

# SAR for Soil Moisture

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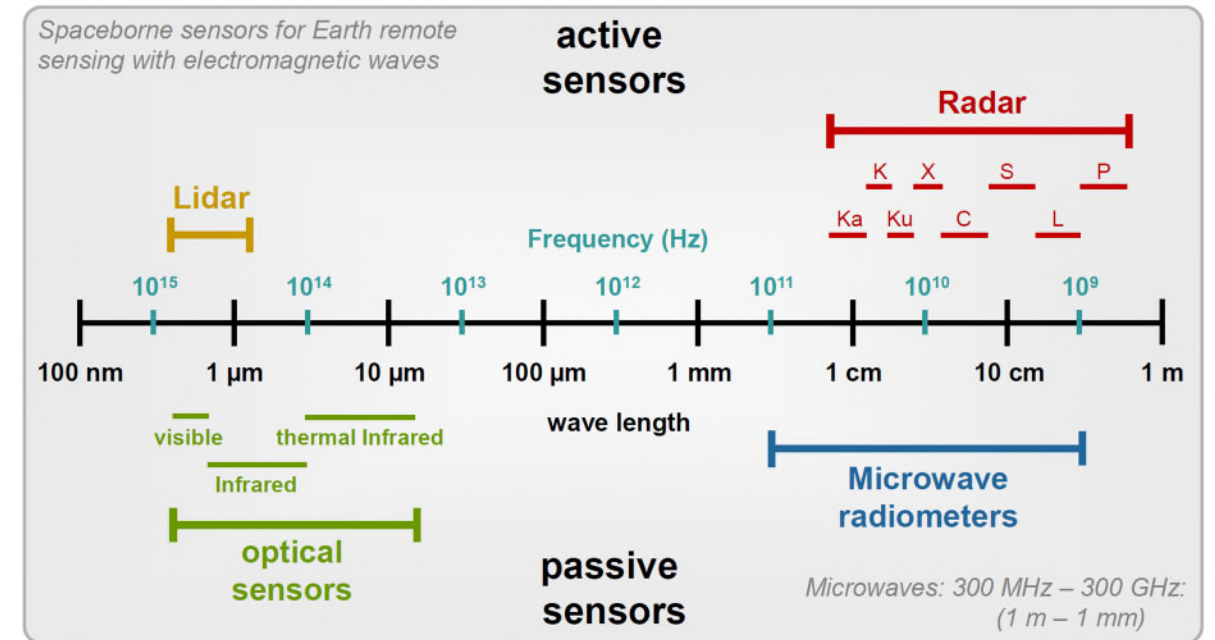
Earth Observation Data Centre for  
Water Resources Monitoring

# What is SAR?

# Approaches for Remote Sensing of Soil Moisture

- Measurement principles
  - No direct measurement of soil moisture possible, only indirect techniques
- Visible to Mid-Infrared (0.4 – 3  $\mu\text{m}$ )
  - Change of soil colour
  - Water absorption bands at 1.4, 1.9 and 2.7  $\mu\text{m}$
  - Vegetation as indirect indicator of soil wetness
- Thermal Infrared (7-15  $\mu\text{m}$ )
  - Indirect assessment of soil moisture through its effect on the surface energy balance (temperature, thermal inertia, etc.)
- **Microwaves (1 mm – 1 m)**
  - Change of dielectric properties

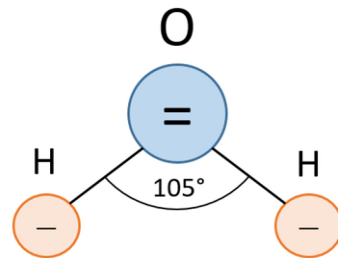
## Electromagnetic Spectrum and Sensor Types



<https://earth.esa.int/documents/10174/642943/6-LTC2013-SAR-Moreira.pdf>

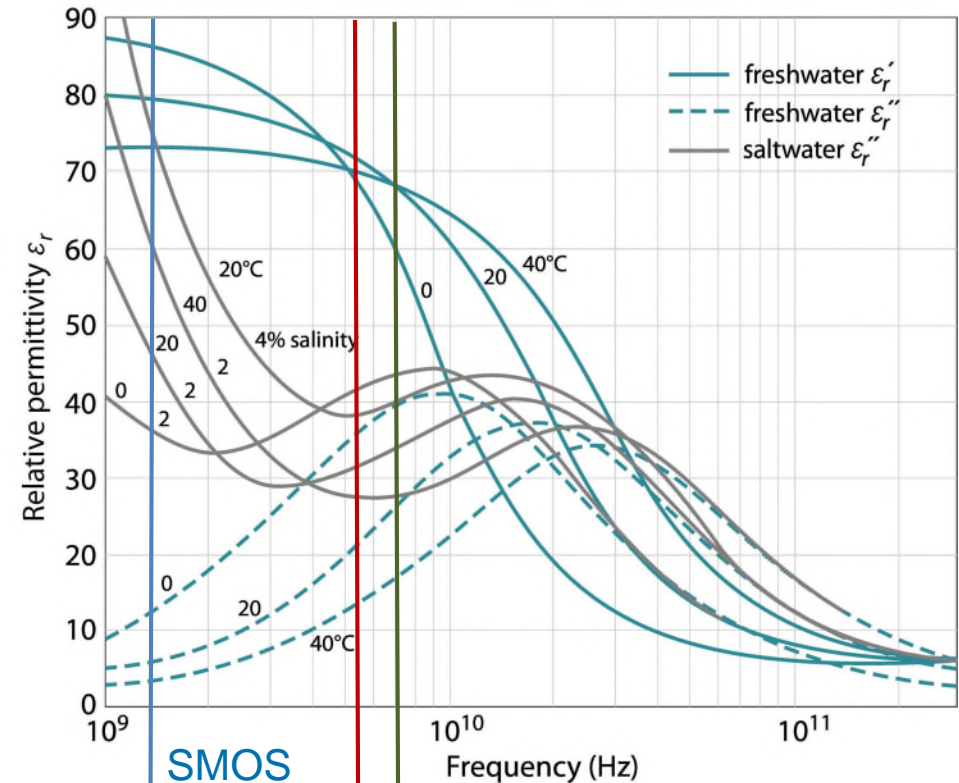
# Microwaves

- All-weather, day-round measurement capability
  - No problems with clouds below about 10 GHz
- High penetration into vegetation and soils
  - Longer wavelengths beneficial
- Microwave measurements are sensitive to
  - Geometric structure
    - Roughness
  - Dielectric properties
    - Water



The separation of positive and negative charges in a water molecule causes a water molecule to react strongly to an incoming electromagnetic wave. It starts to “wobble”, producing heat and reradiating electromagnetic waves. Technically, it is said that water has a permanent dipole moment that leads to orientational polarisation and a **high dielectric constant**.

Dielectric properties of water at microwave frequencies



Graphic by  
Bartalis 2009

SMOS  
SMAP  
NISAR

ASCAT  
Sentinel-1

AMSR2

# Microwave Satellites for Soil Moisture Monitoring

## Radiometers



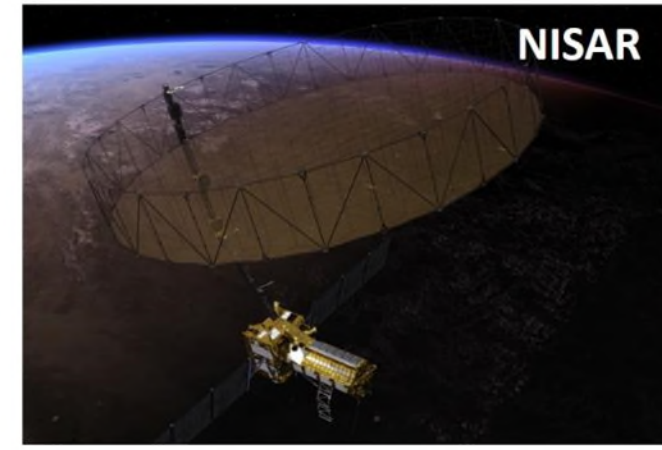
SMOS

## Active/Passive Microwave



SMAP

## Synthetic Aperture Radar



NISAR

L-Band

C-Band



AMSR2



ASCAT



Sentinel-1

Coarse Resolution

Fine Resolution



# Active and Passive Microwave Sensors

## Active Sensors

- Active sensor systems transmit pulses and detect the signals scattered by the objects
- Mono-static **radars** measure the **backscattering coefficient  $\sigma^0$** 
  - a measure of the reflectivity of the Earth surface

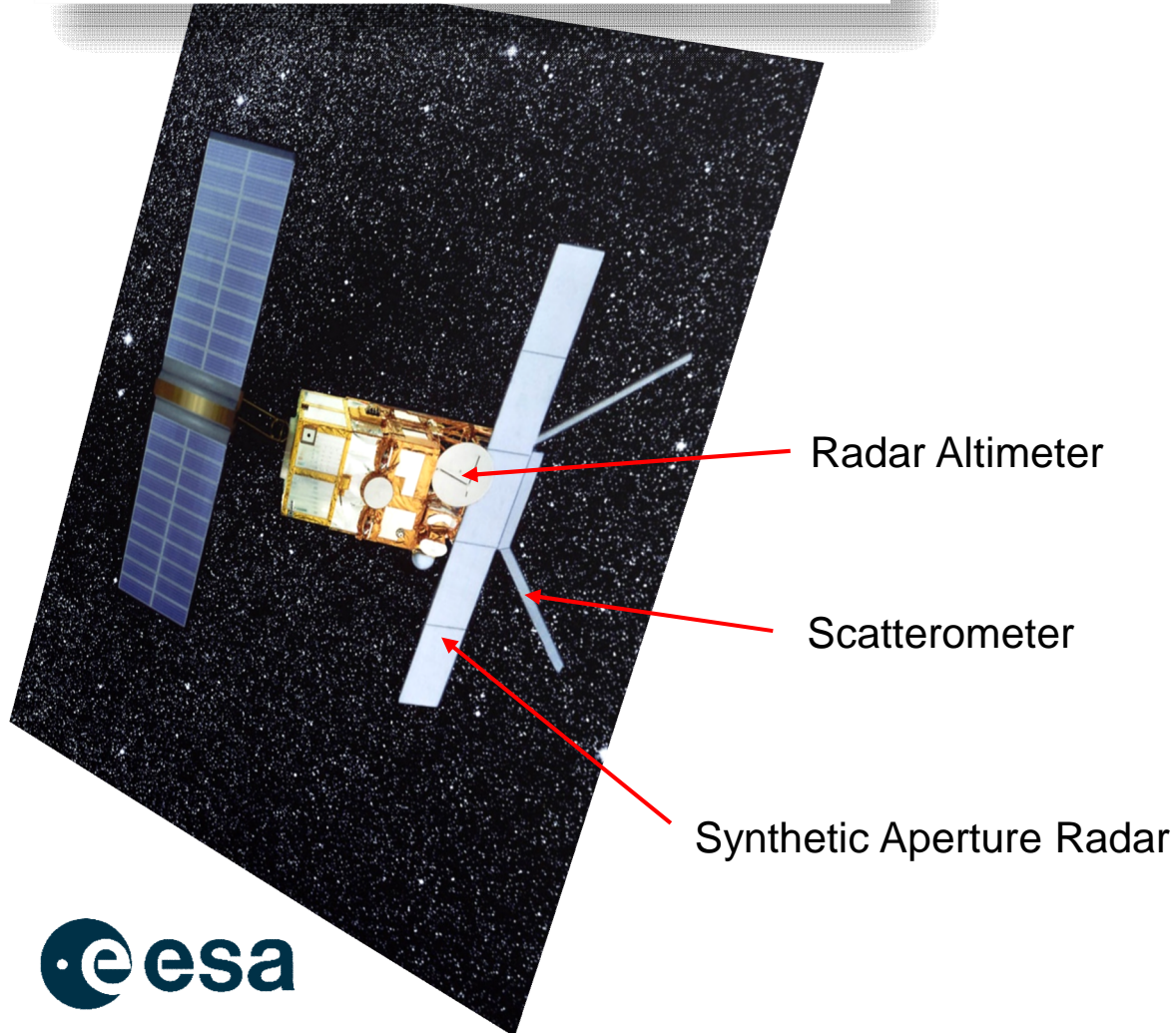
## Passive Sensors

- Passive sensors detect the microwave radiation emitted by the objects themselves
- Microwave **radiometers** measure the **brightness temperature  $T_B$** 
  - $T_B = e \cdot T_s$  where  $e$  is the emissivity and  $T_s$  the physical surface temperature

- Active measurements are more sensitive to roughness and vegetation structure than passive measurements, but
  - are not affected by surface temperature (above 0°C)
  - have a better spatial resolution
- Despite these differences both active and passive sensors are sensitive to the same variables:
  - Passive and active methods are interrelated through Kirchhoff's law:  $e = 1 - r$  where  $r$  is the reflectivity

# Active Microwave Measurement Techniques

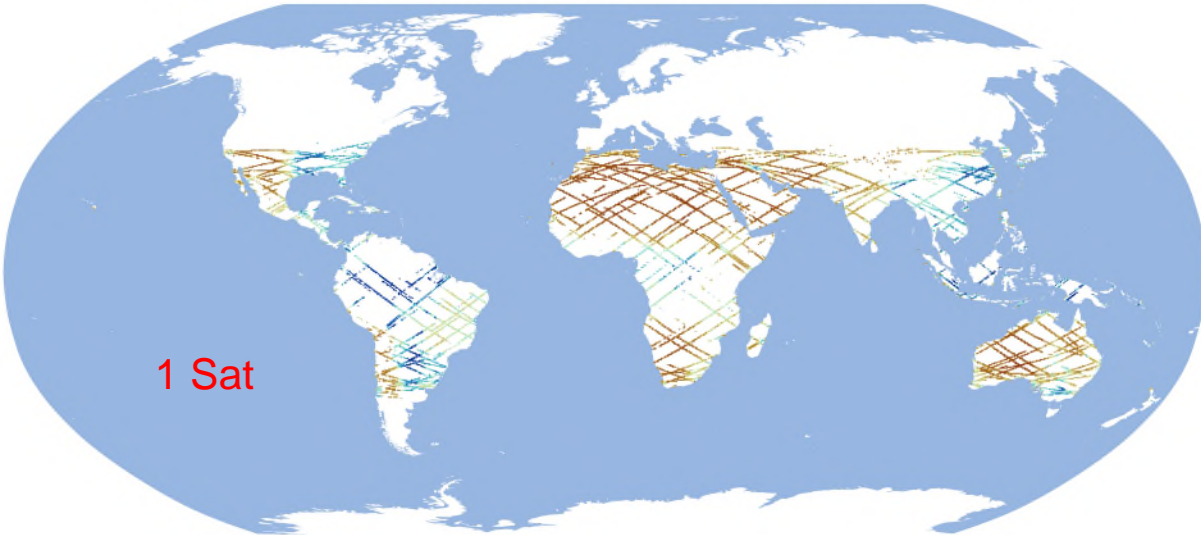
First European Remote Sensing Satellite  
ERS-1 (1991-2000)



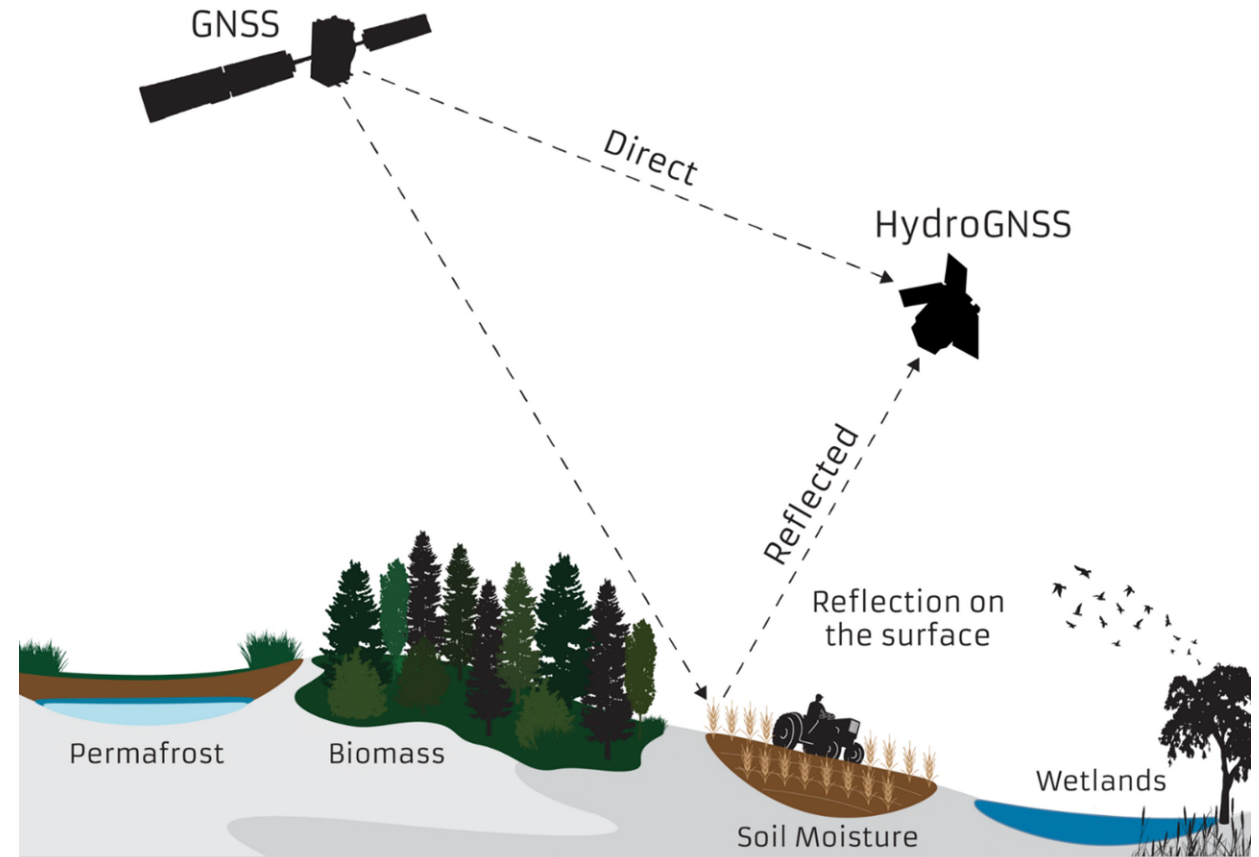
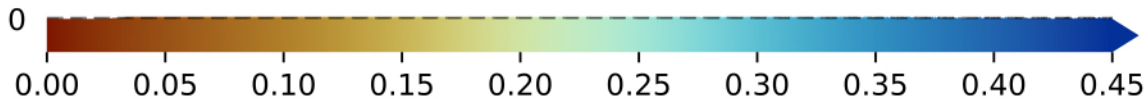
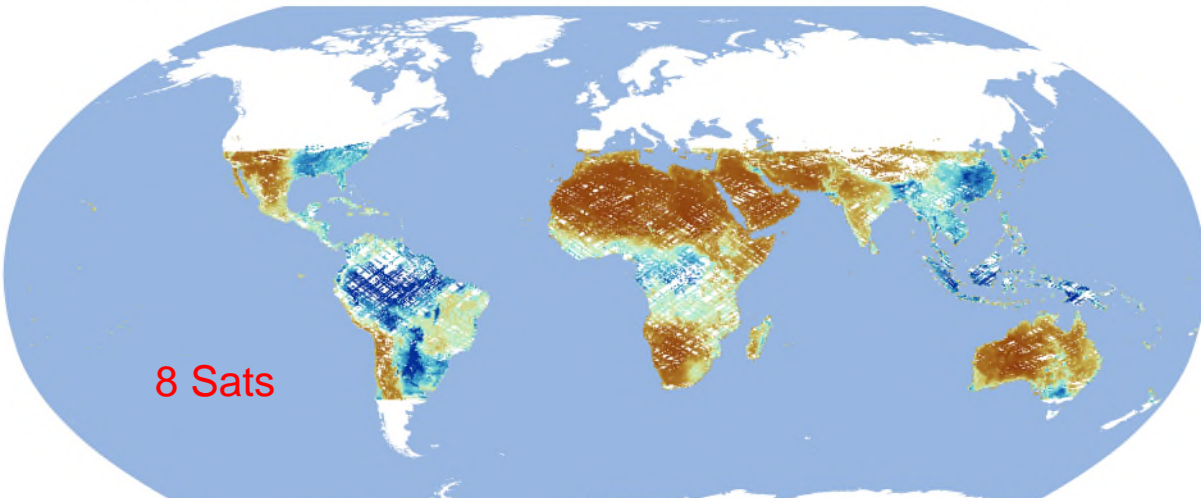
- Altimeter
  - Measurement of height above surface
- Scatterometer
  - Measurement of backscatter from multiple viewing directions
- Synthetic Aperture Radar (SAR)
  - High-resolution imaging
- Bi-static techniques

# Soil Moisture from GNSS Reflectometry

SM Estimates, CYGNSS SMTW, 36 km grid, ( 1 CYGNSS Satellites), 24h, not interpolated



SM Estimates, CYGNSS SMTW, 36 km grid, ( 8 CYGNSS Satellites), 24h, not interpolated



[https://www.esa.int/Applications/Observing\\_the\\_Earth/Second\\_Scout\\_gets\\_the\\_go-ahead](https://www.esa.int/Applications/Observing_the_Earth/Second_Scout_gets_the_go-ahead)

CYGNSS soil moisture data from  
Emanuele Santi, IFAC

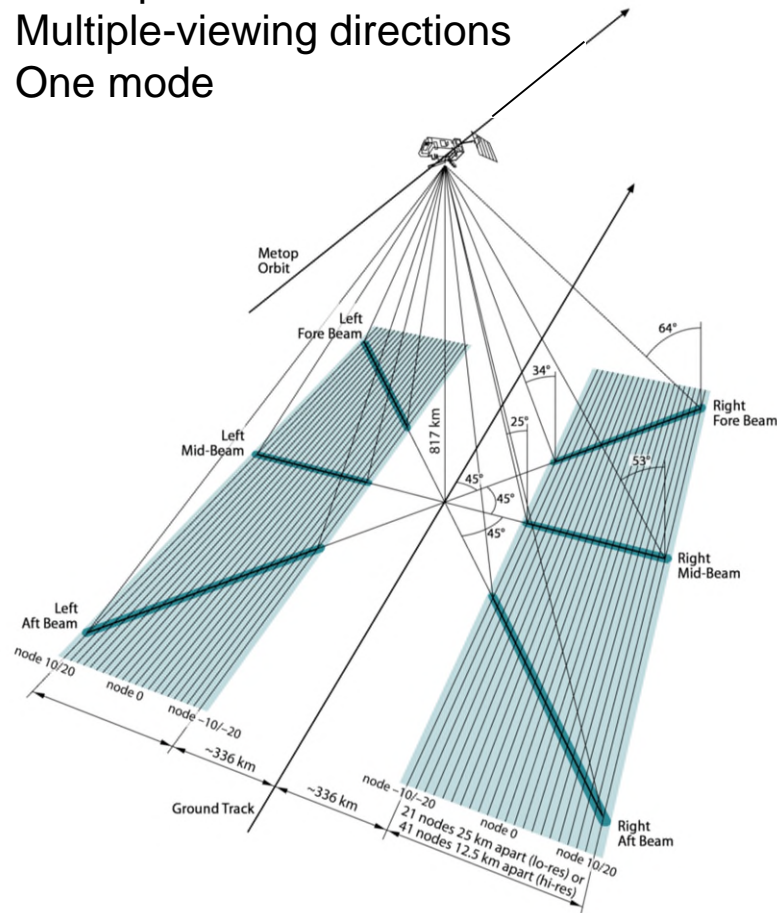


# Side-Looking Radars

- SARs and scatterometers are side-looking radars that measure the backscatter coefficient

