IPWG-11 Training Course
Tokyo 15-18 July 2024

Satellite snowfall retrieval and machine learning: challenges, advancements, and future perspectives

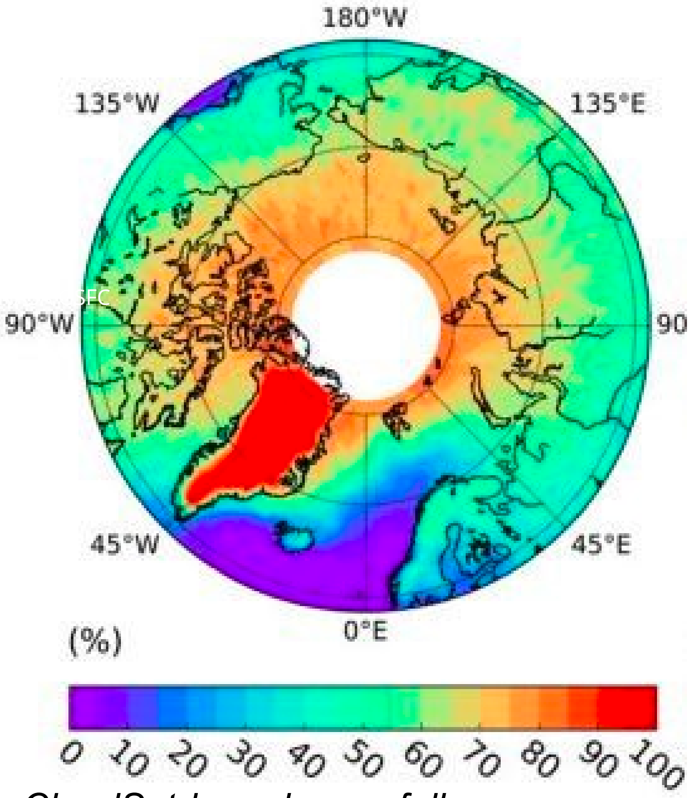
Giulia Panegrossi
National Research Council of Italy
Institute of Atmospheric Sciences and Climate (CNR-ISAC)
Rome, Italy

Contributors:
Daniele Casella, Paolo Sanò, Andrea Camplani (CNR-ISAC)
J-F Rysman, J. Turk, A. Battaglia, M. Kulie, L. Milani, H. Meng, and many others
PMM Science Team
IPWG Snowfall FG

Introduction

Snow plays an important role in the Earth energy exchange processes, and is a fundamental element of the water cycle (higher latitudes!)

Mostly occurs in regions where ground-based measurements are scarce or absent (high latitudes)



CloudSat-based snowfall occuurrence
Edel et al., 2020

Introduction

Snow plays an important role in the Earth energy exchange processes, and is a fundamental element of the water cycle (higher latitudes!)

Mostly occurs in regions where ground-based measurements are scarce or absent (high latitudes)

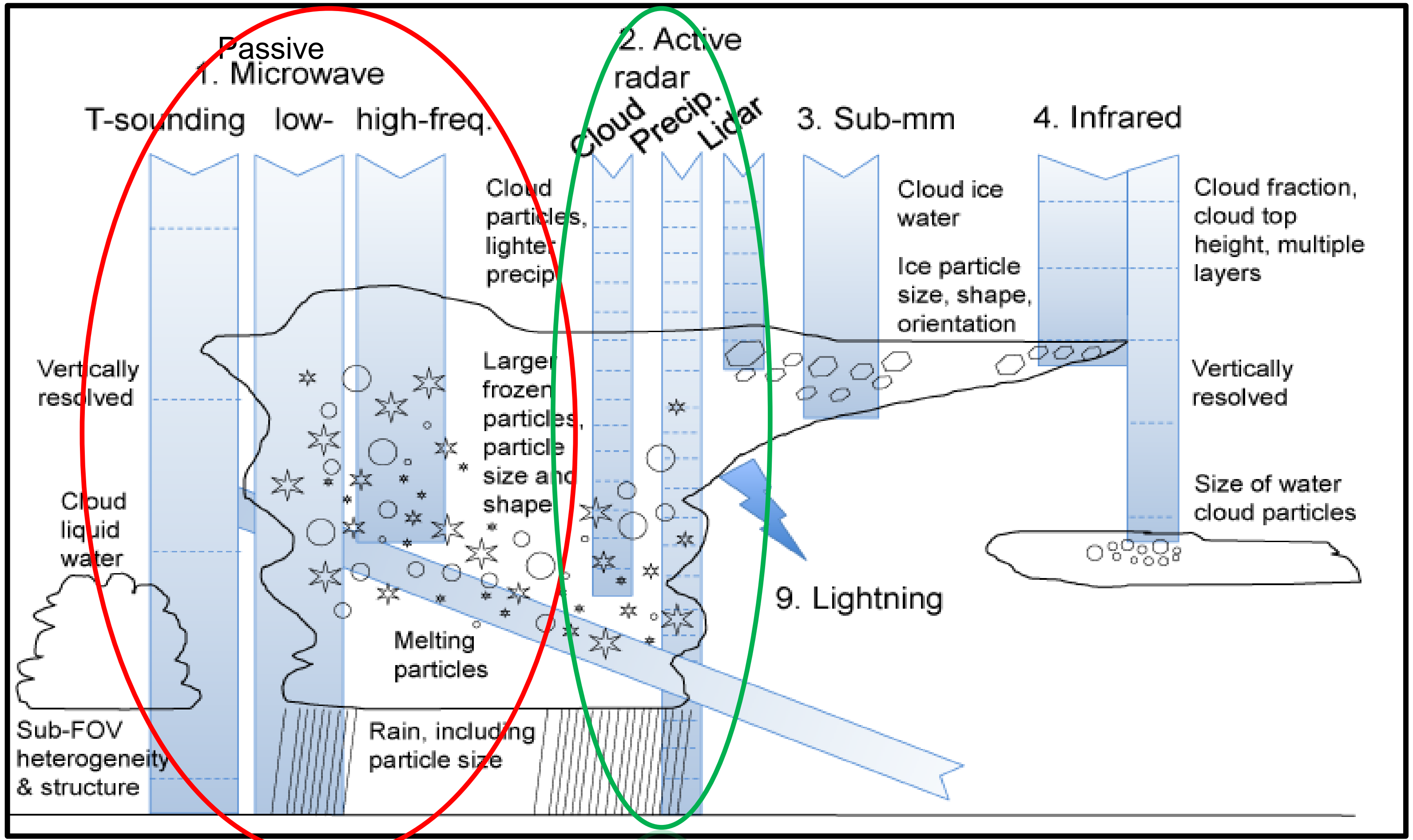
Need to rely on the use of satellite-based remote sensing measurements

Microwave (MW) wavelengths are directly responsive to snowfall microphysics

Active MW: cloud/precipitation space-borne radars

Passive MW radiometers equipped with high frequency channels

Polar-orbiting satellites offer good coverage over the high latitudes

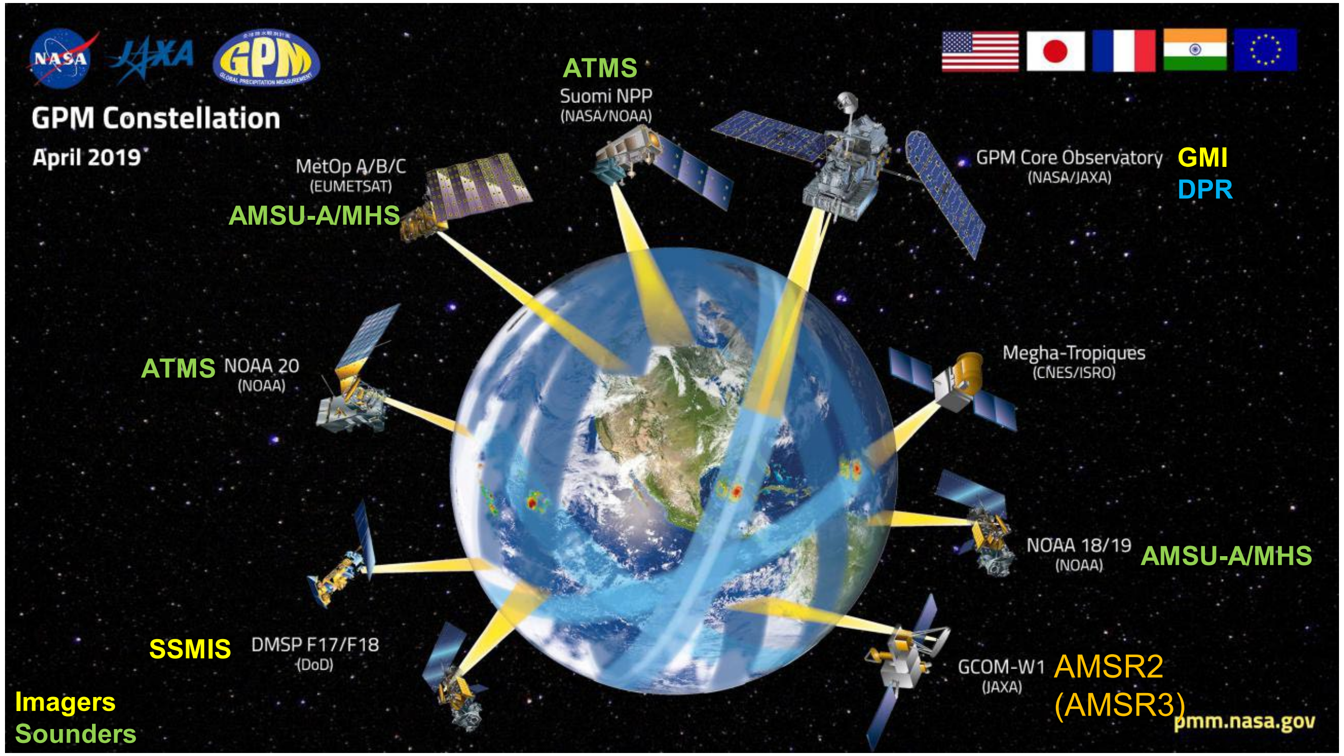


Adapted from: www.ecmwf.int

The GPM constellation and future European LEO MW missions

MetOp-SG-A MWS (Q4 2025)
Met-Op-SG-B MWI ICI (Q4 2026)

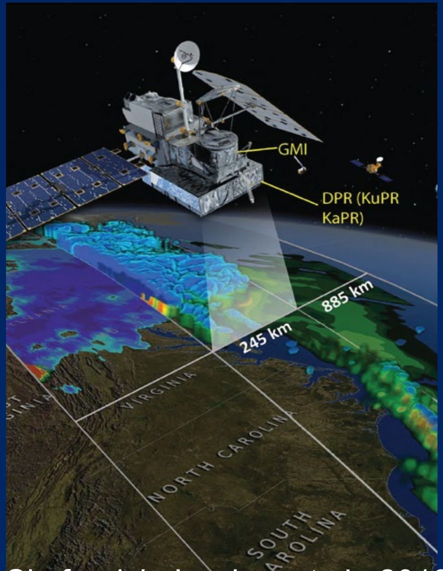
Arctic Weather Satellite
(EPS STERNA)



THE NASA/JAXA GPM CORE OBSERVATORY

GPM Microwave Imager (GMI): 13 precipitation sensing channels (10-183 GHz) with the highest spatial resolution available (5-30 km);

Dual-frequency Precipitation Radar (DPR) (Ku and Ka band)



Skofronick-Jacskon et al., 2018

ESA/JAXA EarthCare (CPR with doppler capabilities)

Since 2024

NASA
CloudSat
CPR
(W band)

Until 2023

MW radiometry and snowfall

Snowfall detection and quantification is one of the main challenges in precipitation retrieval from space

Spaceborne cloud and precipitation radars

	GPM DPR Ku	GPM DPR Ka	EarthCare CloudSat CPR W
Frequency	13.6 GHz	35.55 GHz	94.05 GHz
Sensitivity	12-13 dBZ	16.32 dBZ	-28 dBZ
Swath size	245 km	125 km*	1.5 km
Horizontal Resolution	5 km		1.5 km

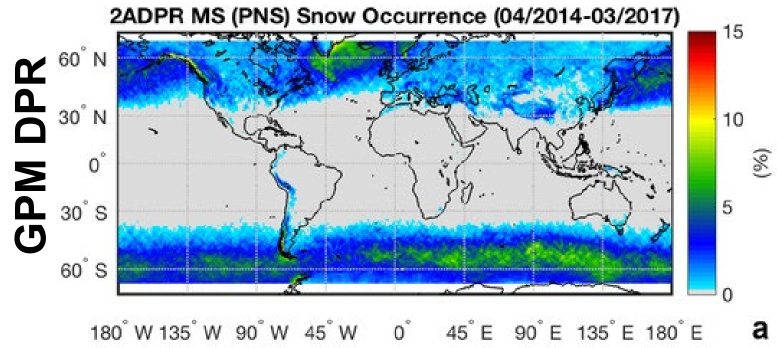
GPM DPR (Ku/Ka-band)
- *Valuable for global rainfall / medium-heavy snowfall*
- Good coverage (large swath, 3D structure)*(but* up to 65°N/S)
- Low sensitivity (not suitable for light snowfall)

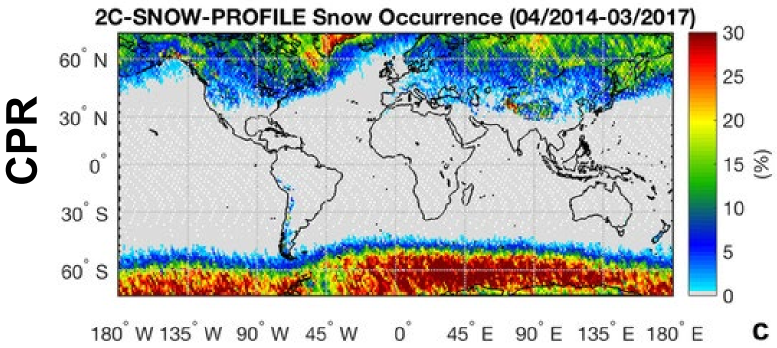
CloudSat (EarthCare launched in May 2024) CPR (W-band):
Considered reference for snowfall global climatology
- *high sensitivity, suitable for snowfall / light precipitation at high latitudes*
- Global coverage (82°N/S)
- Nadir looking (narrow swath)
- **Limitations:** Attenuation, saturation, ground clutter

Large fraction of *higher latitudes snowfall* is missed by GPM DPR(Ku Ka-band) (mostly due to sensitivity limits).

DPR vs. CPR	DPR-Ku	DPR – Ka MS
%missed snowfall events	92.5%	95.2%
% snowfall mass detected	28.08%	33.09%

(Casella et al., 2017, Atmos. Res.)



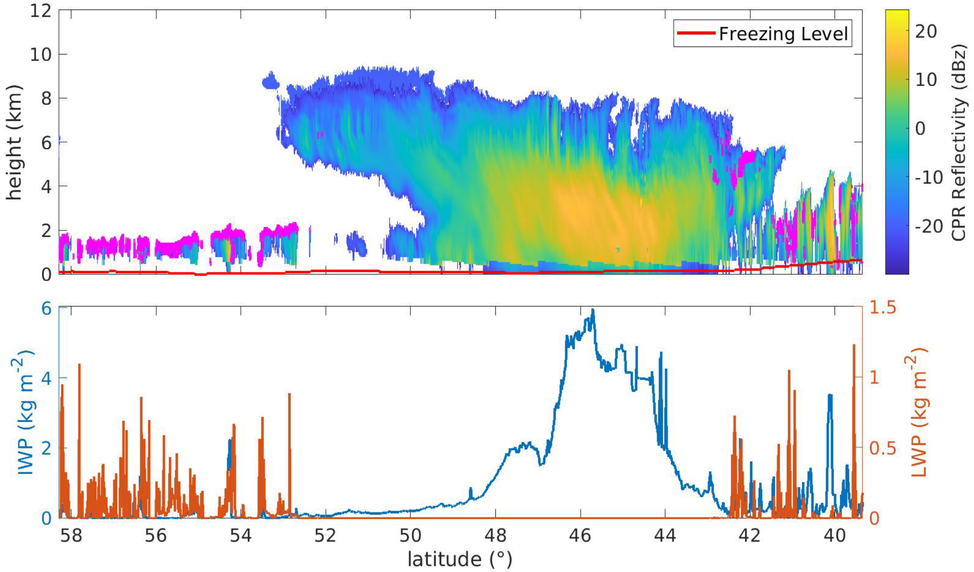


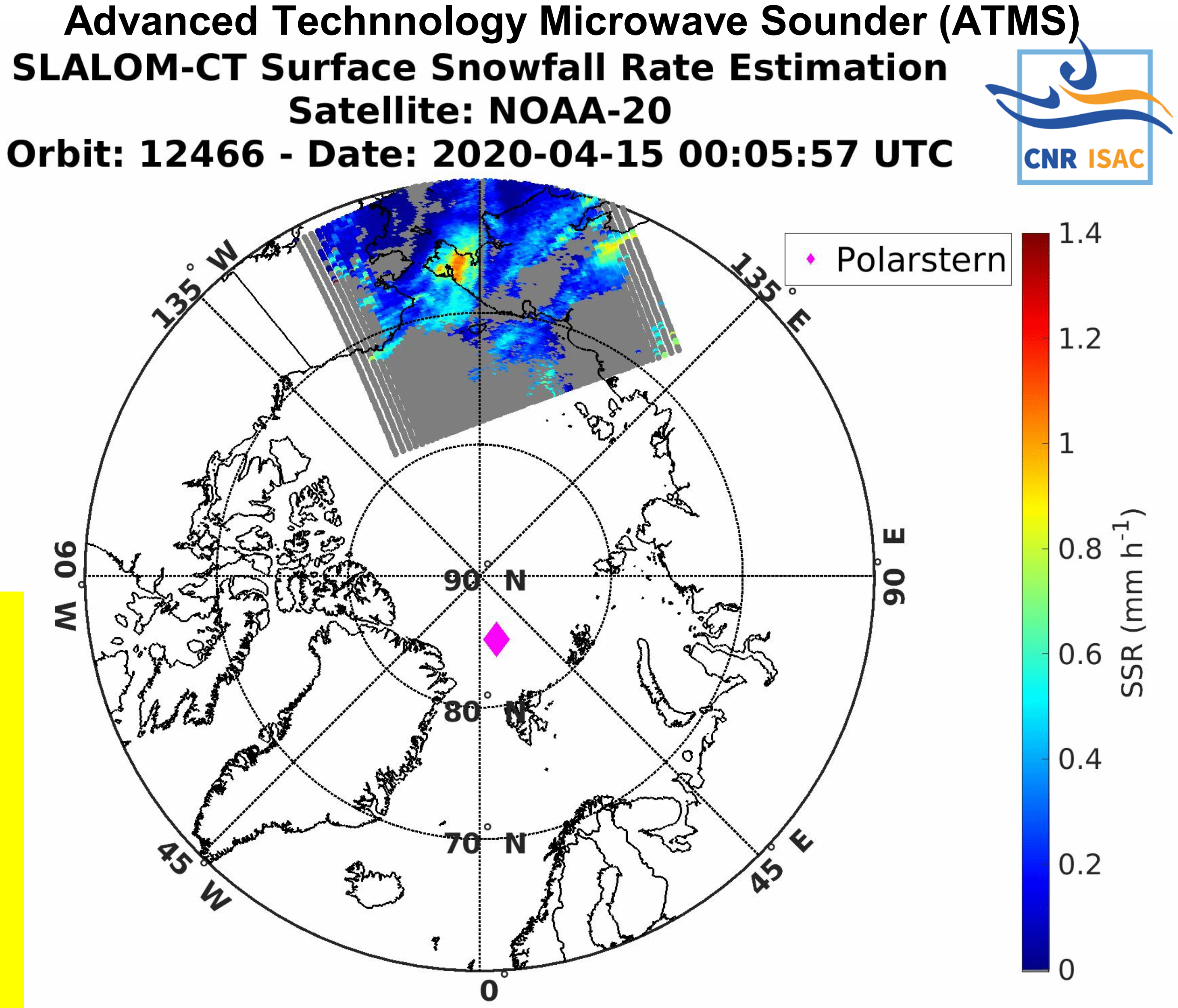
(Skofronick-Jackson et al., 2019)

