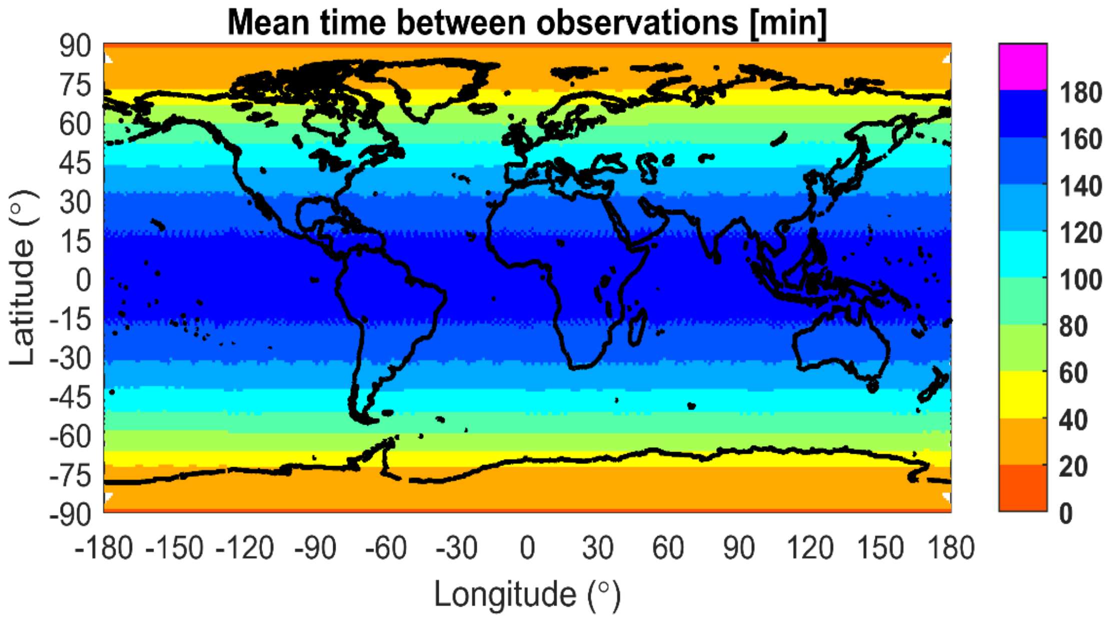


Figure 3. *Revisit time (minutes) for combined observation by Sterna, EPS-SG, and JPSS (Source: Misako Kachi and Takuji Kubota).*

TROPICS Pathfinder On-orbit Results and Status of the NASA TROPICS Constellation Mission

The TROPICS investigation consists of four small satellites (deployed in two separate launches in May 2023) and a pathfinder mission (deployed in June 2021). Each sensor has 12 channels (91 – 205 GHz) (Kidd et al., 2022). TROPICS satellites orbit in separate inclined orbit planes, improving the overall global revisit time. NOAA funded a low-latency experiment in April 2022; provisional data is now available to the general public. The Pathfinder imagery performs favorably compared with operational sensors such as ATMS (**Figure 4**). The sensors are expected to have a life span of two years each; this keeps the cost low, but they are expected to operate much longer. There is no current plan to replenish the sensors. Still, it is envisioned that private sector companies will build and operate similar sensors – in particular, tomorrow.io has announced plans to fly a constellation of 18 microwave-sounding Cubesats based on TROPICS technology.

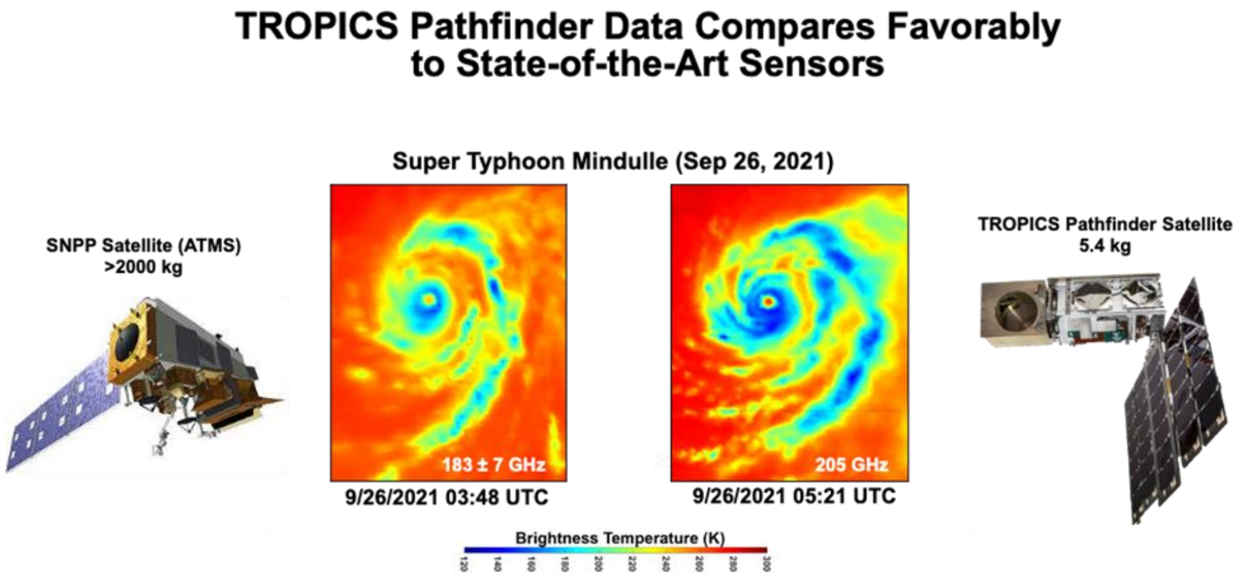


Figure 4. *Comparison of S-NPP ATMS 183 +/- 7 GHz (left) and TROPICS Pathfinder 205 GHz (right) for Super Typhoon Mindulle, 26 September 2021 (Source: William J. Blackwell).*

The high-quality datasets from TROPICS are expected to help address critical science questions, such as the link between environmental conditions and tropical cyclone intensification (Kidd et al., 2022). Preliminary products such as global precipitation fields are comparable to similar products derived from operational cross-track microwave sounders.

Recommendations

The presentations and discussions in the Theme 1 session have generated a set of research strategies and recommendations. These are as follows:

- NOAA requires low-latency data for precipitation analysis and forecasting. All sensor data acquisitions (Level-0) (from NOAA and partner agencies) and downstream products (Level-1, Level-2, Level-3) must meet these requirements. Additional downlink strategies should be considered to acquire legacy sensor data and primary satellites on time.

- NOAA should continue working with national and international partners to sustain and enhance PMW capabilities for NOAA operations. Continuity of operations is critical (e.g., AMSR2 to AMSR3, MetOP to EPS-SG). These should be pursued if coordination of overpass times is feasible with partners and other end-user groups (e.g., NWP).

- NOAA should invest in and sustain studies involving small satellite missions such as TROPICS and emerging commercial datasets to see their impact on Level-2 (L2) and Level-3 (L3) precipitation retrievals.

Theme 2: Precipitation Estimation and Algorithms from LEO and Combined Satellite Sensors and Platforms

The foundation for satellite-based precipitation datasets is built from the PMW imagers and sounders located onboard LEO satellites, such as ATMS on NOAA's JPSS. The fundamental measurements from each instrument are calibrated radiances from different spectral bands, typically provided to users in equivalent blackbody brightness temperature units (denoted by TB) after intercalibration. Kidd et al. (2021) comprehensively describe the current and near-future PMW constellation and sensors utilized for satellite-based precipitation. In summary, PMW-based precipitation algorithms have to accommodate a varying suite of sensors, each with a unique set of channels and associated scanning geometry, and invert each TB measurement into estimates of the near-surface precipitation rate (**Table 5**). For global precipitation, the imaging sensors scan conically, providing a near-constant Earth incidence angle (EIA), with channels in the "emission-based" spectrum (37 GHz and below) coincident with the "scattering-based" spectrum (90 GHz and above). Sounding sensors such as ATMS scan across-track with variable EIA and may or may not include channels below 90 GHz.

Table 5. *Active (AMW) and passive microwave (PMW) sensors that contribute or have contributed to the GPM precipitation constellation (as of mid-2022). The current precipitation constellation missions are highlighted in boldface text (Source: Kidd et al. (2021)).*

Satellite	Instrument Type	Agency	Sensor	Channels	Retrieval resolution
GPM	**AMW**	**NASA/JAXA**	**DPR**	**13.6, 35.5 GHz**	**5.4 km x 5.4 km**
TRMM	AMW	NASA/JAXA	PR	13.6 GHz	4.3 km x 4.3 km
GPM	**PMW imager**	**NASA/JAXA**	**GMI**	**10.7-183.31 GHz**	**10.9 km x 18.1 km**
DMSP F16, -17, -18, -19	**PMW imager**	**NASA/JAXA**	**SSMIS**	**19.35-183.31 GHz**	**45 km x 74 km**
GCOM-W1	**PMW imager**	**JAXA**	**AMSR2**	**6.7-89.0 GHz**	**14 km x 22 km**
TRMM	PMW imager	NASA/JAXA	TMI	10.7-89.0 GHz	20.9 km x 34.6 km
NOAA-18, -19; MetOp-A, -B, -C	**PMW sounder**	**NOAA/ EUMETSAT**	**MHS**	**89.0-183.31 GHz**	**17.12 km x 21.64 km**
NPP, NOAA-20, NOAA-21	**PMW sounder**	**NOAA**	**ATMS**	**23.0-183.31 GHz**	**16.51 km x 16.22 km**
MeghaTropiques	**PMW sounder**	**ISRO/CNES**	**SAPHIR**	**183.31 GHz (x6)**	**7.34 km x 7.27 km**

In addition, most operational PMW sounders include channels whose observations are influenced by the surface (e.g., ATMS channels 1 and 2) and lower tropospheric temperature sounding conditions (ATMS channels 3-7), from which PMW precipitation algorithms have also been optimized for cold season conditions and snowfall.

For a given location, the average revisit time between adjacent satellites is 1-12 hours, the worst-case being within the tropical latitudes where the heaviest precipitation occurs. Owing to this often lengthy and variable revisit time, observations from the PMW sensors are typically complemented with fast-refresh (30 minutes or less) IR observations from GEO satellites. Currently, GEO observations originate from imagers in the VIS-to-IR wavelengths, which provide high-resolution tracking of cloud tops, rather than from precipitation-sized hydrometeors nearer to the Earth's surface. To construct global satellite precipitation datasets that update at the GEO refresh rate, algorithms have been devised to combine the relative merits of LEO passive and active MW and GEO IR observations.

Parametric Rainfall Algorithms from Microwave Sensors: What is Ready and What is Not

Two well-established PMW precipitation algorithms are the GPROF (Kummerow et al., 2015) and the Microwave Integrated Retrieval System (MiRS) products produced operationally by NOAA STAR (Boukabara et al., 2013). GPROF is the basis for the operational products for NASA's Precipitation Measurement Missions (PMM), namely the TRMM and GPM missions. Both algorithms provide L2 swath-level precipitation products across the full orbit swath of each input PMW sensor, estimating the near-surface precipitation rate and other products related to the surface conditions and the environmental state. The current GPROF algorithm uses a Bayesian inversion framework that draws upon a common a-priori dataset for all sensors and is adaptable to other PMW sensors. The GPROF algorithm uses the GPM Combined Radar Radiometer Algorithm (CORRA) data product as a reference to construct a large set of candidate rain profile structures, from which each sensor TB is forward simulated. Since CORRA misses much of the light rain and snow, these precipitation components are accounted for using separate databases. In the GPROF algorithm, the final reported precipitation rate is based on minimizing the weighted difference between the observed TB and candidates from the large a-priori dataset. Recently, the Bayesian framework was changed to a machine learning (ML) framework, which provided a modest improvement in skill score, even though both algorithm variants are identical (in the sense that they use information from the same databases) (Pfreundschuh et al., 2022). GPROF V7 performance (relative to the Multi-Radar Multi-Sensor (MRMS)) appears similar to the CORRA training dataset, which is not surprising since this is what it is trained against (**Figure 5**). CORRA has a higher correlation score, which is to be expected, but even CORRA is not completely unbiased against MRMS. While MRMS is a reference source, obtaining the absolute truth is challenging. Regionally, there are biases, and only ancillary data can help fix this.

