NOAA-NESDIS Snowfall Rate Product - achievements, challenges, and the way forward

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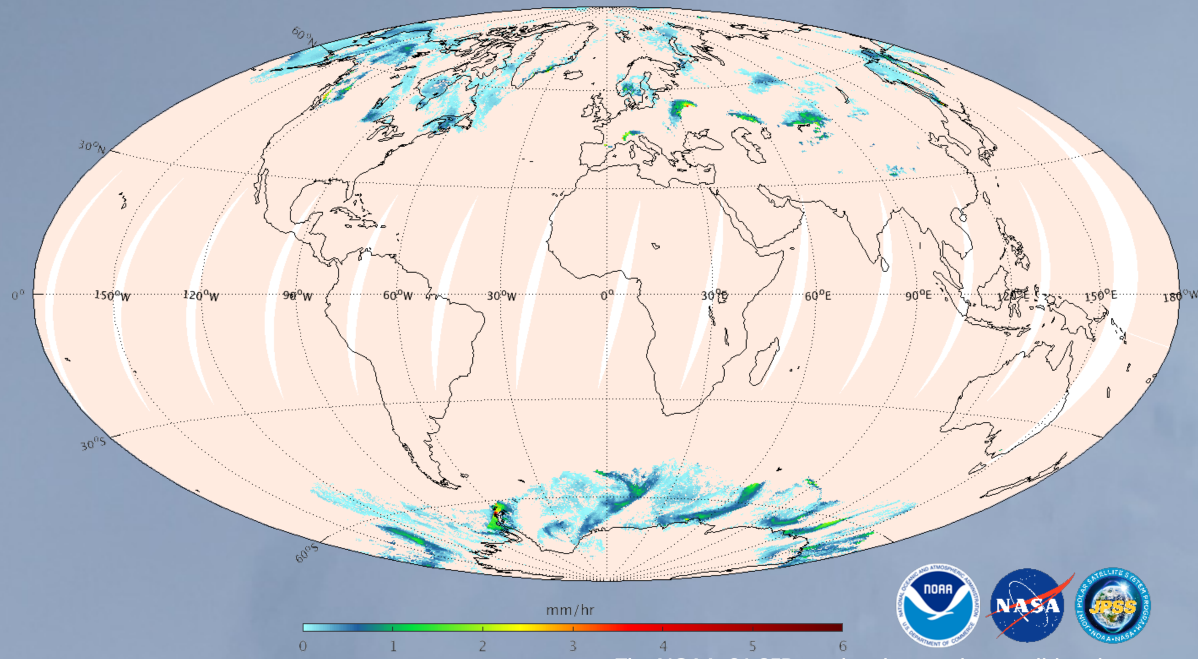
NOAA-NESDIS Snowfall Rate (SFR) Product

- Global liquid equivalent snowfall rate estimate.
- Retrieved from a constellation of Passive Microwave (PMW) sensors.
  - ➢ Five operational SFR from ATMS onboard S-NPP, NOAA-20 and MHS/AMSU-A onboard NOAA-19, Metop-B and Metop-C.
  - ➢ Four experimental SFR from GMI onboard GPM and SSMIS onboard DMSP-F16, F17 and F18.
- Near real-time production
  - ➢ NOAA/NESDIS: five operational SFR
  - ➢ University of Maryland (use Direct Broadcast data): operational + experimental SFR
    - ✓ CISESS: http://sfr.umd.edu
    - ✓ NASA SPoRT: https://weather.msfc.nasa.gov/sport/jpsspg/snowfall.html

NOAA-21 ATMS Liquid Equivalent Snowfall Rate* (11/21/2022)



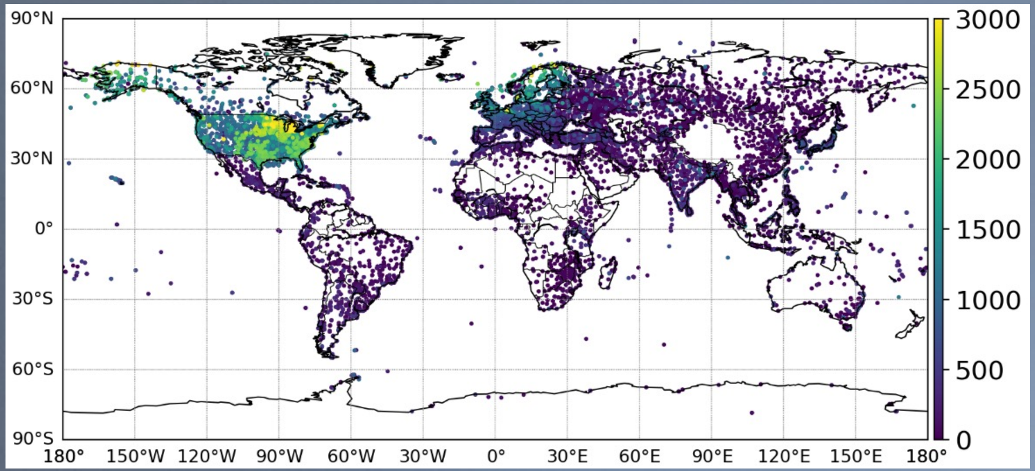
SFR Algorithm

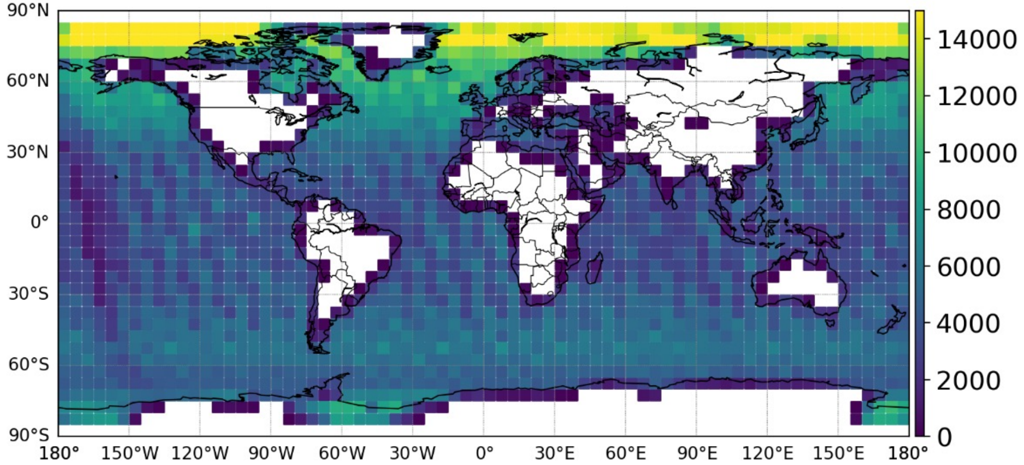
- Snowfall Detection (SD)
- Snowfall Rate estimation
  - ➢ Cloud properties retrieved using a 1DVAR model
  - ➢ Initial snowfall rate estimation from cloud properties and ice particle fall velocity
  - ➢ Snowfall rate bias correction

