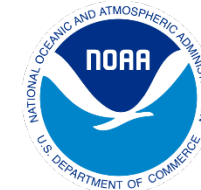




Image Based Deep Learning Snowfall Rate Model for Passive Microwave Sensors

Oliver Jiang

Mentor: Dr. Yongzhen Fan



Objectives

- **Goal:** *Develop a 2D image-based deep learning correction for the operational ATMS Snowfall Rate (SFR) product, using spatial context across a satellite scene rather than per-pixel values alone.*
- Train Residual U-Net (Res UNet) models on 96x96 tiles of 45 ATMS, GFS, and physical-retrieval features against ECMWF ERA5 reference truth (2017–2025).
- Validate Res UNet-corrected SFR against ECMWF ERA5 using independent test set (2020, 2024) and compare with operational SFR.
- Isolate the effects of target configuration (direct vs. bias)
- Apply the trained correction to a real winter storm case study (January 25, 2026) outside the 2017–2025 training/testing period.

Dataset

- **Training Data:** 2017-2025 (SNPP ATMS observations, GFS model data, Initial SFR retrievals, ECMWF ERA5).
- **Quality Control:**
 - Invalid ATMS/GFS values were screened
 - **ERA5 wet-snow flag (precip type = 7)** set to 0,
 - **ERA5 SFR < 0.01 mm/hr** set to 0.
- 45 features span ATMS brightness temperatures, GFS profiles, and physical retrieval outputs

Training Setup

- **Model:** Residual UNet (3 layers , 128 initial filters) - 45 Features, 96x96 tiles –
- **Training:** 2017-2019, 2021-2023, 2025 (Over CONUS); **Testing:** 2020, 2024
- Feature normalization: standard min-max normalization.
- Optimizer: AdamW
- **Loss function:** Weighted MSE loss
- Training **target** configuration
 - Direct:** predicts ERA5 SFR
 - Bias:** predicts (bSFR - ERA5), recovering final SFR estimate by (bSFR - predicted bias)
- An optional step-wise resampling was combined to resample training tiles containing heavier snowfall (up to 9x for the most extreme bin) but was found to counteract the weighting benefit.
- Trained using PyTorch Distributed Data Parallel across 4 GPUs (torchrun --nproc-per-node=4)

Table 1. 45 Feature Count and Category

Category	Count	Examples
ATMS Brightness temperatures	15	23.8, 50.3, 88.2, 165.5, 183.31 $\pm$ 7 GHz (15 of 22 ATMS channels)
Atmospheric profile (GFS)	20	HGT, RH, T, WEL: 4 Variables x 5 pressure levels (250-850 mb)
Column / Surface (GFS)	5	CWAT, PWAT, HGT 0m, RH 2m, T 2m
Geometrical + physical retrieval	5	cos(LZA), a53L (Limb Corrected), bSFR, IWP, De
Total	45	



EARTH SYSTEM SCIENCE
INTERDISCIPLINARY CENTER

Image Based Deep Learning Snowfall Rate Model for Passive Microwave Sensors

Oliver Jiang

Mentor: Dr. Yongzhen Fan

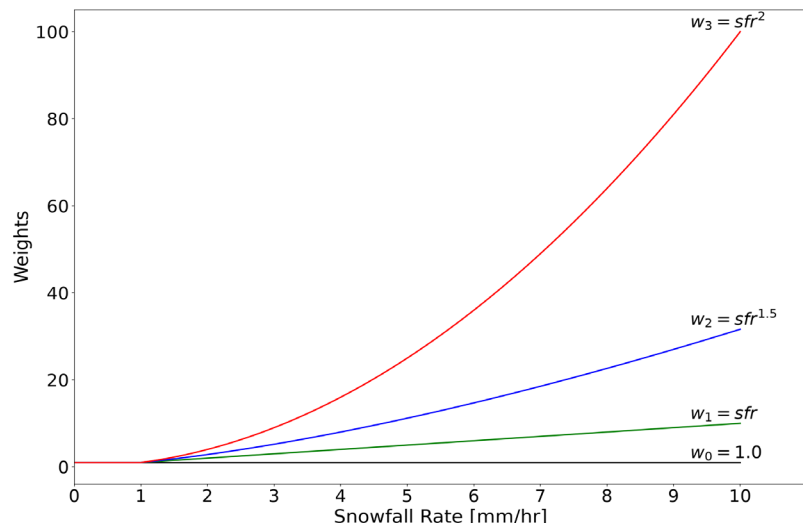


Figure 1. Weighted mean-square-error (WMSE) loss design. Pixels with SFR > 1 mm/hr are weighted by SFR^a , with four tested exponents: w_0 ($a = 0$, baseline), w_1 ($a = 1$), w_2 ($a = 1.5$), and w_3 ($a = 2$).