The algorithm's performance depends on the capabilities of the PMW sensors. When the sensor channel range is limited to the high-frequency (HF) channels (> 90 GHz), the retrieval performance degrades relative to GMI-like sensors (co-located channels across the 10-183 GHz range). Low frequencies (37 GHz and lower) help guide the algorithm over water and coastal surfaces but do not substantially improve GPROF overland precipitation estimates. In contrast, the higher frequency channels (150 GHz and higher) are advantageous for snowfall, especially fully frozen (not partially melted) snow. The relatively weak scattering signals render snow difficult to detect and quantify, due to the poor radiometric contrast between the snow and the background surface and temperature state.

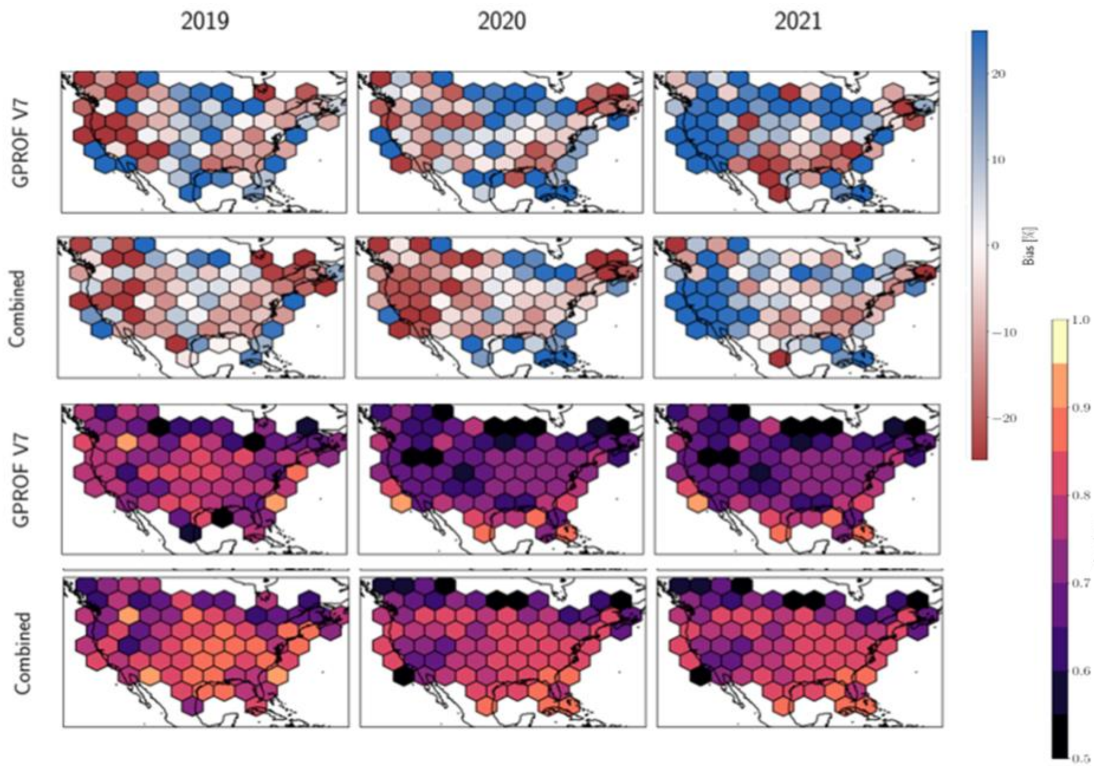


Figure 5. *Regional bias (top two rows) and correlation (bottom two rows) of GPROF V7 relative to the MRMS reference for three different years (Source: Christian Kummerow).*

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

The NOAA MiRS, a physical PMW algorithm, seeks to minimize a loss function. MiRS uses a variational approach that finds the most likely atmospheric and surface states that best match the satellite measurements and an a-priori estimate of these conditions (Boukabara et al., 2013). The same core software accommodates a variety of satellites/sensors, currently including ATMS on Suomi NPP, NOAA-20, and NOAA-21; MHS on NOAA-18, NOAA-19, and Metop-A/B/C; SSIMS on DMSP F-17, F-18; GPM/GMI, and Megha-Tropiques/SAPHIR (experimentally on TRMM, AMSR2, TROPICS) which facilitates scientific improvements and the extension of new sensors. Version V11.9 was delivered in 2022 and transitioned to operations in early 2023.

MiRS precipitation datasets are routinely validated using the Next Generation Weather Radar (NEXRAD) Stage-4 and MRMS products over the continental United States (CONUS) and nearby waters. The algorithm usually meets performance requirements, with slightly better performance during summer. In North America, the MiRS algorithm tends to overestimate precipitation rates with reference to the Global Precipitation Climatology Program (GPCP) and other ground-based references (**Figure 6**). Implementing a U-NET convolutional neural network (CNN) improved the MiRS overestimation issue (**Figure 7**). The statistics show that bias decreased and the skill score increased (Liu et al., 2020). The main improvement occurs in the cold season.

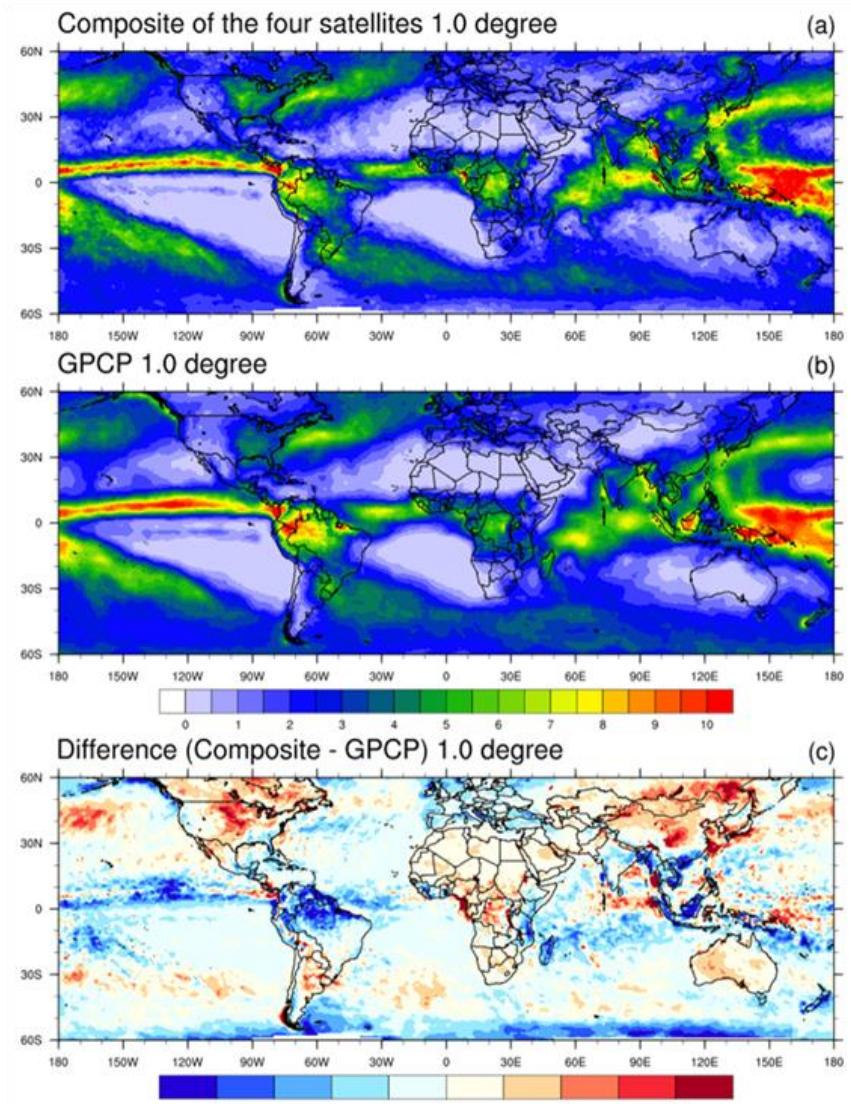


Figure 6. *MiRS composite based on ATMS on Suomi NPP and NOAA-20, and MHS on Metop-B and Metop-C (upper). While there is a good qualitative agreement with the Global Precipitation Climatology Program (GPCP) 1-degree product (center), there is a tendency for MiRS to overestimate (relative to GPCP) over North America and Asia (lower) (Source: Chris Grassotti).*

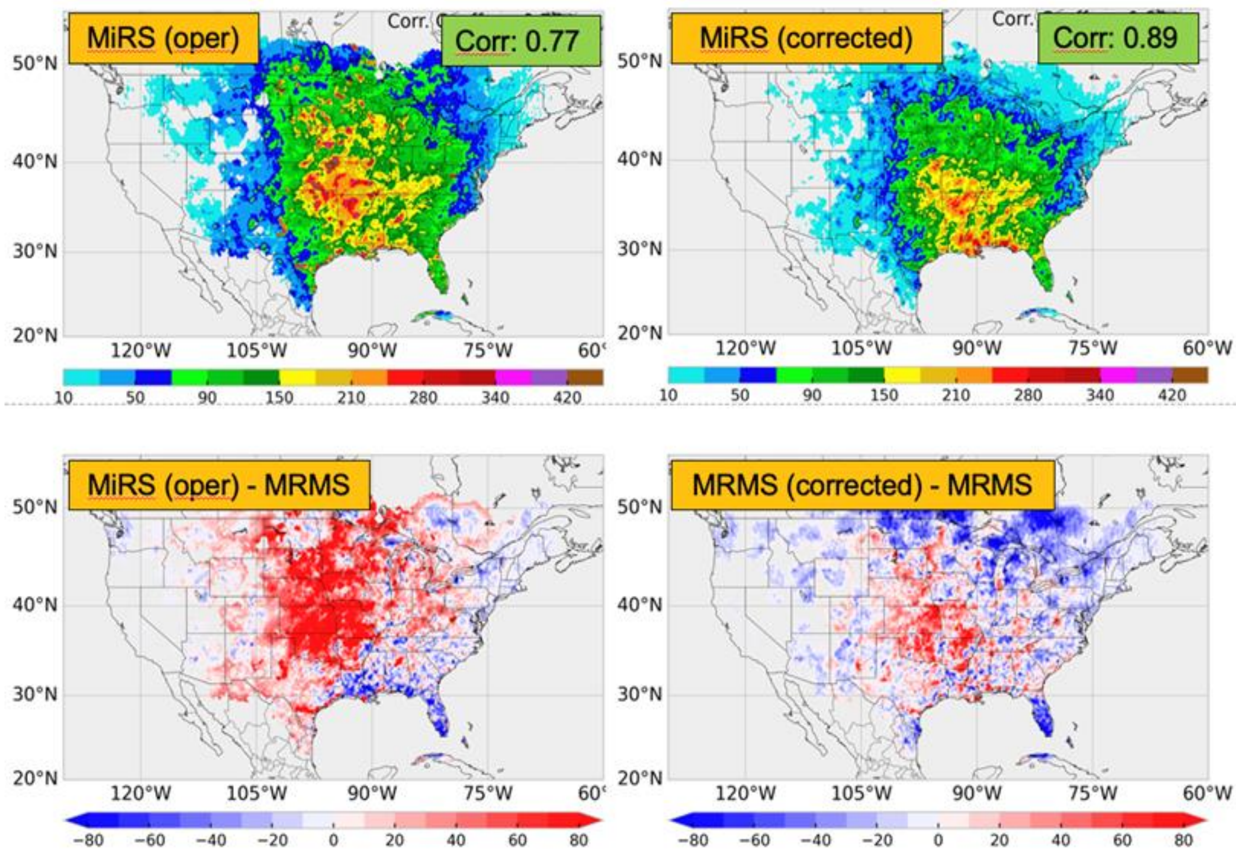


Figure 7. *Bias correction using AI-trained MiRS products, using one year (2021) of collocated MiRS NOAA-20 and MRMS data to train the U-Net. The four panels show results when the trained MiRS is tested on independent data from 2022. Upper row: Operational MiRS and the resulting bias-corrected MiRS. Lower row: Same as above, but showing the MiRS – MRMS difference (red=overestimate, blue=underestimate) (Source: Chris Grassotti).*

