International Precipitation Working Group

Snowfall Focus Group

Co-chairs

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IPWG Snowfall FG

- Established under the IPWG in November 2022
- Purpose:
  - to provide a forum for members to share their research results and foster collaborations for the advancement of satellite snowfall study;
  - to facilitate the transition of satellite snowfall products from research to operations;
- Solicited members: invitation email sent to IPWG members to join the FG -> we have 58 members
- Interested people are invited to sign up, please contact the Co-Chairs
- **A dedicated Snowfall FG web page is available URL https://ipwg-snowfall-fg.umd.edu.**
  - **Home:** Snowfall FG description and objectives
  - **Telecons:** link to all presentations
  - **Products**: link to web site of snowfall products
  - **Data:** information and link to snowfall-related datasets (including ground-based dataset)
  - **Contact**

IPWG Snowfall FG

- Telecons held every 2-3 months with two presentations and discussion

Topics:

1. **Retrieval techniques (mostly ML) (5 presentations)**
2. **Snowfall processes: e.g. microphysics and snowfall mode (1 presentation)**
3. **Snowfall measurements: campaigns (e.g., IMPACTS) and validation (1 presentation)**
4. Product applications: nowcasting/weather forecasting, hydrology, climatology, case studies, etc.
5. **Other snowfall-related topic (1 presentation)**

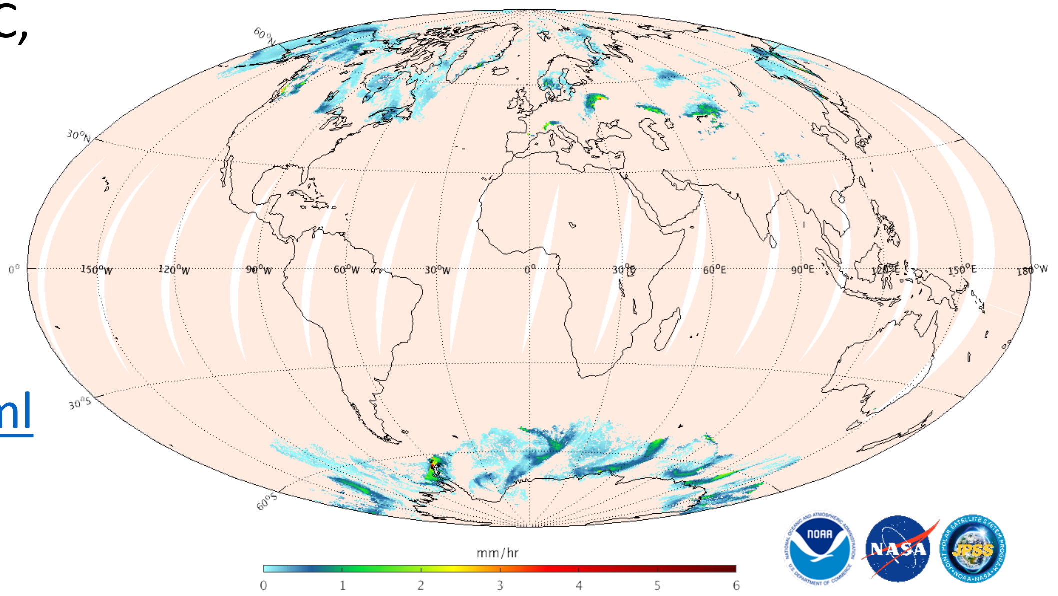
We have had 4 telecons with 8 speakers. All presentations are available on the Snowfall FG website.

Enhancing NOAA Snowfall Rate Product through Machine Learning

Yongzhen Fan (University of Maryland), H. Meng, J. Dong, C. Kongoli, Y. You, R. Ferraro; **Feb 7, 2023**

- The NOAA snowfall rate (SFR) product is retrieved from passive microwave observations
  - Sensors: ATMS, AMSU-A/MHS, GMI, SSMIS
  - Satellites: NOAA-21, NOAA-20, S-NPP, NOAA-19, MetOp-C, MetOp-B, GPM, DMSP-F16, DMSP-F17, and DMSP-F18
- SFR has been produced operationally since 2012
  - University of Maryland: https://sfr.umd.edu
  - NASA SPoRT: https://weather.msfc.nasa.gov/sport/jpsspg/snowfall.html
- Algorithm
  - Snowfall Detection (SD) – machine learning (ML) model
  - Snowfall Rate estimation – physically-based model enhanced with ML

NOAA-21 First Light Snowfall Rate (11/21/2022)



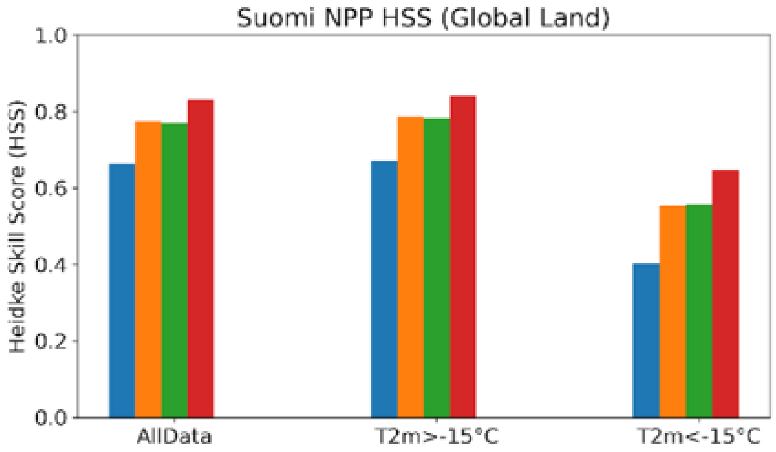
SD and SFR Validation

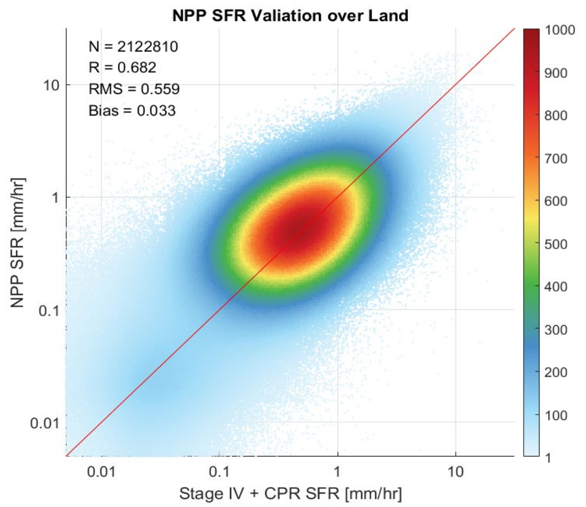
❑ SD model

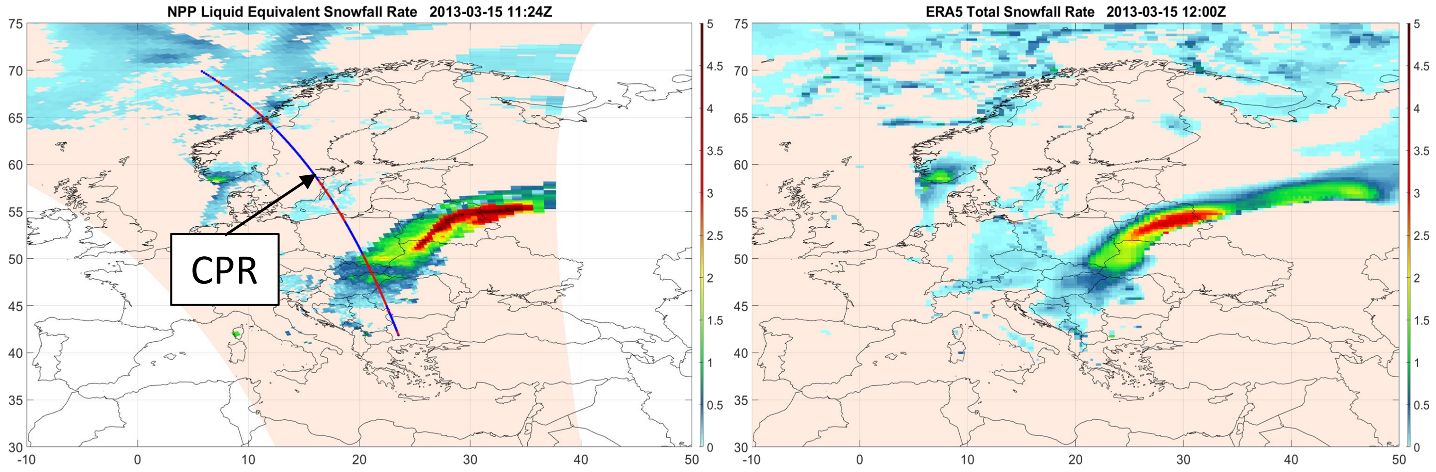
- XGBoost
- Ground truth: global manual weather reports
- Features: satellite TBs and GFS model parameters

