12th Workshop of the International Precipitation Working Group (IPWG-12)

PMW-PrecipNet: A U-Net–Based Deep Learning Framework for Passive Microwave Precipitation Retrieval

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Motivation & Objectives

- **Passive microwave (PMW) precipitation retrieval** is essential for global hydrological monitoring, **and deep learning** provides a data-driven approach for learning complex relationships between multi-channel GMI brightness temperatures and DPR-based rain rates.
- Operational DPR version updates (e.g., V06 → V07) alter the target distribution and introduce label-space shift, which can degrade model transferability.
- This work aims **to (1) develop PMW-PrecipNet for end-to-end PMW rain-rate retrieval, (2) evaluate its performance against DPR/GPROF, and (3) explore fine-tuning as an adaptation strategy under evolving retrieval products.**

Dataset

- **Inputs**
  - GPM GMI Level-1B brightness temperatures (13 channels)
  - Latitude / Longitude information
- **Labels**
  - DPR near-surface precipitation products
- GMI and DPR observations are matched and cropped into 40 × 40 patches.
- **Period**
  - Baseline development dataset: 2016–2018
  - Independent verification: June–August 2019
  - Additional updated datasets for fine-tuning experiments
    - Training and validation: 2020–2022
    - Independent test: 2023
- **Region**
  - 100°E–180°E and 0°–60°N

Method

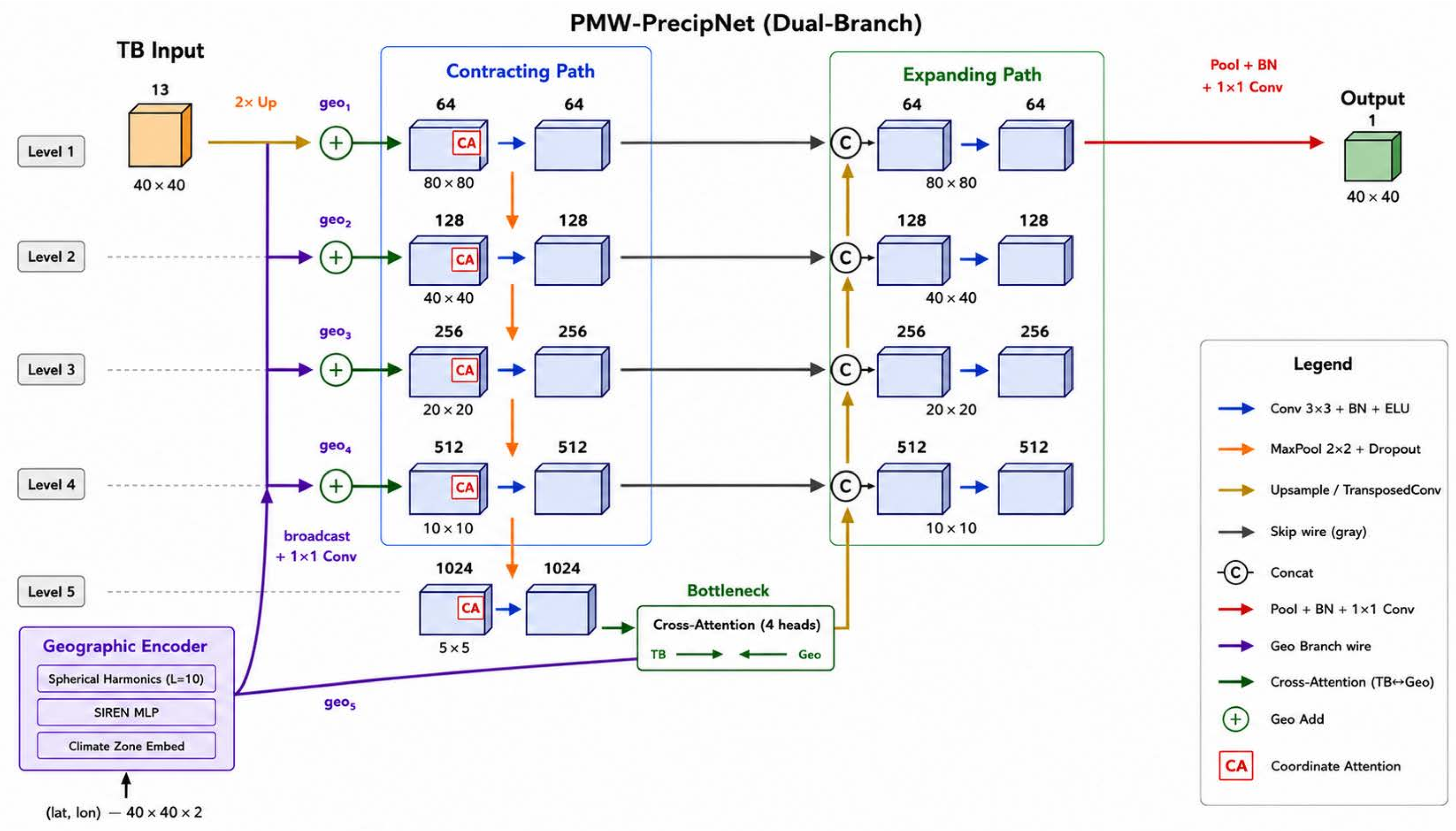
- **Training strategy:**
  - Geometric data augmentation
  - 5-fold cross-validation (CV)
  - MAE (L1) loss, Adam optimizer, polynomial learning-rate decay, and multi-GPU training.
  - For evaluation purposes, we additionally compute the MAE over F1-score (MOF) metric defined as follows:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i|$$