MiRS uses the Community Radiative Transfer Model (CRTM) for its hydrometeor profiles, where particle shapes are simplified (e.g., spherical shapes). Future innovations should incorporate innovations in the radiative transfer modeling of various non-spherical shapes and compositions (e.g., Brath et al., 2020). The MiRS product strongly depends on the precipitation types at the satellite overpass time. A method to ascertain the precipitation type (convective or stratiform) related to microphysical processes, atmospheric dynamics, and hydrometeor distributions would better align the microphysics used in the algorithm and the TB observations. Additionally, the a-priori model needs to be better trained upon frozen precipitation scenes over snow/ice-covered surfaces. Currently, MiRS contains little information on the uncertainty in the estimation procedure, which would be useful for users. MiRS has been extended to process eventual TROPICS TMS data, the NOAA QuickSounder/EDU (2025-2026) regarding linkages to future small satellites. Regarding linkages to future small satellites, MiRS is planned for EPS-SG/MWS data (Q1 2025). While there are upcoming or current opportunities for the Compact Ocean Wind Vector Radiometer (COWVR), the Temporal Experiment for Storms and Tropical Systems (TEMPEST), and EPS-SG/MWI+ICI (Q4 2025); MiRS currently has no plans to accommodate these sensors.

PMW Snowfall Techniques: Achievements, Challenges, and the Way Forward

Snowfall accounts for a large fraction of winter precipitation in mid and high latitudes. At high latitudes near the Arctic, temperatures are increasing faster than in places closer to the equator, affecting the fraction of precipitation that falls as snow. The capability to detect snowfall from PMW satellite observations provides an independent means to evaluate weather and climate model forecasts and future climate scenarios.

Observed from the viewpoint of the LEO satellite, the detection and quantification of precipitation below or near 0°C pose significant difficulties (Levizzani et al., 2011). The PMW snowfall algorithm has to adapt to the wide variability in the precipitation microphysics, such as hydrometeor size, shape, orientation, and composition (including ice, liquid, or mixed forms). These algorithms must also distinguish desired precipitation characteristics against/from the radiometrically cold surface and environmental conditions.

Currently, operational NOAA-NESDIS snowfall rate (SFR) products are generated near-real-time from the ATMS and MHS PMW sensors onboard LEO satellites operated by NOAA and its partner agencies. The SFR method estimates the liquid-equivalent snowfall rate over global land and has operated since 2012. The SFR algorithm consists of two main components: snowfall detection (SD) and SFR estimation. ML algorithms have been developed to improve both components (You et al., 2021; Fan et al., 2022). SD is based upon an ML algorithm based on eXtreme Gradient Boosting (XGB), trained on a diverse global precipitation dataset consisting of collocated ground weather reports, CloudSat CPR observations, and NWP model analysis. Compared to the previously developed deep neural network (DNN) SD model (Meng et al., 2017), the XGB model significantly improved the SD performance under cold conditions (i.e., 2-meter temperature < -15°C). For the ML Enhanced SFR, two NNs were developed to enhance the ice water path and SFR bias correction. The ML Enhanced SFR agrees well with NOAA Stage IV radar and the gauge combined precipitation rate.

A case study of the two winter storms in December 2022 (**Figure 8**) shows the SFR product agrees well with ground observations from various sources; however, the results from the two events show the limitation of SFR under very cold conditions. In addition, some orographic snowfall near the Appalachian Mountains and lake effect snowfall near the Great Lakes was not well captured.

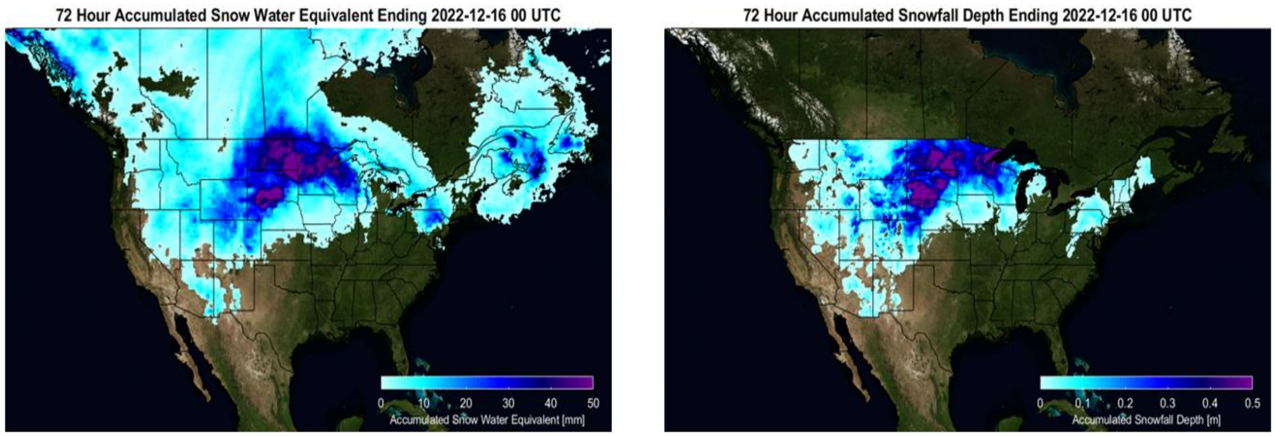


Figure 8. *A case study from the December 2022 snowstorms. (Left) 72-hour accumulated snow water equivalent from SFR (top) and (right) associated snowfall depth from SNODAS. While the SFR snowfall detection performed well, SFR missed the intensive but shallow lake effect snow in the late-December event (Source: Yongzhen Fan).*

In general, the application of PMW Snowfall Techniques encounters various challenges. The retrieval of orographic snowfall, lake effect snow, and extremely cold conditions presents certain limitations. The current algorithm assumptions, which are relatively simplistic, demonstrate suboptimal performance under these circumstances. There are some revisit time gaps exceeding 3 hours, which is not ideal from the perspective of weather system analysis. To overcome these challenges, ongoing advancements incorporate additional sensors (e.g., the GPM suite; Skofronick-Jackson et al., 2019) to improve the spatial and temporal resolution of SFR. Moreover, further enhancements to the ML algorithm are being explored to determine the optimal combination of snow particle shapes. Other research directions focus on using ML techniques to represent the spatial distribution of the snowfall systems more accurately, as well as incorporating other datasets (e.g., combining IR and MW observations) to enhance SFR.

CMORPH2: Where We Are and What Challenges We Are Facing

The original Climate Prediction Center Morphing (CMORPH) algorithm started production in 2004. CMORPH derived a high-resolution (8 × 8 km^2) half-hourly precipitation analysis over a quasi-global domain (60S–60N latitude) through the integration of PMW L2 estimates from all available LEO satellites, using a Lagrangian-based framework (Joyce et al., 2011). L2 PMW-based precipitation data products arrive with variable latency, depending upon the production source, but can range from under one hour (GMI) to 3 hours (ATMS or SSMIS). Other L3 global precipitation products have been developed and are in operational production (e.g., GSMaP, Kubota et al., 2020; IMERG, Huffman et al., 2020). The updated CMORPH2 (Xie et al., 2023) product improves upon the original CMORPH in several ways. The CMORPH2 real-time production has been migrated to the NWS standard operational environment to provide lower latency precipitation products. The production schedule generates CMORPH2 updates at one-hour intervals, with additional updates once every 30 minutes with newly available L2 inputs (until 12 hours of latency). The resulting data products are pushed to the Aviation Weather Center (AWC), the Weather

Prediction Center (WPC), and the Earth System Science Interdisciplinary Center (ESSIC) as part of the JPSS AWIPS Package and NESDIS/STAR for public release.

In addition to the latency improvement, the updated CMORPH2 incorporates IR data from various LEO satellites, providing a full (90S-90N) coverage area. The representation of cold season precipitation has been improved by incorporating the NOAA SFR product (Fan et al., 2022), and the fraction of solid precipitation is also estimated using the surface meteorological conditions (Sims & Liu, 2015). Bias correction procedures are applied to the CMORPH2 real-time production system using Probability Density Function (PDF) matching against CPC daily gauge analysis over land and calibration against the GPCP over the ocean. CMORPH2 near real-time captures snow storms fairly well. A winter storm (Feb 2019) covering much of the Central U.S. is shown in **Figure 9**.

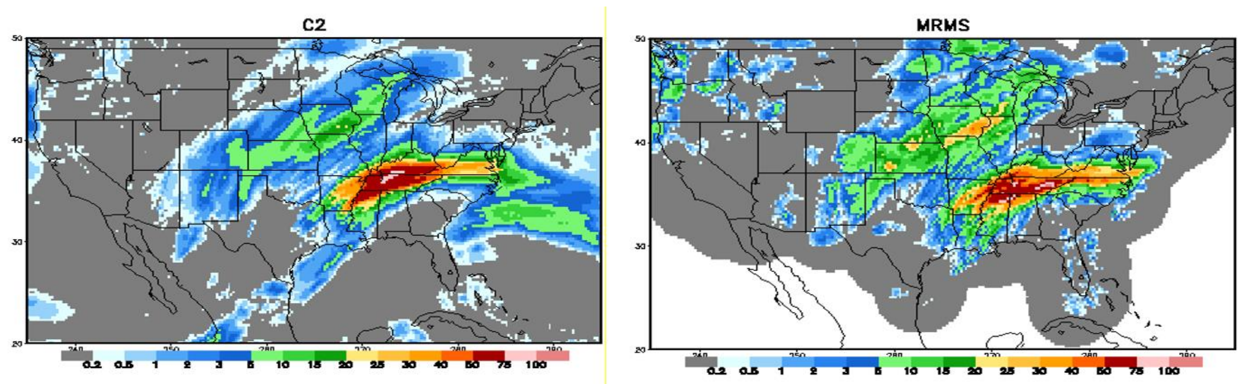


Figure 9. *Daily precipitation (mm) for February 23, 2019, derived from CMORPH2 near real-time production (left) and compared to MRMS radar observations (right).*

Ongoing work involves migrating the real-time production system to the NOAA super-computer to enhance the efficiency and stability of the data, along with lowering the latency of the associated L2 PMW precipitation retrievals. Many applications, such as landfalling hurricanes or periods of intense rainfall, require less than one-hour latency. Updated bias correction procedures are installed into the CMORPH2 real-time production system using matching PDF against CPC daily gauge analysis over land and calibration against GPCP over oceans. Large-scale bias in the raw CMORPH2 is removed after matching the PDF against daily gauges.