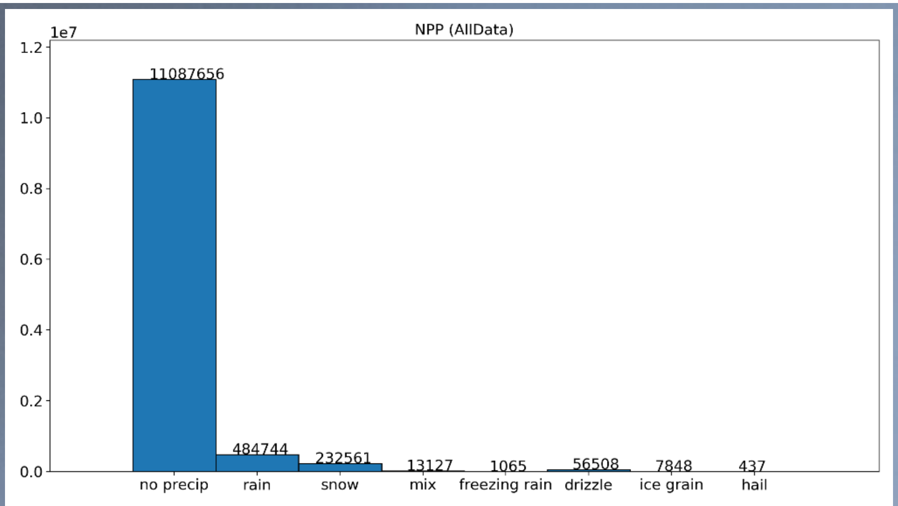
* The NOAA-21 SFR product has not been validated yet

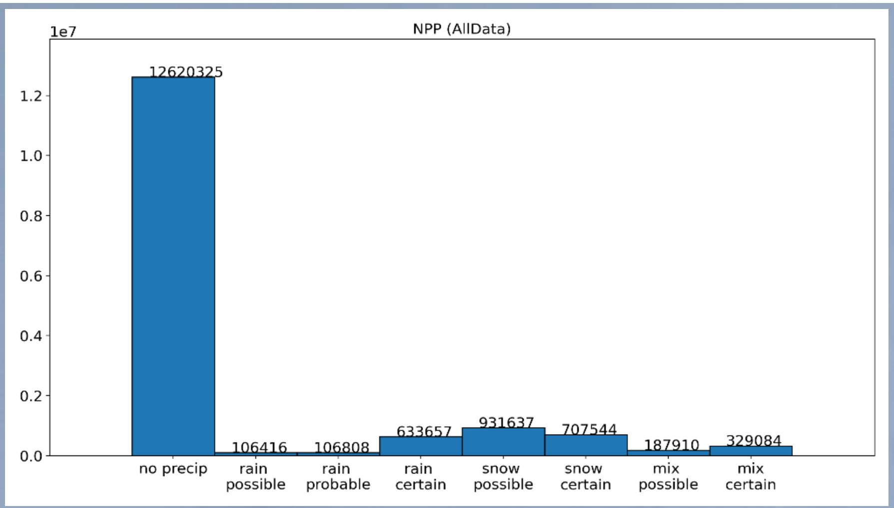
Machine Learning Snowfall Detection (SD) Algorithm

- Global Surface Precipitation Type Database
  - ➢ Ground Truth:
    - ✓ Over land: Manual weather reports (MW) ground observations from NOAA Integrated Surface Database (ISD) for the year 2012-2020.
    - ✓ Over ocean: Cloud Profiling Radar (CPR) precipitation flag product for the year 2012-2019.
  - ➢ Features: collocated satellite brightness temperature (Tb) observations and GFS model data.









Machine Learning Snowfall Detection (SD) Algorithm

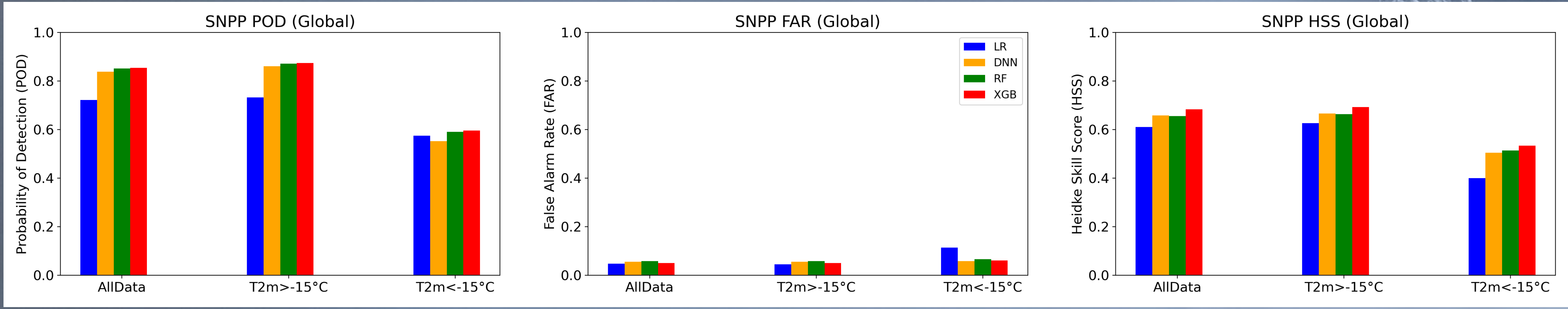
- Additional quality control applied, e.g., no rainfall for $T_{air} < -4°C$, no snowfall for $T_{air} > 8°C$.
- Training data resampled to ensure balance between snowfall and non-snowfall cases.
- The global SD training database include over 150 features and some of them are highly correlated.
- Automated Forward Sequential Feature Selection algorithm developed to select 30 important features.
  - ✓ 15 features from satellite Tb.
  - ✓ 15 features from GFS model data.
- **3** types of machine learning models, namely, Deep Neural Net (**DNN**), Random Forest (**RF**) and eXtreme Gradient Boosting (**XGB**), were trained and hyper tuned to ensure best performance.
- Performance of the trained machine learning models were evaluated using Probability of Detection (**POD**), False Alarm Rate (**FAR**) and Heidke Skill Score (**HSS**).

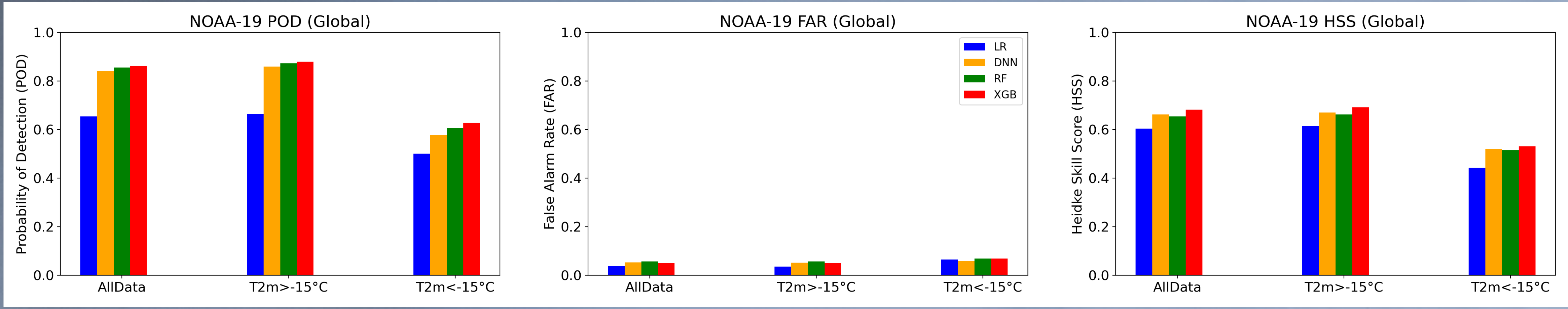
Prediction	Truth: Snowfall	Truth: Non-Snowfall
Snowfall	A	C
Non-Snowfall	B	D