$$F1 = 2 \cdot \frac{Recall \cdot Precision}{Recall + Precision}$$

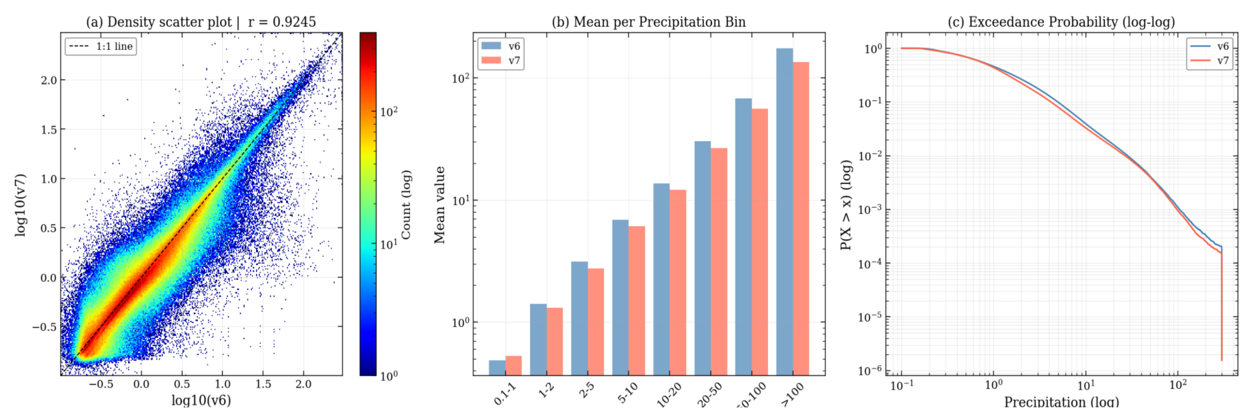
$$MOF = \frac{MAE}{F1}$$

PMW-PrecipNet Architecture



- **Dual-branch U-Net** using 13 GMI brightness-temperature channels together with geolocation information.
- A TB encoder extracts multi-scale microwave features, while a geographic encoder injects latitude/longitude context.
- The decoder reconstructs 40 × 40 near-surface rain-rate fields for end-to-end instantaneous retrieval.
- Expected strengths: clearer precipitation structures, improved surface-type generalization, and flexible adaptation to updated products.

Fine-tuning (Label Shift)



- For the same PMW input, precipitation targets can differ across versions (V06 vs. V07), creating a label-space shift that violates the stationary-label assumption and may degrade performance on updated products.
- We therefore compare training from scratch with a standard fine-tuning strategy initialized from a model pretrained on legacy data.

Comparison design: Standard fine-tuning vs. Training from scratch vs. Progressive unfreezing
➔ evaluate robustness to V06→V07 label space shift

A. Standard fine-tuning

Initialize from V06 checkpoint

- ✓ Use the pretrained model as the initial state
- ✓ Additional training: 100 epochs on the 2020–2022 V07 dataset

Purpose: isolate the effect of pretrained weights under updated labels.

B. Training from scratch

Random initialization

- ✓ Baseline model trained directly on the same 2020–2022 V07 dataset
- ✓ No legacy checkpoint is used

Purpose: evaluate learning entirely from the target distribution.

C. Progressive unfreezing

Staged adaptation · total 30 epochs

Phase 1 · 15 epochs
Update decoder + cross-attention + geographic projection freeze encoders

