EARTH SYSTEM SCIENCE INTERDISCIPLINARY CENTER

The NOAA NESDIS Snowfall Rate Product: Development and Applications

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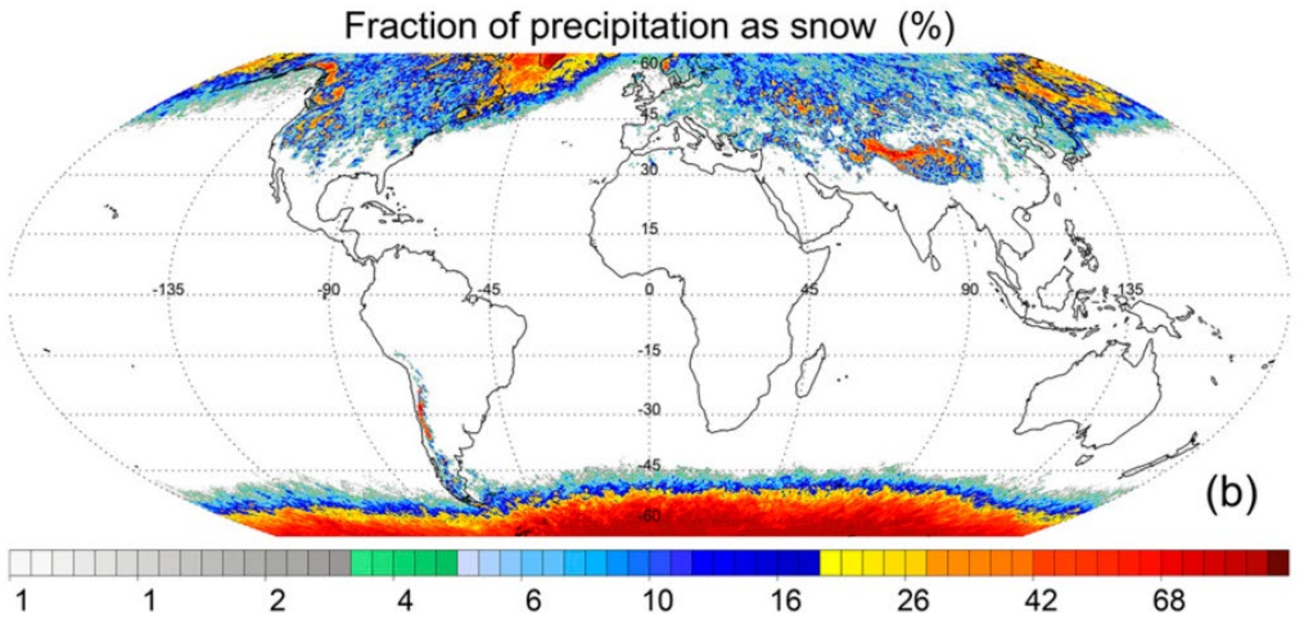
Background

- Snowfall plays an important role in energy balance and water cycle in our Earth-atmosphere system.

- Snowfall is the most common type of precipitation in high latitudes, providing a major source of freshwater for many counties.



Adhikari et al. 2018

- Snowfall affects our social and economic activities such as transportation disruptions, risk of accidents, school and work closures, etc.

Satellite observations continue playing significant roles in better tracking and predicting snowfall events.

