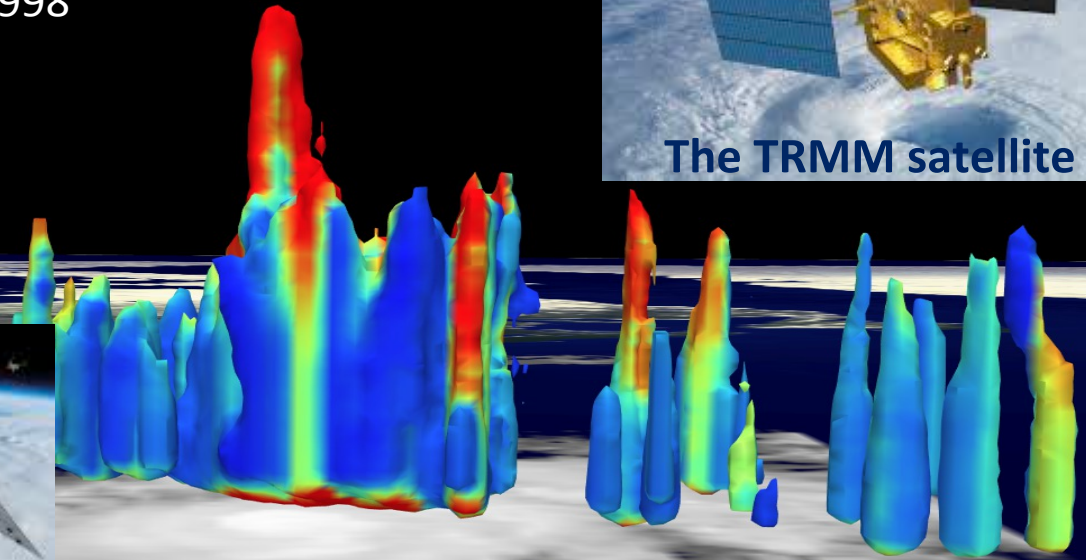


Remote Sensing of Precipitation from Space

Hurricane Bonnie from TRMM
August 22, 1998



Giulia Panegrossi

H SAF Science Manager

Institute of Atmospheric Sciences and Climate (ISAC)

National Research Council (CNR), Rome, Italy

Email: g.panegrossi@isac.cnr.it

Web site: <http://www.isac.cnr.it/en/users/giulia-panegrossi>



- Basic principles for satellite-based precipitation retrieval
- Passive microwave radiometers and retrieval history
- Precipitation retrieval techniques
- H SAF precipitation products and future perspectives

- Precipitation is the key hydrologic variable linking the atmosphere with land surface processes and playing a dominant role in hydrology, weather, and climate
 - Role in Water cycle, Earth radiation budget (latent heat), weather patterns
 - Feedback mechanisms with climate change
 - Natural hazards (floods/droughts/landslides)
 - Hydrology and water management
- *Accurate and continuous global* precipitation estimation is necessary for improving our understanding of climate, weather, and meteorological extremes, and their impact in hydrology



Precipitation “measurements”

Radars: Excellent space and time resolution; real time

Not available everywhere

Estimate depends upon Z-R relationship and calibration

Correction for: Attenuation; Beam blocking;

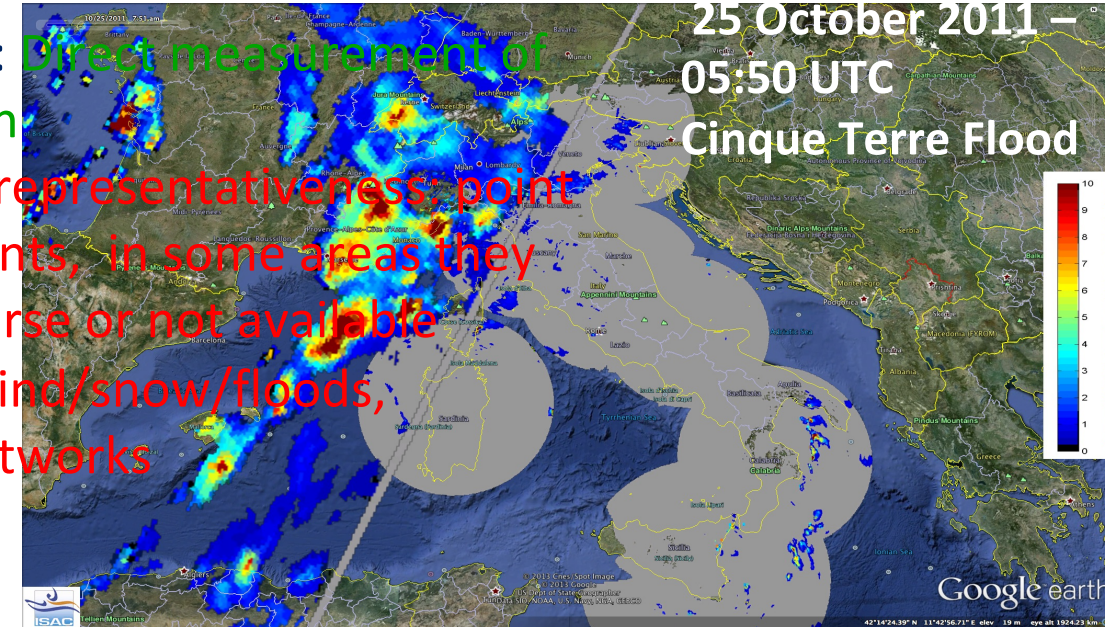
viewing geometry; DSD assumption; snowfall;

lack of inter-calibration between national radar networks

Raingauges: Direct measurement of precipitation

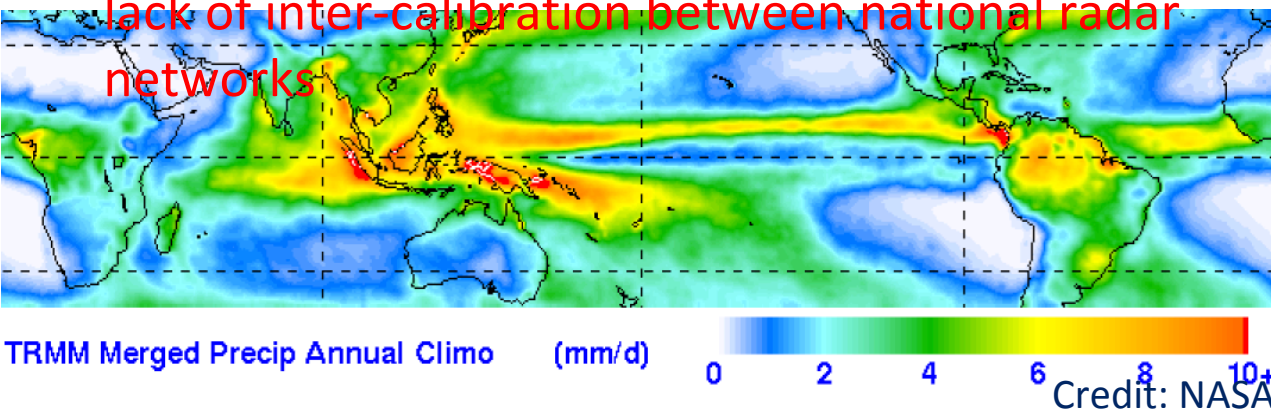
Problem of representativeness: point measurements, in some areas they are very sparse or not available

Impact of wind/snow/floods, different networks



First TRMM
satellite Rainfall
Global
Climatology
1998-2000

Italian Radar Network Mosaic (DPC)+
Rainfall rate retrieval
SSMIS overpass at 5:50 UTC



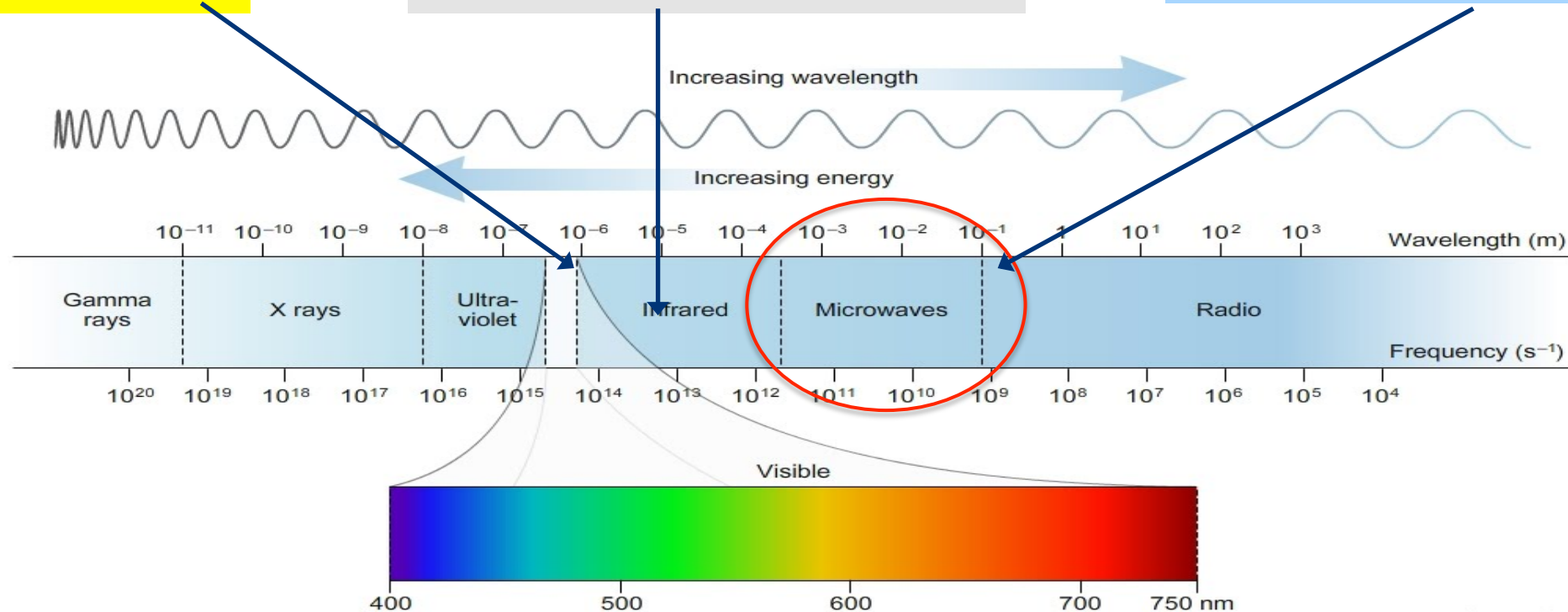
Satellite-based remote sensing of precipitation:
Global, provides precipitation at different temporal/spatial scales but...
It is based on a very complex retrieval process

Electromagnetic Spectrum Utilized For Remote Sensing of Precipitation

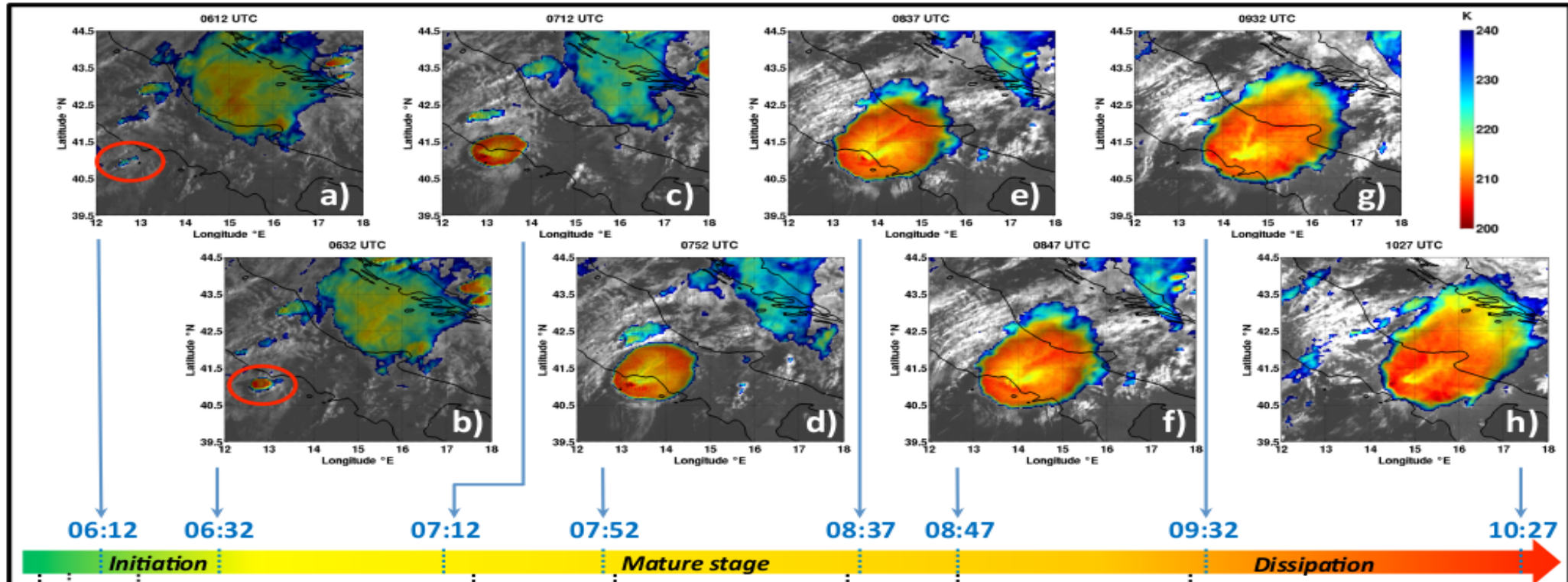
VIS: Maximum emission from the sun ($T=6000\text{ K}$) is from 0.4-0.7 microns wavelength (Visible spectrum)

IR: Maximum thermal emission from the Earth ($T=300\text{ K}$) is in the infrared (IR) wavelengths near 11 microns

Passive Microwave (PMW) (10-200 GHz) emission is much weaker, but able to penetrate clouds and more directly “sense” rainfall.