Current products show large discrepancies in snowfall climatologies (especially at higher latitudes)

Active vs. Passive Snowfall retrievals

CloudSat CPR/Calipso observations



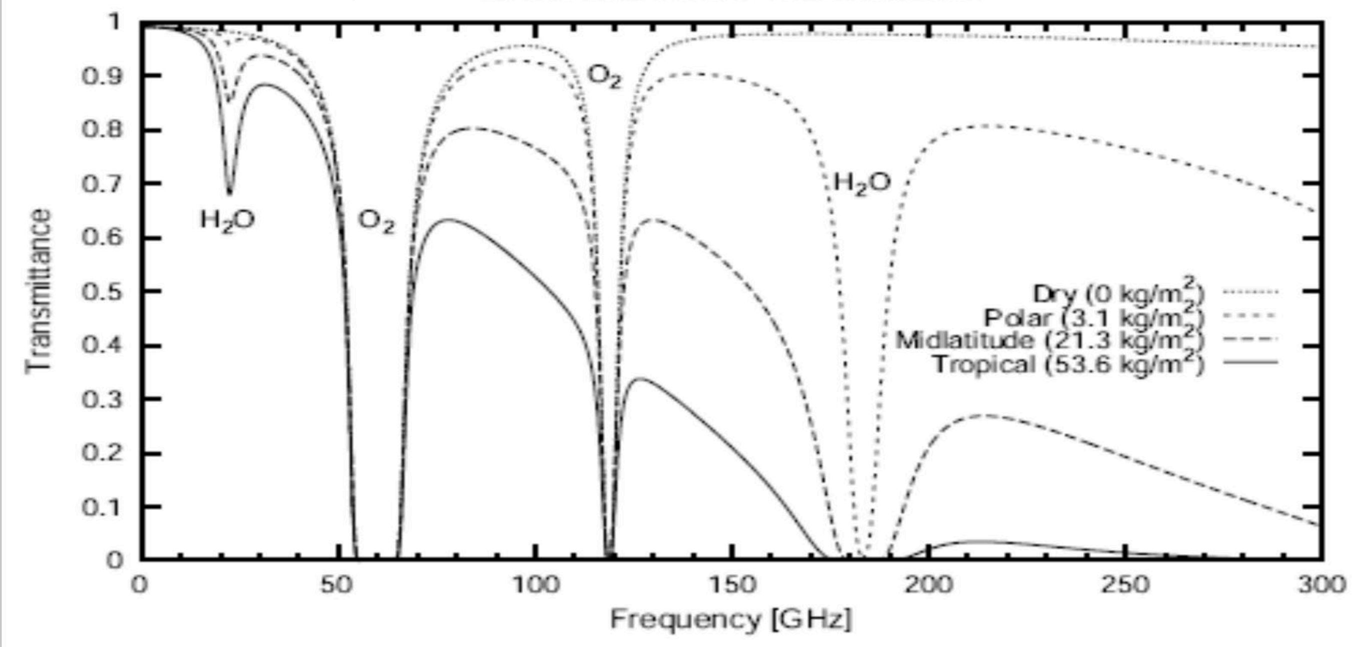


Spaceborne radars do not provide the needed coverage for snowfall global monitoring ->

We need to rely on PMW radiometers: GPM constellation and future missions (JAXA AMSR3, EPS-SG, AWS (EPS-Sterna))

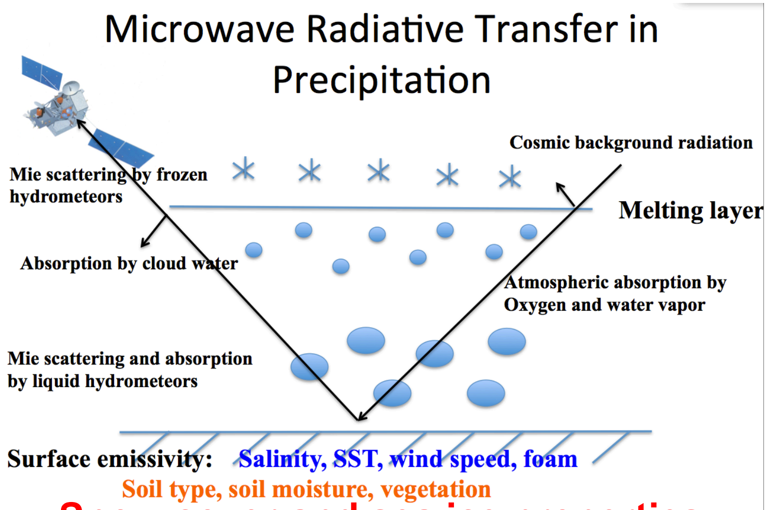
PMW radiometry and precipitation

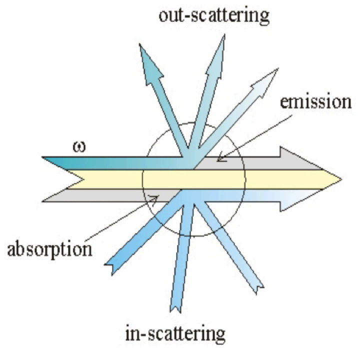
Clear-sky Zenith Microwave Transmittance



Percentage trasmission of surface emitted radiation through the Earth's atmosphere along the vertical direction, under clear-sky conditions. *[Adapted from Ulaby et al, 1981]*

Frequency range: 10-200 GHz

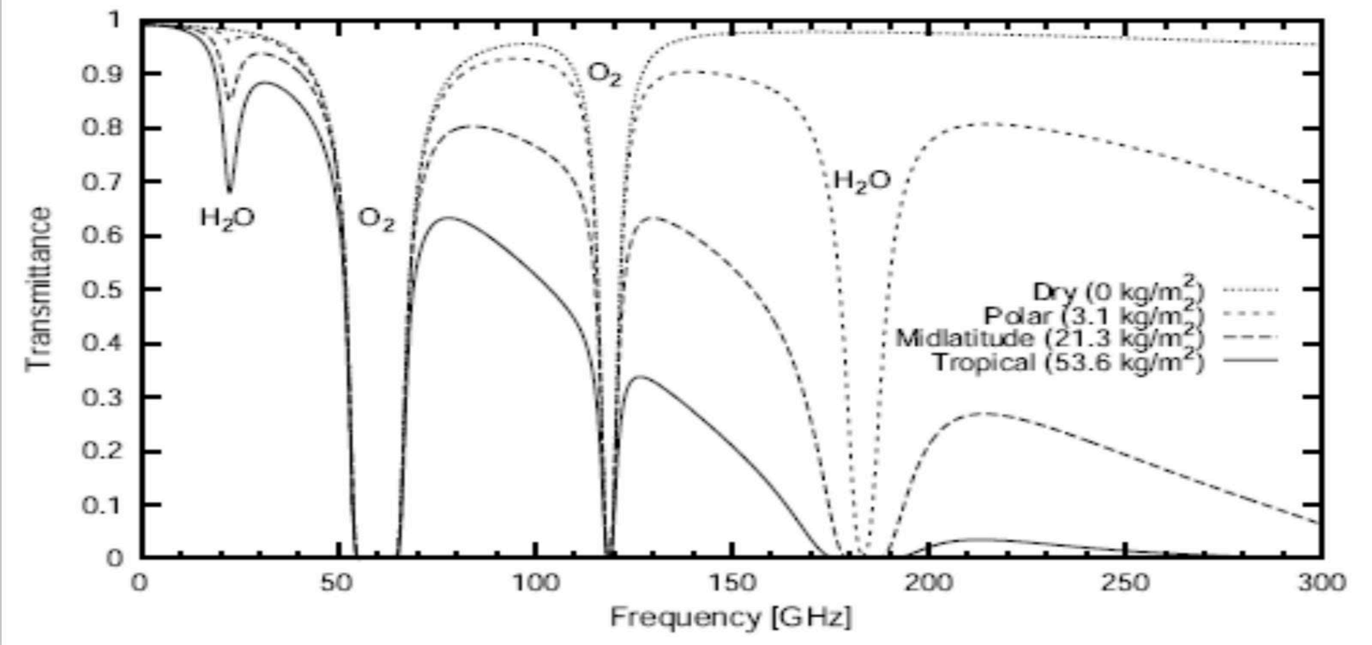




Measured radiance (or brigthness temperature) in each MW channel depends on surface properties (T, emissivity), atmospheric moisture/temperature, 3-D distribution of hydrometeors, microphysics (absorption and scattering properties), radiometers viewing geometry

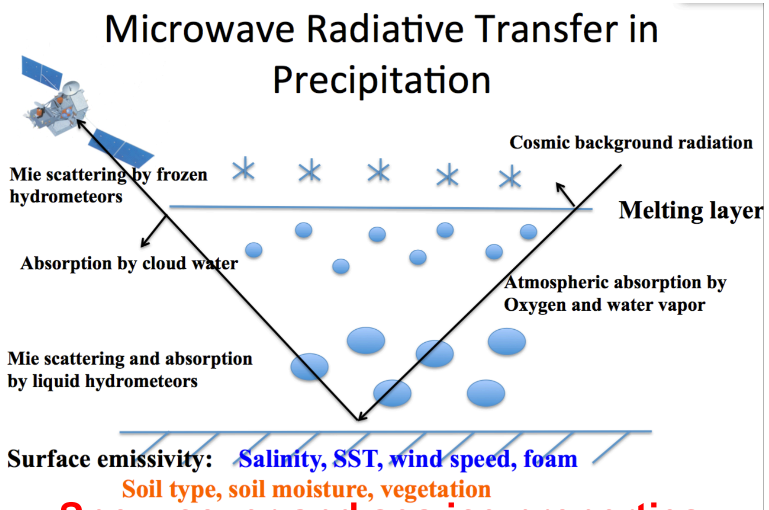
PMW radiometry and precipitation

Clear-sky Zenith Microwave Transmittance

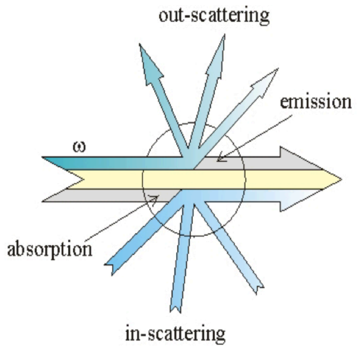


Percentage trasmission of surface emitted radiation through the Earth's atmosphere along the vertical direction, under clear-sky conditions. *[Adapted from Ulaby et al, 1981]*

Frequency range: 10-200 GHz



Snow cover and sea ice properties

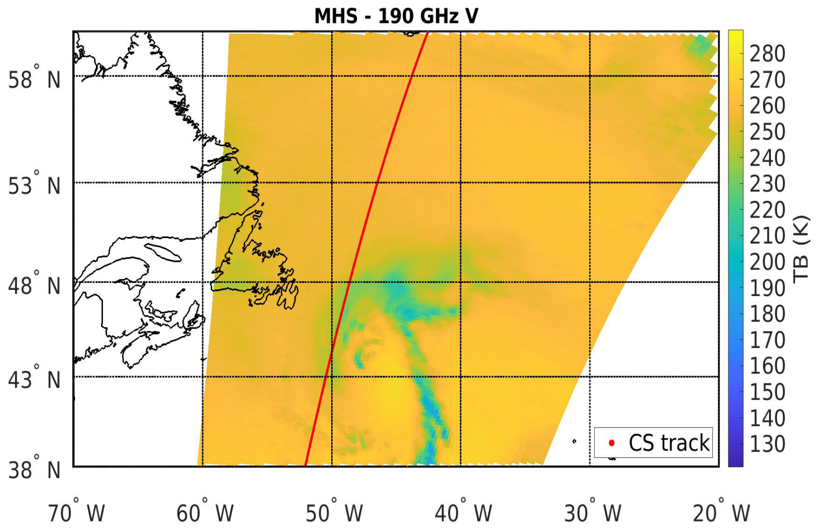


- **Higher frequency channels (>= 90 GHz) mostly respond to scattering by ice hydrometeors (snowflakes mostly at > 150 GHz) and emission by water vapour and cloud liquid water**
- **The lower the transimissivity -> the less affected by the background surface (except in very dry conditions).**

PMW remote sensing of snowfall

Passive microwave (PMW) radiometers equipped with high frequency channels have sensitivity to snowfall microphysics and are used for snowfall retrieval

Snowfall retrieval is mostly based on the scattering signal of snowflakes on the upwelling radiation at high frequencies (> 150 GHz).



High frequency channels (> 90 GHz) are mostly sensitive to:

- snowfall scattering -> TB cooling
- supercooled liquid water (SLW) emission -> TB warming
- water vapour emission (mostly at frequencies > 150 GHz)
- background surface emissivity (depending on moisture conditions)

There is a complex interconnection between snowfall intensity, cloud properties, and environmental conditions (i.e., surface emissivity, atmospheric humidity) on PMW snowfall signature

This poses several challenges

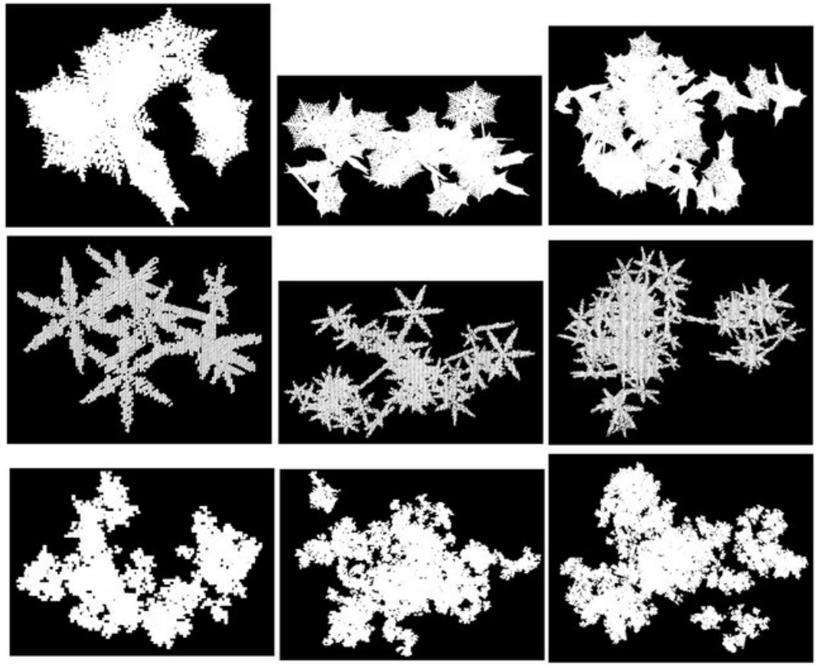
PMW Remote Sensing of Snowfall: Challenges

Challenge 1

The (mostly) weak scattering signal at high frequency is highly dependent on the complex microphyscal properties of snowflakes

Need for high-quality, global snowfall database to be used as a priori or training information in the PMW retrieval process

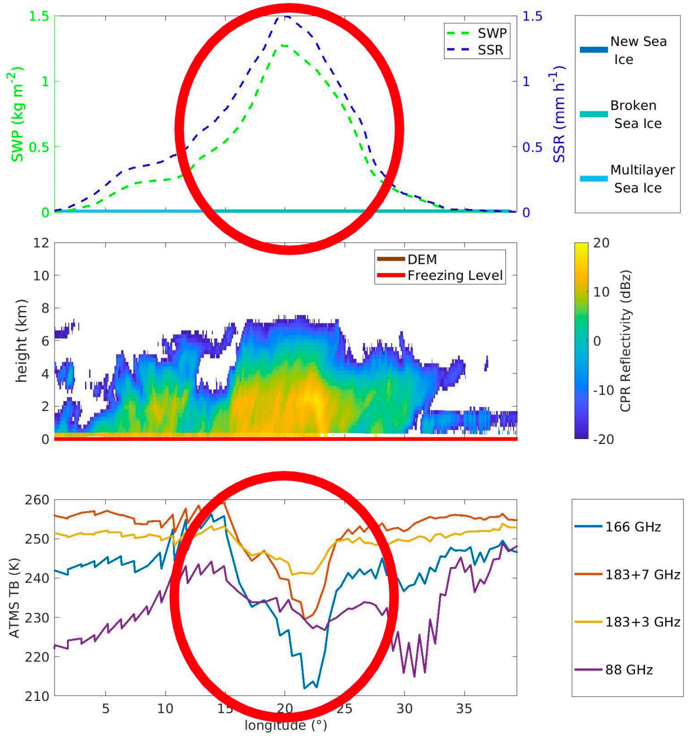
Field campaigns (e.g., IMPACTS): For snow, density, size, shape and mass co-vary very widely even at the same altitude at same time in the same winter storm … the presence of **varying mixtures of shapes and degrees of riming means we cannot well constrain properties of ice particles based on environment** and greatly complicates retrievals compared to rain



Strategy

1) Highly sophisticated single scattering models and cloud microphysics models are now available, but still large uncertainties in cloud-radiation model simulations

2) Use of observational datasets relating snowfall profiles with PMW measurements allows to associate PMW measurements to snowfall intensity



PMW Remote Sensing of Snowfall: Challenges

Challenge 2

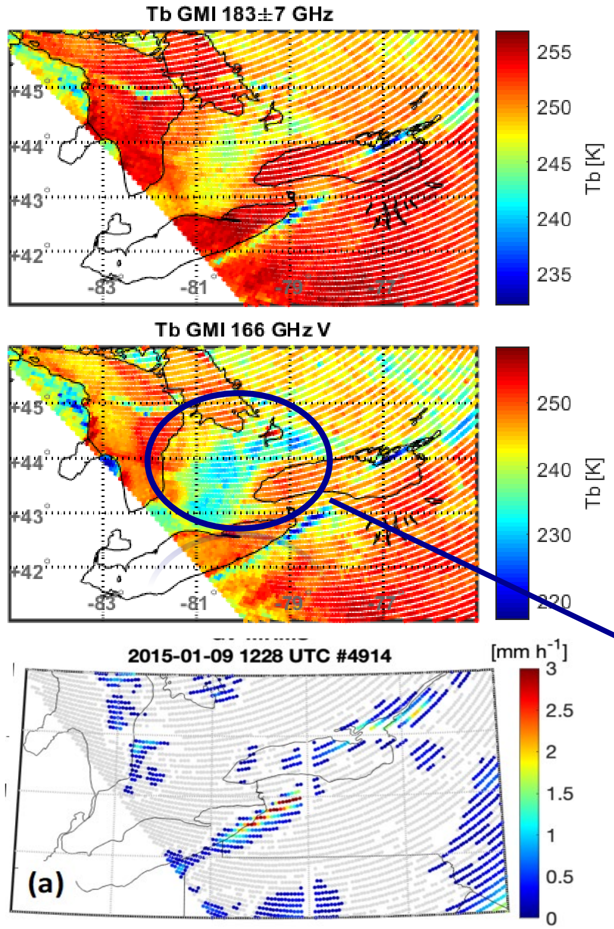
Multi-channel PMW radiometer measurements respond to both snowfall and background surface (snow cover and sea ice) properties (especially in very dry conditions)

Sea ice and snow-covered land surface emissivity is extremely variable due to rapid changes of sea ice properties of snow cover extent, snow accumulation on the ground, and snowpack and sea ice physical properties.