- ❖ **POD = A/(A+B)**
- ❖ **FAR = C/(C+D)**
- ❖ **HSS = 2(AD-BC)/[(A+B)(B+D)+(A+C)(C+D)]**

Machine Learning Snowfall Detection (SD) Algorithm

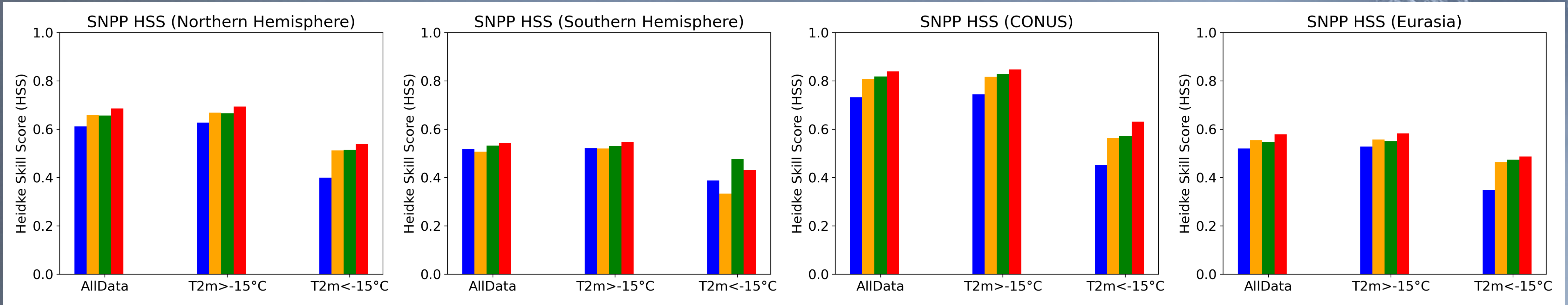
- Performance of the machine learning SD models evaluated using an independent testing dataset.
- All three machine learning SD models outperform the previously used logistic regression(LR) model.
- XGB model show better performance than RF and DNN model.
- Consistent performance for different PMW sensors, i.e. ATMS from SNPP and MHS/AMSU-A from NOAA-19.

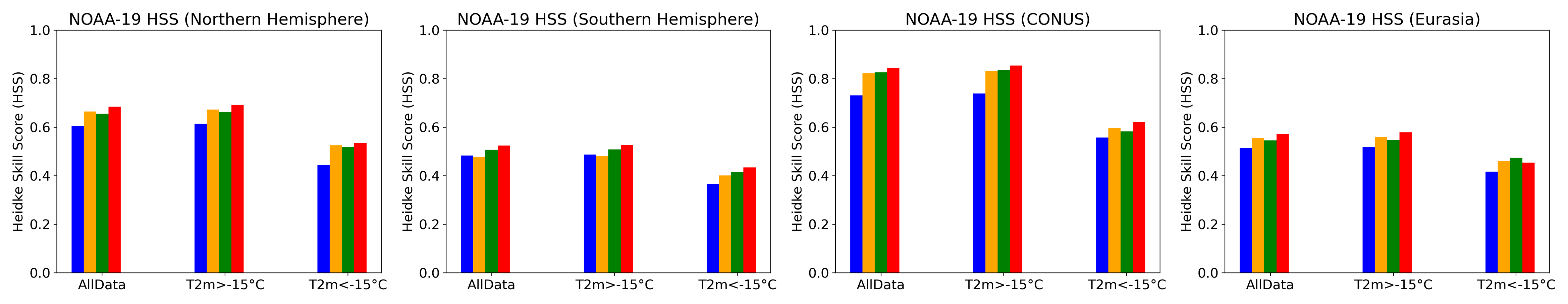




Machine Learning Snowfall Detection (SD) Algorithm

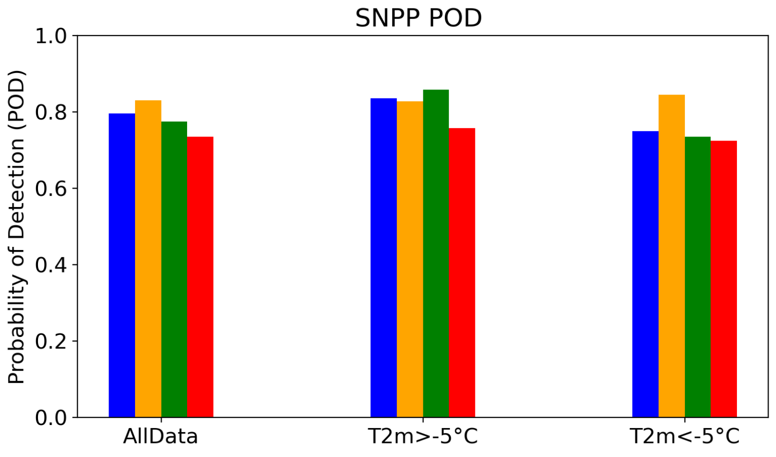
- Detailed validation shows a region dependent performance of the land SD models.
- The land SD models performed better in northern hemisphere, especially in CONUS.
- Southern hemisphere has a relatively inferior performance due to lack of training data.

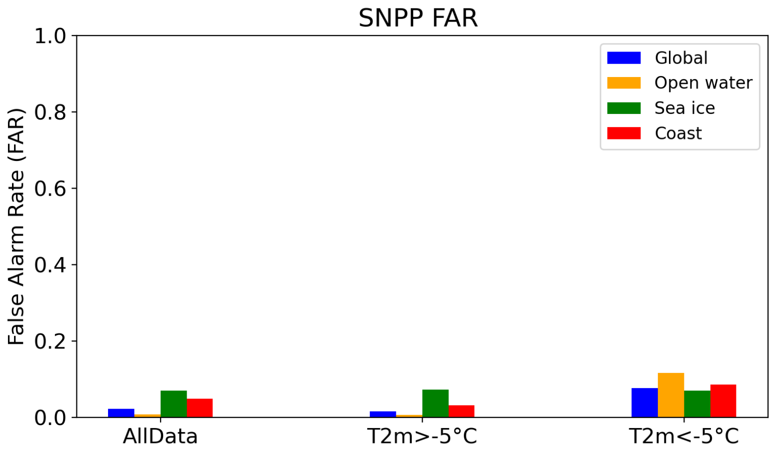


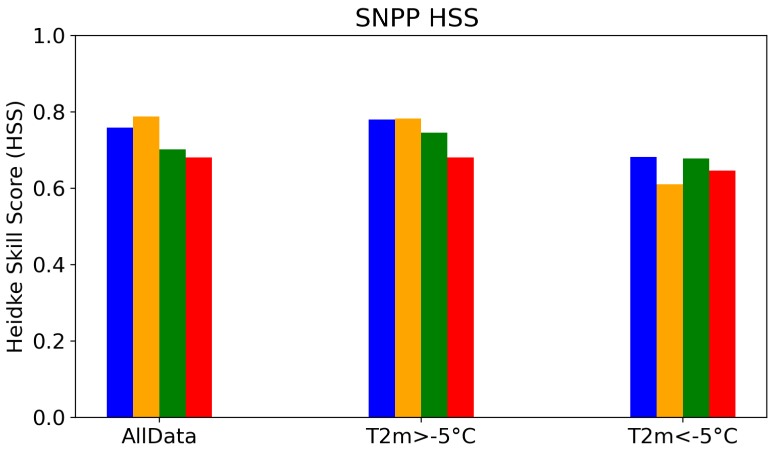


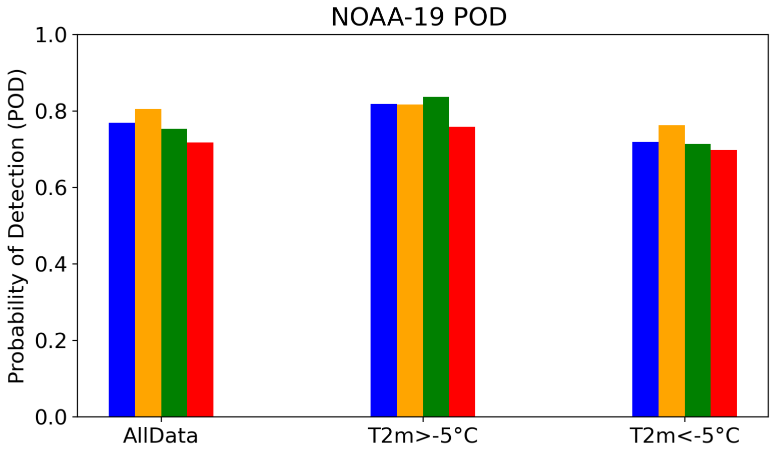
Machine Learning Snowfall Detection (SD) Algorithm

