

# Incremental Learning for Passive Microwave Precipitation Retrievals using Advanced Technology Microwave Sounder

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**Abstract**—Spaceborne passive microwave (PMW) radiometry is central to global precipitation monitoring, yet retrieval uncertainties remain substantial, particularly for cross-track sounders whose variable footprints and channel configurations are optimized for atmospheric temperature and moisture profiling rather than precipitation. Consequently, existing operational products often exhibit angular-dependent biases, limited effective swath utilization, unrealistic rainfall probability distributions, and systematic misclassification of precipitation phase. These limitations are further compounded by the scarcity of globally accurate and representative precipitation observations, as training data from the Dual-frequency Precipitation Radar (DPR) and the Cloud Profiling Radar (CPR) are spatially sparse, lack uniform global coverage, and exhibit heterogeneous error characteristics across precipitation regimes. To address these challenges, this study presents a supervised retrieval algorithm that incrementally trains an ensemble of extreme gradient-boosted decision trees by augmenting base learners with pre-training on reanalysis data and post-training on coincident DPR and CPR observations matched with the Advanced Technology Microwave Sounder (ATMS). By transferring prior information from reanalysis to posterior constraints from radar observations and adopting a sequential detection–estimation strategy for precipitation phase and rate retrieval, the proposed approach yields retrievals across the full ATMS swath that are largely free from persistent deficiencies in current Global Precipitation Measurement (GPM) passive microwave operational products. In particular, the method resolves bimodal artifacts in rainfall retrievals and mitigates systematic high-latitude snowfall biases, including overestimation across the Arctic and underestimation across the Antarctic. Validation against independent Multi-Radar Multi-Sensor (MRMS) data over the Contiguous United States (CONUS) further demonstrates improved performance in precipitation phase detection and rate estimation relative to both reanalysis and current GPM PMW products.

**Index Terms**—Precipitation, Passive Microwaves, GPM,

This work was supported mainly by NASA’s Making Earth System Data Records for Use in Research (MEa- SUREs, 80NSSC24M0048) through Dr. Lucia Tsoussi, and Global Precipitation Measurement (PMM, 80NSSC22K0596) through Dr. Will McCarty. (*Corresponding author: Ardeshtir Ebtehaj*)

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ATMS, Machine Learning, Incremental Learning.

## I. INTRODUCTION

**P**RECIPITATION plays a central role in regulating Earth’s water and energy budgets and significantly influences weather dynamics, land surface hydrology, and ecosystem vitality. Accurate global monitoring of its space-time dynamic is essential for a wide range of applications, including water resource management [1], food security [2], and hydro-meteorological hazard mitigation [3]. Currently, satellite remote sensing of precipitation provides critical support for these applications, particularly over oceans and remote terrestrial regions that remain severely undersampled by in situ observations.

Unlike visible and infrared sensors, which can only probe the cloud-top temperature and, to some extent, suspended cloud water particles [4]–[6], microwaves can penetrate precipitating clouds [7]–[10] and interact with the microphysical properties of the hydrometeor profile [11]–[13].

Instruments such as the Dual-frequency Precipitation Radar (DPR) on the Global Precipitation Measurement (GPM) Core Observatory Satellite [14]–[16] and the Cloud Profiling Radar (CPR) on board CloudSat [17] satellite can resolve the vertical distribution of hydrometeors with high precision, offering valuable insights into storm microphysics and vertical cloud structures [14]. However, their high spatial and vertical resolution comes at the cost of a narrow observational swath and limited coverage (e.g., DPR spans approximately 65°S–N), resulting in relatively low temporal revisit frequency. These limitations constrain their ability to capture rapidly evolving weather systems and reduce their suitability for continuous global precipitation monitoring.

In contrast, passive microwave (PMW) radiometers provide a much wider swath than active radars, enabling near-global, sub-daily revisit coverage. Based on their scanning geometry, PMW radiometers are broadly classified into conical-scanning imagers, such as the GPM Microwave Imager (GMI), and cross-track-scanning sounders, such as the Advanced Technology Microwave Sounder (ATMS) [18]. The constant viewing angle of conical scanners maintains uniform footprint size and polarization across the swath, simplifying precipitation retrieval. In contrast, cross-track sounders experience substantial variations in footprint size from nadir to the swath edges, and their channel frequencies are primarily optimized for

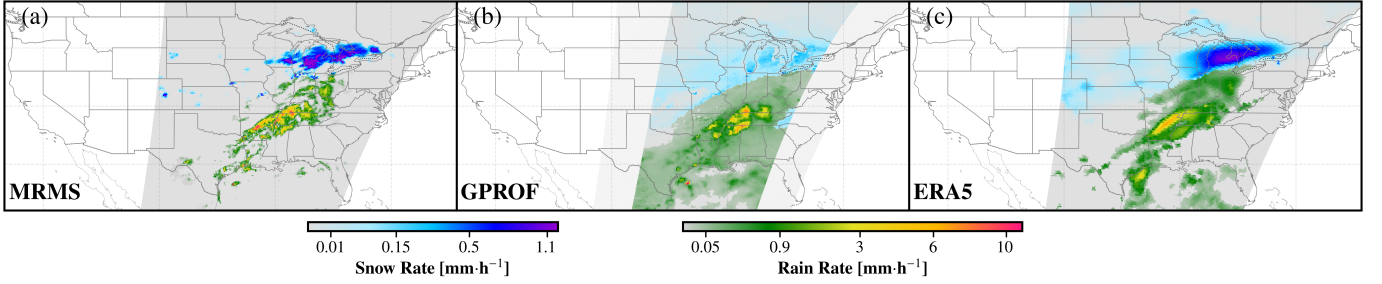


Fig. 1. The differences in estimates of a two-phase storm over the United States on January 29, 2023 – captured by MRMS (a), ATMS-GPROF-V07 (b), and ERA5 reanalysis (c) data, all mapped onto the ATMS orbit 58323, on board the Suomi-NPP satellite.

temperature and water vapor profiling rather than precipitation. These factors introduce greater uncertainty in precipitation retrievals for cross-track radiometers [19], which account for nearly half of the sensors in the GPM constellation. Nevertheless, algorithm development has historically focused on conical scanners [20], owing to their simpler geometry and precipitation-optimized spectral channels [21].

In PMW atmospheric radiometry, frequencies below 40 GHz lie in the Rayleigh regime, where liquid raindrops enhance atmospheric emission relative to radiometrically cold surfaces (e.g., over the ocean), resulting in warmer brightness temperatures (TBs). At higher frequencies above the oxygen absorption line, where wavelengths approach the size of ice particles, scattering of upwelling surface emission by the ice aloft leads to cooling in the observed TBs [22]. However, these multi-frequency signatures are not uniquely linked to the vertical distribution or phase (i.e., liquid versus solid) of hydrometeors when only a limited number of channels are available. Consequently, PMW precipitation retrieval constitutes an ill-posed inverse problem, in which sparse TB observations must be used to infer vertically varying microphysical properties. This ill-posedness is further compounded by uncertainties in the background surface emission (e.g., over land), which is often unknown and dynamically variable [23]–[25].

Early precipitation retrieval algorithms sought to leverage the physical relationships between hydrometeors and microwave signatures through empirical and physically based regression models [26]–[31]. These approaches later evolved into Bayesian retrieval frameworks, which invert the radiative transfer equation using large a priori databases populated with simulated or observed precipitation profiles and their corresponding microwave TBs [32]–[40].

More recently, advances in high-performance computing and large active–passive satellite archives have driven a shift toward machine learning (ML) and deep learning (DL) methods that learn relationships between  $T_B$  and precipitation [41], [42], [42]–[46]. These approaches rely on coincident passive–active observations to define inputs and output labels for PMW retrieval model training [47]–[49]. Although supervised learning has improved retrieval accuracy, performance remains limited by the quality and availability of active radar data, as regional ground-based radar observations lack global generalization. Consequently, spaceborne radar datasets from DPR (Ku/Ka band, 13.6/35.5 GHz) and CPR (W-band, 94 GHz)

are widely used for training [50], [51].

However, DPR has limited sensitivity to light rain and snowfall [52] and misses a substantial fraction of global snowfall due to weak snow-particle reflectivity [53] and its near-surface blind zone [54]. Its coverage is also restricted to 65°S–N, leaving no training information for high-latitude precipitation, particularly in the Arctic and Antarctic regions.

In contrast, CPR is highly sensitive to light precipitation, especially snowfall, and provides near-global coverage up to 82° latitude. However, it is susceptible to high raindrop attenuation in deep convective systems [55], [56]. Another key limitation is that CPR is a profiling radar with a footprint of approximately  $1.4 \times 1.7$  km, yielding sparse coincidences with PMW radiometers, which are not spatially continuous but instead provide structured (tabular) data. This limitation is further exacerbated by daylight-only operations since October 27, 2011, following a battery anomaly in April 2011 [57]. Consequently, locally aware deep learning models (e.g., convolutional neural networks such as U-Net [58] and Vision Transformers [59]), which rely on spatially coherent inputs, are not well suited for such data.

To the best of our knowledge, no study has demonstrated that spatial deep learning models can provide operational snowfall retrievals that outperform reanalysis. Several studies [60], [61] have suggested that the reanalysis precipitation from ERA5 [62], the fifth-generation ECMWF atmospheric reanalysis of global climate, outperforms NASA’s Integrated Multi-satellite Retrievals for GPM (IMERG, [63]) snowfall, which combines information mainly from the Goddard Profiling (GPROF, [64]) PMW retrievals of the GPM satellite constellation. Fig. 1 illustrates these differences for a storm over the United States, comparing ERA5, GPROF-V07, and ground-based MRMS observations [65] during an ATMS overpass on January 29, 2023.

Modern reanalysis datasets [66]–[69] provide physically consistent, spatially complete, and globally gridded precipitation estimates [70], albeit with notable uncertainties [71]. Their coarse resolution limits representation of fine-scale convective precipitation [72]–[74] and its diurnal cycle [75]. While satellite radiance assimilation has been a key driver of improvements [76], an open question is whether reanalysis can be used to enhance PMW retrievals—especially at high latitudes where active observations are sparse. Specifically, can low-level PMW precipitation signatures be learned from reanalysis

and refined incrementally using active satellite data? Can this approach improve global precipitation estimates beyond current satellite products and reanalysis?

To address these challenges, this study builds on prior work using ATMS observations from NOAA polar-orbiting platforms. We train an ensemble of Extreme Gradient Boosting (XGBoost) decision trees [77] in two stages. Stage I performs prior learning from coincident ATMS  $T_B$  and ERA5 data, while Stage II applies posterior learning using ATMS collocations with DPR rainfall and CPR snowfall observations. This framework, termed **Transfer Learning of global Precipitation from Reanalysis data to Satellite observations (TLP-R2S)**, leverages the strengths of both datasets.

Given the tabular nature of CPR data, we employ XGBoost, which has been shown to outperform deep learning models for such data [78]–[80]. Unlike prior approaches [81] that retrieve only 60% of the ATMS swath, TLP-R2S enables full-swath retrieval by resolving the unrealistic bimodal rain-rate distribution over oceans [19], [82] and significantly improves high-latitude snowfall retrievals relative to GPROF-V07 [64], [83].

Section II describes the data, and the methodology is explained in Section III. The results, findings, analysis, and validation are presented in Section IV, with the discussion presented in Section V. Finally, Section VI concludes the article.

## II. DATA SETS

### A. ATMS Brightness Temperatures

The Advanced Technology Microwave Sounder (ATMS) is currently operational onboard the Joint Polar Satellite System (JPSS) constellation, including Suomi-NPP, NOAA-20, and NOAA-21 [42]. The cross-track instrument scans  $\pm 52.8^\circ$  from nadir at an orbital altitude of approximately 824 km, yielding 96 field-of-view (FOV) samples per scan line. It has 22 channels (Table I) whose spatial resolution varies significantly with frequency, from along-track  $\sim 74.8$  km at nadir for the low-frequency channels below 32 GHz to  $\sim 15.8$  km for the higher-frequency channels above 165 GHz [21]. This resolution degrades substantially toward the edges of the swath, where a single FOV can encompass a vast area (e.g.,  $323.1 \times 74.8$  km and  $68.4 \times 15.8$  km at 23.8 and  $183.31 \pm 1.0$  GHz, respectively). The observed TBs are a mixture of vertical and horizontal polarizations depending on the incident angle in response to changes in surface emissivity, atmospheric composition, and path length [84].

### B. Reanalysis Data

To provide the retrieval algorithm with essential surface and atmospheric variables that implicitly encode their microwave emissivity values, we incorporate ancillary data from the fifth-generation ECMWF Reanalysis (ERA5, [62]), produced by the Copernicus Climate Change Service. ERA5 provides hourly global estimates of numerous atmospheric and surface variables at a resolution of  $0.25^\circ$ . The specific ERA5 variables used as a part of TLP-R2S's input features are summarized in Table II. The ERA5 precipitation labels and rates are also used as the TLP-R2S pre-training outputs.

TABLE I  
A SUMMARY OF ATMS CHANNEL CHARACTERISTICS.

| Channel | Band | Frequency [GHz]               | Pol.* | Beam Width [°] |
|---------|------|-------------------------------|-------|----------------|
| 1       | K    | 23.8                          | QV    | 5.46°          |
| 2       | Ka   | 31.4                          | QV    | 5.55°          |
| 3       | V    | 50.3                          | QH    | 2.30°          |
| 4       |      | 51.76                         | QH    | 2.27°          |
| 5       |      | 52.8                          | QH    | 2.26°          |
| 6       |      | 53.596 $\pm$ 0.115            | QH    | 2.24°          |
| 7       |      | 54.4                          | QH    | 2.24°          |
| 8       |      | 54.94                         | QH    | 2.22°          |
| 9       |      | 55.5                          | QH    | 2.26°          |
| 10      |      | 57.29                         | QH    | 2.23°          |
| 11      |      | 57.29 $\pm$ 0.217             | QH    | 2.23°          |
| 12      |      | 57.29 $\pm$ 0.322 $\pm$ 0.048 | QH    | 2.23°          |
| 13      |      | 57.29 $\pm$ 0.322 $\pm$ 0.022 | QH    | 2.23°          |
| 14      |      | 57.29 $\pm$ 0.322 $\pm$ 0.01  | QH    | 2.23°          |
| 15      |      | 57.29 $\pm$ 0.322 $\pm$ 0.004 | QH    | 2.23°          |
| 16      | W    | 88.2                          | QV    | 2.15°          |
| 17      | G    | 165.5                         | QH    | 1.14°          |
| 18      |      | 183.31 $\pm$ 7.0              | QH    | 1.10°          |
| 19      |      | 183.31 $\pm$ 4.5              | QH    | 1.10°          |
| 20      |      | 183.31 $\pm$ 3.0              | QH    | 1.10°          |
| 21      |      | 183.31 $\pm$ 1.8              | QH    | 1.10°          |
| 22      |      | 183.31 $\pm$ 1.0              | QH    | 1.10°          |

\*Pol.: Polarization (QV: Quasi-Vertical, QH: Quasi-Horizontal)

TABLE II  
KEY ERA5 INPUT ANCILLARY VARIABLES USED IN THIS STUDY.

| Type        | Variable Name                         | Abbr.  | Unit                           |
|-------------|---------------------------------------|--------|--------------------------------|
| Atmospheric | Total Column Cloud Liquid Water       | tclw   | kg m <sup>-2</sup>             |
|             | Total Column Cloud Ice Water          | tciiw  | kg m <sup>-2</sup>             |
|             | Total Column Water Vapor              | tcwv   | kg m <sup>-2</sup>             |
|             | Convective Available Potential Energy | cape   | J kg <sup>-1</sup>             |
|             | 2-meter Air Temperature               | t2m    | K                              |
|             | 10-meter U-component of Wind          | u10    | m s <sup>-1</sup>              |
|             | 10-meter V-component of Wind          | v10    | m s <sup>-1</sup>              |
|             | Total Column Water                    | tcw    | kg m <sup>-2</sup>             |
| Surface     | Total Column Supercooled Liquid Water | tcslw  | kg m <sup>-2</sup>             |
|             | Land-Sea Mask                         | lsm    | -                              |
|             | Sea Ice Area Fraction                 | siconc | -                              |
|             | Skin Temperature                      | skt    | K                              |
|             | Snow Depth                            | sd     | m                              |
|             | Volumetric Soil Water Layer 1         | swvl1  | m <sup>3</sup> m <sup>-3</sup> |

### C. Satellite Coincidences

1) *ATMS and DPR*: To obtain rainfall labels and rates for algorithm training, we use retrievals from the active DPR aboard the GPM Core Observatory, which provides a 3D reflectivity field at a 5 km horizontal and 250 m vertical resolution. For this study, we utilize `phaseNearSurface` and `precipRateNearSurface` of the Solver (SLV) module from the official 2A-DPR V07 product over a 245 km inner swath width [85]. An ATMS-DPR coincidence dataset is collected by first identifying  $\pm 7.5$  min time coincidences between the Suomi-NPP and GPM orbits using daily two-line element (TLE) data from the calendar years 2015 and 2023. An example is shown in Fig. 2, and the mapping process is described later.