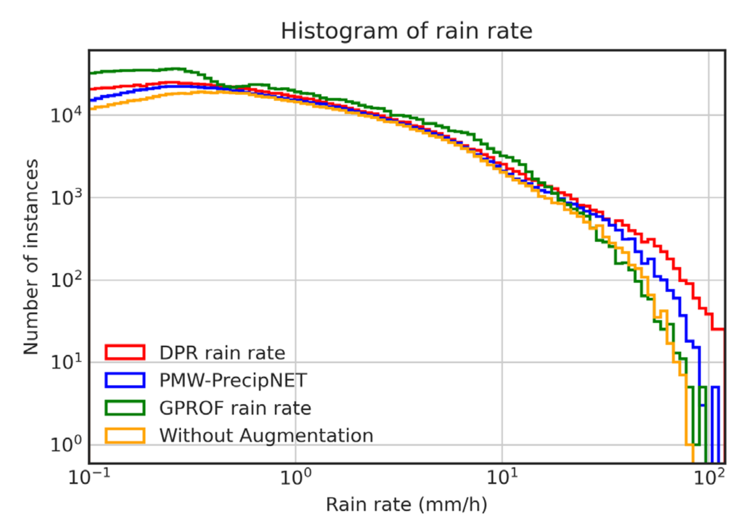
Phase 2 · 10 epochs
Unfreeze TB encoder with lower learning rate preserve microwave features

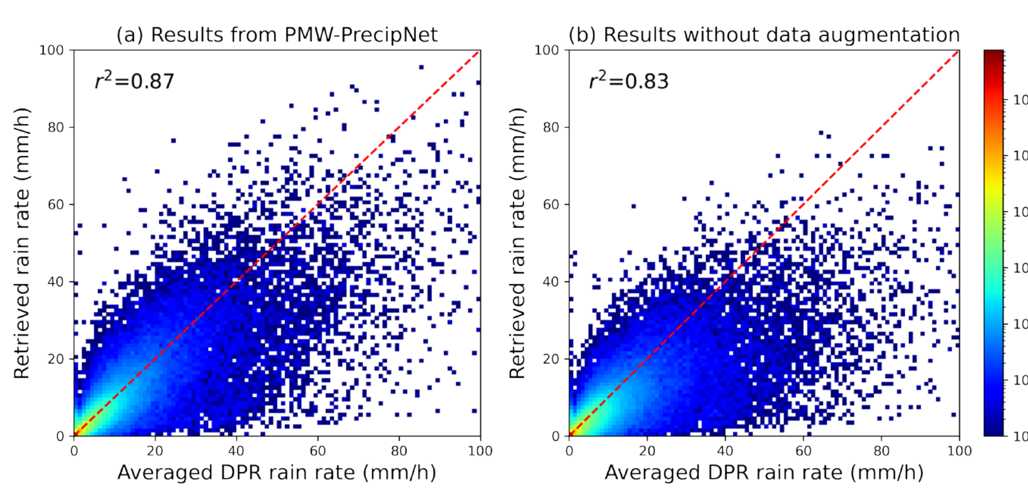
Phase 3 · 5 epochs
Fine-tune all except geographic encoder at very low learning rate

Purpose: reduce training cost while retaining transferable V06 representations.