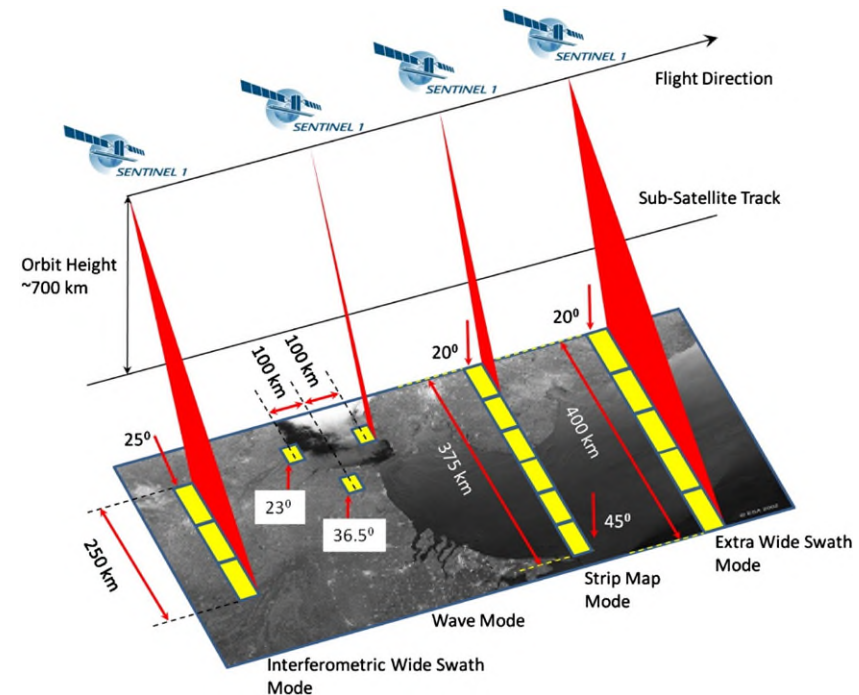
## METOP ASCAT

Real aperture radar  
Multiple-viewing directions  
One mode



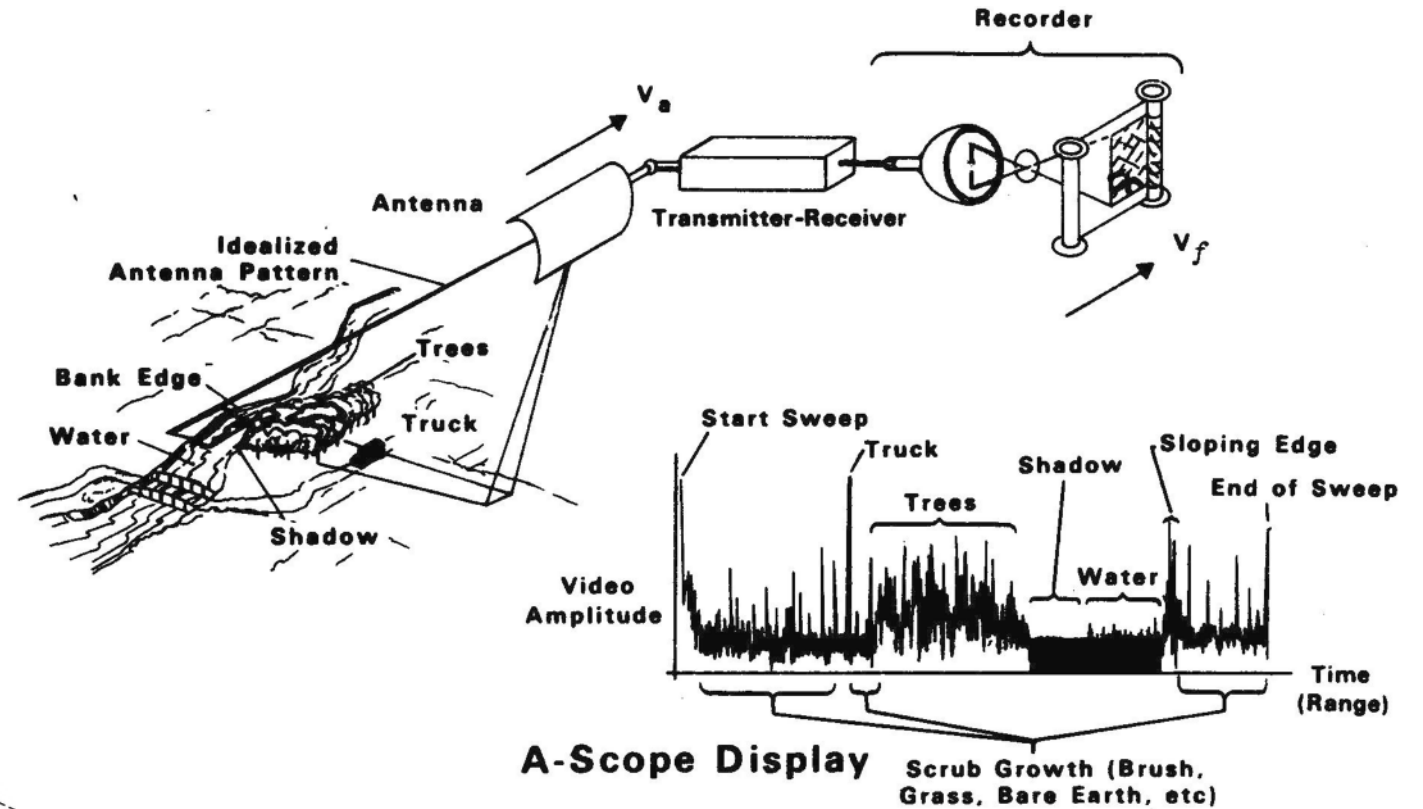
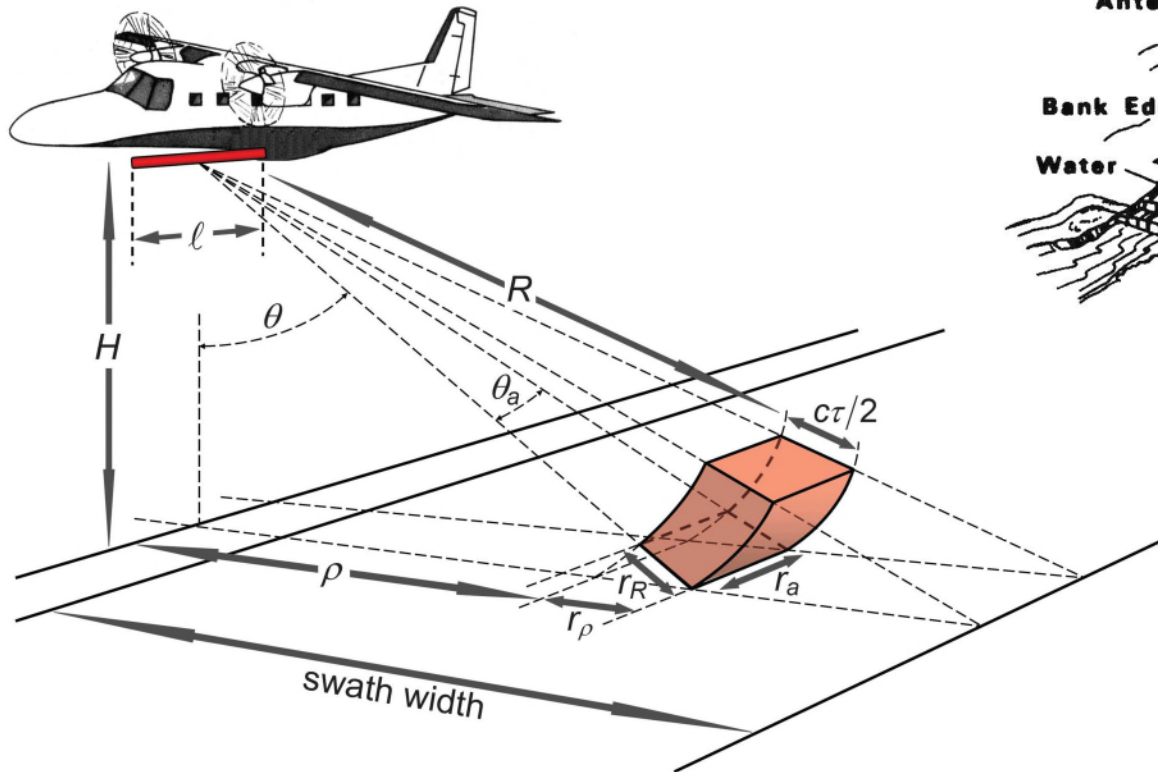
## Sentinel-1 SAR

Synthetic aperture radar  
Single-viewing direction  
Several modes



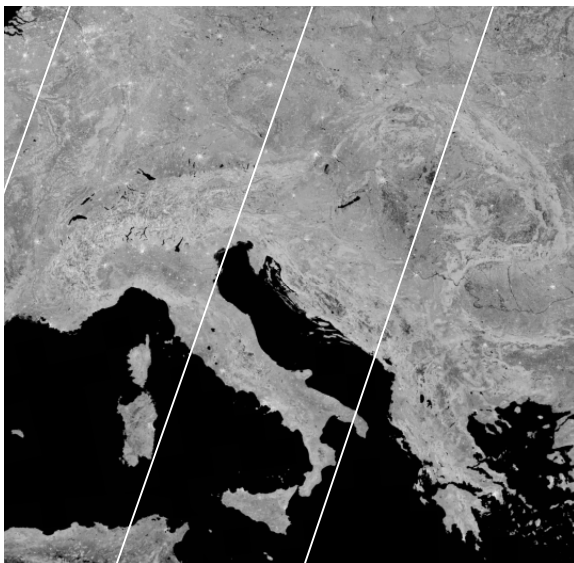
# Measurement Principle of Side-Looking Radars

- Side-looking radars use antennas to send out short pulses (chirps) and measure the echoes coming from the objects
- The long wavelength implies a large beamwidth and poor native resolution

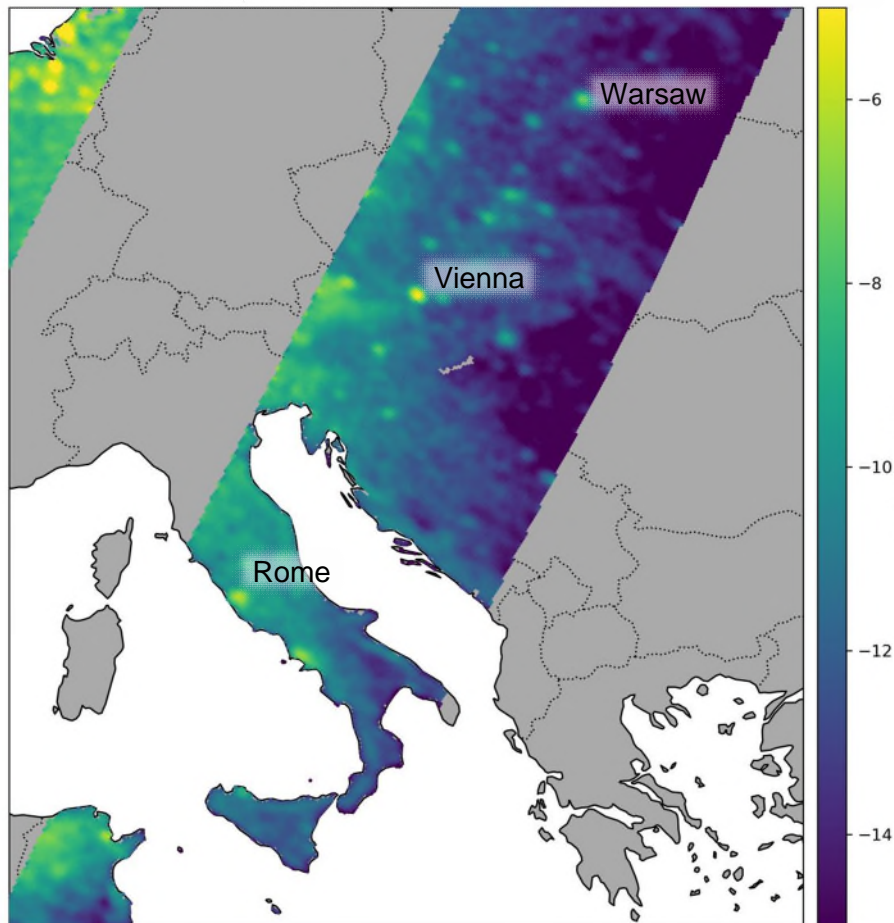


# Spatial Resolution of ASCAT

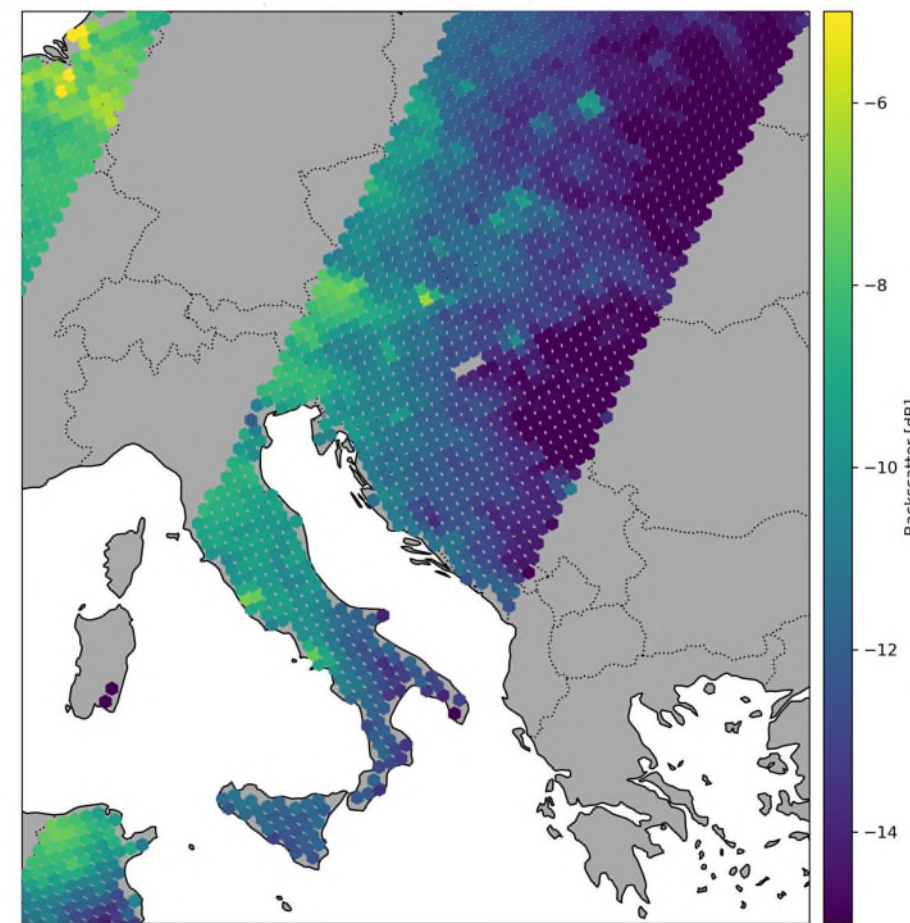
Sentinel-1 Mean Backscatter



METOP-A ASCAT Fore Beam @ 6.25km Grid



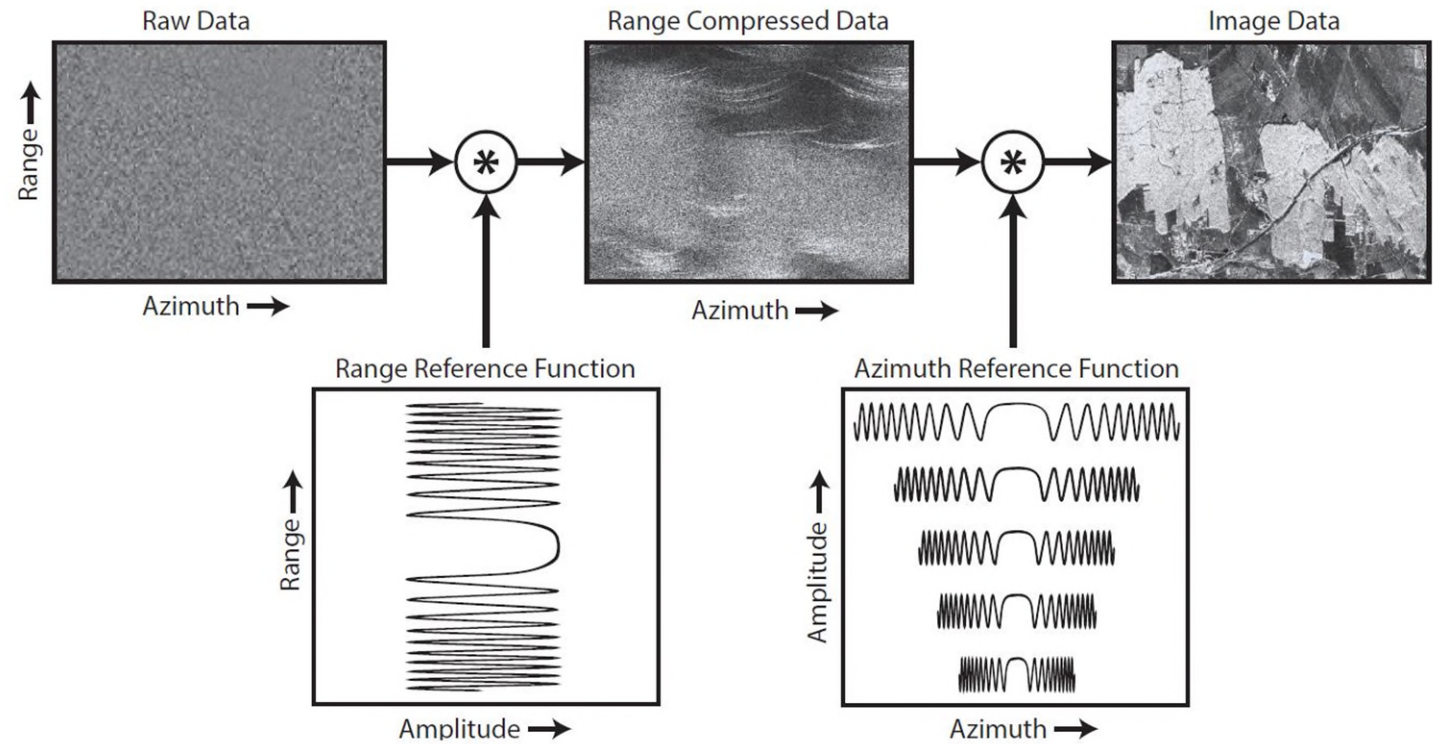
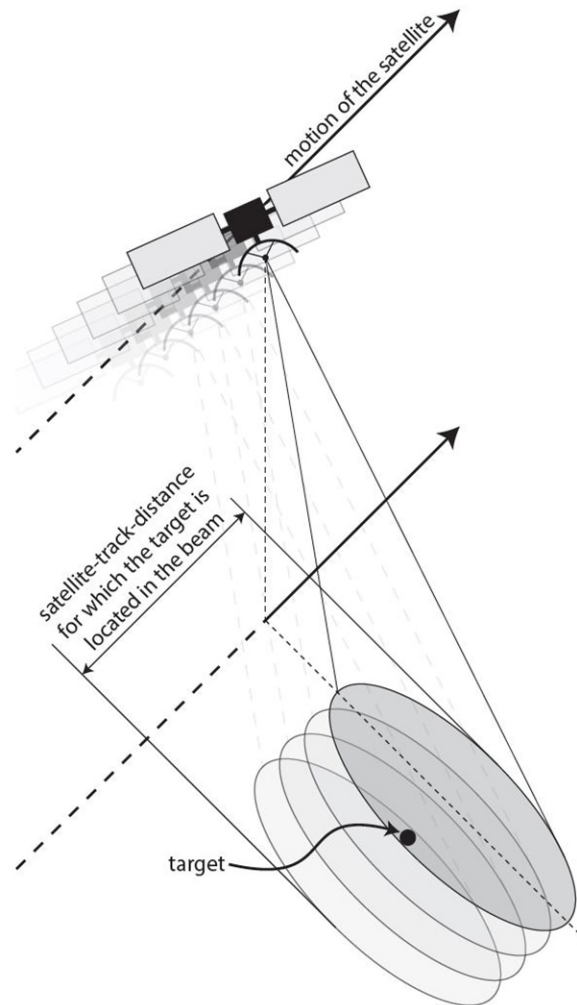
METOP-A ASCAT Fore Beam @ 25km Grid



ASCAT Images by Sebastian Hahn

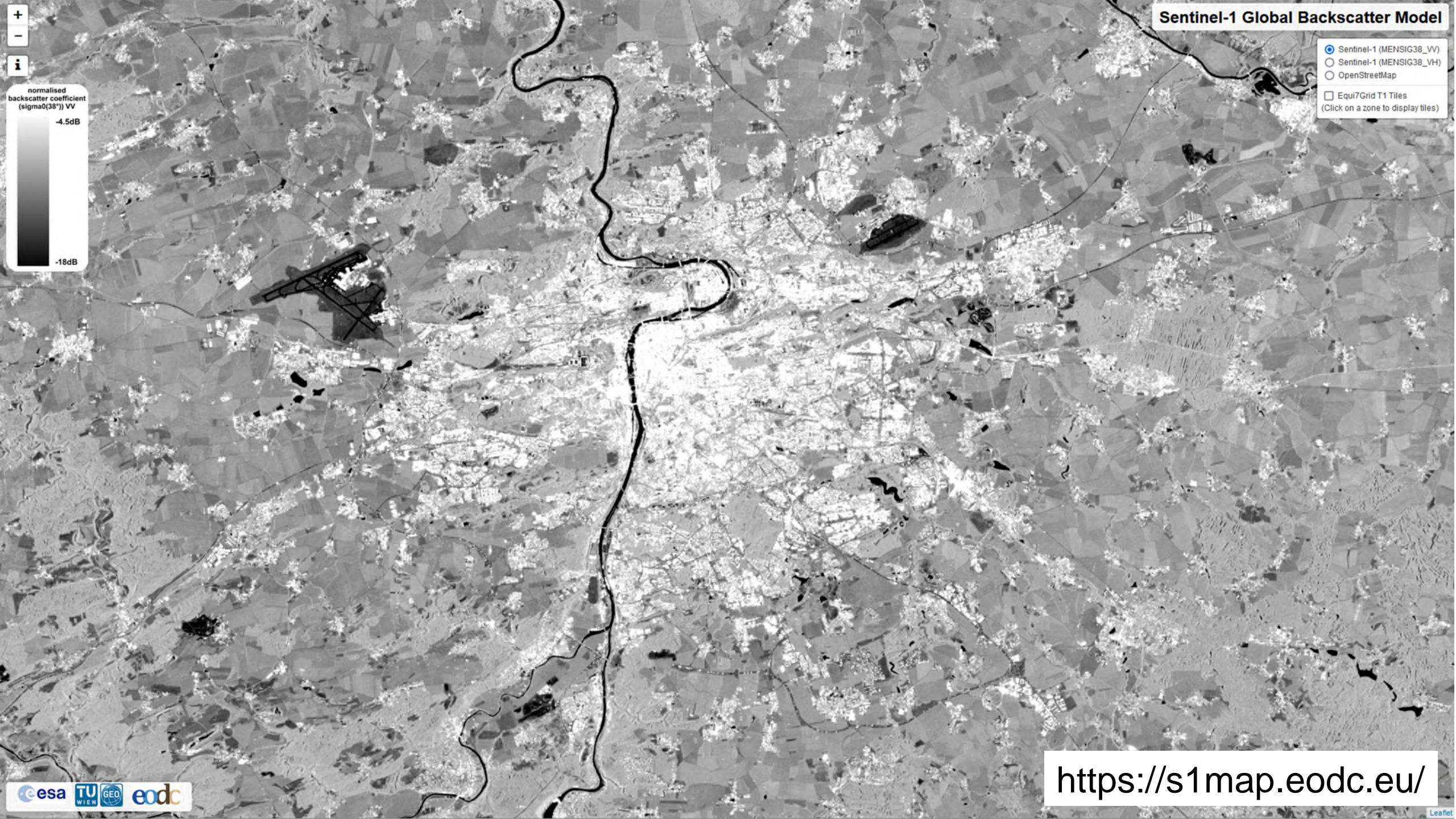
# SAR Measurement Principle

- A SAR sends out many short pulses and measures amplitude and phase of the echoes (coherent measurement system)



SAR processing steps where the raw data are decompressed by convoluting the data first with a range reference function (chirp) and second with an azimuth reference function (Doppler shifts). From Moreira et al. 2013.