The limitations associated with the input Level 2 PMW data, such as underestimation of extreme precipitation events by specific sensors, will be manifested in the L3 CMORPH2 products. A persistent issue that affects CMORPH2 and similar global precipitation products is the systematic underestimation of orographic rainfall and snowfall. Accurately determining mixed precipitation (snow/rain mixture) and detecting light rain pose additional challenges, including estimating the probability of zero rain. The L3 processing needs the zero-rain probability to perform satellite inter-calibration (converting zero rain to a non-zero value). For an independent assessment of CMORPH2 outside of the CONUS (OCONUS) and surrounding waters (where US MRMS data is openly available), it would be advantageous to have access to high-quality radar and gauge network data performance in other areas. The deployment of the first DMSP satellite dates back to 1987, and the TRMM/GPM record extends to 1997, providing sufficiently long-duration information for CMORPH2 and similar products to establish a CDR across the 35S-35N latitude belt using a common precipitation radar reference. Enhancing collaboration and engagement with the user community would be valuable to better define the requirements for establishing a robust CDR.

Recommendations

Based on the presentations and discussions in the Theme 2 session, the following research strategies and recommendations have emerged:

- It is recommended to use satellite/sensor impact study results to define and specify desired channel requirements, including resolution and polarization for PMW-based rainfall and snowfall retrieval, including window channels near 6, 10, 19, 37, and 89 GHz, together with temperature and water vapor sounding bands near 23, 50, 118, 166, and 183 GHz and higher. Some recommended frequencies are listed in **Table 6**.

Table 6. *Recommended channels for PMW-based rainfall and snowfall retrievals*

Frequency (GHz) / Characteristics	10 H/V	19 H/V	23 H/V	31-37 H/V	50-55 H/V	89 H/V	166 H/V	183 H/V
Light rain over land					x	x	x	x
Heavy rain over land	x	x	x	x	x	x	x	x
Light rain over ocean	x	x	x	x	x			
Heavy rain over ocean	x	x	x	x	x	x	x	x
Snowfall detection over land		x	x		x		x	x
Snowfall detection over ocean		x	x	x	x		x	x
Snowfall rate over land		x	x	x	x	x	x	x
Snowfall rate over ocean				x	x	x	x	x

  - 10, 19, 23, 37, and 89 GHz (HV) channels have traditionally been the primary frequencies used for L-2 rain retrieval. Additionally, when available, frequencies in the cover 50-55, 166, and 183 channels provide additional vital information.

  - Rain over land, several studies have shown that the 10-37 GHz provides improvement over certain surfaces where the emissivity is lower due to soil moisture.

  - Limb-corrected 53.6 GHz (correction using 52.8 GHz and 53.6 GHz) is critically important for both snowfall detection and snowfall rate estimation.

  - The importance of channels is dependent on surface type, e.g. 89 GHz has a high correlation with snowfall in the presence of snow cover while having much less information on snowfall over other surface types. The land results shown in the above table for snowfall include over snow cover and other land covers, and the over ocean results include over sea ice, ice-free ocean, and coast.

  - A recent study (Yang et al., 2023) on the temperature-sounding channels at 118 GHz from the TROPICS missions indicates that they are also sensitive to rainfall (and potentially to snowfall), and should be considered for future LEO MW sensors.

  - Microwave frequencies higher than 183 GHz, e.g. the 205 GHz on the TROPICS, are more sensitive to precipitation hydrometeors than the 183 GHz channels (Blackwell et al., 2018), especially for light rainfall and snowfall. It is recommended that future NOAA MW sensors should include frequencies higher than 183 GHz.

- The quantitative precipitation community needs a methodology to quantify the impact of a change to the satellite observing system upon the resultant global precipitation products. There are limited validation efforts over areas with high-quality radar/gauge networks but no accurate “benchmark” for what current and planned satellite constellations can achieve globally. This is especially relevant with the rapidly expanding number of Cubesats/small satellites, which will be dominated by observations at 90 GHz and higher, which sense precipitation only indirectly through ice scattering processes. While this growth in the number of small/Cubesats contributing to the space-based precipitation constellation is welcome, PMW imagers that include the low frequency, dual-polarized channels (37 GHz and below) have remained steady or declined (frequencies near 10 GHz are particularly under-represented). It is recommended that NOAA invests in personnel to engage in such a benchmarking capability through sensor impact studies such as Observing System Simulation Experiments (OSSE), similar to efforts routinely carried out in the NWP community.

- International Precipitation Working Group (IPWG) is a central platform for the scientific community to collaborate on issues related to precipitation retrievals, supporting the future of precipitation-oriented missions. NOAA should continue its active engagements with IPWG to refine existing techniques, develop innovative methodologies and most importantly address the challenges in the field (Levizzani et al., 2018).

- Currently, the GPM core spacecraft operates as the reference for precipitation monitoring with both a satellite precipitation radar (DPR) and a conically scanning passive microwave radiometer (GMI). The DPR provides the precipitation profile, and the GMI radiometer provides the reference to transfer the DPR-based precipitation to other PMW sensors. Such a joint radar and radiometer capability must be sustained in the eventual post-GPM core satellite era.

- Current precipitation evaluations heavily rely upon MRMS products, which cover only the precipitation regimes encountered in the CONUS and surrounding waters. Access to high-quality radar and gauge network data performance over other areas is needed to independently assess L2 and L3 products outside of this region.

- Current PMW algorithms perform reasonably well for precipitation over open oceans. Additional development is needed for training datasets encompassing variable land and mixed water/land conditions, snow cover, steep terrain, low-to-moderate vegetation.

- Further use of multi-frequency radar observations, both space- and ground-based, to train algorithms and design empirical databases are encouraged to properly represent the precipitation microphysics (hydrometeor structure).

- Satellite/sensor package size does not appear to be a limitation. Depending on channel diversity small-sized sensors are a suitable alternative over land and water backgrounds depending on their channel diversity. PMW sensors such as TROPICS, COWVR, and TEMPEST exhibit sufficient quality (with respect to their noise-equivalent delta-T, denoted as NEDT) to produce precipitation datasets. Instead of the traditional and lengthy calibration and validation processes often required for a sensor to be approved for NWP operations, earlier distribution of these data for non-NWP applications would accelerate their use in precipitation data processing, complementing the large operational satellite systems.

- The first operational PMW satellite was deployed in 1987, and the record of TRMM/GPM extends nearly unbroken back to 1997. This duration is such that CMORPH2 and similar products can begin to produce a sustained CDR across the 35S-35N latitude using a common precipitation radar reference. Enhancing collaboration and engagement with the user community would be valuable to define the requirements for establishing a robust CDR.

Theme 3: Precipitation Estimation Products and Uncertainties

The third session of the workshop provides insight into quantifying uncertainties and errors, validating datasets, and removing biases. It is paramount to understand the uncertainties that come with satellite data. Datasets with higher temporal resolution usually have higher uncertainties. IR data is especially useful as it is available at short latencies and critical for near-real-time satellite precipitation products. PMW data is essential for providing higher-quality precipitation data than IR, but the data's intermittent nature is an issue. Furthermore, data is always accompanied by uncertainty, and understanding it and being able to account for it is necessary.

Perspectives on Maintaining High-Quality Global Precipitation Records

Providing reliable precipitation estimation, especially heavy precipitation, at fine spatial and temporal resolutions is crucial for many hydrological applications. It is critical to integrate current and past satellites to provide consistent CDRs. For example, the SSMI/SSMIS instruments have provided us with continuous and consistent observations at approximately 6 am/pm orbits since the 1980s. Combining these observations with data from newer satellites ensures continuity and consistency in retrieved products. Preserving a consistent long-term record of PMW instruments holds significant importance in scientific research (Huffman et al., 2016).

Gridded IR data from GEO satellites are available at high spatial and temporal resolution, extending to long data records. Two IR data sources are widely used in the generation of precipitation products: (1) NOAA Gridded Satellite (GridSat) B1 data and (2) NOAA Climate Prediction Center (CPC) (**Figure 10**). GridSat B1 data are used to generate precipitation CDRs, such as GPCP and PERSIANN-CDR (Ashouri et al., 2015). The B1 data is available from 1979 with a latitude coverage of 70ºN to 70ºS (Knapp, 2008). NOAA CPC IR is used in multi-sensor precipitation products such as CMORPH, IMERG, and PERSIANN. This dataset has a high spatial and temporal resolution, specifically 4km and 30 minutes. This data covers the IR-window channel and can go back to 2000 (Joyce et al., 2001). PERSIANN-CDR, for example, uses GridSat B1 IR channels to estimate rainfall and uses GPCP rainfall at the monthly scale for bias-adjusting. The next generation of International Satellite Cloud Climatology (ISCCP-NG), initiated by the Global Energy and Water Exchanges (GEWEX) project, aims to enhance the sensors' capabilities by expanding to approximately 16 channels and improving temporal resolution to 10 minutes. These advancements will enable the inclusion of cloud microphysics data, including precipitation. Leveraging the higher resolution offered by recent sensors, extending the dataset availability to a latitude of 70º would be advantageous. This expansion will facilitate the integration of global products and enhance the overall understanding of cloud-related processes on a broader scale.

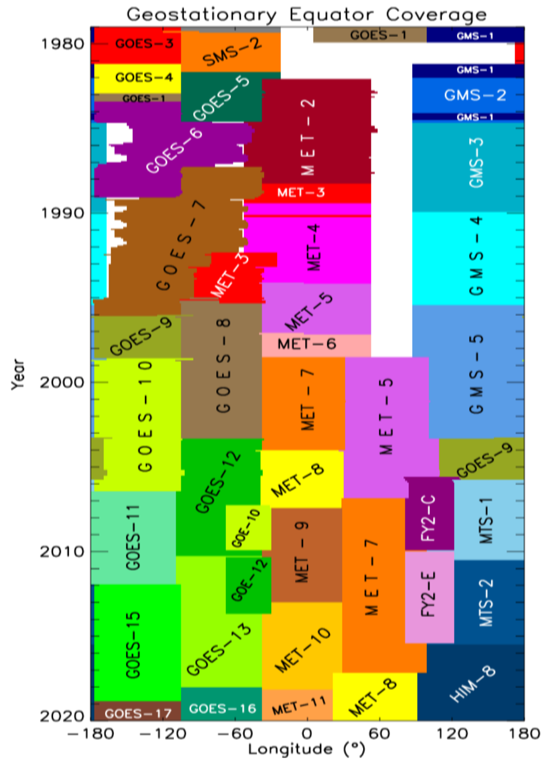


Figure 10. *Time series IR observations from GEO satellites (Source: Ali Behrangi)*

On the other hand, PMW precipitation products have played a crucial role in increasing the accuracy of IR-based precipitation estimates. PMW sensors include SSMI/S, AMSU/MHS, AMSR, GMI, ATMS, and a few others becoming available that will provide additional high-frequency channels. Following 35 years of SSMI/SSMIS, DMSP will continue with the Weather System Follow-on Microwave (WSF-M), ensuring consistency and continuity of long data records. Several other missions, such as JPSS, EPS-SG, AMSR3, and AOS, will continue PMW observations, offering the potential for merging their respective precipitation products. However, meeting the rigorous consistency standards of CDRs poses a significant challenge in the process. Radar precipitation products are essential to inform PMW precipitation products. TRMM PR, CloudSat CPR, and GPM DPR have played critical roles in advancing precipitation products. However, these datasets have been limited by their temporal resolution and consistency. Future missions such as EarthCARE, AOS radar, and other resources (e.g., Tomorrow.io Ka radars) will be critical for the modeling and remote sensing community.