$$WMSE = \frac{1}{n} \sum_{i=1}^n w_i * (y_i - \hat{y}_i)^2$$

$$w = \begin{cases} 1 & SFR \leq 1.0 \text{ mm/hr} \\ SFR^a & SFR > 1.0 \text{ mm/hr} \\ 2 & \text{False Positive} \end{cases}$$

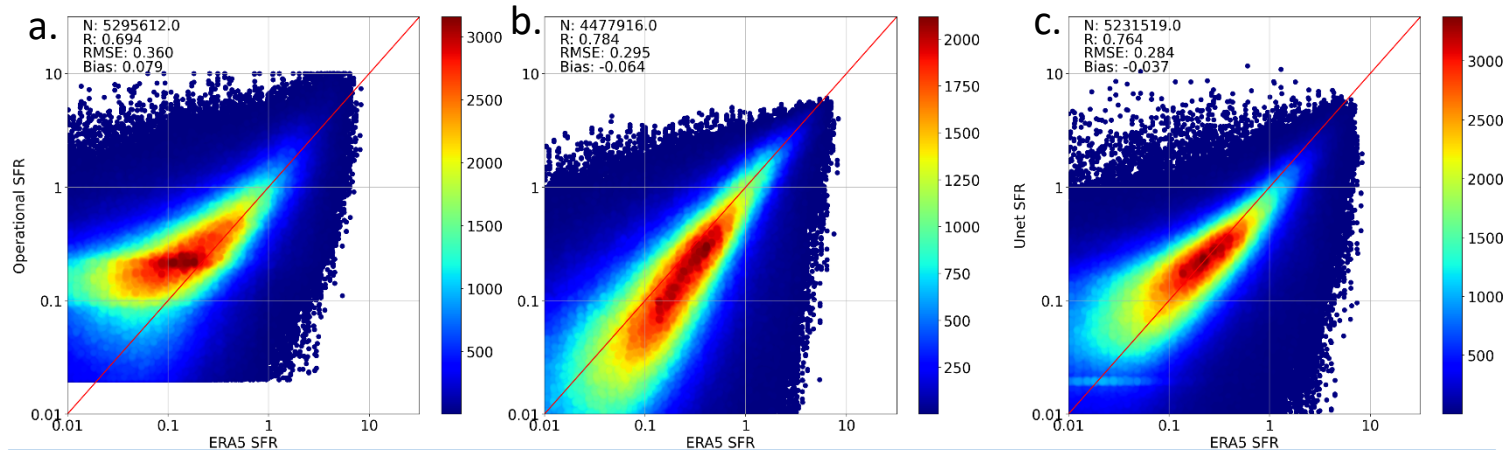


Figure 2. Density scatter plots performance (relative to the reference truth) comparison of the operational SFR (a.), ResUNet Direct SFR (b.), ResUNet SFR-Bias (c.) weighted w_2 without resampling. The operational SFR shows a wider spread (RMSE = 0.360, R = 0.694) and a persistent positive bias (0.079); the ResUNet Direct SFR configuration (w_2) is tighter around the 1:1 line (RMSE = 0.295, R = 0.784) with a small negative bias (-0.064). The ResUNet SFR-Bias configuration shows a small negative bias (-0.037) and minimal spread (RMSE = 0.284, R = 0.764), however tends to overestimate lighter snow pixels relative to the reference.

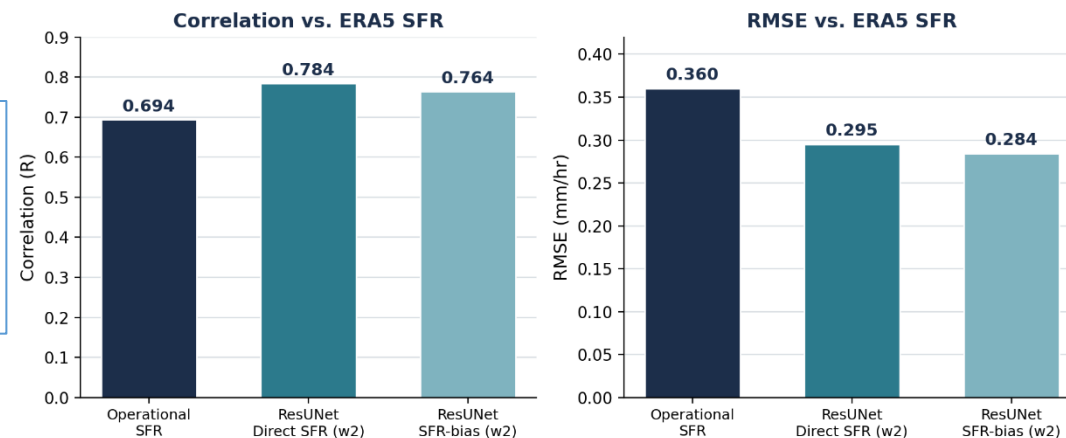


Figure 3. Validation stats for the operational algorithm and the two ResUNet configurations both weighted at w_2 , computed over the 2020 & 2024 test set.