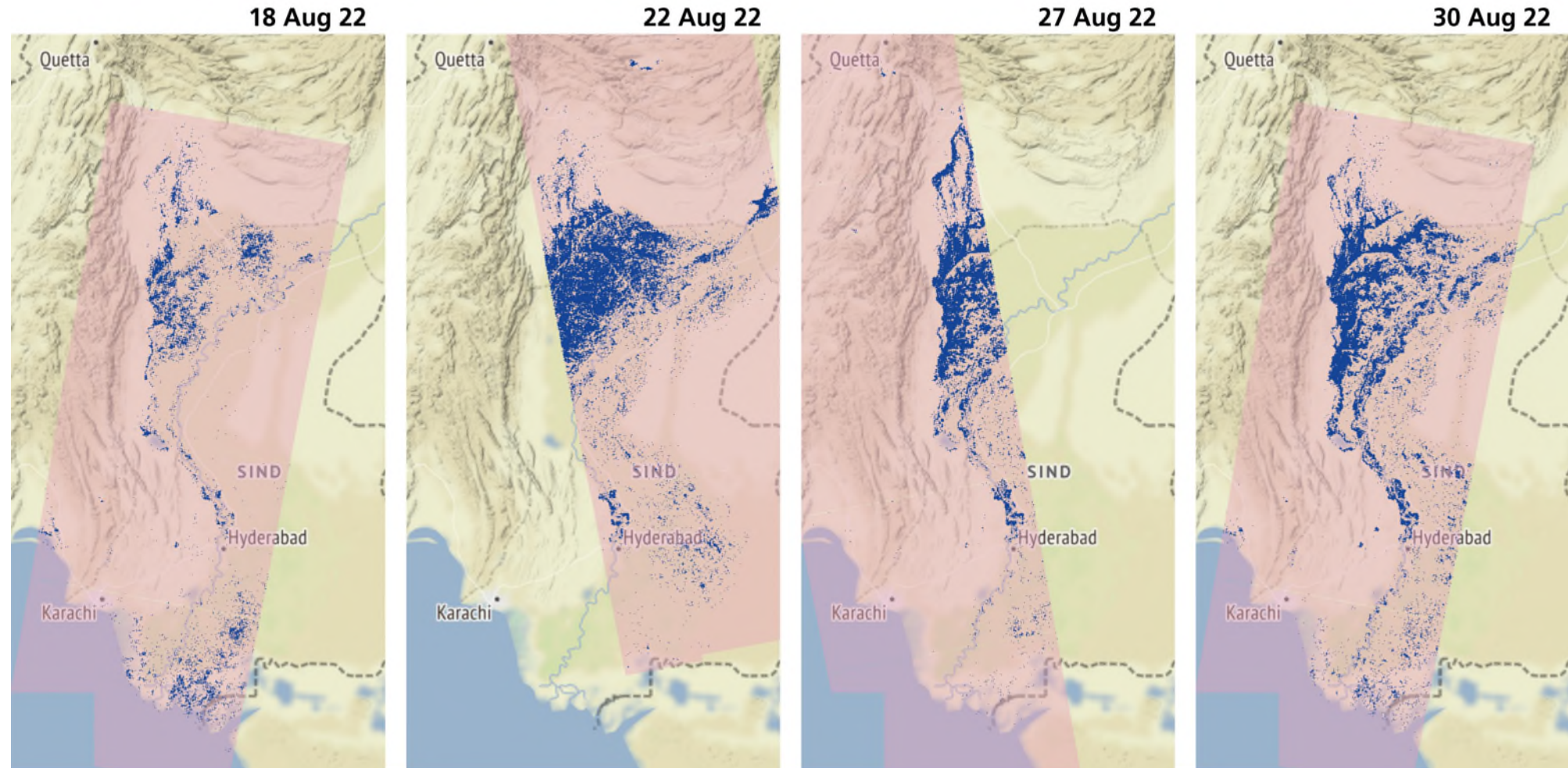
- Sentinel-1 (MENSIG38\_VV)
- Sentinel-1 (MENSIG38\_VH)
- OpenStreetMap
- Equi7Grid T1 Tiles  
(Click on a zone to display tiles)



<https://s1map.eodc.eu/>

# Monitoring of the Flood in Pakistan in 2022

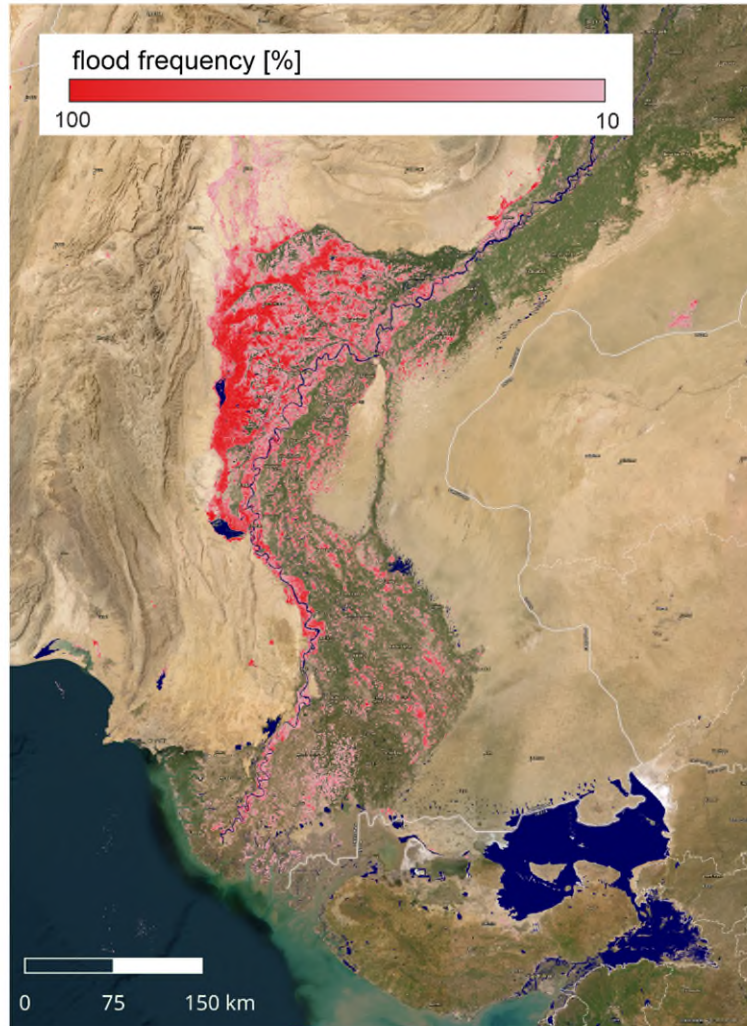
**Flood progression** covered by Sentinel-1 overpasses



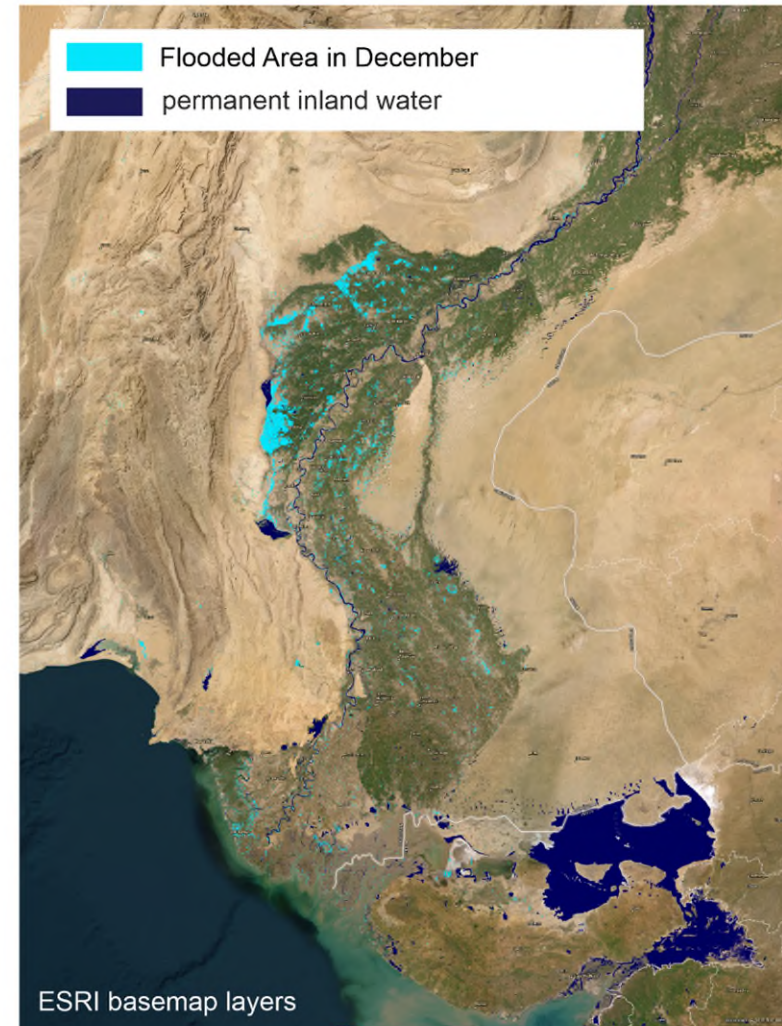
Roth et al. (2022) Sentinel-1 based analysis of the Pakistan Flood in 2022, EGU sphere [preprint], <https://doi.org/10.5194/egusphere-2022-1061>.

# Pakistan Floods 2022 - Persistence into December

Flood maps based on TU Wien algorithm as part of the **CEMS Global Flood Monitoring (GFM)** ensemble product which automatically analyses images acquired by the **Copernicus Sentinel-1** radar satellite



**flood frequency** | Pakistan / Indus Valley  
frequency of flood detection in period 18 Aug - 23 Sep 2022



**remaining flood area**  
flood area remaining in period 1 Dec - 15 Dec 2022

# Why Soil Moisture?



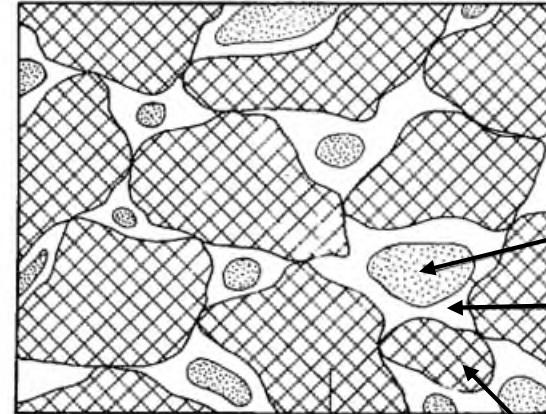
# Soil Moisture

- Definition, e.g.

$$\theta = \frac{\text{Water Volume (m}^3\text{)}}{\text{Total Volume (m}^3\text{)}}$$

- Average

$$\langle \theta \rangle = \frac{1}{\text{Area} \cdot \text{Depth}} \int_{\text{Area}} \int_{\text{Depth}} \theta(x, y, z) dz dx dy$$

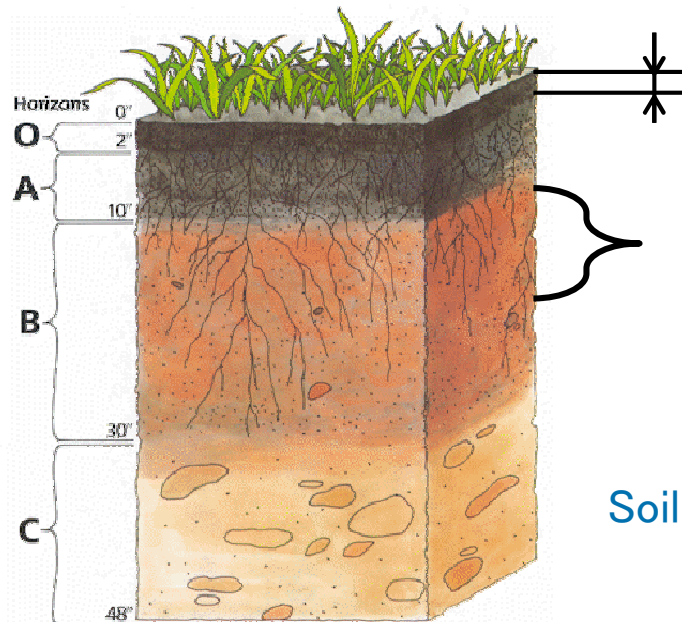


Cross-section of a soil

Air

Water

Solid Particles

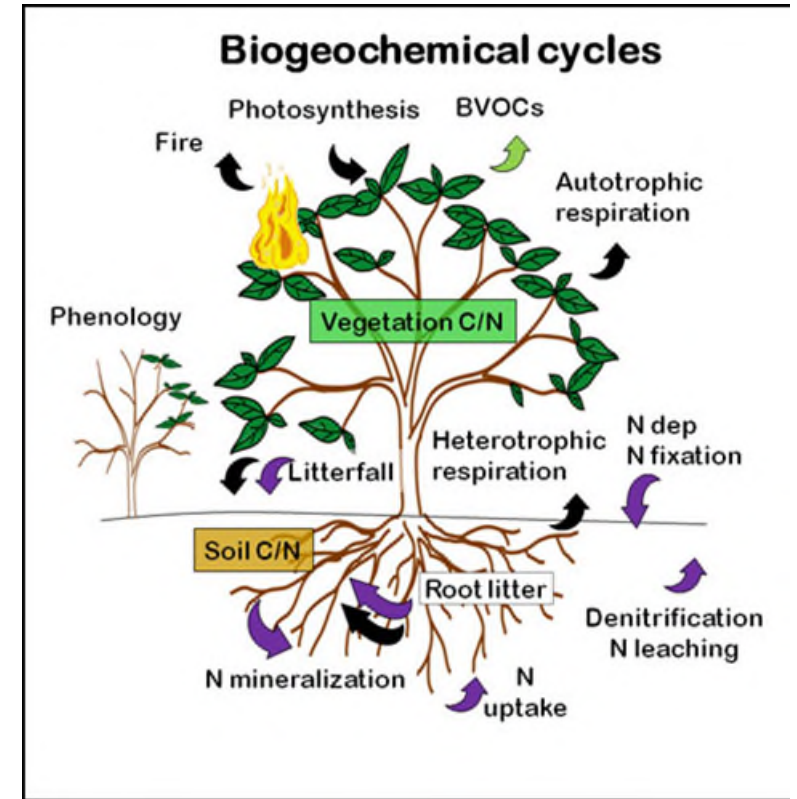
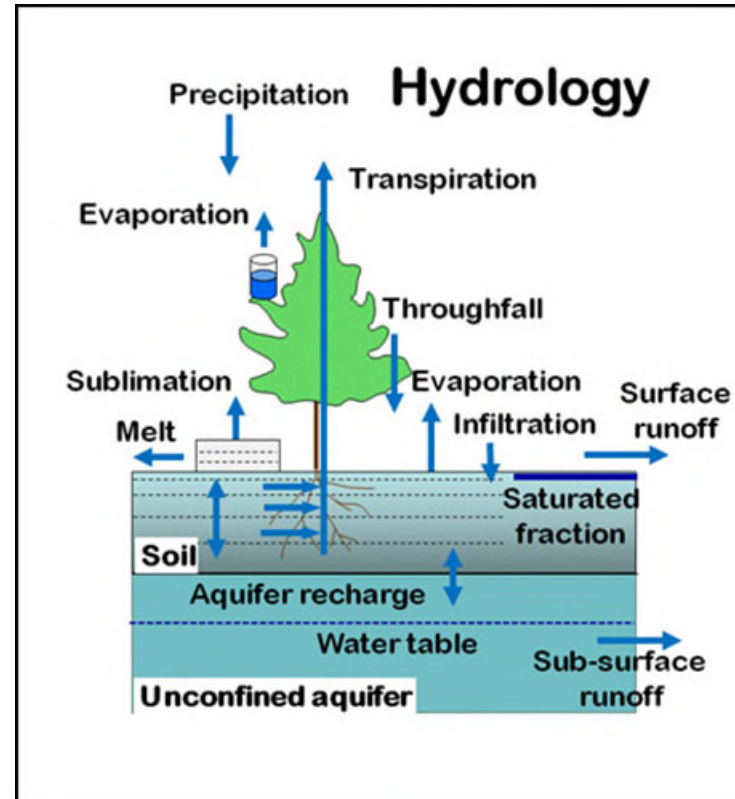
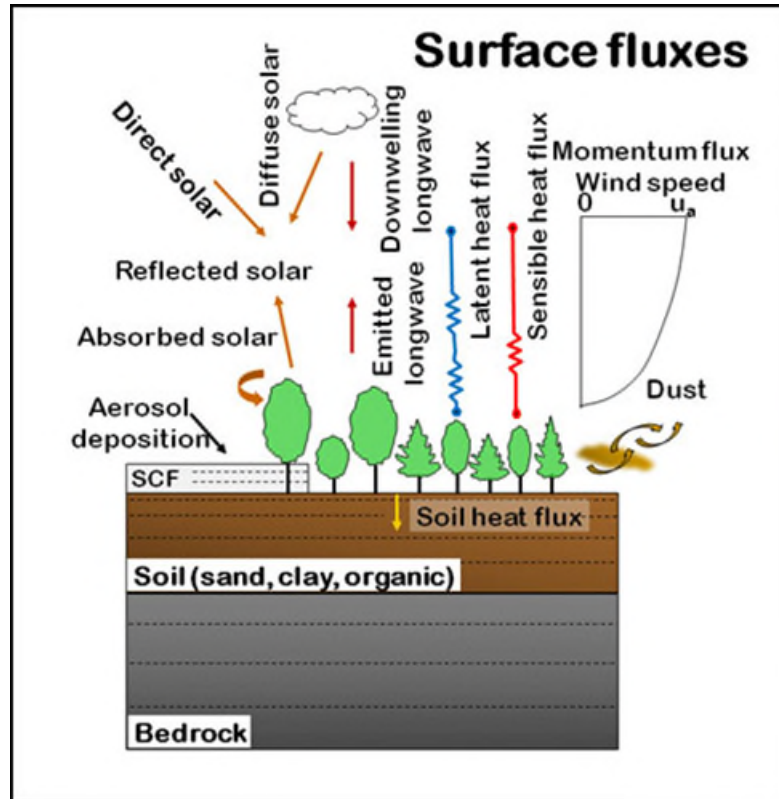


Thin, remotely sensed soil layer

Root zone: layer of interest for most applications

Soil profile

# Soil Moisture plays a Key Role in Water, Energy and Biochemical Cycles

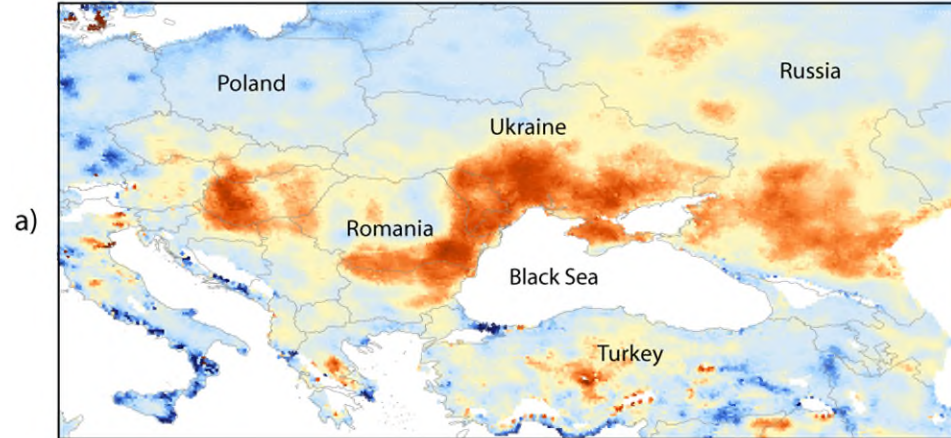


Schematic diagram depicting processes represented in the Community Land Model (<http://www.cesm.ucar.edu/models/clm/>)

Lawrence and Fisher (2013) The Community Land Model Philosophy: model development and science applications. iLEAPS Newsletter, 13, 16-19.

# Soil Moisture and Vegetation

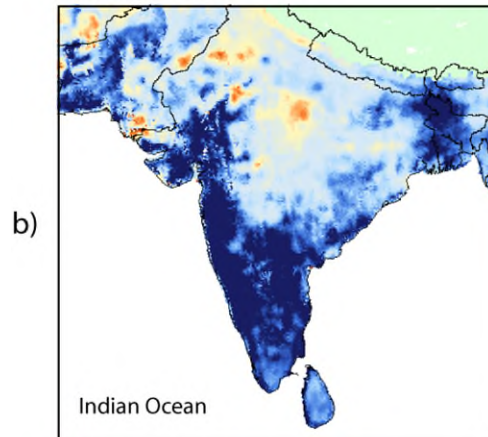
July, 2007



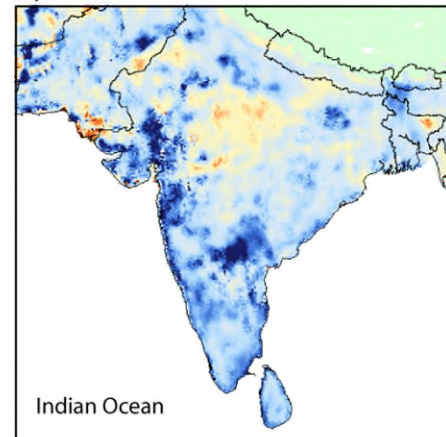
July 28 - August 12, 2007



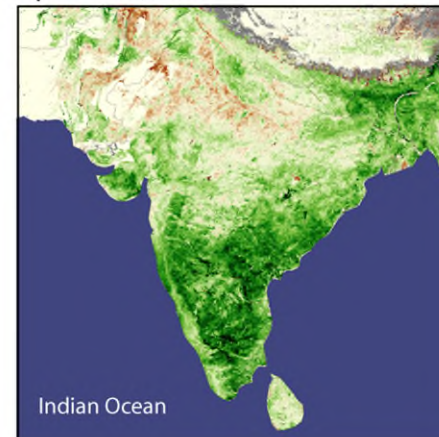
March, 2008



April, 2008

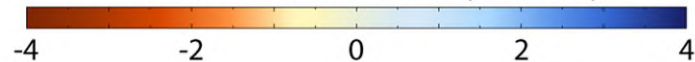


April 1-10, 2008

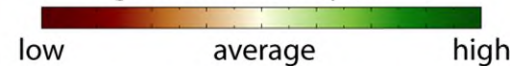


■ Snow Cover, Frozen Soil

ASCAT Soil Moisture Monthly Anomaly



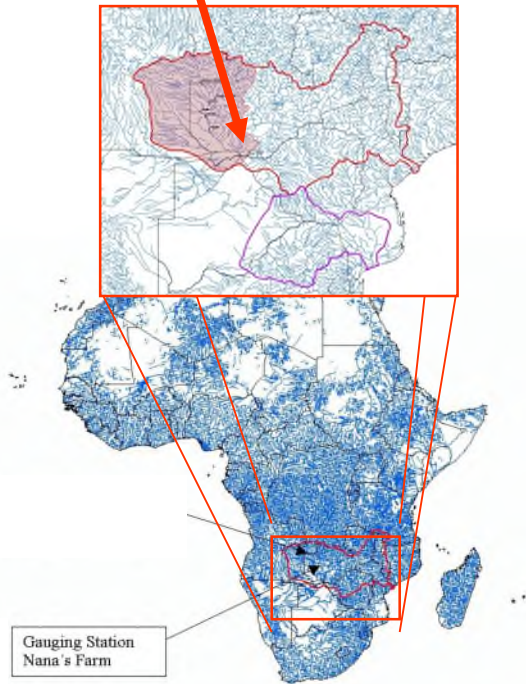
Vegetation Anomaly (NDVI)\*



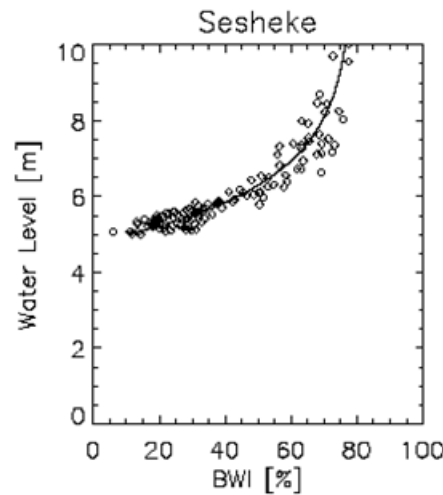
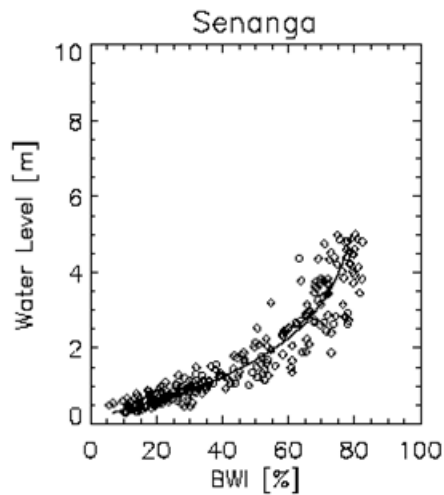
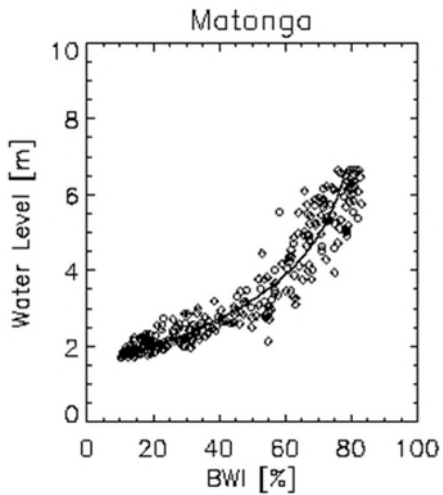
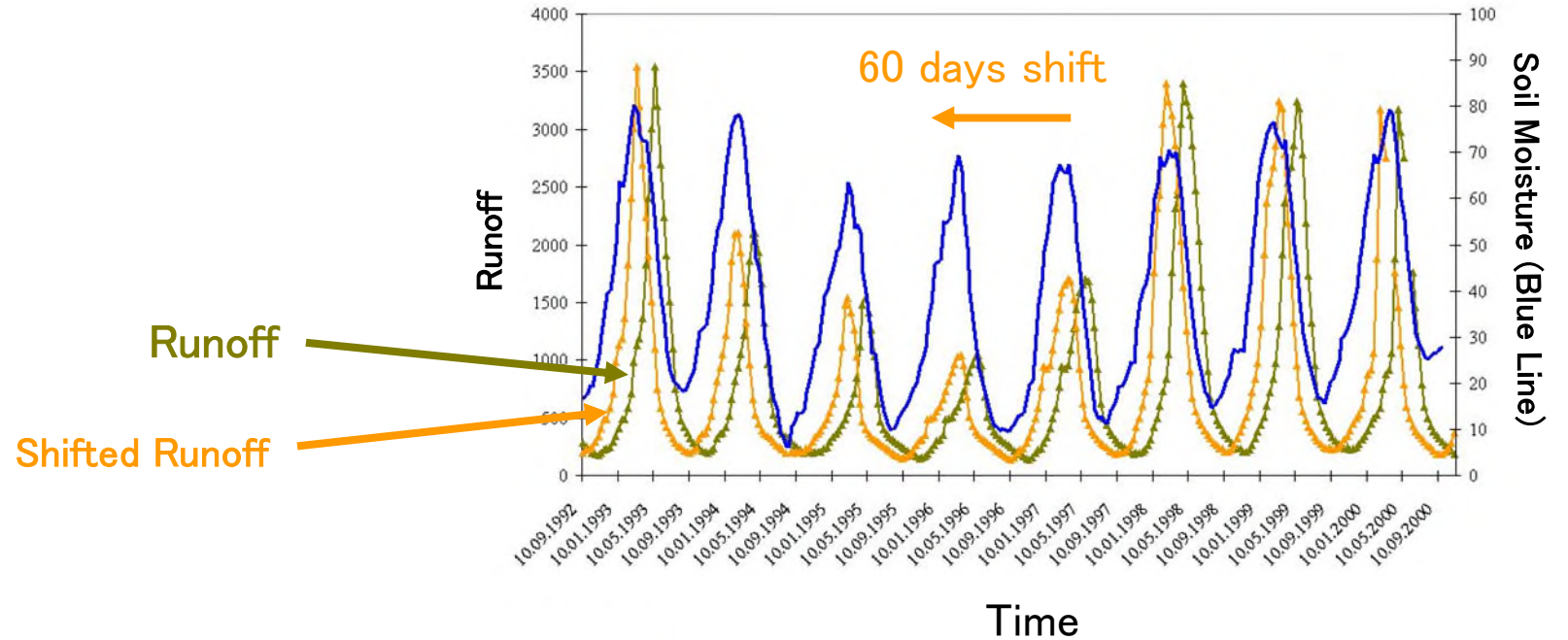
\* NASA's Earth Observatory (MODIS instrument)

Naeimi and Wagner (2010) C-band Scatterometers and their Applications, Chapter 13 of "Geoscience and Remote Sensing New Achievements", P. Imperatore and D. Riccio (Ed.), INTECH, Vukovar, Croatia, 230-246.