For further advancement of CDRs, two important questions need to be addressed. First, how can the new instruments be effectively integrated into long-term precipitation products? This involves exploring these instruments' potential and capabilities to generate reliable and consistent precipitation data over extended periods. Second, how can we leverage the information from the past and/or current sensors while preserving critical features of long-term precipitation records, including consistency, accuracy, spatiotemporal resolution, and timelessness? To illustrate, GPCP has substantially updated its version 3 by incorporating advanced precipitation estimates from sensors such as TRMM, GPM, CloudSat, and GRACE data (Behrangi et al., 2022).

Studies have shown that the skill of precipitation estimation algorithms varies based on different regimes and surface conditions. Therefore, conducting regime-dependent error analysis is crucial to understanding the limitations and strengths of satellite-based products. As we move towards lower temperatures and drier atmospheric conditions, PMW and IR products exhibit reduced skill. Acquiring "high-quality" reference observations in these challenging conditions remains limited, particularly over snow/ice surfaces and lower temperatures. As a result, sensors like Atmospheric Infrared Sounder (AIRS)/TIROS Operational Vertical Sounder (TOVS)/Advanced Very High Resolution Radiometer (AVHRR) still hold relevance and are important options for generating long-term CDRs. Satellite products often are bias-adjusted using in-situ observations and show more consistency over land, using rain gauges. However, the decline in the number of gauges poses a significant challenge. Over the ocean, satellite-based precipitation products face high levels of uncertainty. Verifying these products against in-situ measurements is critical to narrow down the uncertainties associated with ocean-based precipitation estimates. However, accurately estimating uncertainties remains challenging due to the limited availability of reference data over oceans.

Uncertainties in the Precipitation Estimates from Space-borne Radar Observation

Space-borne precipitation radars are used to calibrate and verify global satellite precipitation estimates. Although space-borne radar observations are more directly related to precipitation parameters than other passively sensed information, it is essential to acknowledge that they are not entirely devoid of uncertainties. The major sources of uncertainty include variability in the radar reflectivity factor-rain rate (Z-R) relationship, attenuation in the observed radar reflectivity, snow issues, ground clutter, light precipitation, and variability in the radar beam footprint. The Z-R relationship requires at least two parameters, the mass-weighted diameter (Dm) and the normalized intercept parameter (Nw) (Battaglia et al., 2020). **Figure 11** illustrates the variabilities of these parameters within the Z-R model. Nw needs to be estimated independently on the radar observations. Ground observations may be used to impose constraints on Nw. However, such constraints are ineffective for Particle Size Distribution (PSD) models characterized by large mean particle sizes, Dm. Regarding radar profiling, additional constraints can be imposed by considering Nw in the radar profiling context. That is, the attenuation correction process needs to be consistent with the Nw parameter. When available, the analytical path integrated attenuation (PIA) must be consistent with the surface reference technique (SRT) PIA estimate and Ka-band reflectivity observations.

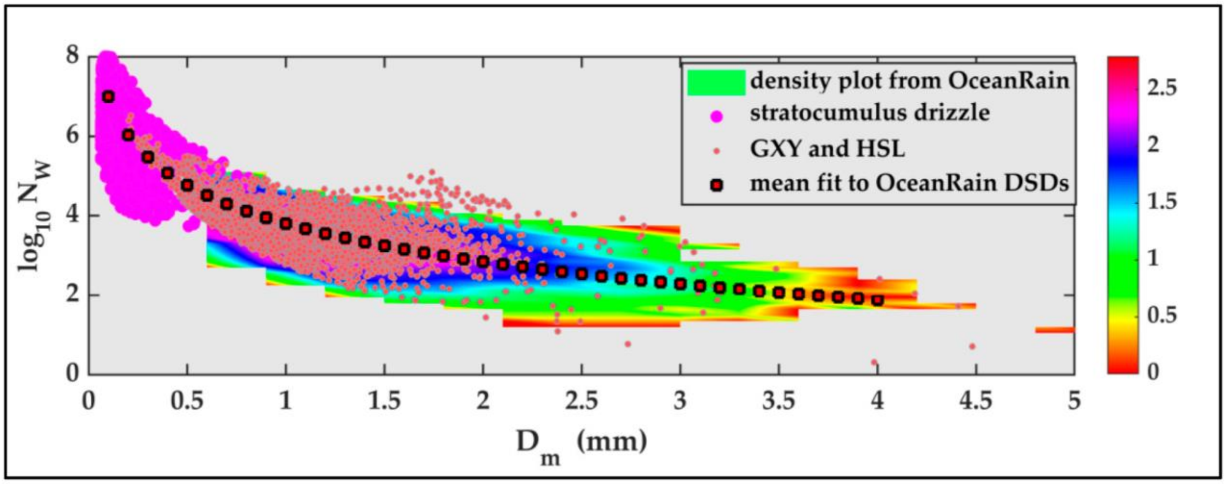


Figure 11. *Variabilities of parameters Dm and Nw in the Z-R model (Source: Mircea Grecu).*

Regarding snow estimation, the variability of Nw remains a challenge due to the limited attenuation of snow, making it difficult to use PIA as a constraint. Dual frequency observations offer the Dm estimation and, consequently, Nw through the dual frequency reflectivity ratio (DFR). However, the DFR can exhibit significant noise, posing a limitation in accurate estimation. To address this issue, more robust approaches, such as ML-based methods, can be used to incorporate "in-situ" information and enhance the accuracy of snow parameter estimates.

Ground clutter refers to a strong echo in radar observations caused by the presence of the Earth's surface. It can extend vertically up to 2 km above the surface, leading to the complete obscuration of precipitation echoes. However, nadir observations experience minimal interference from ground clutter and can thus be utilized in developing statistical methodologies to mitigate clutter effects. DPR can capture light precipitation associated with a given point in the brightness temperature (Tb) space. An empirical algorithm is employed when the DPR fails to detect precipitation, and a decision is made based on estimates greater than zero.

Parameterizations and "a priori" information derived from ground-based observations can be used to address uncertainties associated with space-borne radar observations. These techniques minimize uncertainties by utilizing available information and data from ground-based sources in conjunction with space-borne radar observations.

Modeling Errors in Satellite-based Precipitation Products: Past Achievements, Present Situation, Future Developments

Re-gridding and aggregating satellite retrievals adds uncertainty and sometimes reduces maximum rainfall rates and spatial details (Hartke et al., 2022). The performance of gridded precipitation products depends on the spatial scale at which the validation is performed. Usually, coarser grids produce better error metrics. **Figure 12** shows how the maximum precipitation changes from its original resolution when downscaling the Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA 2).

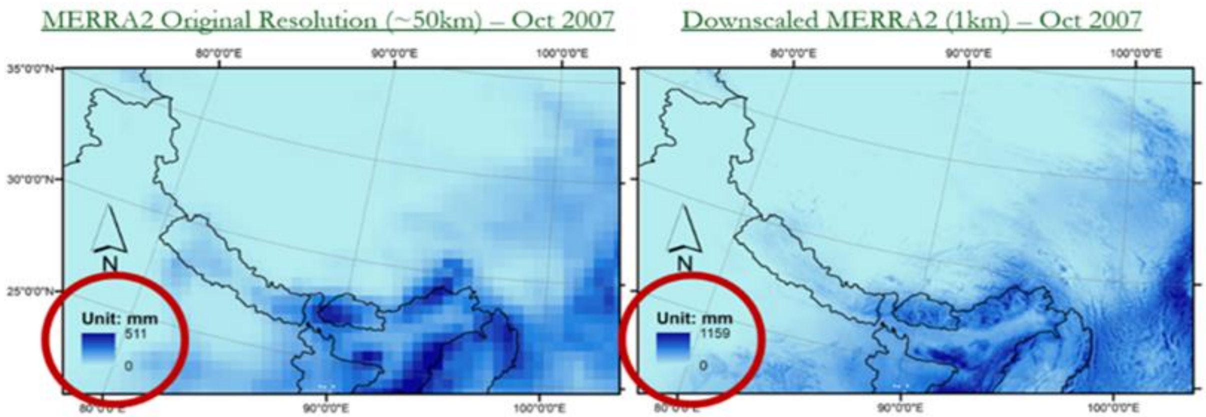


Figure 12. *MERRA2 at its original resolution and 1km. The maximum amount of rainfall increases from one to another, showing the effects of re-gridding (Source: Viviana Maggioni).*

Satellite-based precipitation validation is the quantification of the differences between the satellite precipitation product and a reference. There are different ways of validating precipitation datasets, such as using indices like the correlation coefficient and root-mean-squared error and comparing the Cumulative Density Function (CDF) of daily rainfall for different datasets to select the one that best matches the reference dataset. When deciding on a dataset to use as a reference, it is vital to consider data availability, the type of products that will be validated, and the objective of the validation. An assumption commonly made is that if the observational error is random and is smaller than the error in the satellite dataset, then the reference dataset can be used. If a valid reference dataset is unavailable, alternative validation approaches exist, such as Triple Collocation Analysis (TCA), which allows provisioning errors and correlation coefficients among three different datasets without using a reference (Khan & Maggioni, 2019). Validation over oceans is complicated because of their inaccessibility and extent. Some available reference datasets include weather radars on coastlines and islands, rain gauges onboard ships, and buoy gauge arrays, whose measurements are highly affected by wind speeds and snowfall.

Accurate modeling of errors and uncertainties is necessary to appropriately utilize satellite products in hydrological modeling, water resources management, and climate studies (Li et al., 2023). It is unlikely that a single error model would yield consistent performance globally across different periods, precipitation events, and applications.

There is a growing emphasis on enhancing the validation of satellite precipitation products by integrating ground-based observations and other independent datasets. The future direction for estimating errors and uncertainties is expected to involve a combination of these approaches, along with advancements in satellite technology and data processing algorithms. By leveraging these multiple approaches, the accuracy and reliability of satellite-derived precipitation data can be further improved, leading to more robust applications in various fields of study.

Probabilistic Precipitation Estimation from Satellites

One of the current challenges in remote sensing hydrometeorology, including deterministic quantitative precipitation estimation (QPE), is the indirect relationship between observation and precipitation.

Classical parameterization approaches used in existing algorithms need to be revised because they ignore precipitation variability and only partially resolve the mixture of precipitation processes observed within the sensor resolution volumes. These approaches limit the characterization of extremes because they primarily describe average precipitation intensities/properties. The Probabilistic QPE (PQPE) algorithm quantifies the certainty bounds for data fusions and assimilations from multiple sensors by considering uncertainty as an integral part of the estimation. It quantifies the likelihood of extreme weather for hazard and risk analysis (Kirstetter et al., 2015, 2018).

PQPE models provide the opportunity for prognostic error analysis that consider biases/uncertainties as a function of algorithm parameters. For example, the DPR QPE algorithm depends on the adjustment factor (ε) and estimated mean diameter D_m and assumes uniform precipitation in the field of view in stratiform or convective events. It is important to avoid introducing conditional biases in QPE as a function of these algorithm parameters. **Figure 13** shows the relative bias with respect to the adjustment parameter ε (top panels) and with respect to D_m (bottom panels) for DPR QPEs (black lines) when compared to the bias obtained by ingesting the same parameter to the PQPE approach (red lines) for stratiform and convective precipitation types. This figure demonstrates that using these parameters as an input to PQPE can significantly and conditionally reduce relative biases by providing estimates of the uncertainty and characterizing extreme precipitation.

