Applications of H SAF Soil Moisture Data

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http://www.geo.tuwien.ac.at/

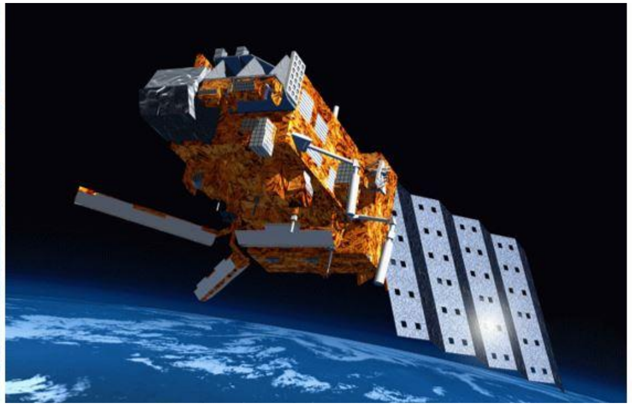
European C-Band Scatterometer Series

AMI Scatterometer

Frequency: 5.3 GHz
Polarisation: VV

Resolution: 50 km
Daily coverage: <40%

Satellites
ERS-1: 1991-2000
ERS-2: 1995-2011



METOP ASCAT

Frequency: 5.255 GHz
Polarisation: VV

Resolution: 25 km
Daily coverage: 82%

Satellites
METOP-A: 2006-2021
METOP-B: 2012 ongoing
METOP-C: 2018 ongoing

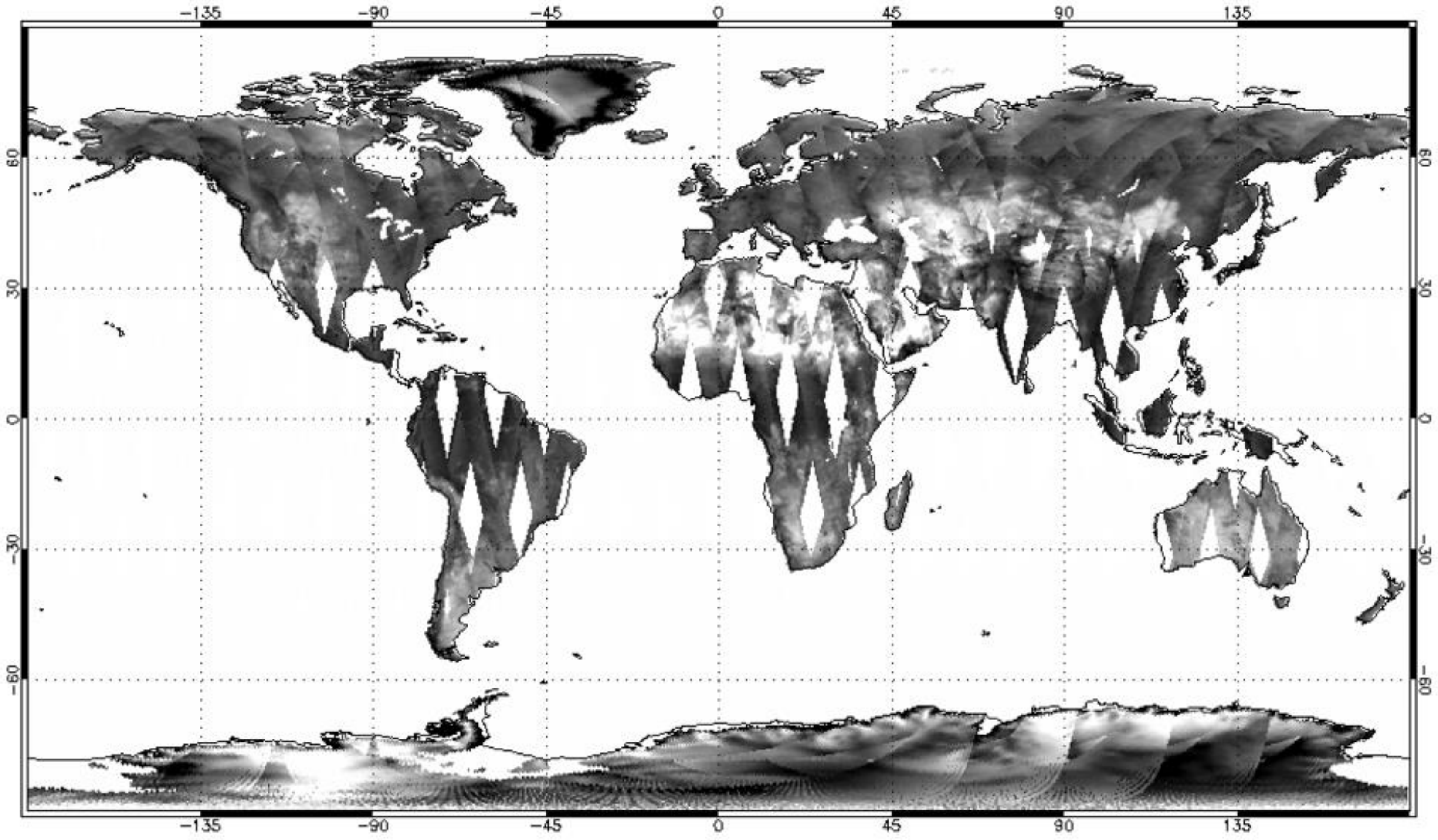
METOP-SG SCA

Frequency: 5.355 GHz
Polarisation: VV + VH + HH

Resolution: ~12.5 km
Daily coverage: ~88%

Satellites
METOP-SG-B1: 2025
METOP-SG-B2: 2032
METOP-SG-B3: 2039

Spatio-Temporal Sampling of ASCAT



Daily global ASCAT coverage achieved by Metop-A and Metop-B constellation

Wagner et al. (2013) The ASCAT soil moisture product: A review of its specifications, validation results, and emerging applications, Meteorologische Zeitschrift, 22(1), 5-33.

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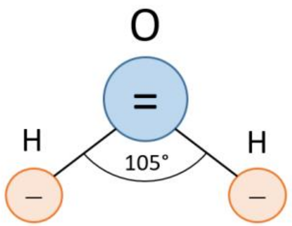
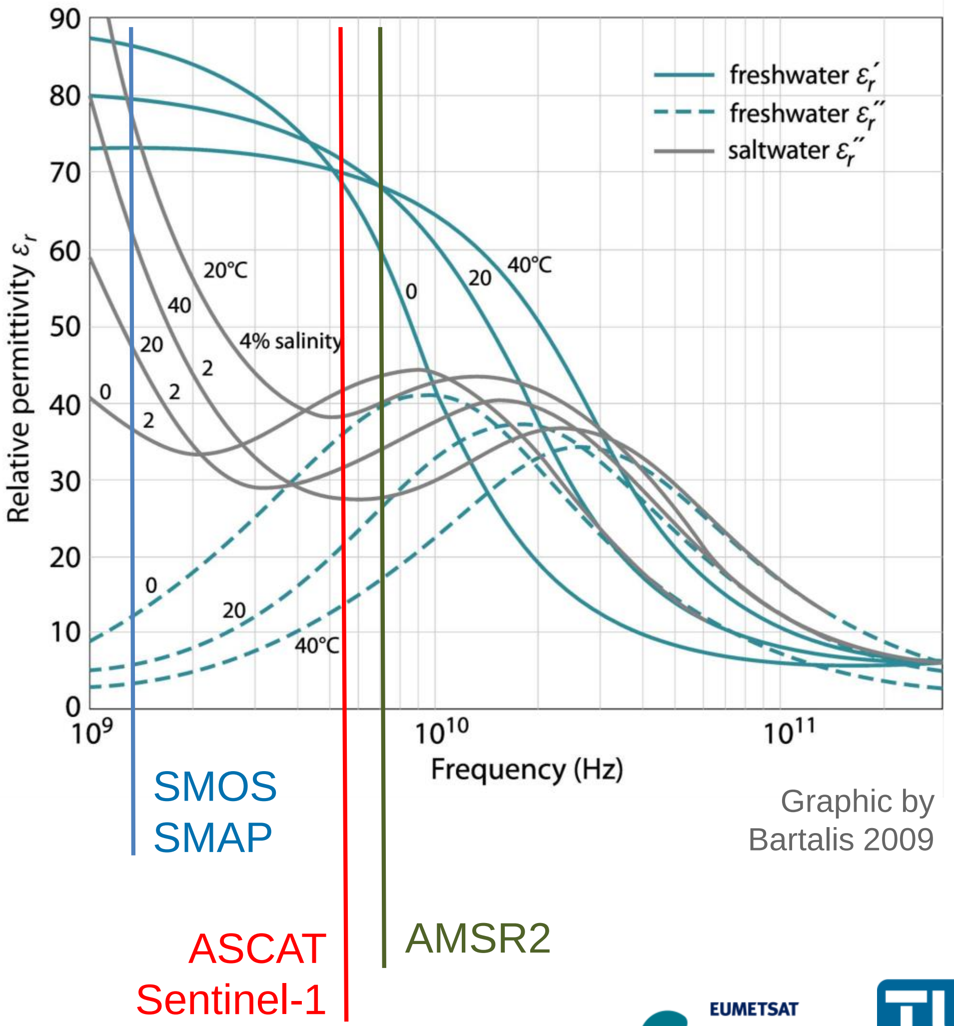
Microwaves

- All-weather, day-round measurement capability
- Microwave measurements are sensitive to
  - Geometric structure
    - Roughness
  - Dielectric properties
    - Water
- High penetration into vegetation and soils
  - Longer wavelengths beneficial
- Target quantities
  - Soil moisture
  - Vegetation water
  - Freeze/thawing
  - Surface water
  - Etc.