MSG VIS/IR composite, Naples hailstorm, 5 Sept., 2015



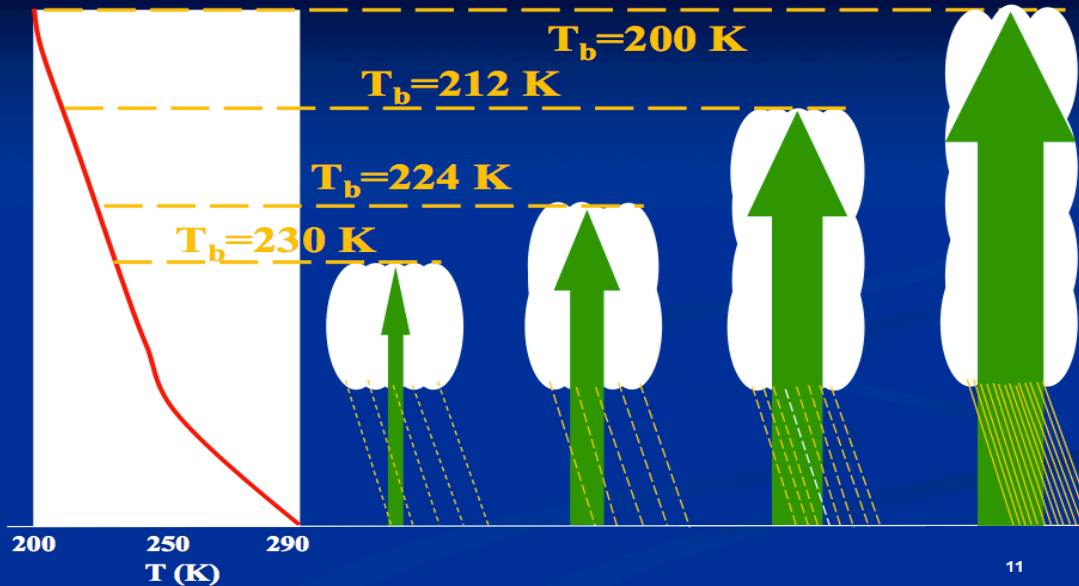
Marra et al., 2017, Atmos. Res.

Signal originates from the cloud top or a short distance below it (Rain clouds are optically thick in the VIS/IR)

IR brightness temperature (T_b) roughly corresponds to the cloud top T

Strong signal in VIS/IR, allows to monitor from geostationary orbit (GEO) (i.e., every 5-15 min), and at very fine spatial resolution (0.5-1 km VIS, 2-5 km IR)

Illustration of the IR signal from different rainfall intensities



Poor assumption for

- stratiform clouds (warm, but sometimes with significant rainfall)
- cirrus clouds (cold, but rain-free)

VIS/IR cloud detection and classification is very useful to better constrain precipitation retrieval

IR Assumption:

Colder in IR (deeper) -> heavy rain

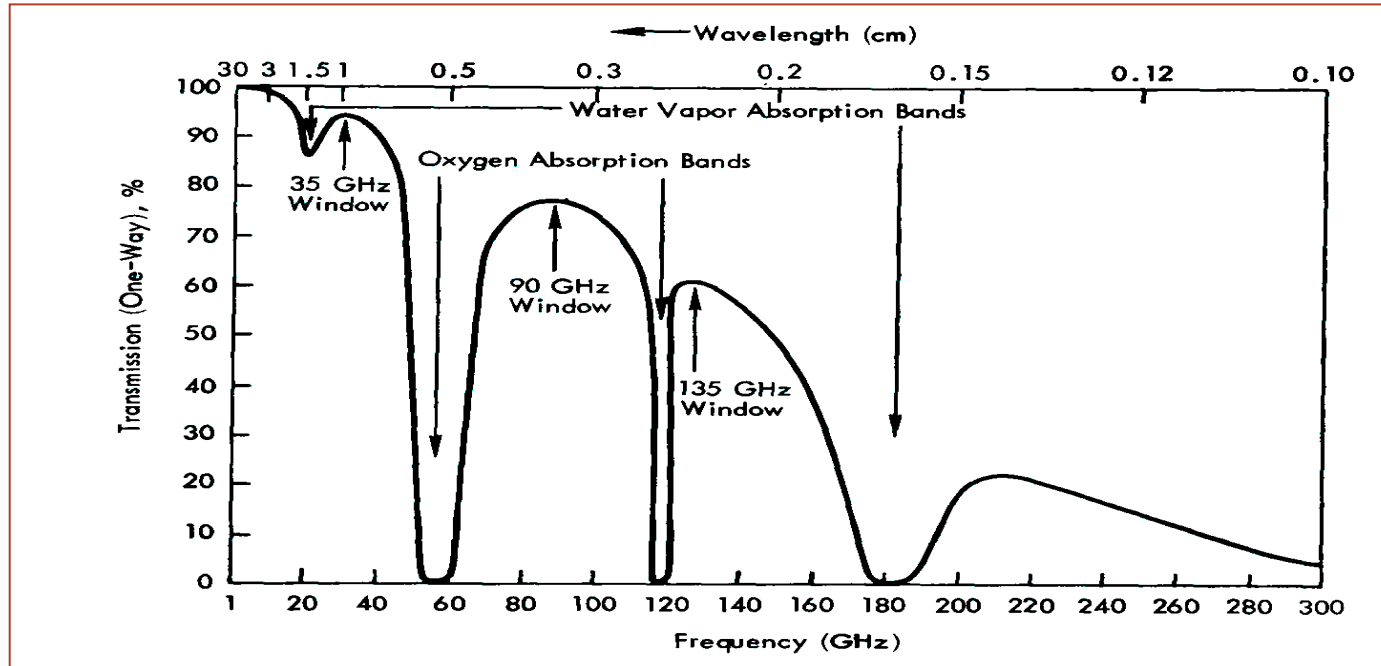
Reasonable assumption for convective clouds

Illustration of the IR signal from different cloud types



Credit: Kuligowski 8° IPWG Workshop

Clear-sky Zenith Microwave Transmittance

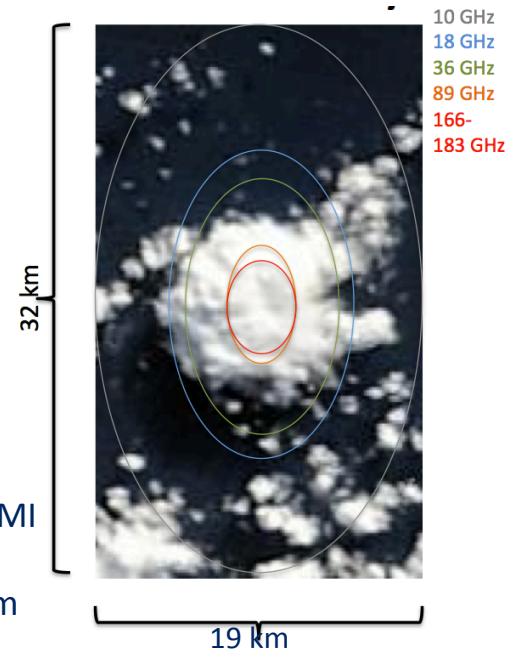


Percentage transmission of surface emitted radiation through the Earth's atmosphere along the vertical direction, under clear-sky conditions. [Adapted from Ulaby et al, 1981]

Frequency range for precipitation: 10-200 GHz
Wavelength 3 - 0.1 cm
Typical precipitation sizes:
Raindrops (0.01-0.8 cm) Snowflakes (0.1-2 cm)

- Angular resolution is diffraction limited
- $\sin(\theta) = \lambda/d$ (d = antenna size)
- Low orbits allow higher spatial resolution

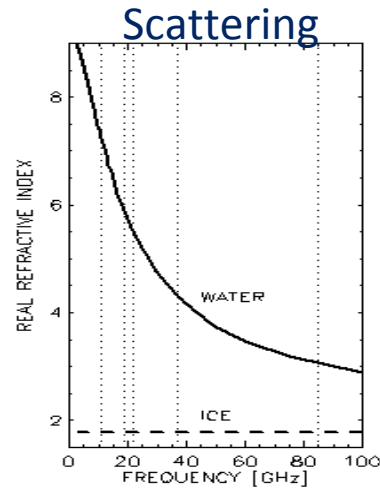
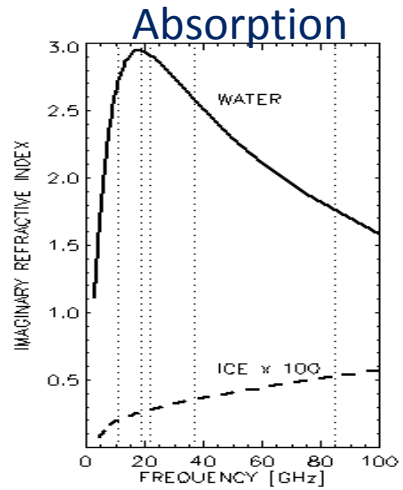
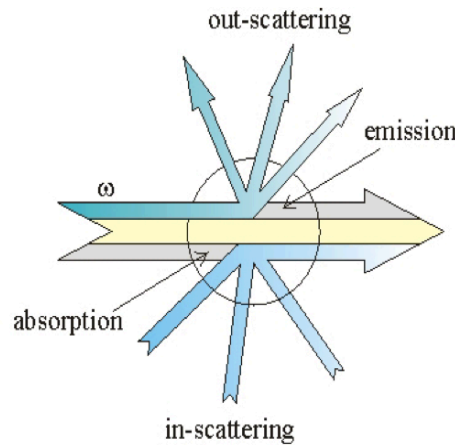
Imager IFOV: GMI
 $d = 1.2$ m
Altitude: 407 km



Weak energy source: only on LEO satellites (low temporal sampling), low spatial resolution (5-50 km)

In PMW radiometry the field of view must be large to detect enough energy to record a signal.

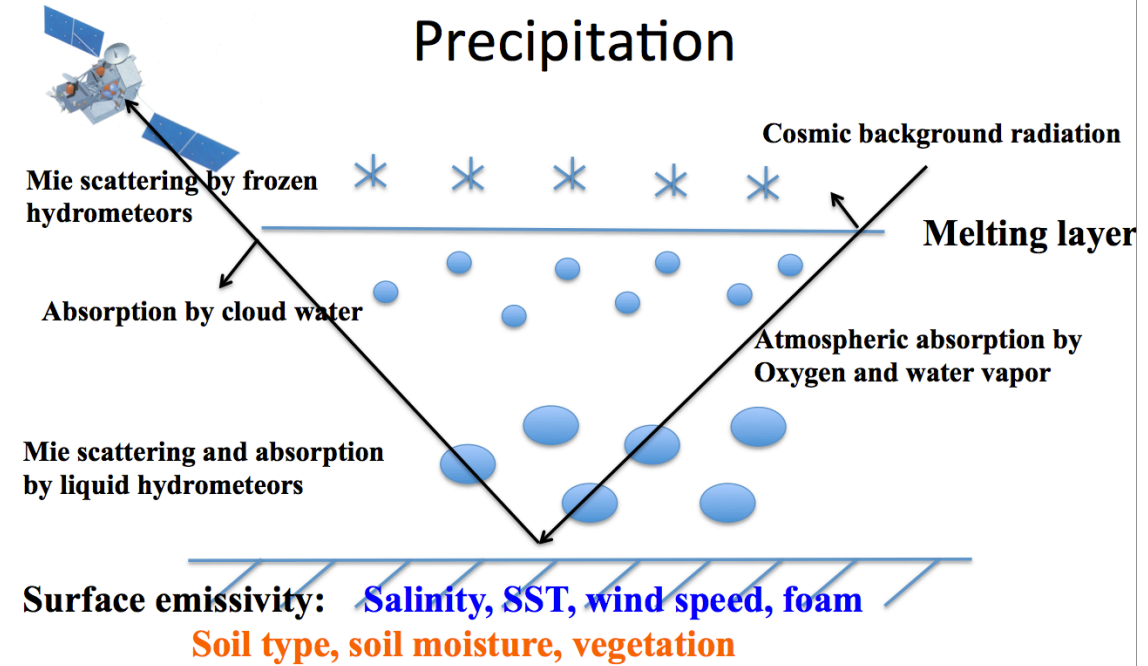
Microwave (MW) radiation emitted by the **Earth's surface** interacts with gases (oxygen and water vapour) and **liquid and solid hydrometeors** within the clouds. Interaction depends on optical properties: **scattering geometry and absorption (emission)**