Significant effects on the upwelling microwave signal in presence of snowfall (especially in dry conditions/high latitudes) which is difficult to interpret

Need for better characterization of frozen surface (sea ice and snow cover) conditions

Strategy: Exploitation of low frequency MW channels for the characterization of the frozen surface (sea ice and snow cover) at the time of the overpass



Measured TBs (including high-frequency channels in very dry conditions) are affected by snow cover (and sea ice) properties

Snowfall or Snow at the surface?

GMI overpass at 12:26 UTC for Extreme Lake Effect Snow event on 9 January 2015 (Milani et al., 2020, Turk et al., 2021)

PMW Remote Sensing of Snowfall: Challenges

Challenge 3

The snowfall scattering signal tends to be masked by the water vapor and supercooled cloud liquid water (SLW) emission

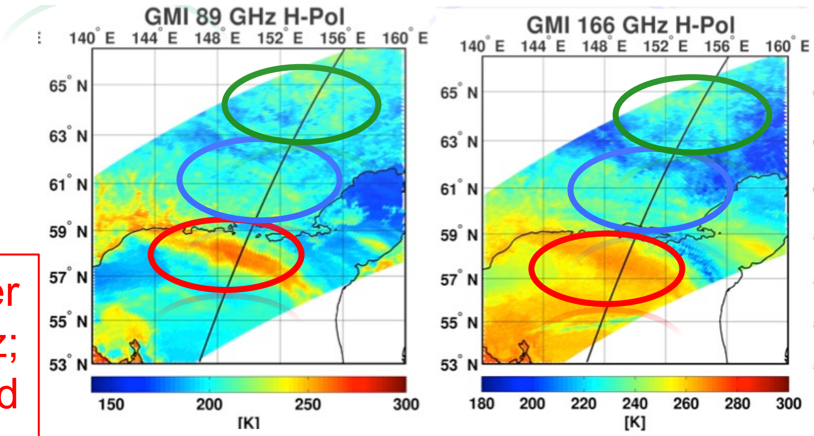
Siberia snowfall event 30 April 2014

Effect depends on atmospheric moisture

Need to characterize atmospheric moisture and SLW at the time of the overpass

Strategy: Exploitation of all WV sounding channels and 90 GHz channels combined with active sensors (radar/lidar) able to retrieve SLW (mostly at the cloud top)

Dampening effect of water vapor at 166 GHz; effect of supercooled droplets emission at 89 GHz



Deep cloud; mostly scattering signal at >166 GHz

Shallow/weak snow clouds with supercooled liquid water

Panegrossi et al. 2017 Rem. Se

Why Machine learning for Snowfall retrieval?

Advantages

- Improve automation and discovery of new insights from complex data sets
- Increase our understanding of complex environmental systems
- Fast and accurate retrieval of environmental parameters

Limitations

- **Training dataset:** accessibility, representativeness, accuracy;
- **Computational power and storage;**
- **Uncertainty and error inherent to remote sensing:** difficult to handle and poorly understood

Increasing interest in using machine learning for snowfall retrieval. It allows:

1. Synergy and full exploitation of multiplatform, multi-satellite multichannel datasets
2. To handle underdetermined highly non-linear inverse and forward problems
3. To extract information from large amounts of heterogeneous data and exploit synergy between different sensor characteristics (multi-platform, multi-sensor approaches)

Examples of ML approaches:

- Shallow Neural Network: used for the detection/classification/estimate
- Random Forest: used for the detection/classification
- Gradient Boosting: used for the estimate
- Deep learning (convolutional NN):
  - pattern analysis
  - classification
  - estimate

Training datasets: spaceborne cloud and precipitation radars

Turk et al., 2021 doi: 10.3390/rs13122264

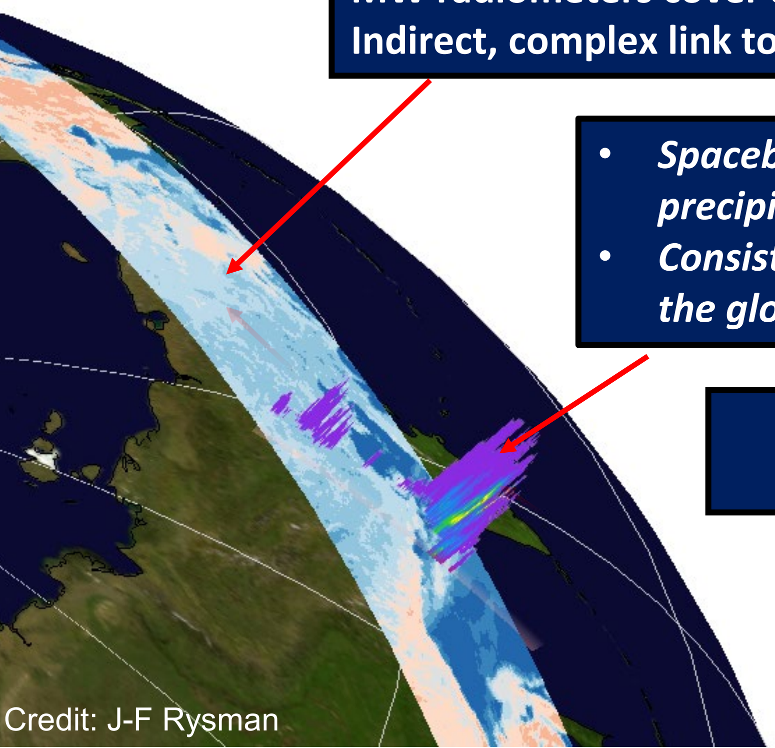
- ❑ 2B-CSATGPM dataset (J. Turk, JPL):
- ❑ GPM (GMI-DPR)/CloudSat coincidences
- ❑ Updated to V7 GPROF, DPR and CMB

Training datasets for PMW precipitation retrieval algorithms based on ML are mostly built from nearly coincident measurements from active and passive microwave sesnors

MW radiometers cover a large swath
Indirect, complex link to surface precipitation

- ***Spaceborne radars provide vertical profiles of precipitation***
- ***Consistency of precipitation measurements around the globe but limited coverage***

Observational precipitation datasets built from coincident active/passive measurements



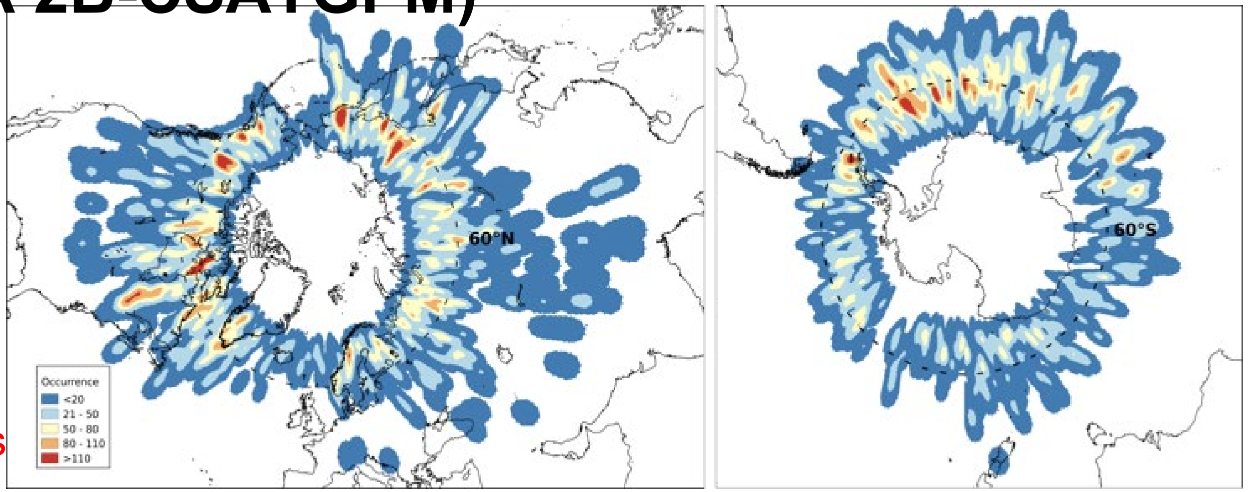
Credit: J-F Rysman

Limitations:
- **Representativeness over large PMW radiometer IFOV**
- **CPR and DPR capabilities**
- **Sensitivity, attenuation, saturation**
- **Uncertainity of reference precipitation products**
  - **Z-S relationship uncertainties associated to snow microphysics**
  - **Ground clutter (lower 1200-2000 m are missed) which affects surface snowfall detection/estimate**

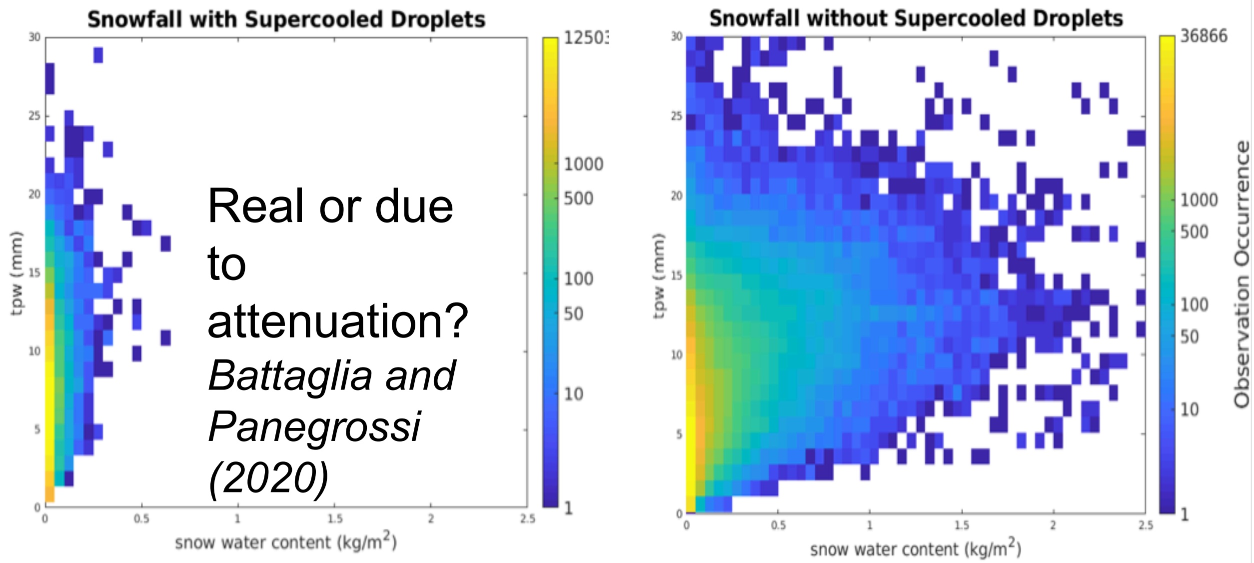
Other examples of CloudSat/GMI and CloudSat/ATMS coincidences

CloudSat/Calipso-GMI (extension of NASA 2B-CSATGPM)

Period	10/03/2014 – 01/09/2016
Geographical area	65 °S–65° N, 180° W–180° E
Number of GMI orbits	6,502
Number of triple coincidences (GPM-CPR-ATMS)	5,801
Number of elements	5,870,903
Number of elements with snowfall	400,145
Number elements with snowfall and SLCT	289,905 70% of snowfall profiles
Horizontal resolution	1.2 km CPR ; 10 km GPM



Geographical distribution of GPM/CPR coincidences
(Panegrossi et al., 2017)



Real or due to attenuation?
Battaglia and Panegrossi (2020)

CPR 2C-SNOW +Calipso

CloudSat/Calipso-ATMS

Period	1/01/2015 – 1/09/2016
Geographical area	90°S–90° N, 180° W–180° E
Number of ATMS orbits	3,049
Number of elements	4,670,442
Number of snowfall elements	745,533
Number of snowfall elements with SLCT	456,391 60% of snowfall profiles

SLALOM: *First PMW snowfall retrieval algorithm based on ML using CloudSat / Calipso as reference*

Machine Learning approach based on the GMI/CloudSat/Calipso coincidence observational dataset used for training (CPR 2C-SNOW product for snowfall with *liquid fraction < 15%* ***(no mixed phase or liquid precip.)*** **(extended 2B-CSATGPM dataset developed by J. Turk)**

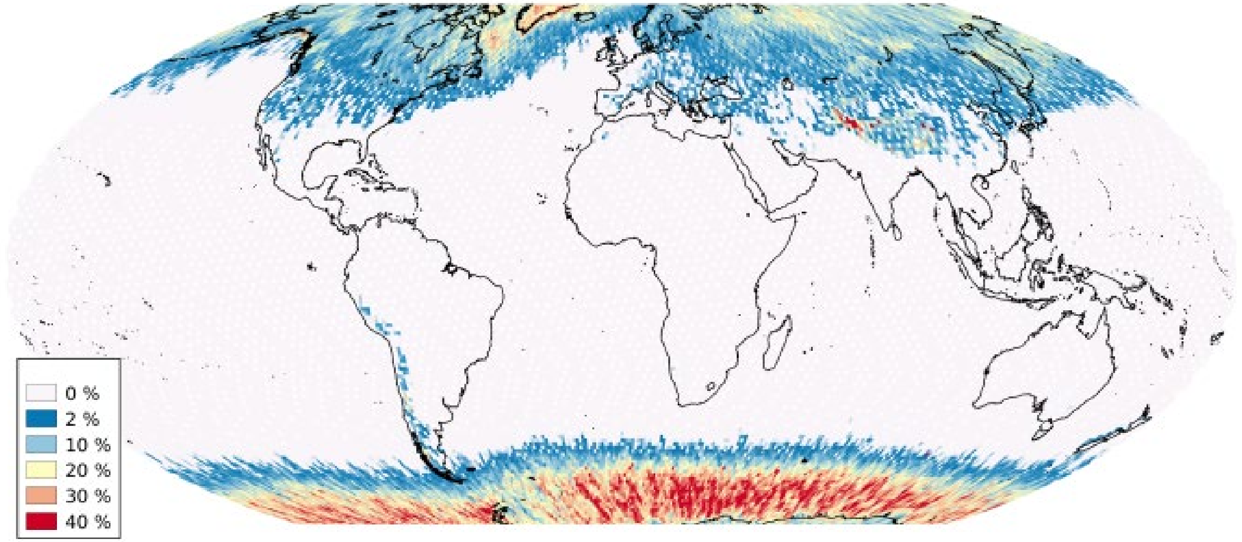
Input: GMI L1c TBs (all channels) and auxiliary ECMWF analysis variables on atmospheric state (T2m, moisture profiles)

No auxiliary info on background surface conditions but exploitation of all GMI low frequency channels

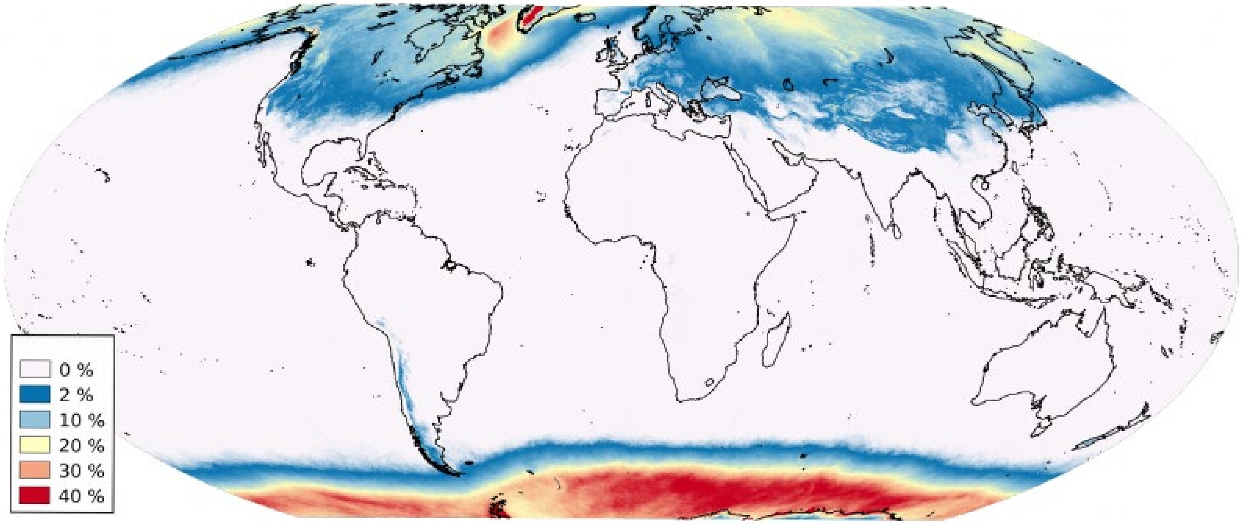
- **Random forest modules** for snowfall detection and supercooled liquid water detection;
- **Multi-linear regression module**: snow water path (SWP) estimates
- **Gradient boosting module**: Surface snowfall rate (SSR)

Global snowfall Occurrence 05/2014 - 05/2016

CPR



SLALOM



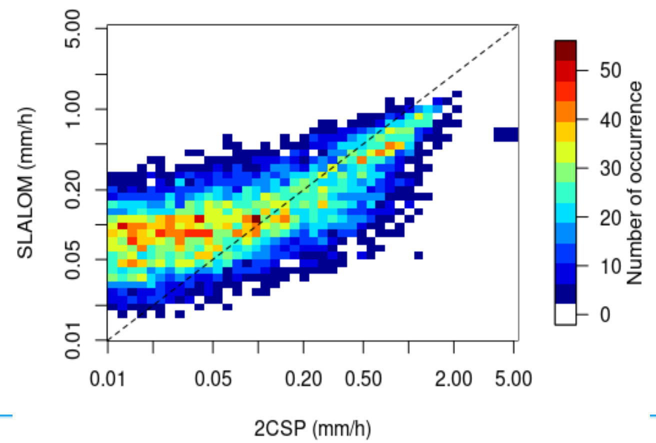
SLALOM is able to reproduce CloudSat CPR snowfall climatology

(Rysman et al., 2018,2019)