❑ SFR

- Cloud properties retrieved using a 1DVAR model
- Initial snowfall rate estimation from cloud properties and ice particle fall velocity; ML Ice Water Path initialization
- ML snowfall rate bias correction







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

ML-based algorithms for remote sensing of snowfall: recent developments in view of the EPS-SG mission

Andrea Camplani (CNR-ISAC), G.Panegrossi , P. Sano` D. Casella, J. Turk, A. Battaglia; **7 February 2023**

Motivations

- **Snowfall retrieval at the high latitudes** is more challenging due to cold/dry conditions:
  - extremely variable background surface
  - impact of supercooled water layer on snowfall signature
- development of the day-1 precipitation products for the European MetOp-SG mission at CNR-ISAC within the EUMETSAT HSAF program

SLALOM (for GMI)
first ML-based approach based on CloudSat/Calipso dataset for training (Rysman et al., 2018, 2019)

PMW Empirical cold Surface Classification Algorithm (**PESCA**) for **GMI** and **ATMS:** classification of the frozen background surface **at the time of the overpass (Camplani et al, 2021)**

ML-based snowfall retrieval algorithms for ATMS

ATMS/Cloudsat CPR coincidence dataset

Period	2014-2016
Area	82°S-82°N 180°W-180°E
Total Observation Number	6.5 M
Snowfall Observation Number	1.1 M
Resolution (km)	15.8 x 15.8 (nadir) 30 x 68.4 (scan edge)

SLALOM-CT

- Snow retrievaL ALgorithm fOr gpM - Cross Track
- supercooled droplets detection module
- Shallow/Convolutional Neural Networks
- ANN Input dataset: ATMS TBs, PESCA output, environmental single level parameters, temperature/humidity profile PCs

HANDEL-ATMS

- High lAtitude sNow Detection and rEtrieval aLgorithm for ATMS
- **high-latitude environmental conditions** - dry and cold atmosphere, snowpack over the ground, supercooled water layer in/over the clouds
- Shallow Neural Networks
- ANN Input dataset: ATMS TBs, $\Delta TB_{obs-sim}$, PESCA output

HANDEL ATMS

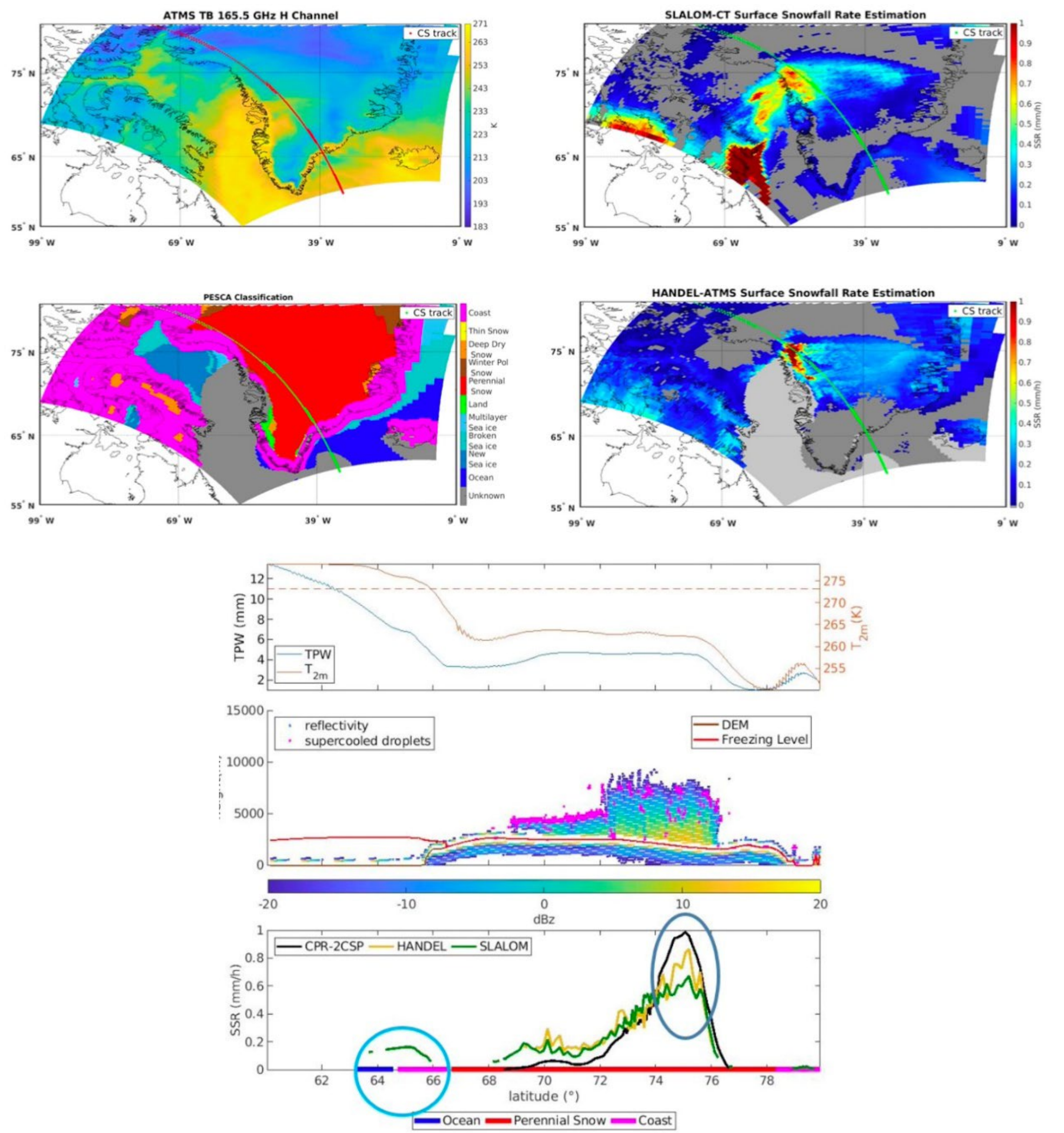
	RMSE	bias	R^2 (-)	POD	FAR	HSS
SWP ($\frac{kg}{m^2}$)	0.047	0.001	0.72	0.85	0.15	0.70
SSR ($\frac{mm}{h}$)	0.079	0.002	0.61	0.84	0.16	0.69

- SLALOM-CT performs a snowfall retrieval on a global scale
- HANDEL-ATMS is focused on high-latitude conditions

	POD		FAR	
	SLALOM CT	HANDEL ATMS	SLALOM CT	HANDEL ATMS
T2m<280 K TPW<10 mm	0.82	0.84	0.19	0.16
T2m<250 K TPW<5 mm	0.64	0.68	0.27	0.23
T2m<240 K TPW<3 mm	0.45	0.54	0.33	0.28

Greenland - 2016/04/24

Date	CPR Orbit	ATMS Orbit	CPR Time UTC	ATMS Time UTC
2016/04/24	53148	23271	14:51:23-14:57:27	20:42:09-20:51:02



Future development:

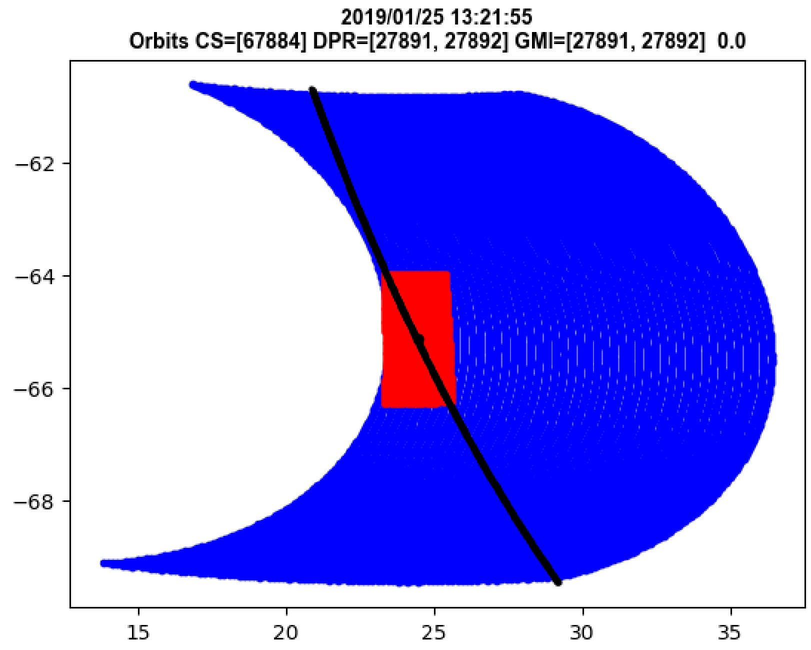
- integration between HANDEL-ATMS and SLALOM-CT approach in order to optimize the global snowfall application for the high-latitudes regions
- Implementation in MetOp-SG products within EUMETSAT H SAF