## Sambesi – Nana 's Farm



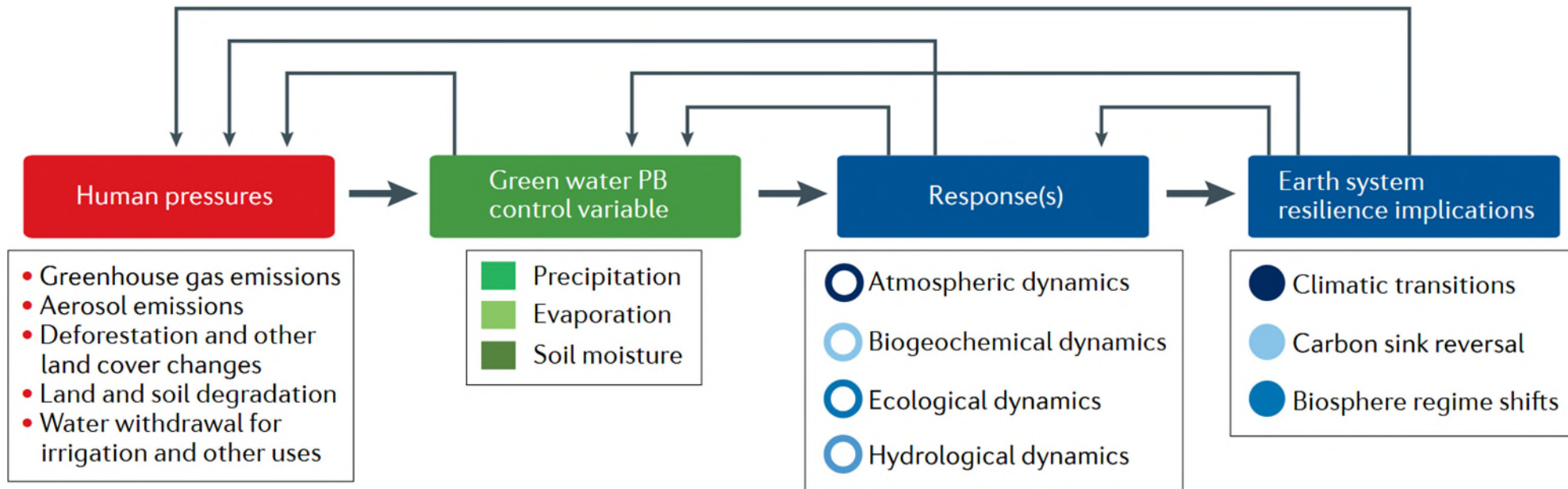
# Soil Moisture and River Runoff



Scipal et al. (2005) Soil moisture-runoff relation at the catchment scale as observed with coarse resolution microwave remote sensing, *Hydrology and Earth System Sciences*, 9(3), 173-183.

# Soil Moisture as a Planetary Boundary

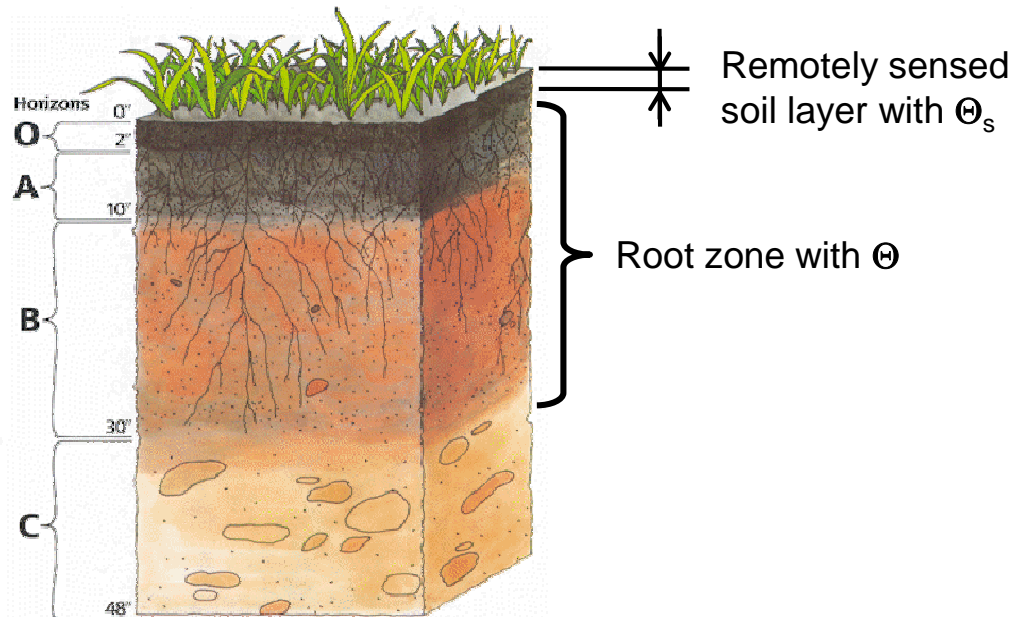
- Green water - terrestrial precipitation, evaporation and soil moisture - is fundamental to Earth system dynamics and is now extensively perturbed by human pressures
- Wang-Erlandsson et al. (2022) recently proposed a green water planetary boundary
  - percentage of ice-free land area on which root-zone soil moisture deviates from Holocene variability for any month of the year.



# Estimating Root Zone Soil Moisture from Surface Time Series

- The method rests upon simple differential model for describing the exchange of soil moisture between surface layer ( $\Theta_s$ ) and the “reservoir” ( $\Theta$ )
  - T ... characteristic time

$$\frac{d\Theta}{dt} = \frac{1}{T} (\Theta - \Theta_s) \quad \Rightarrow \quad \Theta(t) = \frac{1}{T} \int_{-\infty}^t \Theta_s(t') \exp\left[-\frac{t-t'}{T}\right] dt'$$



- Mathematically, this model corresponds to a first-order Markov process
- The autocorrelation function of  $\Theta(t)$  is given by  $r(t) = e^{-t/T}$ 
  - First suggested theoretically for soil moisture by Delworth and Manabe in 1988
  - Confirmed with in situ observations by Robock, Vinnikov, and collaborators in the 1990s

# Some Applications of Remotely Sensed Soil Moisture Data

- Runoff forecasting
- Numerical Weather Prediction
- Vegetation monitoring
- Agricultural monitoring
- Tree-Ring studies
- Landslide monitoring
- Epidemiological prediction
- GHG budget
- Climate studies
- Ground water modelling
- Drought monitoring
- Rainfall estimation
- Etc.

## How are the data used?

Model validation

Model calibration

Direct model input

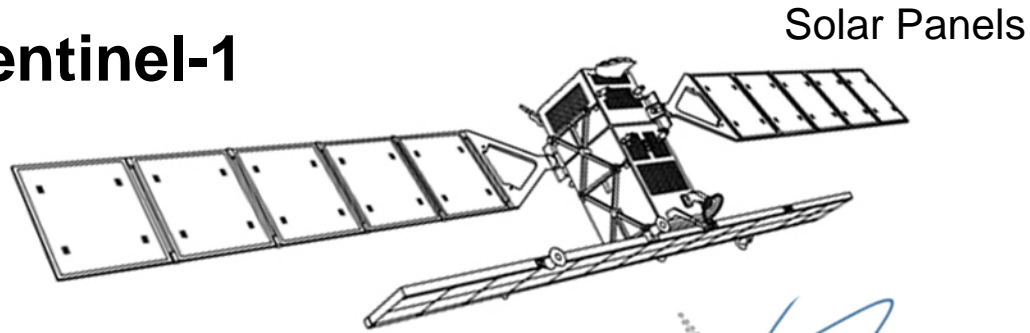
Data assimilation

# Soil Moisture Retrieval



# Active Microwave Remote Sensing of Soil and Vegetation

## Sentinel-1



$$\mathbf{E} = e^{i(\mathbf{kx} - \omega t)}$$

Electromagnetic Wave

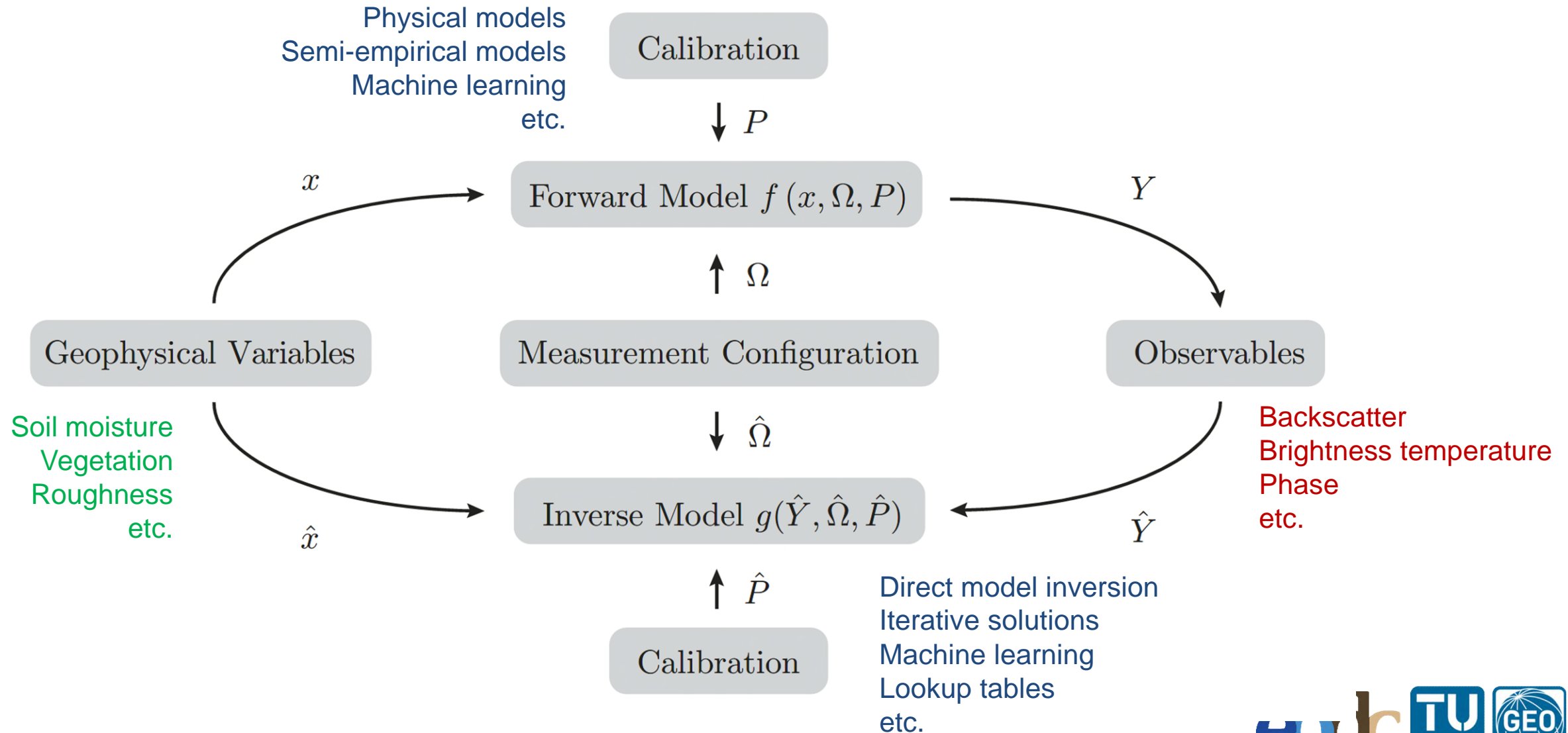
Backscatter model for vegetated soil surface

$$\sigma^{\circ} = \sigma_{soil}^{\circ} e^{-2\tau} + \omega (1 - e^{-2\tau})$$

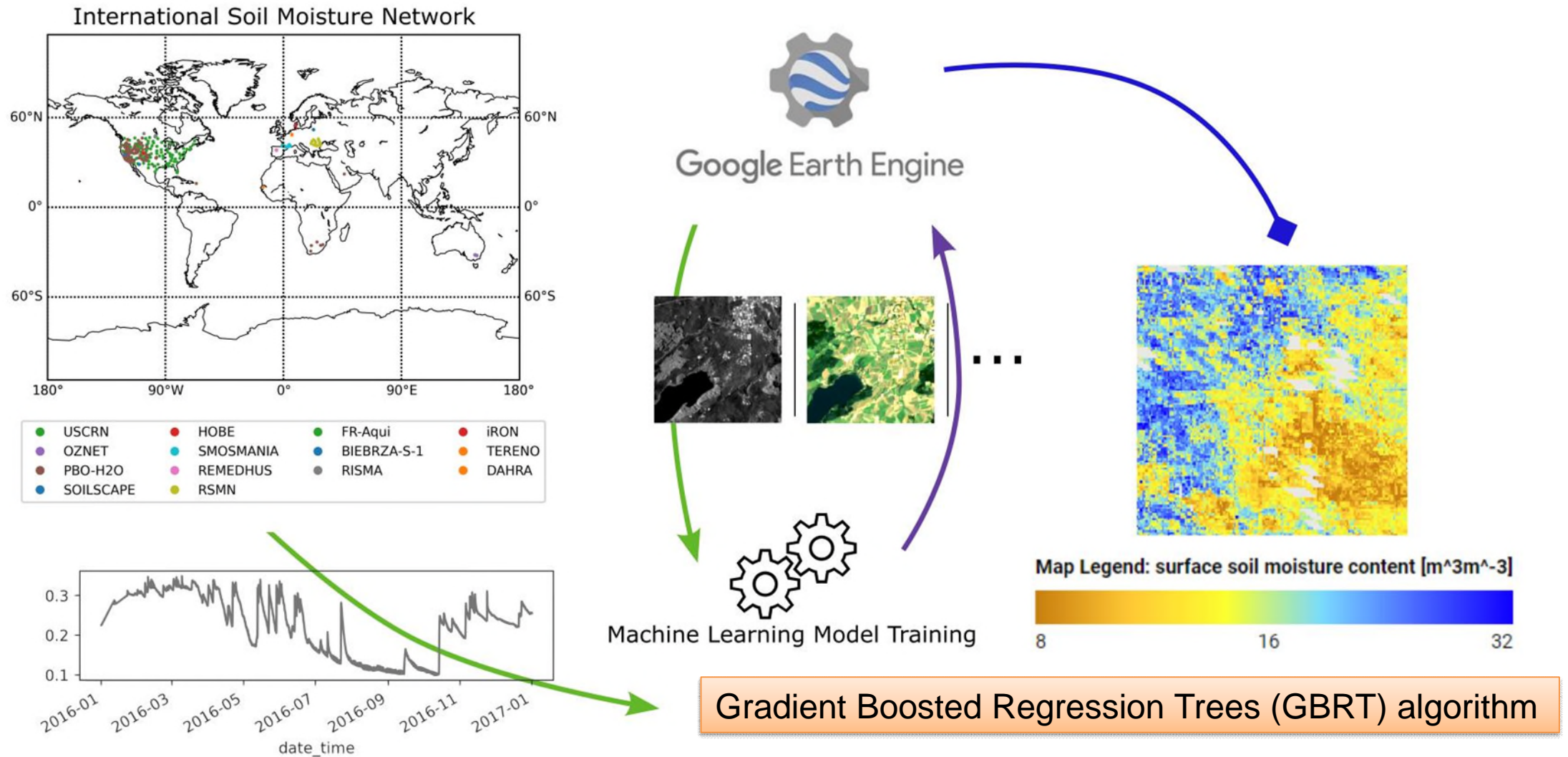
Vegetation

Soil

# Soil Moisture Data Retrieval



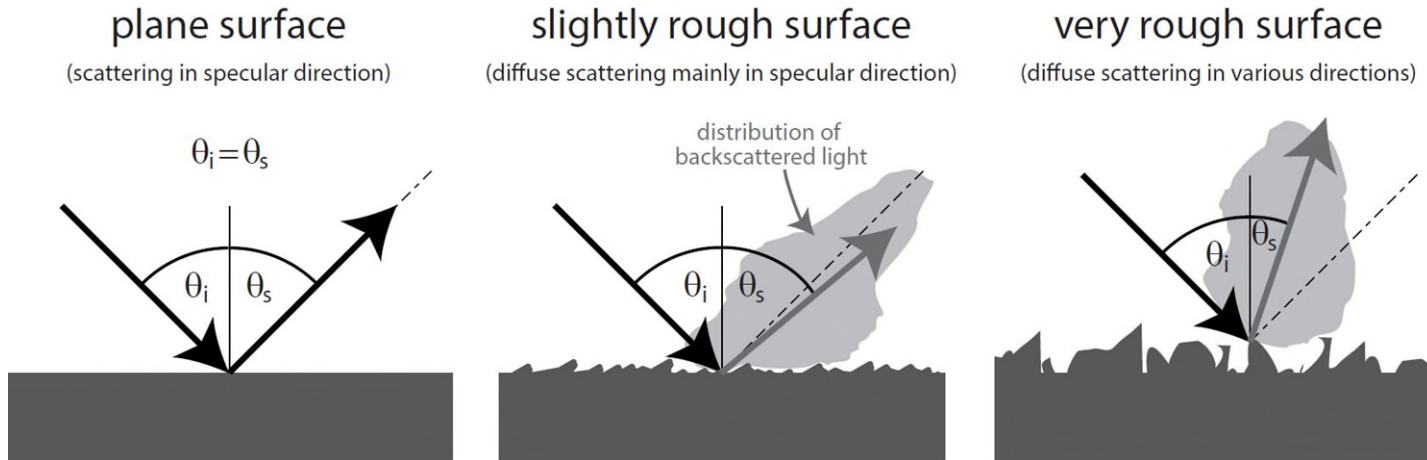
# Sentinel-1 Soil Moisture Retrieval using Machine Learning



Greifeneder et al. (2021) A machine learning-based approach for surface soil moisture estimations with Google Earth Engine, Remote Sensing, 13, 2099, 21p.

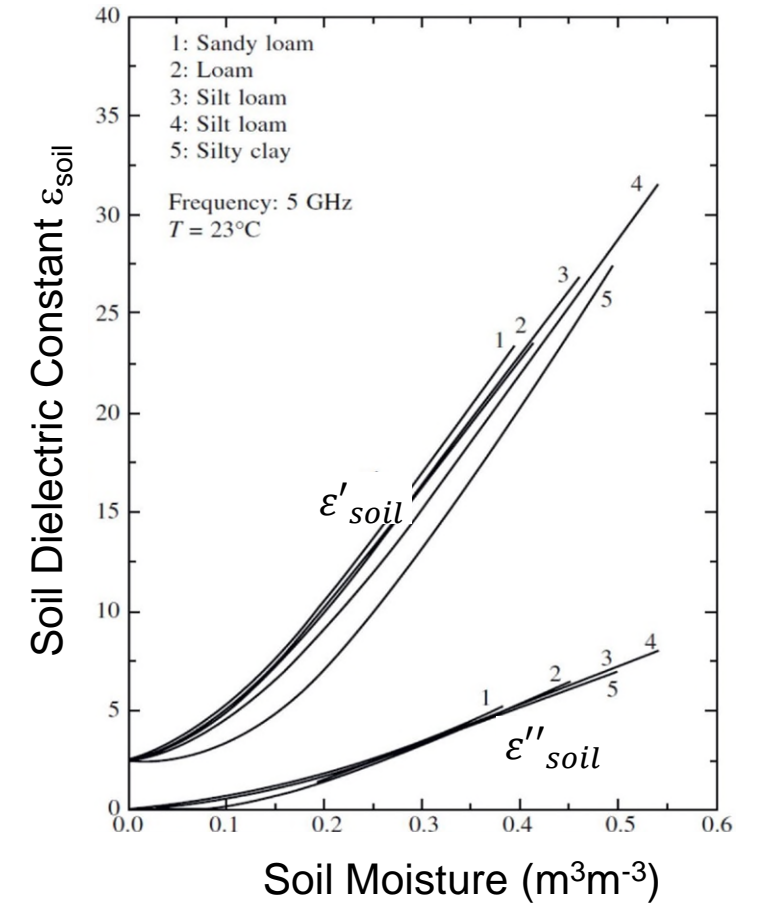
# Soil Scattering

- Soil scattering is principally driven by
  - Soil dielectric constant
    - Soil moisture
    - Texture
  - Soil surface “roughness”
    - Relative to wavelength
    - Dependent on soil moisture

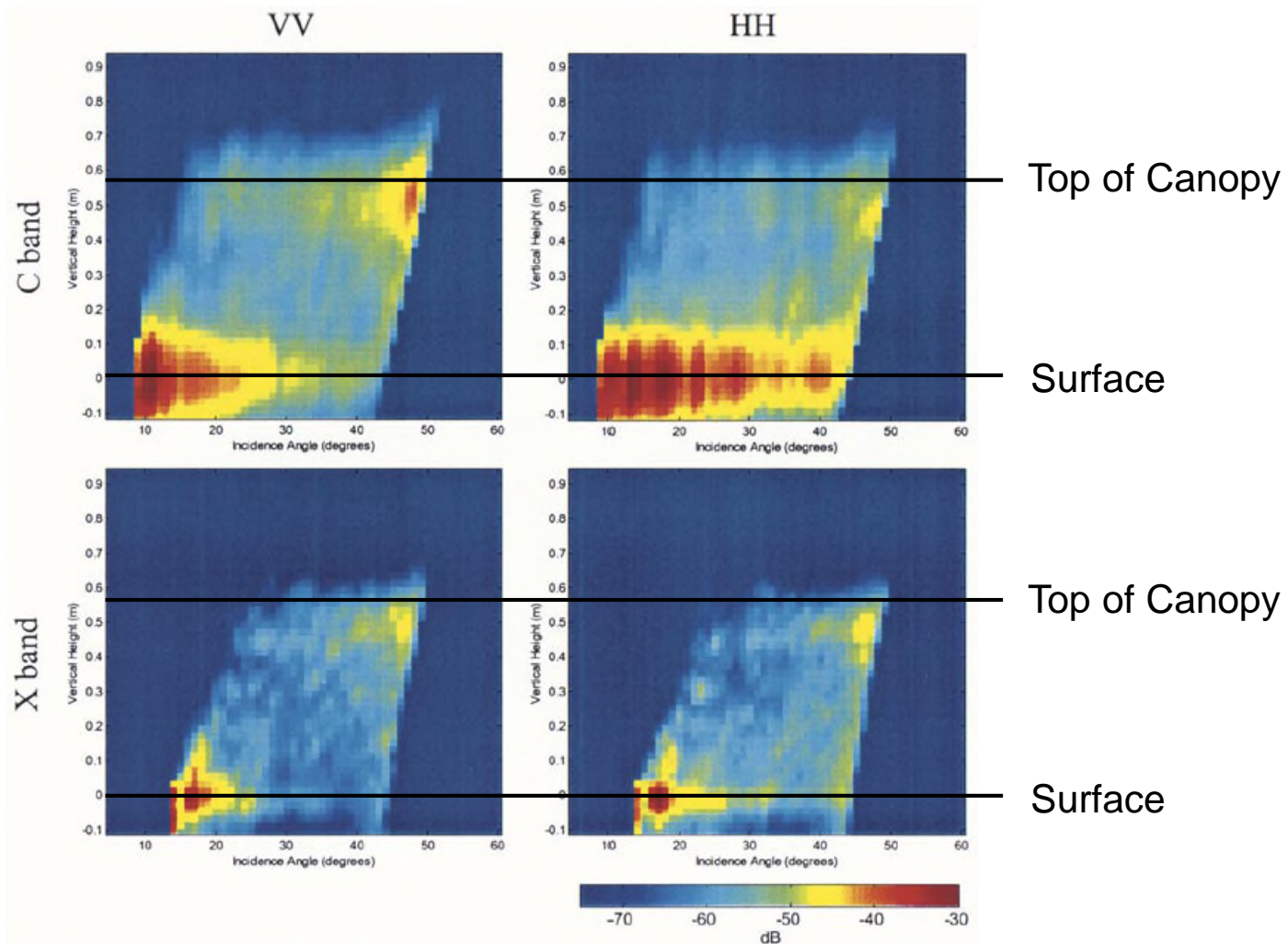


Graphic by R. Quast, TU Wien

Behari (2005) Microwave dielectric behaviour of wet soils, Springer, 164 p.



# Vegetation Scattering



3D radar measurements of a 58 cm high wheat canopy



# Three Backscatter Models

## ■ Change detection backscatter model

- Developed for ENVISAT ASAR and adopted for Sentinel-1
- Used in Copernicus

Bauer-Marschallinger et al. (2019) Towards global soil moisture monitoring with Sentinel-1: Harnessing assets and overcoming obstacles, IEEE Transactions on Geoscience and Remote Sensing, 57(1), DOI 10.1109/TGRS.2018.2858004

## ■ Zero-order radiative transfer model RT0

- Modified water cloud model developed for studying subsurface scattering

Wagner et al. (2022) Widespread occurrence of anomalous C-band backscatter signals in arid environments by subsurface scattering, Remote Sensing of Environment, 276, 113025, DOI 10.1016/j.rse.2022.113025.