Image Based Deep Learning Snowfall Rate Model for Passive Microwave Sensors

Oliver Jiang

Mentor: Dr. Yongzhen Fan

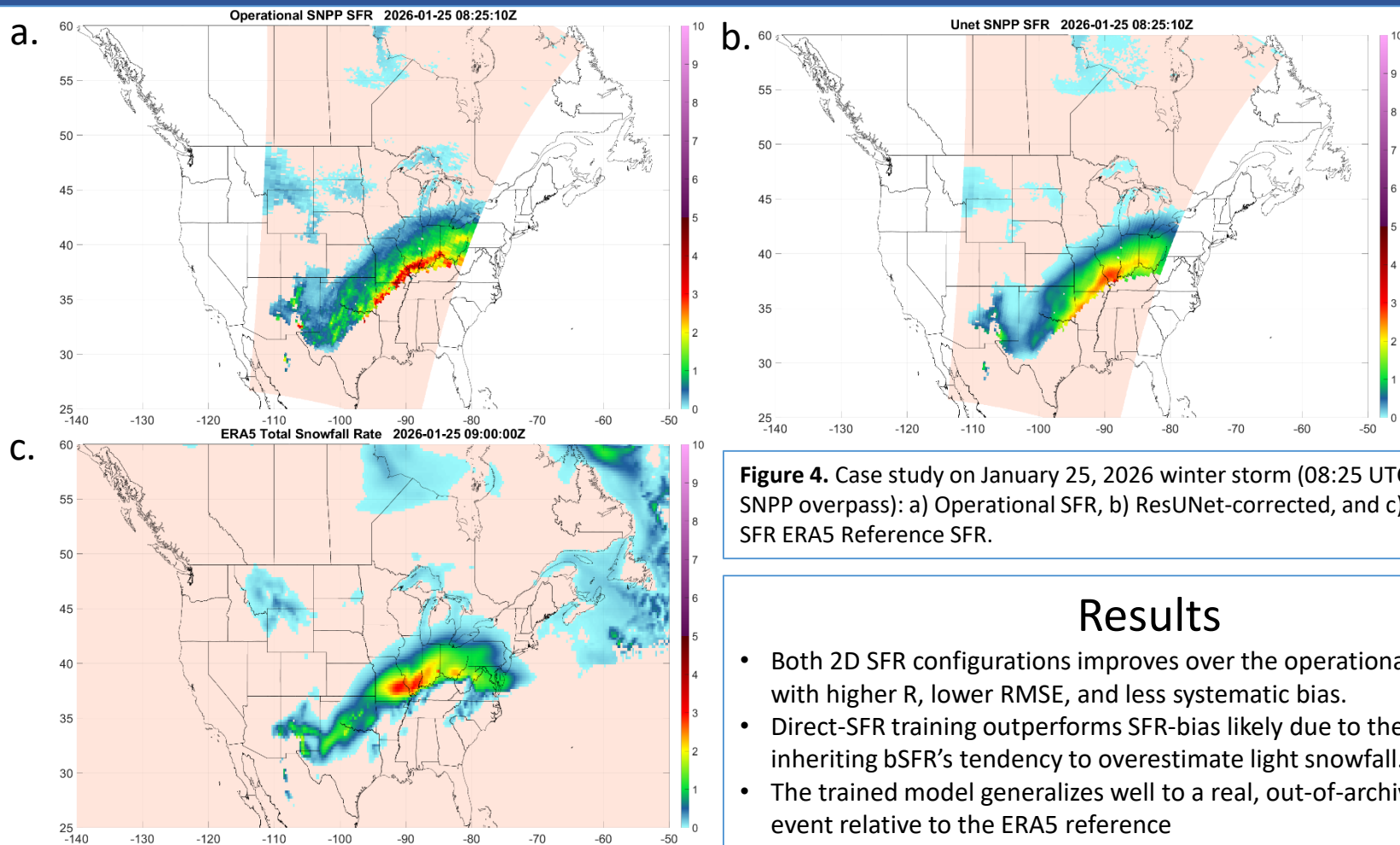


Figure 4. Case study on January 25, 2026 winter storm (08:25 UTC SNPP overpass): a) Operational SFR, b) ResUNet-corrected, and c) SFR ERA5 Reference SFR.

Results

- Both 2D SFR configurations improves over the operational algorithm with higher R, lower RMSE, and less systematic bias.
- Direct-SFR training outperforms SFR-bias likely due to the bias target inheriting bSFR's tendency to overestimate light snowfall.
- The trained model generalizes well to a real, out-of-archive storm event relative to the ERA5 reference
- The model still needs improvement on heavy-snowfall estimation.