Product Overview

- **Snowfall Rate (SFR) product derived from passive microwave measurements**

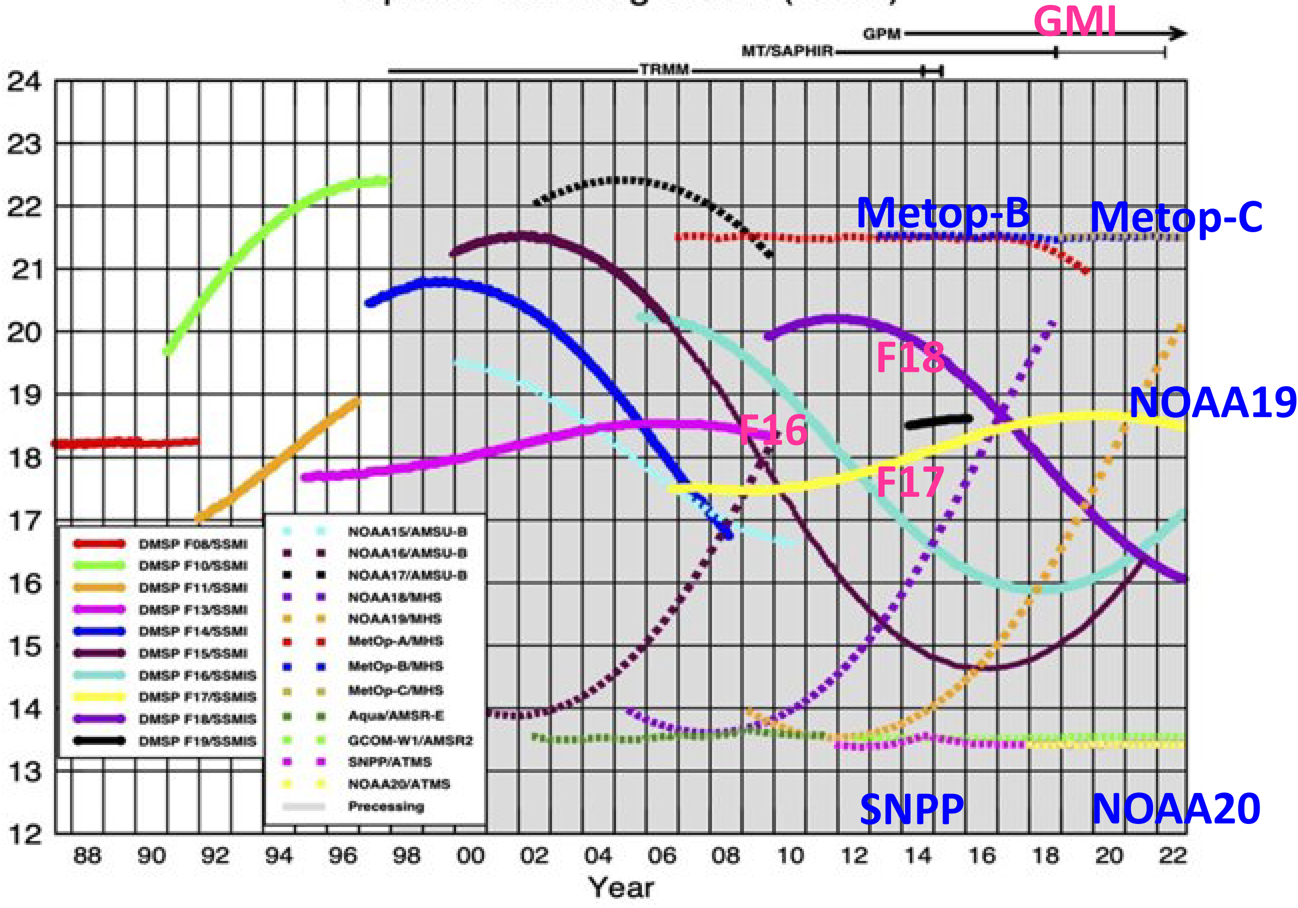
➢ Water equivalent snowfall rate estimate

➢ Operation at NOAA/NESDIS since 2012

➢ Operation for the sensors at five platforms: *S-NPP/ATMS, N20/ATMS, N19/MHS, Metop-B(C)/MHS*

➢ Experiment for sensors: *N21/ATMS, GPM/GMI, SSMIS on DMSP-F16, F17, F18*

Equator-Crossing Times (Local)



Ascending passes (F08 descending); satellites depicted above graph precess throughout the day.
Image by Eric Nelkin (SSAI), 29 November 2022, NASA/Goddard Space Flight Center, Greenbelt, MD.

Product Algorithms – ML-based Snowfall Detection (SD)

Training

Land: NOAA Integrated Surface Database (ISD), 2016-2020.
Ocean: Cloud Profiling Radar (CPR) near-surface precipitation product, 2012-2019.
Features: Satellite-observed brightness temperatures (Tbs) and GFS model data (temperature, humidity, cloud information, etc.).

ML models

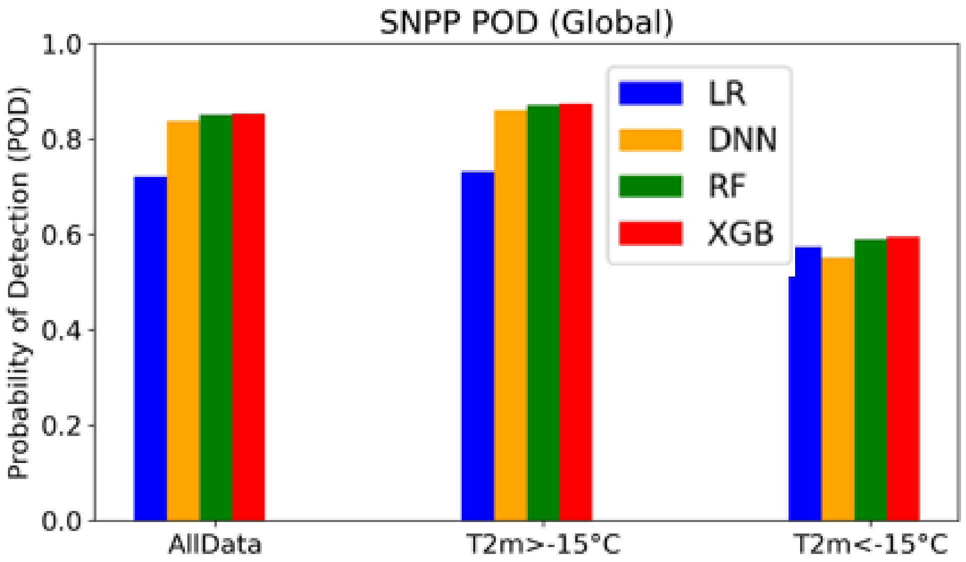
Logistic Regression (LR), Deep Neural Network (DNN), Random Forest (RF) and eXtreme Gradient Boosting (XGB)

Validating

SD models were evaluated using an independent testing dataset.