Use and Applications for Coincident CloudSat + GPM Data

Joe Turk (Jet Propulsion Laboratory); **7 September, 2023**

- The 2BCSATGPM dataset consists of near-coincident observations between GPM and the CloudSat Profiling Radar (CPR)
- Dataset applications:
    - CPR W-band "fill in" the missing upper level ice that DPR is insensitive to
    - Passive MW snowfall, to train snowfall algorithms
    - Surface emissivity effects
    - Use CloudSat ICE or DARDAR products to forward simulate passive mm-wave and higher radiometric observations of ice clouds
    - Quantify the precipitation "missed" by GPM products
    - Large collection of Ku/Ka/W band profiles, "actual" clouds, globally distributed- PSD variables
    - Etc.

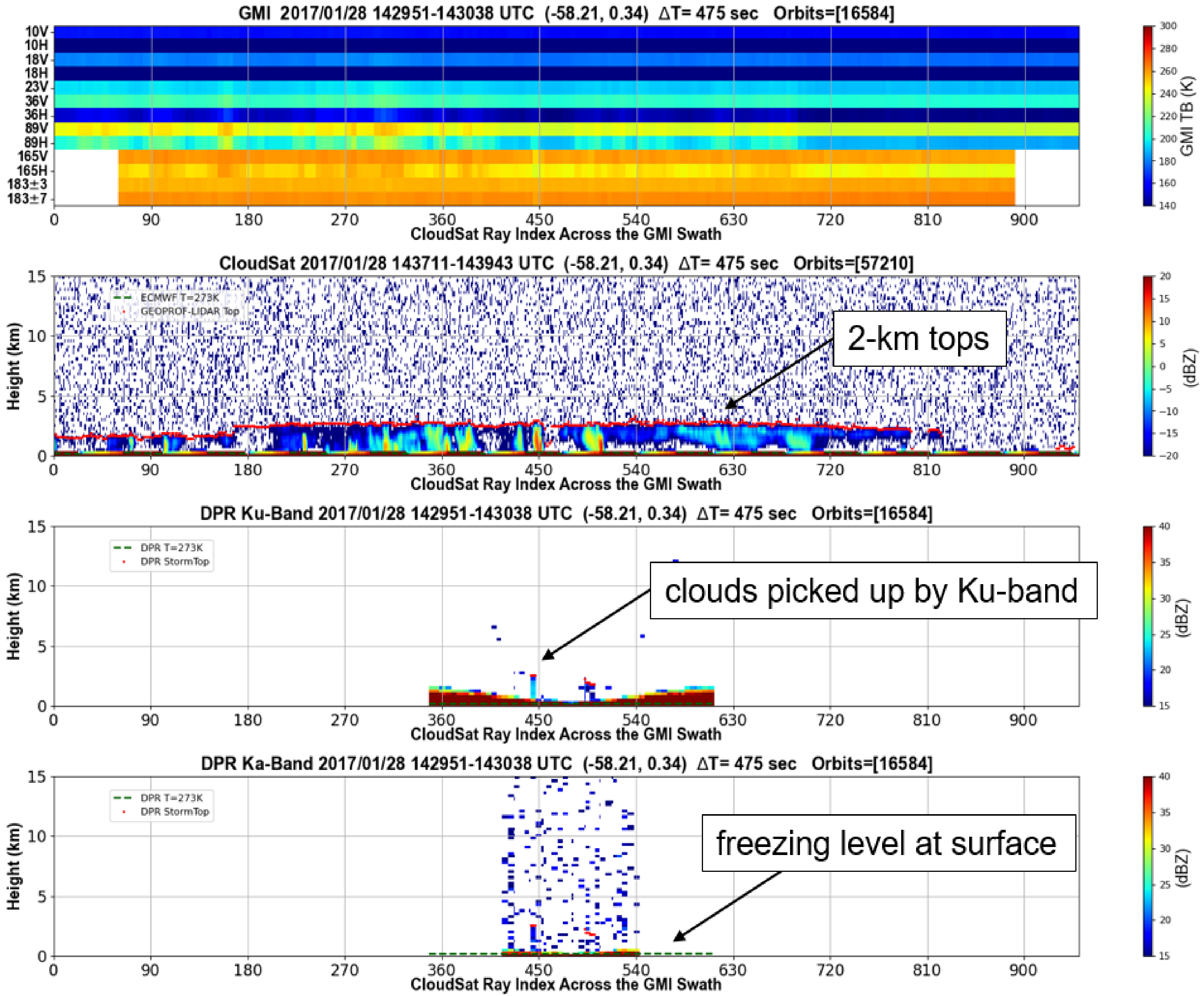
GPM descending and the coincidence segment crosses its southernmost latitude



GMI (scanning "ahead" of DPR) is in the "next" GPM orbit file, so two DPR and/or GM files need to be concatenated

Shallow Convection, Freezing Level Near Surface

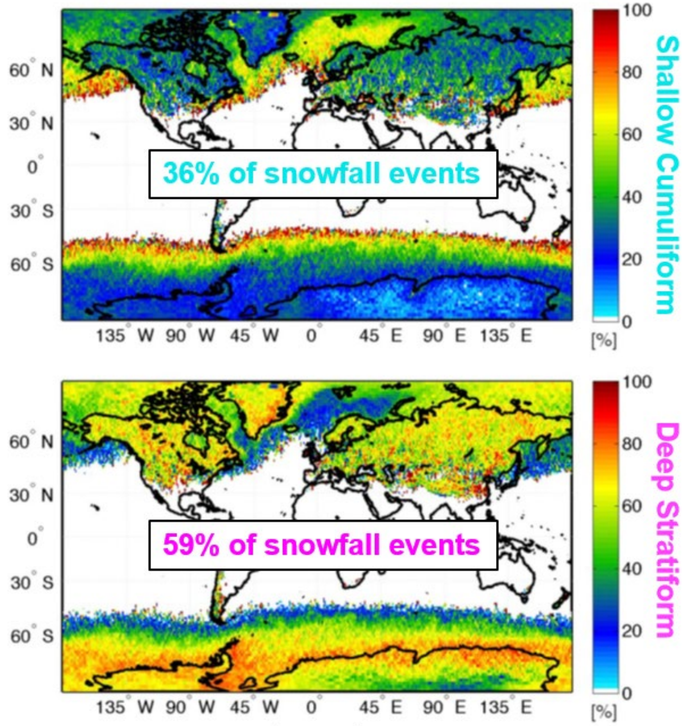
- 2BCSATGPM has been updated to V7 GPROF, DPR and CMB
  - ~7500 cases thru mid-2019
  - NetCDF4 with associated images
  - Filenames follow PPS syntax; sub-groups, name, type, units the same as in the original PPS file
- The updated dataset has been provided to PPS (as of Sept 2023)
- The dataset is available on the cloudsatgpm google drive (~500 GB)



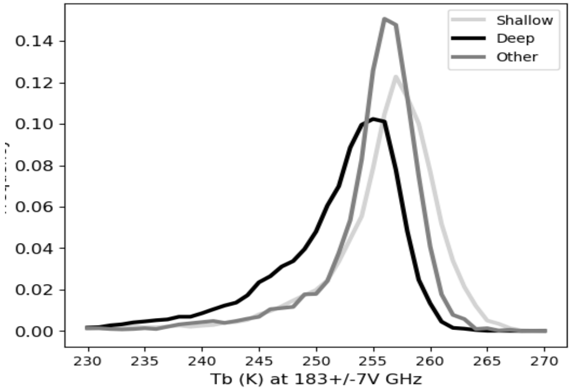
Retrieving Snowfall Class from Satellite Passive Microwave Observations

Veljko Petković (University of Maryland), Yulan Hong, Lisa Milani; **22 April, 2024**