Spaceborne radars are mostly used to calibrate other passive sensors. Thus, it is crucial to diagnose and quantify the errors related to precipitation parametrization with these instruments because they propagate to PMW QPE and then to the integrated multi-sensor precipitation retrievals such as NASA's IMERG (Kirstetter et al., 2020; Petković et al., 2019).

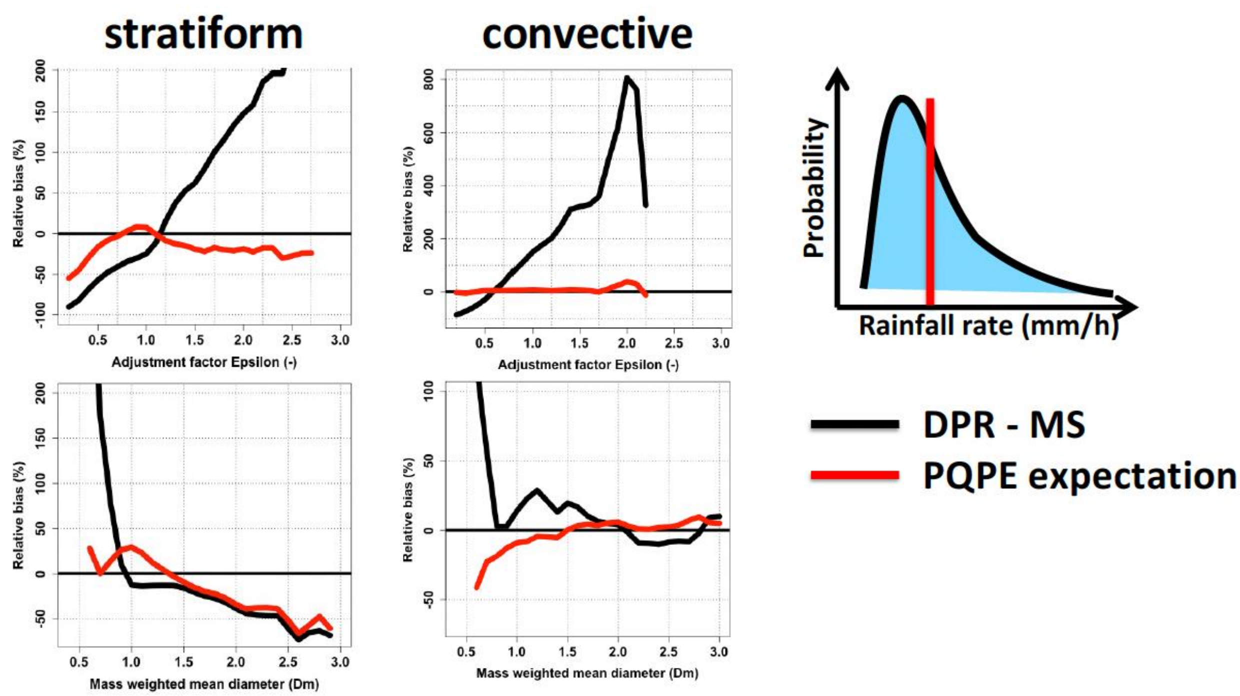


Figure 13. *Dual-frequency Precipitation Radar conditional biases with ε and D_m (Source: Pierre Kirstetter).*

Recommendations

The presentations and discussions held during the Theme 3 session have resulted in the formulation of the following recommendations:

- Spaceborne radars are critical for calibrating passive sensors, emphasizing the need to diagnose and quantify errors in precipitation parameterization to minimize their impact on integrated multi-sensor precipitation retrievals. It is advisable to leverage parameterizations and "a priori" information from ground observations to mitigate uncertainties in space-borne radar observations and improve their accuracy.

- To enhance the accuracy and robustness of sensor-based precipitation estimation, it is recommended to assess uncertainty using prognostic approaches quantitatively, employ probabilistic methods for multi-sensor products, encourage interdisciplinary collaboration, leverage parameterizations and "a priori" information from ground observations, and consider more robust techniques like Machine Learning to incorporate "in-situ" information.

- To enhance the validation of satellite precipitation products, it is recommended to adopt a multifaceted approach by incorporating ground-based observations, independent datasets, advancements in satellite technology, and data processing algorithms to estimate errors and uncertainties accurately. Moreover, moving beyond the pixel level and considering precipitation's spatial and temporal properties is crucial, allowing for a more comprehensive evaluation and validation.

- To enhance the development of CDR products for precipitation, the following recommendations are proposed: (1) Explore the integration of new instruments into long-term precipitation products while ensuring consistency, accuracy, spatiotemporal resolution, and continuity for improved quality and utility of CDRs; (2) Leverage the valuable features of past/current sensors in CDR development; (3) Perform regime-dependent error analysis to account for variations in precipitation estimation skill based on different regimes and surface conditions; (4) Consider the utilization of instruments such as AIRS, TOVS, and AVHRR, which offer extended data records and are relevant in colder and drier atmospheric conditions where other satellite products may exhibit lower skill.

- To effectively utilize satellite products in hydrological modeling, water resources management, and climate studies, it is recommended to incorporate location-specific error and uncertainty models that account for the variability of errors across different regions, timeframes, precipitation events, and application domains.

Theme 4: Users and Applications

Satellite precipitation and water vapor products are widely used in nowcasting and short-term forecasting, tropical cyclone monitoring, NWP model bias correction, extreme precipitation studies, and drought monitoring at NWS and NESDIS. This last theme focuses on NOAA operational users and applications since the data products and services provided by NOAA are critical for societal applications, including the private weather forecasting industry. This theme also seeks to inform the NOAA LEO Program of the assessment and recommendations from the satellite precipitation community, including product developers and users, on the optimal future satellite constellation. However, it is equally important to point out the myriad of users and applications outside of what is covered in this session.

LEO Precipitation Products that Aid Forecasters in Monitoring/Tracking Heavy Precipitation & Their Needs in the Future

The NWS Weather Forecast Office (WFO) in Juneau, Alaska, is located in the panhandle of southeastern Alaska. Its area of responsibility is the third largest among all NWS WFOs. The region has many islands intertwined with water, covering 75% of the forecast area. The surrounding mountains further complicate the terrain with elevation changes from sea level to 15,000 ft in 8 miles in some cases. Southeastern Alaska is a land of precipitation where most areas receive over 2 m of precipitation annually. Atmospheric rivers (ARs) from the Pacific Ocean and the Gulf of Alaska cause the heaviest precipitation. Orographic precipitation is widespread. The diverse topography and the associated climatic variations make weather forecasting challenging. This area often experiences flooding, debris flow, and landslides from the excessive precipitation that causes casualties and property damage. Ground-based observations in Alaska are sparse; only seven radars are across the entire state (**Figure 14**). Most radars suffer from beam blockage and provide limited data further inland. Consequently, forecasters heavily rely on satellite observations and products for situational awareness of the approaching weather systems, forecasting watch, and warning products, and providing Impact-Based Decision Support Services (IDSS) to emergency managers (Uccellini and Ten Hoeve, 2019).

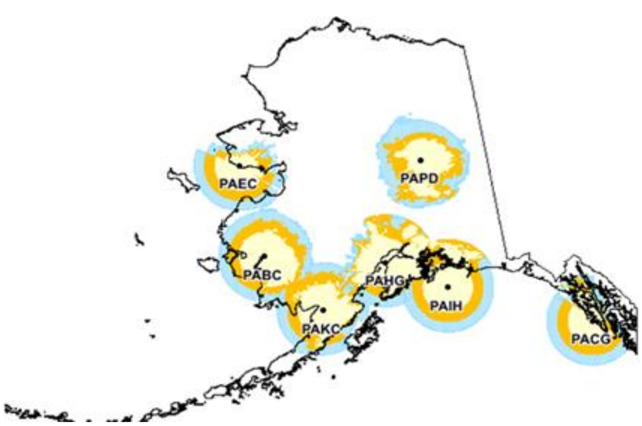


***Figure 14**. Land-based Observations in Alaska*

Juneau Alaska WFO has access to a number of LEO (L2) or LEO-GEO combined (L3) precipitation and water vapor products developed by NESDIS and its Cooperative Institutes, NWS CPC, and NASA. In particular, the Advected Layer Precipitable Water (ALPW) product (**Figure 15**) developed by the Cooperative Institute for Research in the Atmosphere (CIRA) provides the depth and vertical distribution of atmospheric water vapor. The LPW is derived from the MIRS water vapor profile and advected with model forecasted winds to fill gaps and smooth features. The 4D water vapor product is widely used in NWS weather forecasting operations, including the Juneau, Alaska WFO. This Office receives a set of satellite precipitation products: the MIRS rain rate, NESDIS snowfall rate (SFR), NCEP CPC MORPHing (CMORPH2) global blended precipitation, GPM constellation precipitation, and AMSR2 rain rate (RR). Among them, the MIRS, SFR, and AMSR2 RR are produced at the Geographic Information Network of Alaska (GINA) of the University of Alaska Fairbanks using the Community Satellite Processing Package (CSPP) from Direct Broadcast (DB) data. This arrangement allows very low latency (< 30 min) compared to products derived from non-DB data with a latency greater than 2 hours. The precipitation products provide situational awareness to support forecasters in operations. **Figure 16** shows the MIRS RR and SFR products during a February 28, 2023 storm. The intense system moved from the Bering Sea to the Gulf of Alaska before reaching the SE Alaska coast and causing blizzard conditions in the Juneau area. The SFR and MIRS RR products provided valuable insights to forecasters about the expected weather conditions before the storm came onshore.

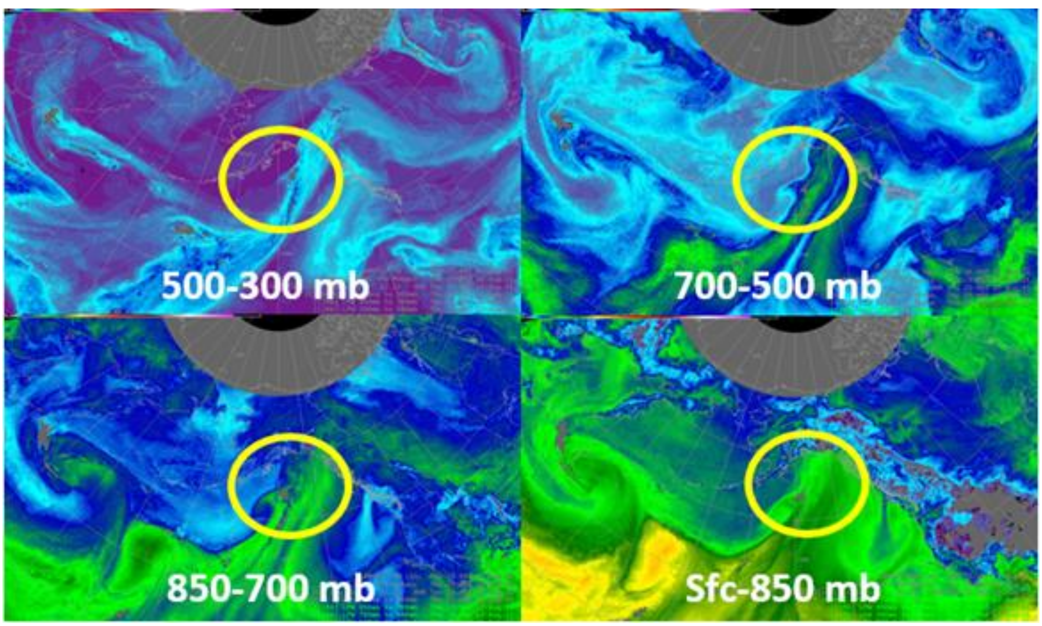


Figure 15. *The CIRA ALPW product depicts an atmospheric river that extends four atmospheric layers. The system produced heavy precipitation over the interchannel region of southeastern Alaska (Source: Aaron Jacobs).*