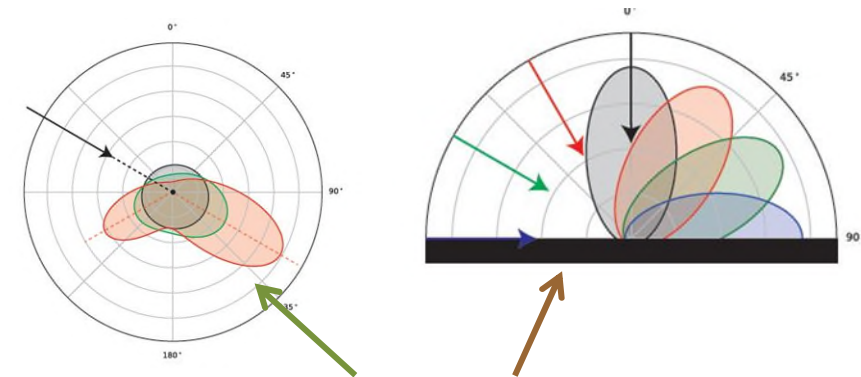
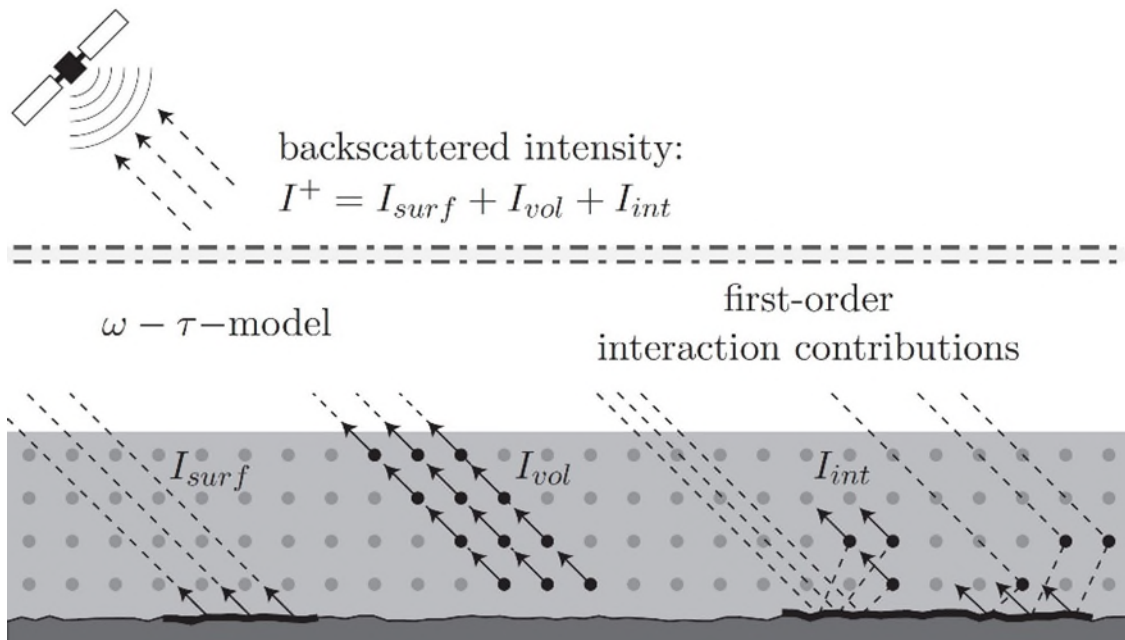
## ■ First-order radiative transfer model RT1

- Developed to describe soil-vegetation interaction mechanisms and a new way of modelling soil scattering

Quast et al. (2023) Soil moisture retrieval from Sentinel-1 using a first-order radiative transfer model - a case-study over the Po-Valley, Remote Sensing of Environment, 295, 113651, DOI 10.1016/j.rse.2023.113651

# RT-1 Model: Scattering by Vegetation and Soil

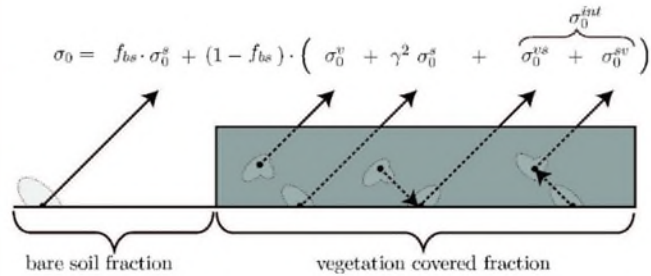
- Radiative transfer model for bi- and monostatic scattering
- Generalised phase functions for modelling surface-volume interactions
- Available on GitHub: <https://github.com/TUW-GEO/rt1>



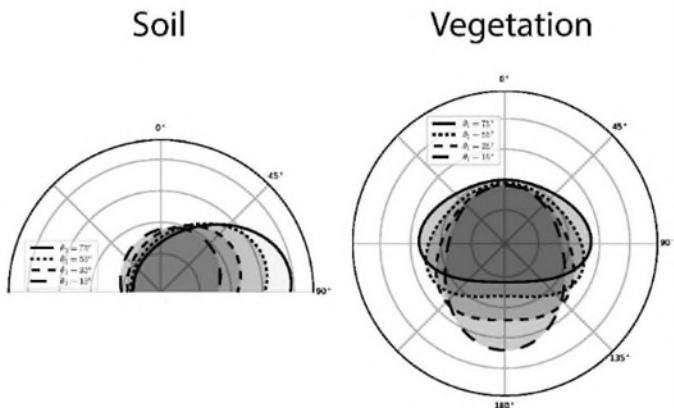
$$I_{int} \propto \iint \dots \mathcal{P}_{vol} \cdot \mathcal{P}_{surf} d\mu d\varphi$$

## Model formulation

### First order Radiative Transfer Model



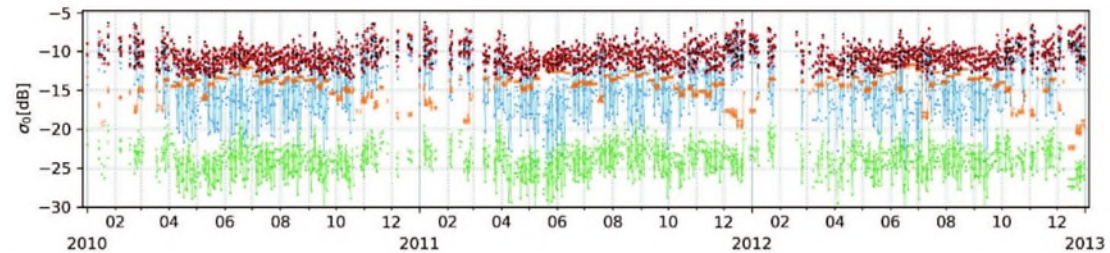
### Parametric scattering distributions



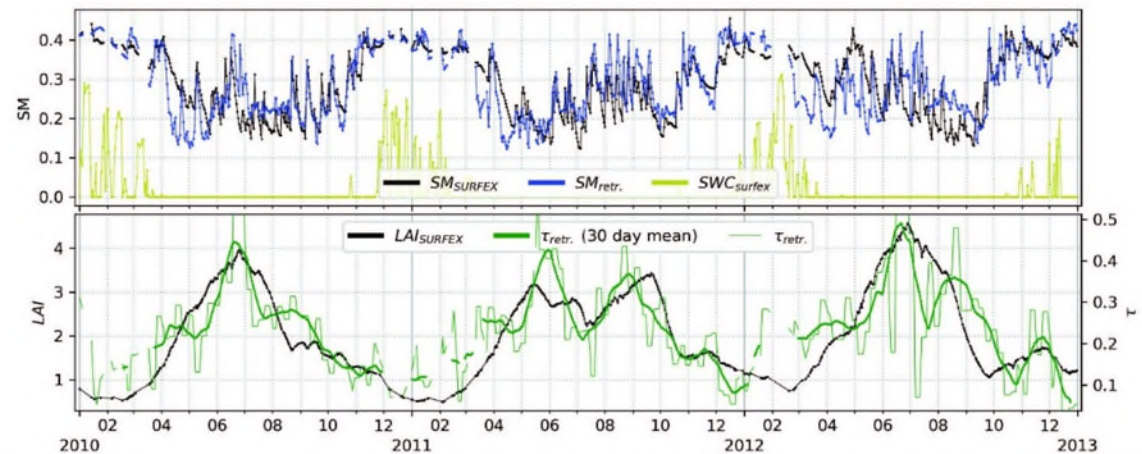
## Application of model to 157 test-sites in France

### Calibration with SURFEX soil-moisture (SM) and LAI

### decomposition of ASCAT backscatter timeseries



### Soil- and vegetation-parameter timeseries

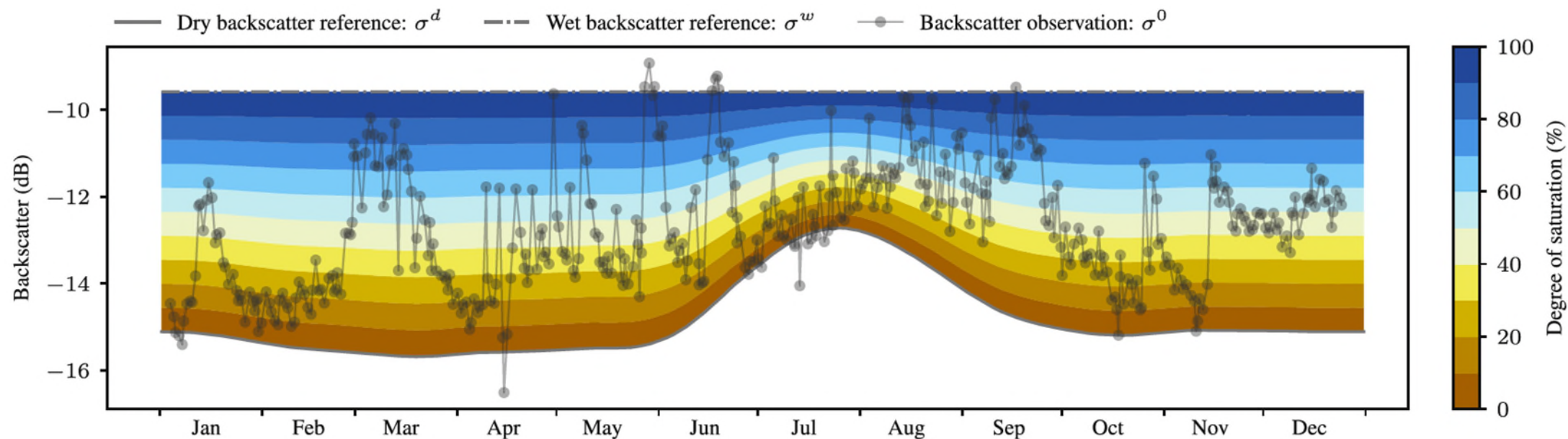




# Soil Moisture Retrieval using a Change Detection Model

- For the EUMETSAT H SAF ASCAT soil moisture data product a change detection model is used which separates changes in backscatter due to soil moisture variations and seasonal vegetation phenology

$$\text{Soil moisture } \theta(t) = \frac{\sigma^0(t) - \sigma_{dry}^0(t)}{\sigma_{wet}^0(t) - \sigma_{dry}^0(t)}$$

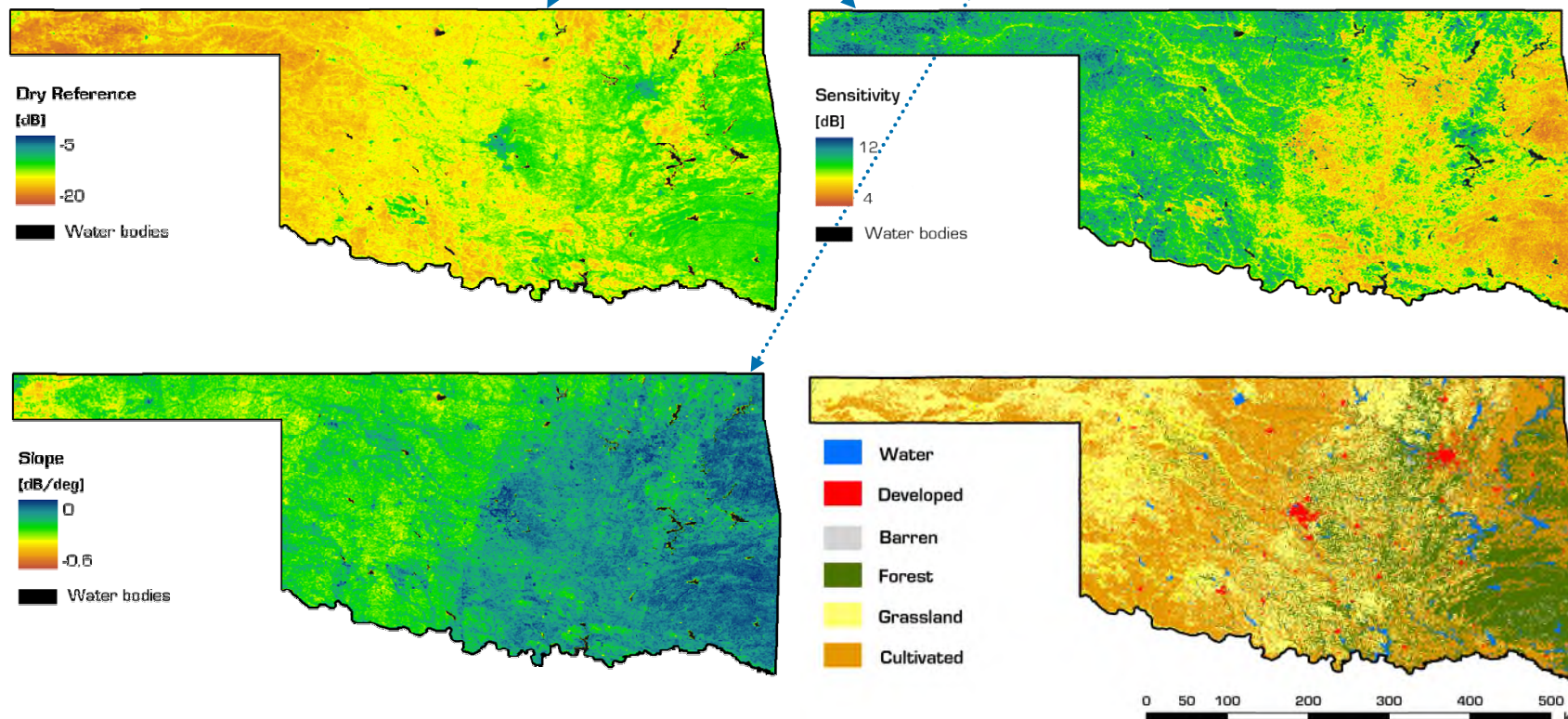


Hahn et al. (2021) Improving ASCAT soil moisture retrievals with an enhanced spatially-variable vegetation parameterization, IEEE Transactions on Geoscience and Remote Sensing, 10, 8241-8256.

# SAR Backscatter Model

- Retrieval method is based on a backscatter model originally developed for the ERS scatterometer and later adopted to ENVISAT ASAR and Sentinel-1

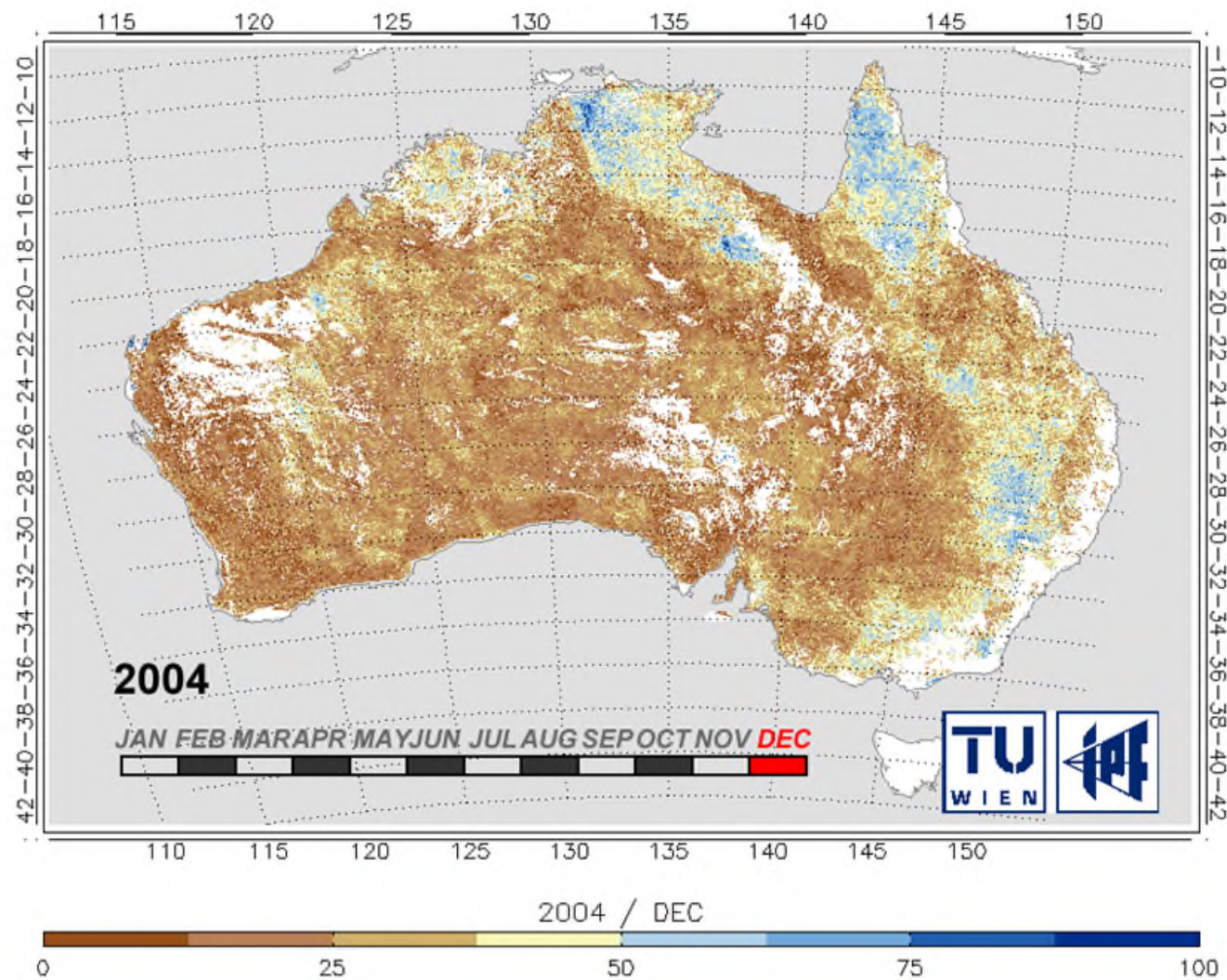
$$\sigma^0(t, \theta) = \sigma_{dry}^0(30) + S \cdot m_s(t) + \beta(\theta - 30)$$



ASAR backscatter model parameters and land cover map of Oklahoma, USA.

Pathe et al. (2009) Using ENVISAT ASAR Global Mode data for surface soil moisture retrieval over Oklahoma, USA, IEEE Transactions on Geoscience and Remote Sensing, 47(2), 468-480.