- ❑ Retrievals from some algorithms, e.g. GPROF, need an *a priori* (i.e., training) database to constrain the solution. A priori knowledge must be "complete".
- ❑ Previous work (e.g., Milani et al. 2021) confirms the value of snowfall regime information in PMW snowfall retrievals
- ❑ Different snowfall regimes often appear radiometrically similar, preventing the retrieval to converge.
- ❑ Non-linear relationships between Brightness Temperatures (TBs) at different frequencies, or combination of frequencies
- ❑ Machine learning techniques can enable finding the "hidden" relationships and help with the PMW classification of snowfall regimes, taking advantage of the entire range of information carried by the PMW channels

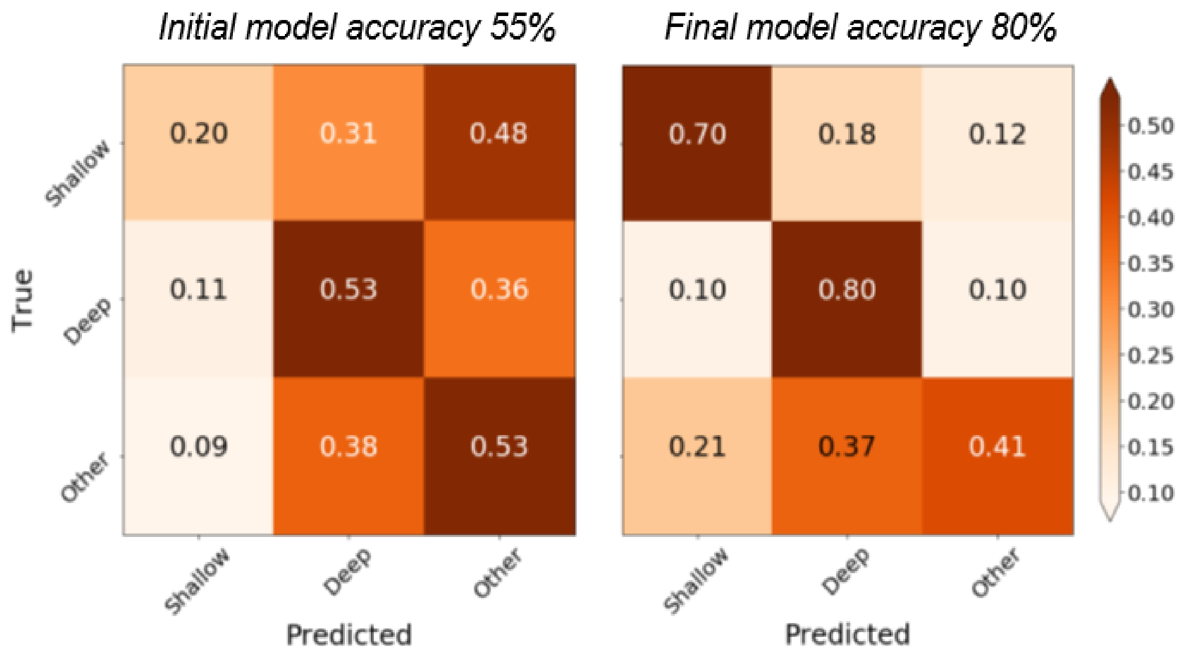


Kulie et al. 2016



- Built training dataset using the matched GPM–CloudSat dataset (2BCSATGPM)
  - Features: GMI 13 channels TBs, TBs polarization differences, TPW, and T2m
  - Target: CloudSat snowfall regime class
  - Total number of scenes: ~60K – limited data size is a challenge
- Models trained: Fully Connected NN, XGBoost
- Fully Connected NN
  - Shallow class: 70%; Deep class: 80%; Other class: 41%
  - Overall accuracy: 80%
- XGBoost
  - Shallow class: 62%; Deep class: 61%; Other class: 41%; Dry 91%
  - Overall accuracy: 89%
- The achieved accuracy sets the scene for implementation to PMW retrieval

Results of Fully Connected Neural Network



A Neuro-Bayesian Algorithm for Passive Microwave Retrieval of Precipitation using CloudSat/GPM Coincidences

Reyhaneh Rahimi and Ardeshir Ebtehaj (Univ. of Minnesota); **7 September, 2023**

Research Questions

- How can modern machine learning algorithms improve PMW retrieval of precipitation beyond the state-of-the-art Bayesian algorithms?
- What is the best available machine learning model for PMW precipitation retrievals in terms of the detection and estimation quality metrics?
- What are the optimal architectures and cost functions?
- What are the effects of input physical variables (e.g., cloud water content) on the retrieval accuracy?
- Can we unravel the black-box nature of machine learning algorithms?

Data
GMI-CPR, and GMI-DPR coincidences (2014–2016) - Brightness Temperatures (TB) from GMI
- Snowfall from CPR + DPR for high SR
- Rainfall from DPR
+ERA5 (LWP, IWP, TPW, T2m, CAPE) and 5 Surface types

Two Step PMW Retrieval

- Detection of occurrence and phase
  - k-nearest neighbor (kNN)
  - Random forests and XGboost decision trees (DT)
  - Deep learning neural networks (DNN)
- Estimation of rates

- NeuroBayesian algorithm
  - Xgboost

	metric	ML	Surface Type: ocean	land	coast	snow cover	sea ice
rain	rmse $[\mathrm{mm\,hr}^{-1}]$	NeuroB	4.9	4.6	5.9	1.1	0.75
		XGB	5.1	4.8	3.4	1.2	0.81
	wsd $[\mathrm{mm.hr}^{-1}]$	NeuroB	0.09	0.13	0.18	0.07	0.05
		XGB	0.1	0.13	0.08	0.07	0.06
snow	rmse	NeuroB	0.20	0.25	0.45	0.14	0.2
		XGB	0.23	0.28	0.17	0.12	0.16
	wsd	NeuroB	0.01	0.03	0.04	0.02	0.01
		XGB	0.03	0.05	0.01	0.03	0.03

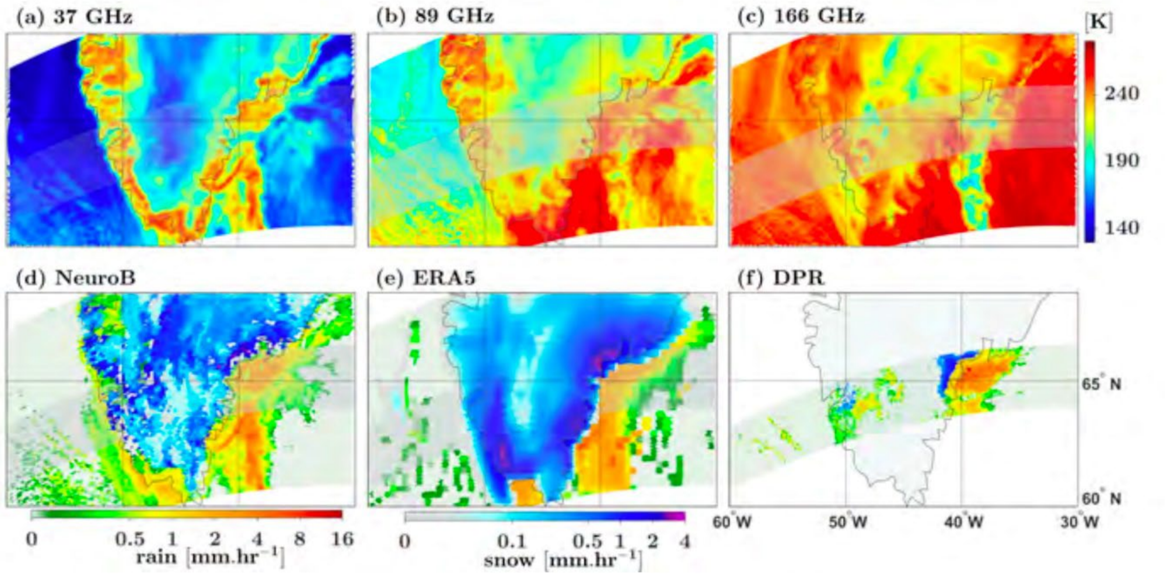
For rain, NeuroB has slightly better performance except coast
For snow, NeuroB has better performance over ocean and land