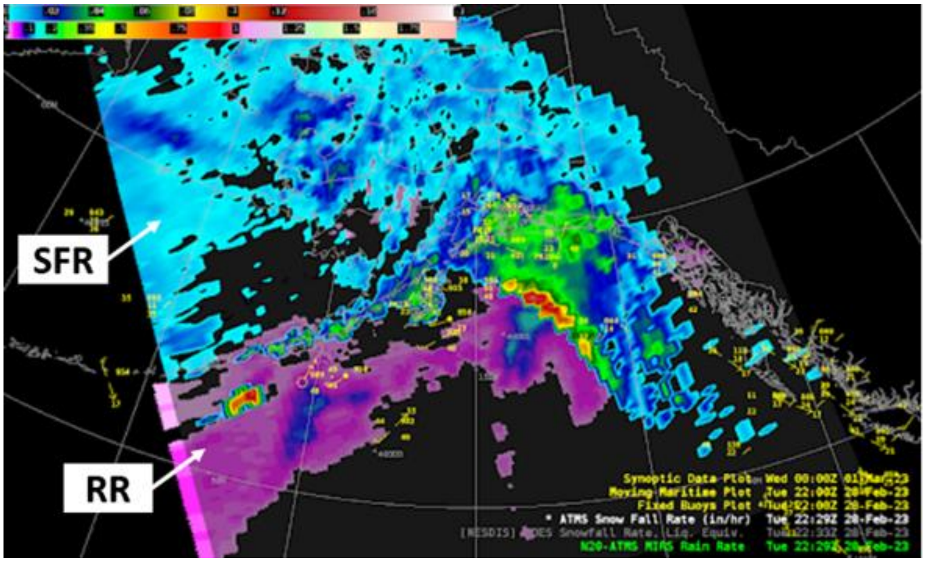


***Figure 16**. MIRS rain rate and NESDIS snowfall rate products during an intense storm on February 28, 2023 (Source: Aaron Jacobs).*

Satellite Applications and User Needs at the Weather Prediction Center

To a certain extent, NWS WPC is responsible for short to medium-range weather forecasts over CONUS and OCONUS. WPC forecasters use LEO and GEO satellite datasets to gain insights into atmospheric conditions. In particular, the PMW products from the constellation of polar-orbiting satellites play a crucial role in OCONUS and CONUS threats by providing a deep layer account of the moisture and temperature profiles and thus providing information on precipitable water, rain rates, and instability. The current GPM constellation of LEO satellites is very important to heavy precipitation analysis and forecasting of high-impact seasonal events (Skofronick-Jackson et al., 2017, 2018). A sustainable constellation of polar orbiters in conjunction with NOAA's Geostationary Extended Observations (GeoXO) satellite system planned to be launched in the early 2030s will be critical to future real-time heavy rainfall prediction success. AR-induced heavy precipitation is an excellent example of the importance of PMW products to weather forecasting. **Figure 17** shows the tracks of 9 AR events with at least moderate strength hitting the East Pacific coast for 21 days from Christmas 2022 through mid-January 2023, resulting in historic rain and snow levels that caused widespread damage. **Figure 18** includes an excerpt of the WPC Mesoscale Precipitation Discussion during one of the AR events where the CIRA Layered Precipitable Water product was used to quantify the intensity of the AR.

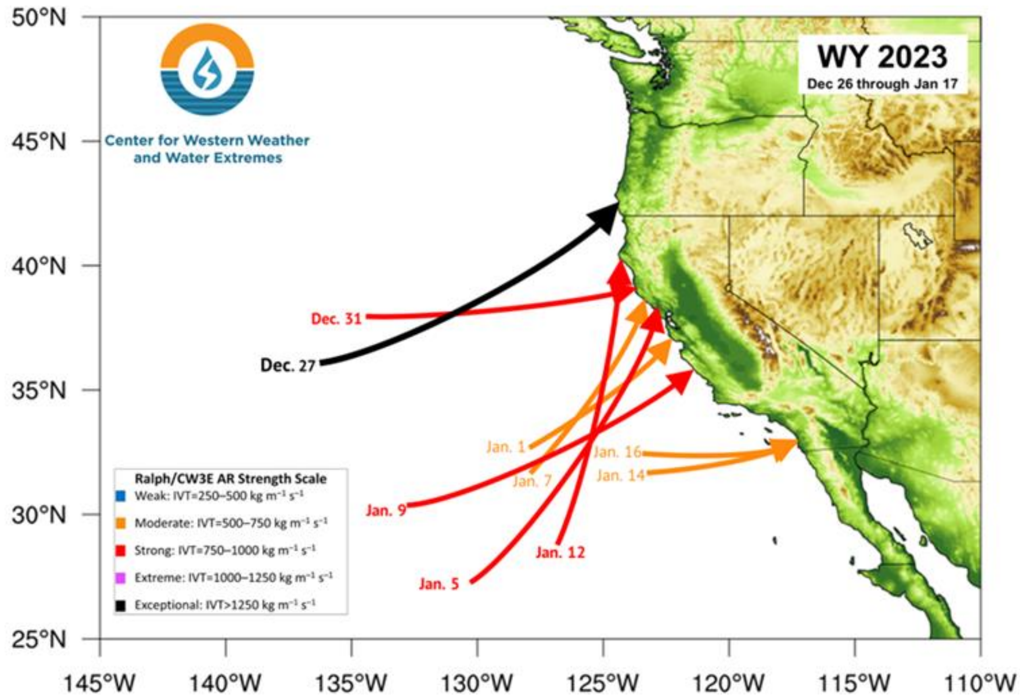
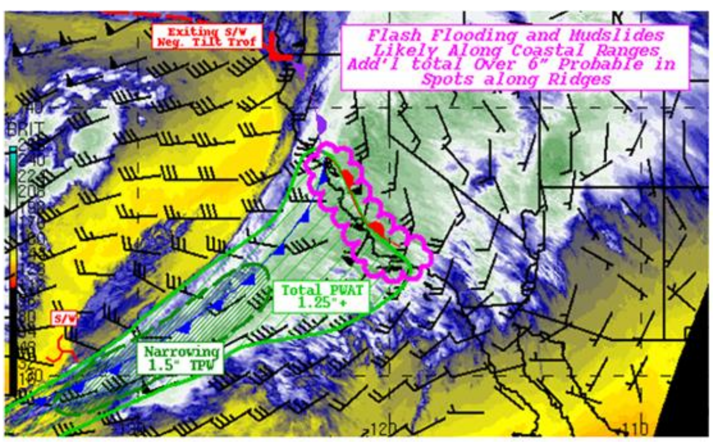


Figure 17. *East Pacific atmospheric rivers from Christmas 2022 through mid-January 2023. The image is provided by the Center for Western Weather and Water Extremes (Source: Andrew Orrison).*



Mesoscale Precipitation Discussion 0032
NWS Weather Prediction Center College Park MD
1123 AM EST Mon Jan 09 2023

Areas affected...Central Coastal to western Transverse Ranges of California...

Concerning...Heavy rainfall...Flash flooding likely

Valid 09 1630Z – 100230Z

... CIRA LPW shows nose of .6-.7" sfc-850mb and .3-.4" 850-700mb moisture intersecting the coast. This has resulted in record total PWAT values at OAK and VBG this morning with 1.3" and 1.25" and generally running slight below greatest moisture values for this part of the month. Combined with the strong deep flow, IVT values are over 800 kg/m/s occasionally ticking to 1000 kg/m/s...

Figure 18. *WPC Mesoscale Precipitation Discussion #32. Left: 230109/1616 GOES18 CH10 WV 7.3 and RAP32 850 MB WINDS 230109/1400f000. Right: Except for MPD #0032, including discussion about the CIRA Layered Precipitable Water (LPW) product (Source: Andrew Orrison).*

Four guidelines are provided based on the discussions about the importance of low latency for heavy precipitation nowcasting. Latencies of more than 6 hours would be of limited benefit, but without other remotely sensed data, it would still be worth looking at. Latencies between 3 to 6 hours would be of benefit in conjunction with other remote sensing data (polar in conjunction with GEO satellites). Latencies between 1 and 3 hours would help drive nowcast and short-range forecasts. Latencies of less than an hour provide optimal/excellent end-user support with strong benefits to nowcast and short-range forecast products.

LEO products and capabilities for tropical cyclone monitoring

The tropical cyclone (TC) community relies on PMW window channels, 88-92H GHz and 37H GHz, to monitor the convective structures and the physical attributes of TCs (Hawkins et al., 2008). These satellite observations are essential for retrieving precipitation and water vapor products. The ALPW product is used to monitor the environmental moisture around TCs since moisture reaching the eyewall regions can weaken the intensity of the storms. **Figure 19** demonstrates this effect in the case of TC Freddy in the South Indian Ocean. The ALPW product indicates that some moisture has reached the dry eyewall region and contributes to the weakening of the TC system. The central panel in the figure is the maximum wind, and the orange arrow points to when moisture is in the storm's center. In addition, MIRS water vapor and temperature soundings are the input to the Hurricane Structure and Intensity Algorithm (HISA) product used at the National Hurricane Center and the Joint Typhoon Warning Center of the US Navy and US Air Force. The discussions in this theme agreed on the need for high spatiotemporal resolution PMW images with low latency and including surface wind measurements in future precipitation missions.

One of the Significant Meteorological Information (SIGMETs) for aviation is icing because of its danger to aircraft. AWC has some unmet needs for identifying icing conditions, and satellite products may help to fulfill these needs. For instance, a product that can highlight areas of stratiform precipitation under non-glaciated clouds since this condition favors icing. Satellite-derived supercooled cloud water will also inform forecasters of the icing potential. Finally, precipitation intensity combined with cloud tops can also help forecasters at the AWC Tropical Desk when issuing tropical storm SIGMETs.