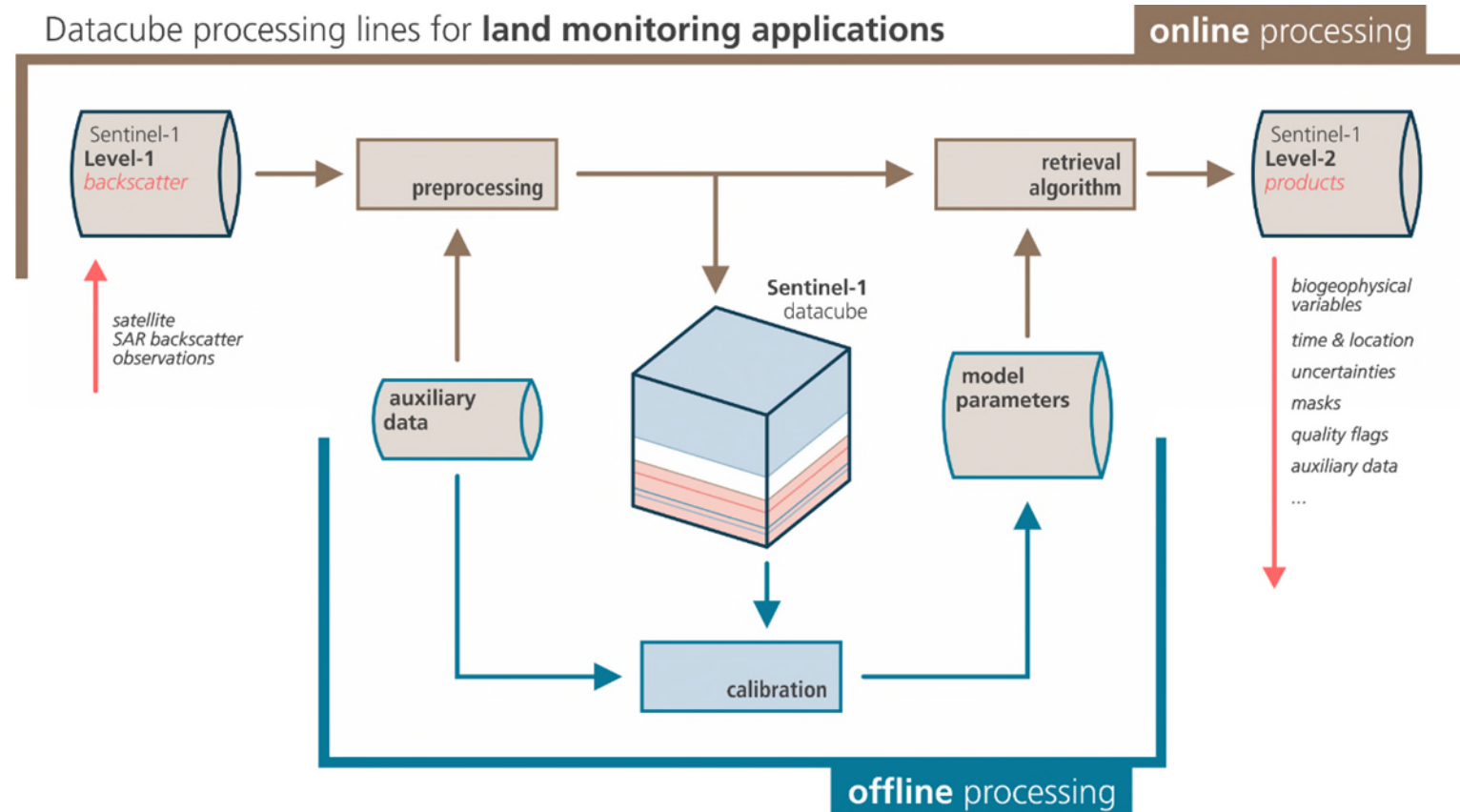
# ENVISAT ASAR SSM



# Sentinel-1 Pre-Processing

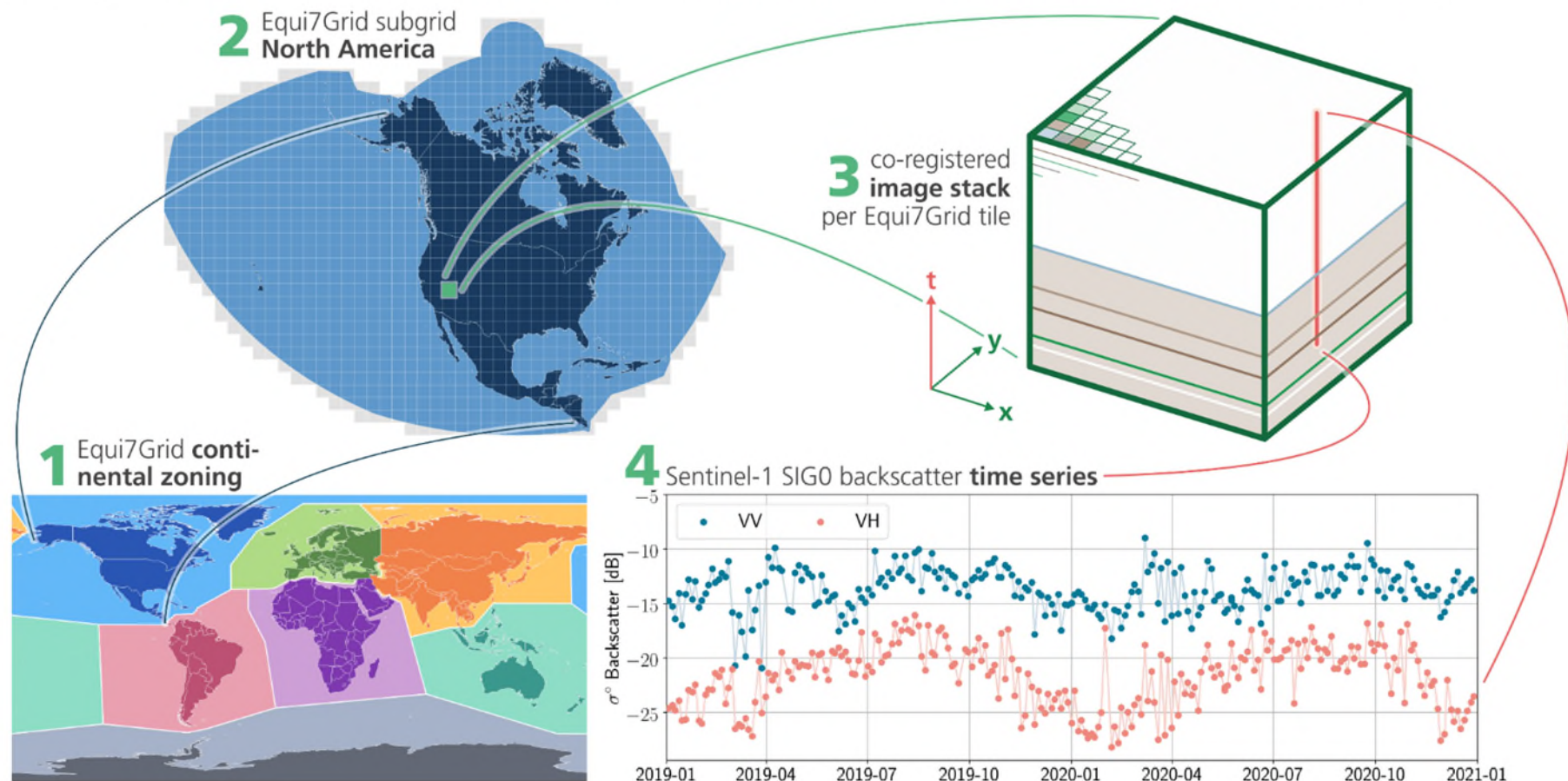
# Datacube Processing Architecture

- From offline scientific analysis and model calibration to online operations



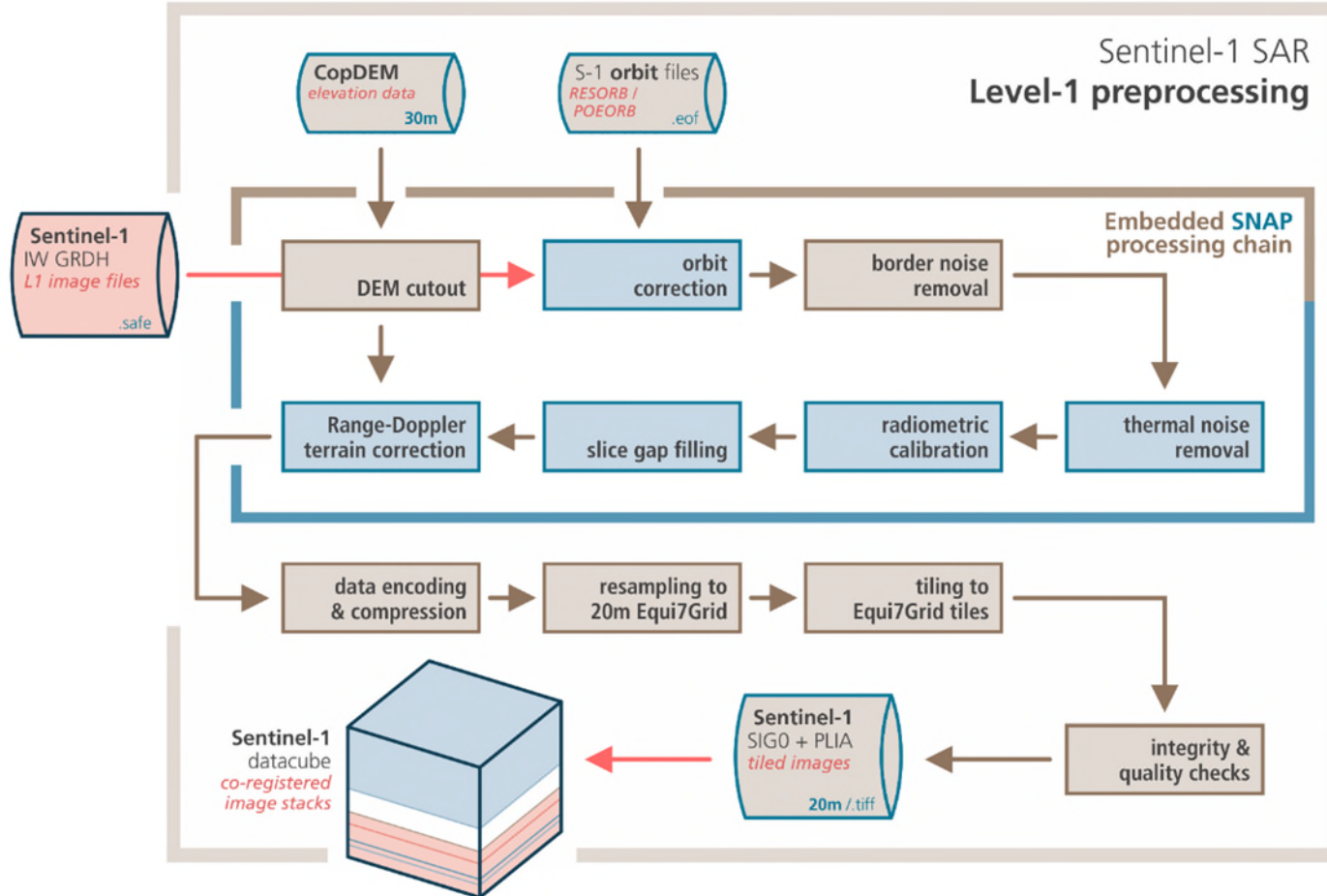
# Datacube System based upon the Equi7Grid

Sentinel-1 ARD datacube: Concept of **Equi7Grid data structure** & **time series access** | Example for T3-tile over the USA



Bauer-Marschallinger et al. (2014) Optimisation of global grids for high-resolution remote sensing data, *Computers & Geosciences*, 72, 84-93. Figure from Wagner et al. (2021) A Sentinel-1 Backscatter Datacube for Global Land Monitoring Applications, *Remote Sensing*, 13, 4622.

# Sentinel-1 Preprocessing



## Data Volume in TB

Level-1 Sentinel-1 IW GRD data

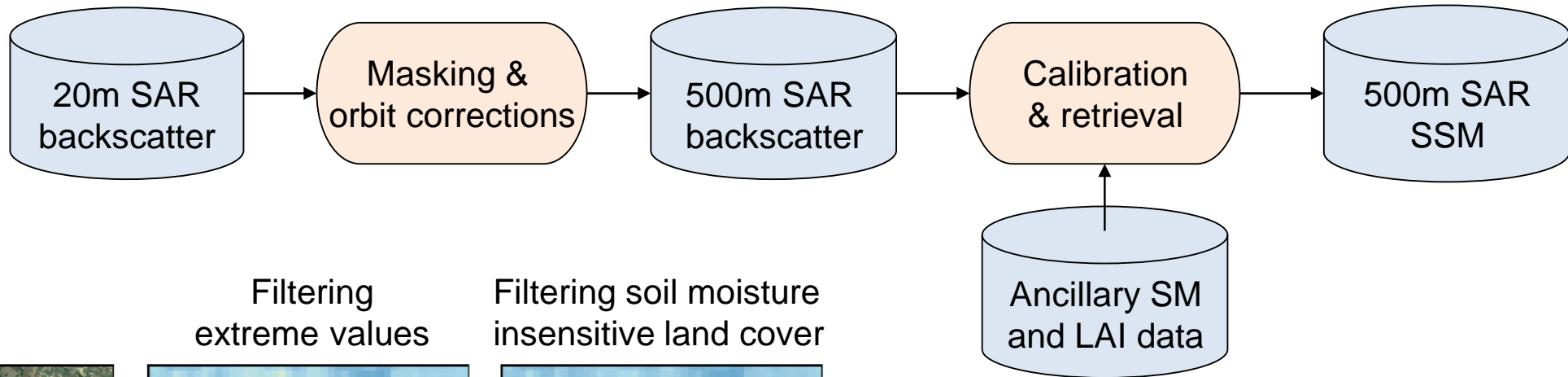
Year	Africa	Asia	Europe	NA	Oceania	SA	Total
2015	12.7	15.1	22.0	6.2	4.9	5.3	66.2
2016	20.6	19.2	31.9	11.5	6.6	9.0	98.8
2017	45.0	53.9	71.8	31.4	18.4	23.1	243.6
2018	48.0	58.1	70.3	35.3	20.2	24.7	256.6
2019	94.4	61.1	119.9	38.5	21.1	26.9	361.9
2020	97.3	63.3	130.7	41.4	21.3	28.6	382.6
<b>Total</b>	<b>318.0</b>	<b>270.7</b>	<b>446.6</b>	<b>164.3</b>	<b>92.5</b>	<b>117.6</b>	<b>1409.7</b>

20 m Sentinel-1 datacube

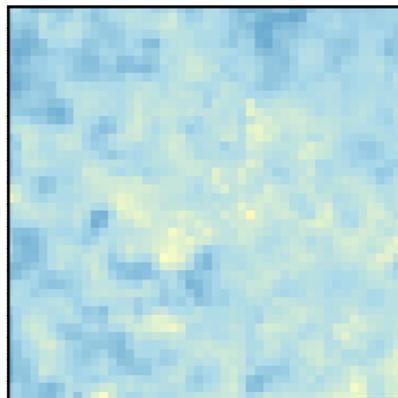
Year	Africa	Asia	Europe	NA	Oceania	SA	Total
2015	2.5	2.9	4.3	1.2	1.1	1.0	13.0
2016	4.4	4.0	6.4	2.5	1.5	1.9	20.7
2017	9.8	11.9	14.6	6.9	4.3	4.9	52.4
2018	10.3	12.8	12.8	7.6	4.7	5.2	53.4
2019	16.9	19.4	23.5	13.4	7.6	8.6	89.4
2020	17.3	20.1	25.0	14.6	7.7	9.4	94.1
<b>Total</b>	<b>61.2</b>	<b>71.1</b>	<b>86.6</b>	<b>46.1</b>	<b>26.9</b>	<b>31.0</b>	<b>323.0</b>

# From 20m to 1km Sentinel-1 Backscatter Data

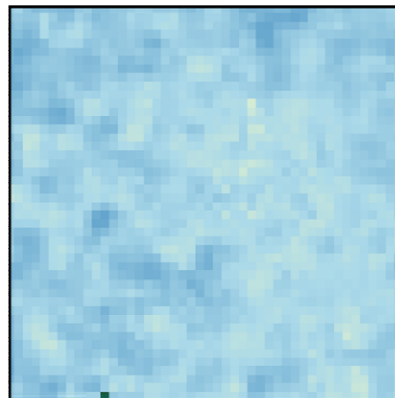
- Improving soil moisture retrievals by masking high resolution input
- Correcting orbit and incidence angle effects



Filtering extreme values



Filtering soil moisture insensitive land cover



Higher correlation to reference ERA5-Land soil moisture by masking extreme values and pixels insensitive to soil moisture, e.g. urban areas



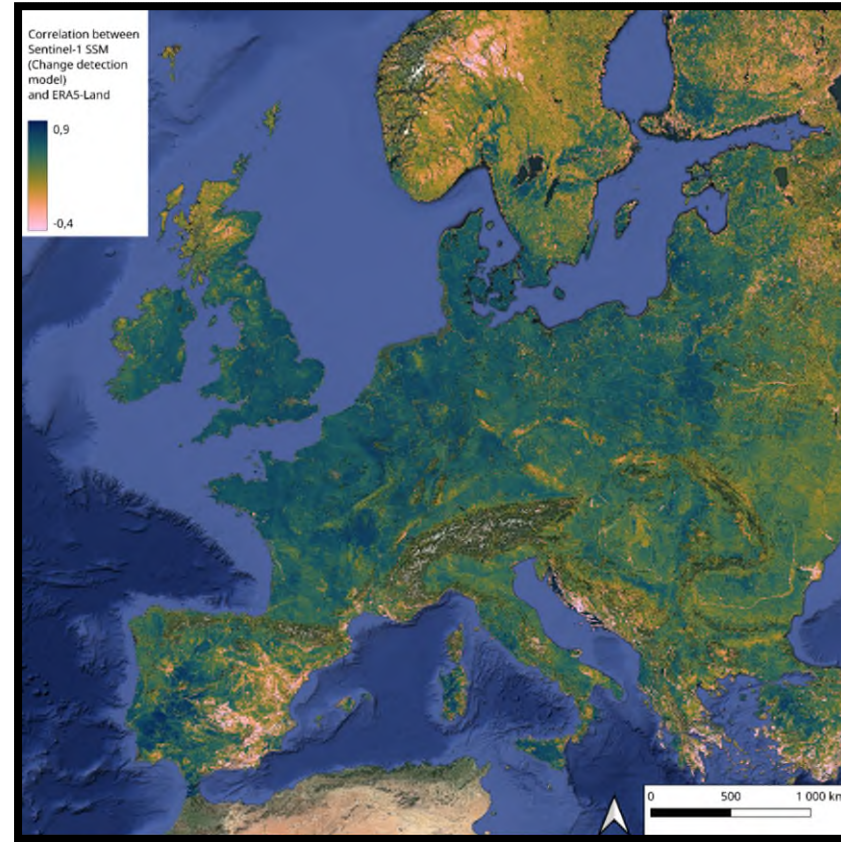
# Masking of Non-Soil-Moisture-Sensitive Areas

- Urban areas, dense forests, water bodies/inundated areas, etc.

Without Masking Forests



With Masking Forests



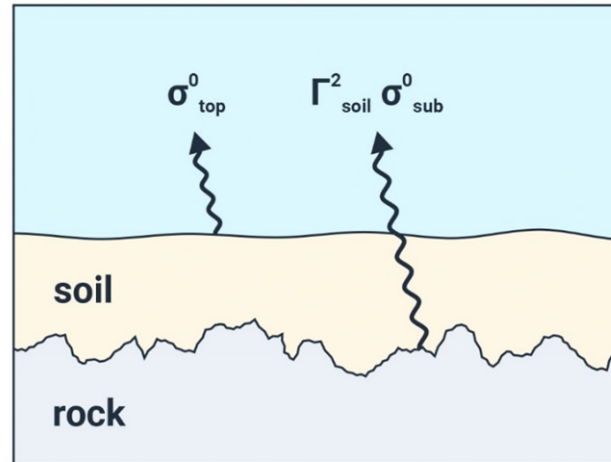
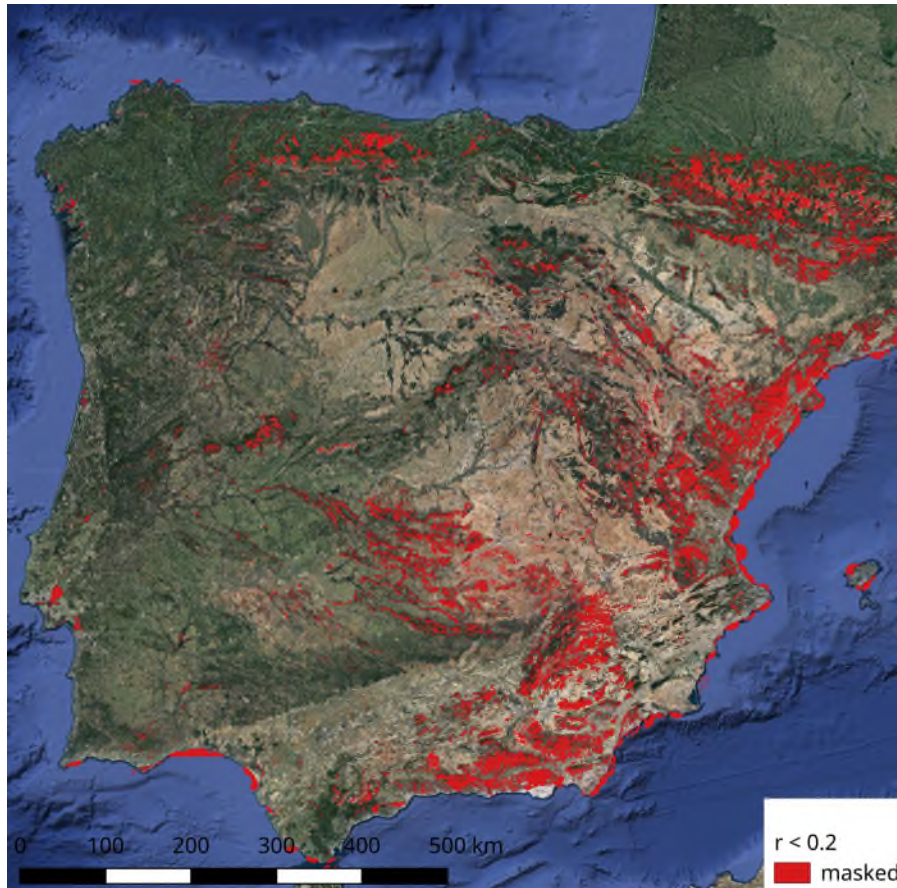
Correlation improves when masking dense forest areas before aggregating to 1 km scale

Massart et al. (2023) Mitigating the impact of dense vegetation on the Sentinel-1 surface soil moisture over Europe, EGU General Assembly 2023, <https://doi.org/10.5194/egusphere-egu23-12269>, 2023.

Masking was done based on the Sentinel-1 derived forest map by Dostálová et al. (2021) European wide forest classification based on Sentinel-1 data, Remote Sensing, 13, 337, 10.3390/rs13030337

# Subsurface scattering in Arid Regions

- Backscatter may increase due to near-surface rocks and stones when soil dries



Red pixels indicate subsurface scattering areas. Processing by Bernhard Raml

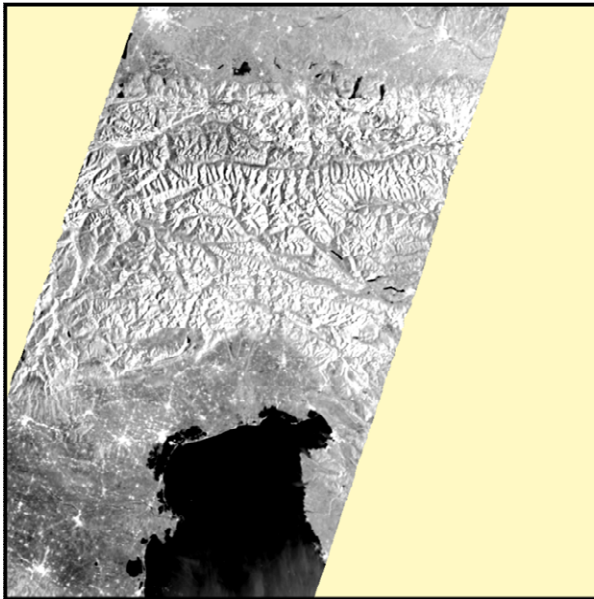


Wagner et al. (2022) Widespread occurrence of anomalous C-band backscatter signals in arid environments by subsurface scattering, Remote Sensing of Environment, 276, 113025, DOI 10.1016/j.rse.2022.113025.

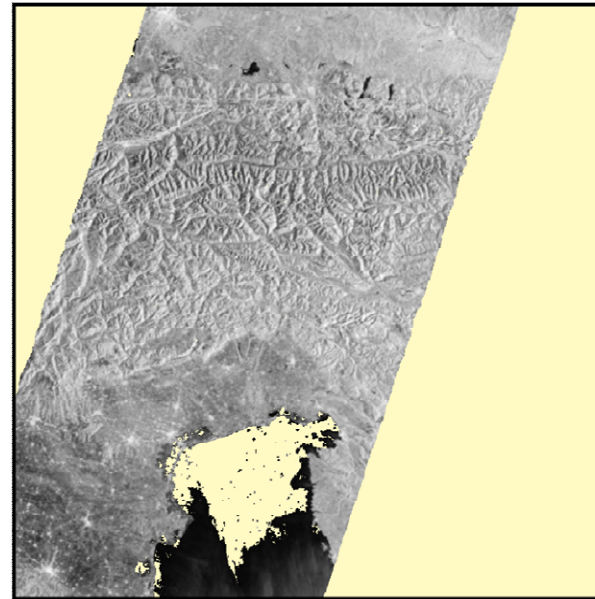
# 1km Backscatter Data Optimised for Soil Moisture Retrieval

- Aggregate to 500m grid after masking for soil moisture insensitive areas
  - Dense forest, urban areas, water bodies, wetlands, subsurface scattering areas, snow, frost, ...
- Efficient processing thanks to optimised I/O operations (“streaming”)

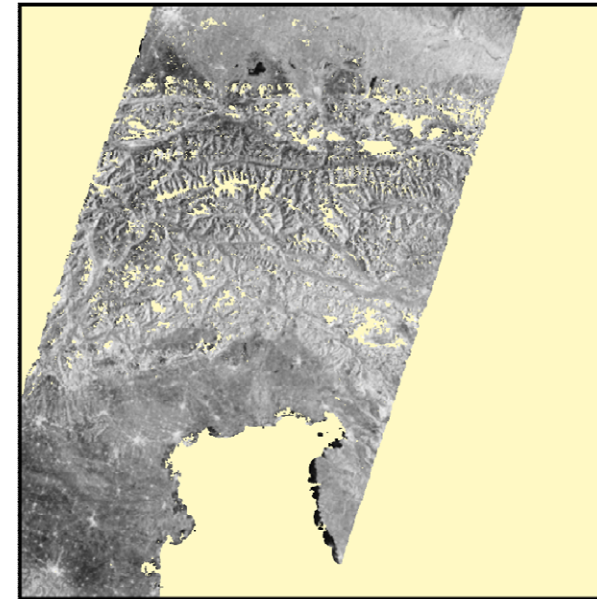
Without filtering



Filtering extreme values



Filtering soil moisture insensitive land cover



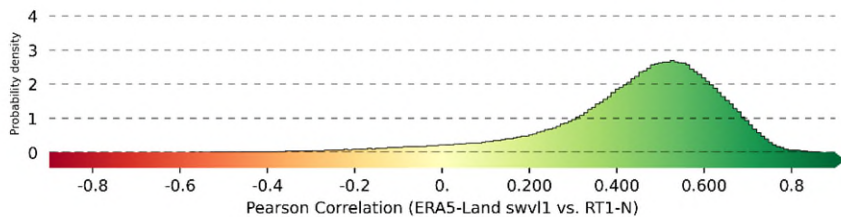
VV  $\sigma$  nought [dB]

-19

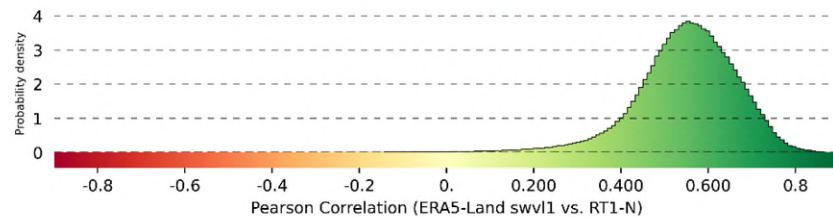
-6

# Impact of Masking on Sentinel-1 SSM Retrievals

Without Masking



With Masking



Correlation between Sentinel-1 SSM and ERA5-Land.

The Sentinel-1 SSM were derived with RT1 using a trust-region-reflective least squares algorithm and only LAI as ancillary data set.

Quast et al. (2022) Soil moisture retrieval from Sentinel-1 using a first-order radiative transfer model - a case-study over the Po-Valley, submitted.