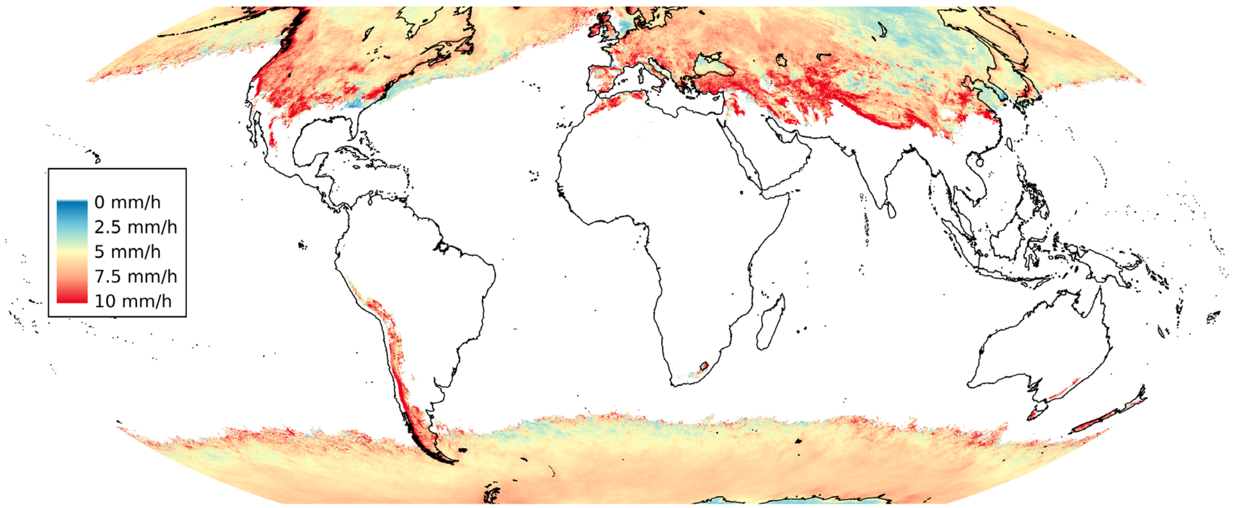
SLALOM: CloudSat-based PMW snowfall retrieval

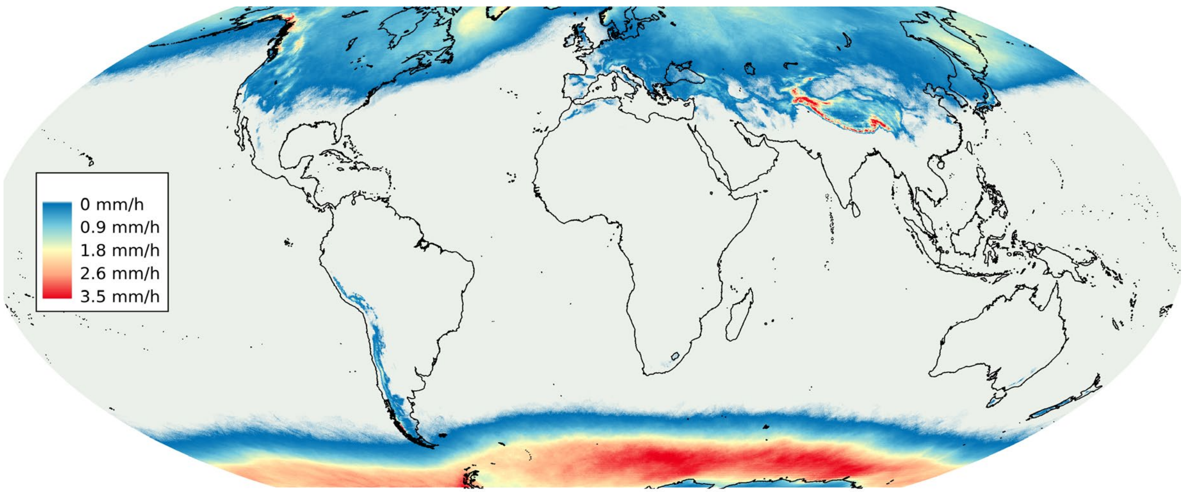
SLALOM main limitations:

- **SLALOM fully relies on the 2C-SNOW-PROFILE CPR product (V04)**;
- GMI/CPR observations mostly occur around 60°N/S;
- Overestimation lower snowfall rates (< 0.1 mm/h) (sensitivity issues) and **underestimation of higher rates (not well represented in the training dataset)**



Conditioned (SSR > 0 mm **Mean SSR (mm/h) between May 2014 and May 2017** **Unconditioned**

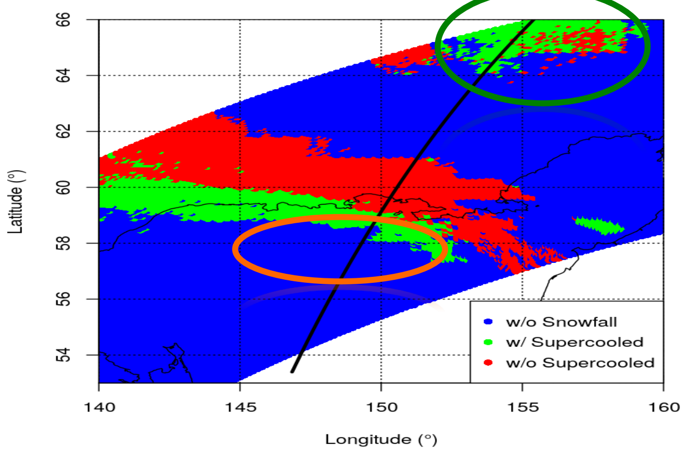


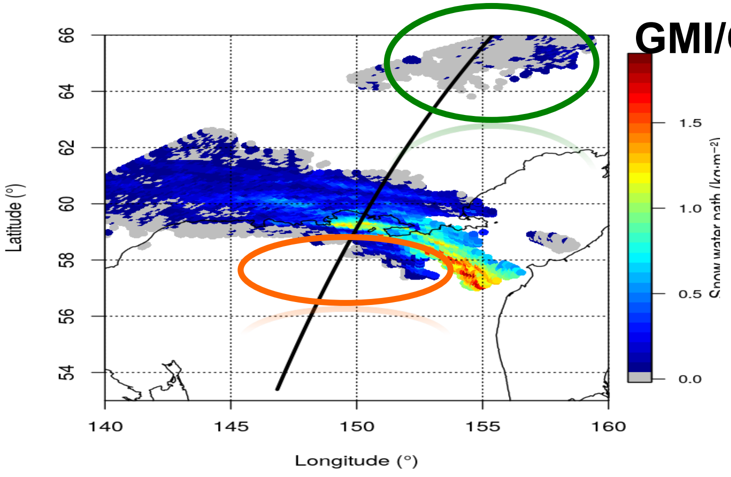


(Rysman et al., 2018,2019)

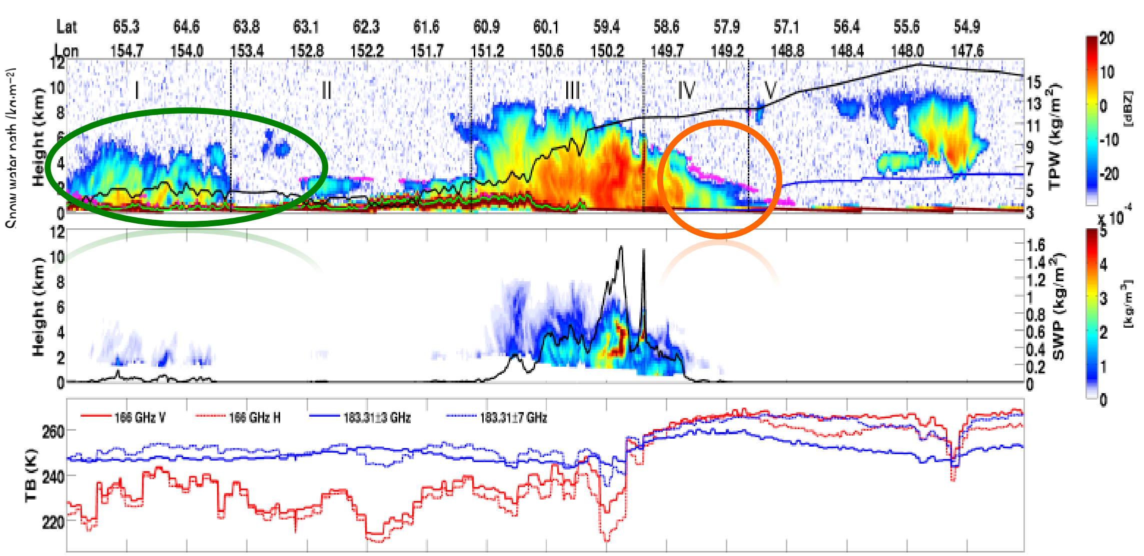
SLALOM: CloudSat-based PMW snowfall retrieval

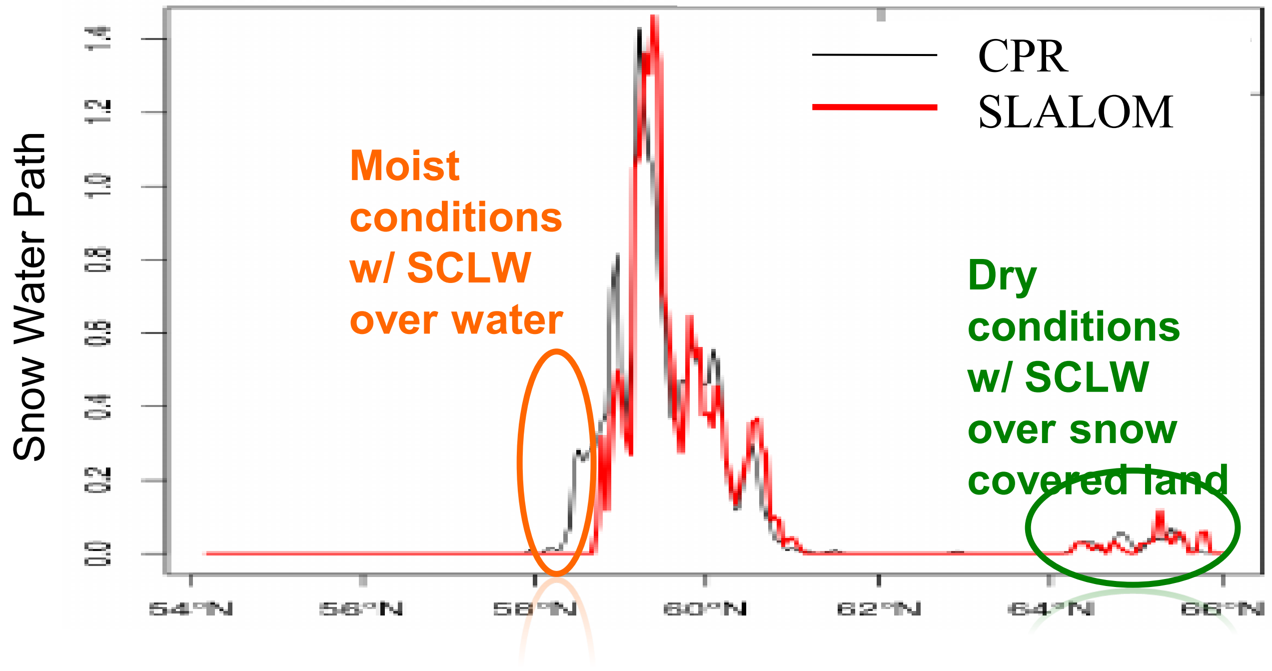
(in preparation for EUMETSAT H SAF EPS-SG day-1 precipitation product)





GMI/CloudSat co-located observations Siberia 30 April 2014





Predicted and observed SWP match very well, even in the weaker snowfall region (around 65°N)

SLALOM misses snowfall in moister conditions over ocean (scattering signal masked by WV emission)

SLALOM matches the SWP in drier conditions over snow-covered land

(Rysman et al., 2018,2019)

4-year SLALOM and GPM products validation over CONUS

(Mroz et al., JHM, 2021)

Ground-based radar reference data

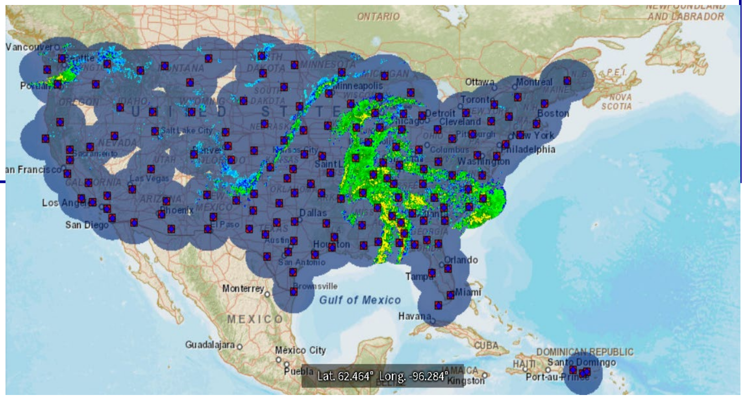
MRMS: Multi-radar-multi-sensor (*Zhang, et al. 2011, Zhang, et al. 2016; Tang et al. 2020*) https://blog.nssl.noaa.gov/mrms/

- ***Products***: Cartesian gridded level II and III radar products over US and Canada
- ***Resolution***: 1 x 1 km horizontal, 2 min time sampling

Variables considered:

- Instantaneous precipitation rate (*S*)
- Radar quality index (RQI)
- Phase precipitation flag

- ***Statistical analysis: 4 year dataset from Jan 2016 to March 2020***



Satellite Snowfall products

SLALOM for GMI

NASA GPM products (GMI and DPR):

GPROF V05 for GMI (NASA GPM)

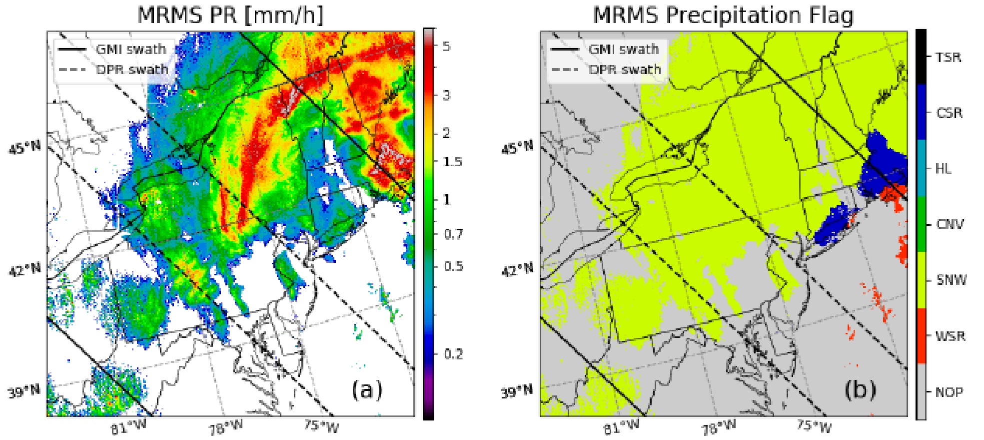
DPR, Ku, Ka V06 (NASA GPM)

CORRA (2B-CMB) V06 (NASA GPM)

CloudSat CPR product

2C-SNOW-PROFILE (NASA)

Snowfall event 14 March 2017 20:02 UTC



(Mroz et al., JHM, 2021)

4-year SLALOM and GPM products validation over CONUS

(Mroz et al., JHM, 2021)

4-year analysis of snowfall retrieval over all surface types (2016-2020)

Score	GMI SLALOM	GMI GPROF	CPR 2C-SNOW
POD (%)	57.3	28.1	70.0
FAR (%)	26.3	39.6	25.5
HSS (%)	58.7	31.3	68.3
CSI (%)	47.6	23.7	56.4

In SLALOM the exploitation of low frequency channels allows to better constrain the snowfall retrieval (based on high frequency channels) over all surfaces

Sea ice

Snow cover

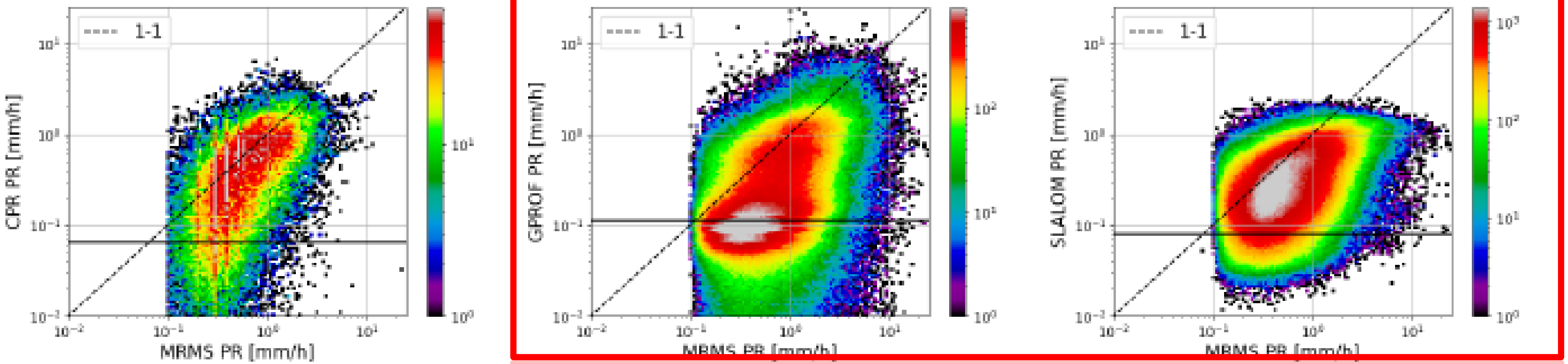
Surface type	HSS (%)		POD (%)		FAR (%)		no. of MRMS pixels	
	SLALOM	GPROF	SLALOM	GPROF	SLALOM	GPROF	"no-snow"	"snow"
Ocean	46.1	18.9	49.5	22.7	24.8	39.5	66219	30940
Sea-Ice	54.4	15.2	59.0	12.3	37.6	48.6	93201	15158
Maximum Vegetation	57.1	31.3	49.1	21.3	18.9	9.1	799283	113169
High Vegetation	54.6	31.3	45.1	21.0	19.2	11.2	1381112	154952
Moderate Vegetation	56.2	28.8	45.8	18.8	16.1	7.5	473357	51387
Low Vegetation	60.6	32.3	50.2	21.7	16.3	16.5	24855	2007
Minimal Vegetation	63.4	24.4	53.0	16.9	12.4	30.3	8109	857
Maximum Snow	58.0	14.0	68.5	26.8	41.7	77.8	309380	38151
Moderate Snow	58.8	30.5	63.0	33.1	33.1	52.3	1641016	291043
Low Snow	60.5	28.2	63.9	29.6	30.9	51.7	1404417	258627
Minimal Snow	61.2	37.3	61.0	33.9	24.0	32.4	3448465	798754
Standing Water and Rivers	53.8	30.5	45.1	21.5	17.1	13.7	203484	33633
Water/Land Coast Boundary	49.4	19.0	45.9	14.1	20.7	12.9	731055	225411
Water/Ice Boundary	54.1	12.3	54.0	8.4	27.1	11.1	80445	20491