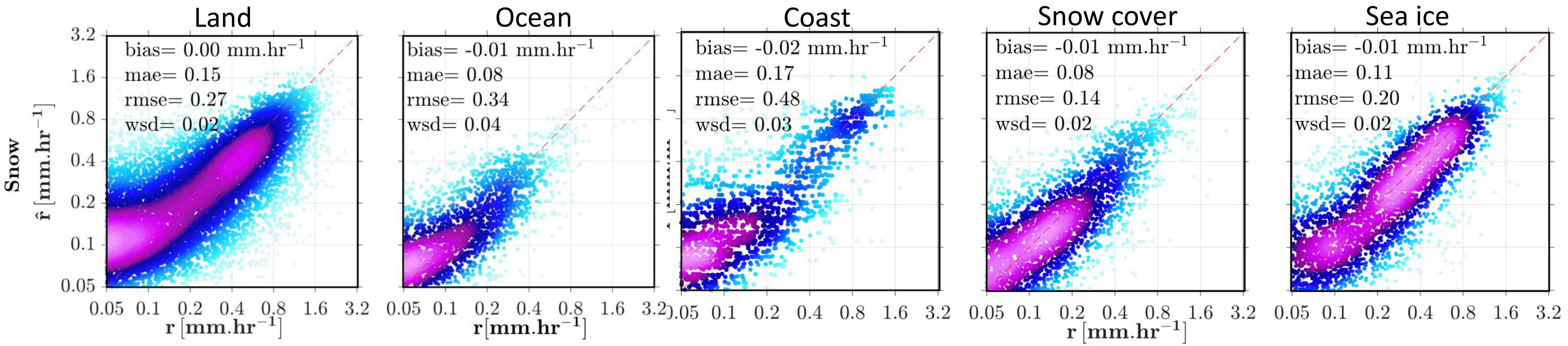
Explainable AI through partial dependence plots

SUMMARY

- Modern machine learning can reduce the uncertainty of PMW retrievals beyond classic Bayesian Algorithms.
- Adding physical variables can significantly improve the quality of retrievals.
- Among the existing machine learning XGBoost and DNN are comparable in the detection of the occurrence and phase.
- Bayesian retrievals in the feature space of a DNN, trained with focal loss function, lead to the best results for the estimation of the rates and quantification of uncertainties.
- **Explainable AI can unravel physical principles governing the PMW precipitation signatures**

orbit #3080 on September 13, 2014 over Greenland

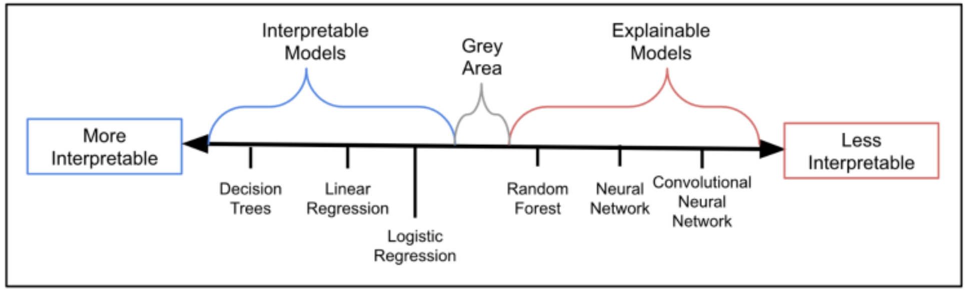




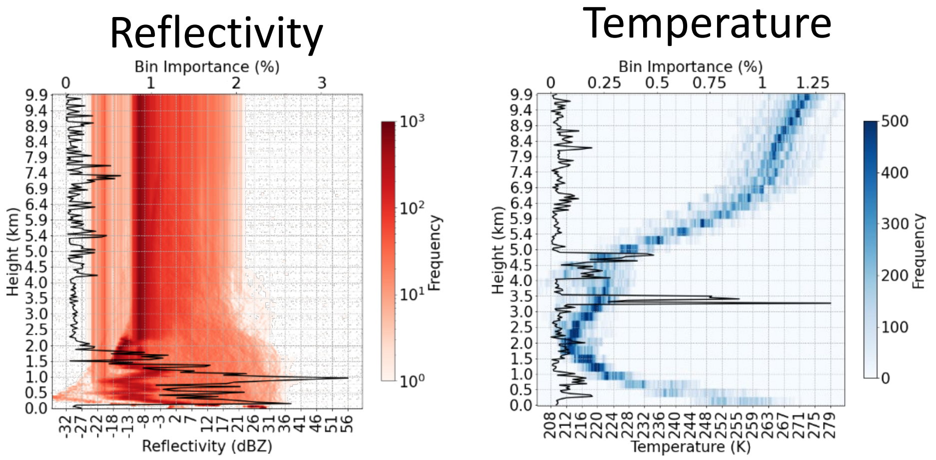
Towards Interpretable Artificial Intelligence in the Atmospheric Sciences

Fraser King (University of Michigan), C. Pettersen, C. G. Fletcher, D. Posselt; **22 April, 2024**

- ❑ The application of ML in the Atmospheric Sciences has surged in popularity (improvements in both SW and HW capabilities, large obs. datasets) but are often considered *black boxes:*



- ❑ Towards interpretability:
  - ❑ biases or errors in the models are difficult to identify;
  - ❑ Explanatory techniques (e.g., LIME, SHAP) can help explain some NN behavior.

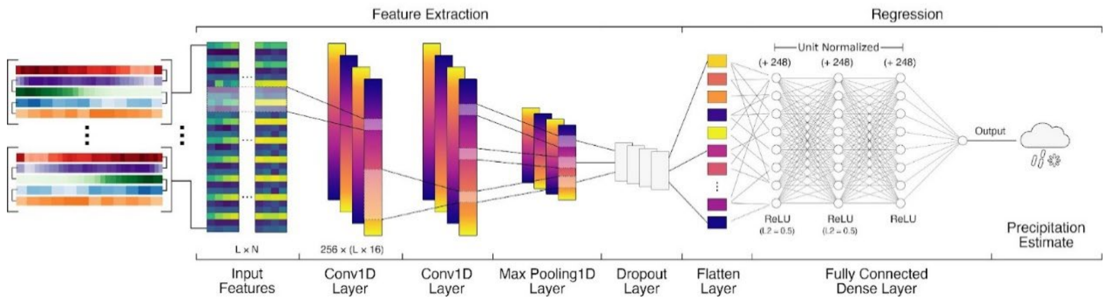


1. **A cm-Wavelength Snowfall Retrieval Algorithm Using Machine Learning**: supervised machine learning algorithm (i.e., a random forest) trained on surface radar observations (GCPEx (MRR and Pluvio gauge) https://doi.org/10.1175/JAMC-D-22-0036.1

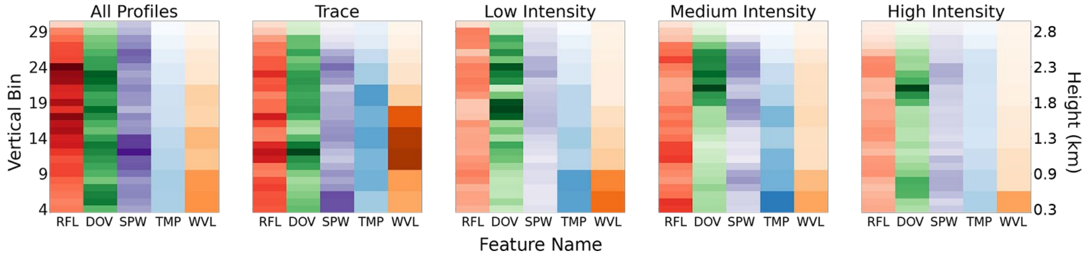
   - ❑ RF explainability through feature importance

2. DeepPrecip: A deep neural network for precipitation retrievals: Can we generalize the previous model to new regional climates? https://doi.org/10.5194/amt-15-6035-2022

- Data collected from 9 sites across the northern hemisphere
  - DeepPrecip is a 1D convolutional neural network with two primary system components responsible for Feature Extraction and Snowfall Regression