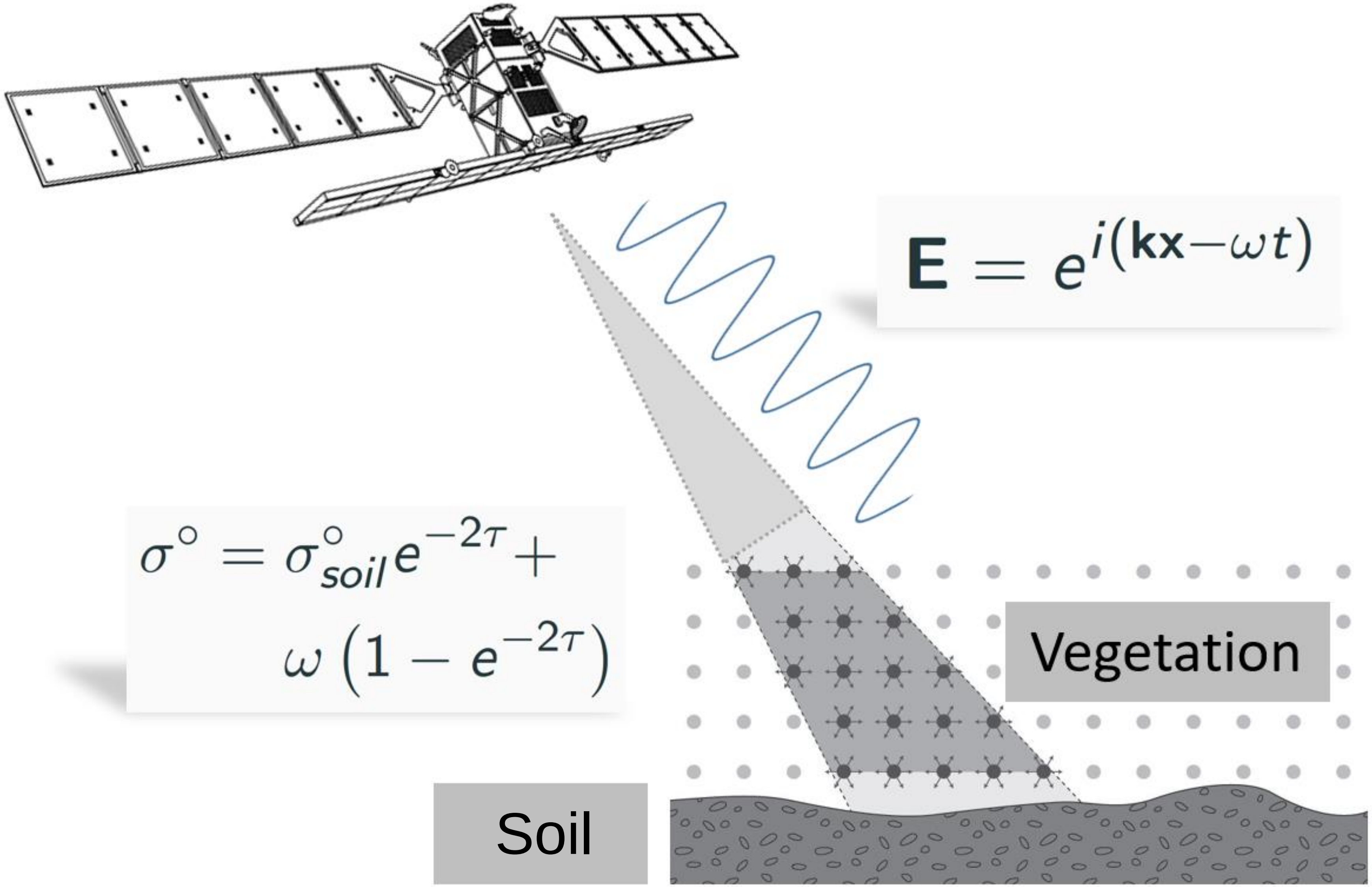
The dipole moment of water molecules causes "orientational polarisation", i.e. a high dielectric constant

Dielectric properties of water at microwave frequencies



Graphic by Bartalis 2009

Soil and Vegetation Retrieval



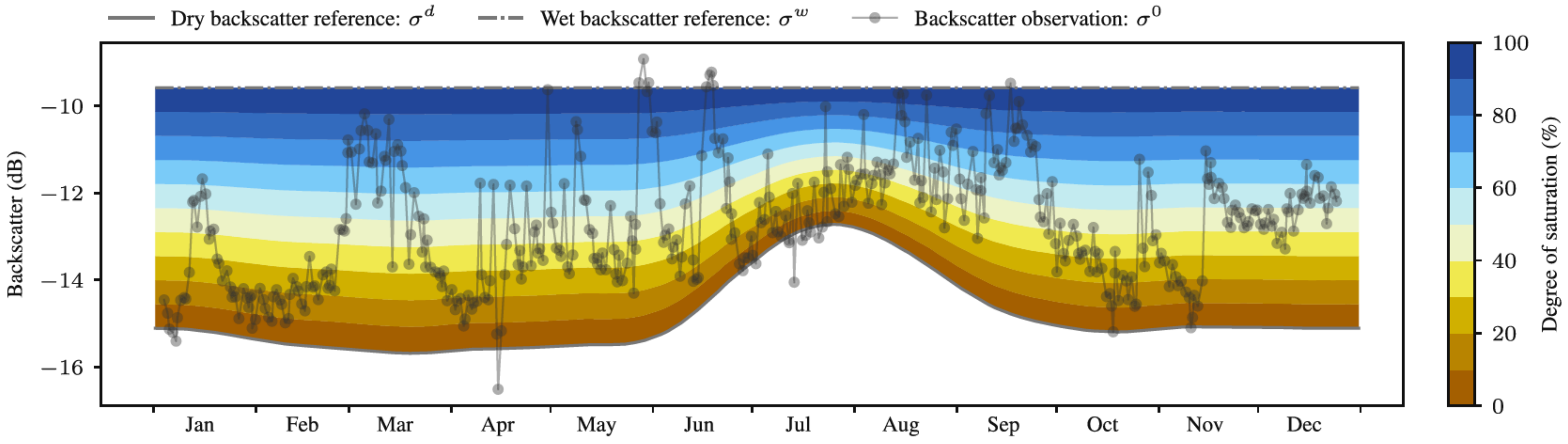
$$\mathbf{E} = e^{i(\mathbf{kx} - \omega t)}$$