Performance is consistently good across different sensors;

XGB yields the best accuracy, which is now used in our algorithm.



- *POD = (snowfall pixels)/(true snowfall pixels)*

POD ~ 0.8 for all data, better for warmer situation.

Product Algorithms – Snowfall Rate Estimate (SFR)

1DVAR optimization framework

Inverse model

$$\boldsymbol{x} = \boldsymbol{F}^{-1}(\boldsymbol{y})$$

I_c and D_e are retrieved from the 1DVAR, then SFR is obtained.

$$SFR = A\int_{D_{min}}^{D_{max}} D^{b_m+\nu-2} D^{-\frac{D}{D_e}} \left[\left(\left(1 + BD^{\frac{b_m}{2}}\right)^{\frac{1}{2}} - 1\right)\right]^2 dD$$

$$A = \frac{\eta I_w \delta_0^2 \Gamma^{b_m+\nu}(\nu+1)}{4\rho_l\rho_a D_e^{b_m+\nu}\Gamma(b_m+\nu)\Gamma^{b_m+\nu}(\nu)}$$

$$B = \frac{8}{\eta\delta_0^2}\sqrt{\frac{2\rho_a g a_m}{\pi A_r^k C_0}}$$

$$\underbrace{\begin{vmatrix} \Delta I_c \\ \Delta D_e \\ \Delta\varepsilon_{23} \\ \Delta\varepsilon_{31} \\ \Delta\varepsilon_{89/88} \\ \Delta\varepsilon_{157/165} \\ \Delta\varepsilon_{190/176} \end{vmatrix}}_{\Delta x} = \left|(A^T A + E)^{-1} A^T\right| \underbrace{\begin{vmatrix} \Delta T_{B23} \\ \Delta T_{B31} \\ \Delta T_{B89/88} \\ \Delta T_{B157/165} \\ \Delta T_{B190/176} \end{vmatrix}}_{\Delta y}$$

Ic: ice water path
D_e: ice particle effective diameter
ε_i: emissivity at 23.8, 31.4, 89(MHS)/88.2(ATMS), 157/165.5, and 190.31/183±7 GHz for AMSU/MHS and ATMS (similar channels for GMI and SSMIS)
T_{Bi}: brightness temperature at 23.8, 31.4, 89/88.2, 157/165.5, and 190.31/183±7 GHz for AMSU/MHS and ATMS (similar channels for GMI and SSMIS)
A: Jacobian matrix, derivatives of T_{Bi} *over Ic*, D_e, *and* ε_i
E: error matrix

Yan et al., 2008

Product Algorithms – ML-enhanced SFR

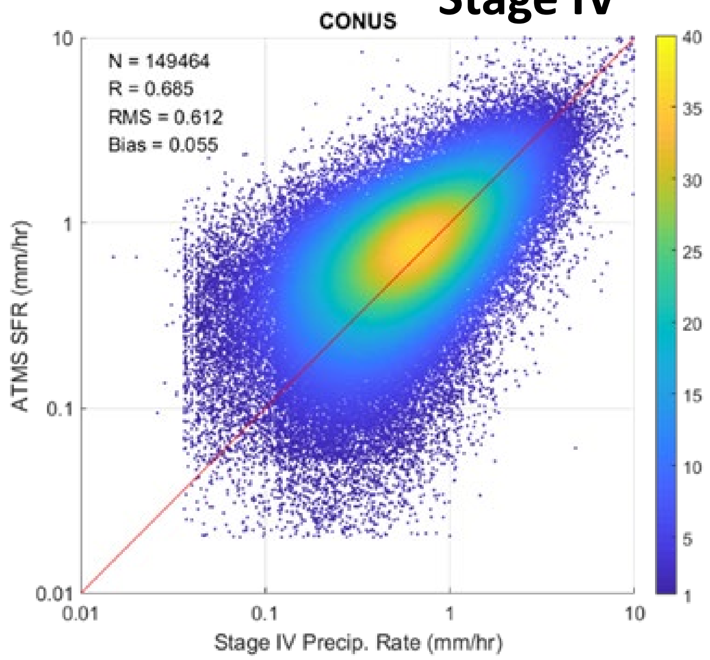
A Deep Neural Network was trained to correct the bias of SFR output from 1DVAR.

Training datasets:
SFR from **NOAA Stage IV + CPR,** satellite Tbs, and GFS model data.