Parameters governing optical properties:

- (1) The wavelength (λ) of the incident radiation
- (2) The size of the scattering particle and shape
- (3) The complex index of refraction (liquid/ice fraction)

Microwave Radiative Transfer in Precipitation

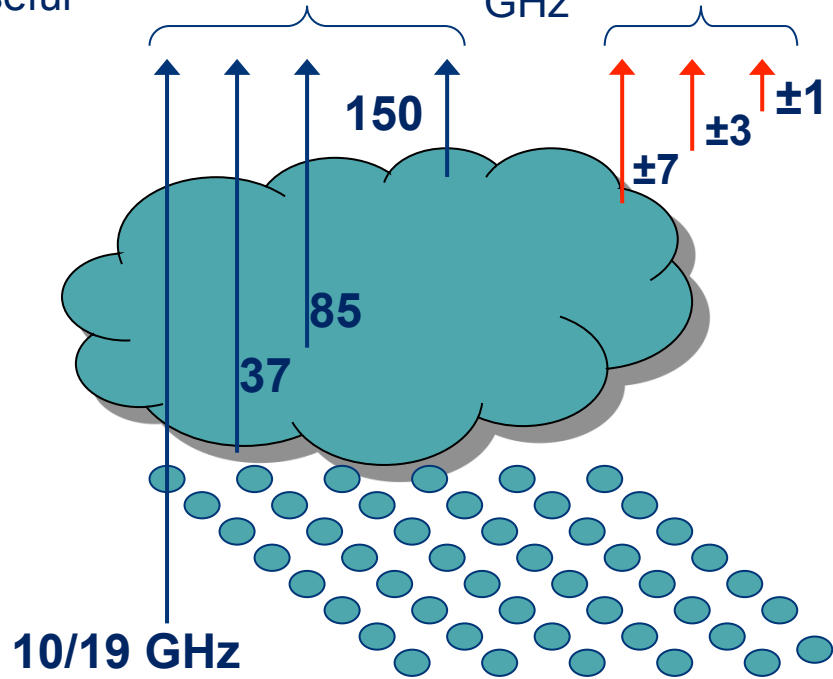


Credit: J. Munchak 8th IPWG workshop

The radiation detected (or T_b) depends on several elements: surf. emissivity and T , air moisture, 3-D distribution of hydrometeors, microphysics processes (optical properties), viewing geometry and spatial resolution

19-150 GHz imaging channels are the most useful

Water vapour absorption band 183.31 GHz

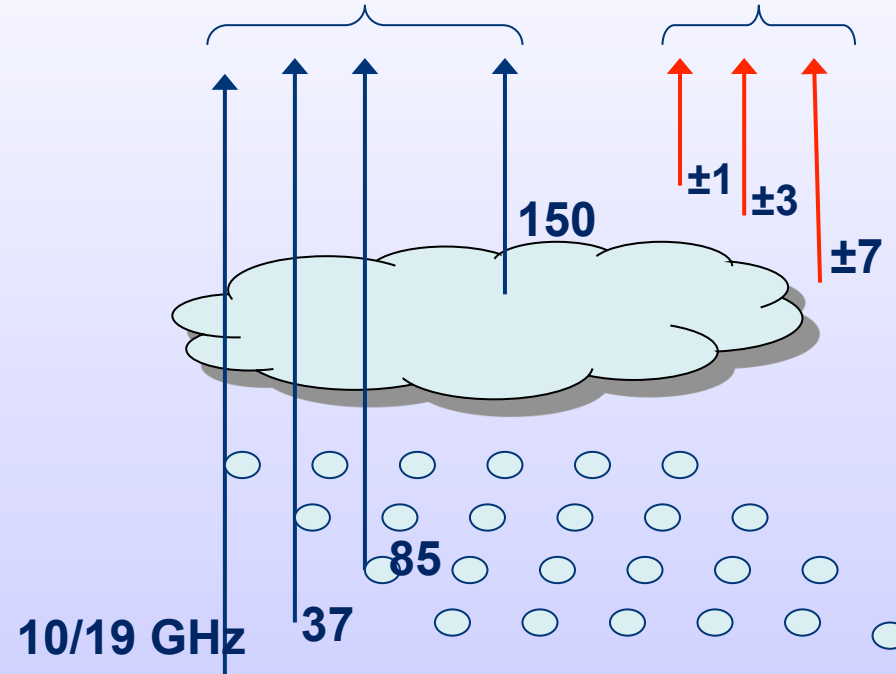


Tropical Rainfall

Convective clouds with ice region above rain

Significant surface contribution between 19-85 GHz

Surface is usually opaque at 150 and 183 GHz – signals due to snow and drizzle



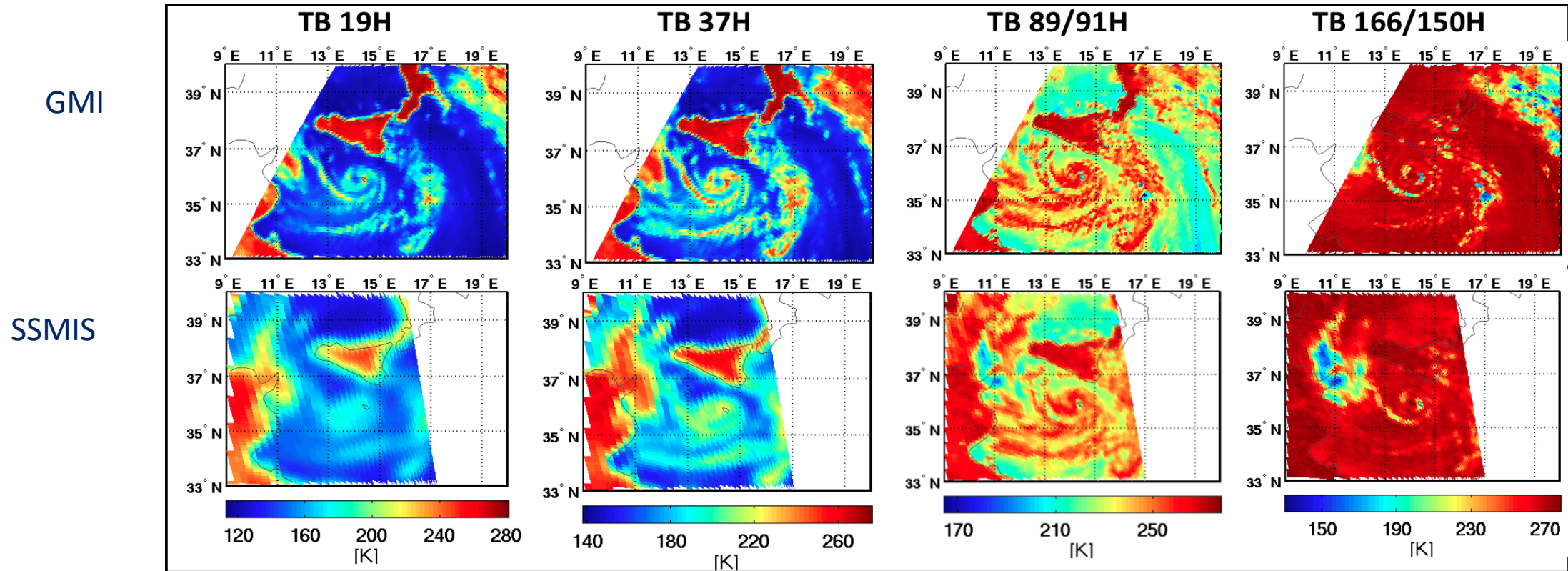
Higher Latitude Drizzle/Snowfall

Lower altitude clouds, mainly non-convective

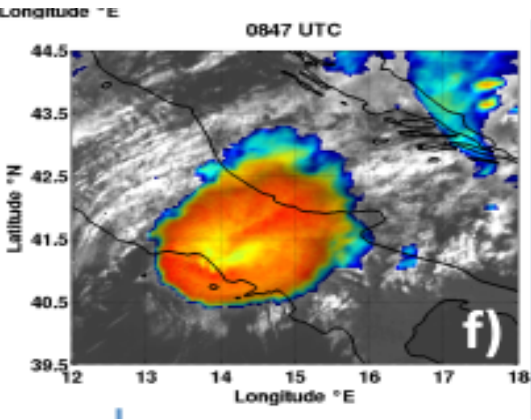
Depending on frequency, cloud microphysical structure, and air moisture, the signal reaching the radiometer originates from different parts within the cloud.

Credit: V. Levizzani

Medicane Qendresa - GMI and SSMIS overpass – November 7, 2014 1600 UTC

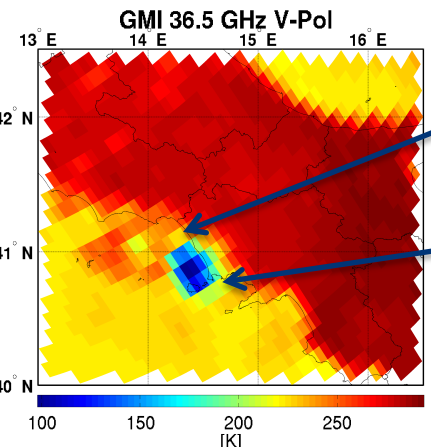
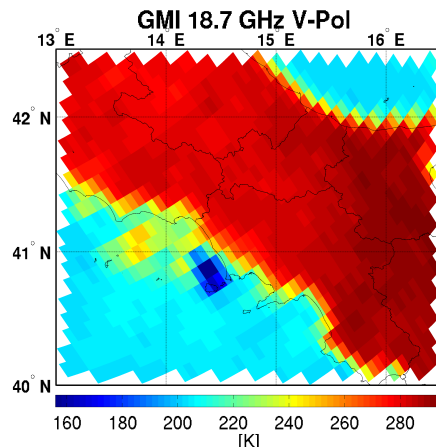


Effect of higher spatial resolution of GMI
(IFOV size $11 \times 18 \text{ km}^2$ at 19 GHz, and $4 \times 7 \text{ km}^2$ above 89 GHz)
SSMIS spatial resolution is three times lower

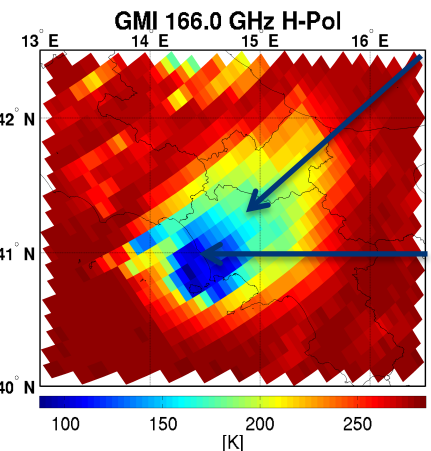
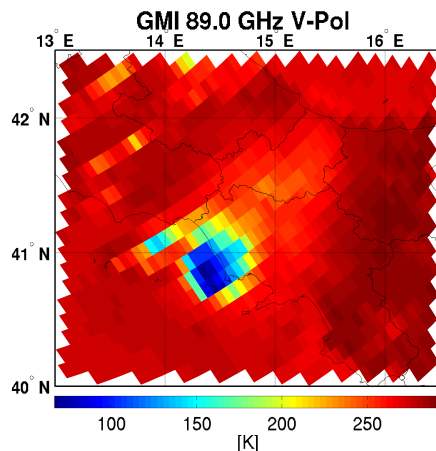


VIS/IR
8:47 UTC

GMI overpass 5 Sept. 2015 8:47 UTC



rainfall
hail



Anvil
Convective
core

MW radiometers spectral signature (TBs behaviour in the different channels) allows to characterize the microphysical structure of the precipitation

Extremely intense and deep convective core appears as area of low TBs also at low frequency (scattering by large hail)

High-frequency channels are sensitive to the different ice microphysics in the core and in the anvil



Marra et al., 2017
Atmos. Res.

Emission: liquid water (rain and cloud droplets) in clouds emits radiation (emission/absorption for ice particles is negligible). At lower frequencies (< 30 GHz) liquid precipitation appears as a radiatively warmer area (higher TBs) against a cold background (i.e. oceans)

- **Strength:** effect visible also for clouds with little or no ice
- **Weakness:** must know terrestrial radiances without cloud beforehand; generally applicable over oceans but not over land

Scattering: Both liquid (rain) and solid hydrometeors scatter the radiation. Scattering by ice increases with frequency; clouds scatters (warm) terrestrial radiation downward, producing cold areas in imagery.

- **Strength:** use of high-frequency channels (higher spatial resolution), effect visible over both land and ocean
- **Weakness:** indirect relation to surface precipitation;

Low precipitation-related TB signal for:

- Orographic precipitation (with warm-topped clouds); warm rain;
- Light precipitation at high latitudes (low moisture and temperature conditions)
- Snowfall and/or with presence of snow/ice at the ground

LEO MW

Advantages:

Samples remote (polar) regions
Consistent measurement system
More physically based, more accurate than VIS/IR estimates

Disadvantages:

- Poorer time and space resolution (~3 hr, ~5-50 km)
- Not a direct measurement of **surface** precipitation (over land)
- Different radiometers' characteristics (e.g. imagers vs. sounders)
- *Underestimates rainfall from warm-top clouds over land (i.e., orographic rain)*

VS.