Results

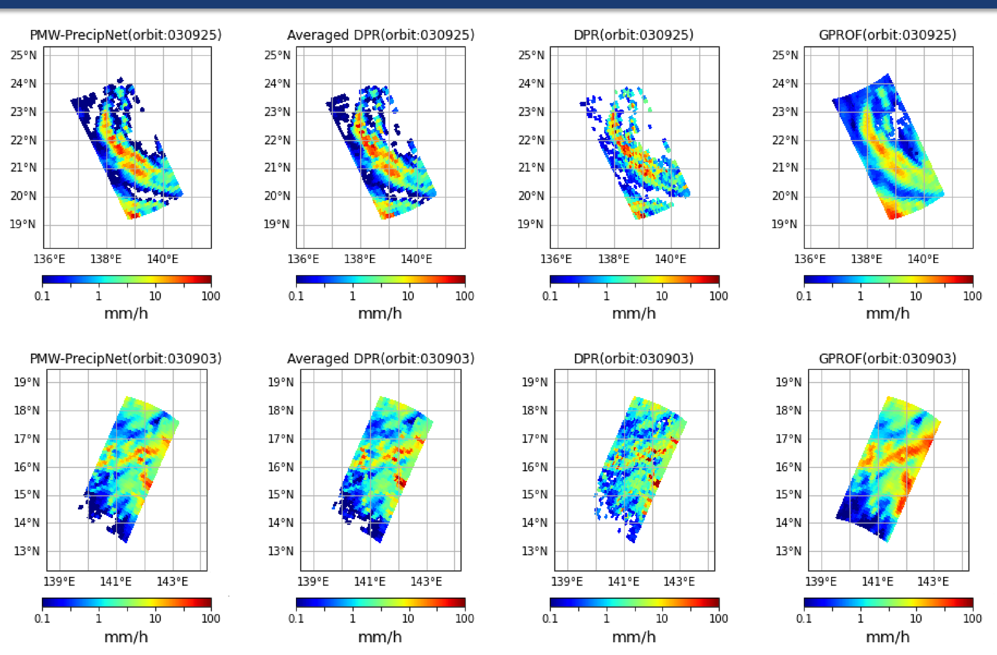
A. Data augmentation effect



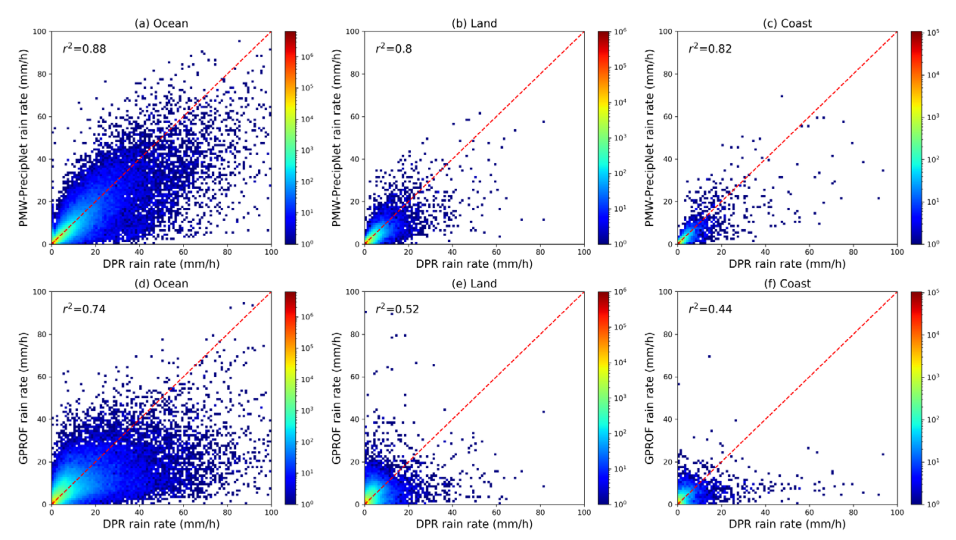


- Data augmentation improves agreement with DPR (R^2 = 0.87 vs. 0.83) and reduces dispersion around the 1:1 line.
- It better preserves rain-system boundaries and heavy-rain structures, improving MAE, F1, and MOF by 21%, 9%, and 26%, respectively.

B. Rain-field examples and surface-type performance



- The PMW-PrecipNet rain-rate distribution is closer to DPR than GPROF and better captures light-to-heavy rain behavior.



- **PMW-PrecipNet shows better agreement with DPR** than GPROF across ocean, land, and coast (R^2 = Ocean 0.88 vs 0.74, Land 0.80 vs 0.52, Coast 0.82 vs 0.44).

C. Adaptation Strategies for V07

Table 1: Performance comparison of the three adaptation strategies on the 2023 V07 test set with the 5-fold ensemble.

Strategy	MAE	F1	MOF	Prec.	Recall	Acc.
V06 baseline (no V07 adapt.)	0.4619	0.8483	0.5445	0.9168	0.7893	0.9677
Scratch	0.3992	0.8584	0.4650	0.9077	0.8141	0.9692
Progressive unfreezing	0.3926	0.8584	0.4574	0.9075	0.8143	0.9692
Standard fine-tuning	**0.3898**	**0.8630**	**0.4517**	**0.9110**	**0.8198**	**0.9702**

Table 2: Ensemble synergy of the three adaptation strategies on the 2023 V07 test set.

Strategy	Fold mean MOF	Ensemble MOF	Synergy
V06 baseline (no V07 adapt.)	0.5641	0.5445	−3.5%
Scratch	0.4864	0.4650	−4.4%
Progressive unfreezing	0.4731	0.4574	−3.3%
Standard fine-tuning	0.4781	**0.4517**	−5.5%

Table 3: Training cost and accuracy gain of the three adaptation strategies on the 2023 V07 test set. Training time is reported as the wall-clock time per fold.

Strategy	Epochs	Time/fold	MOF	vs. Scratch
Scratch	100	5.5 h	0.4650	—
Progressive unfreezing	**30**	**1.3 h**	0.4574	−1.6%
Standard fine-tuning	100	5.5 h	**0.4517**	−2.9%

Key interpretation

- **Standard fine-tuning** gives the best ensemble performance on V07 (MAE = 0.3898, MOF = 0.4517), improving MOF by 2.9% relative to scratch.
- **Progressive unfreezing** is the efficient option: 30 epochs and 1.3 h/fold, reducing training cost by ~76% while still outperforming scratch.

Overall: V06 pretraining remains transferable under the V07 label shift, and the best adaptation choice depends on the accuracy–cost trade-off.

Conclusions & Future Work

- **PMW-PrecipNet retrieves near-surface precipitation from 13-channel GMI TBs and geolocation information.**
- It improves **spatial precipitation representation and agreement with DPR** compared with GPROF.
- Under the V06→V07 label-space shift, **standard fine-tuning gives the best ensemble performance.**
- Extend the adaptation pipeline to broader regions and additional GPM constellation sensors.

Acknowledgements

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