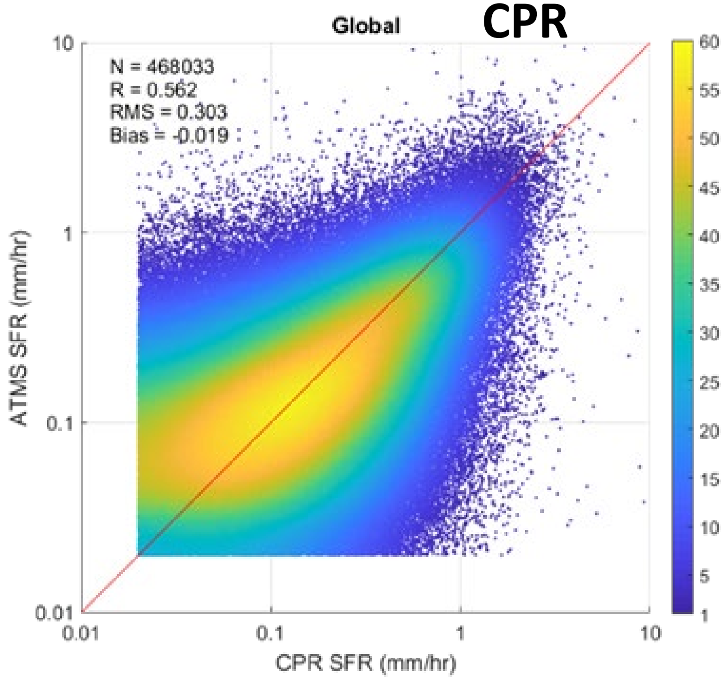
The ML-enhanced SFR shows good statistics compared with Stage IV, CPR, and ERA5: R ~ 0.6 and low biases