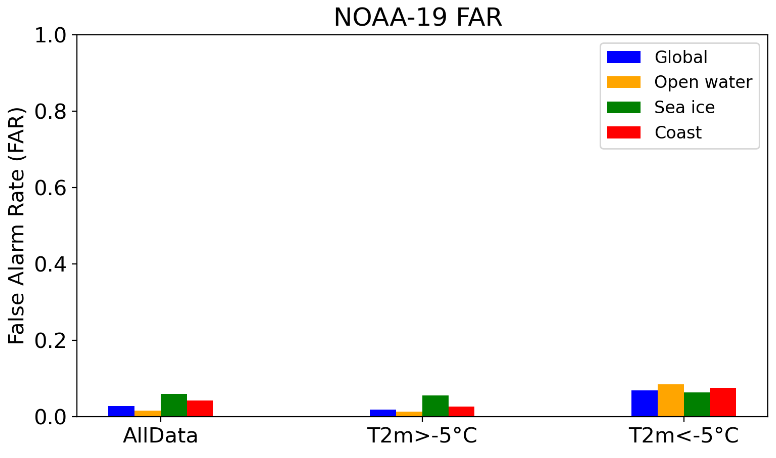
- The XGBoost (XGB) SD model over ocean was validated using CPR near surface snowfall product.
- Consistent performance for different PMW sensors, i.e. ATMS from SNPP and MHS/AMSU-A from NOAA-19.
- Relatively consistent performance over different surface types.