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

H SAF ASCAT Soil Moisture Retrieval

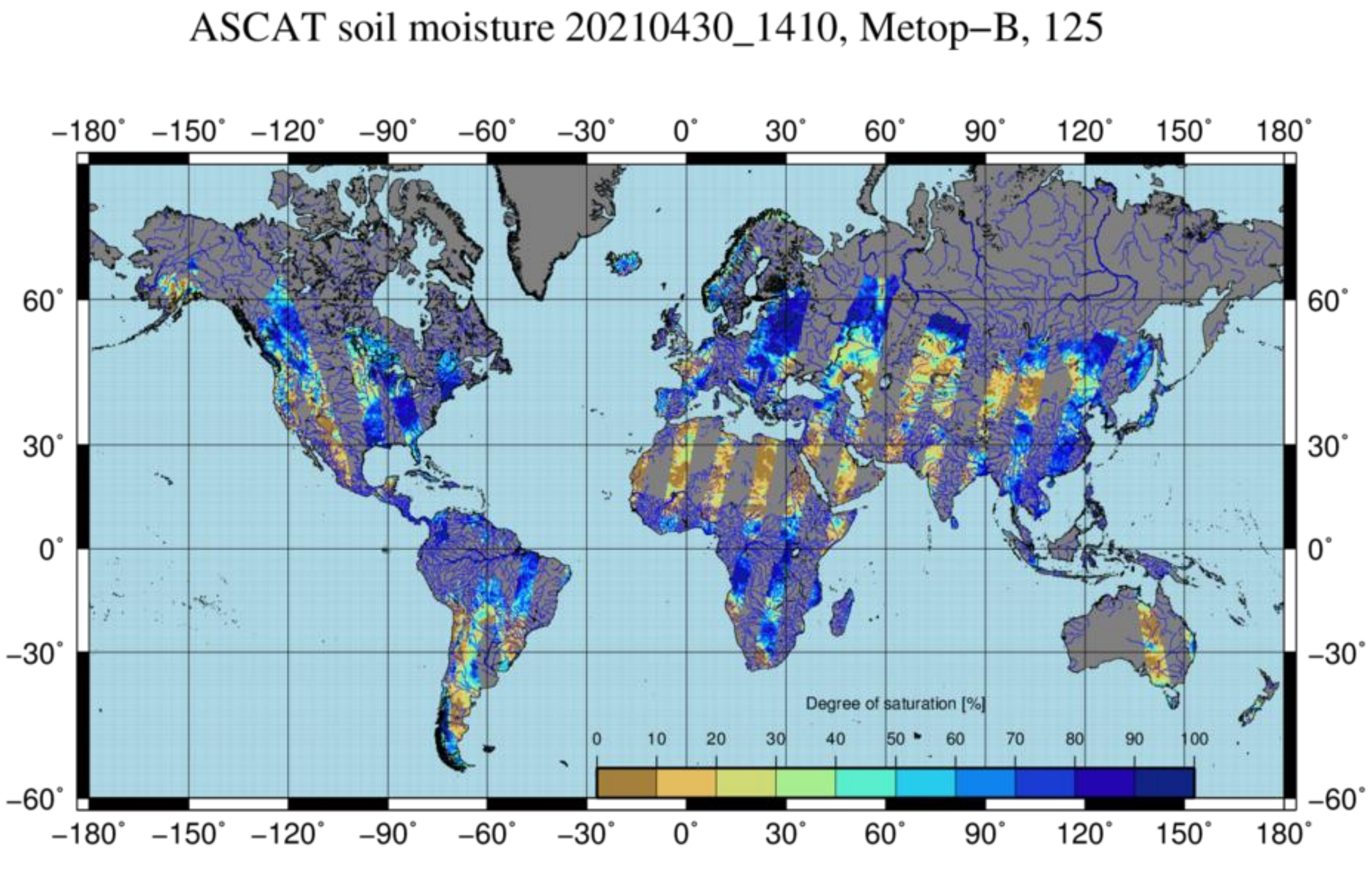
- Soil moisture can be estimated with different types of models
  - Semi-empirical backscatter models using iterative optimization techniques
  - Machine learning
  - Change detection

$$m_s(t) = \frac{\sigma^0(t) - \sigma^0_{dry}(t)}{\sigma^0_{wet}(t) - \sigma^0_{dry}(t)}$$



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.

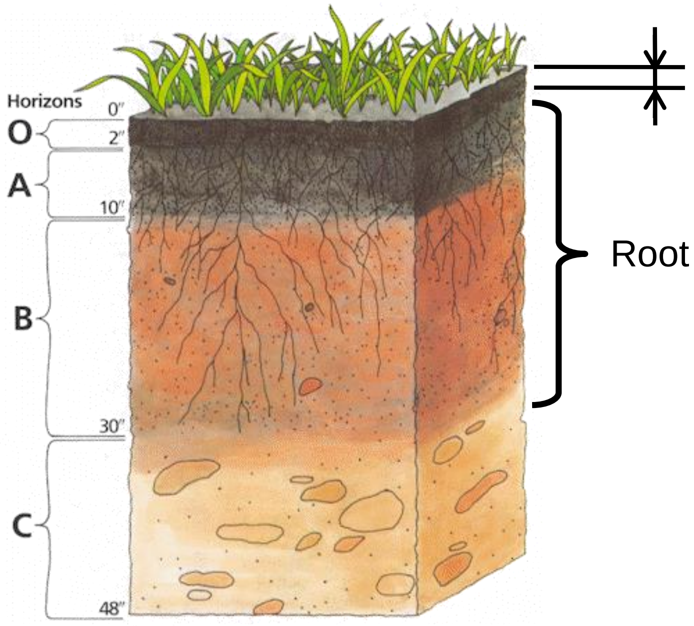
25 km ASCAT Surface Soil Moisture



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 (Θ_s) and the “reservoir” (Θ)
  - T … characteristic time

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



- 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

Wagner, W., G. Lemoine, H. Rott (1999) A Method for Estimating Soil Moisture from ERS Scatterometer and Soil Data, Remote Sensing of Environment, 70, 191-207.

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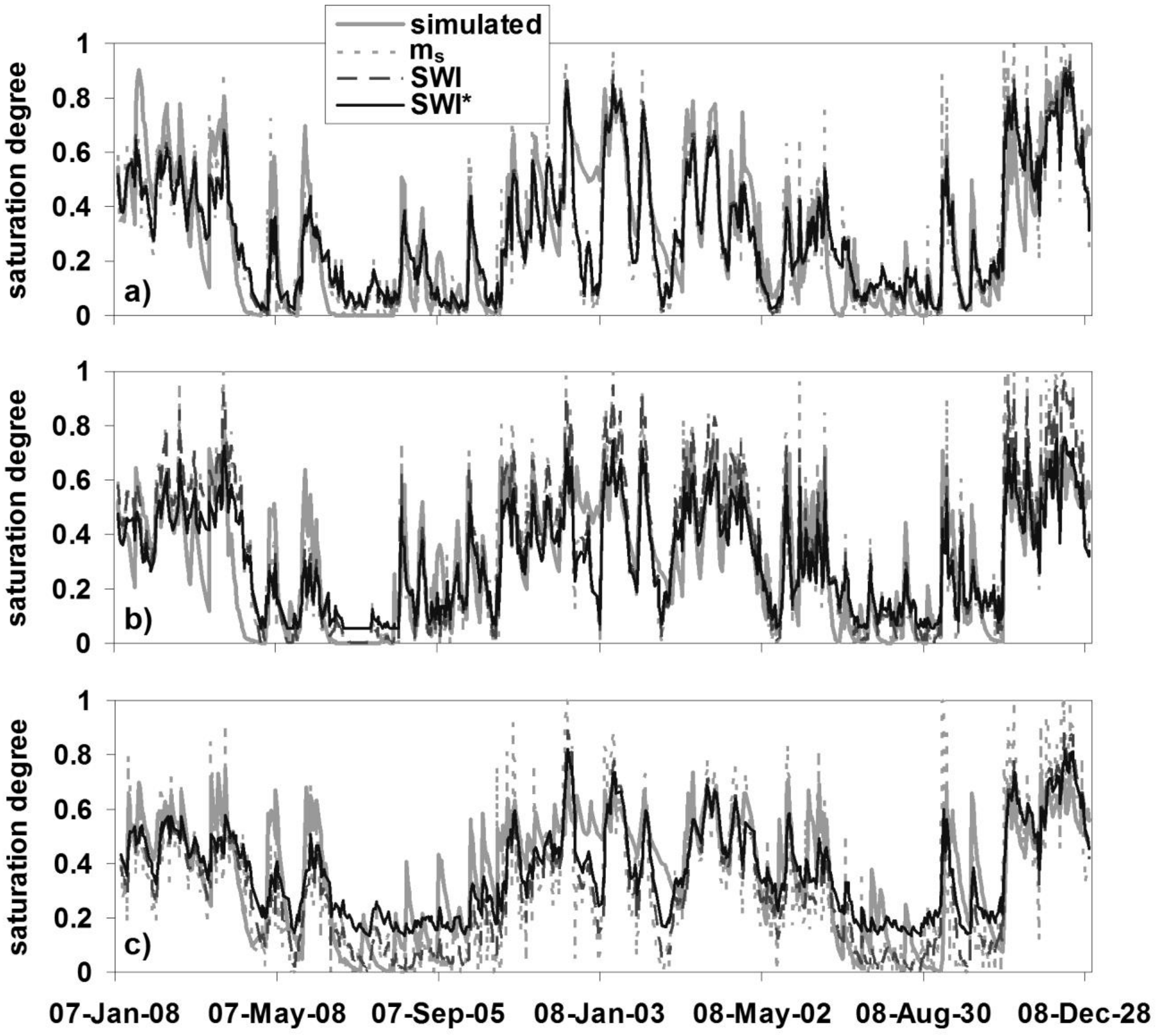
ASCAT versus Modelled Soil Moisture



ASCAT versus 3 cm simulated degree of saturation for products, ms, SWI, and SWI* and investigated sites:

a) Vallaccia
b) Cerbara
c) Spoleto

Brocca et al. (2010) ASCAT Soil Wetness Index validation through in-situ and modeled soil moisture data in Central Italy. Remote Sensing of Environment, 114, 2745-2755.