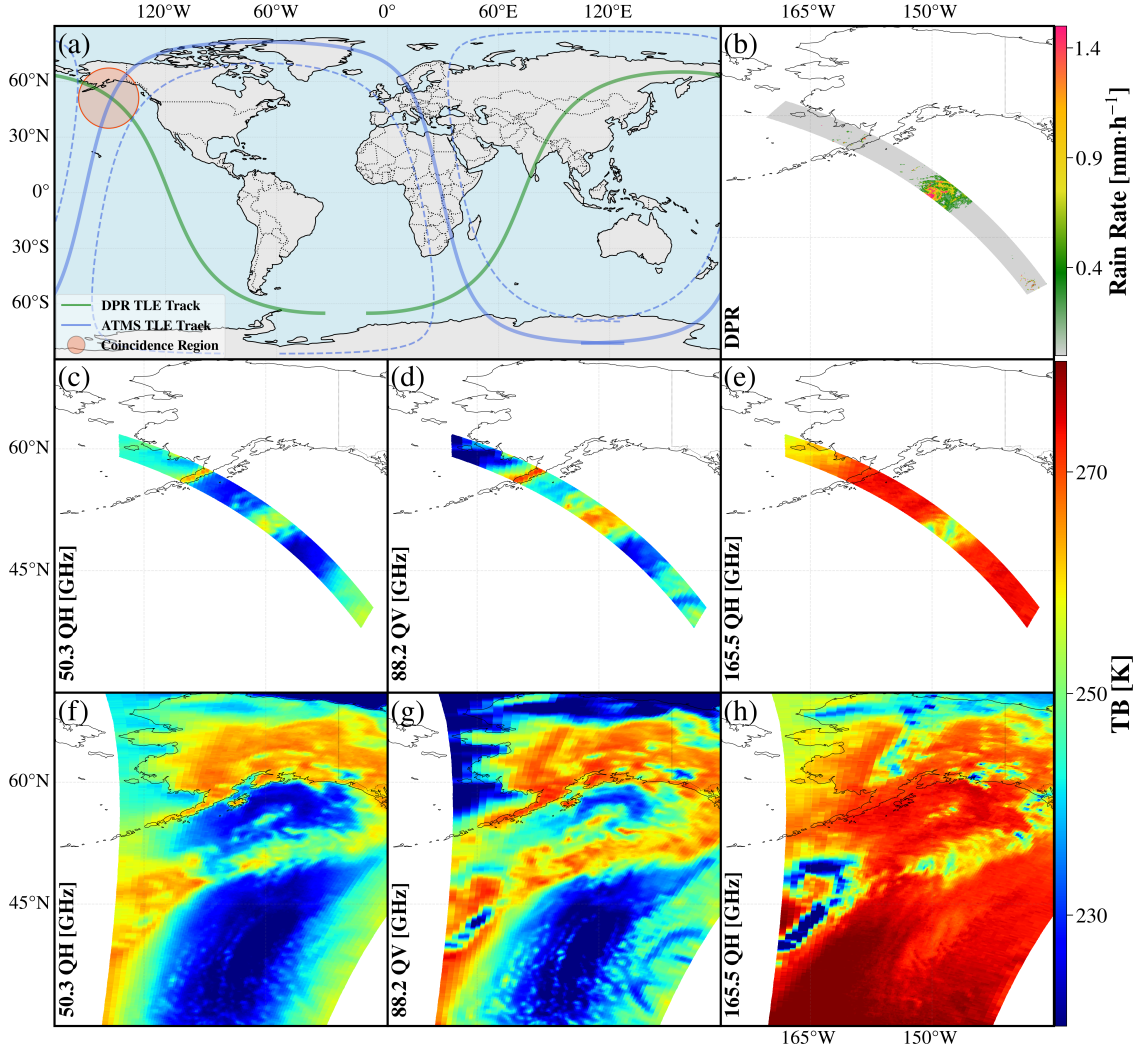


Fig. 2. An example of a coincidence between Suomi-NPP ATMS orbit 20303, from 11:06:53 to 12:48:21 UTC, and GPM DPR orbit 8990, from 11:13:58 to 12:46:30 UTC, over the North Pacific Ocean on September 28, 2015, with a time difference of 0.2 minutes at the point of the closest approach. (a) Orbital ground tracks showing the coincidence region, (b) DPR-observed near-surface rain rate, (c–e) ATMS TBs at 50.3, 88.2, and 165.5 GHz mapped onto the DPR swath, and (f–h) a full swath view of the mapped ATMS TBs.

2) *ATMS and CPR*: For CPR coincidences, we use the Precip\_flag from the 2C-PRECIP-COLUMN product [86] and the snowfall\_rate\_sfc from the 2C-SNOW-PROFILE product [87]. The coincidence dataset comprises the latest version of near-coincident ATMS and CPR observations from 2014 to 2019, as described in [51], [88]. The collocation follows the same methodology used for the ATMS-DPR dataset, but employs a wider temporal window of  $\pm 15$  minutes to increase the sample size, as proved effective in previous studies [42]–[44]. The spatial frequency distribution of the coincidences used to train the retrieval algorithm is shown in Fig. 3 at  $2.5^\circ$  resolution, revealing sparse and uneven global coverage.

3) *ATMS and Ground-based Radar Data*: The Multi-Radar Multi-Sensor (MRMS, [65]) system is a high-resolution, near-real-time data product developed by NOAA’s National Severe Storms Laboratory. It integrates observations from multiple weather radars, satellites, surface sensors, and numerical weather models to produce seamless, three-dimensional anal-

yses of precipitation and storm structure across the United States. MRMS provides products such as quantitative precipitation estimates (QPE), hail size, rotation tracks, and hydrometeor classification at a spatial resolution of about 1 km and a temporal resolution of 2 minutes. For an independent cross-comparison, coincident MRMS and ATMS observations for 2023 are used.

#### D. Coincident Mapping, Data Harmonization, and Partitioning

The ATMS observations are regridded for proper matching with the reanalysis data. The native ATMS footprint, particularly at off-nadir angles, is larger in the cross-track direction and smaller in the along-track direction than for ERA5 grid boxes. To minimize information loss during interpolation, the native 96 ATMS FOVs along each scan line are reprojected onto a new regular grid at approximately 15 km resolution, thereby preventing information loss when ERA5 is mapped onto the new ATMS grids, particularly near the edge of the



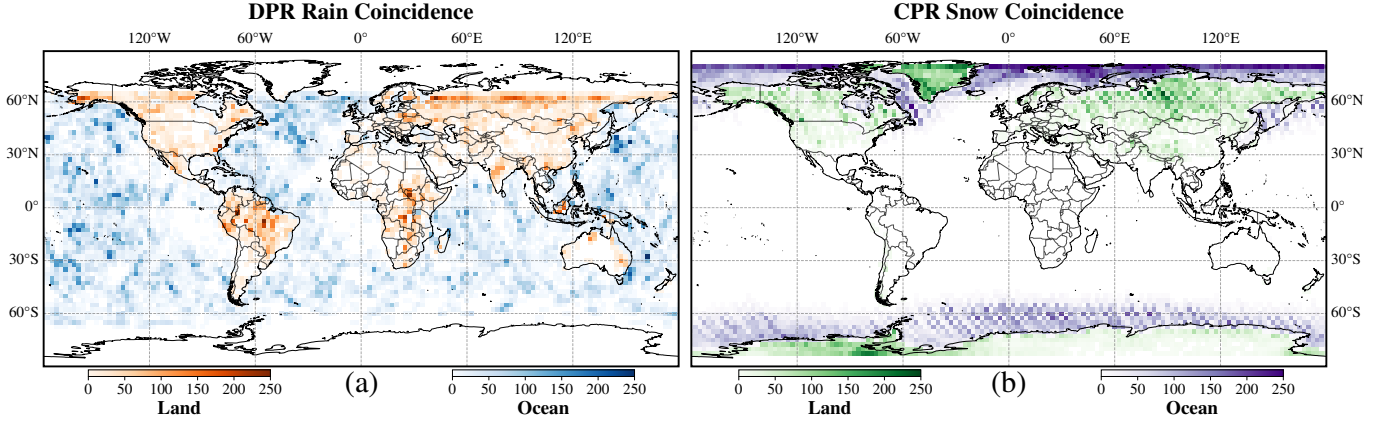


Fig. 3. Spatial density of (a) ATMS-DPR raining and (b) ATMS-CPR snowing coincidences in 2015 and 2014–2018, respectively, shown at a  $2.5^\circ$  resolution.

swath. To address resolution mismatches between the ATMS, DPR, CPR, and MRMS data, we harmonize all datasets by mapping them onto the new ATMS grids. In general, when mapping data with lower native resolution onto a higher-resolution grid, we use nearest-neighbor interpolation for both phase and rate of precipitation. However, when the source data resolution is higher than the target grid resolution, we use the majority-vote rule for phase and averaging for rate to perform the mapping.

TABLE III  
SAMPLE COUNTS OF HARMONIZED ATMS OBSERVATIONS WITH CORRESPONDING PRECIPITATION RATE AND PHASE LABELS. DATA SOURCES INCLUDE ATMS-DPR (2015 & 2023), ATMS-CPR (2014–2019), AND ATMS-ERA5 (2015).

| Data Source | Rainfall Samples | Snowfall Samples |
|-------------|------------------|------------------|
| ERA5        | 3,000,000        | 1,500,000        |
| DPR         | 370,000          | –                |
| CPR         | –                | 240,000          |

The total number of harmonized samples from each data source is reported in Table III. The data from calendar years 2019 and 2023 are withheld for an independent validation and annual retrieval testing. The remaining data are randomly partitioned into 70%, 15%, and 15% for training, validation, and testing, respectively.

#### E. Consistency Analysis

To assess the physical consistency of the coincidence datasets, we analyze the mean spectral signatures of the collected crossings across different precipitation rates over both ocean and land (Fig. 4). For terrestrial rainfall, a weak low-frequency emission signal, below the oxygen absorption channels, is observed and appears to be non-monotonic with rain rate. This signature is more pronounced over the ocean and is monotonically increasing with rain rate.

For overland snowfall TBs, the snowing atmosphere is statistically colder radiometrically across 23.8–52.8 GHz. This may partly be because snowfall occurs primarily on snow-covered surfaces, which have statistically lower surface emissivity than all collected non-snowing TBs. The colder oxygen

channels indicate that the atmosphere is statistically colder thermodynamically over land for snowing clouds. The known snowfall scattering [25] is detected across 88.2 and 165.5 GHz channels, and a modest warming is apparent across water vapor channels at 183 GHz, especially those with larger offsets that probe the near-surface atmosphere at higher pressure levels. Unlike overland snowfall, the oceanic signatures at 23.8 and 31.4 GHz capture a warming emission signal, likely because the collected data consist of frequent snowfall over sea ice, which is more emissive than open oceans. High-frequency snowfall scattering at 88.2 GHz and above is evident and appears stronger than over land, as snowfall samples are more frequent over highly emissive sea ice. Once again, broader offsets provide stronger signatures at 183 GHz.

### III. METHODOLOGY

#### A. Algorithmic Framework

The TLP-R2S framework, sketched in Fig. 5, is a two-step supervised learning algorithm applied primarily to retrieve precipitation phase and rate from ATMS observations. The first step involves phase classification (i.e., rain, snow, or no precipitation), followed by a rate regression step that uses an appropriate regression model to estimate rates based on the detected precipitation phase. Decoupling the classification and regression tasks enables proper model tuning to enhance the detection of less frequent snowfall events and implicitly utilize appropriate Z-R and Z-S relationships for estimating rainfall and snowfall rates [43], [89], based on the adopted radar data. This flexibility also enables the use of distinct loss functions tailored to each task, thereby enhancing control over different sources of uncertainties in phase detection and rate estimation.

1) *Step 1: Precipitation Phase Classification*: The precipitation phase classifier (i.e.,  $f_{\text{phase}} : \mathbb{R}^m \rightarrow \{0, 1, 2\}$ , non-precipitating or clear-sky = 0, rain = 1, and snow = 2) is developed through a two-stage training process. First, a baseline XGBoost model is trained on ERA5 precipitation labels, minimizing a multi-class cross-entropy loss function. The number of boosting rounds (100–300), along with other hyperparameters, including the number of parallel trees (1–10), maximum tree depth (10–30),  $\ell_1$ -norm (0–10) and  $\ell_2$ -norm (0–10) regularization terms, the minimum loss reduction required

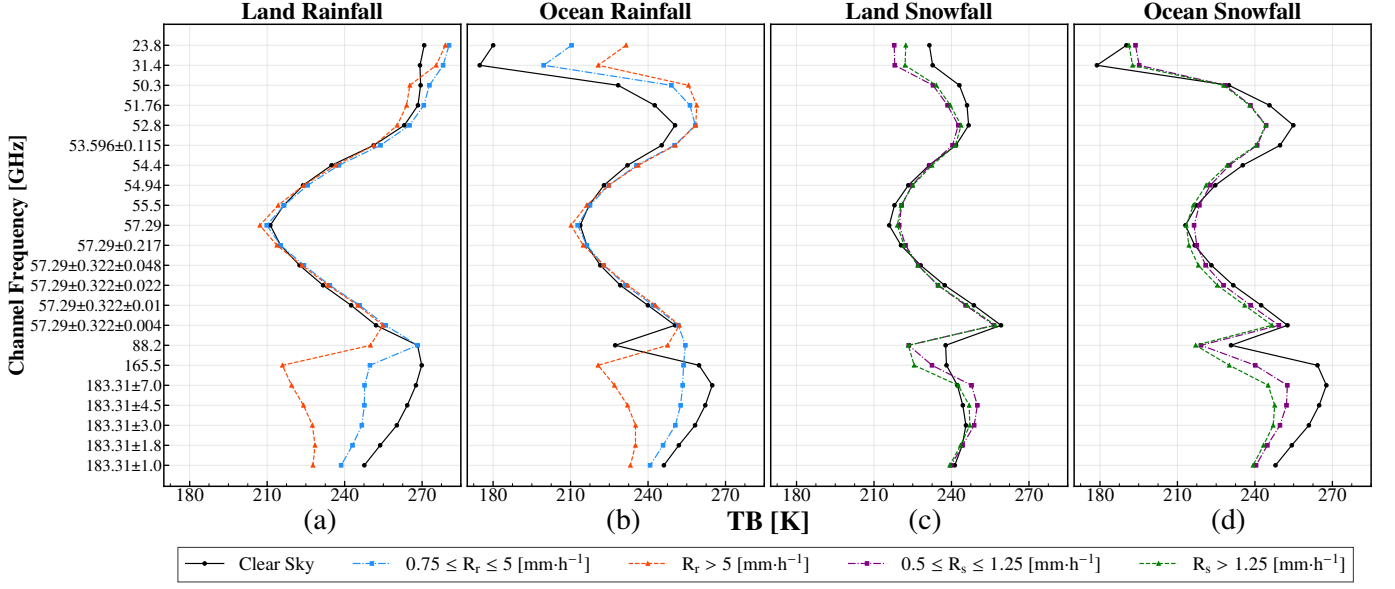


Fig. 4. Observed mean spectral signatures of rainfall (a,b) and snowfall (c,d) on ATMS channels over land and ocean for ATMS-DPR (2015) and ATMS-CPR (2014-2018) coincidences for a different range of rates.

for further partitioning of leaf nodes (0–2), and learning rate  $\eta$  (0.005–0.5) are optimized using Optuna Bayesian optimization algorithm [90] with the optimal parameters reported in Tab. IV. In the second stage, the model is expanded by adding more boosters and training them on the satellite coincidence labels and rates.