# Sentinel-1 Soil Moisture

# Operational Sentinel-1 SSM from Copernicus

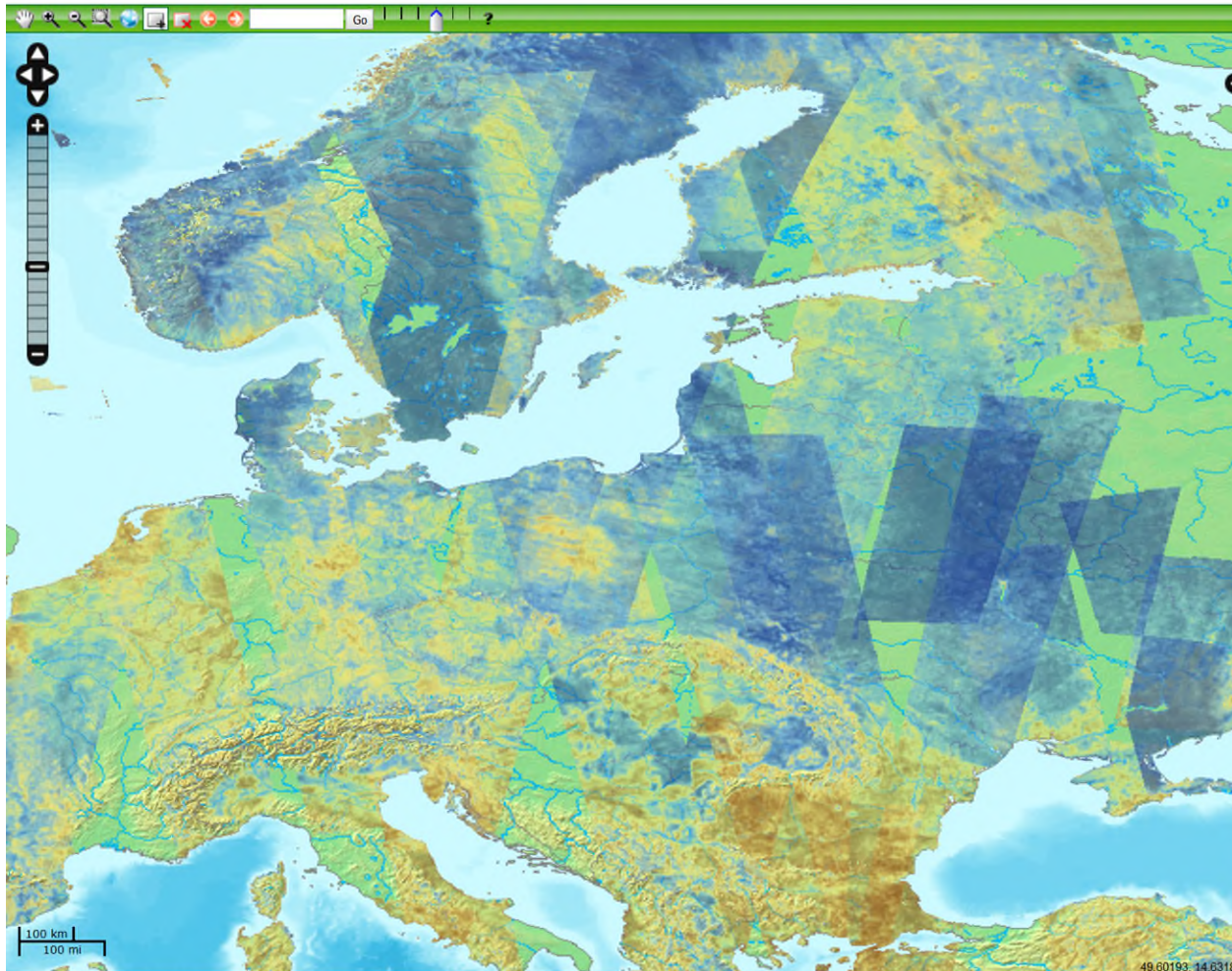
## Copernicus Global Land Service

Providing bio-geophysical products of global land surface



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Surface Soil Moisture - Daily SSM 1km Europe V1

0 products selected on a total of 9      20 Per      << < 1 of 1 > >>

Select all 9 products

<input type="checkbox"/>	Download	Product ID	Start Date	End Date	Size	Thumbnail	Quicklook
<input type="checkbox"/>	↓	SSM1km_202109300000_CEURO_S1	30/09/202	30/09/202	3.9 MB		
<input type="checkbox"/>	↓	SSM1km_202109290000_CEURO_S1	29/09/202	29/09/202	9.4 MB		
<input type="checkbox"/>	↓	SSM1km_202109280000_CEURO_S1	28/09/202	28/09/202	7.6 MB		
<input type="checkbox"/>	↓	SSM1km_202109270000_CEURO_S1	27/09/202	27/09/202	5.9 MB		
<input type="checkbox"/>	↓	SSM1km_202109260000_CEURO_S1	26/09/202	26/09/202	6.2 MB		
<input type="checkbox"/>	↓	SSM1km_202109250000_CEURO_S1	25/09/202	25/09/202	6.9 MB		
<input type="checkbox"/>	↓	SSM1km_202109240000_CEURO_S1	24/09/202	24/09/202	7.3 MB		
<input type="checkbox"/>	↓	SSM1km_202109230000_CEURO_S1	23/09/202	23/09/202	7.6 MB		
<input type="checkbox"/>	↓	SSM1km_202109220000_CEURO_S1	22/09/202	22/09/202	7.4 MB		

<https://land.copernicus.eu/global/>

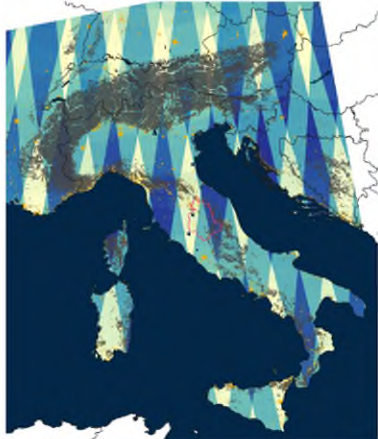


# Sentinel-1 SSM Retrieval

1km Sentinel-1 SSM - Model Parameters & Land Cover

a) Number of Observations

S-1A & S-1B | Oct 2014 - Oct 2017

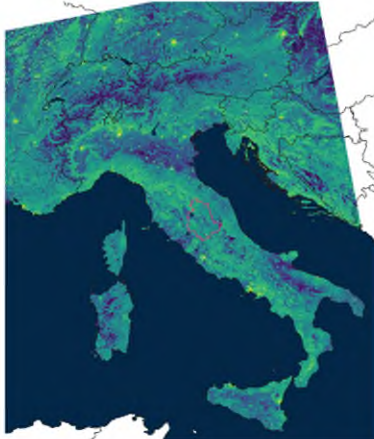


S-1 Observations per Pixel  
180 260 340 420

Terrain Mask  
Sensitivity Mask

b) for Dry Reference:  $\sigma_{10}^0(40)$

10%- Percentile SAR Backscatter



SAR Backscatter  
-14 -12 -10 -8

c) for Wet Reference:  $\sigma_{90}^0(40)$

90%- Percentile SAR Backscatter

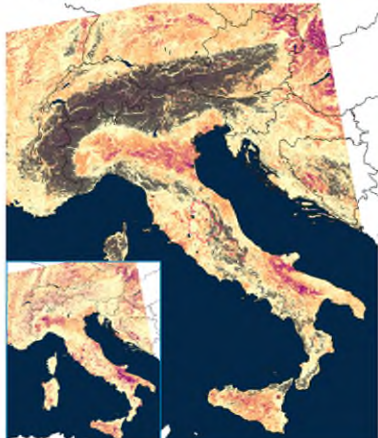


Water Mask  
No Data

Outline Umbria

d) SAR Slope  $\beta$ ,

from regression method

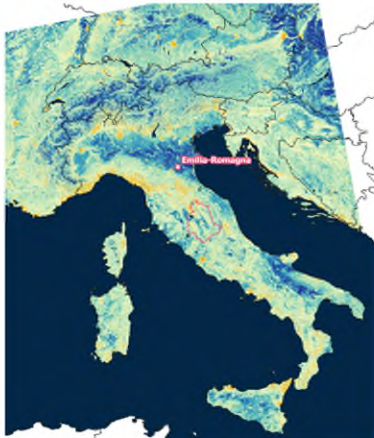


ASAR WS Slope  
2005 - 2012

SAR Slope [dB/°]  
-0.15 -0.12 -0.09 -0.06

e) SSM Sensitivity  $S(40)$

Difference Wet - Dry Reference



Sens. Mask  
SSM Sensitivity [dB]  
0 1.2 2 3 4 5 6

f) Land Cover Classification

CORINE 2012 | major classes grouped



CLC grouped  
arable forest urban water rocks/ice

- Use all orbits to maximise temporal coverage
- Pre-processing workflows to produce 1km backscatter data
  - Masking of extreme values:  $-20\text{dB} < \sigma^0 < -5\text{dB}$
  - Gaussian filtering to resample to 500m grid
  - Standardisation of backscatter  $\sigma^0$  to  $40^\circ$
- Adjustment of algorithms
  - Methods for estimating model parameters

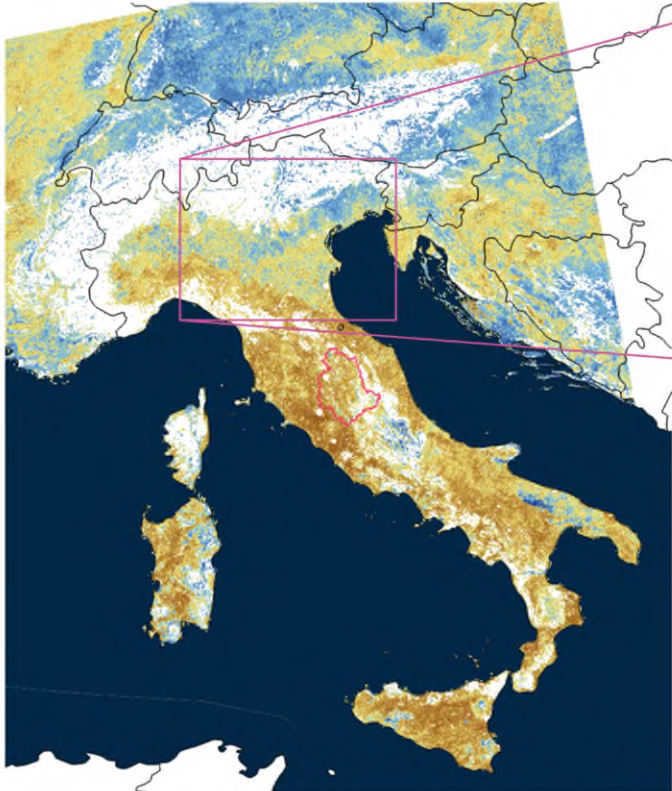
Bauer-Marschallinger et al. (2019) Towards global soil moisture monitoring with Sentinel-1: Harnessing assets and overcoming obstacles, IEEE Transactions on Geoscience and Remote Sensing, 57(1), 520-539.

# Sentinel-1 SSM vs Precipitation

a) Drought: Italy Summer 2017

Sentinel-1 SSM Monthly Mean

2017 July

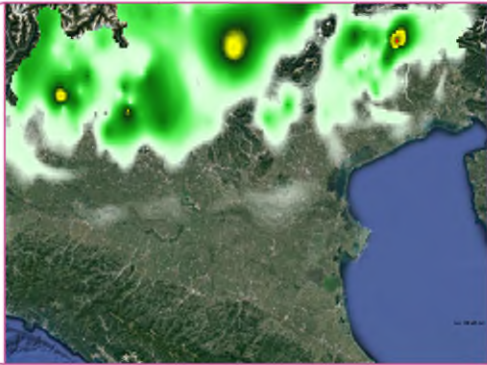


Surface Soil Moisture [%]    Mask / No Data    Outline Umbria  
0    25    50    75    100

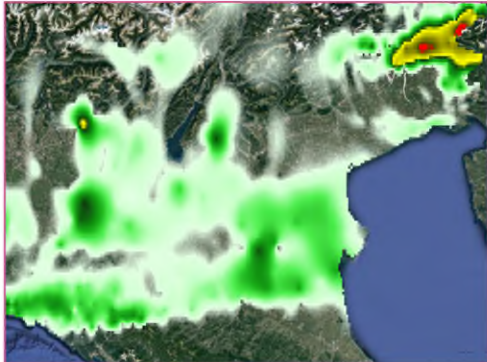
b) Rainfall Event: Po Valley 2017 July 11

Observed Cumulative Rainfall

2017 July 10 | 0-24h



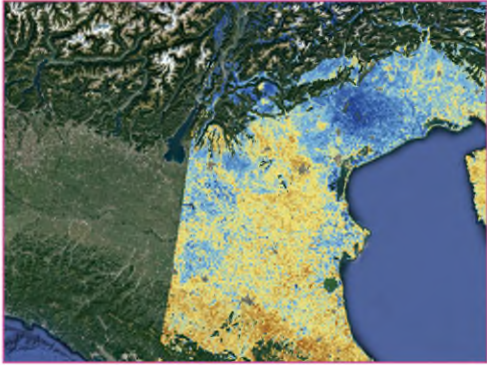
2017 July 11 | 0-24h



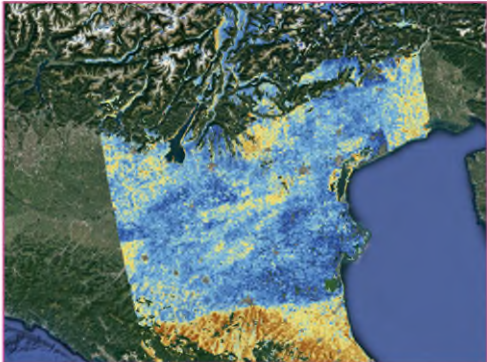
Precipitation [mm]  
0    40    100    200

Sentinel-1 SSM (single observations)

2017 July 10 | 05:18



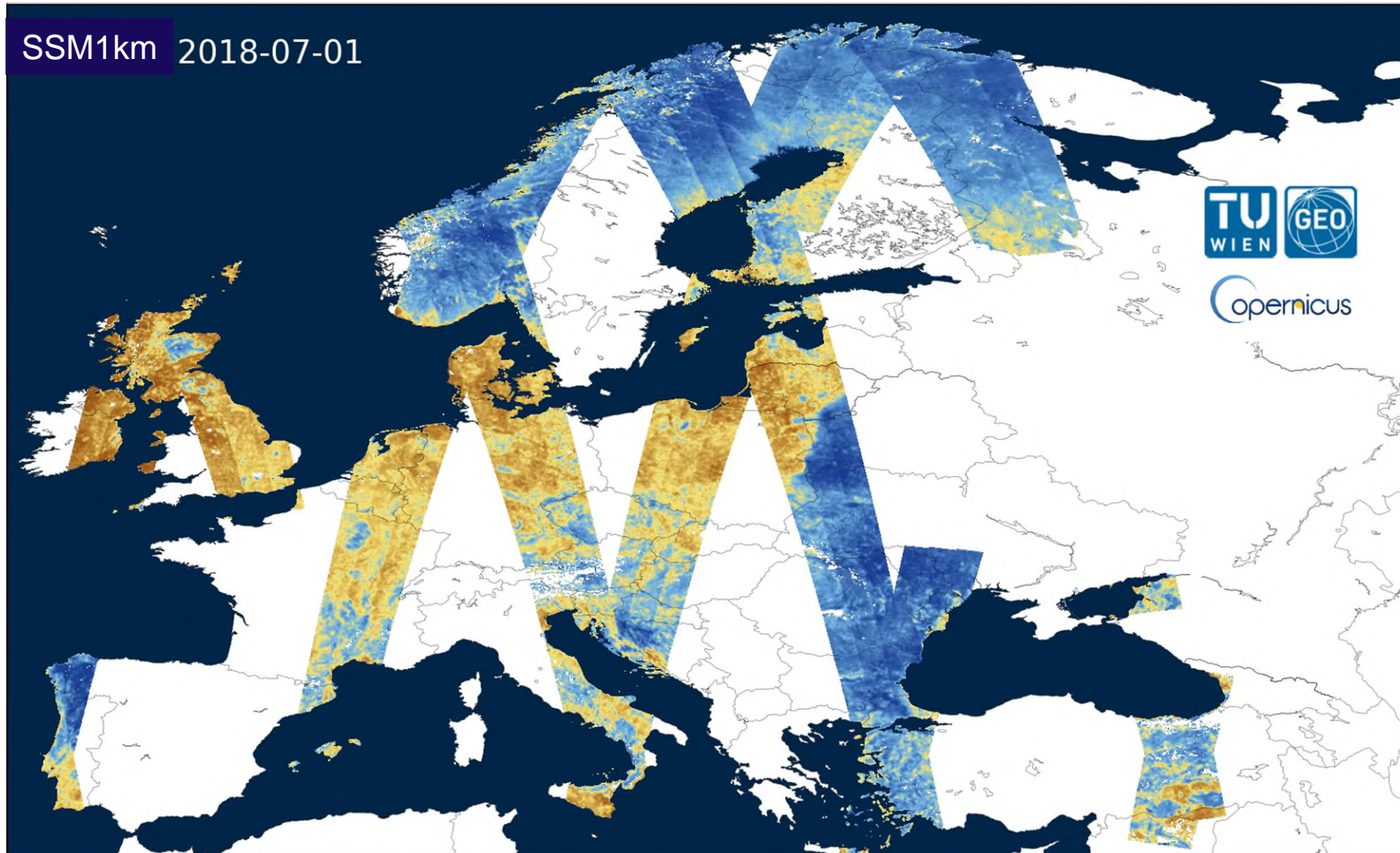
2017 July 11 | 17:04



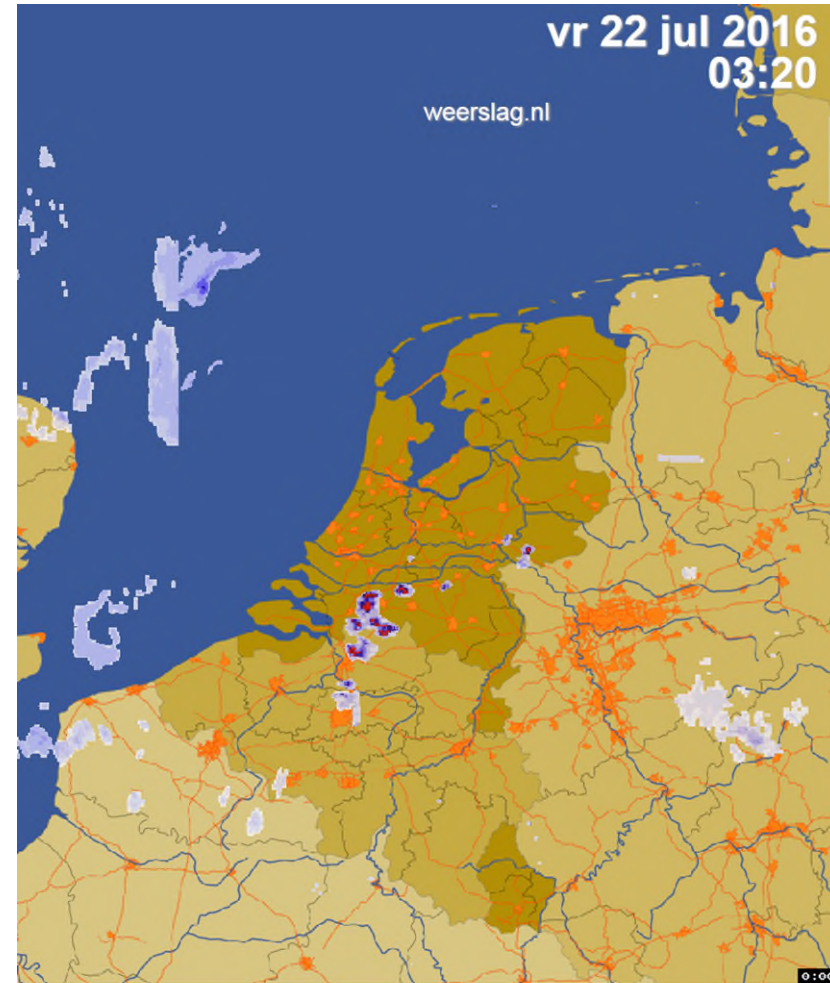
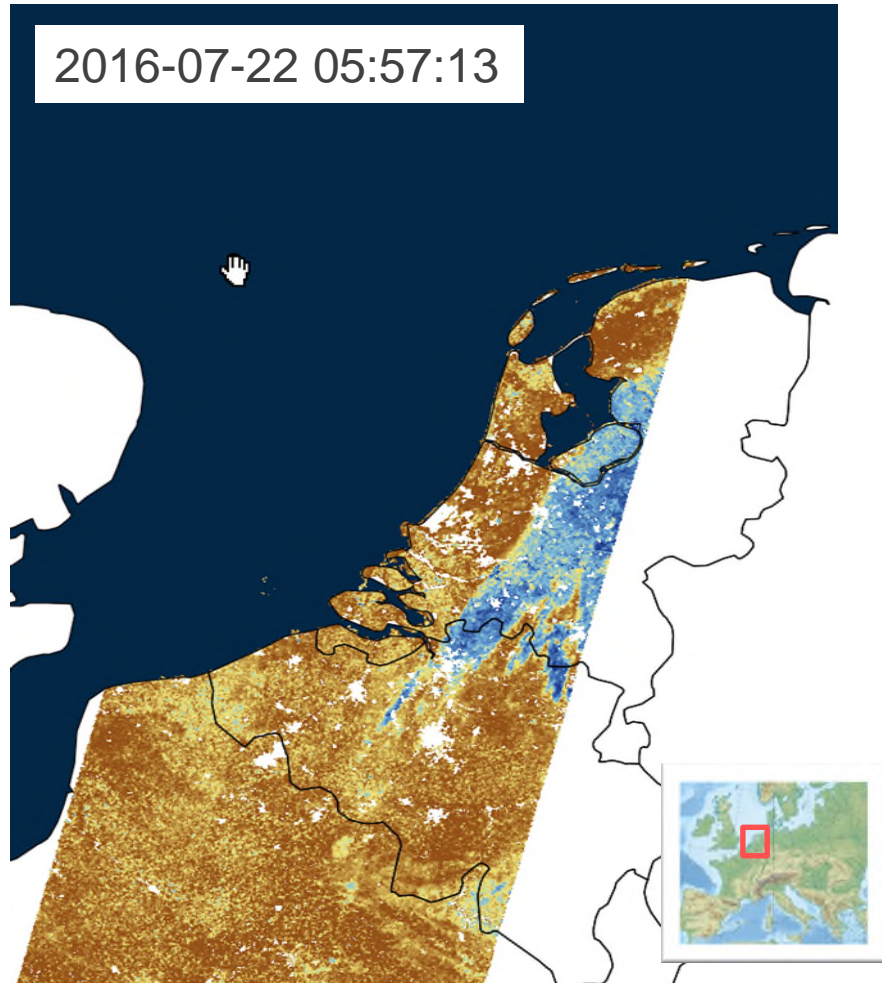
Surface Soil Moisture [%]  
0    25    50    75    100



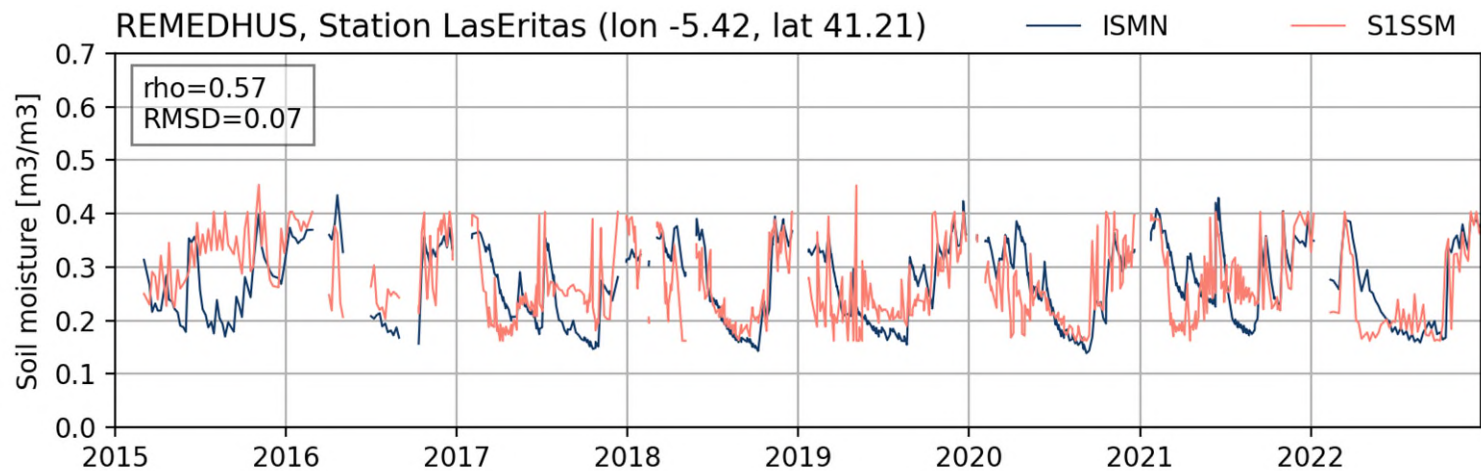
# Copernicus Sentinel-1 SSM Animation



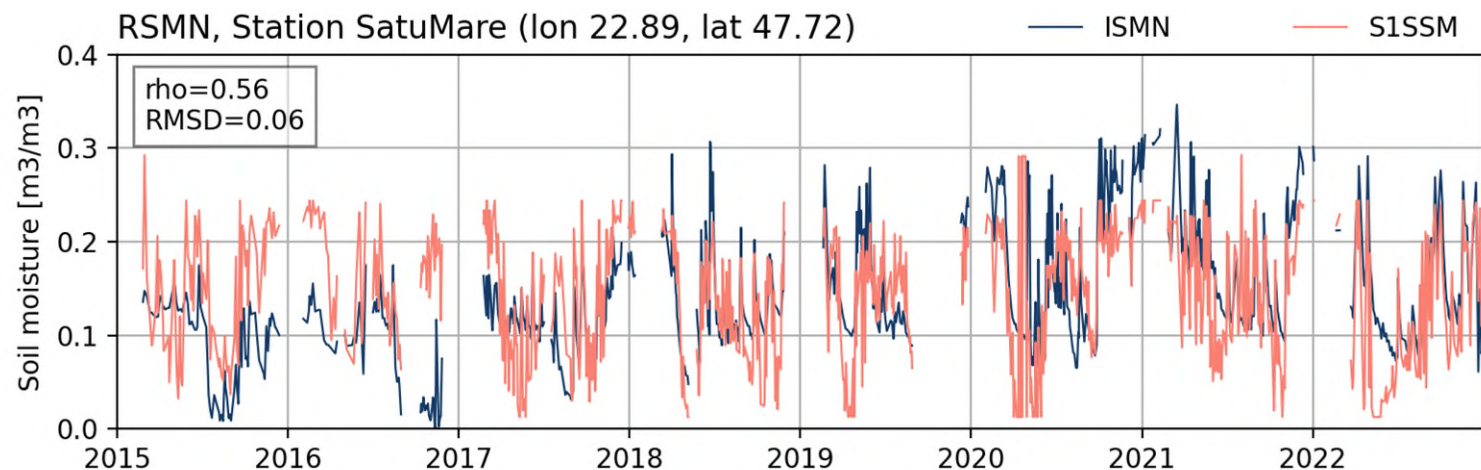
# Sentinel-1 Soil Moisture & Precipitation Radar