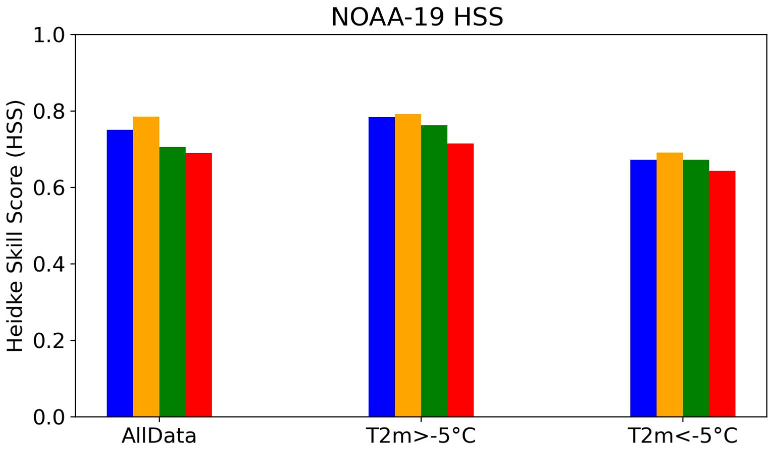






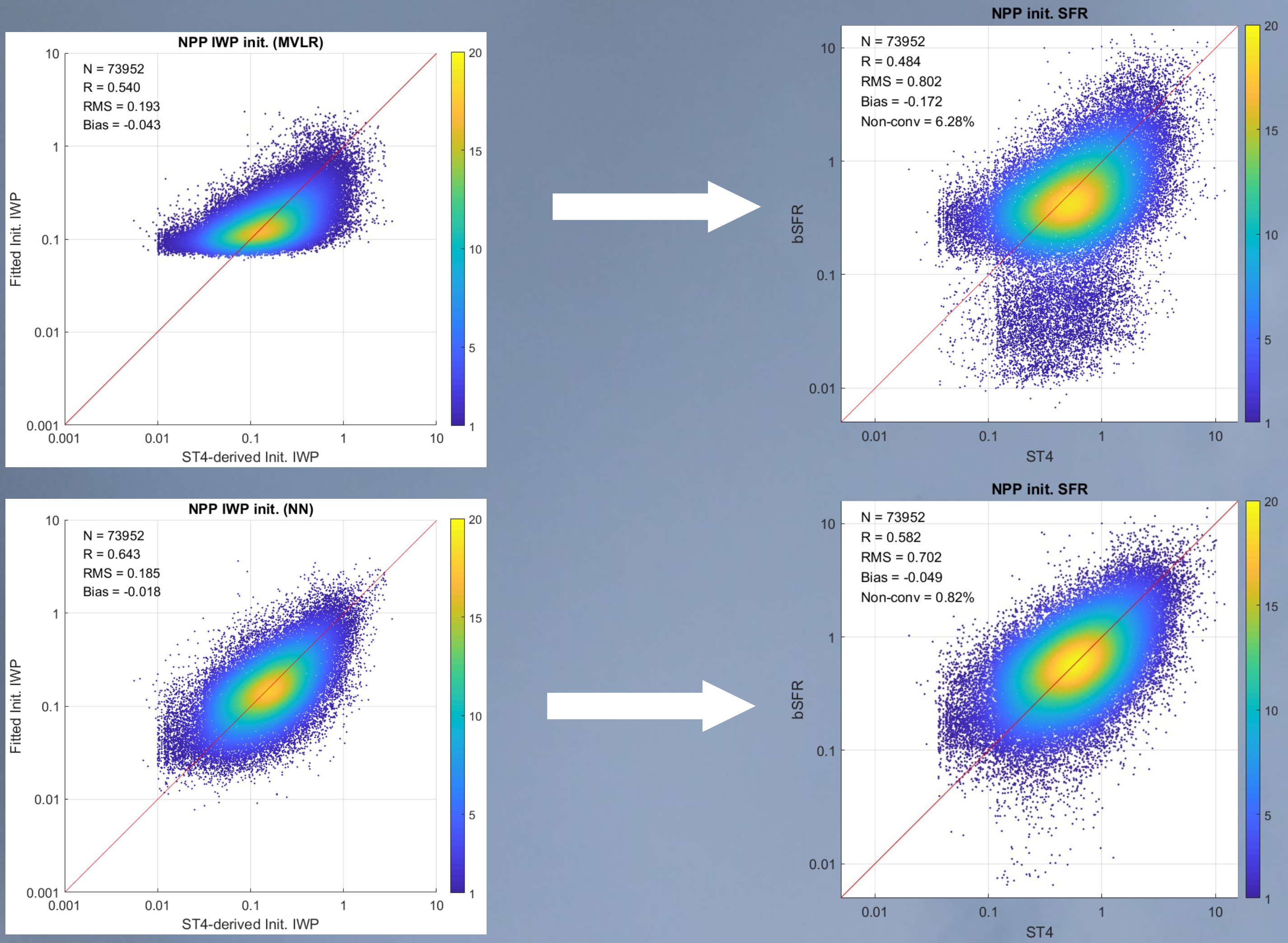






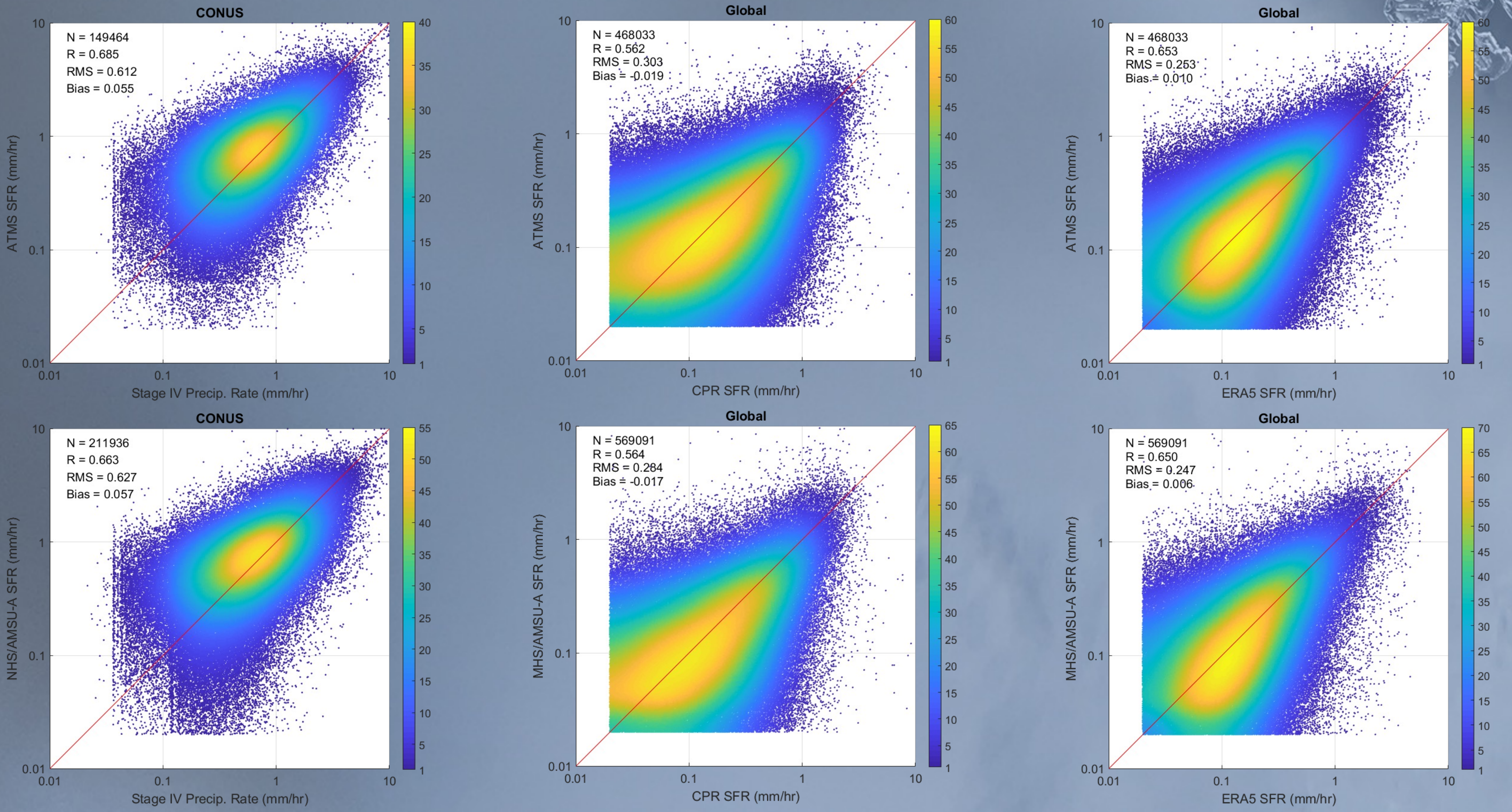
Machine Learning Enhanced Snowfall Rate Estimation

- Two neural networks (NN) was developed to enhance:
  - ✓ Ice Water Path (IWP) initialization
  - ✓ SFR bias correction
- Both NNs trained with NOAA Stage IV radar and gauge combined precipitation rate product using satellite Tb observation and GFS model data as predictors.



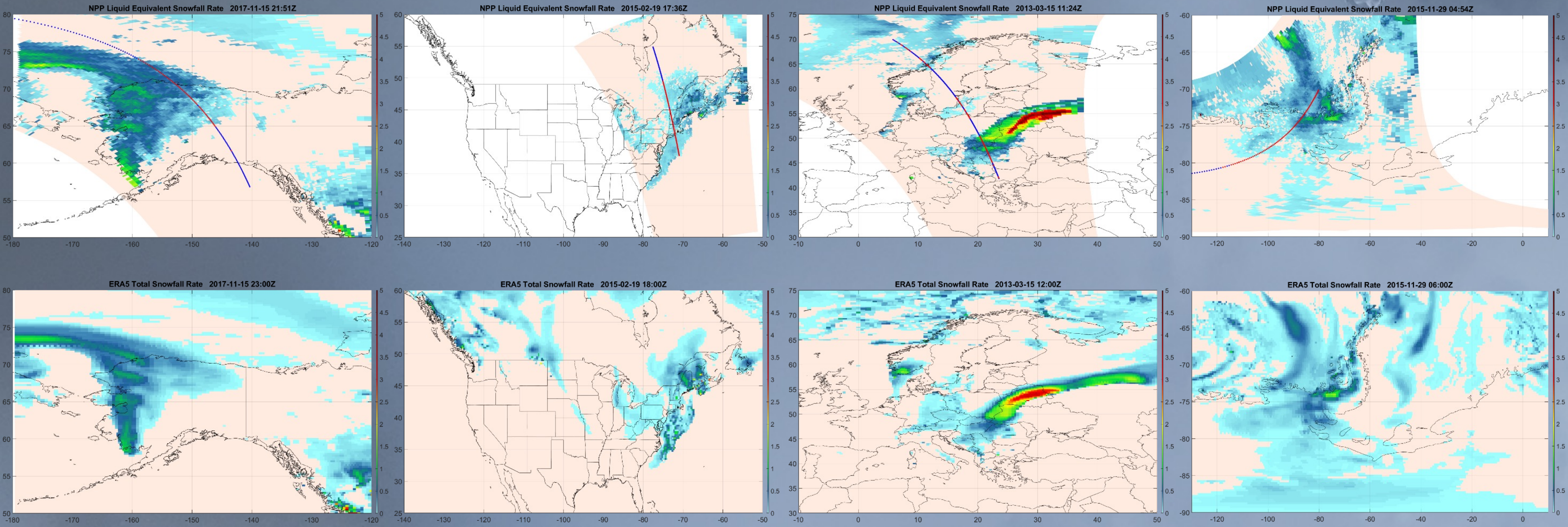
Machine Learning Enhanced Snowfall Rate Estimation

- The ML enhanced SFR product show very good agreement with the Stage IV radar and gauge combined precipitation rate, the CPR surface snowfall rate product and the ECMWF ERA5 hourly snowfall re-analyses.