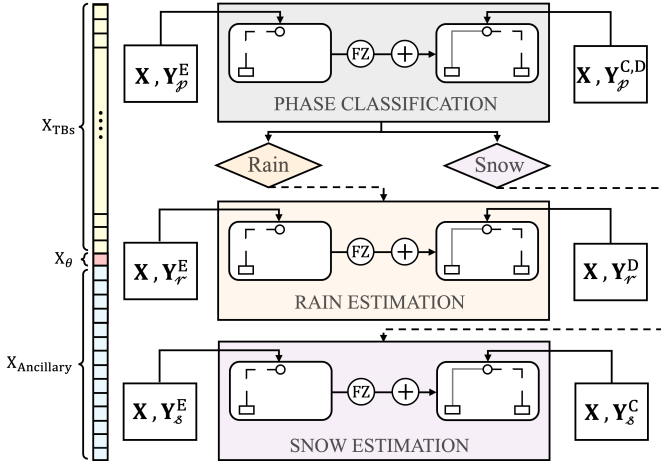


Fig. 5. Schematic representation of the TLP-R2S framework, a two-step algorithmic process consisting of three two-stage XGBoost models: A phase classifier model (Step 1) and two rate regression models for both rainfall and snowfall (Step 2). Each model undergoes a two-stage incremental learning process. In the first stage, models are trained on ERA5 labels for precipitation phase ( $\mathbf{Y}_p^E$ ), rain rate ( $\mathbf{Y}_r^E$ ), and snow rate ( $\mathbf{Y}_s^E$ ). In the second stage, the pre-trained models are frozen (FZ), additional boosters are then added (+), and training continues with satellite labels from CPR and DPR ( $\mathbf{Y}_p^{C,D}$ ,  $\mathbf{Y}_r^C$ ,  $\mathbf{Y}_s^D$ ). Following phase classification, the precipitation rate is estimated using regression models based on the detected phase, with the same input feature vector dimensionality comprising ATMS TBs  $\mathbf{X}_{TB}$ , the incident angle  $\mathbf{X}_\theta$ , and ERA5 ancillary variables  $\mathbf{X}_{Ancillary}$ .

To leverage the strengths of each instrument, labels in this stage are divided by source: rain from DPR and snow from CPR. The decision to separate labels is driven by the specific

uncertainties associated with each radar’s sensitivity. Research suggests that DPR is not sufficiently sensitive to surface snowfall, capturing only about 5–7% of global snowfall events [53], [91]. Furthermore, DPR observations are limited by the clutter-free zone, which can lead to the misidentification of surface rainfall as snow [54]. In contrast, while CPR provides highly accurate estimates for light snowfall [92], it tends to underestimate heavy convective rain because its W-band reflectivity saturates at high precipitation rates [93], [94]. We found that mixing inconsistent labels from the two radars results in a training dataset with non-unique relationships between inputs and outputs, leading to suboptimal training and increased retrieval uncertainties, particularly for precipitation phase detection.

TABLE IV  
HYPERPARAMETERS USED FOR STAGE I (STAGE II) OF TLP-R2S MODELS

| Hyperparameters                 | Phase Class.  | Rain Est.    | Snow Est.      |
|---------------------------------|---------------|--------------|----------------|
| Number of boosters              | 150           | 1000         | 1000           |
| $\ell_1$ regularization         | 0.092         | 0.005        | 0.068          |
| $\ell_2$ regularization         | 7.48          | 2.68         | 3.71           |
| Parallel trees                  | 4             | 5            | 4              |
| Maximum tree depth              | 23            | 15           | 17             |
| Minimum split loss ( $\gamma$ ) | 0.62          | 0.19         | 0.27           |
| Learning rate ( $\eta$ )        | 0.34 (0.0122) | 0.07 (0.008) | 0.06 (0.00032) |

To identify non-precipitating scenes, we rely on the CPR dataset. This choice is primarily motivated by the CPR’s greater sensitivity to low concentrations of hydrometeor particles, particularly ice, compared with DPR, which reports approximately 73% for clear-sky scenes among the available observations. Based on the occurrence frequency of reanalysis

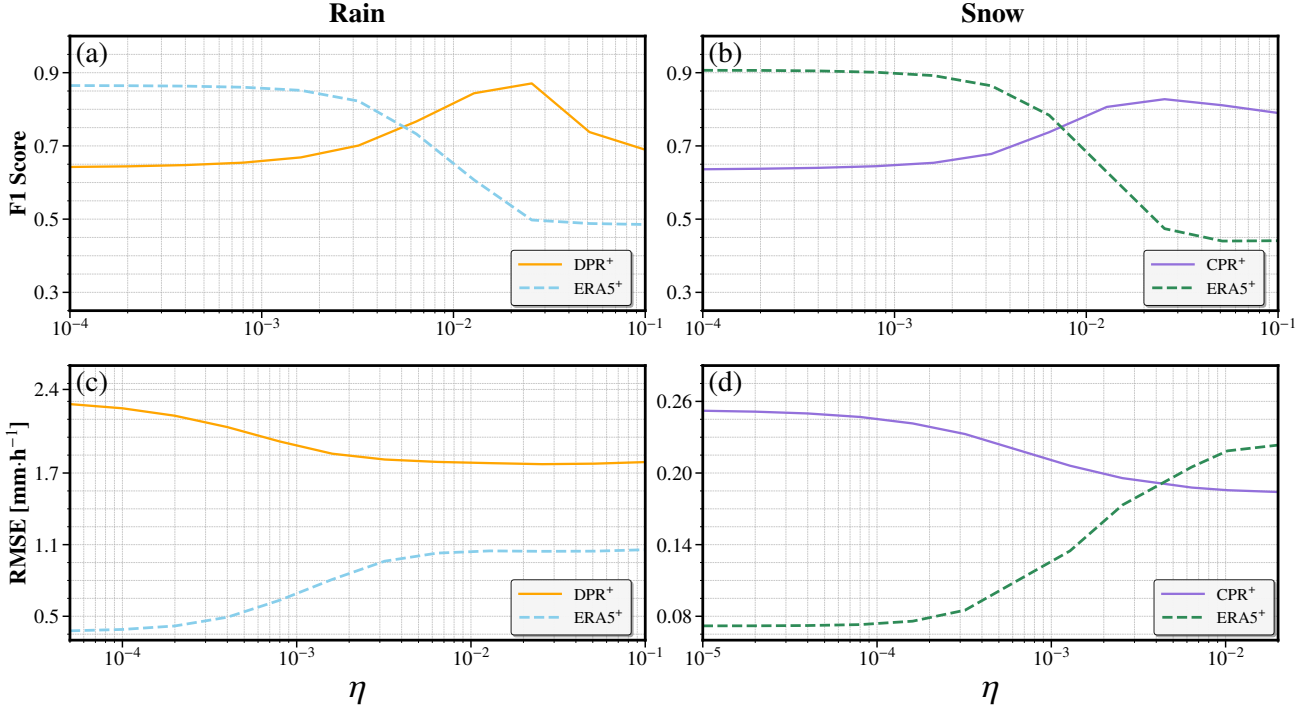


Fig. 6. The F1 score (a, b) and root mean squared error (RMSE) (c, d) for the detection and estimation steps as a function of learning rate  $\eta$  in the second stage of incremental training, showing that the model learns the satellite labels at the expense of forgetting some information of the reanalysis data.

data mapped onto ATMS orbits, a rainfall-to-snowfall ratio of approximately 2:1 was adopted, yielding a final ratio of 73% clear-sky, 18% rainfall, and 9% snowfall.

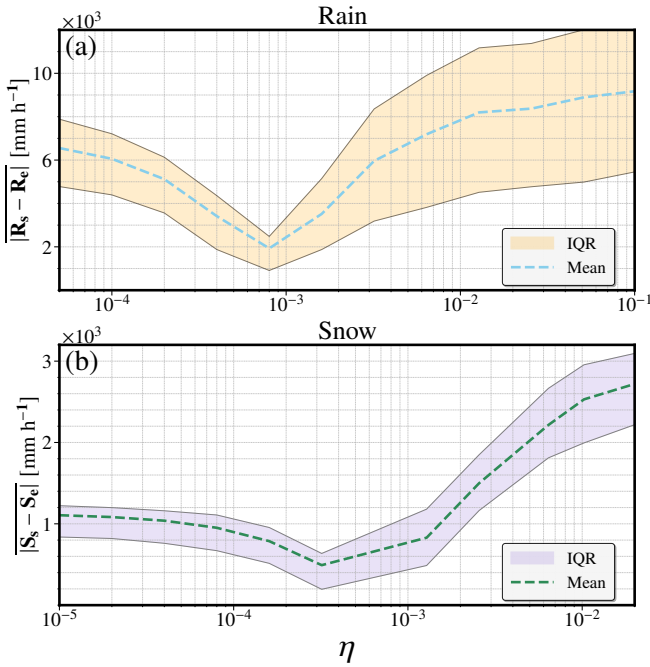


Fig. 7. Mean absolute difference between ATMS total orbital retrievals of rain  $R_s$  and snow  $S_s$  from ERA5 counterpart, namely  $R_e$  and  $S_e$ , as a function of learning rate  $\eta$  for 60 random orbits, selected from withheld calendar year 2023, with shaded areas showing the interquartile range (IQR).

To ensure effective transfer of knowledge from Stage I,

Stage II retains the same optimized hyperparameters and number of boosters (Tab. IV) but uses a different learning rate  $\eta$ . The choice of  $\eta$  balances learning from satellite data and retaining reanalysis knowledge: larger  $\eta$  accelerates adaptation but increases forgetting. The F1 score, harmonic mean of precision and recall, is used to select  $\eta$  for the detection step.

As  $\eta$  increases (Fig. 6a,b), the F1 score improves on satellite data but degrades on ERA5. Beyond  $\eta \approx 0.01$ – $0.015$ , gains on satellite data diminish while forgetting remains steep. Thus,  $\eta = 0.0122$  is selected as a balanced trade-off.

2) *Step 2: Precipitation Rate Regression*: Following phase classification, two parallel XGBoost regression models estimate rainfall and snowfall rates. Both minimize RMSE and follow the same two-stage incremental learning as the classifier: first trained on ERA5, then refined using DPR rainfall or CPR snowfall. Hyperparameters and boosting iterations are optimized in Stage I and fixed in Stage II, except for  $\eta$  (Tab. IV).

As shown in Fig. 6c–d, increasing  $\eta$  reduces RMSE on satellite data but increases it on ERA5, indicating that large  $\eta$  accelerates forgetting of reanalysis information. Notably, unlike CPR and ERA5 (panel d), a persistent RMSE gap remains between DPR and ERA5 (panel c), likely due to the heavier-tailed distribution of DPR rainfall.

A key challenge is maintaining unbiased annual precipitation totals while preserving the global water balance. We address this by using ERA5 as a reference, as it conserves water fluxes across the land–ocean–atmosphere system. Figure 7 shows the mean absolute difference in total orbital precipitation for 60 randomly selected ATMS orbits from 2023 as a function of  $\eta$ . For each orbit, retrieved rain ( $R_s$ ) and snow



TABLE V  
THE HELD-OUT TEST SET ESTIMATION (RMSE IN  $\text{mm hr}^{-1}$ ) AND DETECTION (F1-SCORE) QUALITY METRICS FOR PRIOR (I.E., ERA5<sup>-</sup>) AND POSTERIOR TRAINING SETS (I.E., ERA5<sup>+</sup>, DPR<sup>+</sup> AND CPR<sup>+</sup>).

|             |       | ERA5 <sup>-</sup> |       | ERA5 <sup>+</sup> |       | DPR <sup>+</sup> |       | CPR <sup>+</sup> |       |
|-------------|-------|-------------------|-------|-------------------|-------|------------------|-------|------------------|-------|
|             |       | F1-score          | RMSE  | F1-score          | RMSE  | F1-score         | RMSE  | F1-score         | RMSE  |
| <b>Rain</b> | Land  | 0.836             | 0.525 | 0.658             | 0.730 | 0.833            | 1.828 | -                | -     |
|             | Ocean | 0.870             | 0.335 | 0.609             | 0.613 | 0.843            | 1.994 | -                | -     |
| <b>Snow</b> | Land  | 0.887             | 0.075 | 0.665             | 0.090 | -                | -     | 0.807            | 0.255 |
|             | Ocean | 0.917             | 0.069 | 0.630             | 0.078 | -                | -     | 0.801            | 0.209 |

( $S_s$ ) are summed and compared with ERA5 totals ( $R_e$ ,  $S_e$ ). An optimal  $\eta$  minimizes these differences, reducing cumulative bias and preserving water balance. The source code is available at: <https://github.com/MahyarGarshasbi/TLP-R2S-ATMS/>.

#### IV. RESULTS

This section evaluates the performance of the proposed TLP-R2S algorithm. We present detection and estimation metrics for the holdout test set and assess the impact of incidence angle. The results of the incremental learning framework are analyzed, including the relative importance of input features in relation to the physics of surface emission and atmospheric propagation. Example orbital retrievals across the full ATMS swath are compared with GPROF-V07 (hereafter GPROF), ERA5, and CPR. We then examine selected storm events and extend the evaluation to annual accumulations to assess performance in a global climatological context.

##### A. Detection and Estimation Performance

Table V summarizes the key detection and estimation metrics for the held-out test set during incremental training from Stage I (–) to Stage II (+), as described in the data section. Specifically, ERA5<sup>-</sup> denotes prior performance on ERA5 data after Stage I training. In contrast, the DPR<sup>+</sup>, CPR<sup>+</sup>, and ERA5<sup>+</sup> columns report posterior performance on satellite and ERA5 test sets for Stage II. These posterior metrics quantify the extent to which information from the second stage is learned at the expense of forgetting information learned from the first stage.