(sfc classes are based on GPROF surface classification)

(Mroz et al., JHM, 2021)

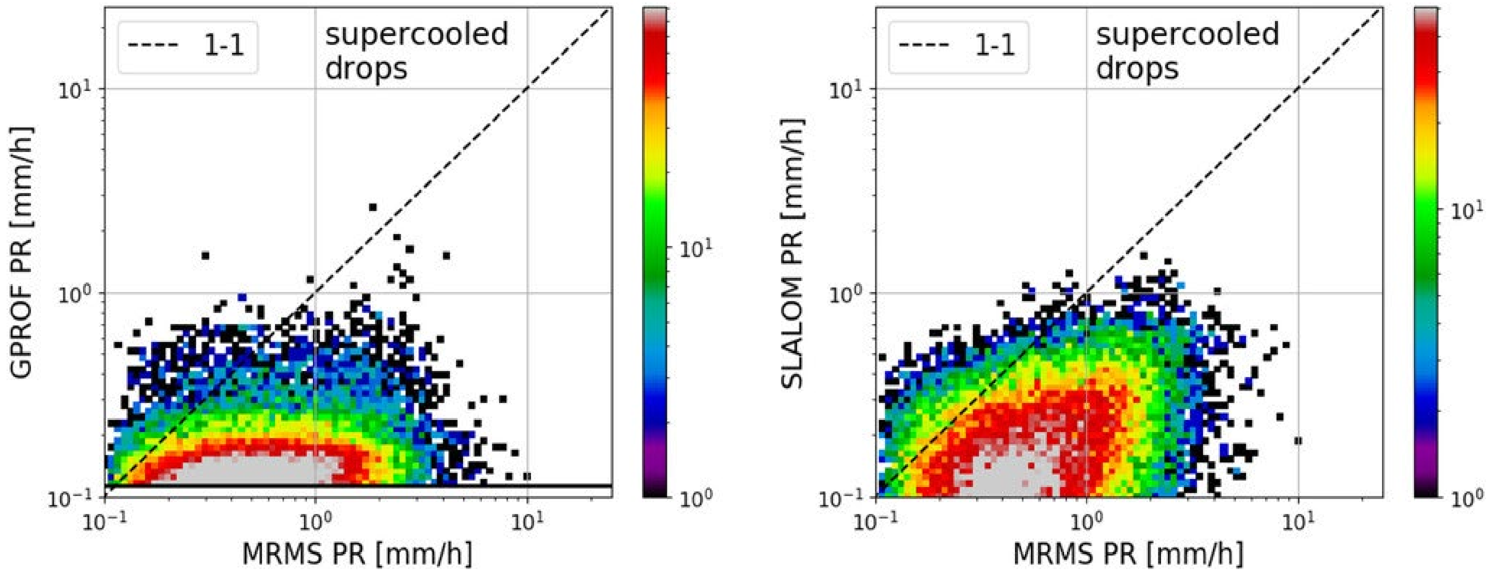
4-year SLALOM and GPM products validation over CONUS

(Mroz et al., JHM, 2021)



Black horizontal lines show the limit on the satellite product that optimizes precipitation detection matching with MRMS

Score	GMI SLALOM	GMI GPROF	CPR 2C-SNOW
POD (%)	57.3	28.1	70.0
FAR (%)	26.3	39.6	25.5
HSS (%)	58.7	31.3	68.3
ME (mm/h)	-0.38	-0.54	-0.21
RMSE (mm/h)	0.74	1.08	0.68
MB %	48.5	48.4	73.0
CC	0.43	0.39	0.45



PESCA: Passive microwave Empirical cold Surface Classification Algorithm (for ATMS and GMI in preparation for EPS-SG MWS and MWI)

(Camplani et al., JHM, 2021)

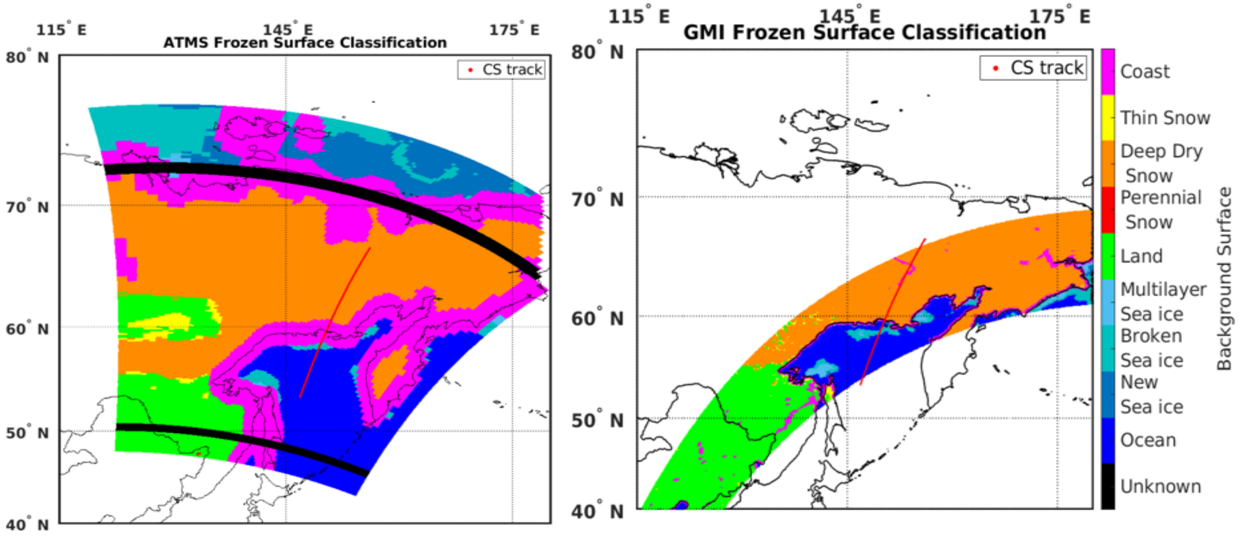
The microwave signal related to snowfall is strongly influenced by the **different surface conditions** (e.g., wet or dry snow cover, snow depth, sea ice concentration and type, etc.). The use of surface classification climatological datasets results inadequate for the **extreme variability of the frozen surface conditions**.

PESCA:

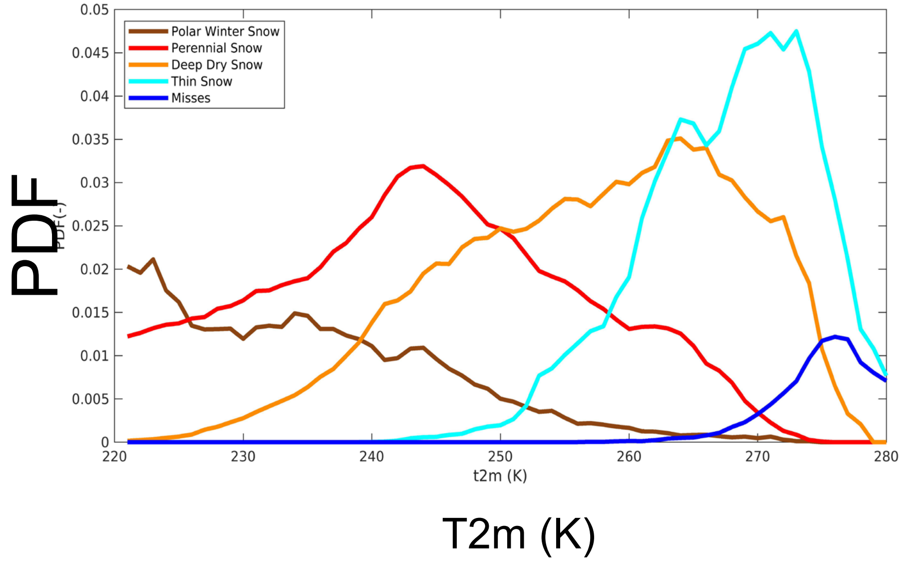
- Empirically-based algorithm for frozen background surface characterization (different types of sea ice and snow cover)
- **Use of low-frequency (<= 90 GHz) channels common to most radiometers;**
- Applicable to both cross-track and conically scanning spaceborne microwave radiometers *at the time of overpass* (for TPW < 10 kg/m²)

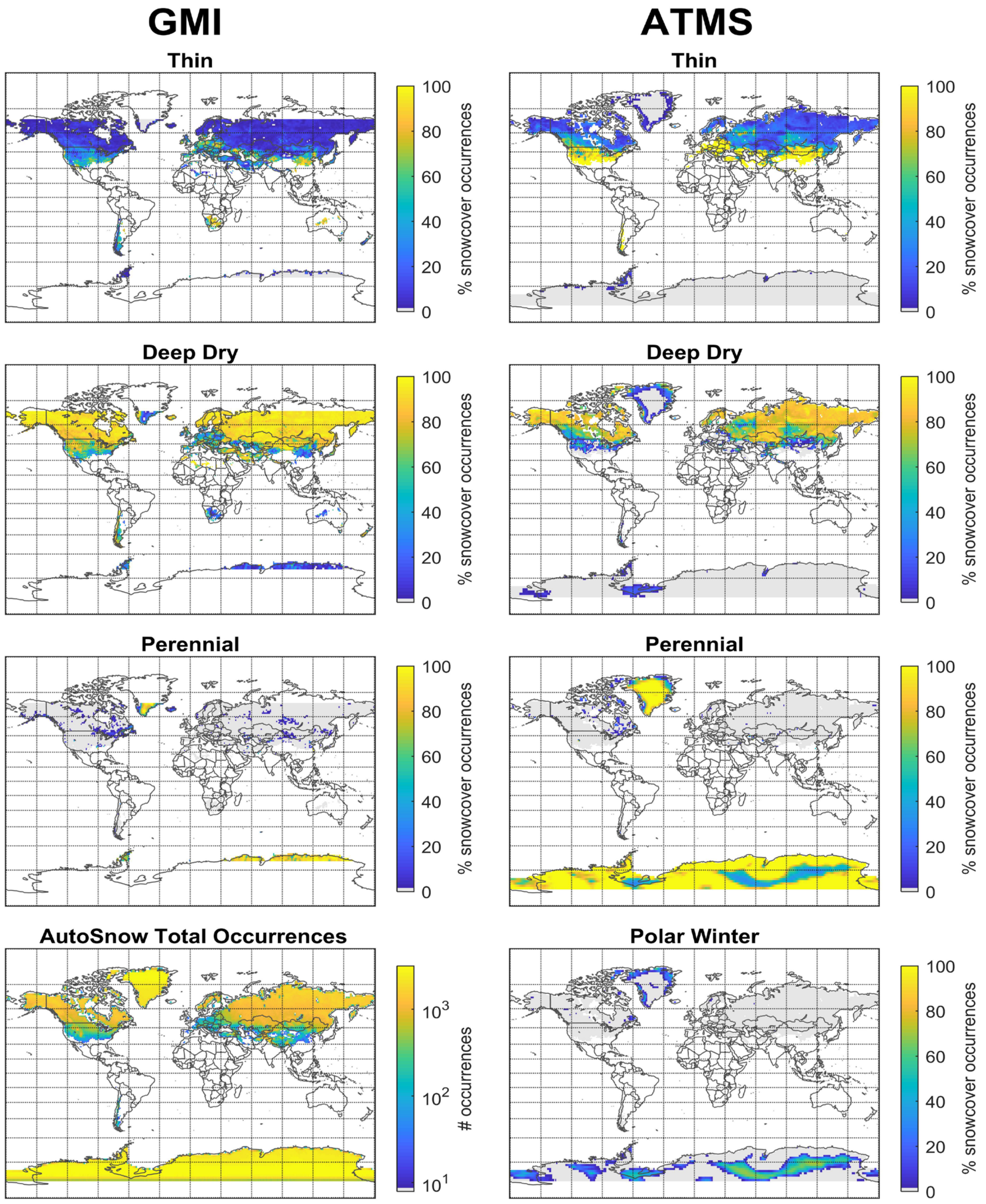
Siberia 30 April 2014

ATMS-based GMI-based



PESCA Snow Cover categories

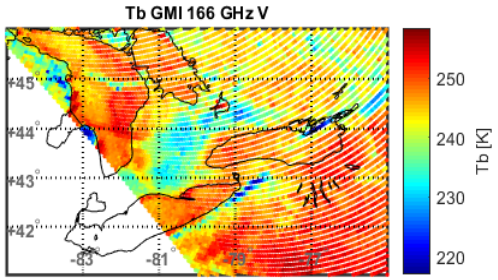


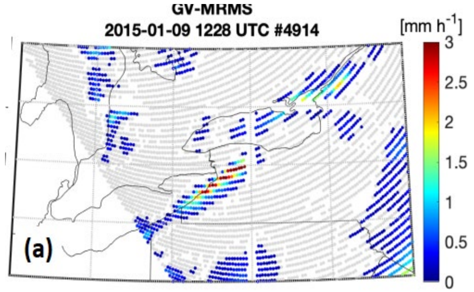


(Camplani et al., JHM, 2021)

PESCA: Snowfall vs. background surface

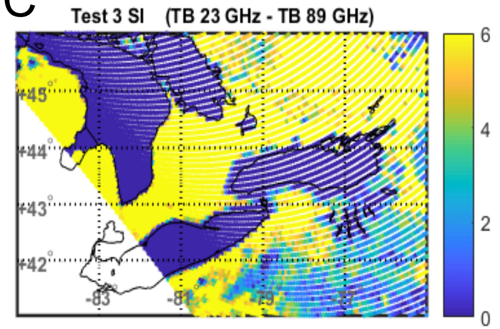
GMI 9 January 2015 at 12:26 UTC

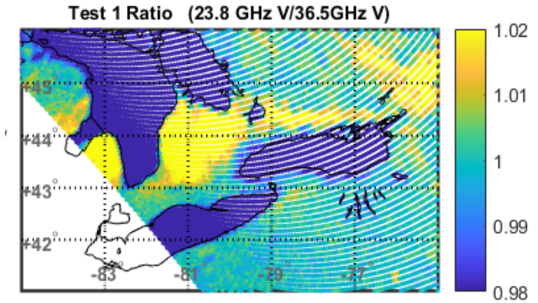


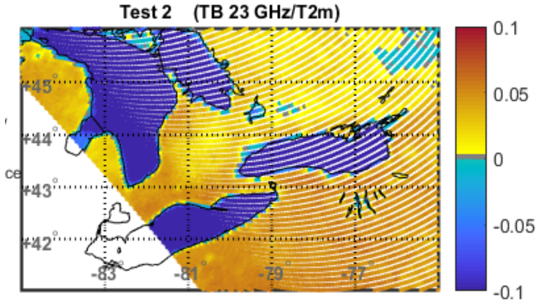


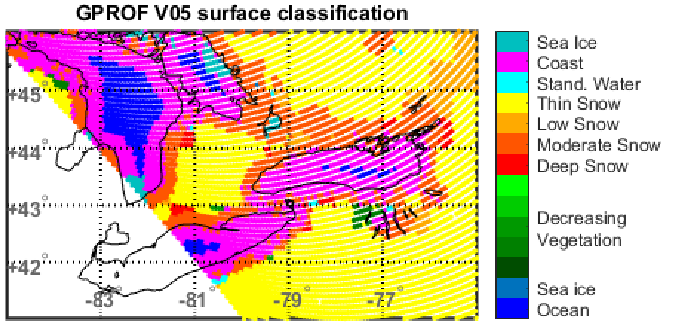
Extreme Lake Effect Snow event on (Milani et al., JHM, 2020)

Low-frequency channels combinations are used in PESCA to identify different types of sea ice and snow cover with distinct radiative properties

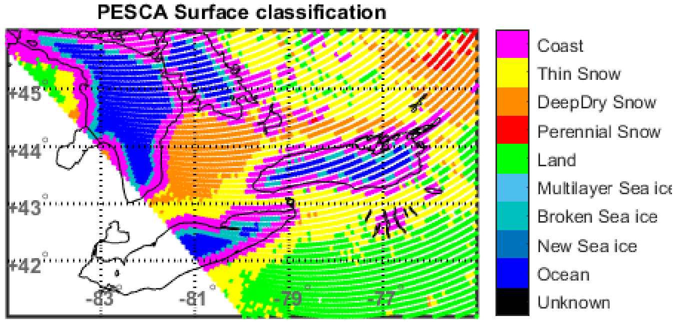




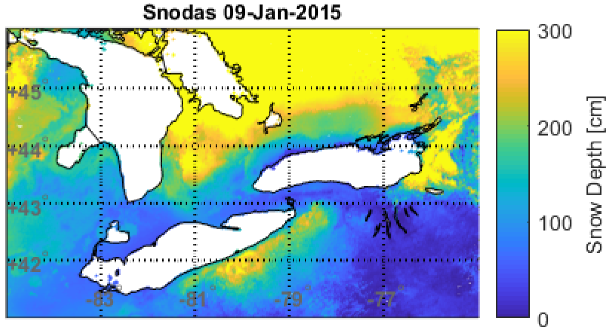




GPROF classification based on climatological and daily snow cover product



PESCA classification at the time of the GPM overpass.