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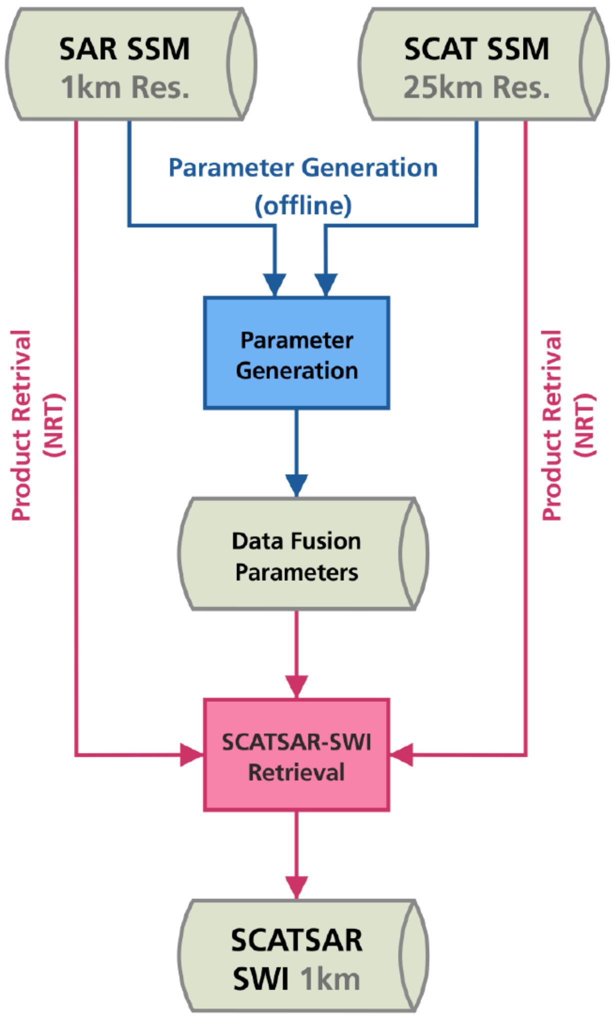
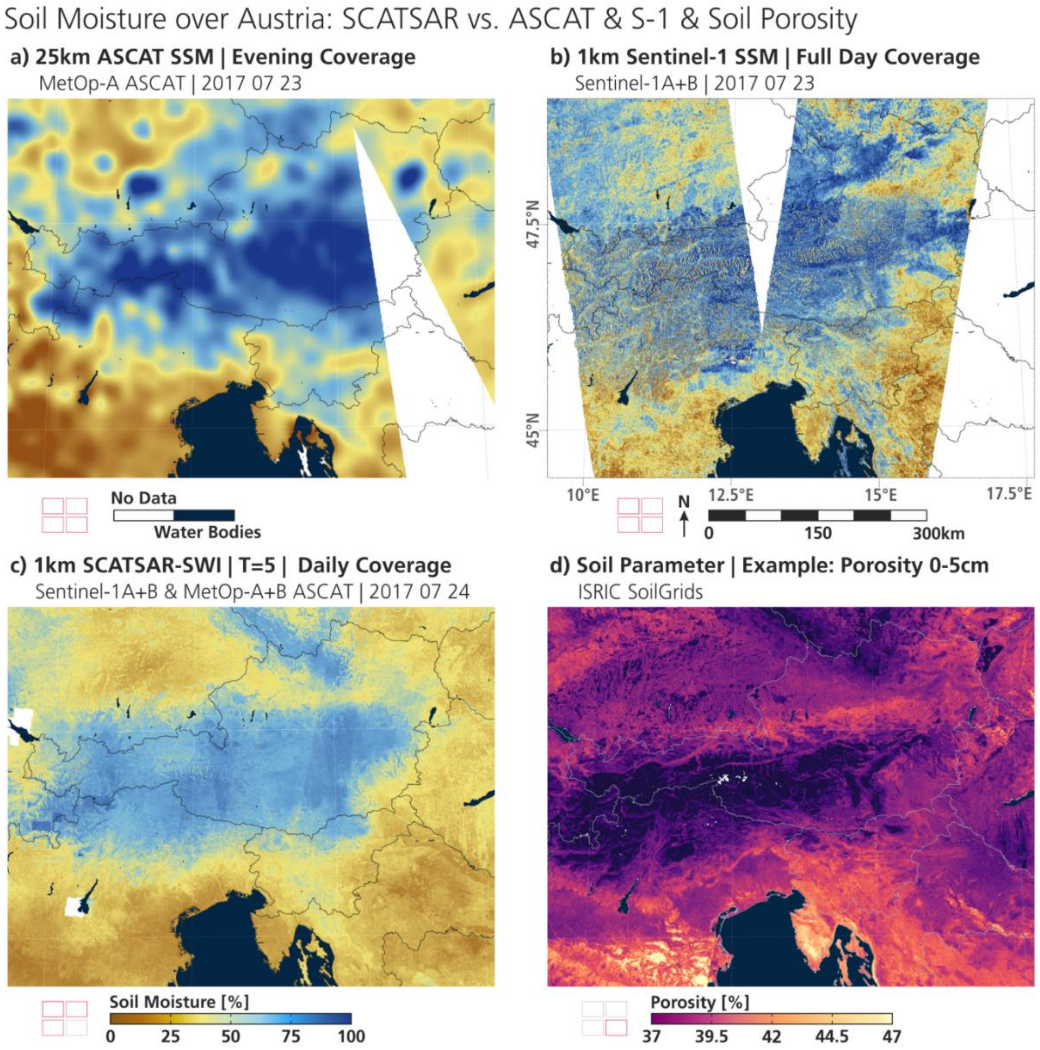
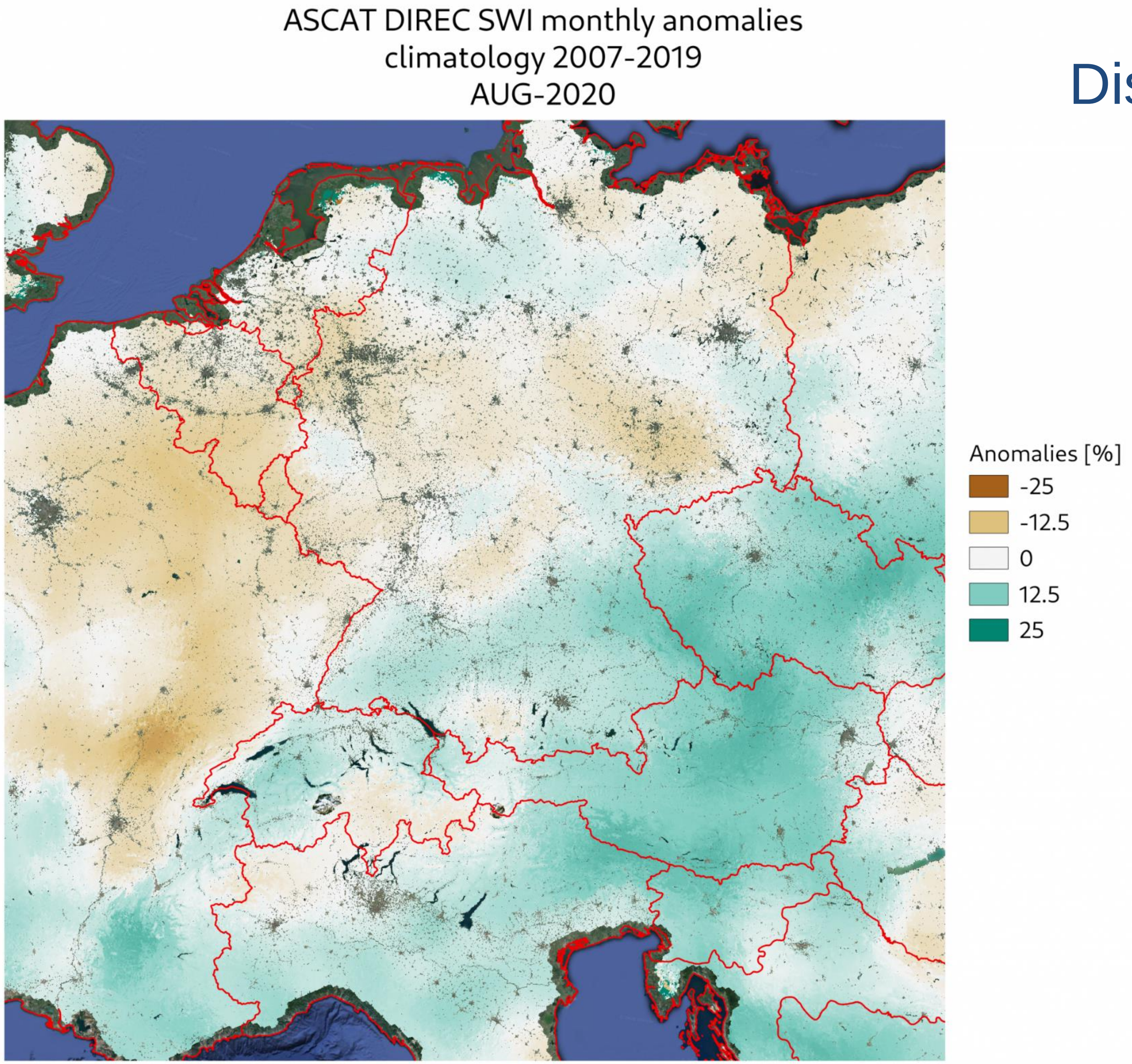
SWI Method for Fusion of Soil Moisture Data





Bauer-Marschallinger et al. (2018) Soil moisture from fusion of scatterometer and SAR: Closing the scale gap with temporal filtering, Remote Sensing, 10(7), 1030, 26 p.