Initial training on reanalysis data (ERA5<sup>-</sup>) yields high F1 scores, indicating that precipitation occurrence and phase are well learned. Posterior DPR F1 scores reach 0.833 and 0.843 for rain detection over land and ocean, respectively, while CPR snowfall detection is slightly lower at  $\sim 0.8$ . The ERA5<sup>+</sup> results reflect the transfer-learning trade-off: reduced F1 scores indicate increased fidelity to satellite data and partial forgetting of ERA5. Nevertheless, final F1 scores for ERA5<sup>-</sup> rainfall (0.6–0.66) and snowfall (0.63–0.66) show that retrievals retain background information from ERA5. Posterior retrievals yield RMSEs of about  $1.8\text{--}2.0 \text{ mm hr}^{-1}$  for rainfall and  $0.20\text{--}0.25 \text{ mm hr}^{-1}$  for snowfall, higher than those for ERA5<sup>-</sup> due to the heavier-tailed nature of active precipitation data.

A key question is how retrieval uncertainty varies with incidence angle. Several competing factors are involved. As the incidence angle increases, the atmospheric path length

grows, enhancing upwelling atmospheric emission and increasing the scattering of surface emission by hydrometeors relative to nadir views. At the same time, oblique observations provide less direct information about the vertical microphysical structure that produces surface precipitation. In addition, larger incidence angles correspond to larger ground footprints, which smooth sub-grid precipitation variability and weaken the intensity of microwave signatures, further influencing retrieval uncertainties.

Figure 8 shows the changes of test sets' F1-score and Symmetric Mean Absolute Percentage Error (SMAPE), defined as follows:

$$\text{SMAPE} = \frac{100}{n} \sum_{i=1}^n \frac{|r_i - \hat{r}_i|}{(|r_i| + |\hat{r}_i|)/2},$$

where  $r_i$  is the active and  $\hat{r}_i$  is the corresponding passive retrieved value. This metric quantifies changes in mean absolute error normalized by the mean retrieval rate, thereby reducing the influence of systematic rate variations across footprint sizes. All metrics shown are further normalized by their nadir values to highlight their relative dependence on incident angle.

For rain detection (panel a), the F1 score remains high, decreasing by less than 10% from its nadir value over both land and ocean. Sensitivity to incidence angle is slightly greater over land, likely because rainfall signatures depend strongly on scattering of surface emission by raindrops, which varies with viewing geometry. In contrast, the more homogeneous ocean surface yields TBs that are less sensitive to viewing angle.

In contrast, snow detection (panel b) shows a much sharper decline in F1 score at larger incidence angles than rainfall. This behavior is driven by two factors. First, snowfall signatures rely solely on scattering of surface emission, which varies spatially and degrades retrieval performance more rapidly at oblique angles. Second, orbital geometry limits CPR–ATMS coincidences: Suomi NPP follows a polar orbit, whereas CloudSat operated within the A-Train constellation, resulting in intersections primarily near the ATMS centerline. In fact, nearly 80% of coincidences occur at incidence angles smaller than  $25^\circ$ . Consequently, CPR-derived information becomes less informative at larger viewing angles. Despite this, the model retains information from the ERA5 prior (Fig. 9). The ERA5 F1 score remains robust across the swath, decreasing by only about 10% (from 0.72 to 0.62) as the incidence angle increases from nadir to  $60^\circ$  during posterior training.

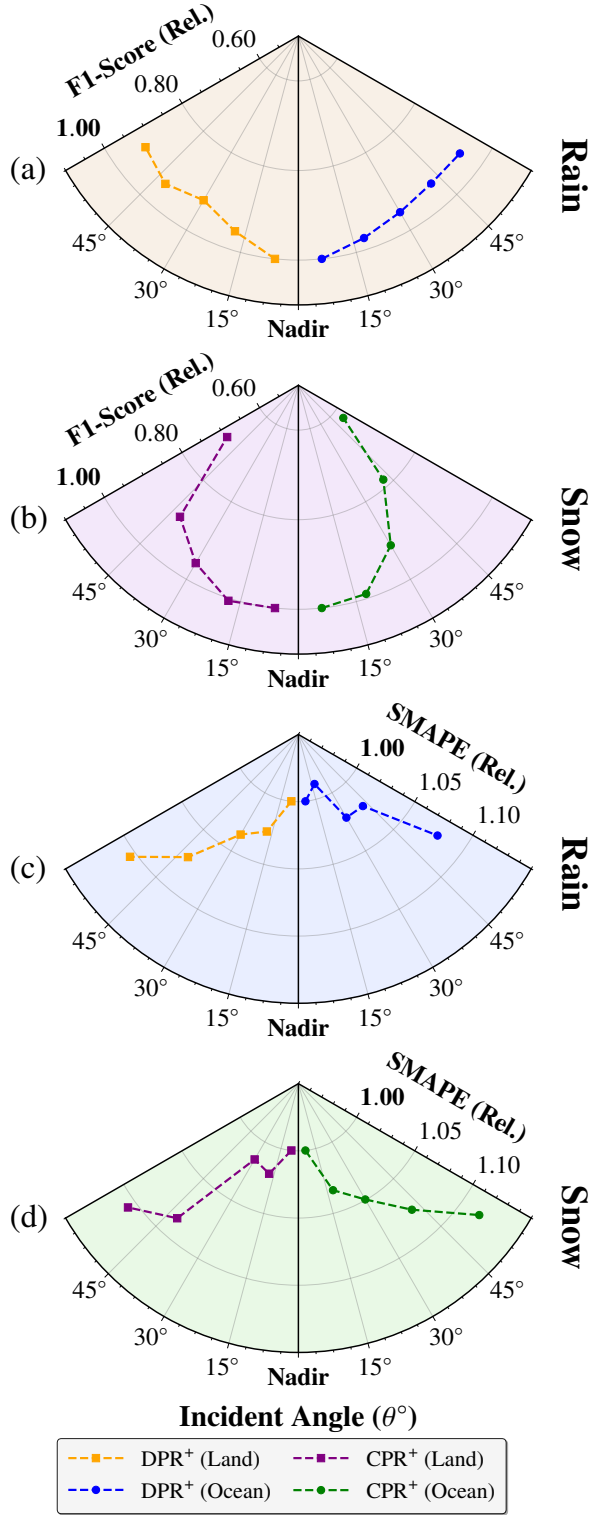


Fig. 8. The relative F1-score and SMAPE metrics as a function of incident angle for rain (a, c) and snow (b, d) retrievals using the relevant test sets.

The SMAPE estimation error (Fig. 8c,d) for rainfall (snowfall) increases by only  $\sim 9\%$  ( $11\%$ ) across the swath width, indicating that rate regression uncertainties are less sensitive to the change in incident angles. There are two competing factors here. The retrieval uncertainty is expected to increase at higher incident angles. However, the thinner-tailed distribution

of rainfall values averaged over a large footprint at higher incident angles can reduce retrieval uncertainties. Nevertheless, the second factor is partially mitigated by normalization of the SMAPE metric.

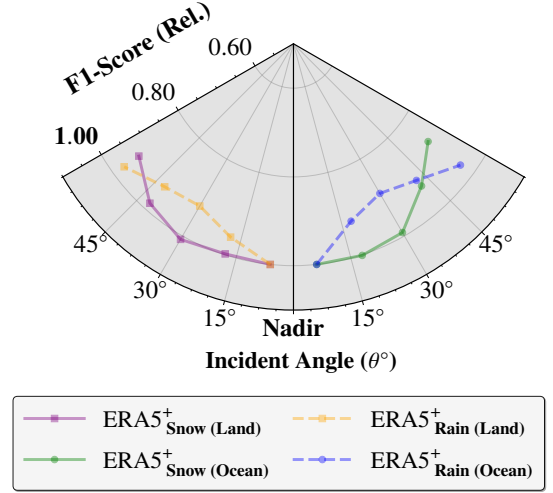


Fig. 9. Relative detection F1-score as a function of incident angle for ERA5+.

### B. Impact of Incremental Learning

Figure 10 illustrates the impact of incremental learning on orbital retrieval of a rainstorm over the South Pacific Ocean. Stage I (Fig. 10b) captures the broad, smoothed structure of ERA5 (Fig. 10a), with peak rain rates below  $8 \text{ mm hr}^{-1}$ . In contrast, Stage II (Fig. 10c) produces a sharper depiction of the storm: the footprint becomes more compact, and convective cores intensify to values exceeding  $16 \text{ mm hr}^{-1}$ . These refinements show strong agreement with coincident DPR observations and associated TB scattering signatures of elevated ice aloft (Fig. 10d,e). This example shows an increase in the F1 score with a more compact storm structure and a reduction in RMSE from Stage I to Stage II due to improved estimation of high rain rates.

To quantify the added value of incremental learning, we consider a baseline in which ERA5 pre-training is omitted and the model is trained solely on sparse satellite data. Figure 11 compares this approach with TLP-R2S, ERA5, and MRMS. The satellite-only model exhibits pronounced overestimation near the swath edges, a behavior that is especially prevalent during cold seasons (not shown). This bias is attributed to limb-darkening effects at large scan angles [95], where CPR coincidences are scarce. In these regions, non-precipitating scenes can resemble snowfall signatures observed near nadir, leading to false detections and overestimation. In contrast, TLP-R2S mitigates this issue by leveraging ERA5 pre-training, enabling consistent learning across incidence angles and improved refinement where satellite coincidences are available.

### C. Feature Ranking

To evaluate model behavior against the physics of microwave-precipitation interactions, we analyze the evolution

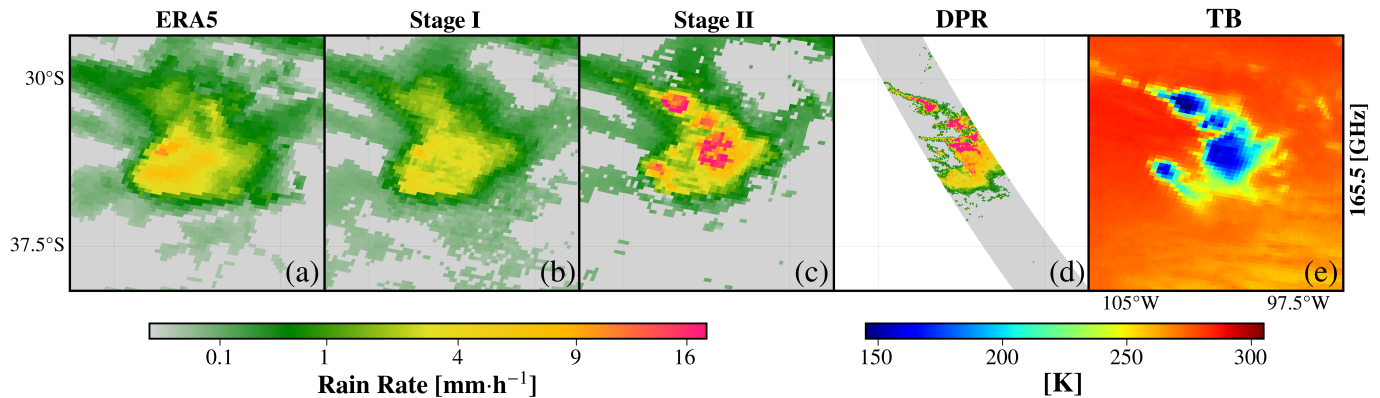


Fig. 10. The impact of incremental learning from Stage I to Stage II training, for a rainfall event over the South Pacific Ocean (a–e) captured by an withheld orbit 58961 on 15 March 2023, where the last panel shows the TBs at 165 GHz.

of feature importance for key inputs during training. This is done for both detection and estimation to assess how the model progressively prioritizes physically relevant predictors (Fig. 12). We use gain-based importance, which quantifies the average improvement from splits on each feature across all trees, and track it across training stages to reveal how feature relevance evolves during incremental learning.

In Stage I, phase detection (Fig. 12a) is dominated by ERA5 features, primarily 2-m air temperature ( $t_{2m}$ ), total column cloud liquid ( $t_{clw}$ ), and ice water content ( $t_{ciw}$ ), with  $t_{2m}$  being the most influential. TBs have relatively low importance at this stage, reflecting their weaker correlation with ERA5 precipitation compared to reanalysis variables.

In Stage II, the importance of TBs increases as the model incorporates direct radiometric information. Off-resonant channels (50–55 GHz) gain modest importance, along with scattering channels, particularly at 165.5 and  $183.31 \pm 7.0$  GHz. While the role of high-frequency channels is expected, the importance of oxygen absorption bands reflects their sensitivity to column temperature and precipitation phase. Nevertheless, ERA5 variables, especially  $t_{2m}$  and cloud water content, remain the dominant predictors of precipitation occurrence and phase.

In the snowfall regression model (Fig. 12b), total column ice ( $t_{ciw}$ ) and supercooled liquid water ( $t_{cslw}$ ) dominate in Stage I. In Stage II, these variables remain important, while the model incorporates information from high-frequency scattering channels and line-wing water vapor channels. Over-

all, cloud microphysical variables appear to remain more influential than TBs in snowfall rate estimation, even after posterior training.

In the rain regression model (Fig. 12c), total ice and cloud water content are again the most important features in Stage I. After Stage II, however, feature importance shifts markedly toward satellite TBs, with the 165.5 GHz channel becoming dominant, followed by the 88.2 GHz channel. This shift reflects the limited representation of convective ice-scattering signatures in ERA5 compared to satellite observations.

#### D. Orbital Retrievals

To demonstrate the TLP-R2S performance on withheld storms, this section evaluates retrievals from two distinct storm events shown in Fig. 13 and Fig. 14, highlighting the algorithm’s performance relative to ERA5, GPROF, and active radar observations (i.e., DPR and CPR).

A mixed-phase extratropical storm over the Labrador Sea on 31 January 2023, observed during a coincidence between ATMS (orbit 58350) and DPR (orbit 50708) with a 403 s time difference, is shown in Fig. 13. The TBs at 51.76 GHz (Fig. 13a), located on the lower wing of the oxygen absorption complex, and at 88.2 GHz (Fig. 13b) reveal two distinct spectral features.

First, a broad region of cold TBs over the southern coast of Greenland at 51.76 GHz likely indicates colder lower-tropospheric conditions over the Labrador Sea, consistent with

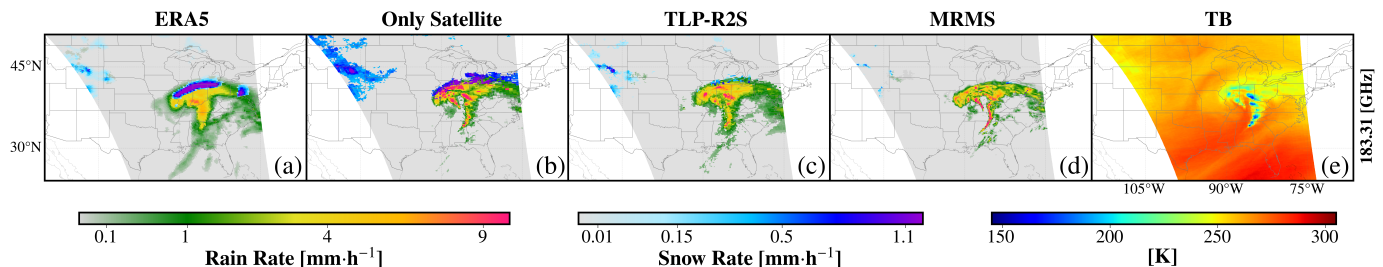


Fig. 11. Comparison of precipitation retrievals for a storm over the Central United States on March 3, 2023, captured by orbit #58798. The panels show (a) ERA5 reanalysis, (b) the baseline “Satellite-Only” model trained without ERA5 pre-training, (c) TLP-R2S retrievals, (d) ground-based MRMS observations, and (e) ATMS TBs at the  $183.31 \pm 3.0$  GHz channel.