GEO VIS/IR

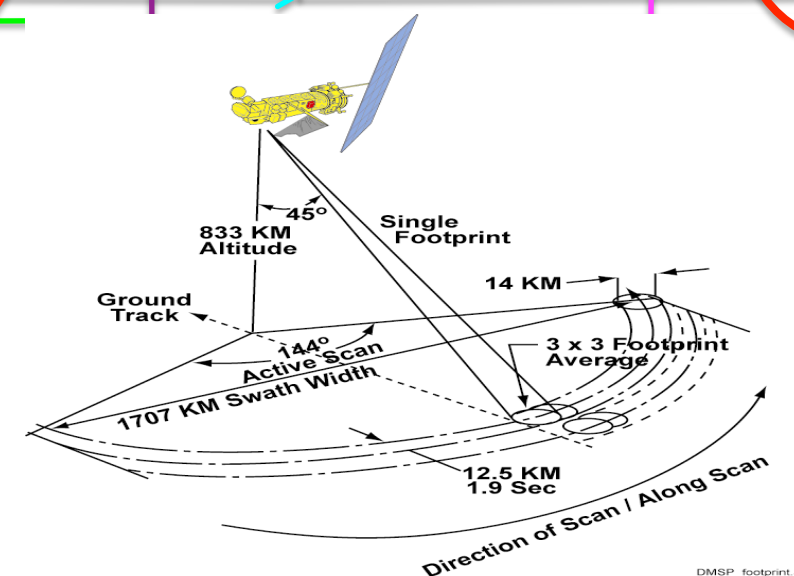
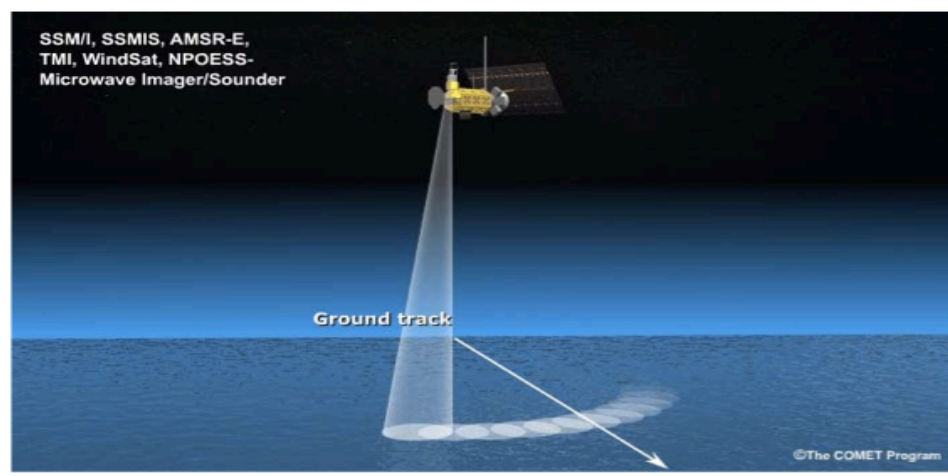
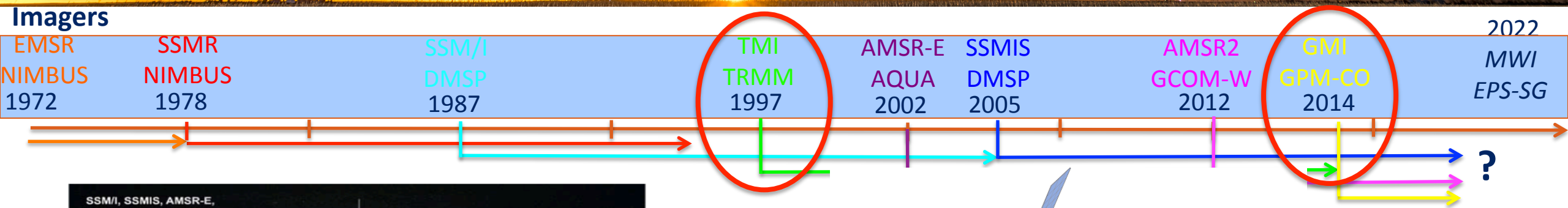
Advantages:

Good space and time resolution
Observations in near real time
Samples oceans and remote regions
Consistent measurement system

Disadvantages:

- Does not sample remote (polar) regions
- Measures cloud-top properties instead of rain
 - *May mistake cirrus for rain clouds*
 - *Does not capture rain from warm clouds*

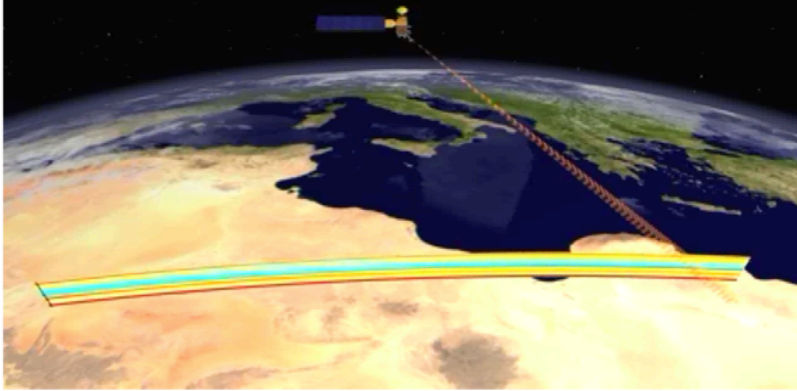
Most used approach for several applications is to combine MW-based precipitation retrievals with GEO IR observations, (e.g., NASA IMERG, JAXA GSMaP, NOAA CMORPH, H SAF)



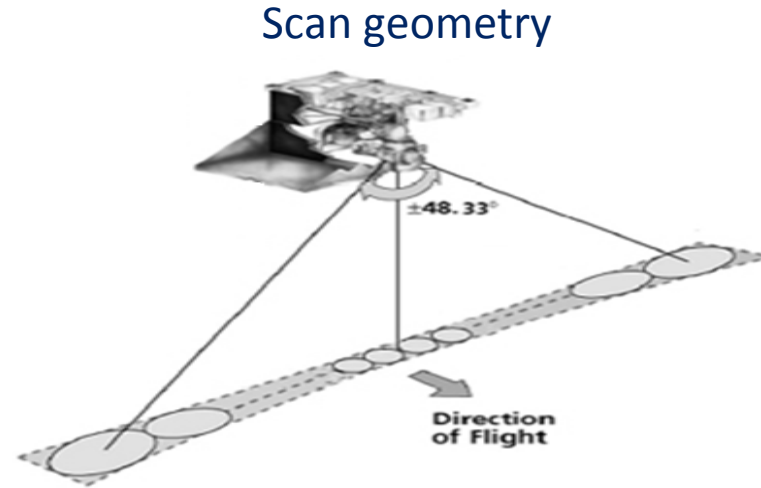
900-1800 km
swath width

- Constant incidence angle
- Primarily window channels (low K_{abs})
- Examples: GMI, AMSR2, SSMIS
- Future: MWI, ICI

IFOV: frequency-dependent (5-50 km)
Sampling distance 5-12.5 km
Frequency range: 10-190 GHz
V and H polarization channels



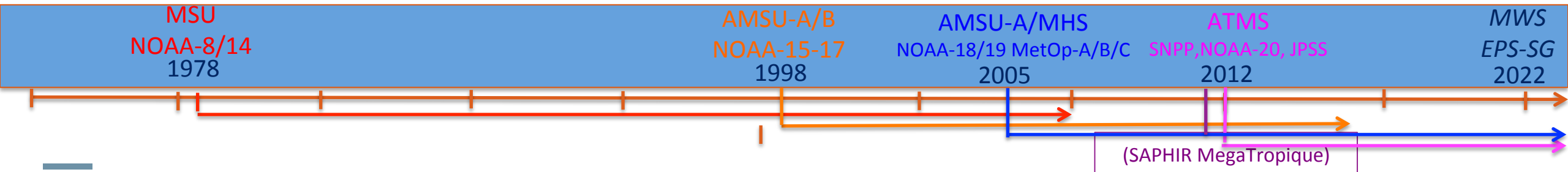
- Variable incidence angle
- Primarily sounding channels (high K_{abs})
- Examples: AMSU-A/B, MHS, ATMS, SAPHIR
- Future: MWS

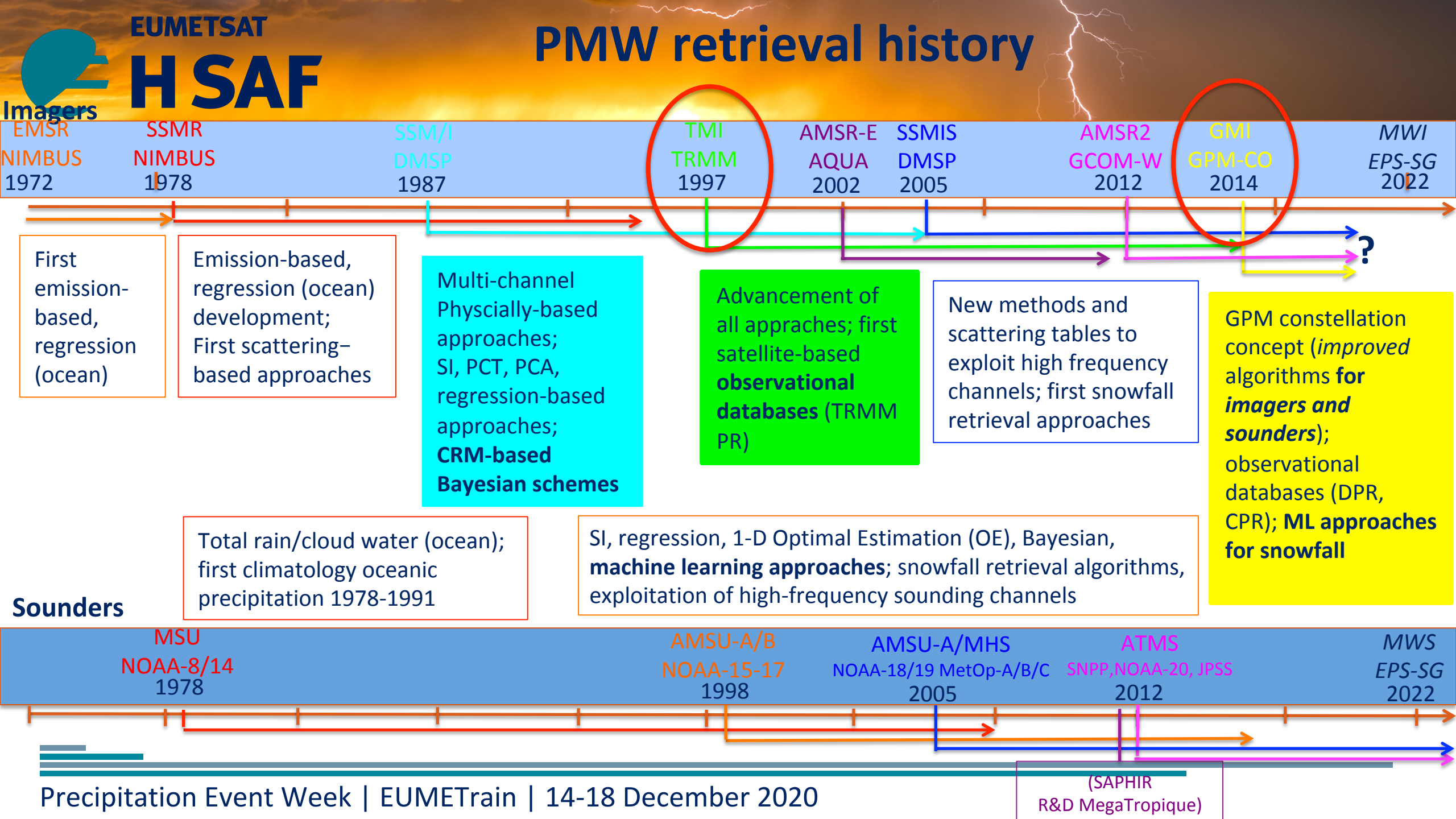


Swath width 2200-2600 km

IFOV: 16 km (MHS/ATMS) at nadir (decreasing towards the edge of the scan)
Sampling distance 16 km
Frequency range: usually 89-190 GHz