ATMS SFR

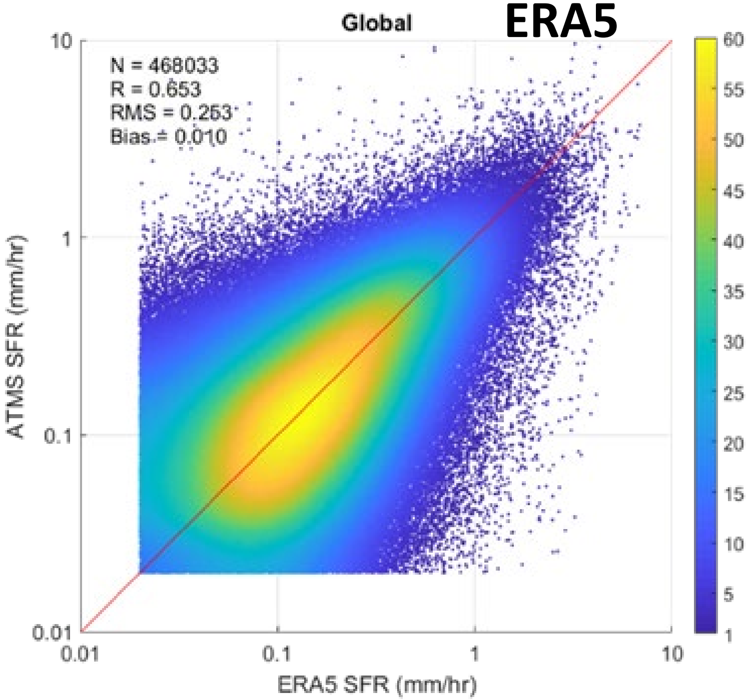
Stage IV



CPR



ERA5

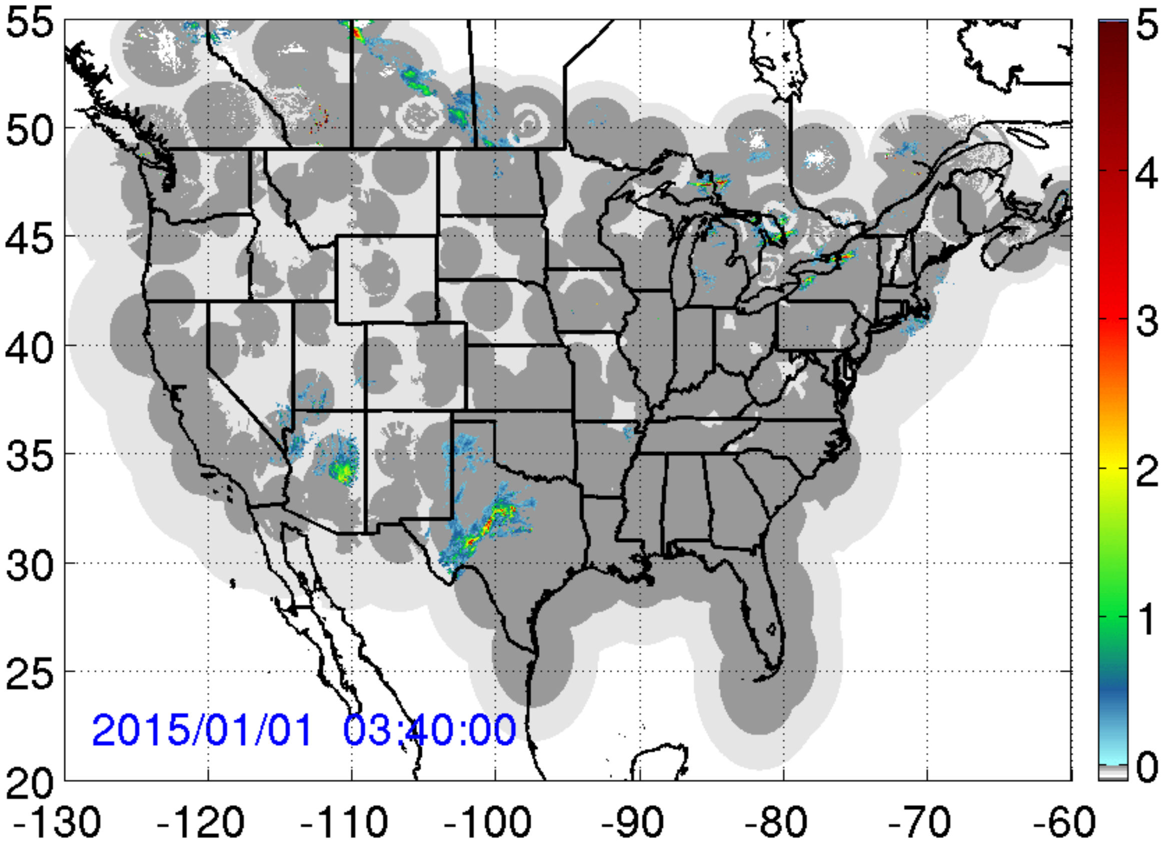


Snowfall Product Applications

- **mSFR (Satellite-radar merged snowfall rate product)**

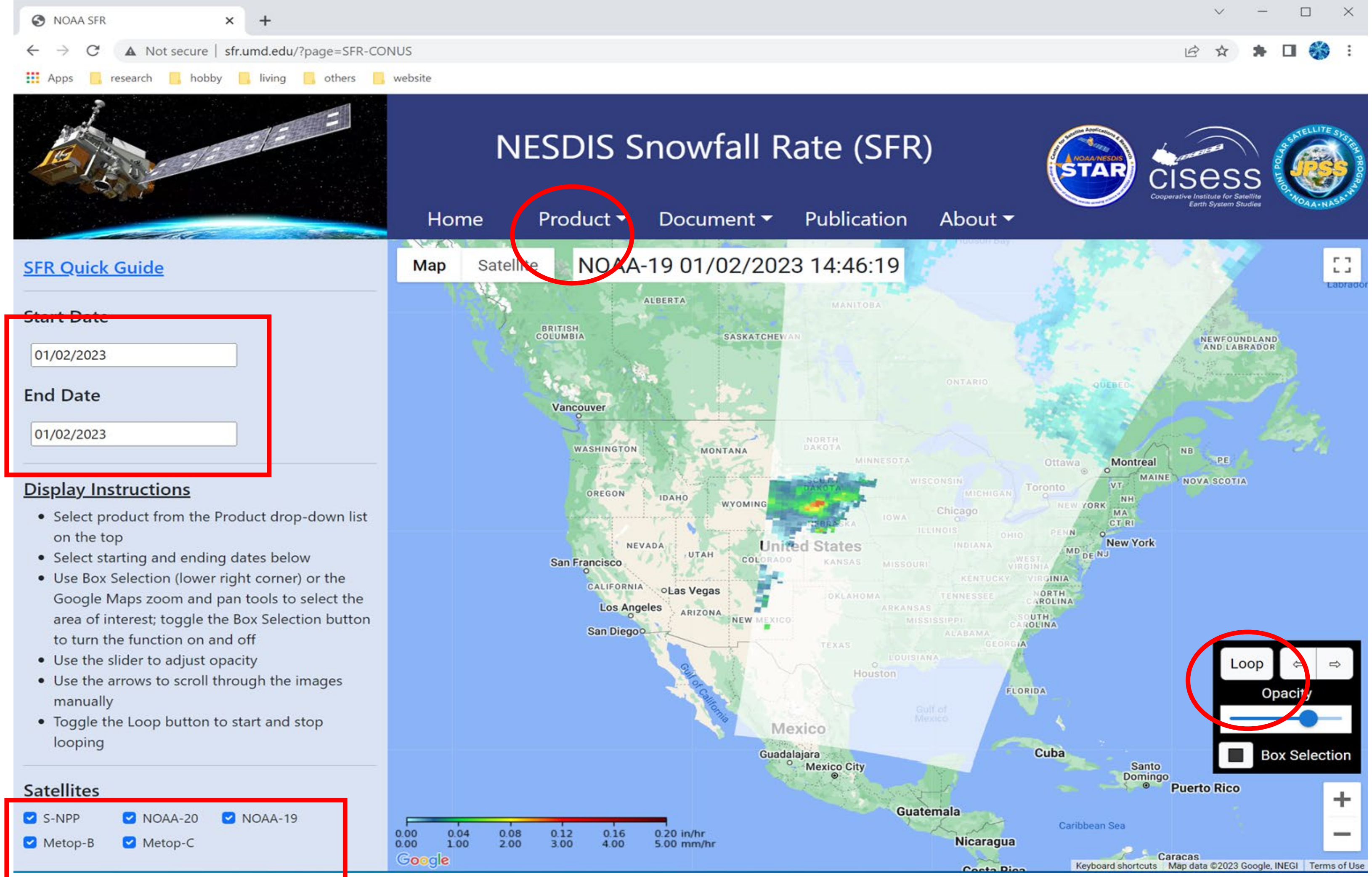
A combination of PWM-based SFR and Multi-Radar Multi-Sensor (MRMS) radar precipitation.