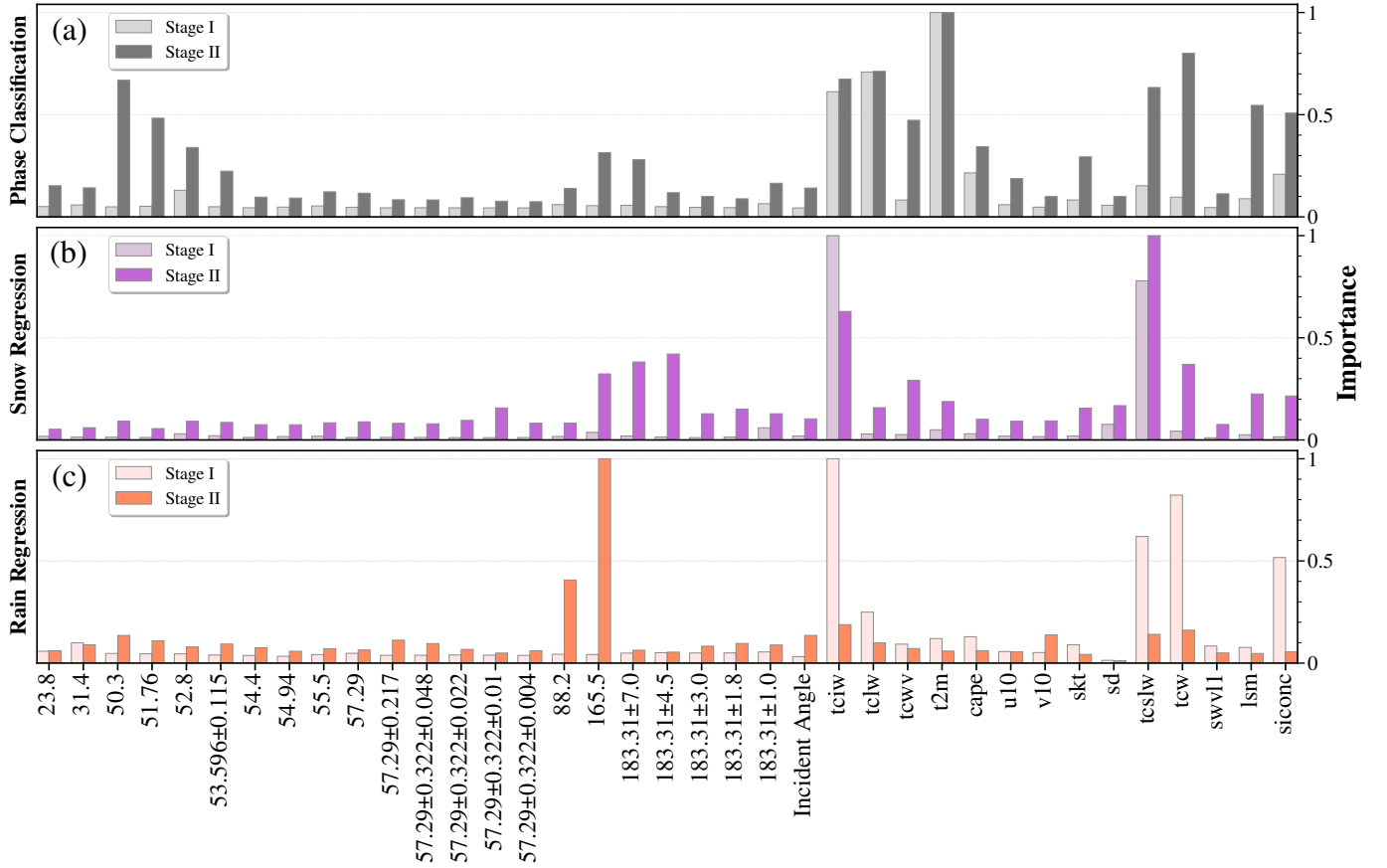


Fig. 12. Feature importance for (a) phase classification, (b) snow regression, and (c) rain regression models for the two stages of training.

the retrieved snowfall. Second, a narrow, warm band of TB values extends at both channels from the southeast, near the coast of Canada's Newfoundland, to the northwest of the swath. At the same time, a radiometrically warm area extends across the southwestern portion of the swath, suggesting low-tropospheric latent heat release from rainfall.

At higher frequencies (Fig. 13c,d), the storm band manifests itself as cooling-scattering signatures, indicating the likely presence of a frontal deep convective rainfall and a melting layer. At the northeast edge of the band, the scattering signatures extend over a broad area, with no clear emission signal at lower frequencies, suggesting possible snowfall and the absence of a melting layer.

In the precipitation products, the ERA5 reanalysis (Fig. 13e) captures the broad storm's morphology; however, it falls short in resolving the cellular structure of the convective core as observed by DPR (Fig. 13h). The ERA5 data indicate that the storm changes its phase from liquid over the North Atlantic Ocean to frozen over the Labrador Sea, consistent with the conceptual explanation of the precipitation signatures.

Although GPROF (Fig. 13f) provides a more refined estimate of rain morphology and variability than that of ERA5, it appears that its retrievals are highly correlated with the shown low-frequency signatures and less responsive to the scattering signals that can govern the location and intensity of convective rain cells in mixed-phased clouds. The frozen part of the storm in the GPROF retrievals significantly underestimates

the ERA5 data and shows little spatial variability. In addition, the retrievals are absent over nearly 450 km on each side of the outer swath, leaving close to 1000 km of observed TBs effectively unused.

The TLP-R2S provides full-swath coverage (Fig. 13g) and appears to interpolate the emission and scattering signals well across low- and high-frequency channels, leading to improved retrieval of the high-intensity convective part of the rain band, as indicated by visual comparisons with DPR. The retrieved snowfall from TLP-R2S exhibits greater variability than that from GPROF and is consistent with ERA5 reanalysis, though with notable differences. TLP-R2S underestimates ERA5 snow over the high-intensity regions of the snowstorm, but overestimates compared to ERA5 over the Labrador Sea, where broad cooling signals across low to high-frequency channels are noticeable.

Quantitative evaluation against DPR (Table VI) shows that TLP-R2S consistently outperforms ERA5 and GPROF across all metrics. The bias magnitude is reduced by about 80% relative to ERA5 and by even more than that relative to GPROF. The mean absolute error (MAE) shows modest improvement over ERA5 and a substantial reduction relative to GPROF. The Critical Success Index (CSI)—defined as the ratio of hits to the sum of hits, misses, and false alarms—increases by about 7.5% relative to ERA5 and 7.8% relative to GPROF. In terms of distributional agreement, the Wasserstein distance ( $d_W$ ) decreases slightly relative to ERA5 and by 57.3% compared



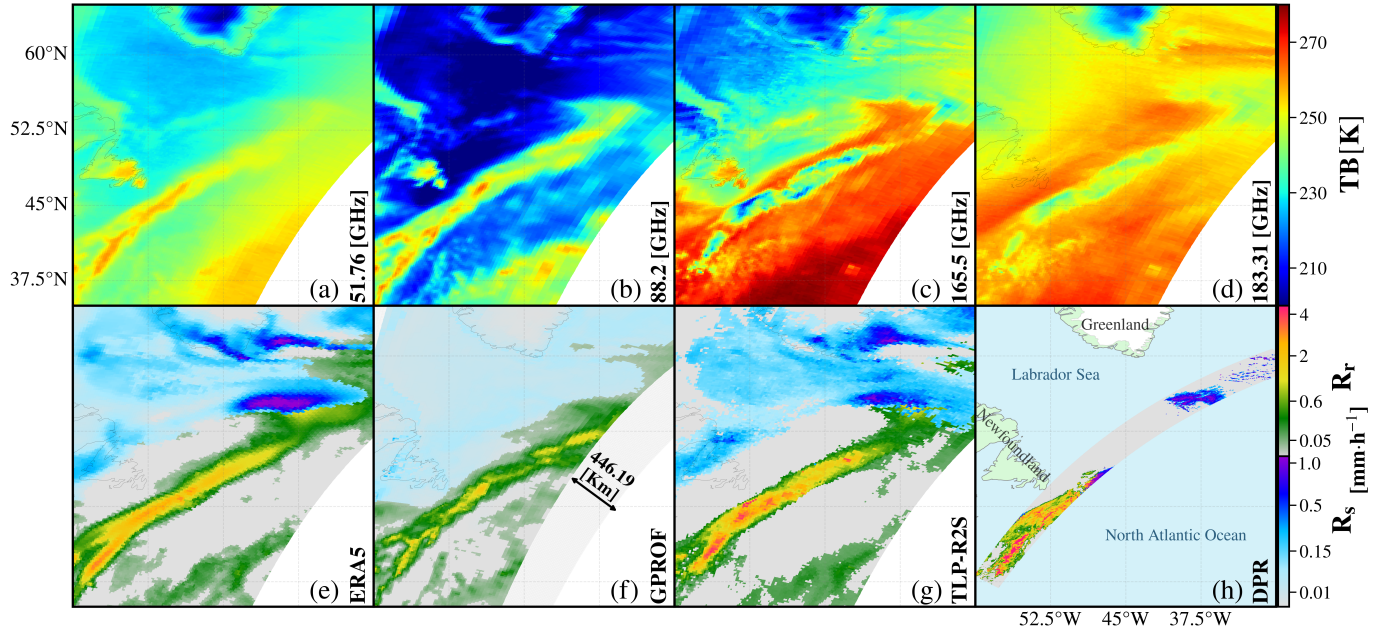


Fig. 13. Comparison of retrievals for a mixed-phase extratropical cyclone over the Labrador Sea on 31 January 2023 (ATMS orbit #58350, DPR orbit #50708). Panels show ATMS TBs at (a) 51.76 GHz, (b) 88.2 GHz, (c) 165.5 GHz, and (d)  $183.31 \pm 4.5$  GHz. The corresponding retrieved precipitation fields are from (e) ERA5, (f) GPROF, (g) TLP-R2S, and (h) DPR.

to GPROF.

The second case study (Fig. 14) examines a withheld high-latitude snowfall event on 08 August 2019 over the southern Indian Ocean near Antarctica. The event was observed during a near-coincident overpass of ATMS (orbit 40306) and CPR (orbit 70731), with a 345 s time difference. ERA5 depicts a broad snowstorm, while TLP-R2S closely reproduces this structure and captures additional variability. In contrast, GPROF appears sparse, capturing only fragmented portions of the storm.

TABLE VI  
COMPARISON OF RAINFALL RETRIEVAL PERFORMANCE METRICS FOR TLP-R2S, GPROF, AND ERA5 AGAINST DPR IN THE CASE STUDY PRESENTED IN FIG. 13

| Product | Bias    | MAE  | SMAPE | CSI    | $d_W$ |
|---------|---------|------|-------|--------|-------|
| ERA5    | -0.3208 | 1.11 | 68.18 | 0.7023 | 0.534 |
| GPROF   | -1.2150 | 1.29 | 99.37 | 0.7006 | 1.215 |
| TLP-R2S | -0.0604 | 1.06 | 58.91 | 0.7552 | 0.519 |

Bias, MAE, and  $d_W$  in  $[\text{mm} \cdot \text{h}^{-1}]$ , SMAPE in  $[0,200]\%$ , and CSI in  $[0,1]$ .

Along the CPR track, the reflectivity profile (Fig. 14b) indicates a relatively deep, perhaps nimbostratus, cloud system with a cloud top nearing 8 km. The reflectivity peaks at more than 16 dBZ around 3–4 km height from 58 to 62°S, indicating a broad distribution of ice particles and snowfall with some isolated convective streaks. The CPR tracks capture a moderate-to-heavy snowfall event with an average of  $1.7 \text{ mm} \cdot \text{h}^{-1}$  and a peak exceeding  $2.6 \text{ mm} \cdot \text{h}^{-1}$ . The PMW signatures of the snowstorm manifest themselves as cooling signals across the 50.3, 51.67, 88.2, and 165.5 GHz channels, and to a lesser extent at  $183.31 \pm 4.5$  GHz. These signals arise

from distinct mechanisms: lower off-resonant oxygen channels respond primarily to lower-tropospheric temperature changes, while higher-frequency cooling is dominated by scattering from ice aloft.

The profile (Fig. 14d) compares the performance of different retrievals. Overall, ERA5, CPR, and TLP-R2S show consistent storm structure and snowfall rates, whereas GPROF largely misses the event. Near the northern edge (latitudes above  $-58.2^\circ\text{S}$ ), TLP-R2S and CPR indicate clear-sky conditions, while GPROF and ERA5 produce light snowfall. Performance metrics against CPR (Table VII) confirm that TLP-R2S is closest to CPR across all metrics. This case highlights the limitations of GPROF for snowfall retrieval and shows that combining CPR and ERA5 information can improve satellite-based snowfall estimates.

### E. Evaluation of Probability Density Functions

In this subsection, we show that, unlike official GPM products, TLP-R2S produces more realistic probability density functions (PDFs) of precipitation. Precipitation is typically positively skewed, with rainfall exhibiting heavier tails than snowfall. Log-normal [96] and Gamma [97] distributions have commonly been used to describe these PDFs.

Previous studies have shown that GPROF retrievals from cross-track scanners exhibit bimodal distributions [19], [82], [98], unlike coincident radar observations and conical-scanner retrievals. Figure 15 compares PMW retrieval distributions with GPROF-V07 and DPR (CPR) for rainfall (snowfall) using coincident samples from the withheld year 2023 (2019), following the harmonization described in Section II.