Disaggregated Soil Moisture

- Uses the DIREX method to interpolate SSM to a 0.5 km grid
  - Does not improve spatial resolution as such but looks for the best direction to interpolate from
  - Improvements in areas with contrasting backscatter behaviour
    - Coastal areas
    - Urban regions
    - Valleys
- DIREX method
  - Directional resampling
  - Parameters calculated from Sentinel-1 time series
  - Correlation between 0.5 km and 12.5 km backscatter time series

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ASCAT Soil Moisture Data Services

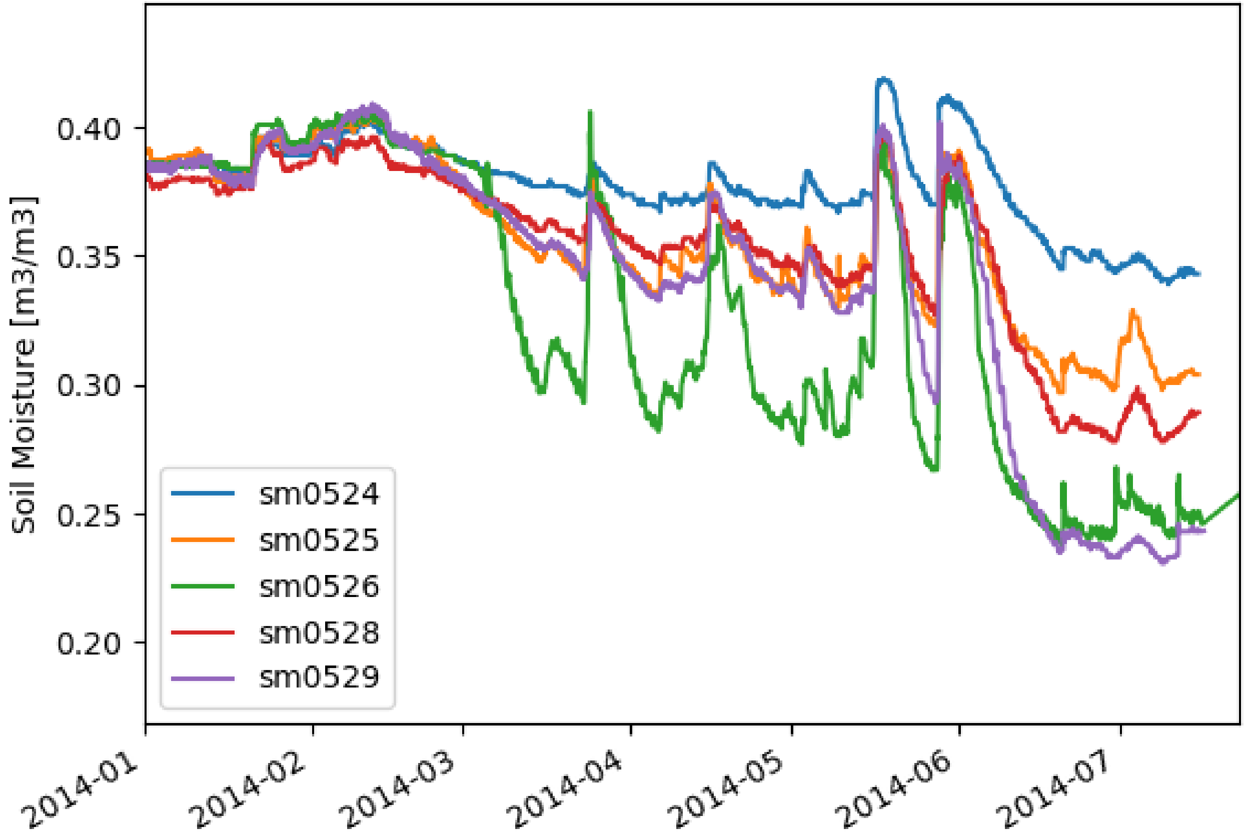
- Hydrology SAF (services provided by EUMETSAT, ZAMG, ECMWF & TU Wien)
  - ASCAT SSM NRT at 6.25/12.5/25 km in NRT
  - ASCAT SSM Data Record
  - Disaggregated SSM at 0.5 km in NRT over Europe
  - Assimilated ASCAT soil moisture profile

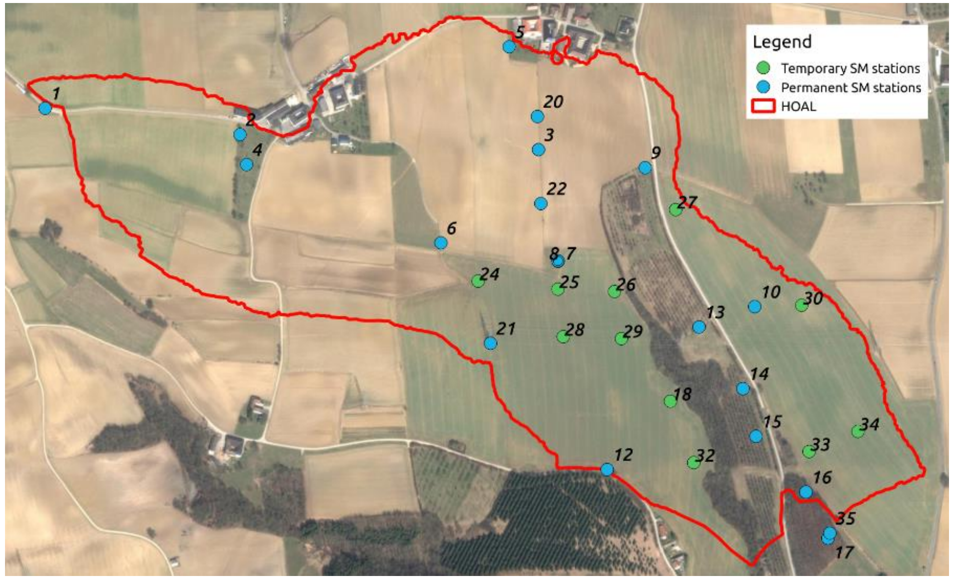
- Copernicus Global Land (services provided by EODC, ZAMG & TU Wien)
  - Daily 0.1° Soil Water Index (SWI)
  - 1 km ASCAT/Sentinel-1 SWI data over Europe

- CCI + C3S (services provided by EODC, Vandersat & TU Wien)
  - Long-term (1978 up to present) 0.25° active-only and merged active/passive microwave soil moisture data

Variation of Soil Moisture Data within Individual Fields

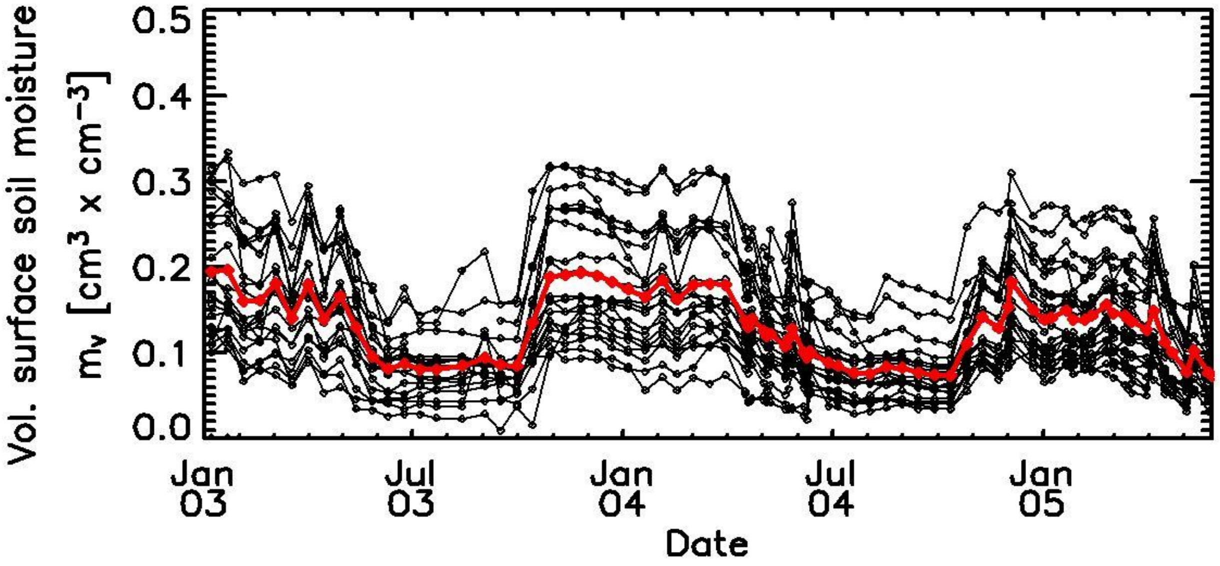
- In situ oil moisture data can vary significantly within one field with the same land cover