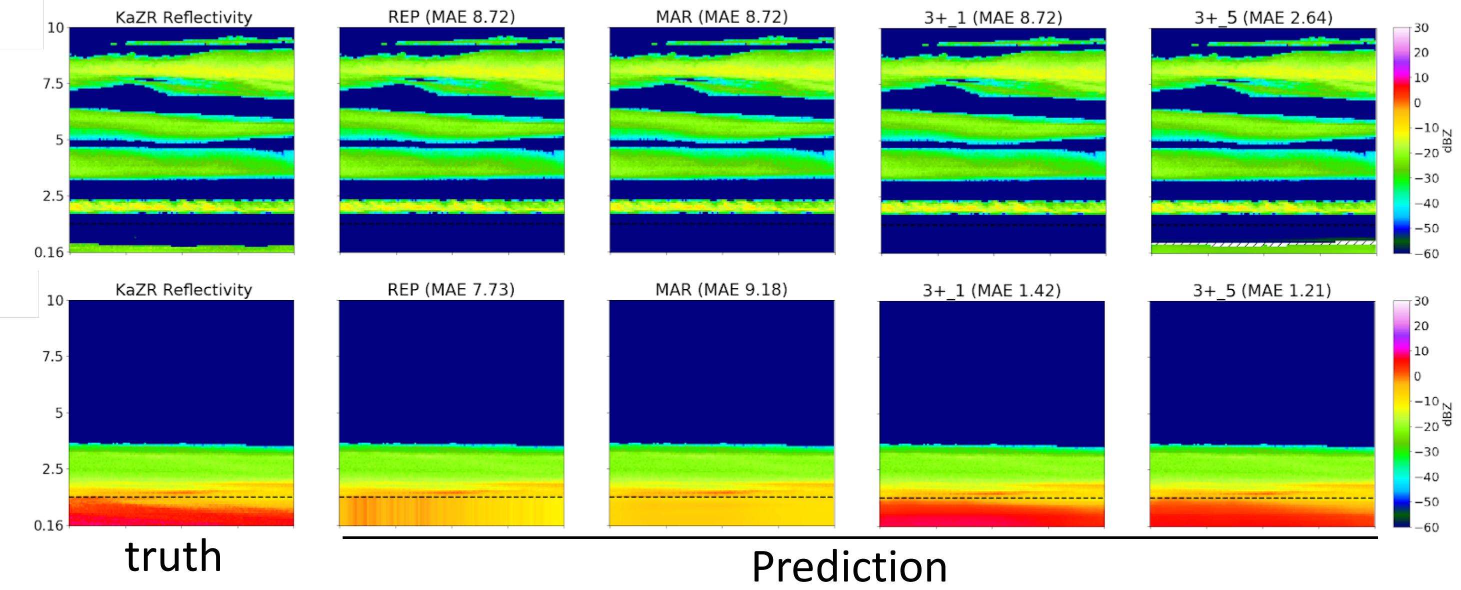


- SHAP: SHapley Additive exPlanations: explainability techniques used to explain how machine learning models make decisions



3. Development of a full-scale connected U-Net for reflectivity inpainting in CPR blind zones

- ❑ Two Arctic locations along northern Alaskan coast (NSA & OLI) (cold season)
- ❑ The model appears to learn to relate features in cloud aloft to blind zone reflectivity structures

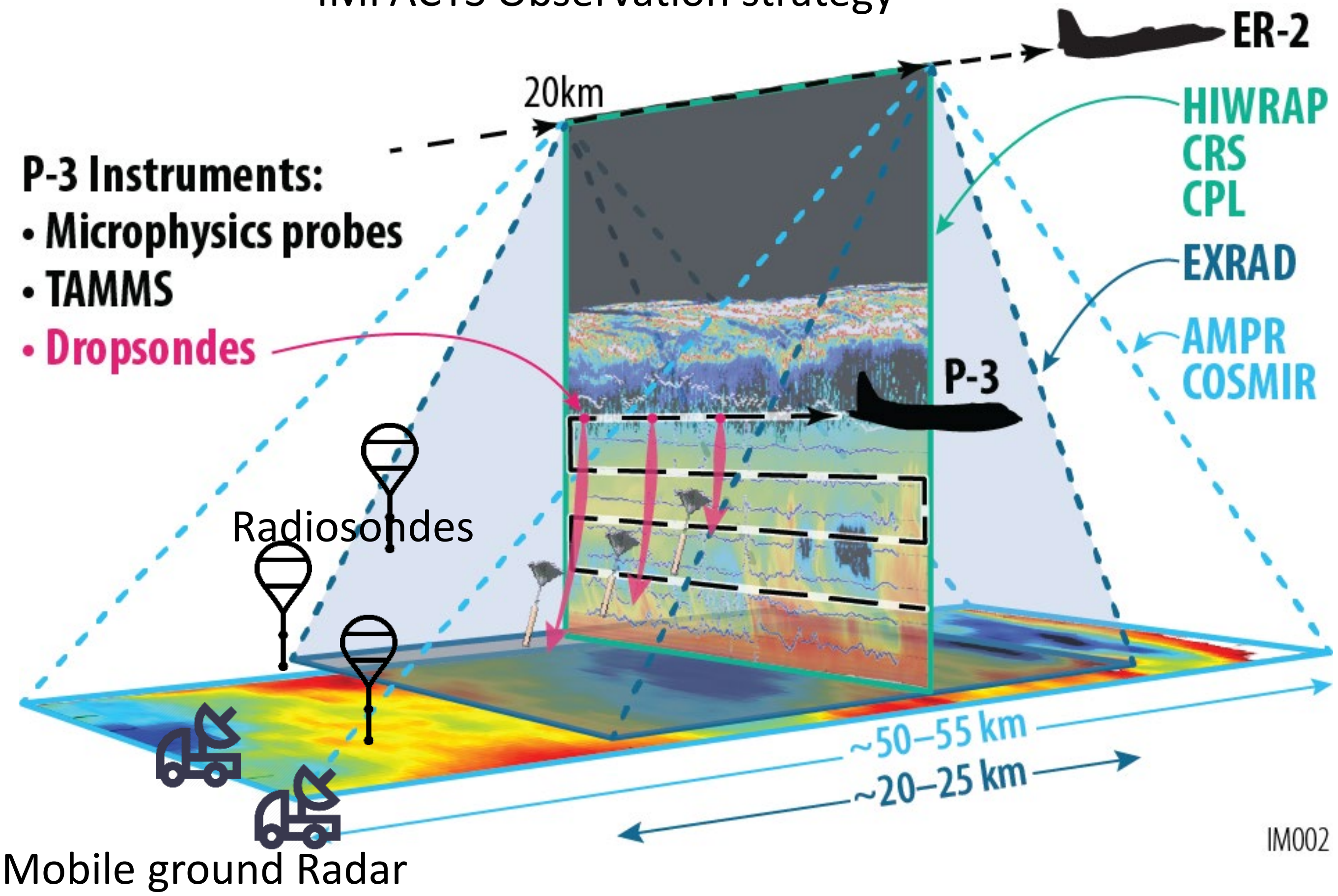


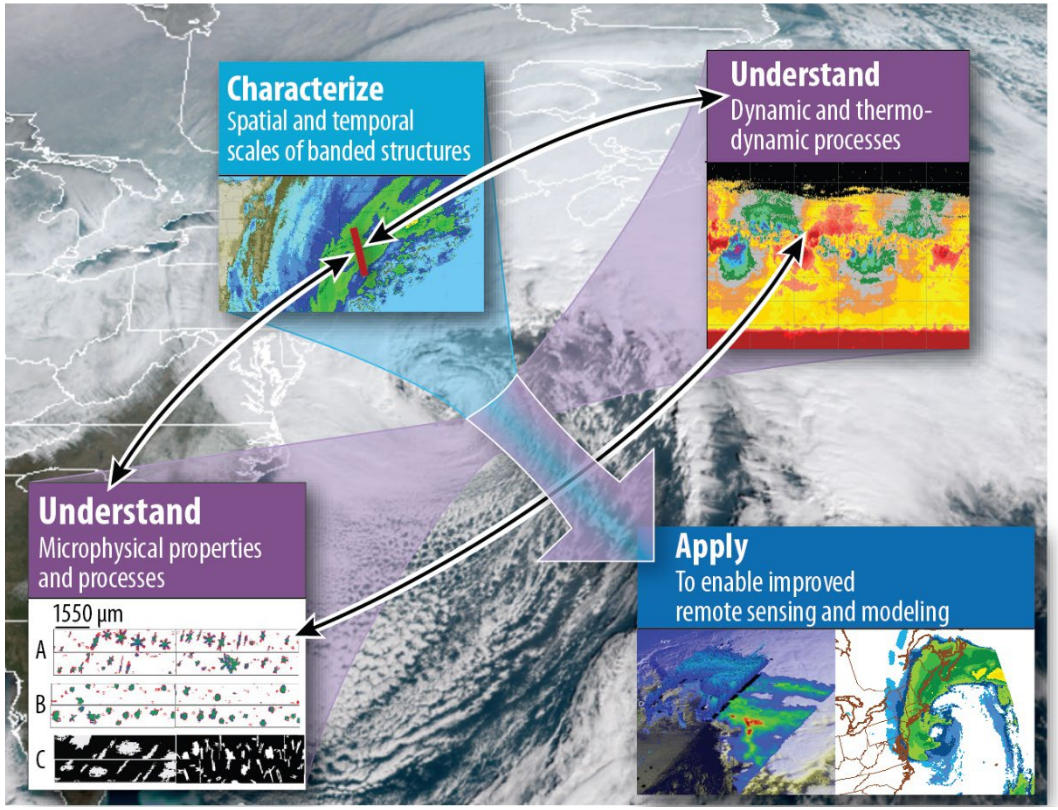
Insights on Microphysics from Airborne and Surface-based Observations of Winter Storms