The analysis of oceanic rainfall (Fig. 15a) shows bimodality of the GPROF retrievals with two modes around 1.3 and

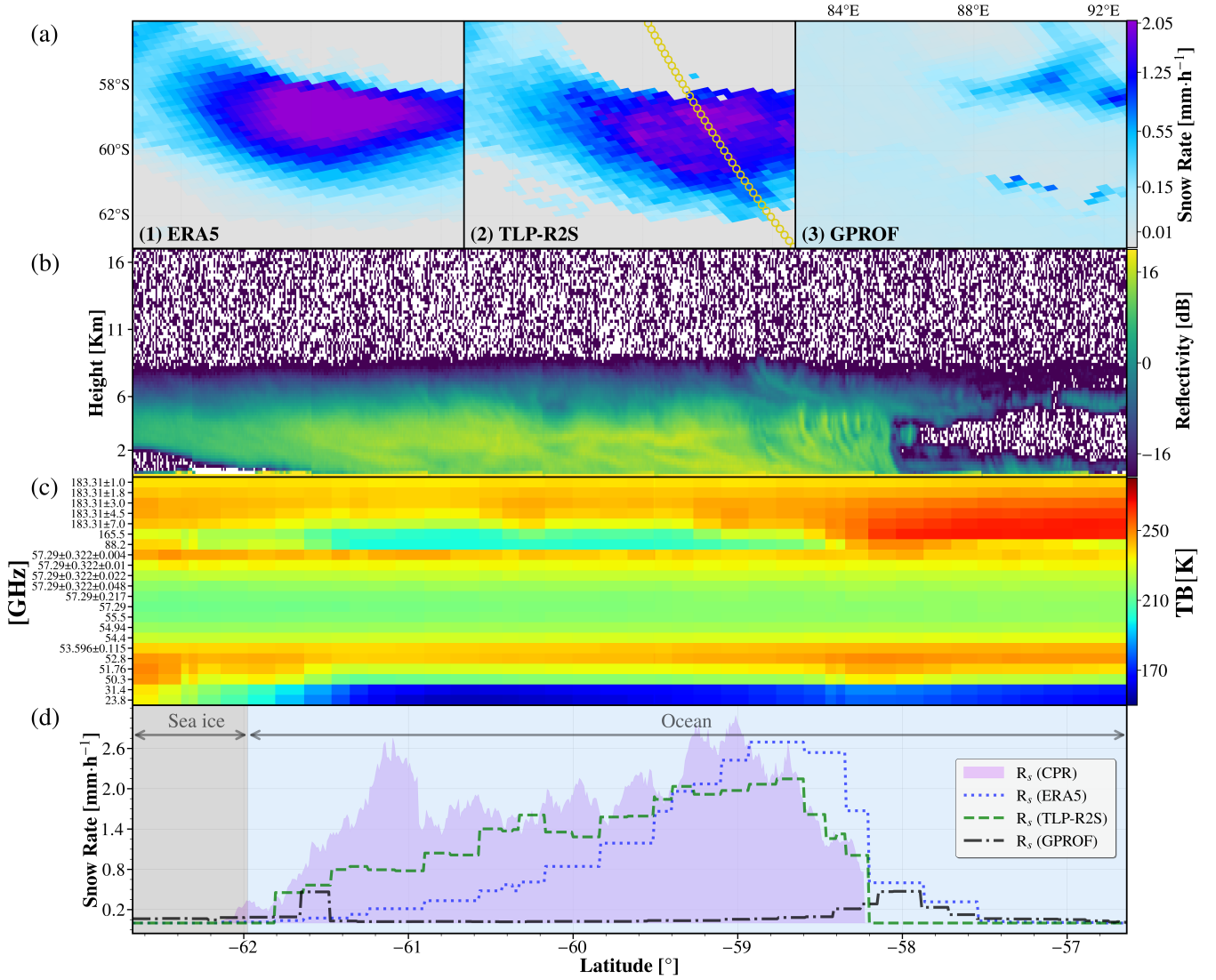


Fig. 14. Profile analysis of a snowfall event over the south Indian Ocean on 08 August 2019 (ATMS orbit #40306, CPR orbit #70731). Panels show (a) map-view retrievals from (1) ERA5, (2) TLP-R2S, and (3) GPROF, with the CPR track overlaid; (b) CPR reflectivity profile; (c) ATMS TBs along the track; and (d) a quantitative comparison of retrieved surface snowfall.

$7.9 \text{ mm hr}^{-1}$ , consistent with the previous findings. In contrast, the TLP-R2S distribution is unimodal and follows the DPR reference. In terms of distributional similarity, TLP-R2S achieves a Wasserstein distance of  $d_W = 0.31 \text{ mm} \cdot \text{h}^{-1}$  relative to DPR, which is approximately 47% lower than that of GPROF. Over land (Fig. 15b), the GPROF bimodality is less pronounced. Nonetheless, its distribution still deviates from the DPR, primarily by showing more light rainfall and fewer moderate-to-high-intensity rainfall rates, as expected, given the DPR's limited sensitivity to light rain. TLP-R2S retrievals remain close to DPR, with a Wasserstein distance that is about one-third of GPROF's.

An analysis of snowfall distributions (Fig. 15c–d) reveals distinct behavior compared to rainfall. Over both land and ocean, PMW retrievals exhibit lower modes than CPR, with a more pronounced shift in GPROF, indicating substantial underestimation. This is consistent with prior findings and is reflected in the Wasserstein distances, which are about three

times lower for TLP-R2S than for GPROF-V07 across both surfaces.

TABLE VII  
COMPARISON OF SNOWFALL RETRIEVAL PERFORMANCE METRICS FOR TLP-R2S, GPROF, AND ERA5 AGAINST CPR IN THE CASE STUDY PRESENTED IN FIG. 14

| Product | Bias    | MAE  | SMAPE  | CSI    | $d_W$ |
|---------|---------|------|--------|--------|-------|
| ERA5    | -0.6420 | 0.90 | 94.27  | 0.7788 | 0.653 |
| GPROF   | -1.6075 | 1.61 | 172.76 | 0.6446 | 1.608 |
| TLP-R2S | -0.4396 | 0.48 | 47.18  | 0.9123 | 0.443 |

Bias, MAE, and  $d_W$  in  $[\text{mm} \cdot \text{h}^{-1}]$ , SMAPE in  $[0,200]\%$ , and CSI in  $[0,1]$ .

#### F. Annual Assessments

In this section, we assess the consistency of retrievals on an annual scale using all ATMS orbits from the withheld

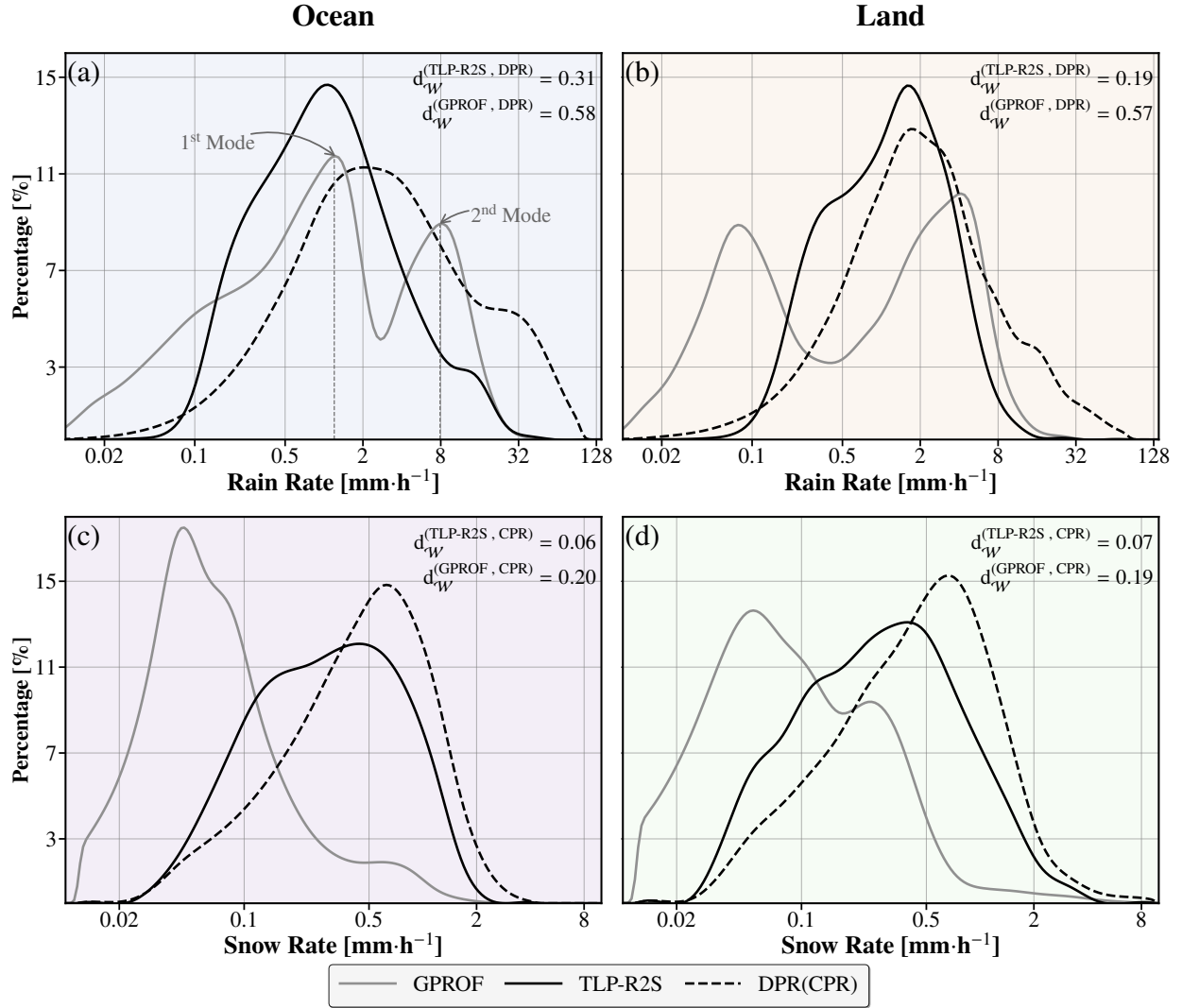


Fig. 15. Probability histograms, in percentages, of precipitation intensity comparing TLP-R2S and GPROF-v07 retrievals against active radar references, showing distributions of (a) ocean rainfall, (b) land rainfall, (c) ocean snowfall, and (d) land snowfall with their corresponding Wasserstein distances ( $d_W$ ).

year 2023 on a 0.15° grid (Fig. 16). Precipitation rates are aggregated by summing grid-mapped values and normalizing by the number of ATMS revisits for both liquid and solid phases. For direct comparison, only inner-swath regions with available GPROF estimates are considered. This analysis is not intended as validation, but rather as a consistency check against ERA5, which conserves annual water fluxes between the surface and atmosphere.

Overall, satellite rainfall retrievals show strong agreement with ERA5 (Fig. 16a–c), capturing the expected high accumulation along the equatorial ITCZ over both land and ocean. Differences relative to ERA5 are shown in Fig. 17. TLP-R2S tends to underestimate rainfall over the ITCZ, particularly in regions dominated by deep convection, including the Amazon, Congo Basin, Guinean forests, the Himalayas, and the western Pacific.

This discrepancy is not primarily due to underestimation within individual storms, but rather reflects the more continuous rainfall production in ERA5. Overestimation is generally sparse and limited, though it is evident in regions such

as the Himalayan rain shadow and orographic zones (e.g., the Coast Mountains and the Andes). In contrast, GPROF exhibits both under- and overestimation near the ITCZ, with mixed biases over the Malay Archipelago, where monsoon and tropical cyclone activity dominate. Orographically driven rainfall (e.g., Coast Mountains, Western Ghats, Himalayas) is often underestimated, while mean rainfall is underestimated over the Amazon and overestimated over the Congo relative to ERA5.

For annual snowfall (Fig. 16d–f), TLP-R2S and ERA5 are broadly consistent, whereas GPROF shows systematic differences relative to ERA5. As shown in Fig. 17c–d, TLP-R2S slightly overestimates ERA5 over the Arctic and underestimates it at mid-latitudes. Underestimation is also evident in regions of orographic coastal snowfall, including the windward slopes of the Coast Mountains, the southern Andes, and the Scandinavian Mountains. Over the Southern Ocean storm tracks, TLP-R2S underestimates ERA5, while overestimating snowfall over Antarctica. The underestimation is primarily associated with nimbostratus systems producing



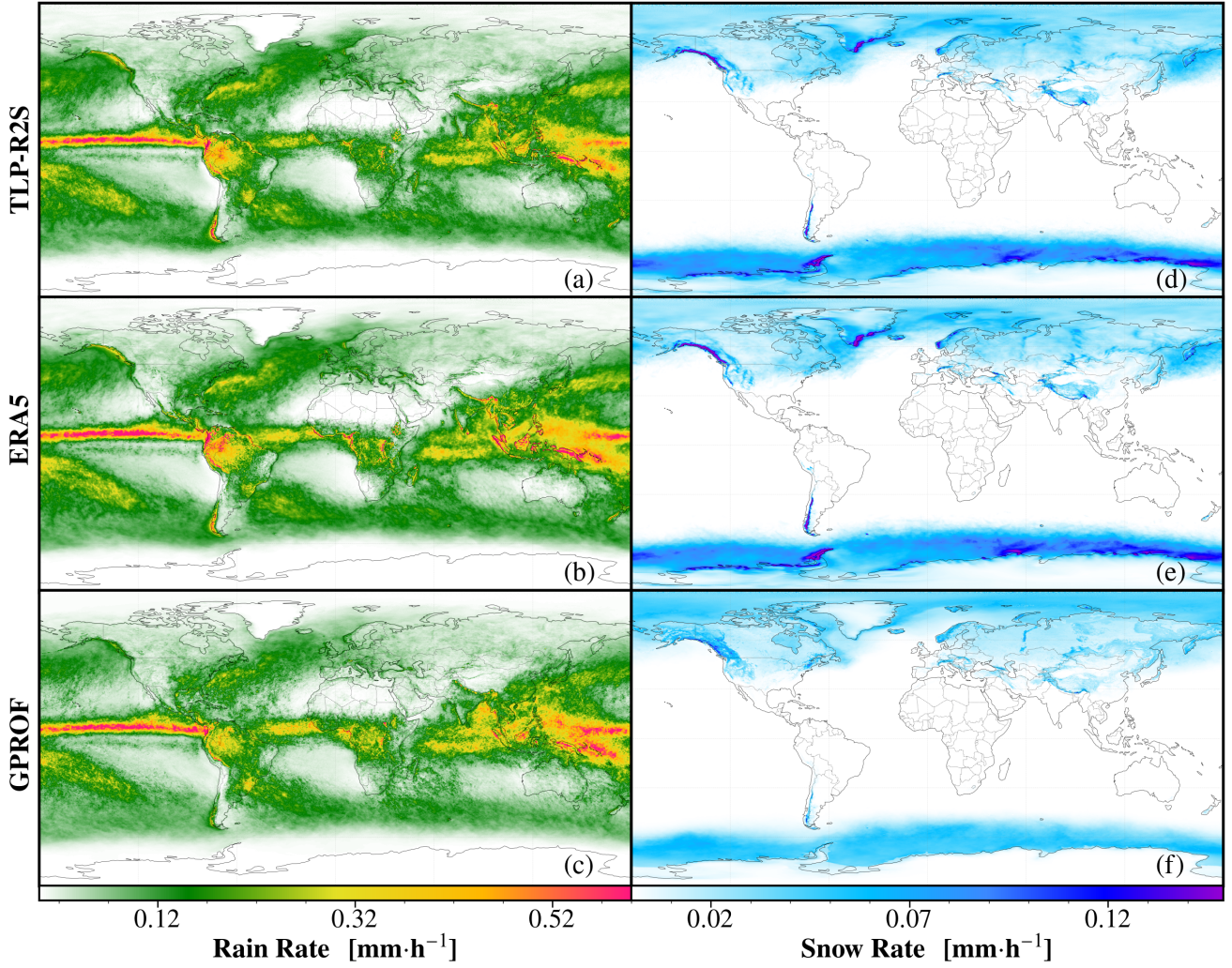


Fig. 16. Annual averaged precipitation retrieval in 2023 from TLP-R2S (top row), ERA5 (middle row), and GPROF (bottom row) for rainfall (a–c) and snowfall (d–f) on  $0.15^\circ$  grid, where all datasets are mapped when partial-swath GPROF data are available.

heavy snowfall, whereas overestimation is linked to shallow cumuliform clouds generating light snowfall over Antarctica (see Fig. 8 in [92]).