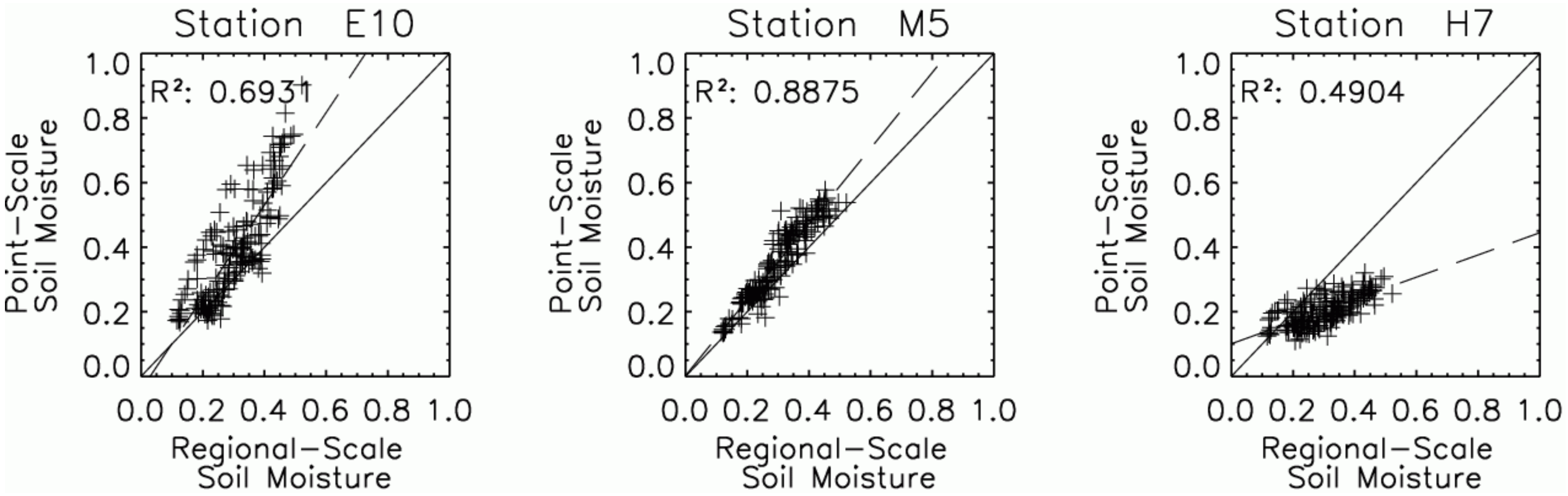


HOAL Soil Moisture Network,
Petzenkirchen, Austria

Temporal Stability of Soil Moisture



Mean (red) and station (black) in-situ soil moisture time series. REMEDHUS network in Spain. © University of Salamanca



Wagner et al. (2008) Temporal stability of soil moisture and radar backscatter observed by the Advanced Synthetic Aperture Radar (ASAR), Sensors, 8(2), 1174-1197.

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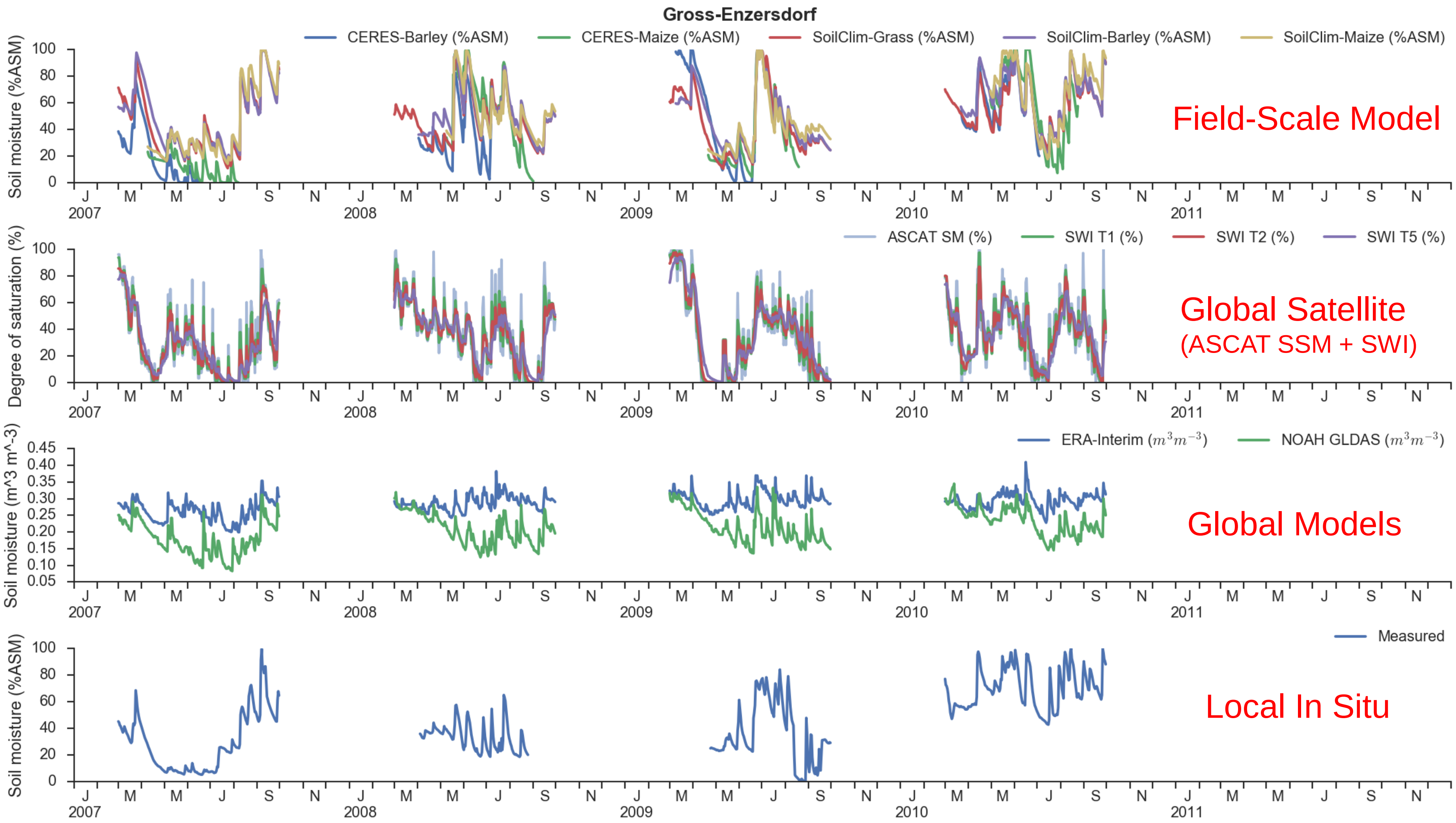
Soil Moisture from Models, In Situ and Satellites



Thaler et al. (2018) The performance of Metop Advanced SCATterometer soil moisture data as a complementary source for the estimation of crop-soil water balance in Central Europe, The Journal of Agricultural Science, 156, 577-598.