Sandra Yuter, Matthew Miller, Laura Tomkins, Luke Allen, Declan Crowe, Jordan Fritz, Logan McLaurin, Toby Peele NASA IMPACTS Science Team; **8 November 2023**

McMurdie et al. 2022, BAMS: https://doi.org/10.1175/BAMS-D-20-0246.1

IMPACTS Observation strategy





Stony Brook University Fixed Site

(Stony Brook Radar Observatory 2020-2022)

KASPR (Ka-band scanning polarimetric Radar)

W-band profiling radar

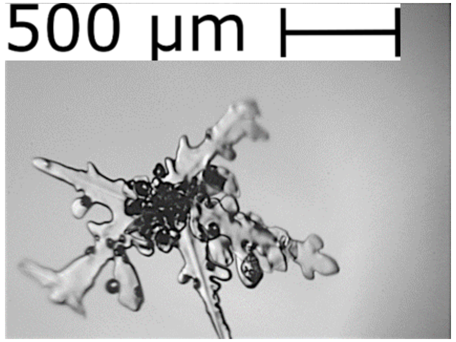
KYLERI (X-band phased array radar)

MRRPro, Celiometer, Pluvio, Parsivel

Big Picture Takeaways:

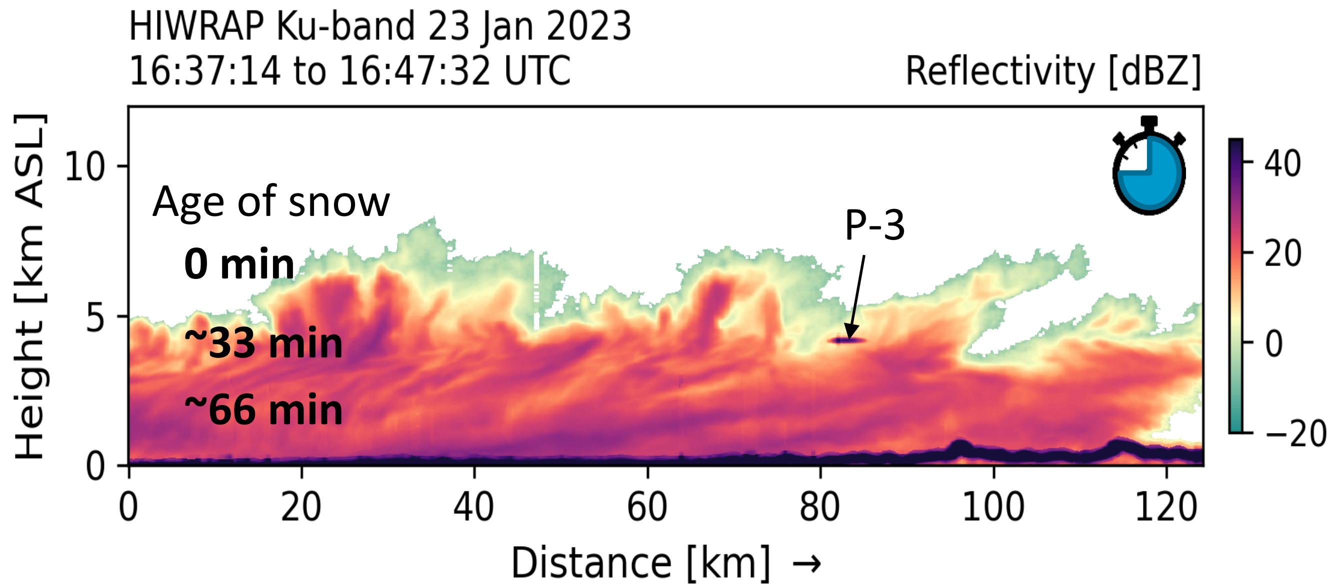
Usually observe mixtures of snow particle shapes and degrees of riming even near cloud top

- Mixtures of shapes, sizes, and densities in the same volume complicate retrievals of snow rate



In the 1-2 hours that it takes a precipitation-sized ice particle to fall from near cloud top to the surface

- Lack of vertical column continuity in local enhancements in radar Z and passive microwave T_b

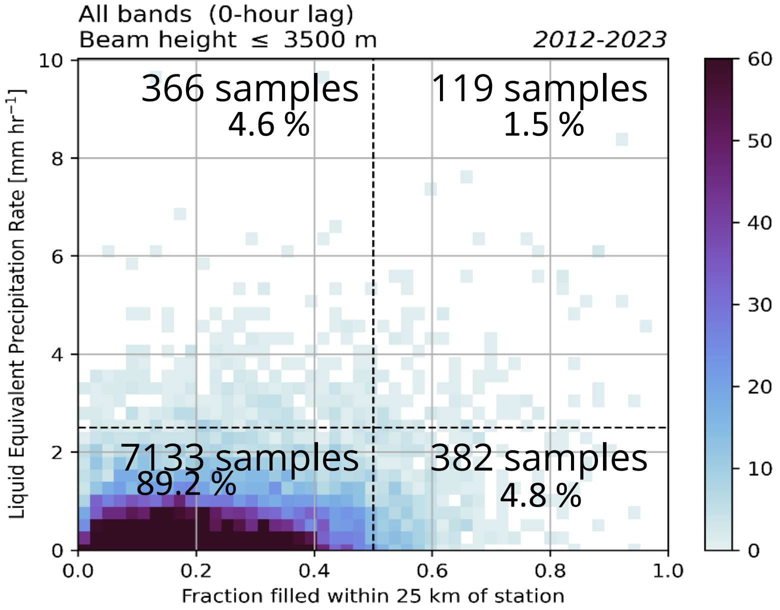


Ambient conditions sampled by aircraft imply episodic ice growth

Updrafts tend to be weak (< 0.2 m/s) and localized (~ 80% are < 2 km in length)

Most of in-cloud storm volume has snow falling thru horizontal wind sheared layers

Low correlation between enhanced Z in snow bands detected on regional scanning radar and surface snow rates



For snow, density, size, shape and mass co-vary very widely even at the same altitude at same time in the same winter storm … the presence of **varying mixtures of shapes and degrees of riming in the same resolution volume means cannot well constrain properties of ice particles based on environment** and greatly complicates retrievals compared to rain