Unlike TLP-R2S, differences between GPROF and ERA5 annual snowfall exhibit more systematic patterns. Over the oceans, GPROF markedly overestimates ERA5 in the Arctic Ocean and underestimates it in the Southern Ocean, with localized overestimation (e.g., the Weddell Sea). It also yields lower annual means along the North Atlantic and Pacific storm tracks, particularly over the Greenland, Norwegian, Barents, and Bering Seas. Over land, biases are mixed, with consistent underestimation in regions of orographic snowfall, including the Coast Mountains, southern Greenland, interior Alaska, western Russia, and the Tibetan Plateau.

Table VIII summarizes differences between annual mean PMW retrievals and ERA5. As TLP-R2S is pre-trained on ERA5, it is expected to align more closely with ERA5 than GPROF, as reflected across all metrics. Over land, TLP-R2S achieves  $R^2 = 0.89$  (0.94) for rainfall (snowfall), representing a 26 (63)% improvement over GPROF (0.70 and 0.35). The Mean Absolute Difference (MAD) and root mean square

difference (RMSD) are reduced by more than 30 (70)% for rainfall (snowfall). Over oceans, TLP-R2S attains  $R^2 \approx 0.93$  (0.98), compared to 0.87 (0.69) for GPROF, with consistently lower MAD and RMSD. In all cases, the lower Wasserstein distance  $d_W$  further indicates that TLP-R2S annual distributions are closer to ERA5 than those of GPROF.

Figure 18 shows zonally averaged precipitation rates from Fig. 16. For snowfall, TLP-R2S yields a MAD of  $0.0011 \text{ mm/hr}^{-1}$ , about five times smaller than GPROF ( $0.0058 \text{ mm/hr}^{-1}$ ). Agreement with ERA5 is most evident near the peak snowfall along the Southern Ocean storm track. The results also show that GPROF underestimates snowfall over the Southern Ocean and Northern Hemisphere mid-latitudes, while overestimating it in the Arctic.

For rainfall, both retrievals capture the ERA5 zonal structure, including the equatorial ITCZ peak and subtropical minima near  $\pm 20\text{--}30^\circ$ . Differences are minor: GPROF aligns more closely with ERA5 near the secondary ITCZ peak, whereas TLP-R2S shows better agreement at mid-latitudes.



TABLE VIII  
RETRIEVAL SKILL OF TLP-R2S AND GPROF FOR ANNUAL MEAN PRECIPITATION, PER REVISITING TIME, AGAINST THAT OF ERA5 OVER LAND AND OCEAN.

|      |       | Product | Bias    | MAD    | RMSD   | R <sup>2</sup> | Rel. Bias | d <sub>W</sub> |
|------|-------|---------|---------|--------|--------|----------------|-----------|----------------|
| Rain | Land  | TLP-R2S | -0.0036 | 0.0128 | 0.0343 | 0.8868         | -6.31     | 0.0063         |
|      |       | GPROF   | -0.0066 | 0.0213 | 0.0554 | 0.7040         | -11.55    | 0.0087         |
|      | Ocean | TLP-R2S | -0.0048 | 0.0147 | 0.0264 | 0.9311         | -4.59     | 0.0049         |
|      |       | GPROF   | -0.0078 | 0.0230 | 0.0364 | 0.8690         | -7.50     | 0.0106         |
| Snow | Land  | TLP-R2S | 0.0002  | 0.0024 | 0.0054 | 0.9419         | 1.53      | 0.0008         |
|      |       | GPROF   | -0.0063 | 0.0083 | 0.0182 | 0.3480         | -42.46    | 0.0063         |
|      | Ocean | TLP-R2S | -0.0004 | 0.0016 | 0.0037 | 0.9802         | -2.35     | 0.0006         |
|      |       | GPROF   | -0.0031 | 0.0069 | 0.0148 | 0.6863         | -19.44    | 0.0040         |

Bias, MAD, RMSD, and d<sub>W</sub> are in [mm·h<sup>-1</sup>] and Relative Bias is in [%].

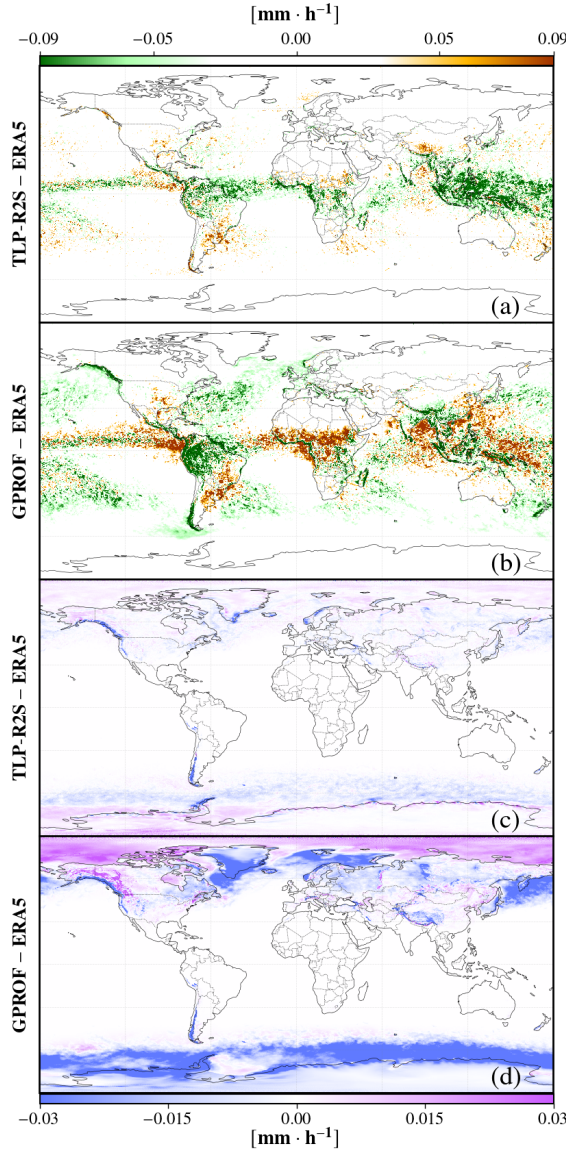


Fig. 17. The differences between annual mean PMW precipitation retrievals and ERA5 in calendar year 2023 for (a) TLP-R2S and (b) GPROF rainfall, as well as (c) TLP-R2S and (d) GPROF snowfall.

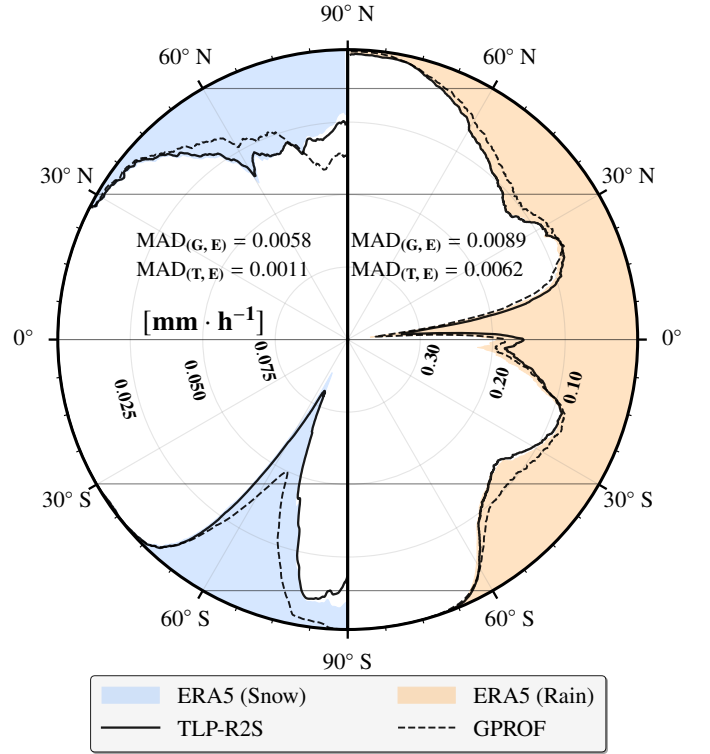


Fig. 18. Zonally averaged annual mean precipitation in 2023 for all ATMS orbital retrievals, comparing TLP-R2S and GPROF with ERA5, where the snowfall and rainfall values are shown in the left and right axes. The Mean Absolute Difference (MAD) for each retrieval algorithm relative to ERA5 for both phases is provided, where “G”, “T”, and “E” denote GPROF, TLP-R2S, and ERA5, respectively.

#### G. Ground-based Validation with MRMS

To assess the generalization of TLP-R2S, we validate its retrievals against ground-based MRMS data over CONUS. We use all ATMS overpasses crossing CONUS during the withheld year 2023 (612 orbits). MRMS data are spatiotemporally collocated with satellite observations for each orbit, and all datasets are mapped to the inner swath where GPROF retrievals are available, as described in Section II.

Figure 19 presents an example orbital retrieval over CONUS for orbit 58585 on February 16, 2023, compared with MRMS.

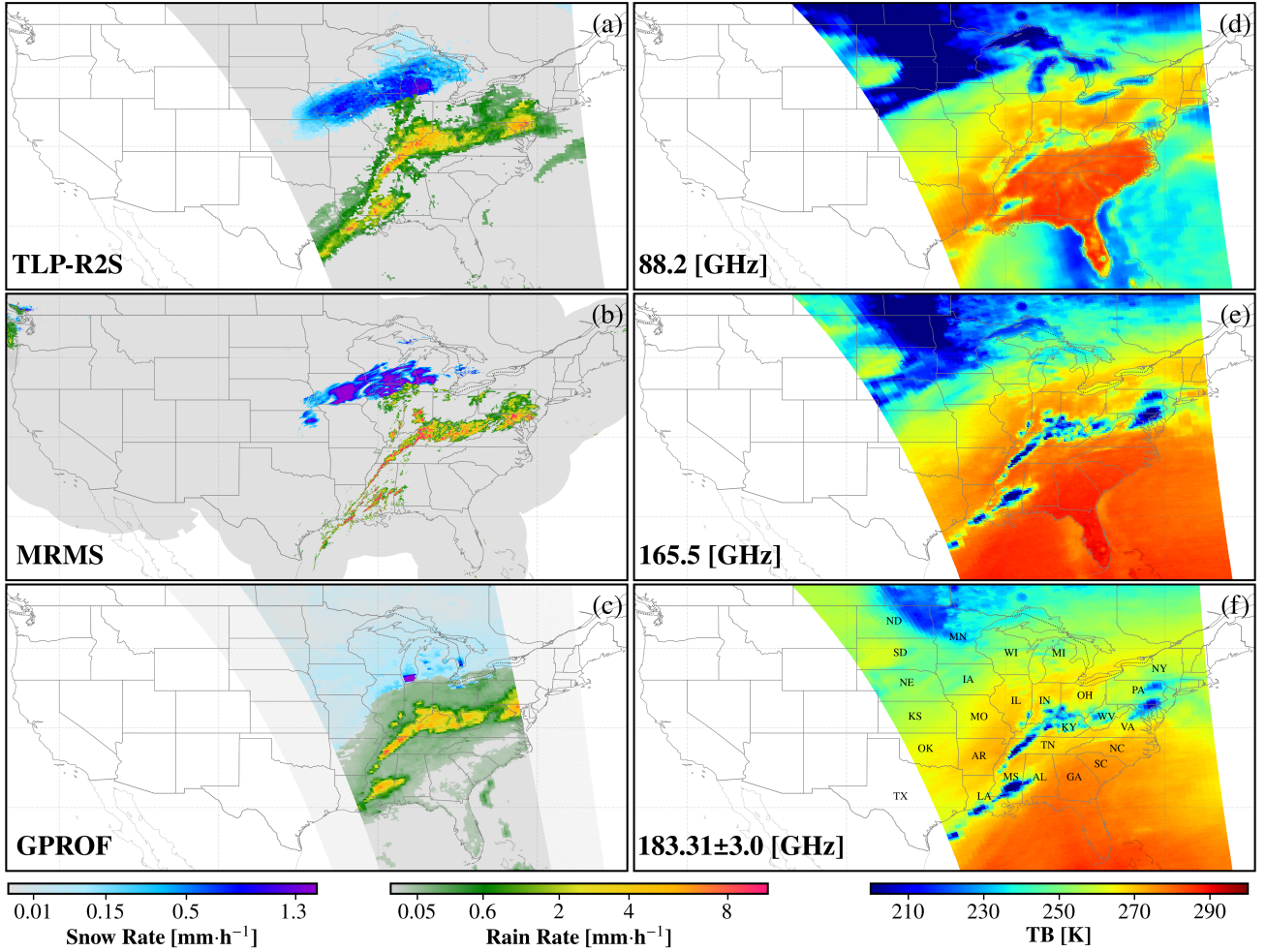


Fig. 19. Case study of orbit #58585 on February 16, 2023 (18:04:14–19:45:43 UTC), showing (a–c) precipitation retrievals from TLP-R2S, MRMS (at 18:40:00 UTC), and GPROF, respectively, and (d–f) corresponding TBs at 88.2 GHz, 165.5 GHz, and  $183.31 \pm 3.0$  GHz channels.

This orbit captured a strong cold frontal system, producing intense convective rainfall over the southeastern United States and a stratiform snowstorm over the Midwest. The corresponding PMW signatures are shown for the 88.2, 165.5, and  $183 \pm 3$  GHz channels.

During the rain event, strong scattering signals at 165.5 and  $183 \pm 3$  GHz indicate deep convective cores associated with supercells. These channels are sensitive to upper-tropospheric ice, which is linked to heavy surface rainfall. Farther north, regions of depressed  $T_B$  reflect combined scattering from surface snow cover and falling snow. Over Minnesota and the Dakotas, strong depressions, below 210–220 K, likely arise from snow-cover scattering, consistent with the absence of MRMS-detected snowfall. In contrast, over Iowa, Wisconsin, and Michigan, weaker but coherent depressions—most pronounced at 165.5 GHz—align with MRMS-observed snowfall.

Visual inspection of Fig. 19 highlights the capability of TLP-R2S to capture high-intensity convective rainfall and, more notably, to improve snowfall detection through joint learning from reanalysis and radar observations. Table IX quantifies this performance. TLP-R2S reduces error metrics relative to GPROF, with SMAPE decreasing by more than

60% for both liquid and solid precipitation. Detection skill also improves, as reflected by higher F1 scores and classification accuracy for both phases. The lower Wasserstein distance further indicates closer agreement with the MRMS distribution and minimal bias.

TABLE IX  
RETRIEVAL PERFORMANCE METRICS FOR TLP-R2S AND GPROF  
AGAINST MRMS FOR THE STORM SHOWN IN FIG. 19

| Product |      | Bias    | SMAPE  | F1     | Acc.   | $d_W$ |
|---------|------|---------|--------|--------|--------|-------|
| TLP-R2S | Rain | 0.0026  | 58.75  | 0.6436 | 0.9114 | 0.69  |
|         | Snow | -0.0128 | 62.94  | 0.6219 | 0.9351 | 0.41  |
| GPROF   | Rain | -0.0970 | 173.33 | 0.5738 | 0.8762 | 1.62  |
|         | Snow | -0.1408 | 188.32 | 0.4221 | 0.8725 | 0.77  |

Bias and  $d_W$  in  $[\text{mm} \cdot \text{h}^{-1}]$ , SMAPE in  $[0, 200]\%$ , F1-Score and Accuracy in  $[0, 1]$ .