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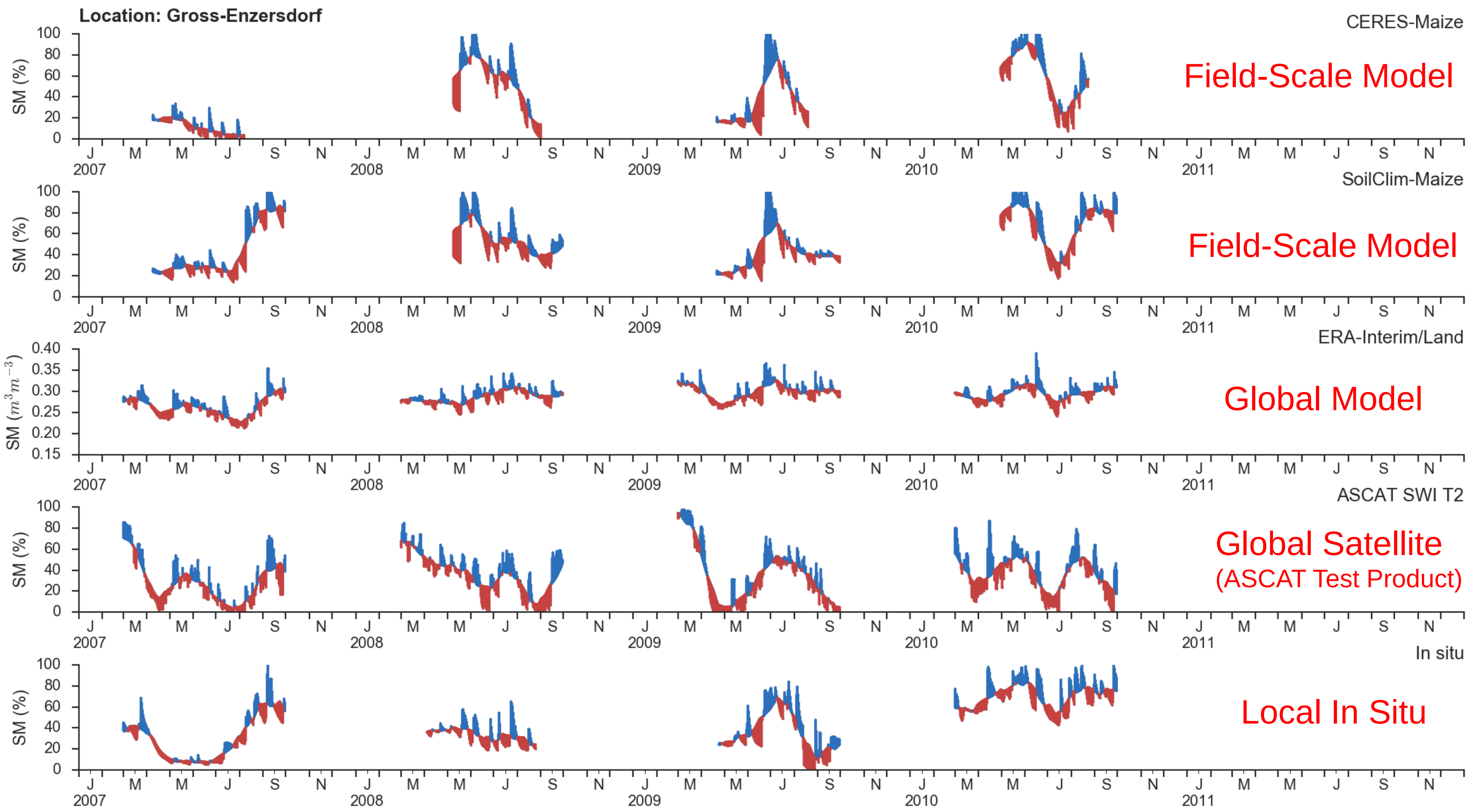
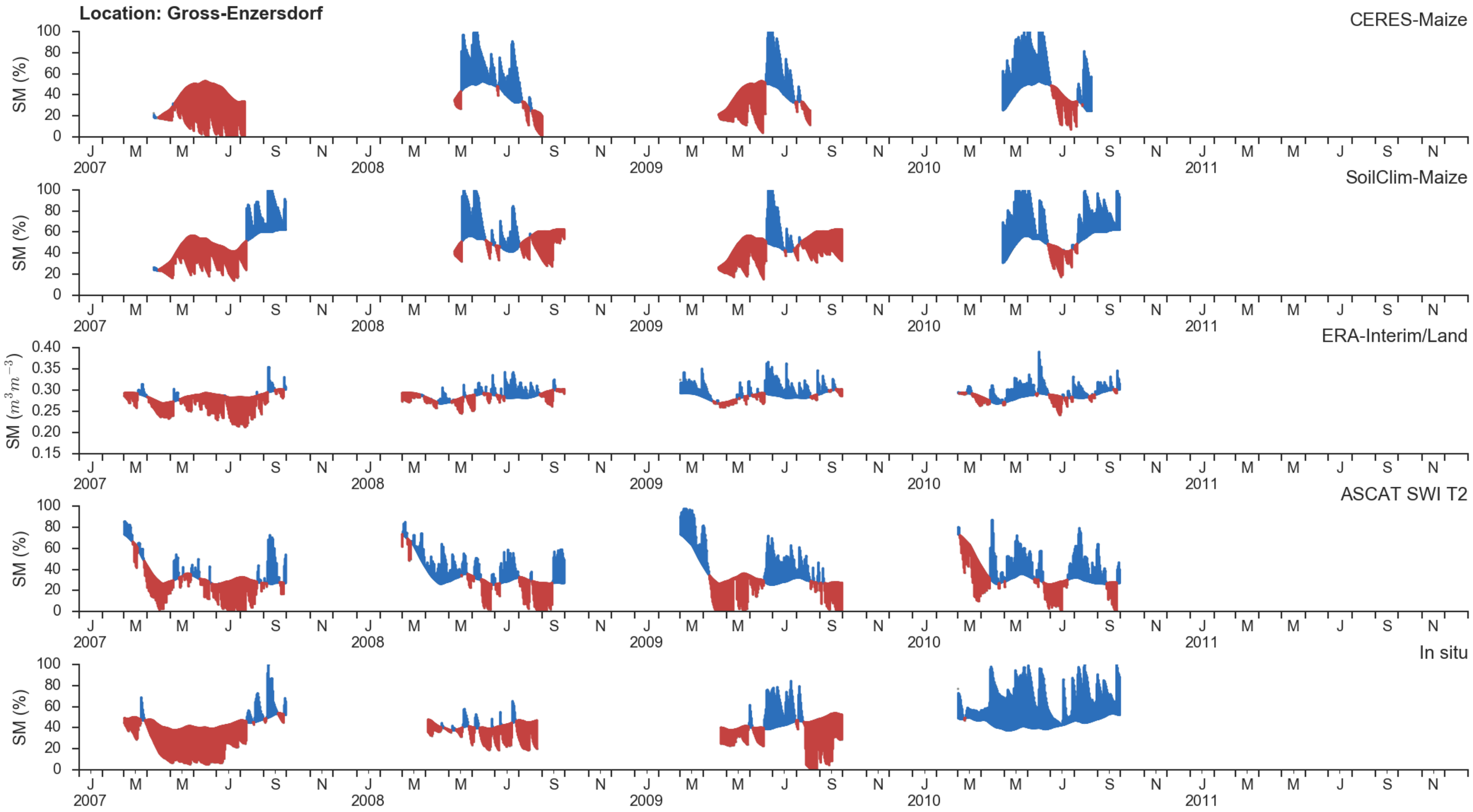
Comparison of Short-Term Anomalies



Based upon Thaler at al. (2018)

Comparison Against Mean Seasonal Signals



Based upon Thaler at al. (2018)

Matching of Satellite, in situ and Model Soil Moisture Data

- To improve the match between satellite, in situ and model data there are different scaling and filtering techniques

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Scaling and Filtering Approaches for the Use of Satellite Soil Moisture Observations

Luca Brocca, Florisa Melone, Tommaso Moramarco,
Wolfgang Wagner, and Clement Albergel

CONTENTS

Brocca, L., F. Melone, T. Moramarco, W. Wagner, C. Albergel (2014) Scaling and filtering approaches for the use of satellite observations, Chapter 17 in "Remote Sensing of Engergy Fluxes and Soil Moisture Content", G.P. Petropoulus (Ed), CRC Press, Boca Raton London New York, 411-425.