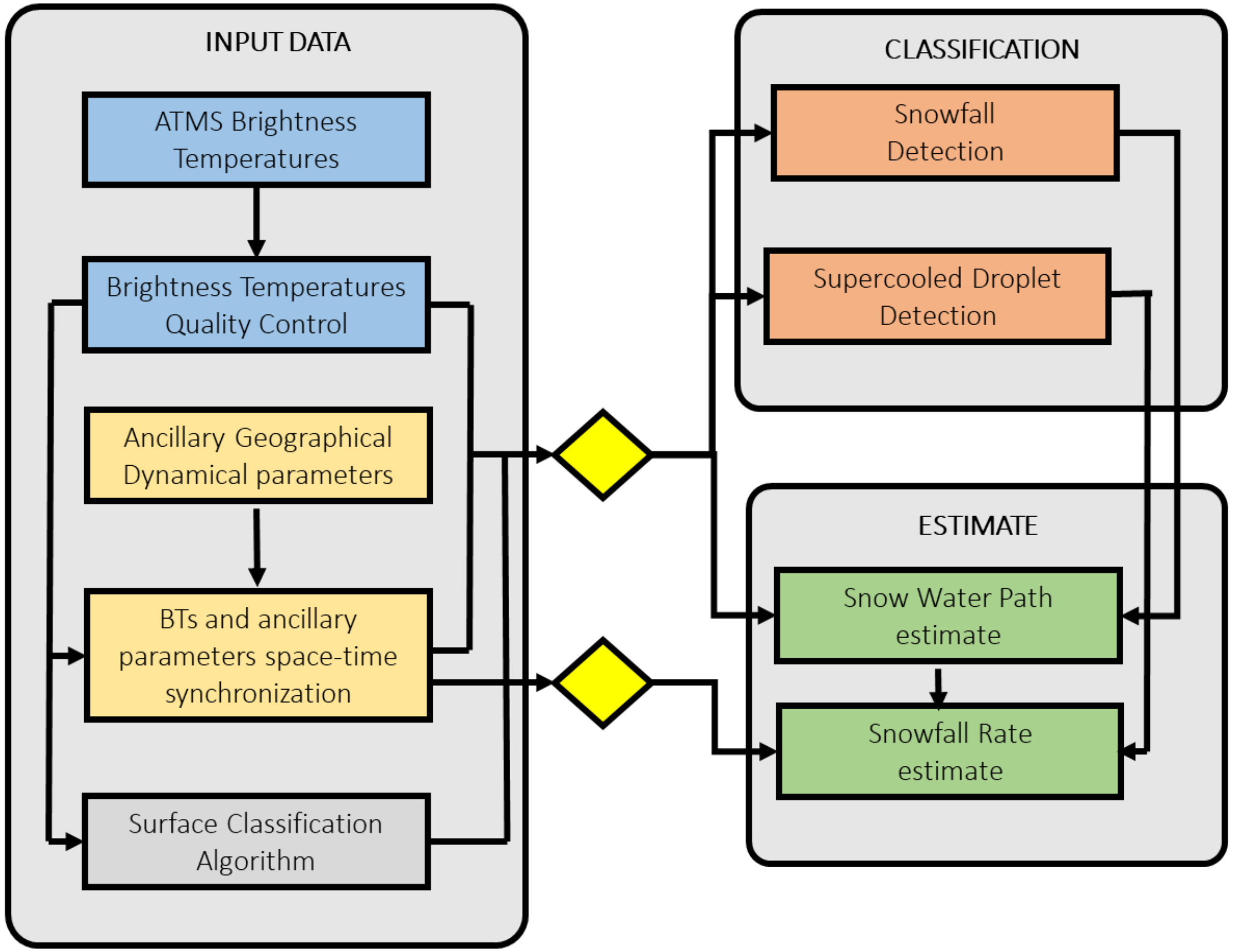
Snow Depth from NOAA NOHRSC SNOw Data Assimilation System (SNODAS) https://nsidc.org/data/g02158

Turk et al., JHM, 2021

SLALOM-CT (Snowfall retrievaL ALgorithm fOr gpM – Cross Track)

CNR ISAC

Goal: achieve snowfall global coverage (polar regions) exploiting all current and future *operational sounders* (ATMS, MWS, AWS)



In preparation for EPS-SG MWS global day-1 precipitation product

H SAF Support to Operational Hydrology and Water Management

SLALOM-CT for ATMS

Intercopmarison of different ML approaches

- Random Forest
- Gradient Boosting
- Shallow Neural Network

Pixel Based

- Convolutinal Neural Network (VGG, ResNet)

➜ Image Based

Sanò, et al., 2022 Doi: 10.3390/rs14061467

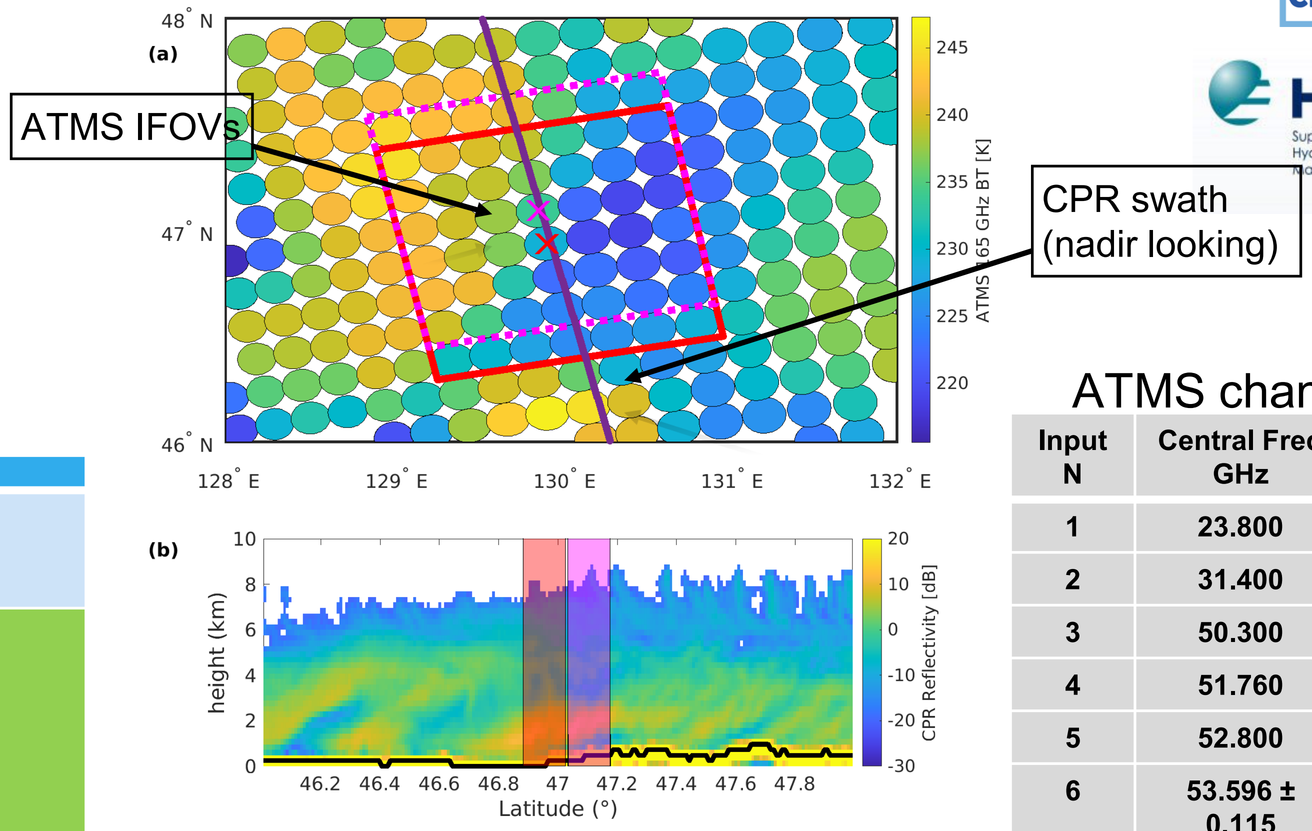
SLALOM-CT: ATMS-CPR Coincidence dataset

Period	**16/01/2014 – 31/08/2016**
Geographical area	82°S–82°N, 180°W–180°E
Number of database points	6.5 M
Number of database points with snowfall	1.1 M
IFOV size	15.8 x 15.8 (nadir) 30 x 68.4 (scan edge)

INPUT Variables	Data source
ATMS BTs	NOAA
ATMS Scan angle	
Temperature @ 2m	ECMWF
Total column integrated water vapor	
Freezing level Height	
Temperature profile	
Relative humidity profile	
Absolute humidity profile	

REFERENCE Variables	Data source
Supercooled Water	DARDAR (raDAR/liDAR) LATMOS-Reading Univ.
Snowfall Rate	2C-SNOW-PROFILE (CPR product)
Snow Water Path	2C-SNOW-PROFILE (CPR product)

One year (2015) for training, two years (2014 and 2016) for test



	Pixel Based	Image Based
Features	Central Pixel	7x7 Matrix
Target	Central Pixel	Central Pixel

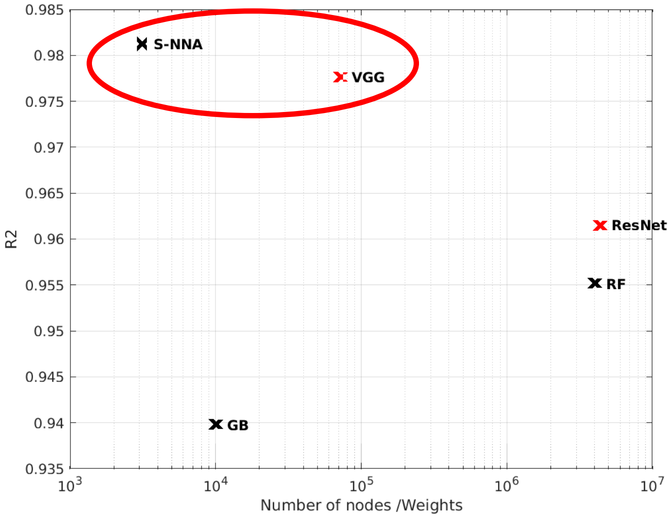
Sanò et al., 2022 doi:10.3390/rs14061467

ATMS channels

Input N	Central Freq GHz	Pol.
1	23.800	QV
2	31.400	QV
3	50.300	QH
4	51.760	QH
5	52.800	QH
6	53.596 ± 0.115	QH
7	54.400	QH
8	54.94	QH
9	55.5	QH
10	89.5	QV
11	165.5	QH
12	183.311±7.0	QH
13	183.311±4.5	QH
14	183.311±3.0	QH
15	183.311±1.8	QH
16	183.311±1.0	QH

SLALOM-CT Intercomparison of Machine Learning techniques

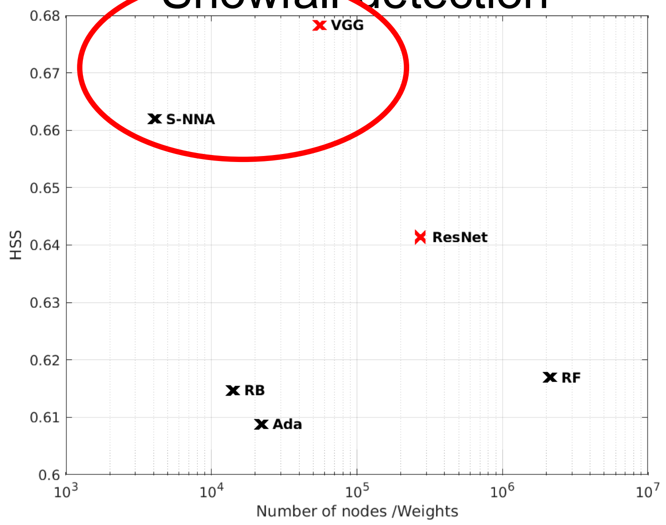
Snowfall estimate



	RandomForest	RobustBoost	AdaBoost	ShallowNN	**VGG**	ResNet
HSS	0.62	0.61	0.61	0.66	**0.68**	0.64
CSI	0.67	0.66	0.66	0.69	**0.70**	0.67
POD	0.80	0.79	0.79	0.83	**0.83**	0.80
FAR	0.20	0.20	0.20	0.19	**0.18**	0.19

	RandomForest	GradientBoosting	**ShallowNN**	VGG	ResNet
RMSE [kg/m^2]	0.078	0.090	**0.050**	0.055	0.072
R^2	0.667	0.553	**0.861**	0.834	0.714
ME [kg/m^2]	-3.66E-03	-1.08E-02	**-1.59E-05**	-5.61E-05	-1.2E-03
Corr	0.86	0.83	**0.93**	0.92	0.87
N_0	$4\ 10^6$	10^4	**$3\ 10^4$**	$7\ 10^4$	$4\ 10^6$

Snowfall detection



Event forecast	Event observed: Yes	Event observed: No
Yes	a	b
No	c	d

Heidke Skill Score:

$$HSS = \frac{2(ad-bc)}{[(a+c)(c+d)+(a+b)(b+d)]}$$

Perfect: HSS =1

No Skill: HSS=0

$$R^2 = 1 - \frac{MSE}{VAR}$$

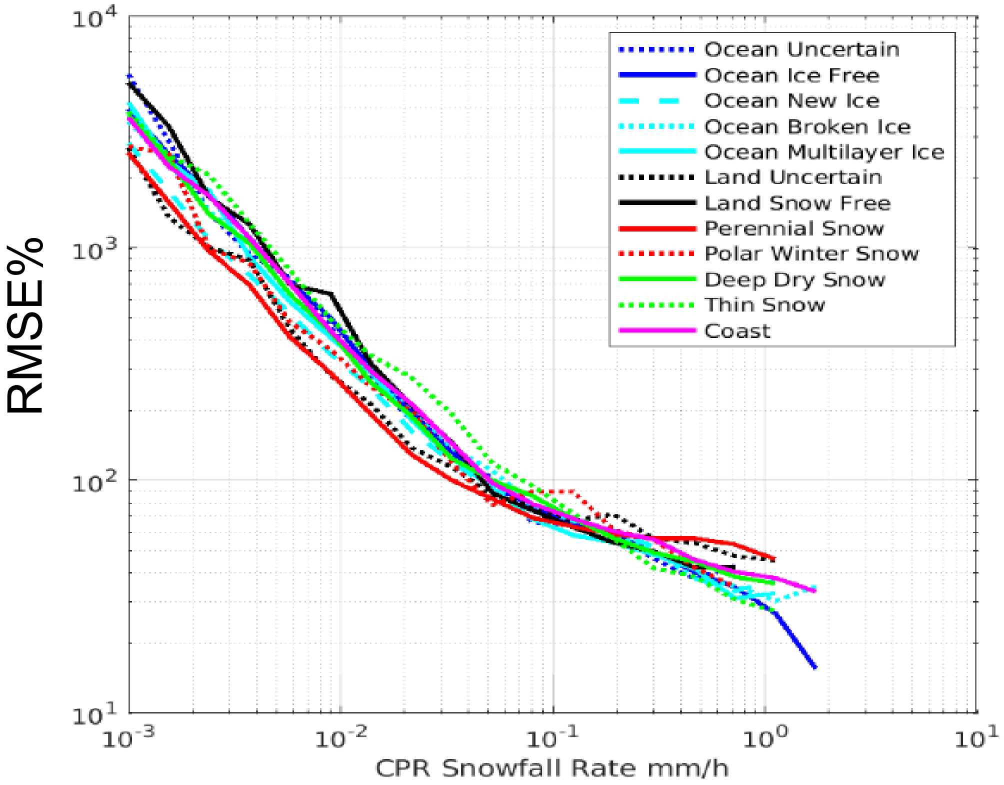
Perfect: R^2 =1

Baseline: R^2 =0

Sanò, et al., 2022
https://doi.org/10.3390/rs14061467

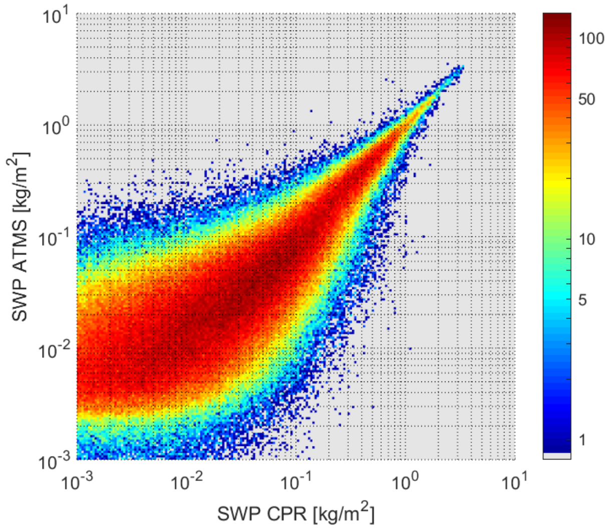
SLALOM-CT: surface characterization at the time of the overpass

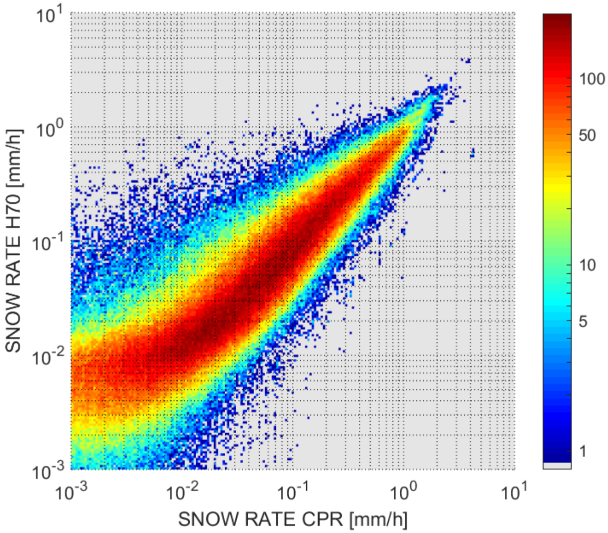
- ***Exploitation of low-frequency channels in SLALOM-CT:***
  - Low sensitivity of results to the background surface variability
  - Very good detection capabilities
  - Very accurate estimates (compared to CPR)



Surface*	SNOW	OCEAN	LAND
RMSE [mm/h]	0.10	0.09	0.10
ME [mm/h]	0.002	-0.002	-0.01
Corr	0.80	0.84	0.79
POD	0.76	0.86	0.80
FAR	0.22	0.15	0.22
HSS	0.63	0.68	0.71

Verification using indipendent two-year (2015-2016) CPR (2C-SNOW-PROFILE v5) dataset as reference