To expand this single-storm example into a statistical evaluation, Fig. 20 summarizes example retrievals and validation statistics for all 612 independent orbital overpasses in 2023, with representative storms shown in the top row. These metrics

include conditional MAE and bias to quantify estimation uncertainty when MRMS detects precipitation. We also use F1 score, CSI, and accuracy to characterize detection uncertainties. These statistics reflect pixel-level mismatch at the satellite footprint, which involves averaging of radar data values after applying a threshold of  $0.05 \text{ mm h}^{-1}$  ( $0.02 \text{ mm h}^{-1}$ ) for rainfall (snowfall).

Visual inspection of the example retrievals indicates that TLP-R2S generally captures the spatial structure of precipitation fields consistent with MRMS (Fig. 20a–c), including the broad-scale features of snow bands and the spatial organization of convective cores, albeit with uncertainties that are partly irreducible due to the coarser spatial resolution of ATMS relative to MRMS. Nevertheless, for rainfall estimation, the products are broadly comparable; however, TLP-R2S outperforms GPROF for snowfall retrievals, as quantified in the box plots.

For rainfall (Fig. 20d–h), TLP-R2S achieves MAE comparable to GPROF (Fig. 20d) but with slightly lower bias. Detection performance improves, with a median CSI of  $\sim 0.38$ , F1 score of 0.55, and accuracy of 0.92, compared to 0.28, 0.42, and 0.85 for GPROF.

For snowfall, TLP-R2S shows lower MAE and bias, with CSI and F1 scores roughly twice those of GPROF. The overall lower snowfall performance relative to rainfall reflects the difficulty of detecting weak scattering signals over complex surfaces. It is also influenced by limitations of MRMS in capturing shallow snowfall [99], [100], which can reduce apparent detection skill.

Figure 21 presents quantile–quantile (q–q) plots of gridded mean precipitation against MRMS for all overpasses in 2023 on a  $0.15^\circ$  grid. While all products exhibit a negative bias, TLP-R2S follows the 1:1 line more closely, indicating improved representation of the rainfall distribution. This is supported by quantitative metrics: TLP-R2S shows the lowest bias magnitude and MAE, with relative MAE reductions of about 7% and 35% compared to GPROF and ERA5, respectively. It also achieves the lowest Wasserstein distance, improving by approximately 35% and 50% over GPROF and ERA5.

For snowfall, the q–q plots exhibit a different behavior: GPROF falls below the 1:1 line, indicating systematic underestimation, whereas TLP-R2S aligns more closely with the MRMS reference, with 80% less bias than GPROF. Unlike rainfall, TLP-R2S snowfall performance is comparable to

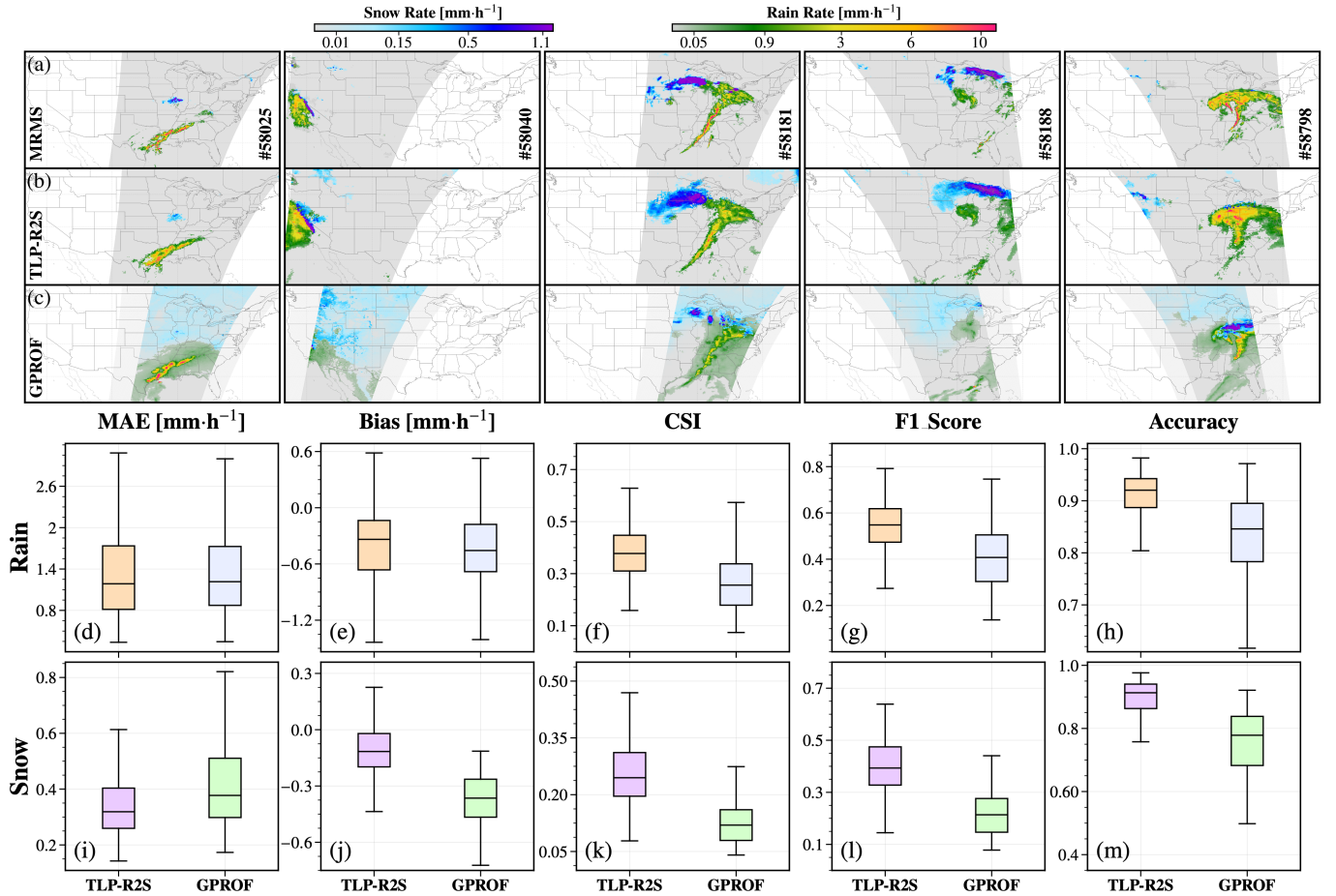


Fig. 20. Validation of TLP-R2S and GPROF against MRMS for 612 ATMS orbits crossing CONUS during the withheld year 2023. Panels (a–c) show five example orbits with mapped MRMS, TLP-R2S, and GPROF retrievals. Panels (d–h) present boxplots of rainfall detection and estimation metrics, and panels (i–m) show corresponding metrics for snowfall over the inner swath where all retrievals are available. A detection threshold of  $0.05 \text{ mm h}^{-1}$  ( $0.02 \text{ mm h}^{-1}$ ) for rainfall (snowfall) is applied for classification metrics (i.e., CSI, F1 score, and accuracy), while estimation metrics (i.e., MAE and bias) are computed only for cases in which MRMS reports precipitation.



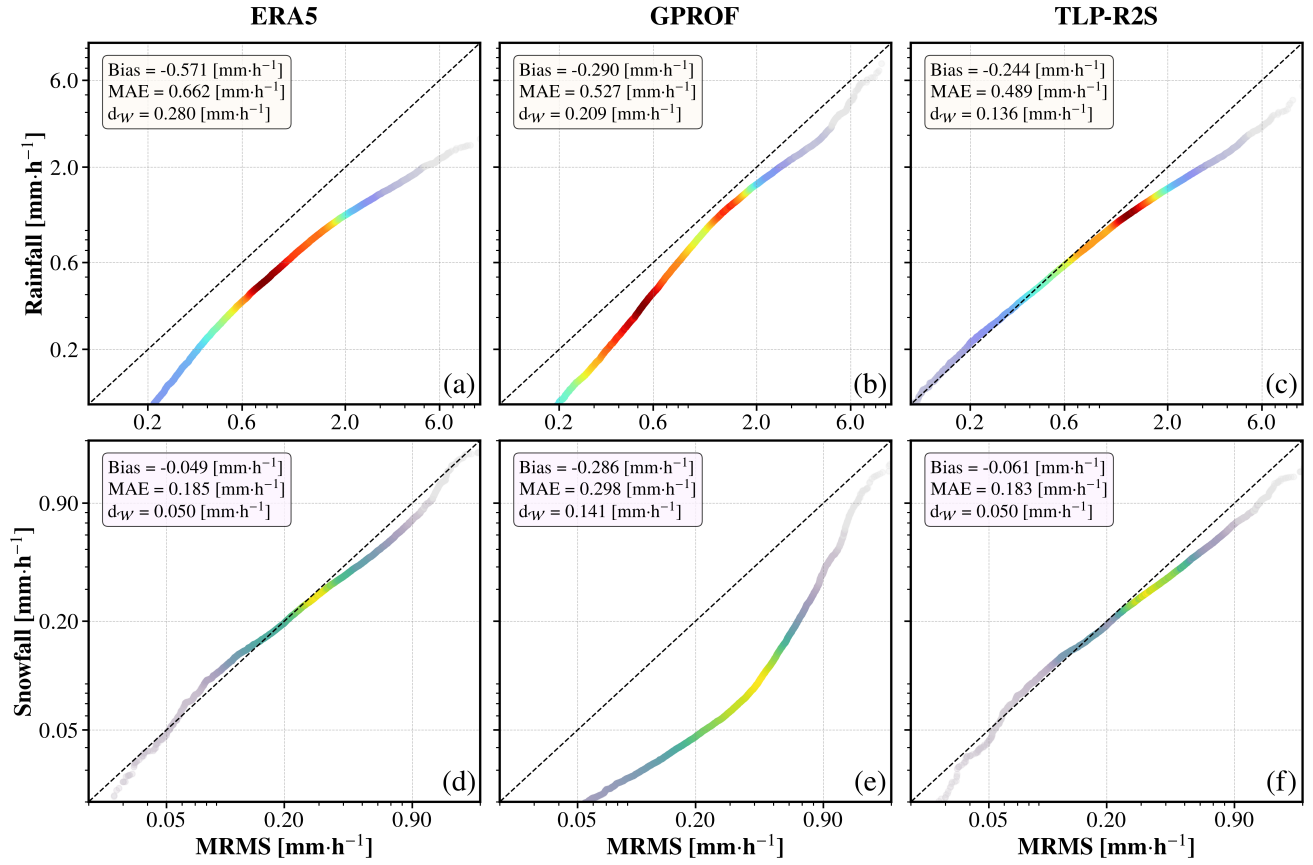


Fig. 21. Quantile-quantile plots comparing grid-wise conditional mean precipitation estimates from ERA5, GPROF, and TLP-R2S against MRMS for (a–c) rainfall and (d–f) snowfall on a  $0.15^\circ \times 0.15^\circ$  regular grid. The comparisons are based on the sum of grid-wise precipitation rates divided by the number of overpasses, given that MRMS detects precipitation.

ERA5, with a slightly higher bias. This is partly attributable to the limited availability of CPR training samples over CONUS (Fig. 3b), which constrains retrieval accuracy to the ERA5 baseline in this region.

## V. DISCUSSION

The TLP-R2S concept is portable to other cross-track microwave radiometers [101], [102], provided active spaceborne coincidences exist, which can be a limiting factor for data-driven methodologies. Therefore, physics-based frameworks remain a cornerstone for advancing precipitation retrieval methodologies [103]. Integration of ML and radiative transfer modeling approaches to further constrain retrievals beyond classic variation methods using full vertical atmospheric profiles rather than path-integrated values remains a worthwhile research endeavor.

Several avenues exist to advance this work in both algorithm development and validation. From an algorithmic perspective, multi-encoder architectures [104] that jointly encode 2-D CPR profiles and 3-D DPR imagery within a transfer-learning framework warrant further exploration. Such approaches would map heterogeneous satellite observations into a shared embedding space, enabling unified classification and regression. Transformer-based architectures [105] are particularly promising, as their attention mechanisms allow

flexible integration of multimodal data. Future work should also quantify the added value of spatially aware deep learning models relative to tabular approaches at a global scale, rather than focusing solely on densely sampled regions such as CONUS.

Investigating the impacts of the ingestion of new orbital products into the next-generation flagship integrated precipitation products, such as IMERG and broader multi-source merged climatological data sets, such as the Multi-Source Weighted-Ensemble Precipitation (MSWEP, [106]), the Global Multisource Merging-and-Calibration Precipitation (GMCP, [107]), and the Global Precipitation Climatology Project (GPCP, [108]) is worth exploring.

Since the primary objective of this work is to accurately retrieve precipitation distributions based on active radar observations while maintaining global mass balance consistency with reanalysis, further investigation is needed to assess performance for extreme precipitation retrievals over the tail of its distribution. Given that ATMS footprint sizes exceed  $250 \text{ km}^2$  at their finest resolution, area-averaged high-intensity rates (i.e.,  $> 20 \text{ mm hr}^{-1}$ ) are statistically rare. Nevertheless, visual inspection and Wasserstein distance metrics indicate that TLP-R2S captures storm-scale extremes more effectively than reanalysis.

Future research is also needed to further validate snowfall retrievals over remote Arctic regions, where ground-based



observations are sparse. To that end, a few data sources can be envisaged, including the observations by (i) the Ka-band ARM zenith radar [109] operated by the U.S. Department of Energy’s Atmospheric Radiation Measurement (ARM) program, (ii) NASA’s Operation IceBridge [110], and (iii) NASA’s ICESat [111]. Airborne data from the IceBridge campaign and ICESat altimetry provide unprecedented estimates of ground-based snow accumulation over ice sheets and sea ice, which can be used to validate snowfall through mass balance analysis [112]. Furthermore, although most CPR training datasets are restricted to daytime observations, the recently launched EarthCARE satellite [113] provides more complete diurnal sampling. The coincidence of EarthCARE and PMW instruments [114] offers a unique opportunity to develop larger training datasets that better capture the diurnal cycle of global snowfall, especially over the Arctic.

## VI. CONCLUSION

This study developed the Transfer Learning of global Precipitation from Reanalysis to Satellite observations (TLP-R2S) framework for the ATMS cross-track scanner. The approach employs incremental learning to mitigate the spatial and temporal sparsity of active satellite observations by leveraging ERA5 as a global pre-training source. The physical consistency of the model, before and after refinement, was assessed using feature-importance analysis, quantifying the relative contributions of brightness temperatures and cloud microphysical variables to retrieval performance.

Results show that TLP-R2S (i) retrieves both rain and snow across the full swath, outperforming current GPM products (i.e., GPROF-V07 ATMS retrieval) in both detection and estimation based on independent validation datasets; (ii) reproduces realistic rainfall distributions; and (iii) provides physically consistent annual precipitation estimates that align with reanalysis and implicitly conserve water and energy exchanges across the land–ocean–atmosphere system.

Assessments against withheld reanalysis and independent MRMS data over CONUS indicate that the proposed transfer-learning framework can significantly improve data-driven PMW precipitation retrievals. In the absence of satellite radar observations, the model learns PMW signatures from reanalysis and refines them as satellite data become available. Consequently, performance is bounded below by reanalysis in regions lacking radar coverage and approaches the active-satellite accuracy when dense, coincident observations are available.

Looking ahead, future work will focus on integrating transformer-based architectures and multi-encoder frameworks to more effectively fuse multimodal satellite data within a unified classification and regression pipeline. Extending transfer learning to incorporate EarthCARE observations for training, along with the use of accurate snow-depth measurements for validation, can further advance predictive understanding of rapidly evolving Arctic systems.

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