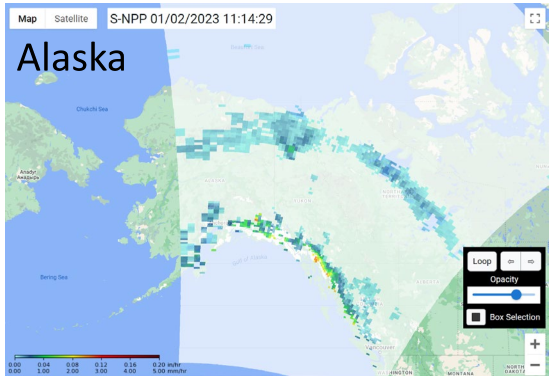
Fill observational gaps in mountainous and remote regions where radar and gauges are sparse, or radar blockage and overshooting are common.

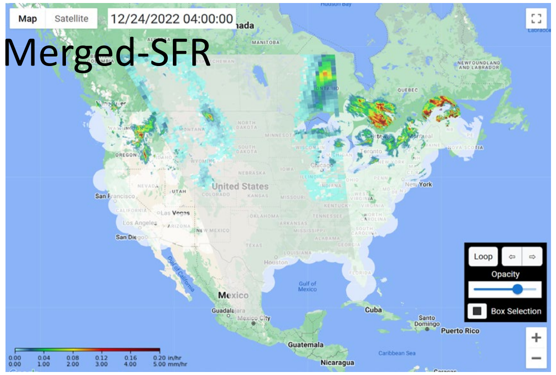


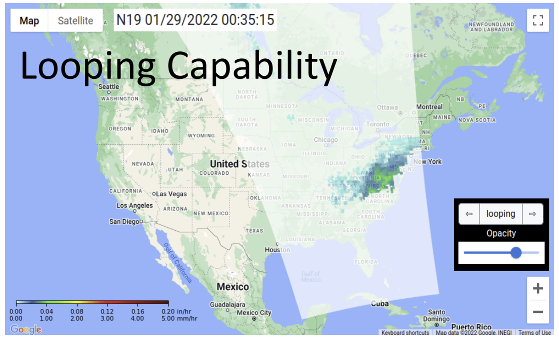
Direct Broadcast-Based Snowfall

website http://sfr.umd.edu   Latency < 20 min







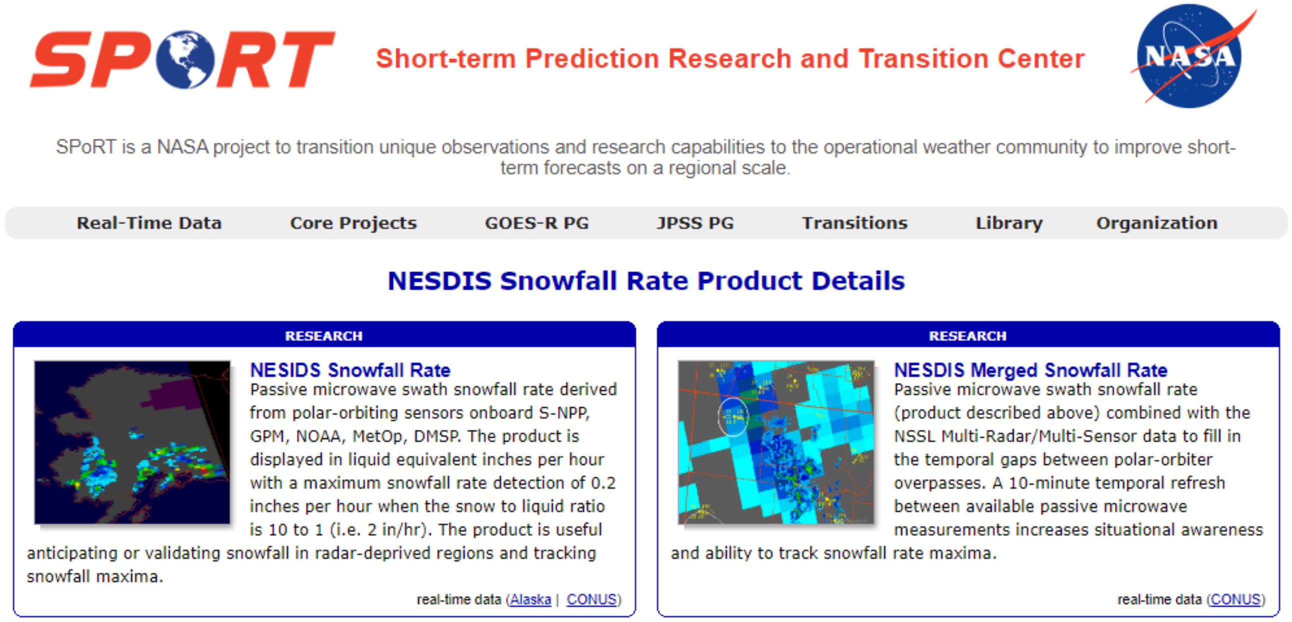


Snowfall Product Applications

- **NCEP/CPC** CMORPH group is ingesting in the **Second-Generation CMORPH (CMORPH2)** to improve CMORPH2 for the support of nowcasting/short-term forecasting.
  https://www.star.nesdis.noaa.gov/jpss/EDRs/products_blended_cmorph.php

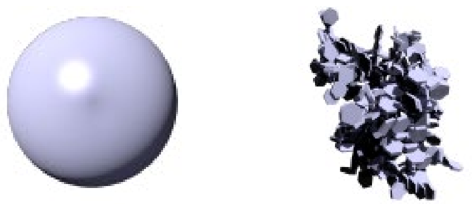
- **NASA/SPoRT** converts the DB SFR data to AWIPS-ingestible format and distributes it to several WFOs (weather forecast office).