Case Study

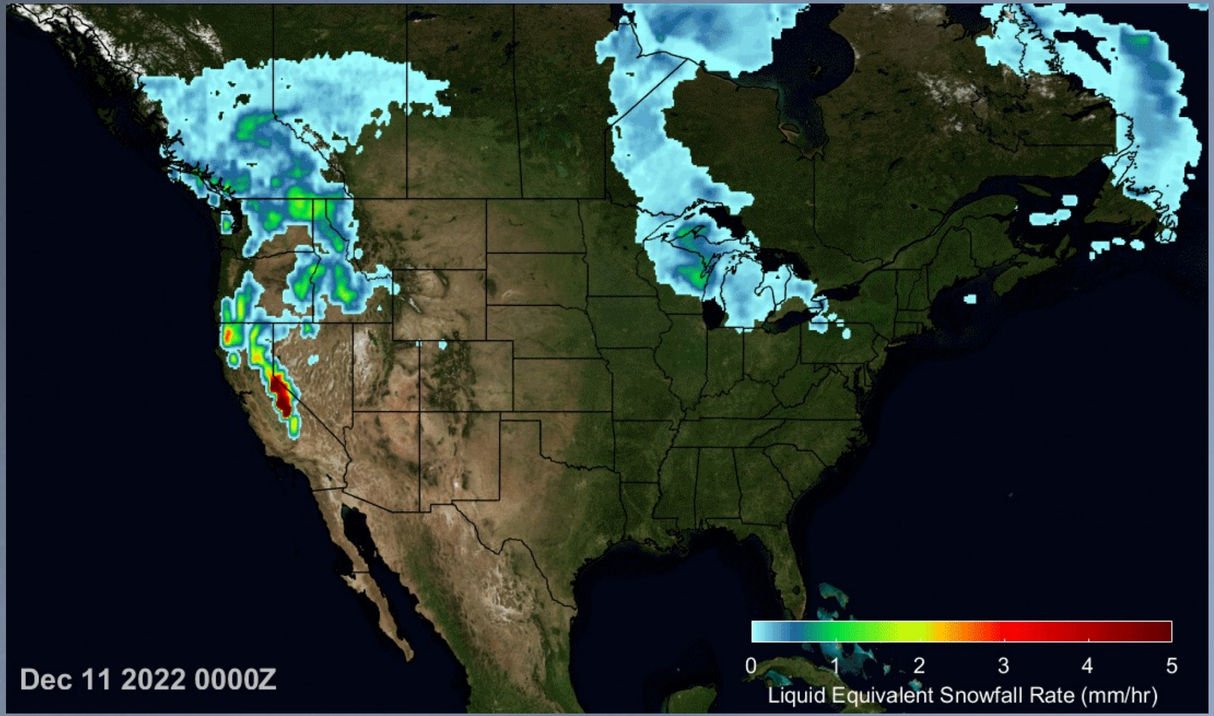
- The machine learning based snowfall detection (SD) agrees well with both CPR and ERA5 snowfall rate product.
- Snowfall rate estimation agrees reasonably well with ECMWF ERA5 snowfall rate product.

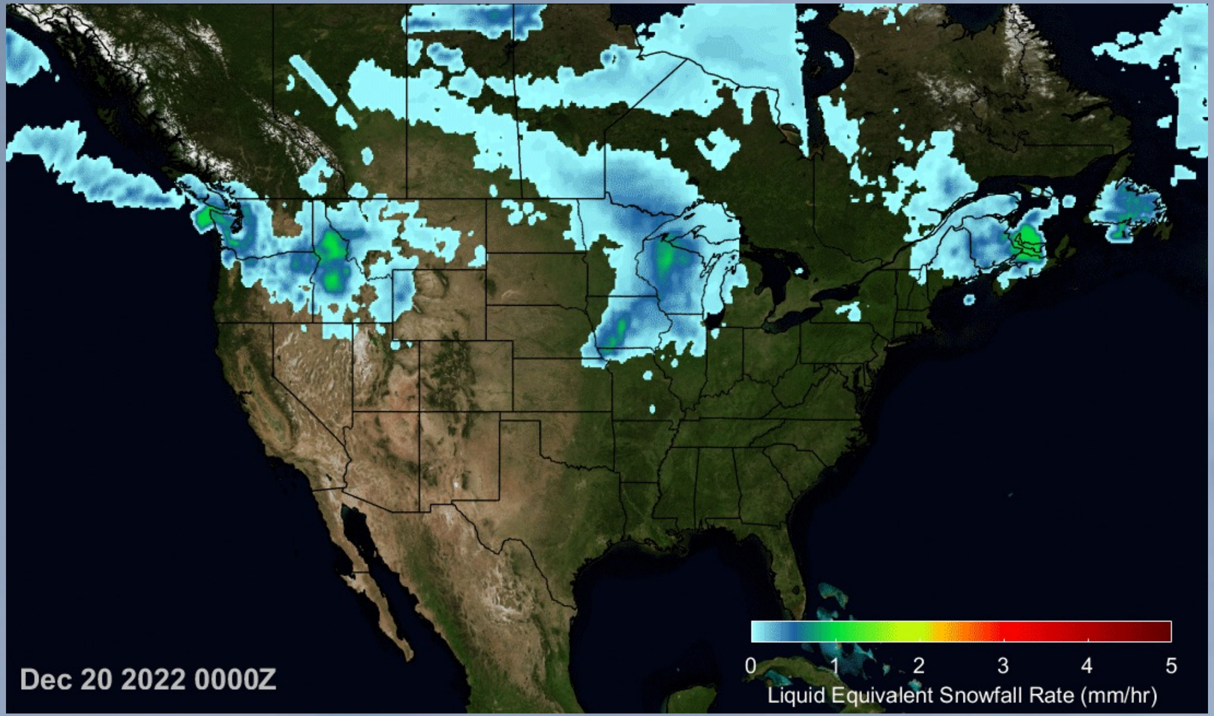


For CPR: red dots = snowfall; blue dots = non-snowfall

Case Study of the December 2022 Winter Storms

- Two almost back-to-back winter storms hit the United States in Dec. 2022.
- The first winter storm hit U.S. in mid Dec. during the week of Dec. 12. A very broad upper trough system slowly traveled across CONUS during the week, resulting in considerable snowfall and widespread winter weather impact in Northern US.
- The second winter storm, unofficially named Winter Storm Elliott by The Weather Channel, hit US in late Dec., just prior to the Christmas holiday. A strong shortwave trough accompanied by a sharp cold front quick swept CONUS in four days, causing significant snowfall and record breaking cold to the Northern US. For example, Cheyenne, Wyoming saw a record-breaking temperature drop of 40°F (22°C) in 30 minutes; Malta, Montana, reported the wind chill reached as low as -72°F (-58°C).

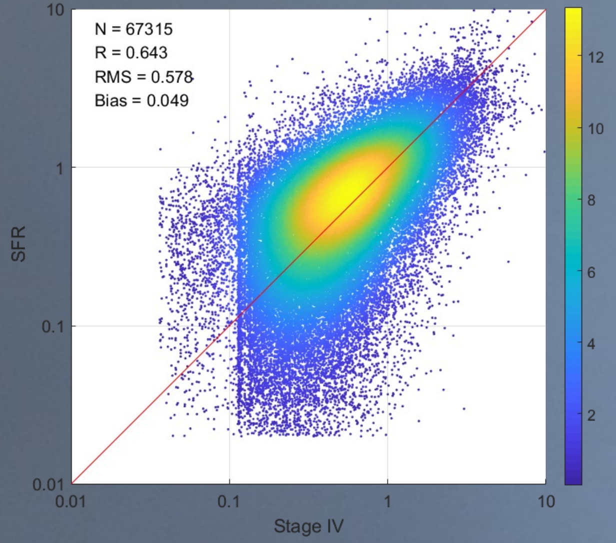




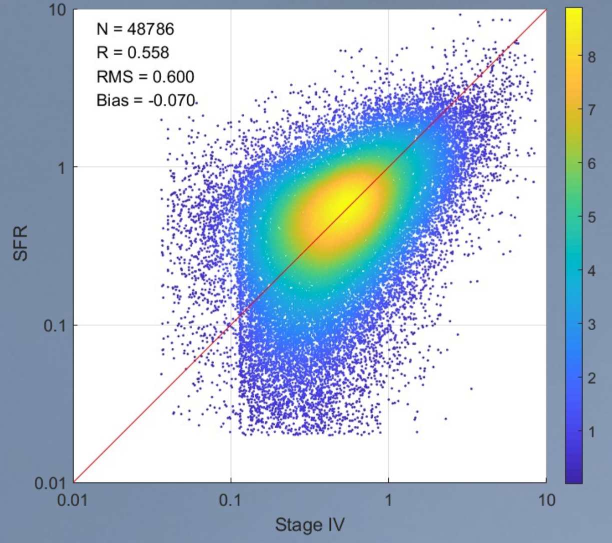
Case Study of the December 2022 Winter Storms