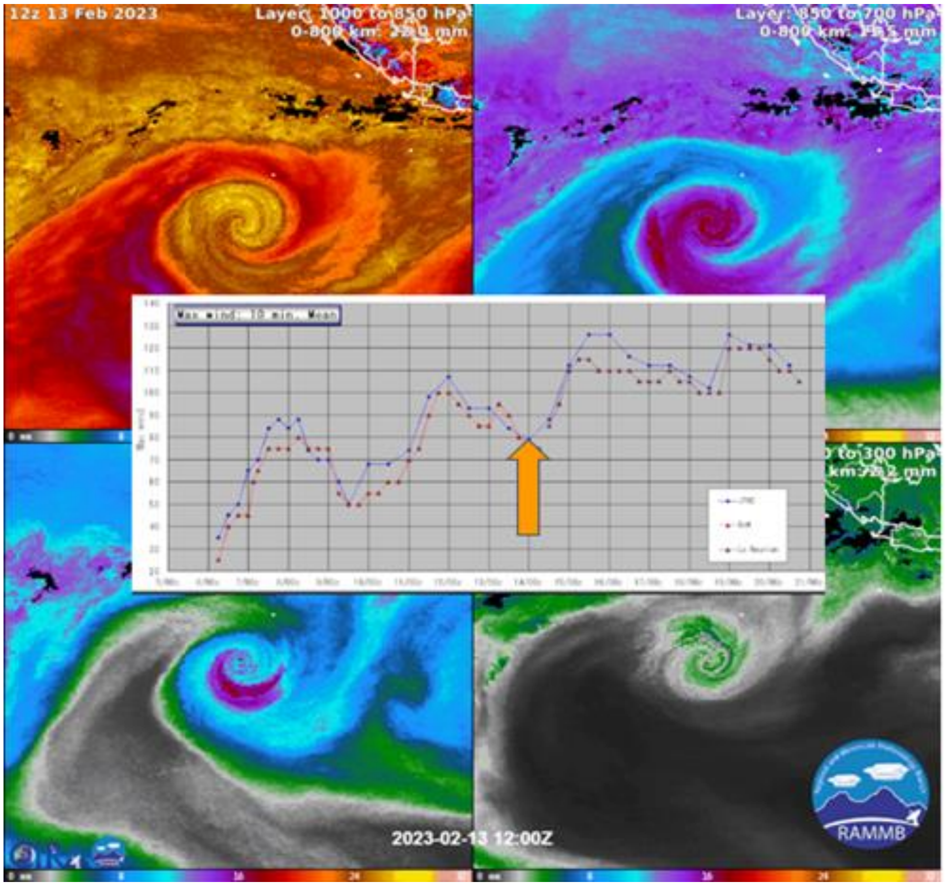


Figure 19. *ALPW shows moisture reaching the eyewall region of TC Freddy on February 12, 2023. It corresponds to the reduced max wind (arrow in the central figure) (Source: John Knaff).*

Satellite-Based Precipitation Estimation at the Aviation Weather Center

The NWS AWC has domestic and international aviation operations that issue SIGMETs and need precipitation-related information. In particular, the Ensemble Prediction of Oceanic Convective Hazards (EPOCH) product directly uses satellite precipitation in production. **Figure 20** illustrates the EPOCH methodology, which first produces NWP ensembles from the Global Ensemble Forecast System (GEFS) and CMCE models. Bias corrects the ensembles with observations, including using CMORPH2 to correct the precipitation field, and finally fuses all information to produce such forecasts as the likelihood of thunderstorm occurrence and convective cloud tops greater than 30, 35, and 40 kFt with long (up to 48 hours) lead times.

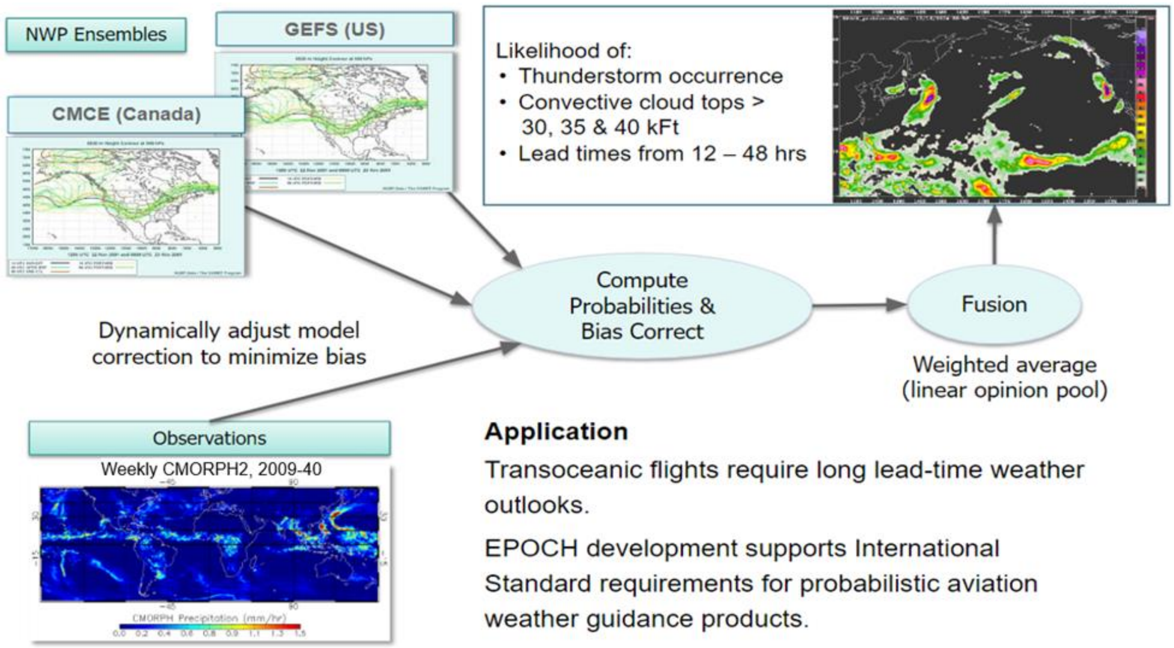


Figure 20. *AWC EPOCH Methodology where CMORPH2 is used to correct the bias in the NWP ensemble precipitation field (Source: Alex Korner).*

Applications of Precipitation Climate Data Records

NESDIS National Centers for Environmental Information (NCEI) supports about 40 CDRs, time series records of scientifically based measurements of the Earth's environment with sufficient length, consistency, and continuity to assess and measure climate variability and change. Among these CDRs are several satellite precipitation products (SPPs), including the CPC operational CMORPH, PERSIANN-CDR, and GPCP (Joyce et al., 2004; Ashouri et al., 2015; Behrangi et al., 2022). NCEI and the Cooperative Institute for Satellite Earth System Studies (CISESS) conduct studies to evaluate these precipitation CDRs against in-situ data from daily to annual scales. For instance, these datasets and other SPPs (TMPA, IMERG) have been utilized in many studies for various applications. In this theme, a list of studies conducted in recent years on extreme precipitation was presented that included applications such as atmospheric rivers, TCs, extreme rainfall frequency, flood forecasting, and landslides. Two examples demonstrate the applications of precipitation datasets, one for the study on TC contribution and extreme rainfall and the other on near real-time global drought monitoring. In the latter case, NCEI computes a daily Standardized Precipitation Index (SPI) based on high-resolution in-situ and satellite precipitation products (CMORPH, IMERG) to provide near real-time drought monitoring resources to the public. **Figure 21** displays the daily CMORPH-SPI on the National Integrated Drought Information System (NIDIS) Drought Portal (https://www.drought.gov/). Current efforts at CISESS include transitioning to the cloud computing environment to significantly reduce the processing time from hours to minutes (i.e., two orders of magnitude). The framework developed could be used for near-real-time applications requiring low latency and large dataset ingesting.

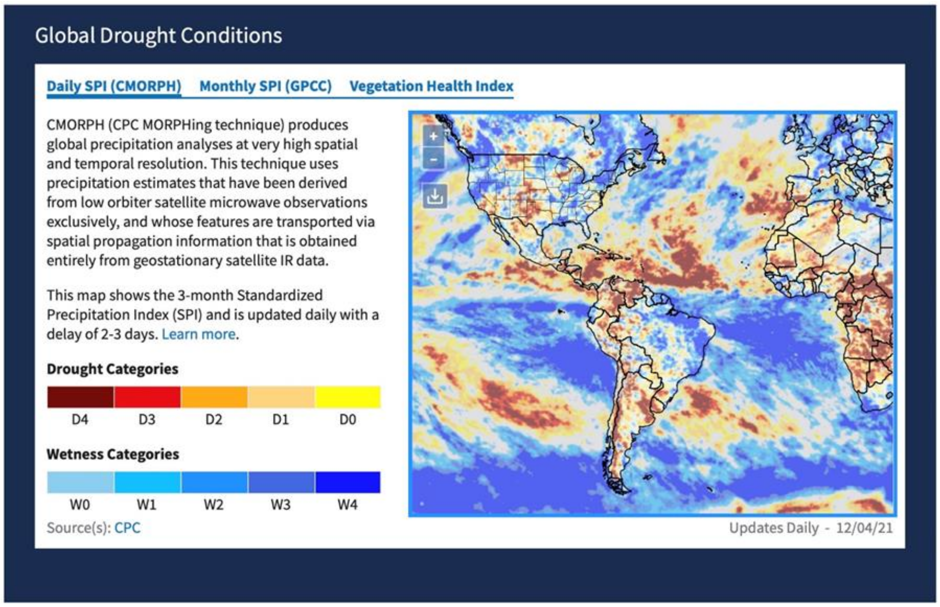


Figure 21. *CMORPH-SPI is available in the NIDIS Drought.gov portal to display global drought conditions. The 3-month Standardized Precipitation Index (SPI) is updated daily with a delay of 2-3 days: https://www.drought.gov/international (Source: Olivier Prat).*

Recommendations

The discussions in the Theme 4 session focused on two topics: What is the optimal satellite configuration by the science community that can satisfy user needs and is achievable within budget constraints? What improvements to the current satellite precipitation products will be most helpful for applications (refresh rate, spatial resolution, latency, accuracy)? A summary of the recommendations from this theme is as follows:

- Product latency is a top priority for NWS users. One hour or less is the optimal latency for nowcasting and short-term forecasting targeting Impact-Based Decision Support Services (IDSS). To meet this need, NOAA should develop capacities to downlink data in as near real-time as possible. Achieving this goal with a network of ground stations will be ideal but expanding and enhancing the Direct Broadcast networks (e.g., the JPSS DB network and the WMO DBNET) is also a viable and economical alternative. This should be a collaborative effort between NOAA and its domestic and international partner agencies.

- Refresh rate or observation frequency enormously impacts the utilization of PMW precipitation products in NWS operations. Hourly or sub-hourly sampling is the target for effective storm monitoring and sufficient diurnal cycle coverage. The latter is crucial for climate studies. With the existing and planned missions by the US, Europe, and Japan, the precipitation satellite constellation will reach a 2-hour refresh rate on average in the next 3-5 years. This is a much-improved capability for precipitation estimation compared to the current configuration. However, additional missions are required to achieve the optimal hourly/sub-hourly sampling that the NWS forecasters need (Fig. 10).

- NOAA does not need to launch additional primary missions besides what has been planned but should consider investing in sustained, more cost-effective Smallsats/Cubesats (S/C) to fill in the temporal gaps between the primary missions. With careful calibration, the S/C sensors may provide "good enough" multi-channel measurements for precipitation retrievals, as demonstrated by the TROPICS Pathfinder Cubesat. This configuration will significantly benefit the precipitation product developers and users by providing a high refresh rate from the additional S/C satellites and the validation reference from the primary missions.

- Support is required to produce operational precipitation products from S/C. This includes all activities from data downlink to product generation and archive.

- Algorithm enhancement is needed for challenging retrievals, including orographic precipitation, shallow precipitation, warm cloud rain, and rain on snow. Innovative approaches, such as AI/ML techniques, should be explored.

- Improving the spatial resolution of products is a high-priority requirement for forecasters. PMW imagers have higher resolution than sounders, but their existing and planned capabilities only support a 4-hour refresh rate. Exploring downscaling methodologies, such as using IR observations to downscale PMW products, should be supported.

- Further development of the L3 integrated precipitation product CMORPH2, including its production from DB data, should be supported. L3 products are gridded in space and time, making them more suitable for NWS applications than their input data, i.e., L2 products.

- Techniques should be developed to seamlessly blend satellite products with other data sources, such as radar, to provide optimal precipitation products for various applications.

- Methods, such as toolkits, should be developed to effectively quality control L2 input to ensure the quality of L3 products.

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Presentations

All presentations are archived at NOAA webpage:

Christophe Accadia (TBA as hyperlinks)

Ali Behrangi (TBA as hyperlinks)

William Blackwell (TBA as hyperlinks)

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