  https://weather.ndc.nasa.gov/sport/jpsspg/snowfall.html

- The Geographic Information Network of Alaska **(GINA)** produced DB SFR is distributed to NWS Alaska.

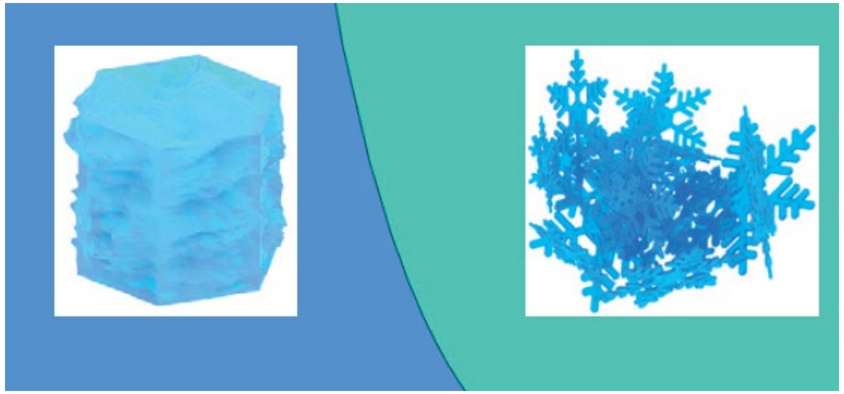


Challenges: Snow Microphysics

The ARTS dataset (Eriksson et al. 2018)



Ping Yang's dataset (Ren et al. 2023)



Current used ice habit: Sphere

Too heavy mass, fast terminal speed, and strong extinction could lead to overestimated SFR.

A first trial of non-spherical ice habit

Comparison between PMW SFR with MRMS and Stage IV in brackets

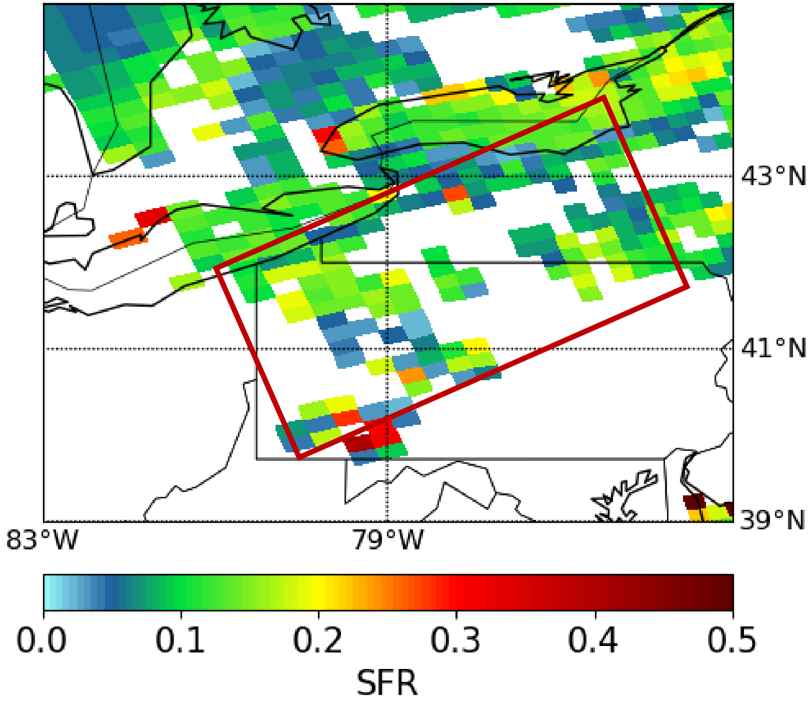
Ice habits	Correlation Coefficient (R)	Bias (mm/h, %)
Sphere (ARTS)	0.48 (0.53)	1.07, 113 (0.80, 119)
LargePlateAggregate(ARTS)	0.43 (0.46)	0.61, 64 (0.45, 66)
Column+Dendrite (PY)	0.48 (0.50)	0.48, 45 (0.19, 29)