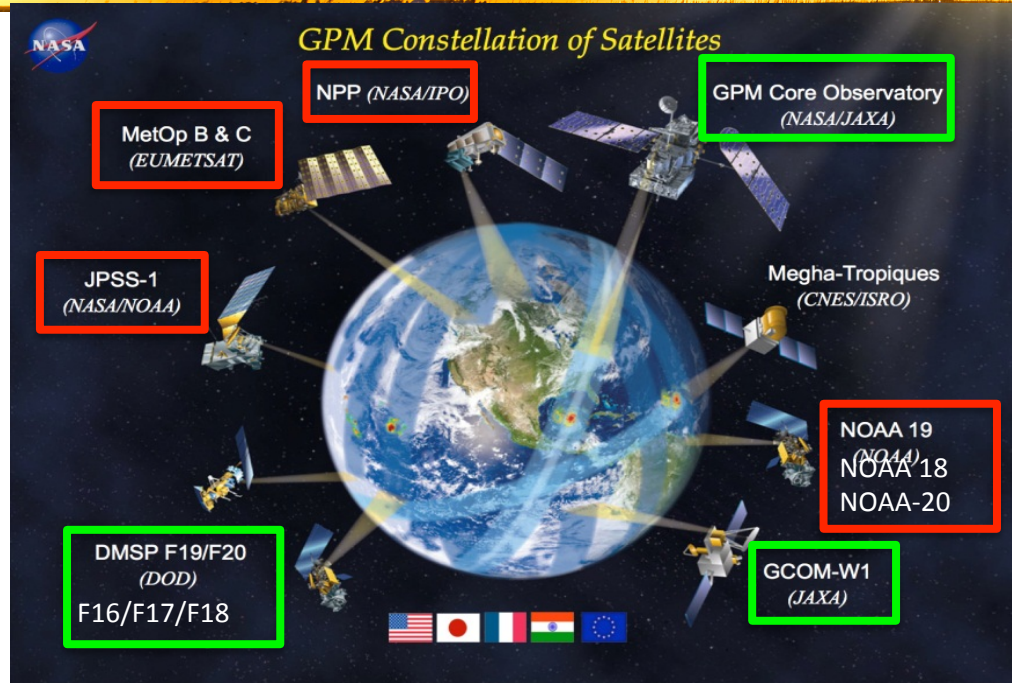
Sounders





The GPM mission concept

<https://pmm.nasa.gov/gpm>



New opportunities for remote sensing of precipitation:

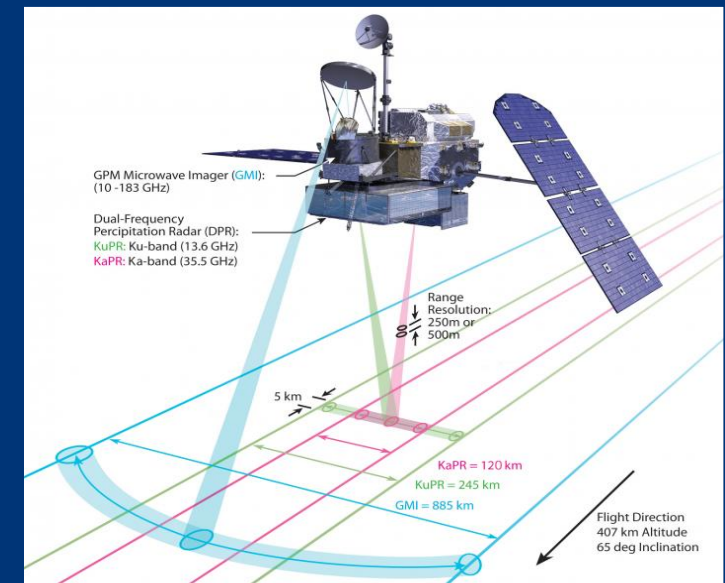
- **Improved global precipitation products** (rainfall and snowfall);
- **Increased use of satellite products for several applications** (i.e., hydrology)
- **Monitoring and analysis of extreme events** (3D structure of precipitation, understand processes, improve forecast)

- *International effort with 12 LEO satellites equipped with 6 different radiometers, 1 dual-frequency precipitation radar (+ CloudSat)*
- 3-h global coverage (1.5-h over the Mediterranean region, on average);

THE NASA/JAXA GPM CORE OBSERVATORY

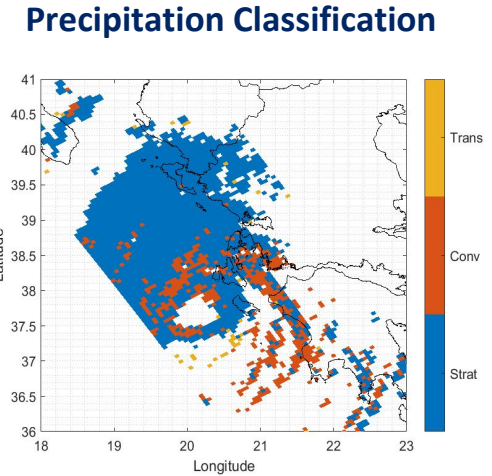
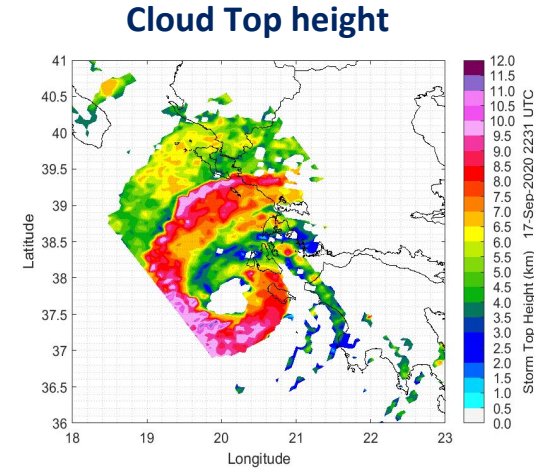
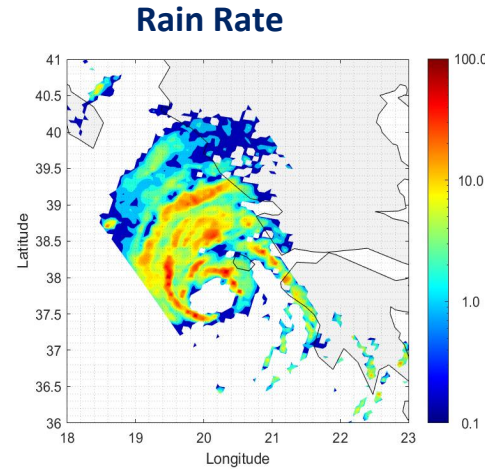
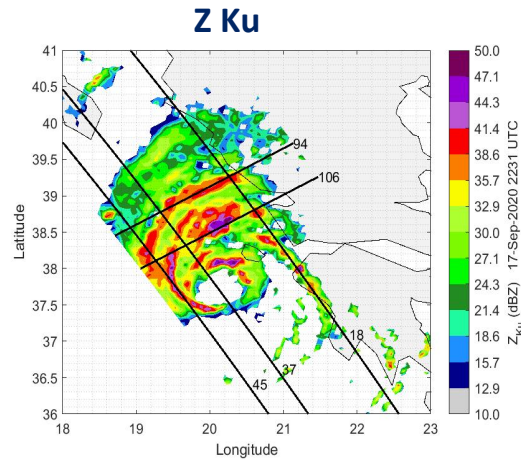
GPM Microwave Imager (GMI): 13 precipitation sensing channels (10-183 GHz) with the highest spatial resolution available (5-30 km);

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



Medicane Ianos – GPM-DPR 17 November 2020 22:28 UTC

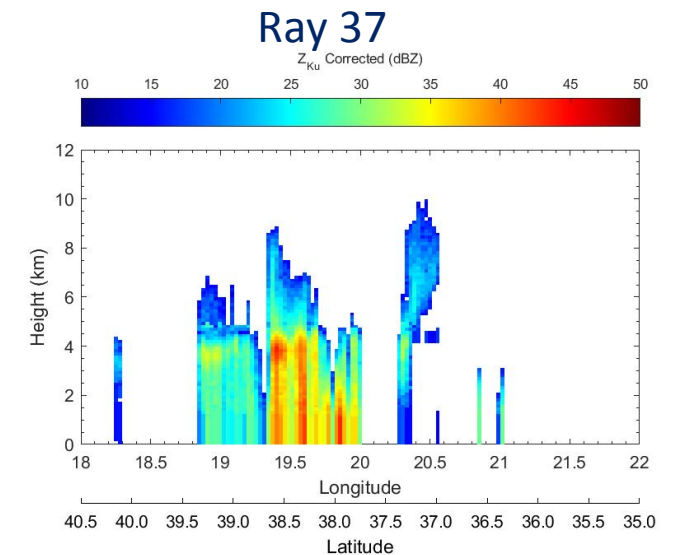
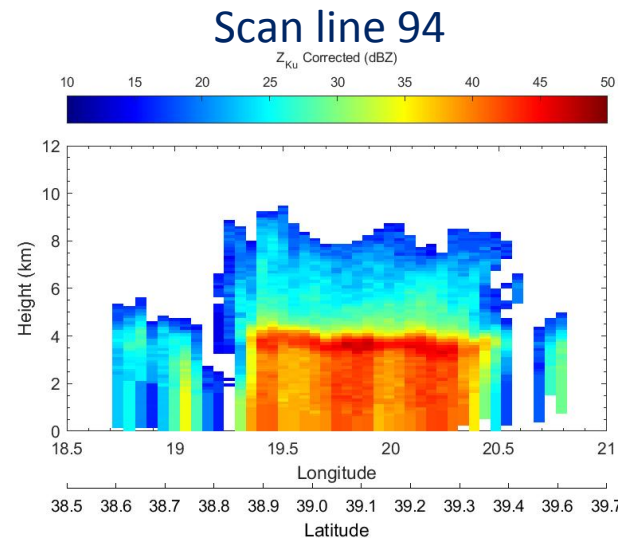
First GPM DPR overpass of a Medicane during its mature phase



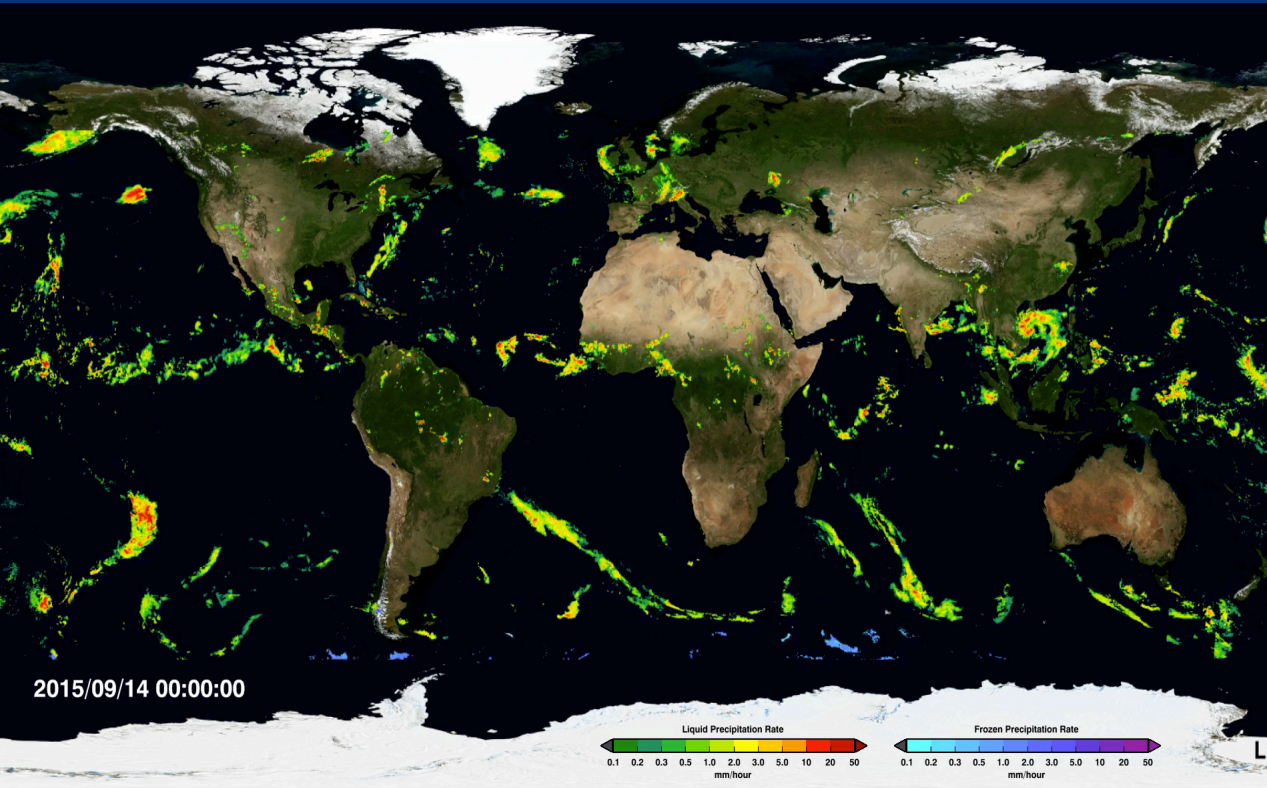
GPM DPR-based products and co-located PMW measurements allow to build near-global observational datasets to be used in PMW retrieval algorithms

Pros: near-global coverage (65°N/S), consistency around the globe (incl. oceans)

Cons: DPR sensing capabilities (e.g., low sensitivity for very light precip. and snowfall), uncertainties of DPR-based products