# Sentinel-1 versus in situ SSM Time Series



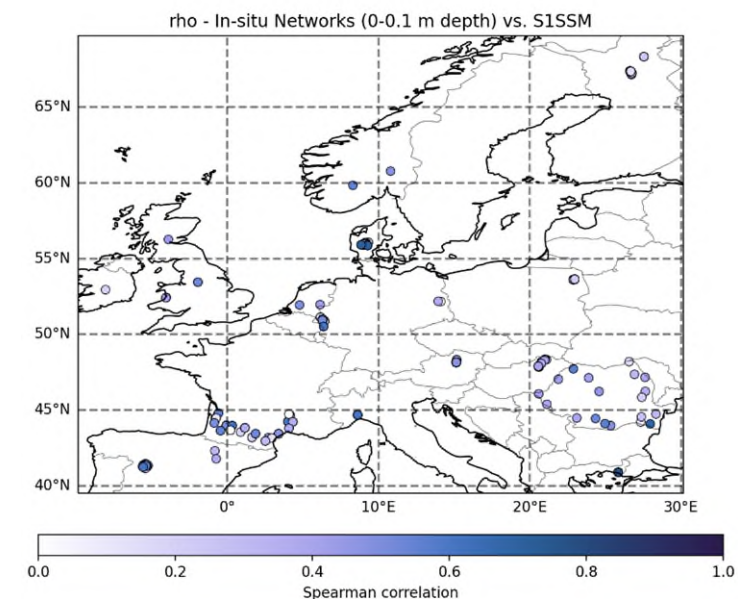
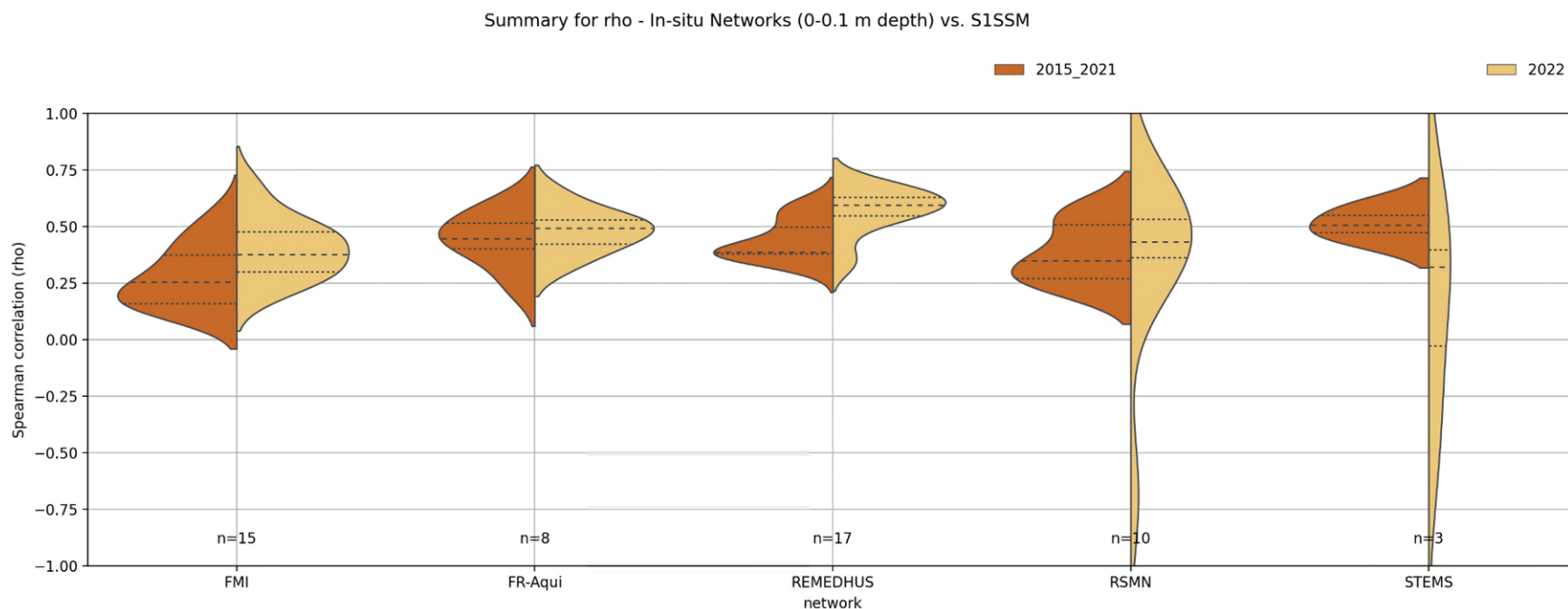
REMEDHUS Network, Spain



RSMN Network, Romania

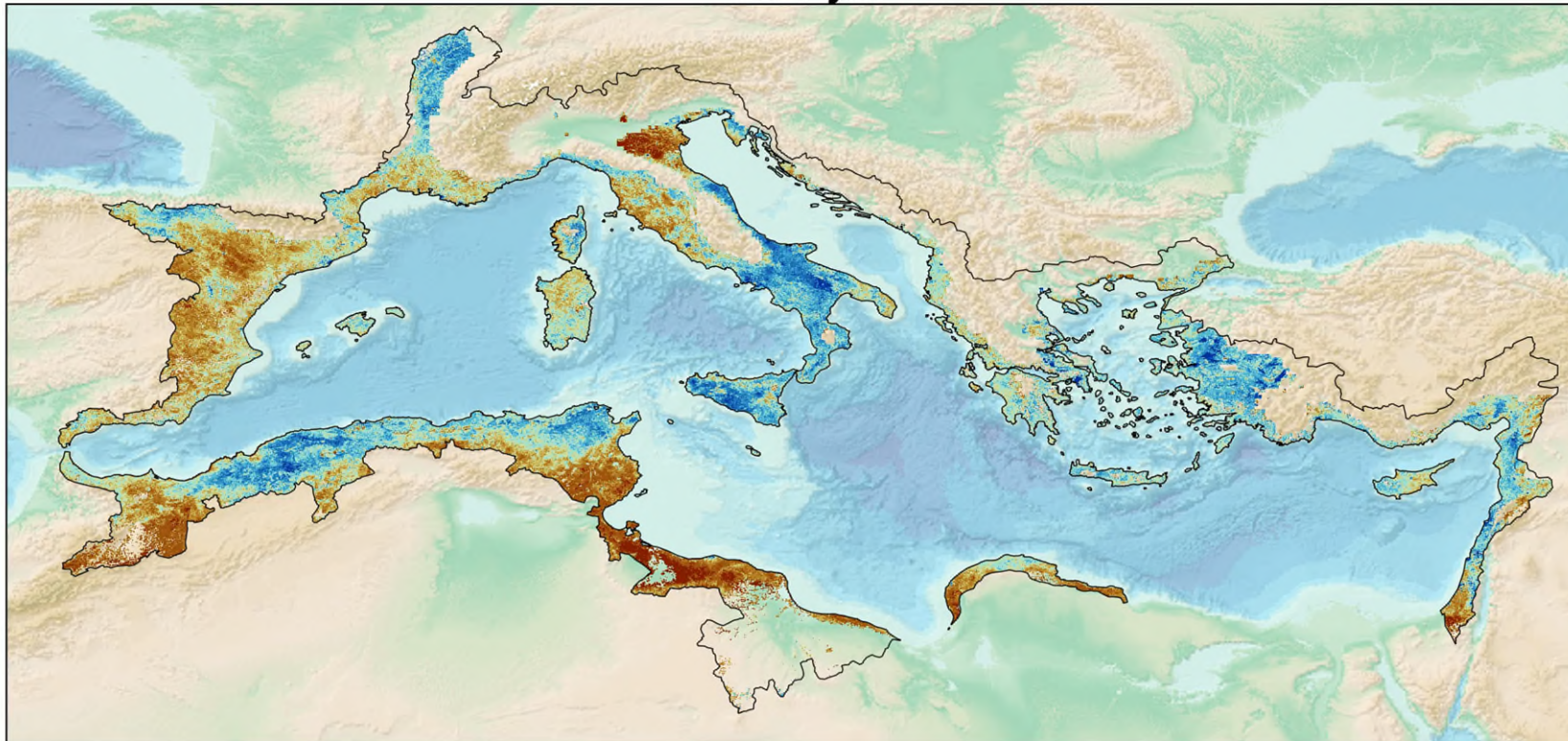
# Sentinel-1 versus in situ SSM Time Series

- Due to a mismatch of spatial and temporal scales and retrieval errors correlation values are low to modest
  - There may be differences from year to year (e.g. due to crop rotation)



# New RT-1 based 1km Sentinel-1 Surface Soil Moisture Retrievals

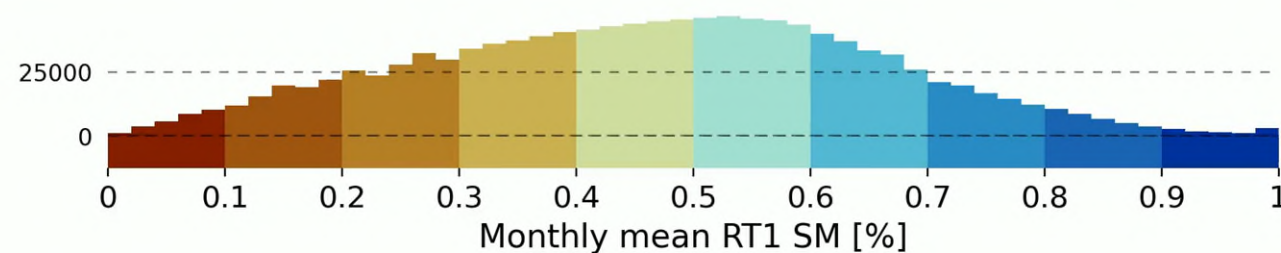
2017 Jan



Mean-monthly Sentinel-1 surface soil moisture retrievals for the Mediterranean region from 2017 to 2021.

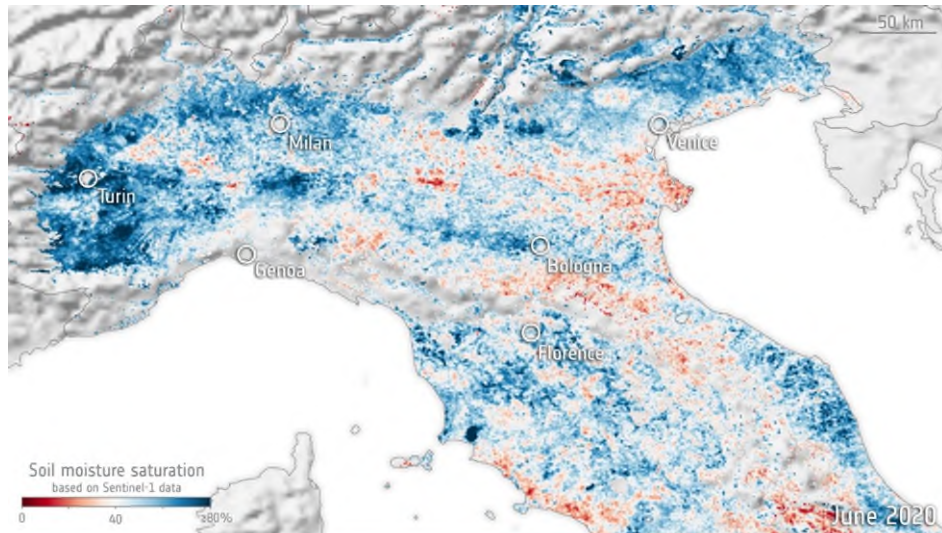
*Sentinel-1 retrievals and animation from Raphael Quast.*

Quast et al. (2023) Soil moisture retrieval from Sentinel-1 using a first-order radiative transfer model - a case-study over the Po-Valley, Remote Sensing of Environment, 295, 113651, DOI 10.1016/j.rse.2023.113651

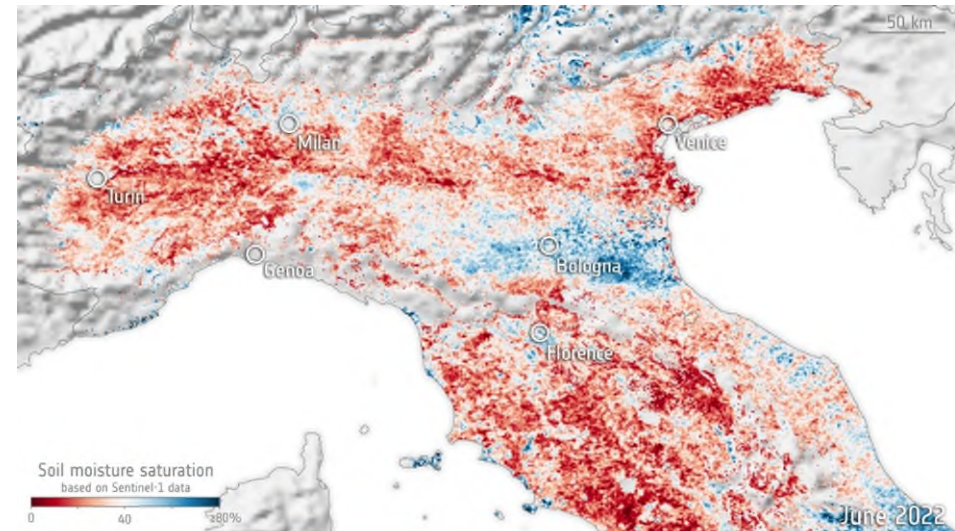


# Drought in Italy in 2022

Mean Sentinel-1 Soil Moisture in June 2020



Mean Sentinel-1 Soil Moisture in June 2022



[https://www.esa.int/Applications/Observing\\_the\\_Earth/Copernicus/Sentinel-1/Zooming\\_in\\_on\\_drought\\_from\\_space](https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-1/Zooming_in_on_drought_from_space)

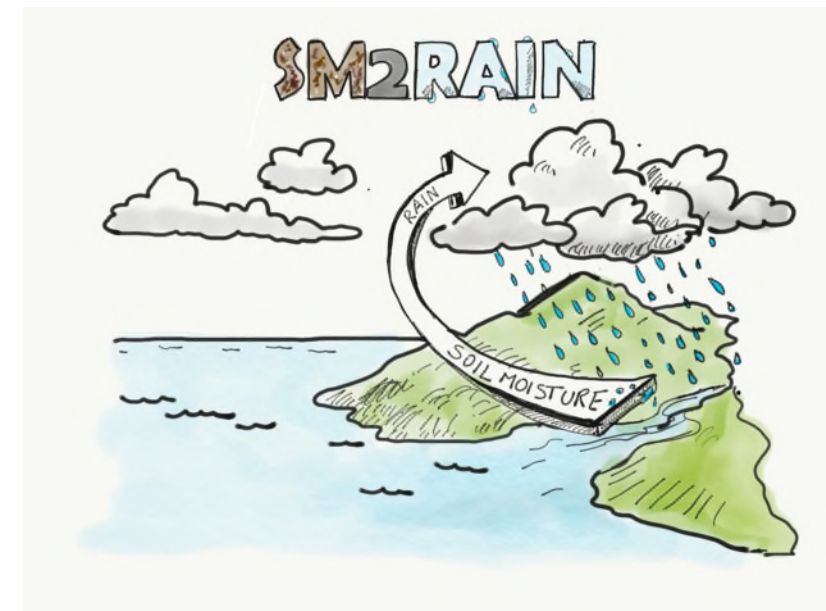


Twitter Tweet by Luca Brocca (IRPI) on drought seen by Sentinel-1 reached over 60000 views within a day.

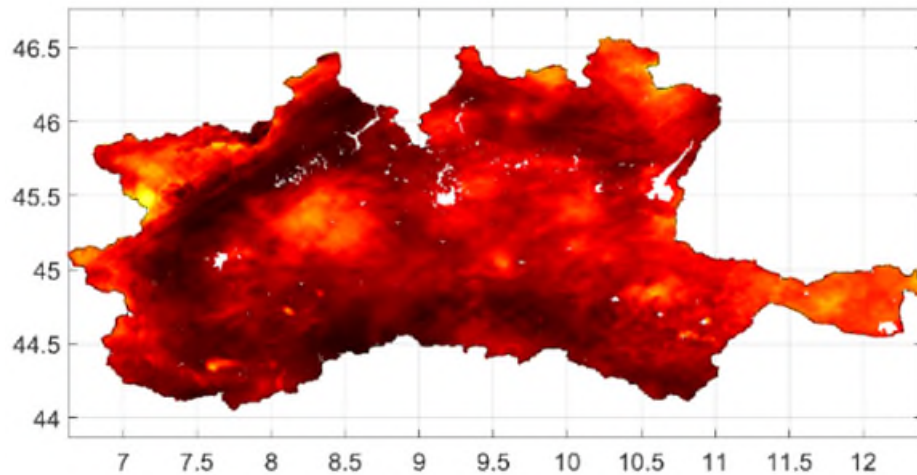


# Rainfall Estimation with SM2Rain

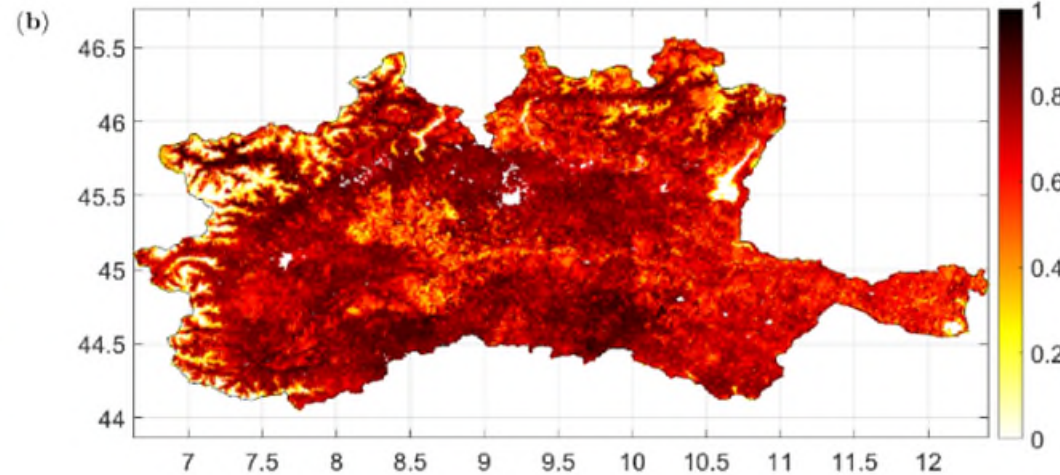
- By inverting the water balance of the land surface rainfall can be estimated by analysing soil moisture changes
  - „Bottom-up method“



SM2Rain for ASCAT



SM2Rain for Sentinel-1



Correlation SM2Rain with gauge measurements, Northern Italy, Po catchment.



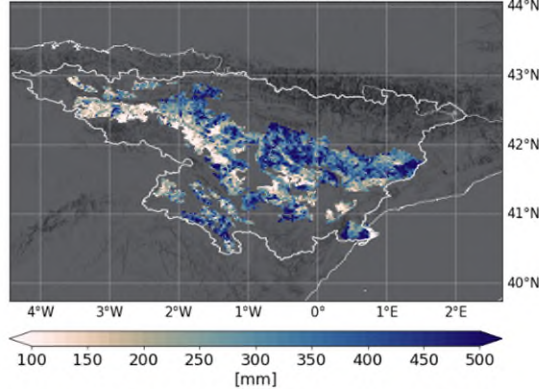
Filippucci et al. (2022) High-resolution (1 km) satellite rainfall estimation from SM2RAIN applied to Sentinel-1: Po River basin as a case study. Hydrology and Earth System Sciences, 26(9), 2481-2497.



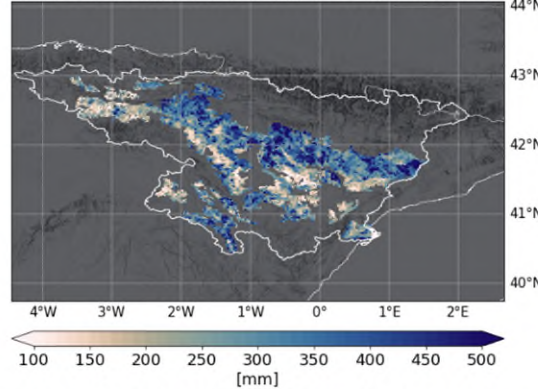
# Estimation of Irrigation

- Irrigation is estimated by comparing SM2Rain with observed rainfall

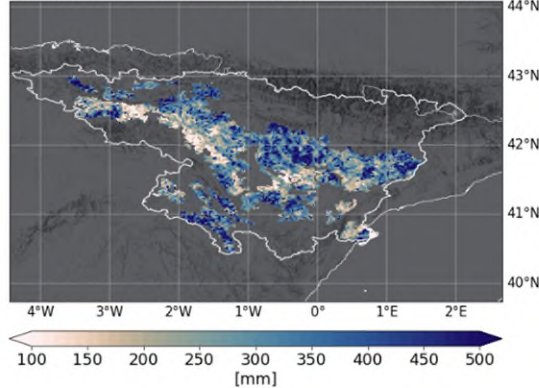
CUMULATED IRRIGATION AMOUNTS MAY-SEP 2016



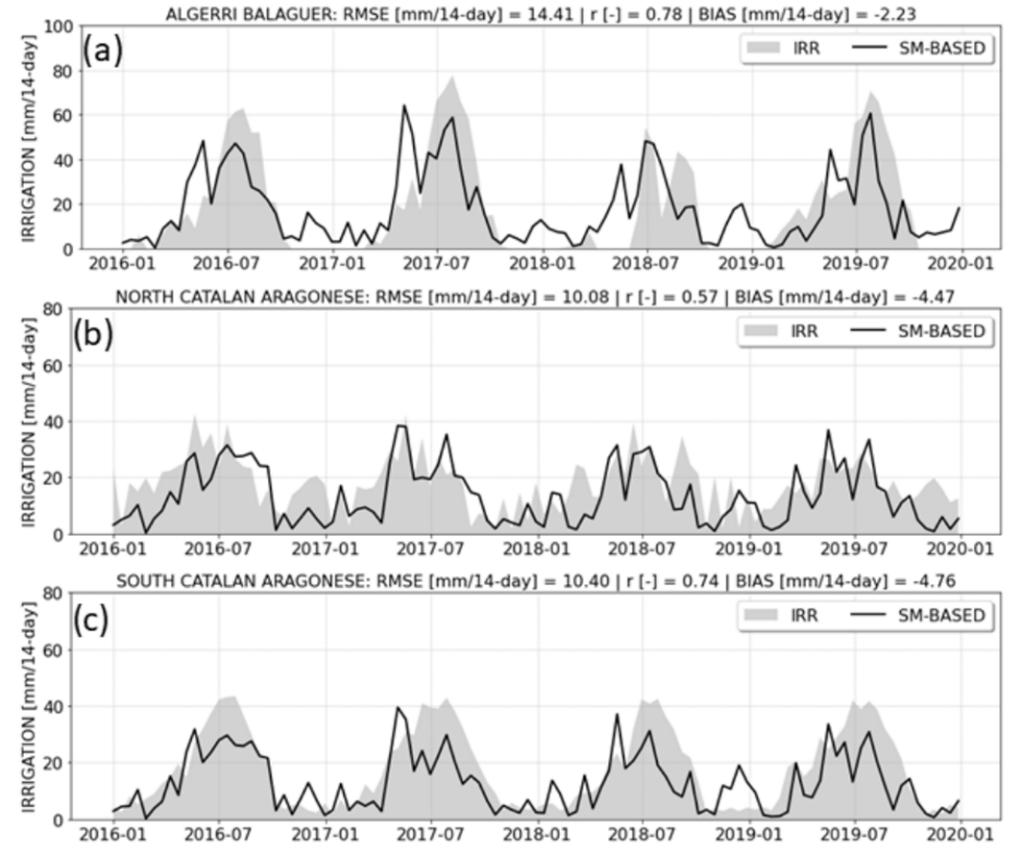
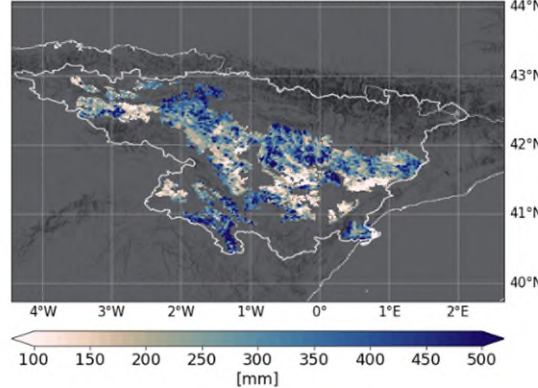
CUMULATED IRRIGATION AMOUNTS MAY-SEP 2017



CUMULATED IRRIGATION AMOUNTS MAY-SEP 2018



CUMULATED IRRIGATION AMOUNTS MAY-SEP 2019

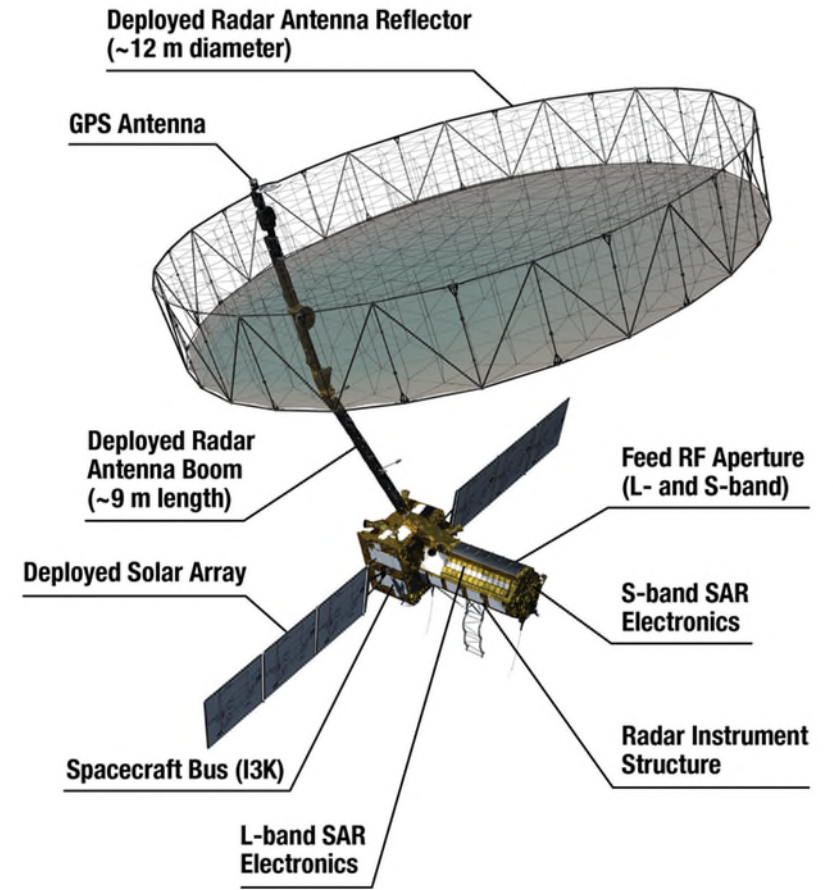


Ebro catchment, Spain



# Outlook

- The number of soil moisture products with a sampling of 1km or better is increasing
  - Many of these products are oversampled, i.e. only the sampling is fine but the effective spatial resolution (information) is much coarser
- SAR-only based soil moisture products are becoming operational for
  - Sentinel-1
  - NISAR (from 2024 onwards)
- The validation and application of SAR-only soil moisture products is an emerging research field



<https://nisar.jpl.nasa.gov/>

## Acknowledgements

ESA: DTE Hydrology, 4DMED, Irrigation+ / EUMETSAT: H SAF / Copernicus: Global Land Monitoring Service / FFG: ROSSHINI, GHG-KIT / ADA: DrySat / CzechGlobe: SustES