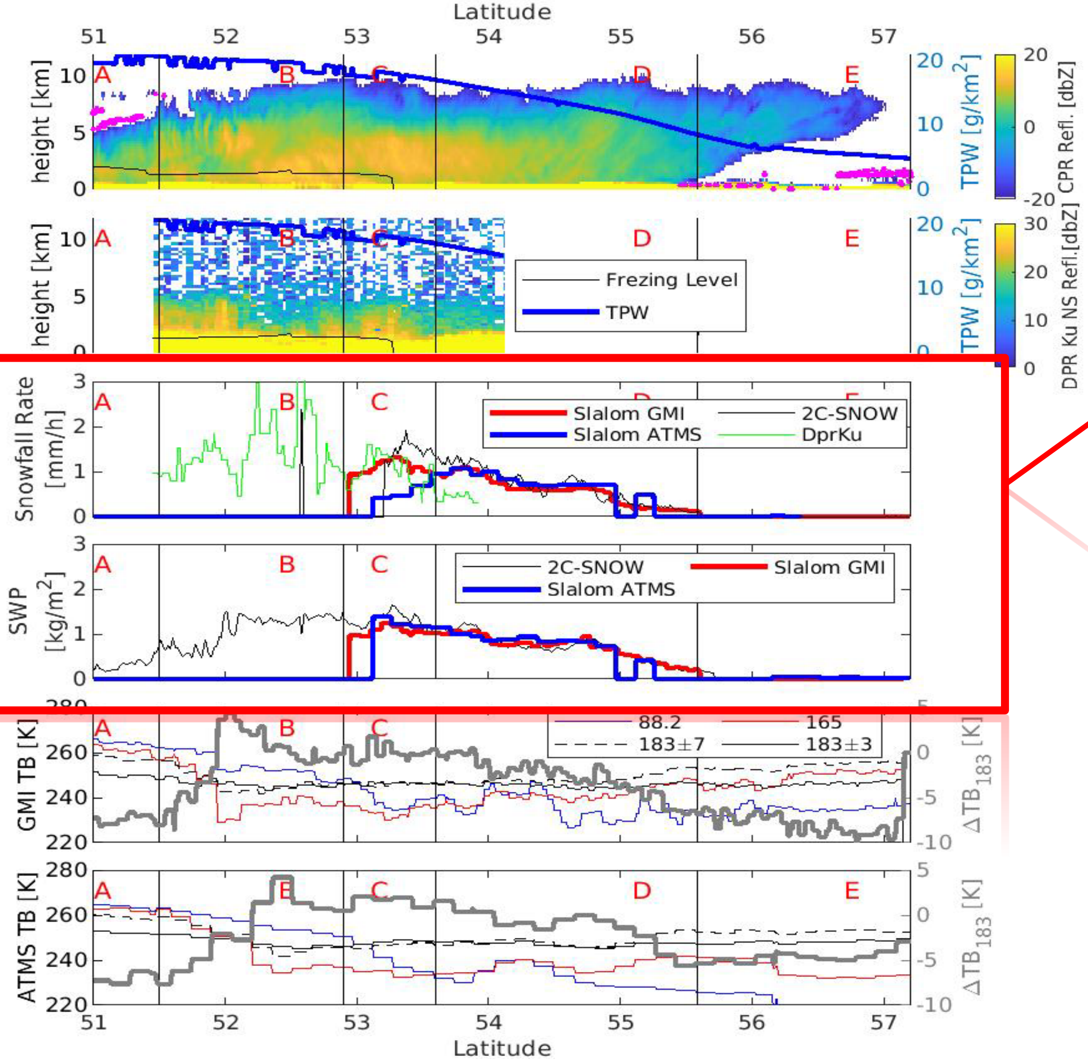


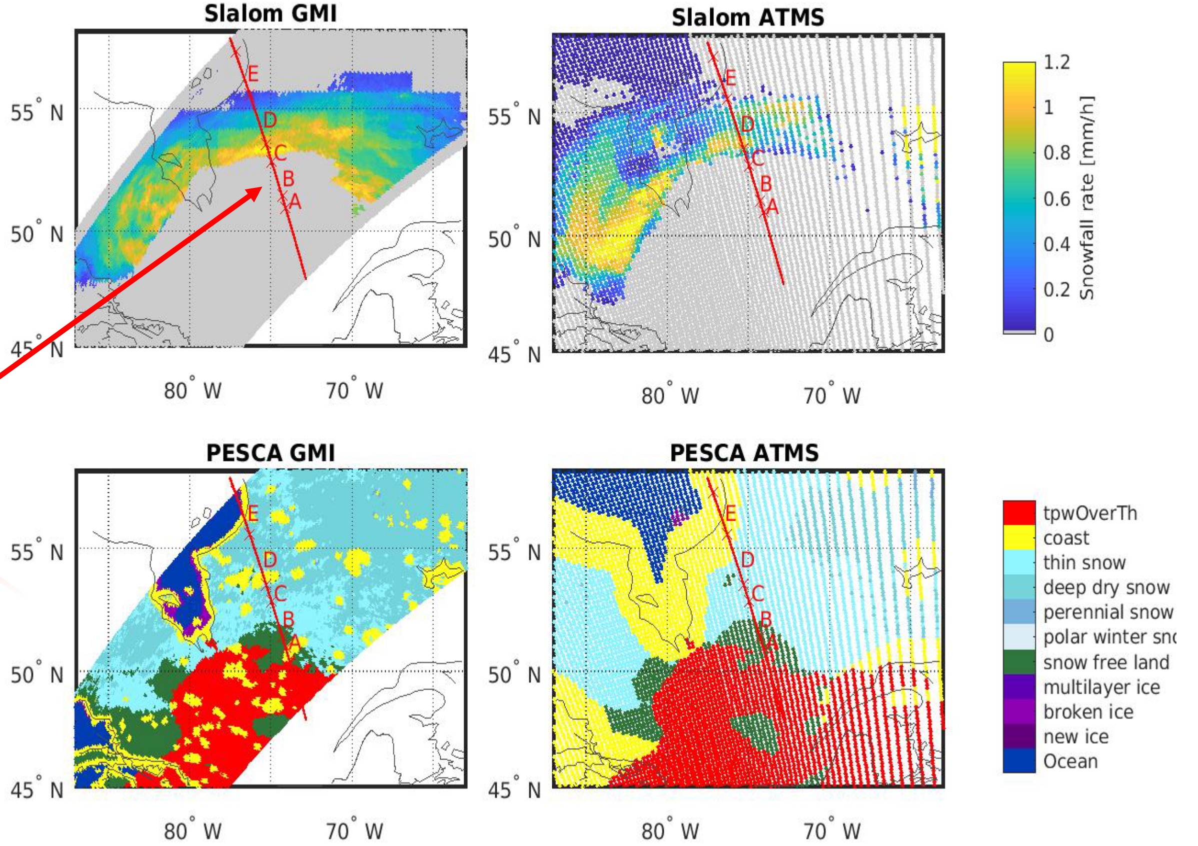
Sanò et al., 2022 doi:10.3390/rs14061467

SLALOM approach for ATMS and GMI

(in preparation for EUMETSAT H SAF EPS-SG MWS and MWI)

Snowfall event over Quebec and Ontario on 24 November 2014

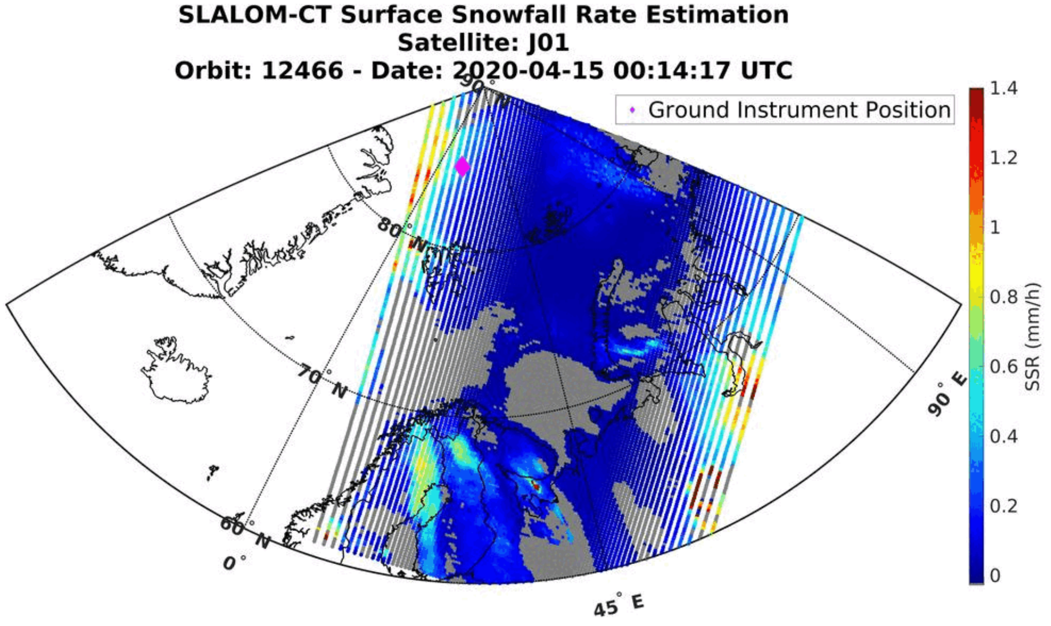


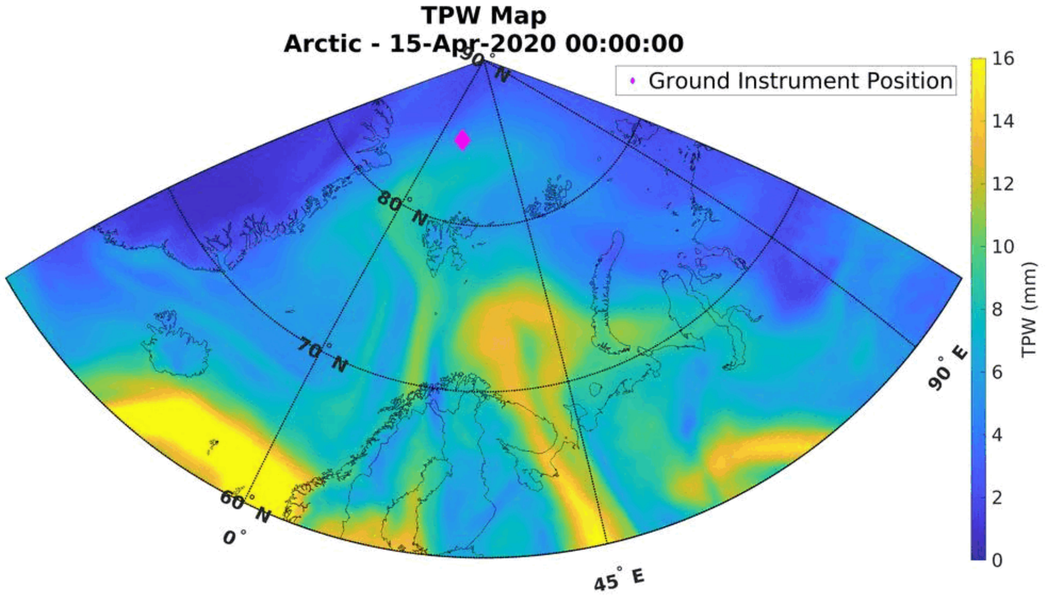


Use of low frequency channels for background surface characteization at the time of the overpass

Turk et al., Rem. Sens., 2021, Doi: 10.1175/JHM-D-20-0296.1

Extreme event in central Arctic Ocean on April 15-16 2020

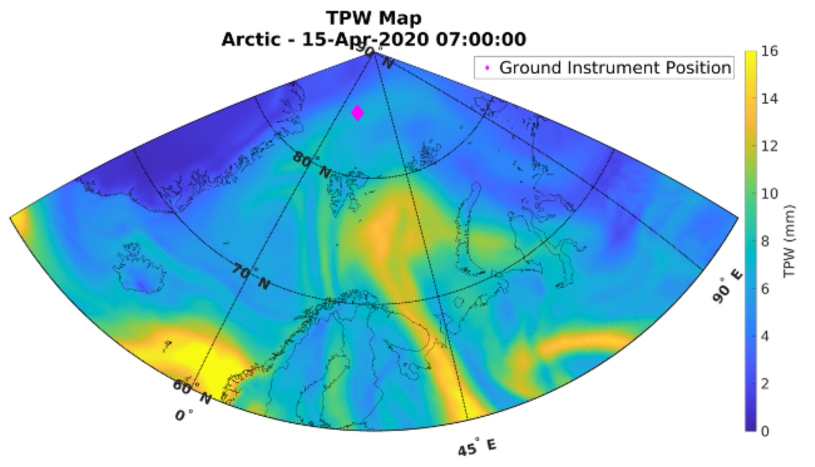


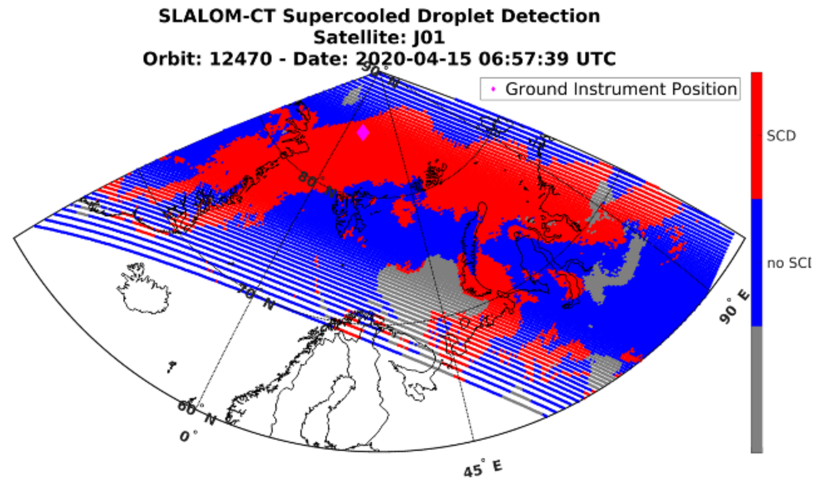


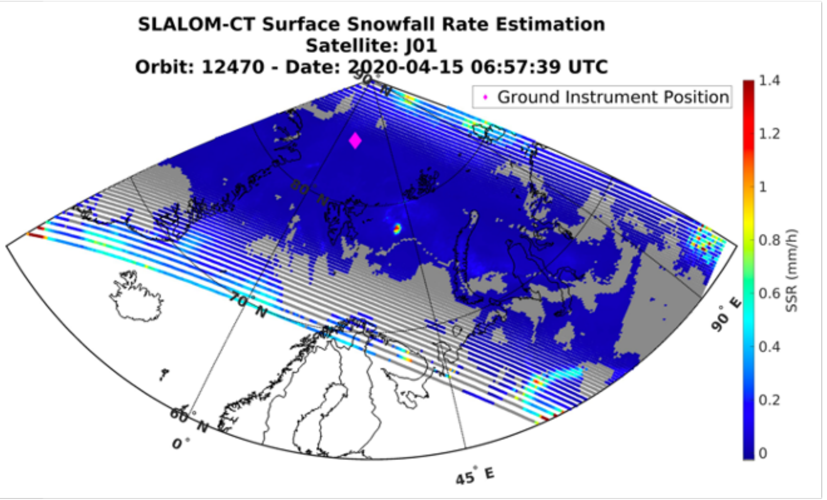
- Between 13-19 April 2020 three Atmospheric Rivers (AR) reached the Arctic (based on the approach by Guan & Waliser (2019)).
- The AR event on April 15 had his origin in the Atlantic moved northward, across central Europe and Svalbard and hit the Polarstern on the 15 April at 19 UTC and lasted until 16 April 20 UTC.
- Intense snowfall was associated to this AR event mainly concentrated in the frontal area
- The Polarstern is hit by the intense snowfall

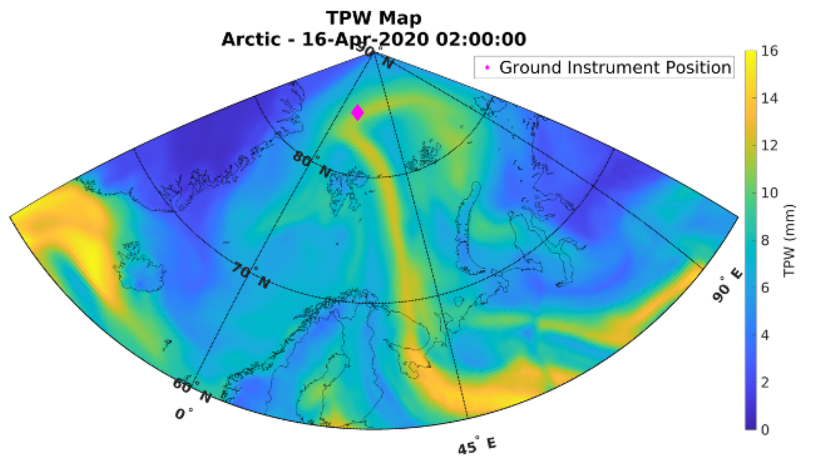
Extreme event in central Arctic Ocean on April 15-16 2020

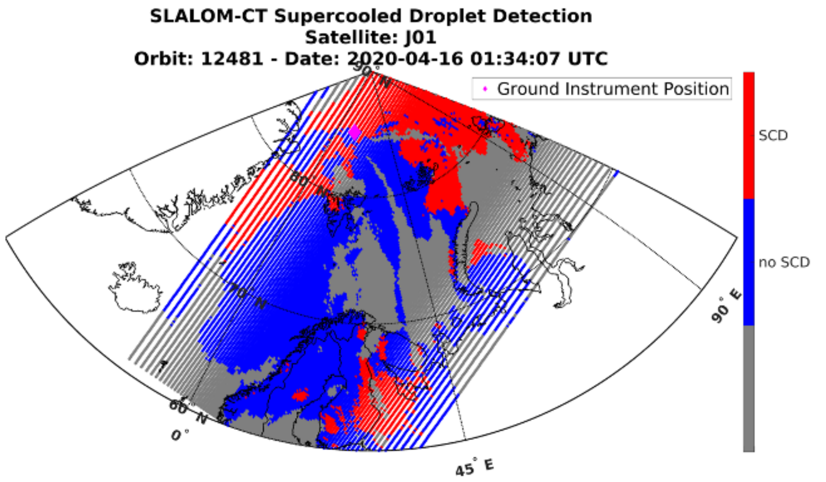
ERA5 TPW and SLALOM-CT SLW detection and Surface Snowfall Rate

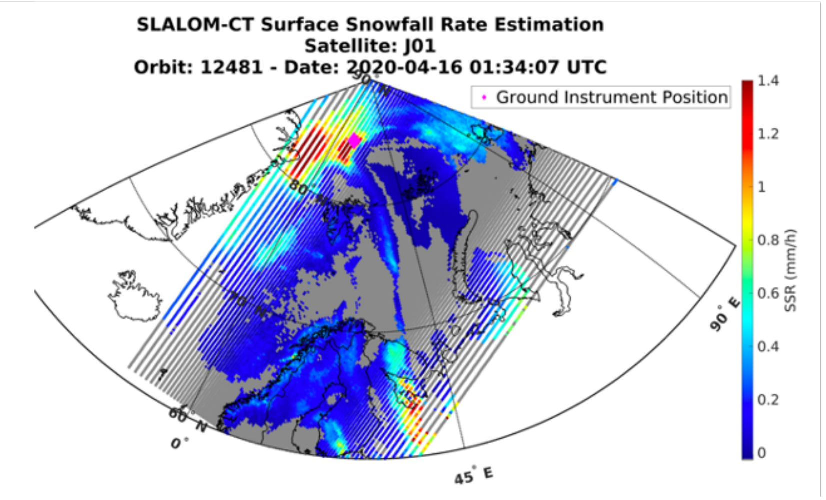












ML-based algorithms High lAtidude sNow Detection and rEtrieval aLgorithm for ATMS (HANDEL) (Camplani et al., 2024, AMT)

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

- **Exploits PESCA classification and ML techniques to retrieve frozen surface emissivity at the time of the overpass**
- **Estimates TB-clear-sky (Tb_{sim}) and uses multi-channel TB_{obs}-Tb_{sim} as input**