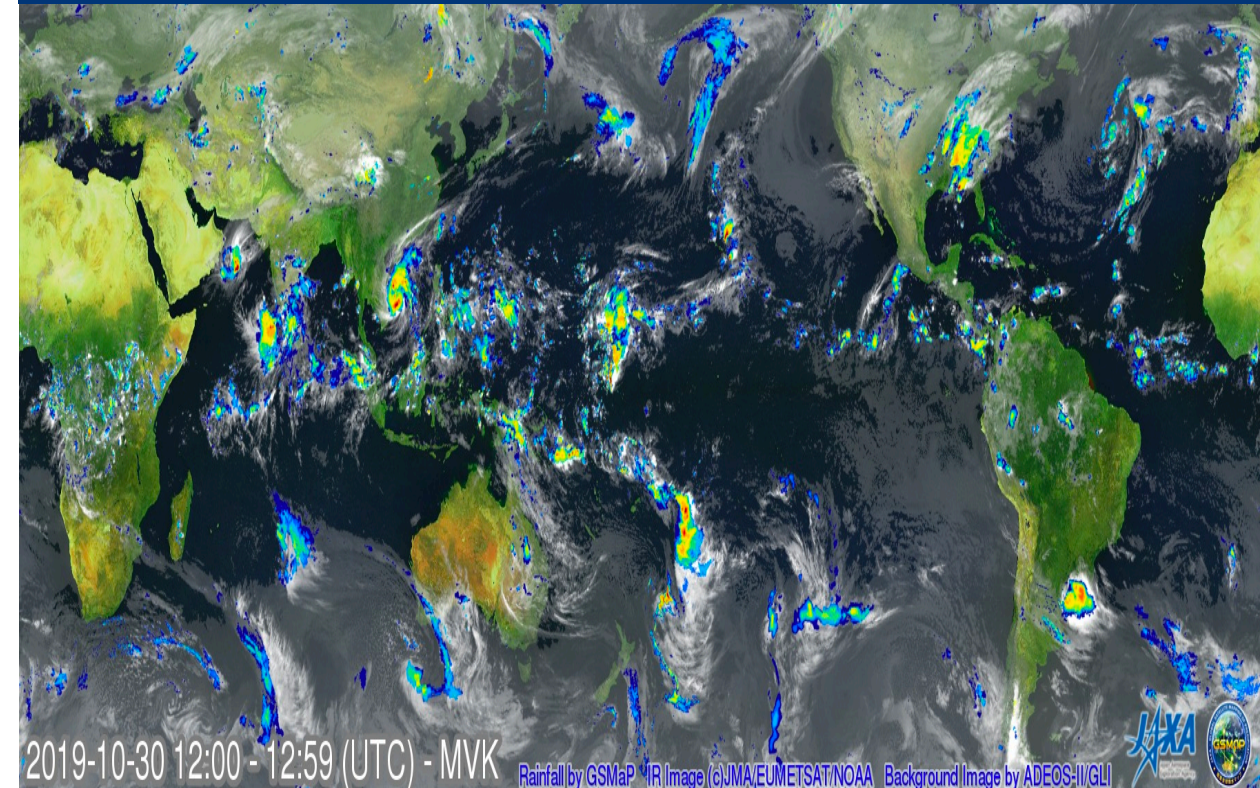


NASA GPM IMERG (<https://gpm.nasa.gov/data/imerg>)



Rainfall rate (mm/h) Coverage 90°N/S Grid resolution: 0.1°x0.1°
Temporal resolution 0.5 h (Credit, NASA PMM, Dr. Huffman)
Latency: Early run 4 h Final run 3-4 months

JAXA GSMaP (<https://sharaku.eorc.jaxa.jp/GSMaP/guide.html>)



Rainfall rate (mm/h) Coverage: 60°N/S Grid Resolution: 0.1°x0.1°
Temporal resolution: 1 h Updated every 30 m
Latency 4 h

H SAF is the most important effort in Europe dedicated to provide satellite precipitation products, i.e., **quantitative precipitation estimation**, for operational hydrology and water management applications

The advent of GPM mission (March 2014) has offered new opportunities and challenges for H SAF PMW precipitation product development and validation

No-cost scientific collaboration proposal approved by the NASA PMM Research Program and endorsed by EUMETSAT (since 2014, ongoing)

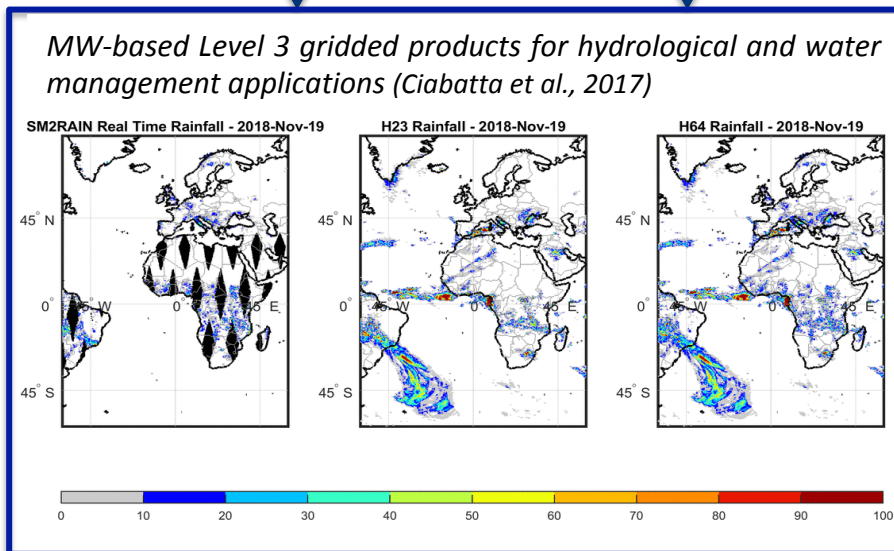
“H-SAF and GPM: precipitation algorithm development and validation activity”

- ***precipitation retrieval algorithm development***, through a fruitful interaction on several critical aspects of interest both to H SAF and GPM; ***Scientific coordinator: Giulia Panegrossi (ISAC-CNR)***
- ***validation activity***, through the connection between the well established H-SAF product validation and hydrological validation programs and the Ground Validation/Calibration activity of GPM; ***Scientific Coordinator: Silvia Puca (DPC)***

H SAF Precipitation Concept



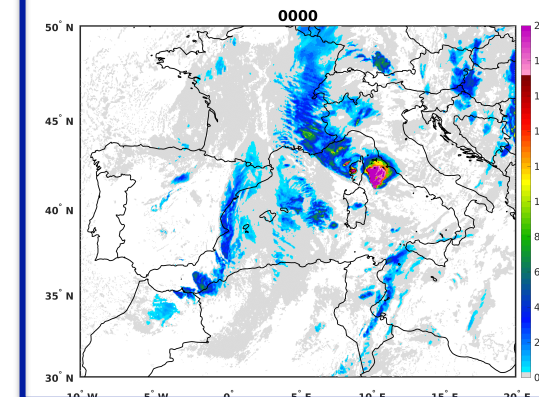
H SAF Soil Moisture-based product (SM2RAIN)



Exploitation of GPM constellation

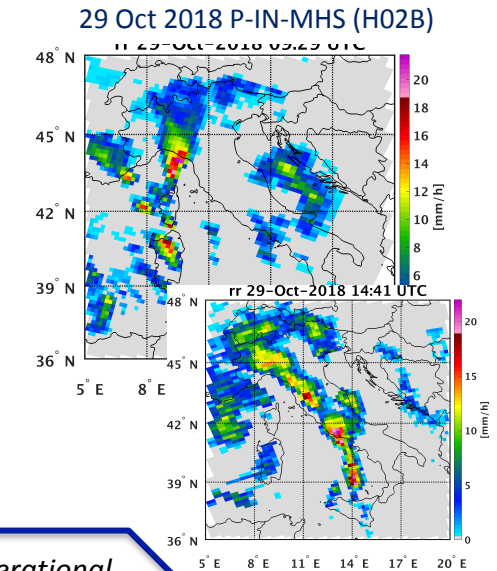
PMW Level 2 NRT products/auxiliary modules: Exploitation of **all current and future PMW radiometers** (conically and cross-track scanning) on board LEO satellites (Bayesian and **Machine Learning approaches**)

MW/IR NRT precipitation products for operational hydrology and precipitation monitoring (for MSG and MTG)



P-IN-SEVIRI (H03) HSAF Product:
MW/IR Rapid Update Technique

- Spatial Resolution: SEVIRI IR
- Temporal resolution: 15 min
- Available in NRT (latency 15-20 min)



H SAF PMW Level 2 Precipitation rate products: exploitation of GPM constellation

Acronym (Product ID) (Instrument)	Product Description	Algorithm	Reference	Currently available satellites	Status/ Availability
P-IN-SSMIS (H01) (SSMIS)	Precipitation rate at ground by MW conical scanner SSMIS (MSG full disk)	Physically-based Bayesian (CDRD) Cloud-radiation model a priori database	Casella et al., 2013, IEEE TGRS Sanò et al., 2013 IEEE TGRS	DMSP F16/F17/F18	Operational
P-IN-MHS (H02B) (AMSU/MHS)	Precipitation rate at ground by MW cross-track scanners AMSU/MHS (MSG full disk)	Neural Network (PNPR) Cloud-radiation model training database	Sanò et al., 2015 AMT	MetOp-B/C NOAA-18/19	Operational
P-IN-ATMS (H18) (ATMS)	Precipitation rate at ground by MW cross-track scanners ATMS (MSG full disk)	Neural Network (PNPR) Cloud-radiation model training database	Sanò et al., 2016 AMT	Suomi NPP NOAA-20 (JPSS series)	Operational
P-IN-AMSR2 (H-AUX-17) (AMSR-2)	Precipitation rate at ground by MW conical scanner AMSR-2 (based on GMI/DPR Observational Dataset) (MSG full disk)	Physically-based Bayesian CDRD GPM-based observational a priori database	Casella et al., 2017 IEEE JSTARS	GCOM W1	Auxiliary: Support to MW-only and MW/IR combined products
P-IN-GMI (H-AUX-20) (GMI)	Precipitation Rate at ground by GMI – (based on GMI/DPR Observational Dataset) (<i>Global</i>)	Neural Network GPM-based observational a priori database	Sanò et al., 2018, Rem. Sens.	GPM-CO	Auxiliary: Support to MW-only and MW/IR combined products

ML techniques and future H SAF Precipitation Products

H SAF precipitation products are evolving toward massive use of *machine learning approaches* (already used since 2006, newly developed Artificial Neural Network (ANN) products since 2011)

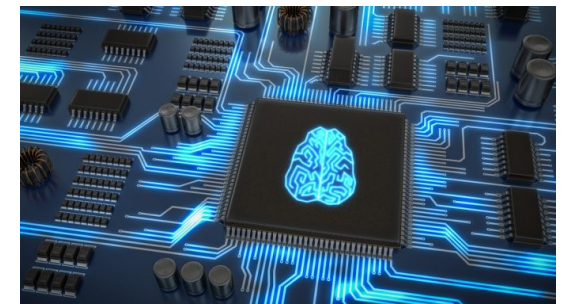
WHY:

- Machine learning algorithms have been successfully adapted to remote sensing and rainfall applications.
- With reference to the rainfall/snowfall retrieval, this approach originates from the consideration that an exact relation between surface precipitation rate and observed multi-channel brightness temperatures is nonlinear and difficult to identify.
- Machine learning algorithms have proven to be suitable for contributing to overcome these difficulties.