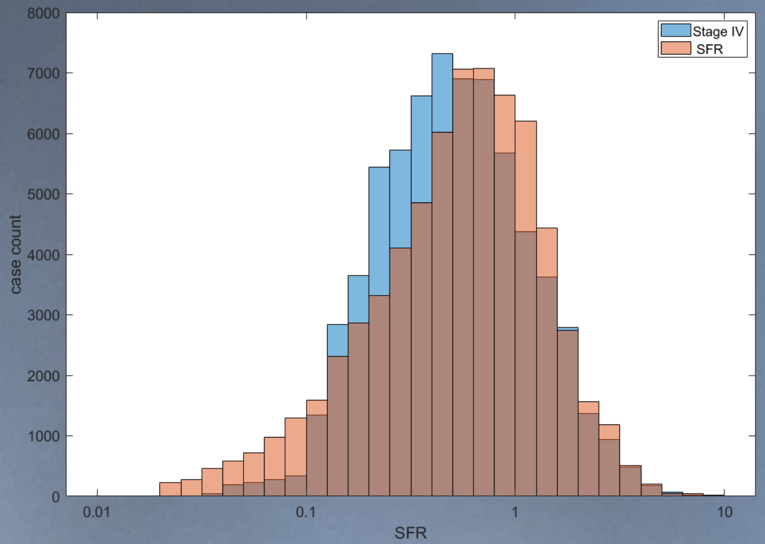
- SFR retrieval show good agreement with the Stage IV gauge-corrected radar hourly precipitation.
- SFR retrieval show slight overestimation for both events.
- SFR retrieval show better agreement with State IV for the mid-Dec event than the late-Dec event.

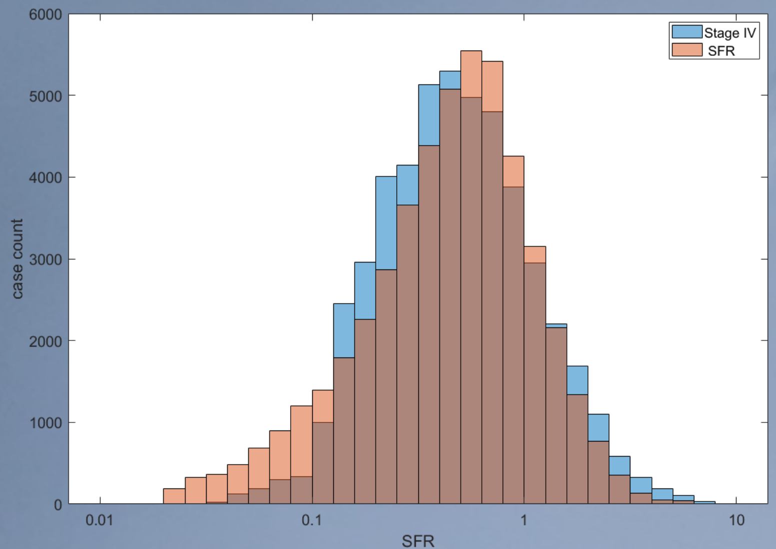
Mid-Dec Event



Late-Dec Event





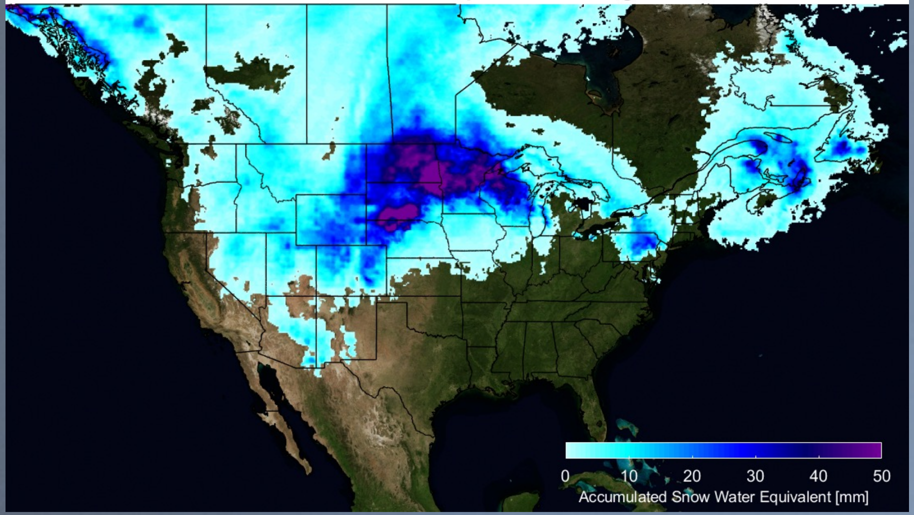


	CC	RMS	Bias
Mid-Dec.	0.64	0.58	0.05
Late-Dec.	0.56	0.60	-0.07

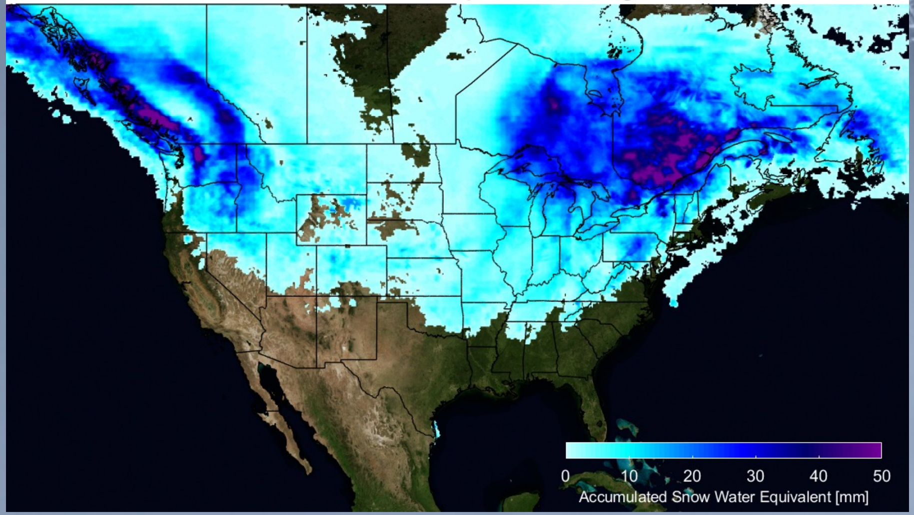
Case Study of the December 2022 Winter Storms

- 72 hour accumulated snow water equivalent from SFR (top) and snowfall depth from SNODAS (bottom) show good agreement for both mid-Dec. (left) and late-Dec. (right) events.
- SFR snowfall detection performs well.
- SFR missed the intensive but shallow lake effect snow in the late-Dec event.