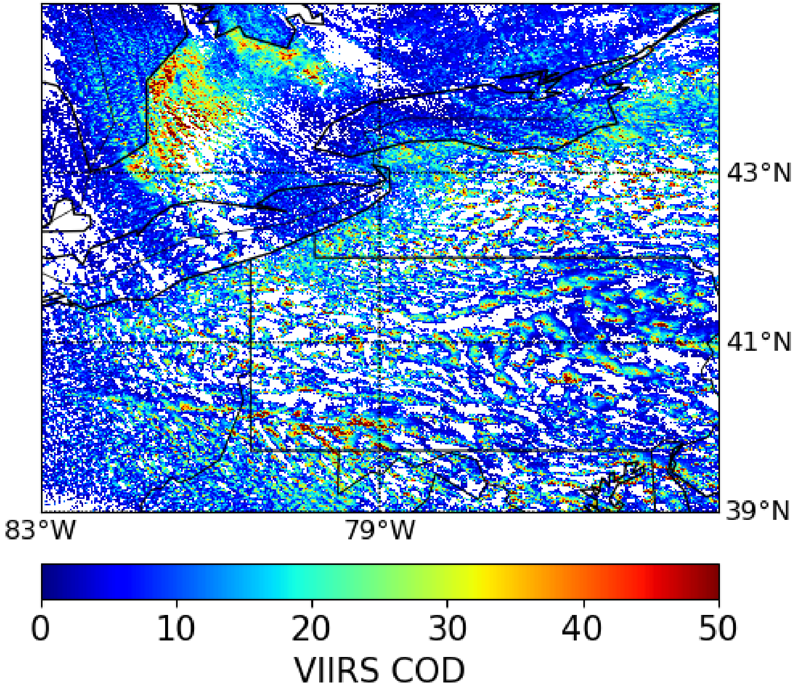
Application of non-spherical ice habits can largely reduce the positive SFR bias from the spherical ice habit.

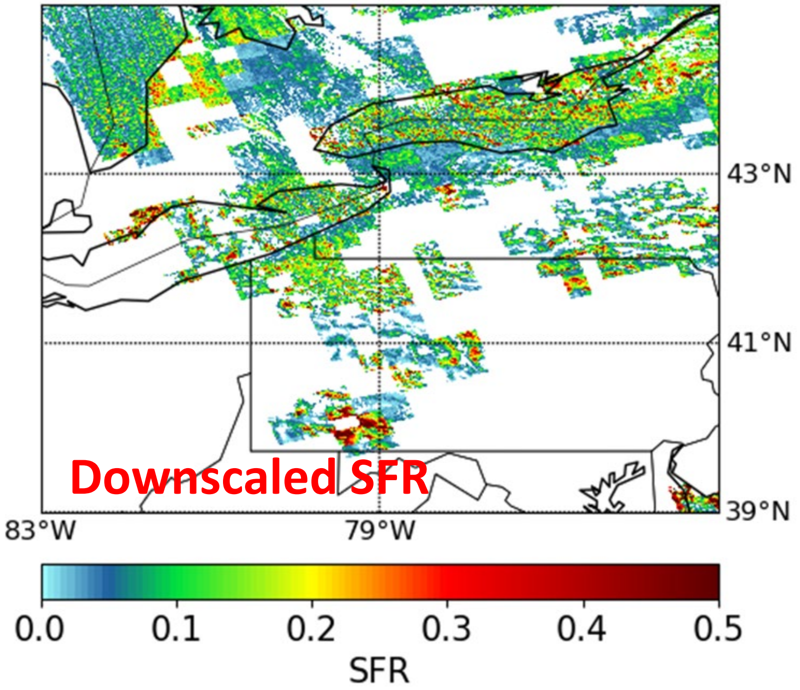
Other Challenges

- **Lake-effect and Orographic Snow**

Can data from IR sensors help improve SFR?







- **Snow Variability in Small Scale**

GOES-R L1 and L2 data are also explored for SFR improvement.

Summary

The NOAA/NESDIS SFR product derived from Passive Microwave Sensors

- ML-based snowfall detection has an **accuracy ~ 0.8** globally, being consistent across different platforms.
- Physics-based and ML-based snowfall rate agrees well with other observations (e.g. CPR, Stage IV, etc.).
- Direct-Broadcast SFR retrieval system has been built with low latency (within 20 min), distributed to WFOs by NASA/SpoRT and GINA to support winter storm nowcasting.

On-going and future work

- Preparing SFR algorithms that will run on new missions: NOAA-21/ATMS, Metop-SG-A MWI/MWS.
- Improving snowfall rate accuracy: spatial resolution, snow microphysical and optical properties etc.

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Check our website!

website http://sfr.umd.edu