Regime-Dependent Variability of Snowfall Properties in the Northern Great Lakes

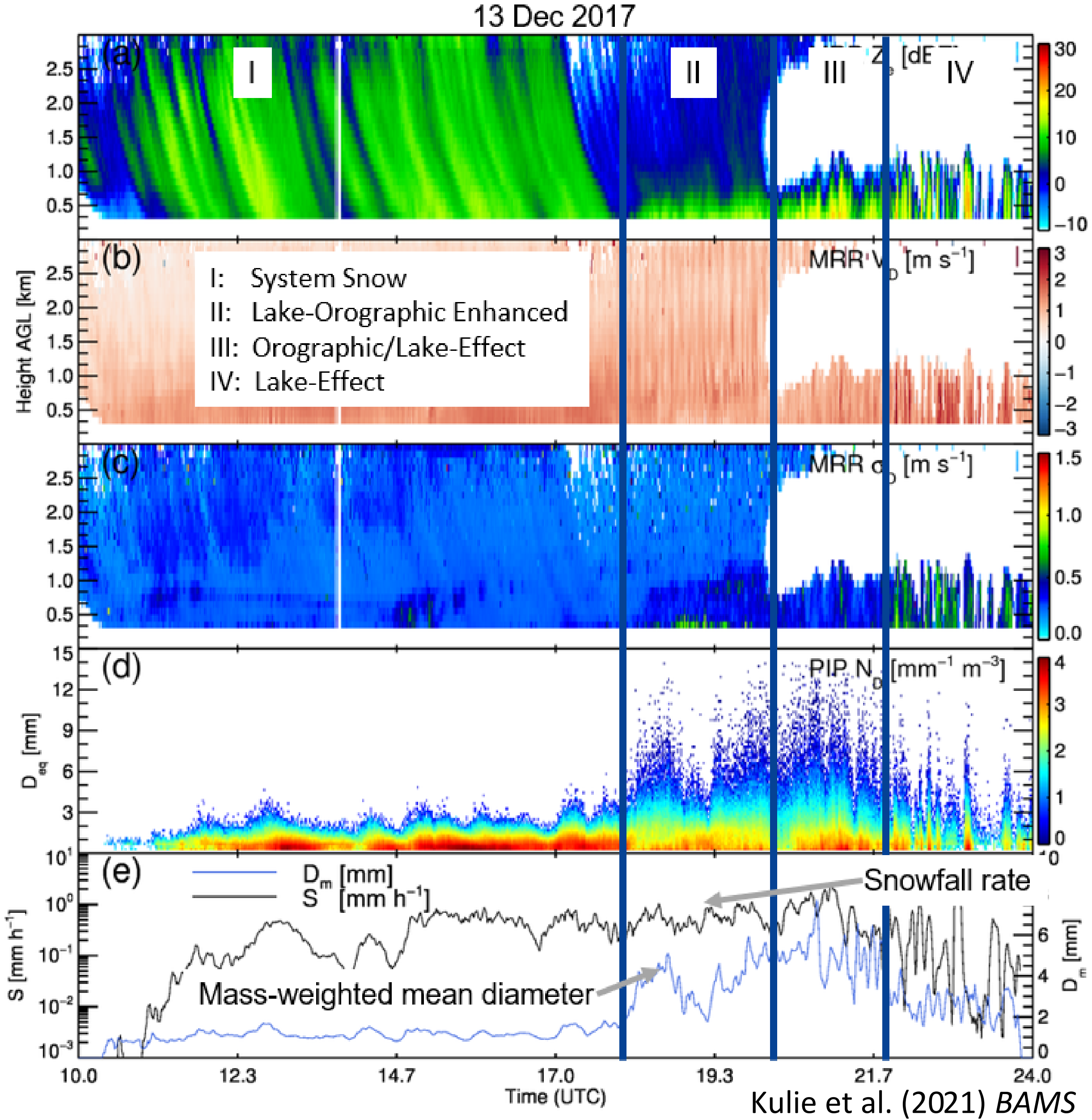
Mark Kulie (NOAA/NESDIS) and Claire Pettersen; 8 November, 2023

- A rich snowfall dataset was collected at Marquette, Michigan Weather Forecast Office (MQT)
  - Instruments: MRR, PIP + MQT NEXRAD radar & surface obs
  - Data duration: January 2014 – November 2023

- Study on snowfall regimes
  - Shallow snow: lake effect, lake-orographic; near-surface enhancement
  - Deep snow: synoptic/system, lake-enhanced

- MQT snowfall observations

	Shallow	Deep
Occurrence:	32%	68%
Accumulation:	51%	49%



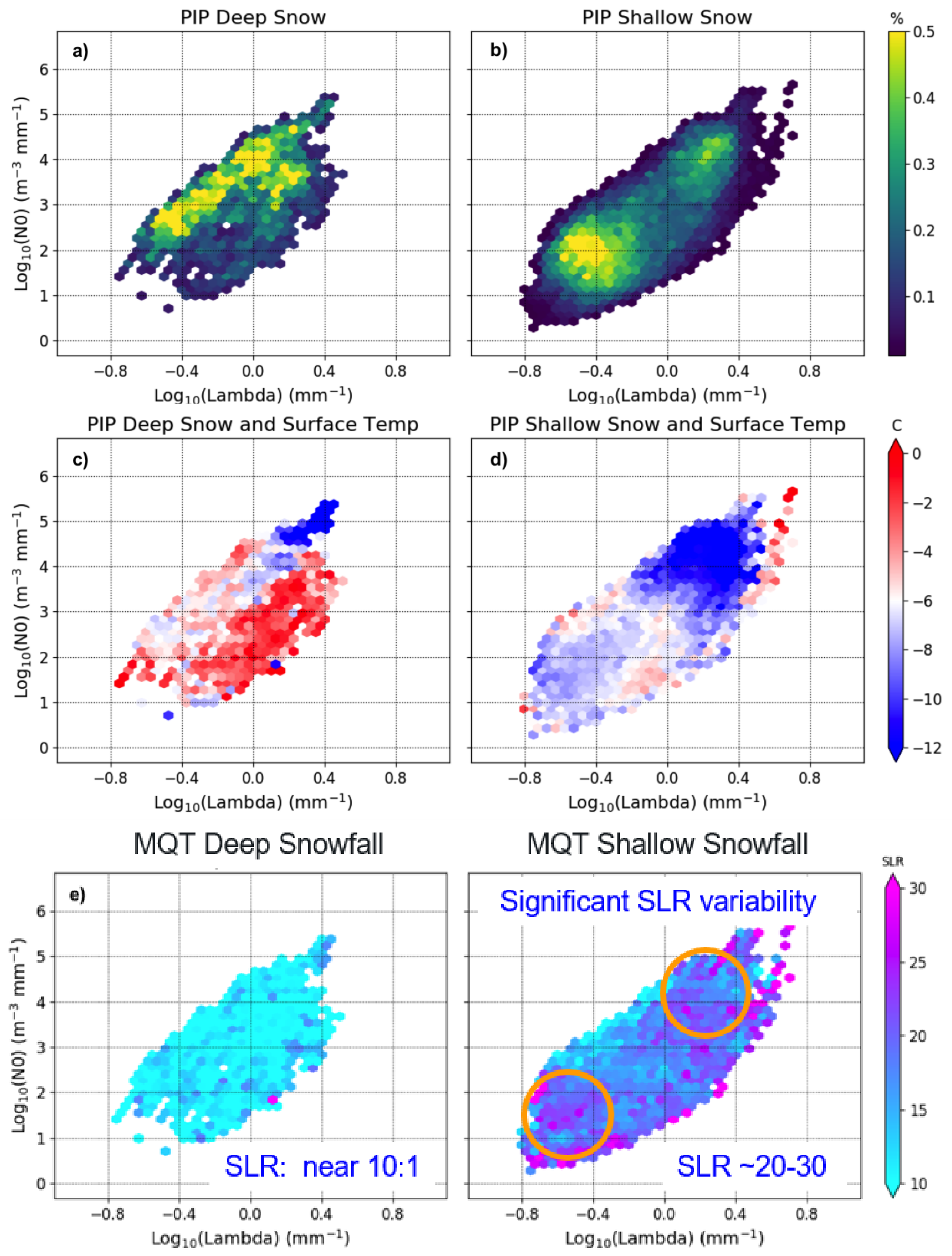
Kulie et al. (2021) *BAMS*

- ❑ Issues with current PSD parameterizations

  Particle Size Distribution: $N(D)=N_o \exp(-\Lambda D)$

  - MQT data reveals connections between microphysics and many factors, e.g. snow regime
  - Non-exponential PSD behavior; inverse exponential fits may mask evolution of particle size populations and lead to errors, e.g. in forward modeling

- ❑ Developing a unified PSD parameterization
  - Regime and environmental condition aware
  - Accounts for snowfall forced by near-surface processes



SURVEY on topics for discussion during the Breakout Session

- Which is your main area of interest among:
  1) retrieval techniques including machine learning;
  2) processes (microphysics, snow mode etc.),
  3) validation and field campaigns
  4) applications (please, specify. e.g., weather forecasting/nowcasting, hydrology, climatology, case studies etc.)
  5) other snowfall remote sensing-related topics (please specify)

- What are the main challenges to be addressed in snowfall retrieval from space?
- What are the potentials brought by new satellite missions? (e.g., EarthCare, AWS, EPS-SG)
- What are your thoughts on the direction(s) that future snowfall remote sensing science should take?
- What actionable advancements (satellites, sensors, algorithms etc.) need to be made to improve the usefulness of satellite snowfall products?
- What are some effective approaches to engage users and promote the applications of satellite snowfall (and precipitation in general) products?

- Answers Here

Conclusions

- ❑ Some takeaways from the telecon presentations
  - ML is becoming the dominant approach for developing snowfall rate algorithms
  - There is a trend towards explainable ML, which will help unravel the important physics impacting the snowfall process and hence improve the snowfall ML algorithms.
  - Another trend is to quantify uncertainty in snowfall retrievals.
  - Snow microphysics is extremely complicated as shown in the IMPACTS and the Great Lakes studies. This is an area that calls for extensive research.
- **Snowfall FG Web site: we have Data and Products sections. We are looking for contributions**

TODAY: FG break-out session for discussion and interactions (2.5 h)

Thur. July 18:

Session for oral presentations (Snowfall, Scattering, Multi-frequency observations): (1.5 h)

Snowfall FG Report by the chiars (5 min)