WHICH ONE:

- Artificial Neural Network : used for the **detection**/**classification**/**estimate** of rainfall/snow
- Convolutional Neural Network : used for the **detection**/**classification** of rainfall/snow
- Random Forest: used for the **detection**/**classification** of rainfall/snow fall
- Genetic Algorithm: used for optimization problems (i.e. the precipitation **estimates**)
- Gradient Boosting: used for the **estimate** of rainfall/snow fall
- Deep learning: is being evaluated for **pattern analysis** and **classification**



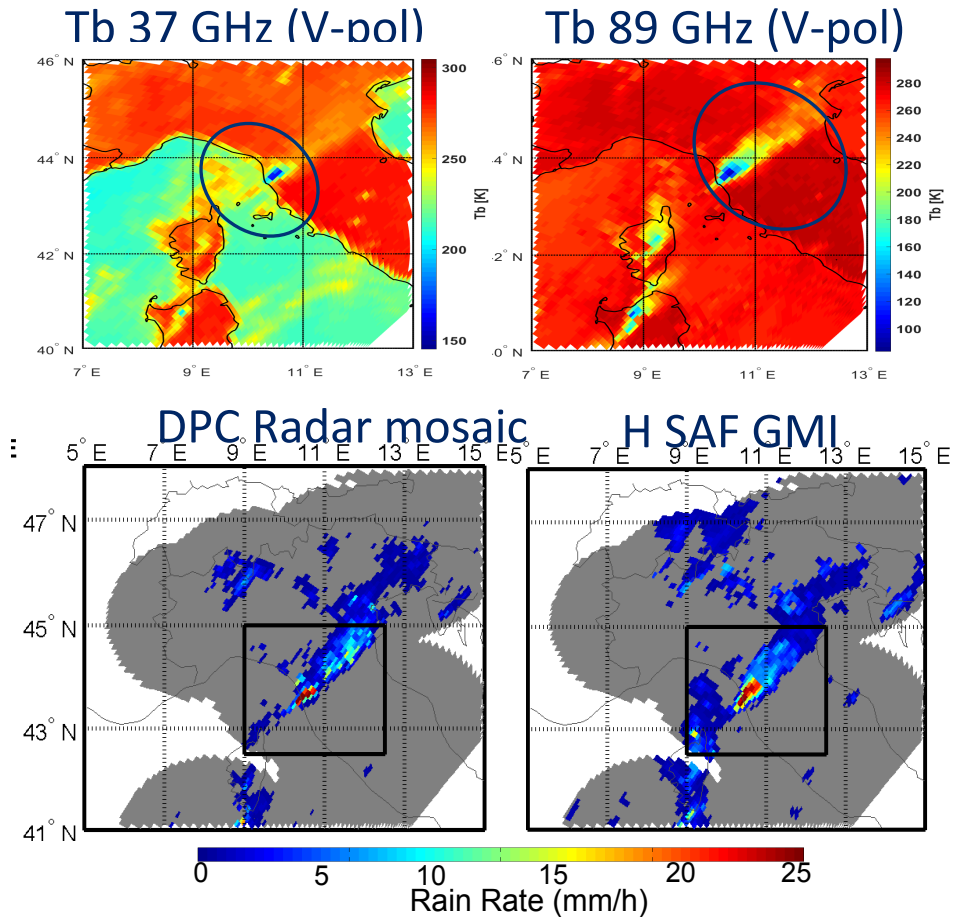
Based on PNPR Artificial Neural Network approach for the GMI conically scanning radiometer

P-IN-GMI (**auxiliary module H-AUX-20**) is based on ANN trained on an global observational database built from GPM-CO global observations

- DPR-based rainfall rate product is used as reference (2B-CMB product).
- Two ANN-based modules one for precip. detection and one for precip. estimation;
- New detection scheme provides different rainfall masks for different probability thresholds

A new auxiliary module for **global rainfall rate estimates from AMSR-2** will be developed during CDOP-4

Livorno flash-flood 9-10 September 2017

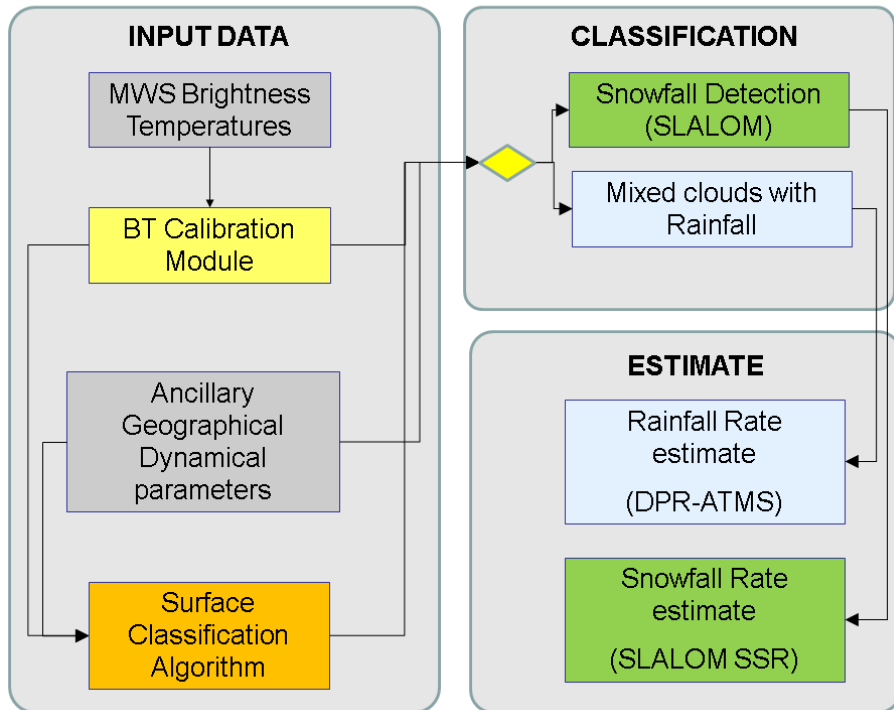


Sanò et al. 2018, Remote Sens.

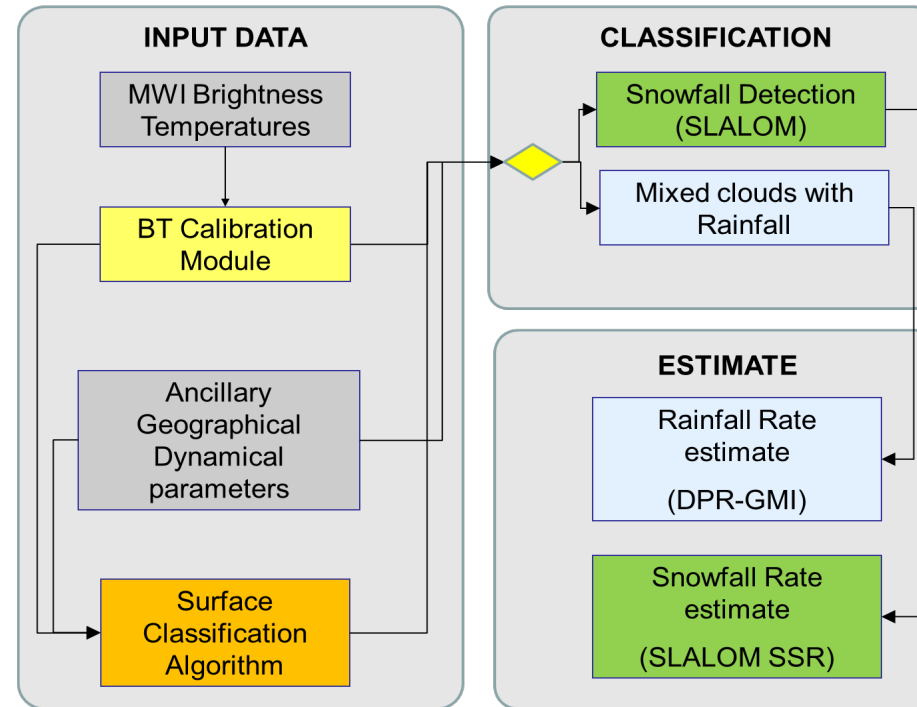
EPS-SG global ML-based precipitation products

Day-1 EPS-SG Level 2 Precipitation rate products (CDOP-3**)

MWS H70 Day-1



MWI H71 Day-1



**** Exp. operational after EPS-SG-A/B commissioning phases, during CDOP-4**

Observational training dataset built from global coincident measurements of existing PMW radiometers (ATMS and GMI) with GPM DPR (for rainfall) and CloudSat CPR (for snowfall)

Day-2 EPS-SG products will be developed during CDOP-4 with additional ML-based dedicated modules

H03B – CDOP 2

- Precipitation from PMW radiometers used as calibrator
- Only IR 10.3 μ m channel

Rapid Update Blending Technique approach

**Session 4
Wed 9 UTC**

H60B/MTG day1 (H40B) – CDOP 3

- Precipitation from PMW radiometers used as calibrator
- Only IR 10.3 μ m channel
- NEFODINA for convective clouds

Machine Learning approach MTG Day2 product– CDOP4

Module 1

- Parallax correction
- Preliminary analysis on clouds structure
- VIS-IR channels
- Testing of different ML approaches: Deep Learning, Convolutional Neural Network, Random Forest.

Run 1

- Precipitation rate derived from a dataset of coincidence FCI TBs-DPR/GMI RR
- Testing of different ML approaches (ML1): Gradient Boosting, Artificial Neural Network, Genetic Algorithm.

Module 2

Run 2

- Calibration of Run 1 outputs with the latest PMW-based (i.e. H68) precipitation rate.
- Testing of different ML approaches (ML2): Gradient Boosting, Artificial Neural Network, Genetic Algorithm.

H SAF Precipitation Cluster

Davide Melfi (ITAF COMET) Precipitation Cluster Leader

Paolo Sanò, Daniele Casella, Leo Pio D'Adderio, Stefano Dietrich, Giulia Panegrossi

CNR ISAC, Rome Italy

Luca Brocca, Luca Ciabatta, Christian Massari

CNR IRPI, Perugia, Italy

Federico Porcù

Department of Physics and Astronomy, University of Bologna

Claudio Giorgi

Geo-K

<http://hsaf.meteoam.it>

(new website available soon)

Questions?

Giulia Panegrossi (CNR-ISAC)

H SAF Science Manager

email: g.panegrossi@isac.cnr.it



H SAF Products Documentation <http://hsaf.meteoam.it/user-documents.php>

- Casella, D., Panegrossi, G., Sanò, P., Mugnai, A., Smith, E.A., Tripoli, G.J., Dietrich, S., Formenton, M., Di Paola, F., Leung, H. W.-Y., and Mehta, A.V.: Transitioning from CRD to CDRD in Bayesian retrieval of rainfall from satellite passive microwave measurements, Part 2: Overcoming database profile selection ambiguity by consideration of meteorological control on microphysics, IEEE Trans. Geosci. Remote Sens, vol.51, no.9, pp.4650-4671, 2013, DOI: 10.1109/TGRS.2013.2258161, 2013.
- Casella, D., et al., 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.
- Casella D. et al., The Cloud Dynamics and Radiation Database algorithm for AMSR2: exploitation of the GPM observational dataset for operational applications, IEEE J. of Sel. Topics in Appl. Earth Obs. and Rem. Sens. (J-STARs), 10(8), DOI : 10.1109/JSTARS.2017.2713485, 2017.
- Ciabatta L., et al., Daily precipitation estimation through different microwave sensors: Verification study over Italy, J. of Hydrology, 545, 436-450, doi: 10.1016/j.jhydrol.2016.12.057, 2017
- Sanò, P., et al.: The Passive microwave Neural network Precipitation Retrieval (PNPR) algorithm for AMSU/MHS observations: description and application to European case studies, Atmos. Meas. Tech., 8, 837-857, doi:10.5194/amt-8-837-2015, 2015
- Sanò, P., Panegrossi, G., Casella, D., Marra, A. C., Di Paola, F., and Dietrich, S.: The new Passive microwave Neural network Precipitation Retrieval (PNPR) algorithm for the cross-track scanning ATMS radiometer: description and verification study over Europe and Africa using GPM and TRMM spaceborne radars, Atmos. Meas. Tech., 9, 5441-5460, doi:10.5194/amt-9-5441-2016, 2016
- Sanò P., G. Panegrossi, D. Casella, A. C. Marra, L. P. D'Adderio, J.-F. Rysman, S. Dietrich, The Passive Microwave Neural Network Precipitation Retrieval (PNPR) algorithm for the Conical Scanning GMI Radiometer, Remote Sens. 10, 1122; doi:10.3390/rs10071122, 2018

Extra slides

Passive remote sensing: Two key terms

Brightness Temperature [K]

T_b is the temperature of a blackbody that would emit the same amount of radiation as the targeted body in a specified spectral band

$$I_{\lambda}(T) = B_{\lambda}(Tb_{\lambda})$$

It is used to measure the Earth spectral radiance *reaching the satellite in a given direction*

Plank Function:

$$B_{\lambda}(T) = \frac{2hc^2}{\lambda^5 \left[e^{\frac{hc}{k\lambda T}} - 1 \right]}$$

Rayleigh-Jeans Approximation:
hc/kλT << 1 (MW spectrum)

$$B_{\lambda}(T) = \frac{2ckT}{\lambda^4}$$

Observed Radiance:

$$I_{\lambda} = \varepsilon_{\lambda} \cdot B_{\lambda}(T)$$

Observed Brightness Temperature: $Tb_{\lambda} \propto \varepsilon_{\lambda} \cdot T$

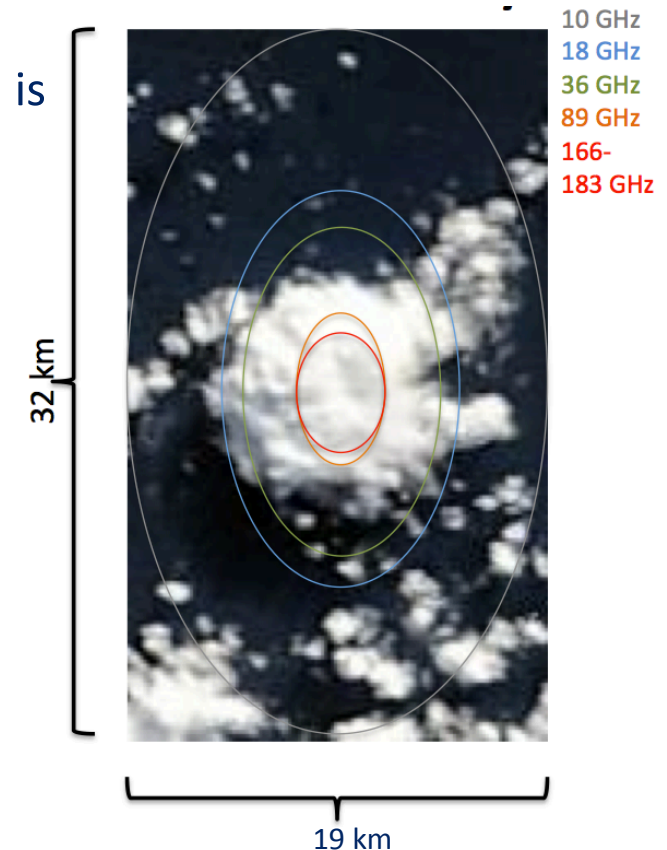
Spatial resolution

It defines the size of the smallest possible feature that can be detected (depends on IFOV)