HANDEL working limiits: T2m < 280 K TPW < 10 mm

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 vs. HANDEL

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

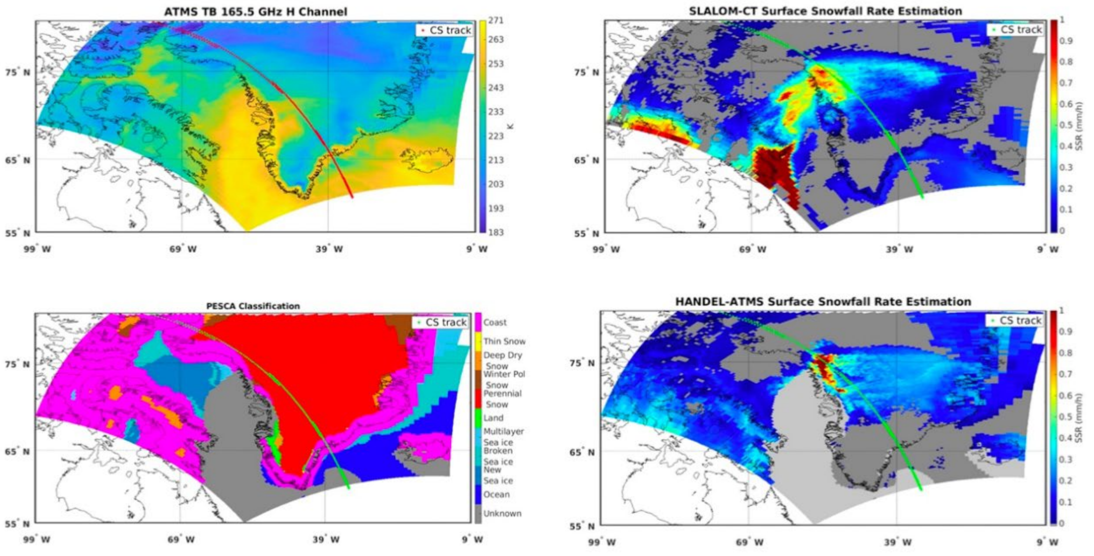
HANDEL-ATMS

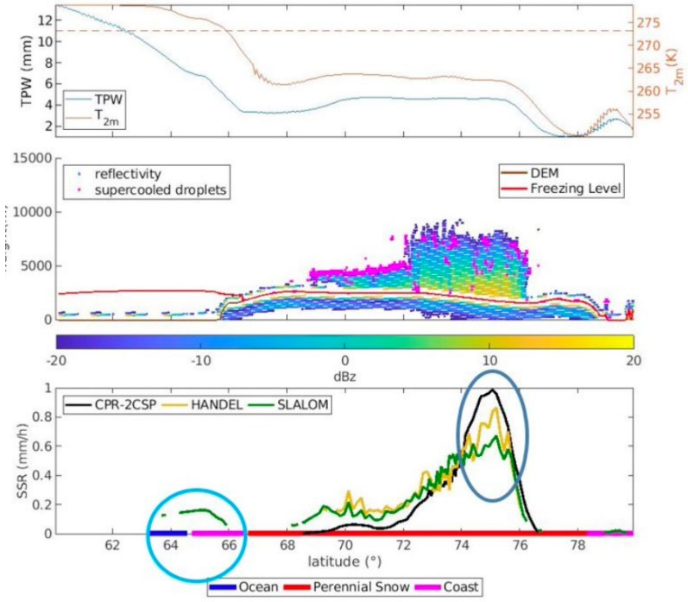
- High lAtitude sNow Detection and rEtrieval aLgorithm for ATMS
- **high-latitude environmental conditions** - dry and cold atmosphere, snowpack over the ground, supercooled water layer in/over the clouds
- Shallow Neural Networks
- ANN Input dataset: ATMS TBs, $\Delta TB_{obs-sim}$, PESCA output

ML-based algorithms High lAtidude sNow Detection and rEtrieval aLgorithm for ATMS (HANDEL) (Camplani et al., 2024, AMT)

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





- 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

	RMSE	bias	R^2 (-)
SWP ($\frac{kg}{m^2}$)	0.047	0.001	0.72
SSR ($\frac{mm}{h}$)	0.079	0.002	0.61

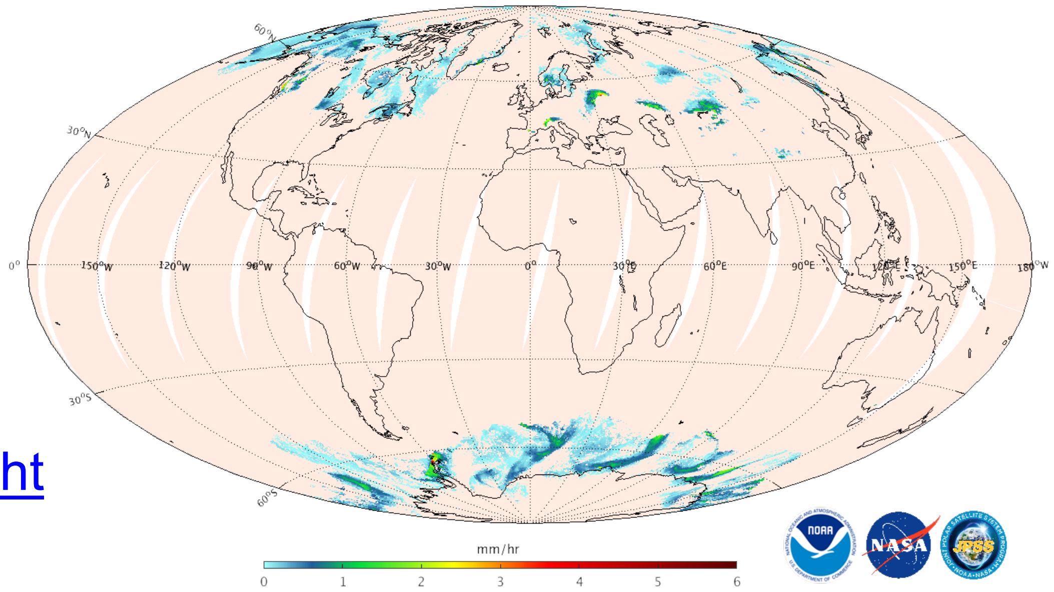
POD	FAR	HSS
0.85	0.15	0.70
0.84	0.16	0.69

NOAA Snowfall Rate Product t hroughMachine Learning

Yongzhen Fan (CISESS/ESSIC/University of Maryland), **H. Meng** (NOAA)

- 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

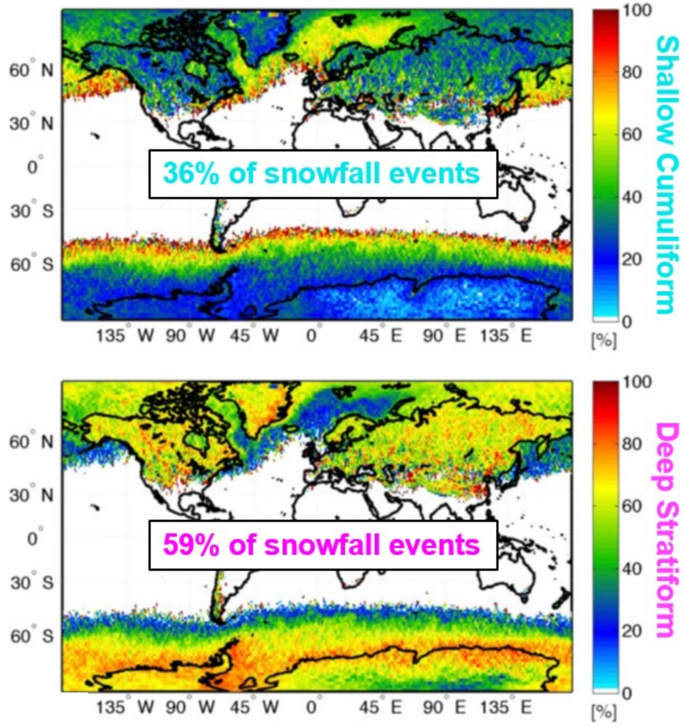
NOAA-21 First Light Snowfall Rate (11/21/2022)



Snowfall regime Classification using ML

Veljko Petković, Lisa Milani (University of Maryland)

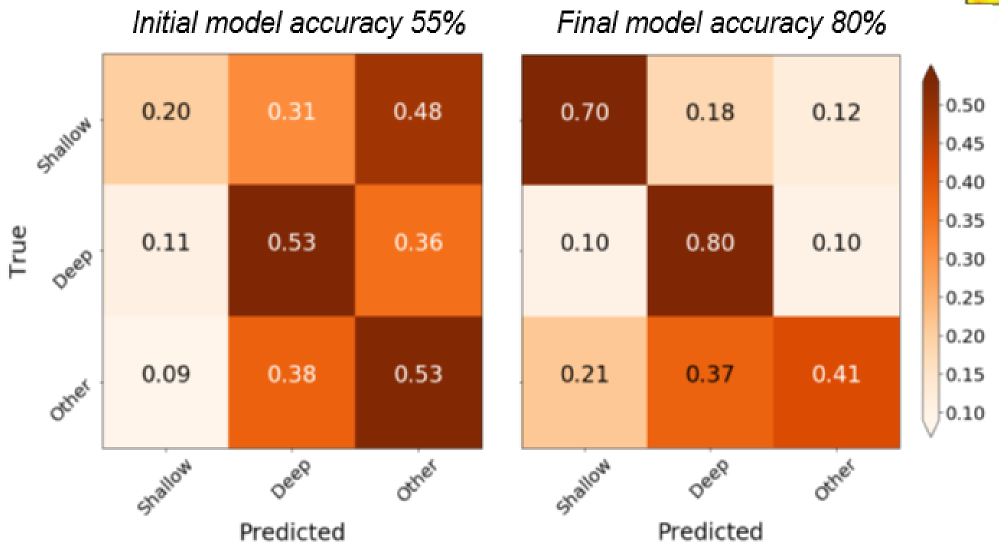
- Different snowfall regimes often appear radiometrically similar, preventing the retrieval to converge.
- Non-linear relationships between Brightness Temperatures (TBs) at different frequencies, or combination of frequencies
- Machine learning techniques can enable finding the "hidden" relationships 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

- Models trained:
  - Fully Connected NN,
  - XGBoost

SNN results



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

Reyhaneh Rahimi and Ardeshir Ebtehaj (Univ. of Minnesota)

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

Explainable AI through partial dependence plots

Data

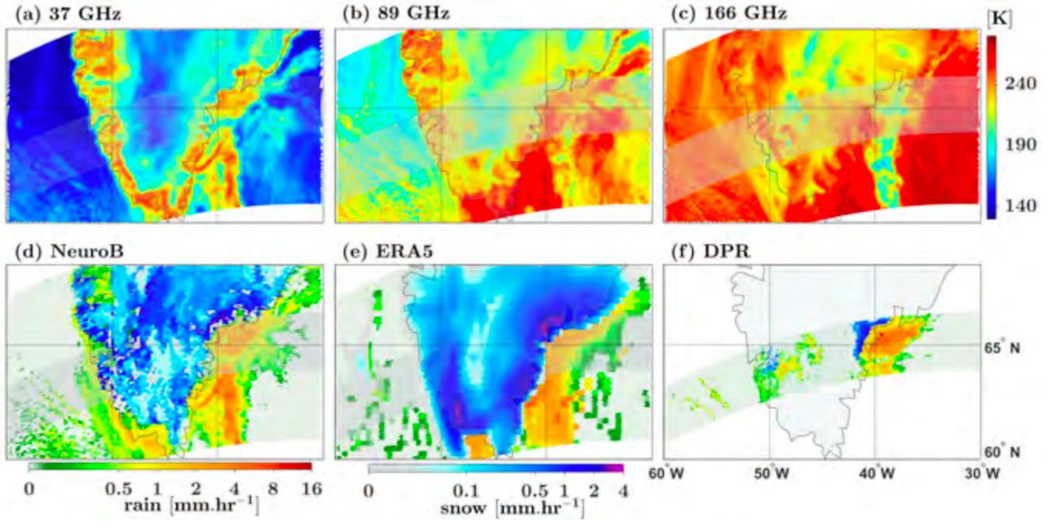
GMI-CPR, and GMI-DPR coincidences (2014–2016) -

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

orbit #3080 on September 13, 2014 over Greenland



	metric	ML	Surface Type: ocean	land	coast	snow cover	sea ice
rain	rmse [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 [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

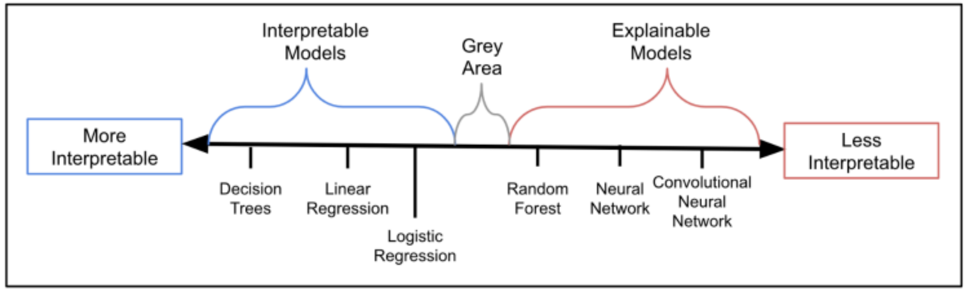
For rain, NeuroB has slightly better performance except coast

For snow, NeuroB has better performance over ocean and land

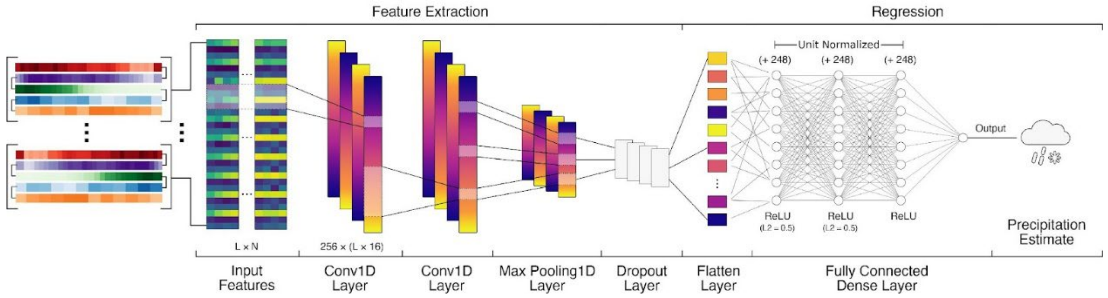
Towards Interpretable Artificial Intelligence in the Atmospheric Sciences

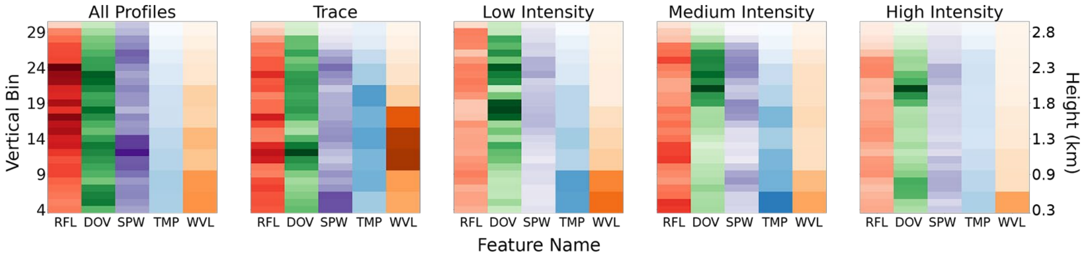
Fraser King (University of Michigan), C. Pettersen, et al.

- ❑ The application of ML in the Atmospheric Sciences has surged in popularity 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.



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





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)
  - **Contacts**

Acknowledgements

EUMETSAT H SAF (Satellite Application Facility on Support to Operational Hydrology and Water Management)

EUMETSAT H SAF: established in 2005 – Current phase: CDOP-4 (2022-2027)
http://h-saf.eumetsat.int/

The **Raincast Study** is funded with ESA contract Nr. 4000125959/18/NL/NA
Raincast (CCN2, 2023-2024) aims at sharpening concepts for future precipitation satellite missions specifically focusing at better understanding processes associated to high latitude precipitation. Raincast project perfectly fits with the goals of Earth Observation science for society https://eo4society.esa.int/

NASA PMM Science Team
in particular Joe Turk (NASA JPL), Lisa Milani (NASA GSFC), Mark Kulie (NOAA NESDIS)
J.F. Rysman (CNRS, France), Alessandro Battaglia (PoliTo, Italy, Univ. of Leicester, UK)

Contact
Giulia Panegrossi g.panegrossi@isac.cnr.it

Some References

- Battaglia A., G. Panegrossi, What Can We Learn from the CloudSat Radiometric Mode Observations of Snowfall over the Ice-Free Ocean?, Remote Sens.,12, 3285; doi:10.3390/rs12203285, **2020**.
- Camplani, A., D. Casella, P. Sanò, G. Panegrossi, The Passive microwave Empirical frozen Surface Classification Algorithm (PESCA): application to GMI and ATMS, J. of Hydrometeorol., https://doi.org/10.1175/JHM-D-20-0260.1, **2021**
- Casella, D., Panegrossi G., Dietrich S., Marra A.C., Sanò P., M. S. Kulie, B. T. Johnson, Evaluation of the GPM-DPR snowfall detection capability: comparison with CloudSat, Atmos. Res., 197, 64-75, doi :10.1016/j.atmosres.2017.06.018, **2017**
- Milani L.,M. S. Kulie, D. Casella P. Kirstetter, G. Panegrossi, V. Petkovic, S. E. Ringerud1, J-F Rysman, P. Sanò, N.-Y .Wang, Y. You, G. Skofronick-Jackson, Extreme Lake-Effect Snow from a GPM Microwave Imager Perspective: Observational Analysis and Precipitation Retrieval Evaluation, *J. of Atmos. and Ocean. Tech*., https://doi.org/10.1175/JTECH-D-20-0064.1, **2020**.
- Mroz K., M. Montopoli, G. Panegrossi, L. Baldini, P. Kirtsetter, Quality assessment of spaceborne active and passive microwave snowfall products over the continental United States, J. of Hydrometeorology, https://doi.org/10.1175/JHM-D-20-0222.1, **2021**
- Panegrossi G., J-F. Rysman, D. Casella, A. C. Marra, P. Sanò, and M. S. Kulie, CloudSat-based assessment of GPM Microwave Imager snowfall observation capabilities, Rem. Sensing, 9(12), 1263; doi:10.3390/rs9121263, **2017**.
- Panegrossi, G., D. Casella, P. Sanò, A. Camplani, A. Battaglia, Recent Advances and Challenges in Snowfall detection and Estimation, pp. 333-376, Chapter 12 in In: Precipitation Science (ISBN: 978-0-12-822973-6), Ed. Silas Michaelides, Eds. Elsevier, Nov. **2021**
- Rysman J.-F., G. Panegrossi, P. Sanò, A. C. Marra, S. Dietrich, L. Milani, M. S. Kulie, D. Casella, A. Camplani, C. Claud, L. Edel, Retrieving surface snowfall with GPM Microwave Imager: A new module for SLALOM algorithm, Geophys. Res. Let., doi :10.1029/2019GL084576, **2019**
- Rysman, J.-F., G. Panegrossi, A. C. Marra, S. Dietrich, L. Milani, M. Kulie, SLALOM: An all-surface snow water path retrieval algorithm for the GPM Microwave Imgaer, Remote Sens. 10(8), 1278; https://doi.org/10.3390/rs10081278, 2018.
- Turk, J. F., S. E Ringerud, A. Camplani, D. Casella, R. J Chase, A. Ebtehaj, J. Gong, M. Kulie, G. Liu, L. Milani, G. Panegrossi, R. Padulles, J.-F. Rysman, P. Sanò, S. Vahedizade, N. Wood, Applications of a CloudSat-TRMM and CloudSat-GPM Satellite Coincidence Dataset, 13, 2264. https://doi.org/10.3390/rs13122264, **2021**
- Turk J., Ringerud, S., You Y., Camplani A., Casella D., Panegrossi G., Sanò P., Ebtehaj A., Guilloteau C., Utsumi N., Prigent C., Peters-Lidard C., Adapting Passive Microwave-Based Precipitation Algorithms to Variable Microwave Land Surface Emissivity to Improve Precipitation Estimation from the GPM Constellation, J. of Hydrometeorol., https://doi.org/10.1175/JHM-D-20-0296.1, **2021**