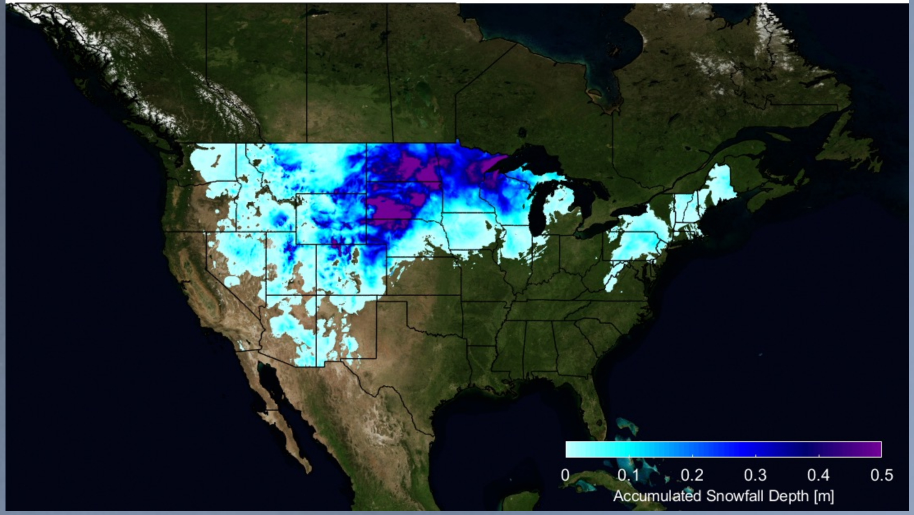
72 Hour Accumulated Snow Water Equivalent Ending 2022-12-16 00 UTC



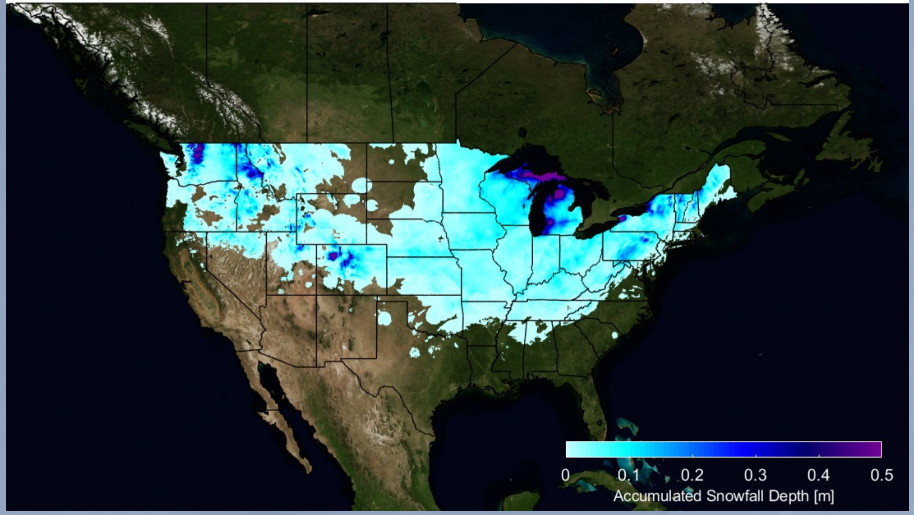
72 Hour Accumulated Snow Water Equivalent Ending 2022-12-25 00 UTC



72 Hour Accumulated Snowfall Depth Ending 2022-12-16 00 UTC

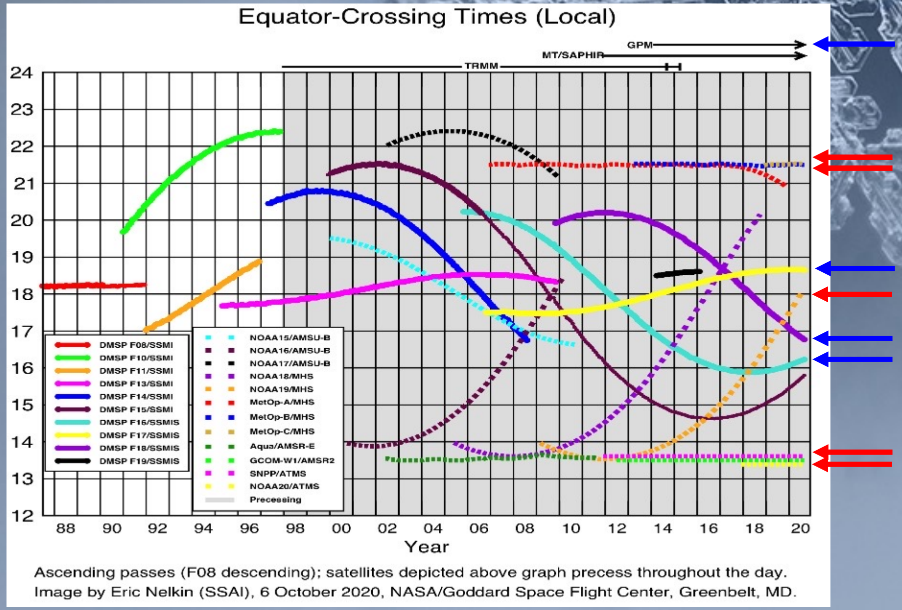


72 Hour Accumulated Snowfall Depth Ending 2022-12-25 00 UTC



Challenges

- The current LEO satellite constellation has large temporal gaps that leads to less-than-optimal SFR refresh rate.
- Challenging snow retrievals: orographic snowfall, lake effect snow, extremely cold conditions etc.
- Simplistic algorithm assumptions, e.g. spherical shape ice particles.
- Limitation with ground observation data, e.g. southern hemisphere



Red: Operational SFR; Blue: Experimental SFR

Future Development

- <u>Develop SFR algorithms for new missions</u> to improve temporal resolution
  - NOAA-21 ATMS
  - GPM GMI
  - GOSAT-GW AMSR3
  - Metop-SG-A MWI
  - Metop-SG-A MWS
- <u>Improvement through innovation, AI/ML</u>
  - Derive more realistic ice particle microphysics
  - Improve algorithms for orographic snowfall and lake effect snowfall
  - Explore AI/ML models to better incorporate information on the spatial distribution of the snowfall systems.
- <u>Improvement through data</u>
  - Explore the possibility to combine IR and microwave observations to improve SFR
  - Collect additional ground observations to improve SD performance over land, especially in southern hemisphere.

Summary

- Machine learning (ML) snowfall detection (SD) models were developed to extend NOAA SFR product to cold regime (T2m < -15 ºC) over land and over water surface (include open ocean and sea ice) The XGB model is currently implemented in the SFR algorithm for SNPP, NOAA-20, NOAA-19, Metop-B and Metop-C.

- The ML SD models were validated globally using NOAA-ISD testing dataset over land and the CPR surface snowfall product over ocean. The results show good SD performance and improved the overall SD accuracy globally. Global comparison with CPR surface snowfall product and the ERA5 hourly snowfall re-analyses showed good agreement in snowfall detection.

- Two neural network (NN) algorithm were developed and implemented to improve the Ice Water Path (IWP) initialization and SFR bias correction using Stage IV radar and gauge combined precipitation rate and ERA5 hourly snowfall re-analyses. Validation of the SFR product show very good agreement with Stage IV radar and gauge combined precipitation rate, the CPR near surface snowfall product and the ERA5 hourly snowfall re-analyses.

- Case study of the two winter storms in Dec. 2022 show SFR product agrees well with ground observations from various sources, however, the results from the two events also show that it is still challenging for SFR under very cold conditions. In addition, some orographic snowfall near the Appalachian Mountains and lake effect snowfall near the Great Lakes was not well captured.

- Snowfall retrieval still faces many challenges.

- Snowfall algorithms can be improved through innovation and exploration of new data sources.

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- JPSS PGRR
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Thank You!