Angular resolution is diffraction limited
 $\sin(\theta) = \lambda/d$ (d = antenna size)

Low orbits allow higher spatial resolution

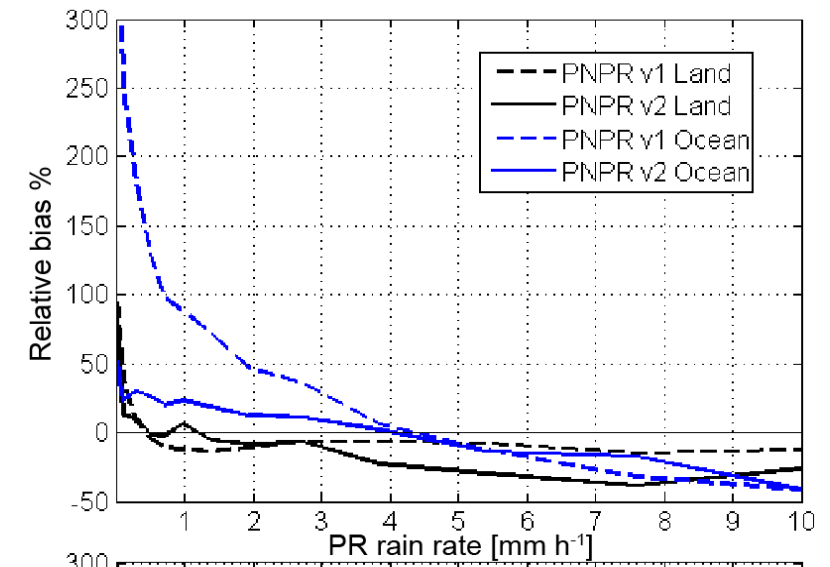
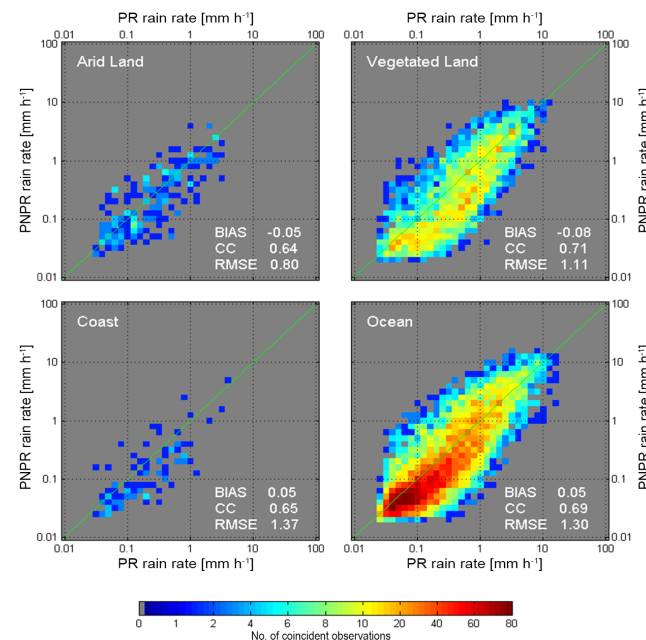
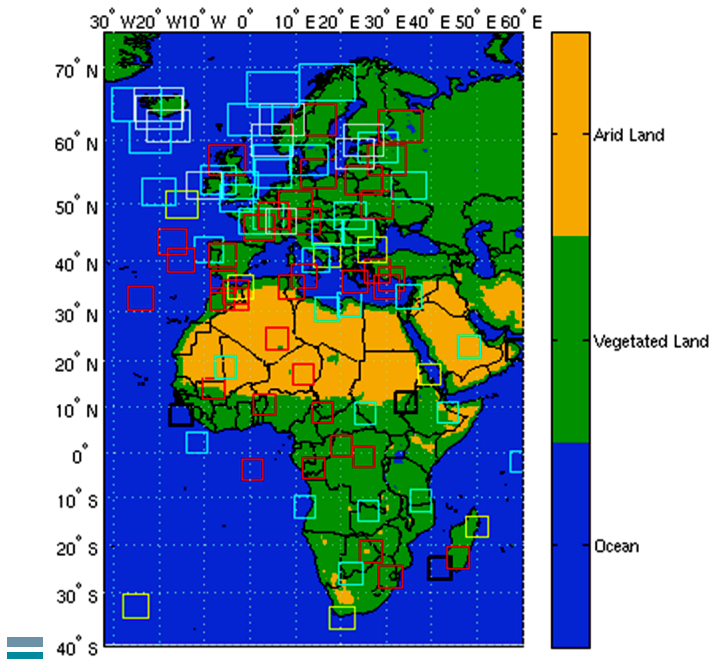
Imager IFOV: GMI
d = 1.2 m
Altitude: 407 km



H SAF ANN-based precipitation products

Operational Products over MSG Full Disk

- Based on PNPR Artificial Neural Network approach used for precipitation rate retrieval algorithms for cross-track scanning radiometers
 - P-IN-MHS (H02B):** PNPR algorithm for AMSU/MHS radiometers for H SAF extended area (60W-60°E, 60°S-75°N); it uses two ANNs (ANN-A for European Area, ANN-B for African Area) trained by the two Databases *based on cloud-radiation model simulations*.
 - P-IN-ATMS (H18):** PNPR algorithm for ATMS radiometer for H SAF extended area (60W-60°E, 60°S-75°N); redesigned single ANN trained using one training database based on 94 cloud-radiation model simulations.

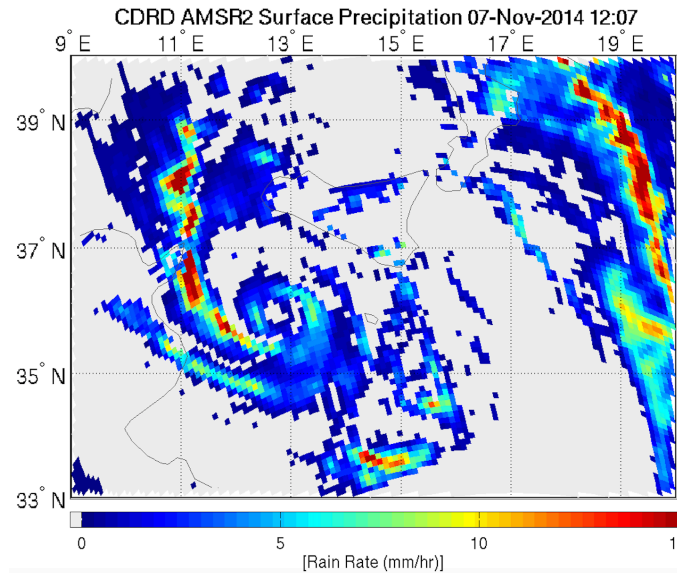


(Sanò et al., AMT, 2015, 2016)

H SAF GPM-based CDRD Bayesian scheme for AMSR-2.

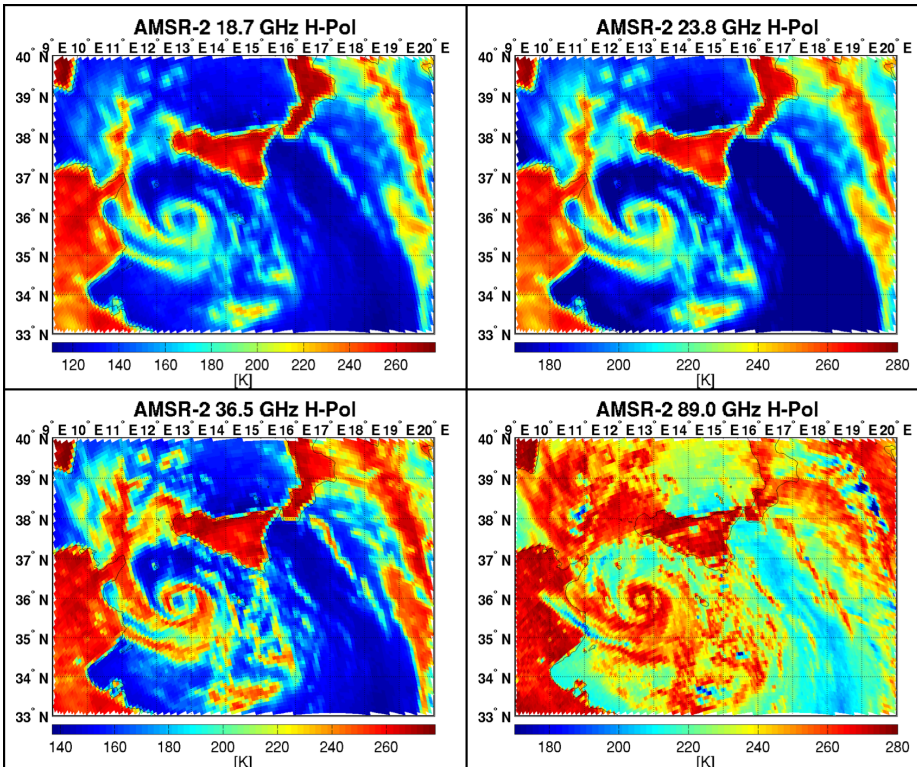
Medicane Qendresa 7 November 2015 - AMSR2

P-IN-AMSR2 (H-AUX-17) rainfall rate estimate

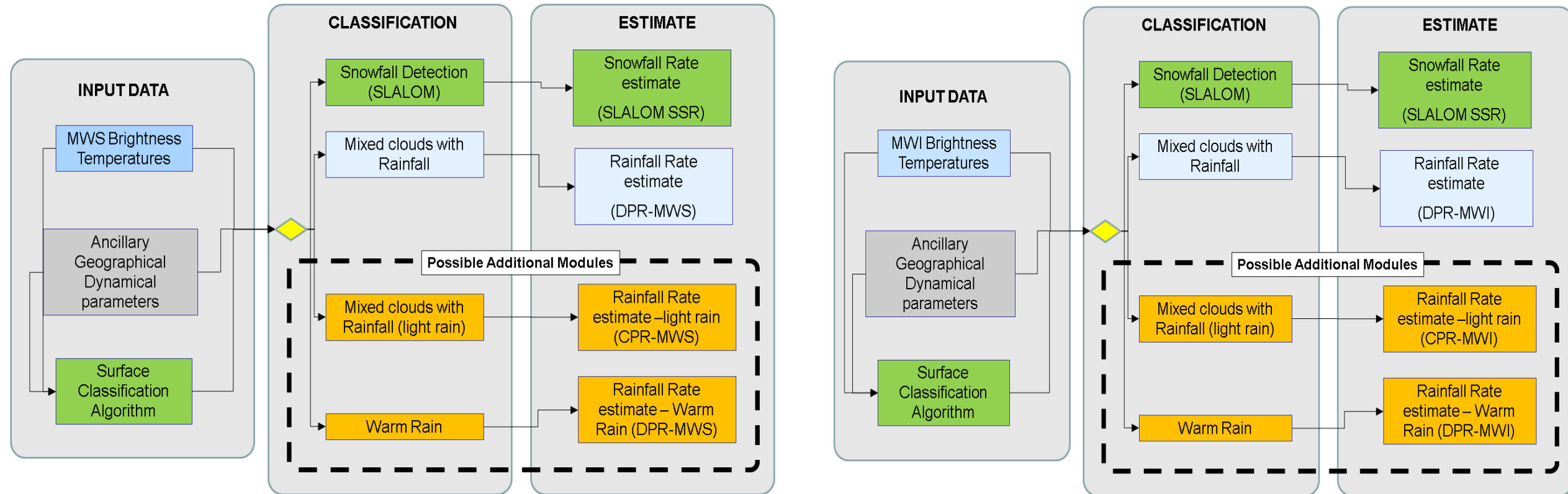


A-priori *observational dataset* built from GPM-CO (GMI and DPR) observations;

- Calibration coefficients and error covariance matrix from AMSR-2/GMI coincidence dataset;
- Space of calibrated pseudo-TBs (CCA), following Petty (2013) and Casella et al. (2015);
- Ancillary data from HRES ECMWF ($0.1^\circ \times 0.1^\circ$ lat/lon).
- Rain/No-rain screening algorithm developed by Casella et al. AMT, 2015.
- **Optimization** to use an extremely large empirical database in NRT (timeliness reduction from 120 min to 20 min)



Casella et al., 2017 IEEE JSTARS



Observational training dataset built from global coincident measurements of **MWS** and **MWI** with GPM DPR (for rainfall) and CloudSat CPR/EarthCare (for snowfall)

Expected operational at the end of CDOP-4