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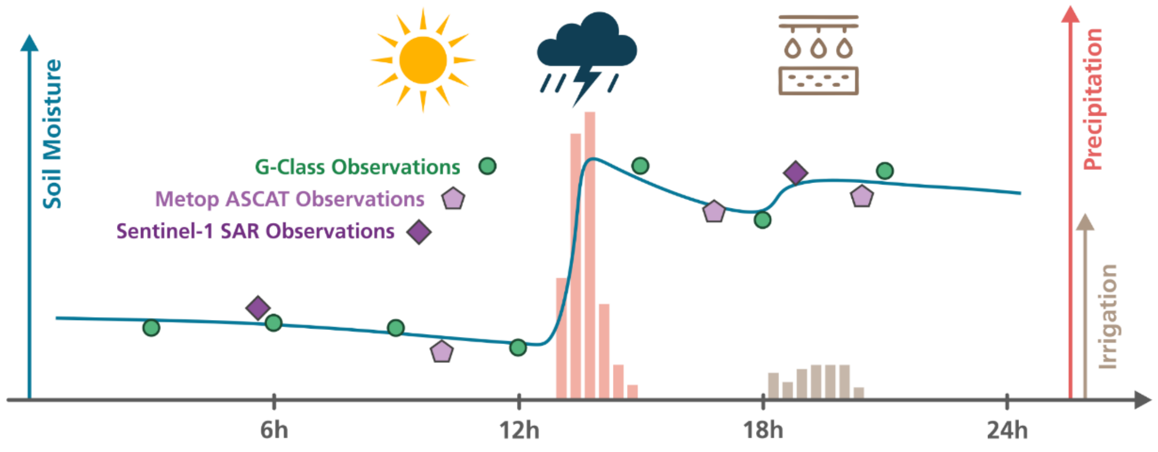
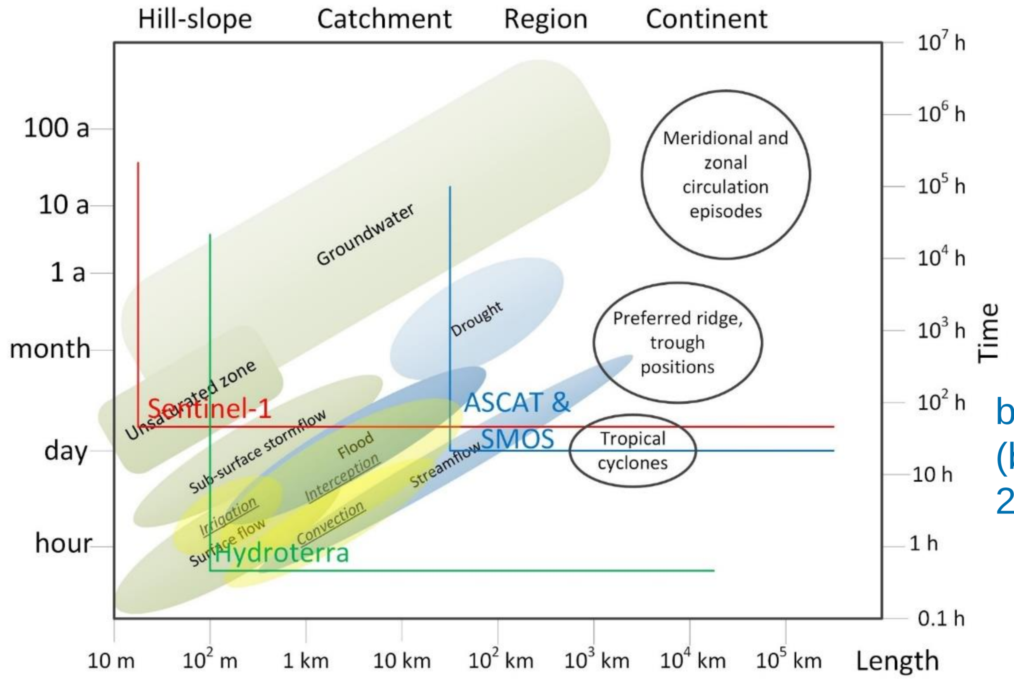
Some Applications of Remotely Sensed Soil Moisture Data

- 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.





by Hydroterra Science Team (based upon Stahl and Hisdal 2004)

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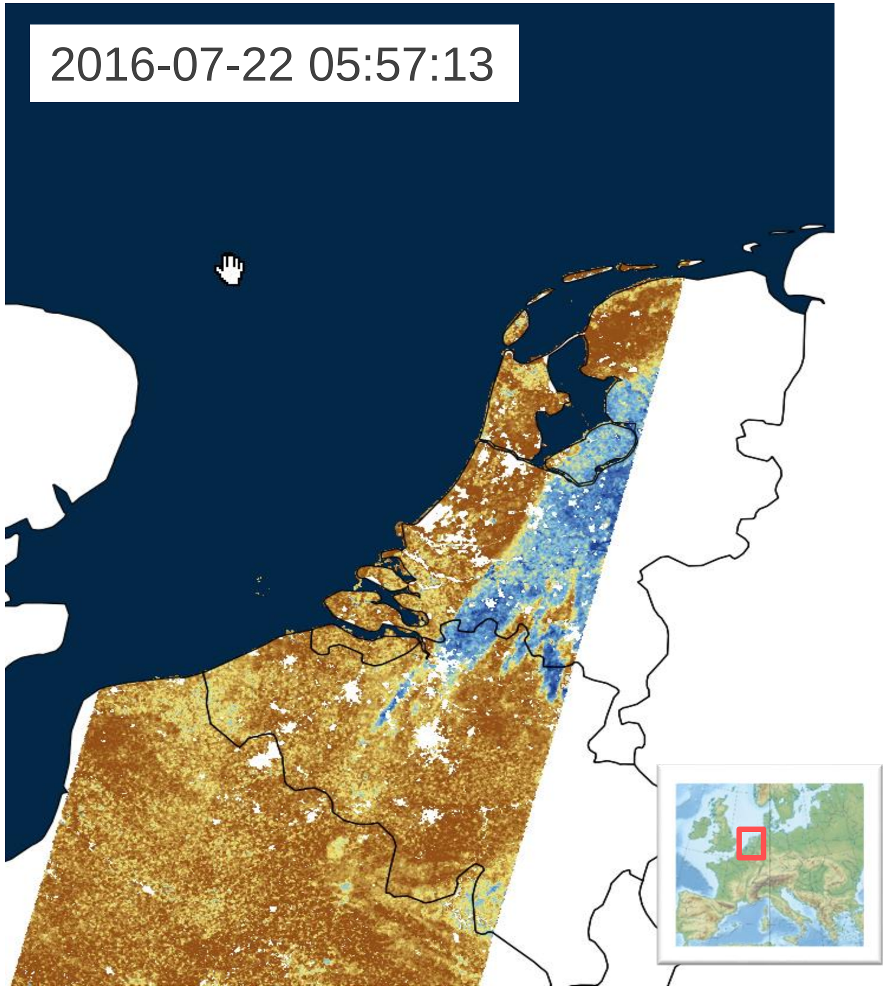
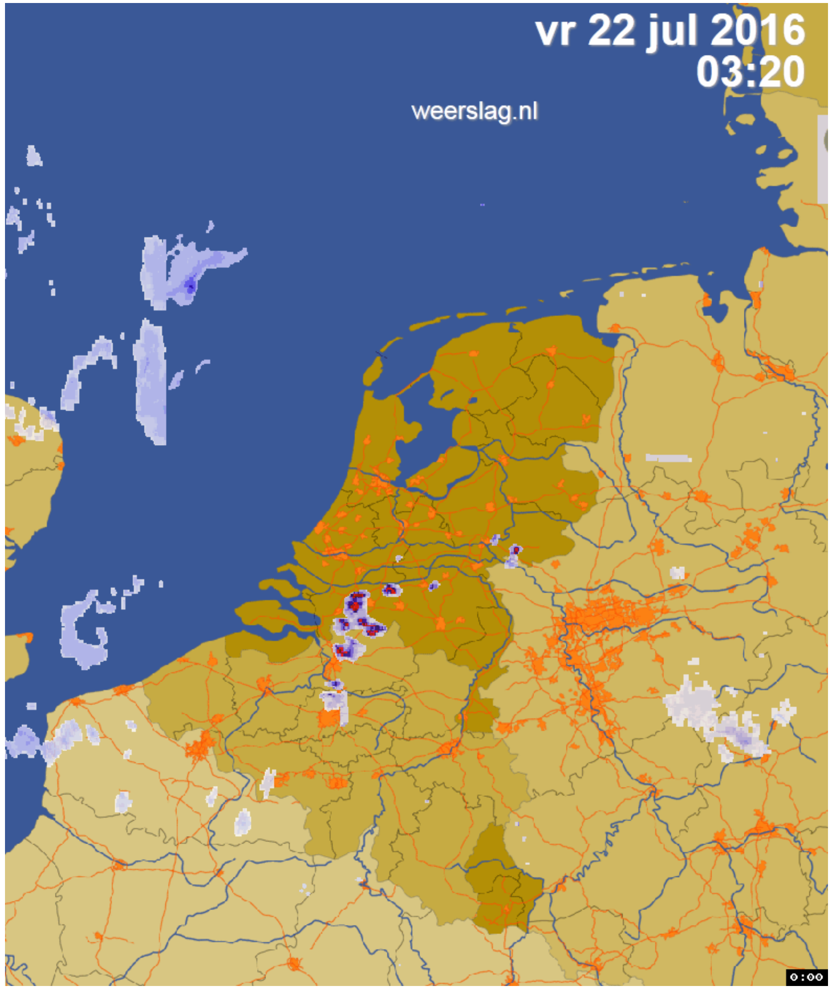
CAPTURING RAINFALL

Sentinel-1 Soil Moisture & Precipitation Radar





Estimating Rainfall Bottom-Up: SM2Rain

Water balance model:

$$Z\frac{ds(t)}{dt} = p(t) - r(t) - e(t) - g(t)$$

Inverting for *p(t):*

$$p(t) = Z\frac{ds(t)}{dt} + r(t) + e(t) + g(t)$$

Assuming during rainfall:

$$g(t) = a\,s(t)^b \quad + \quad e(t) = 0 \quad + \quad r(t) = 0$$

Z ... soil water capacity (= soil depth * porosity)

s ... relative saturation

p ... precipitation

r ... surface runoff

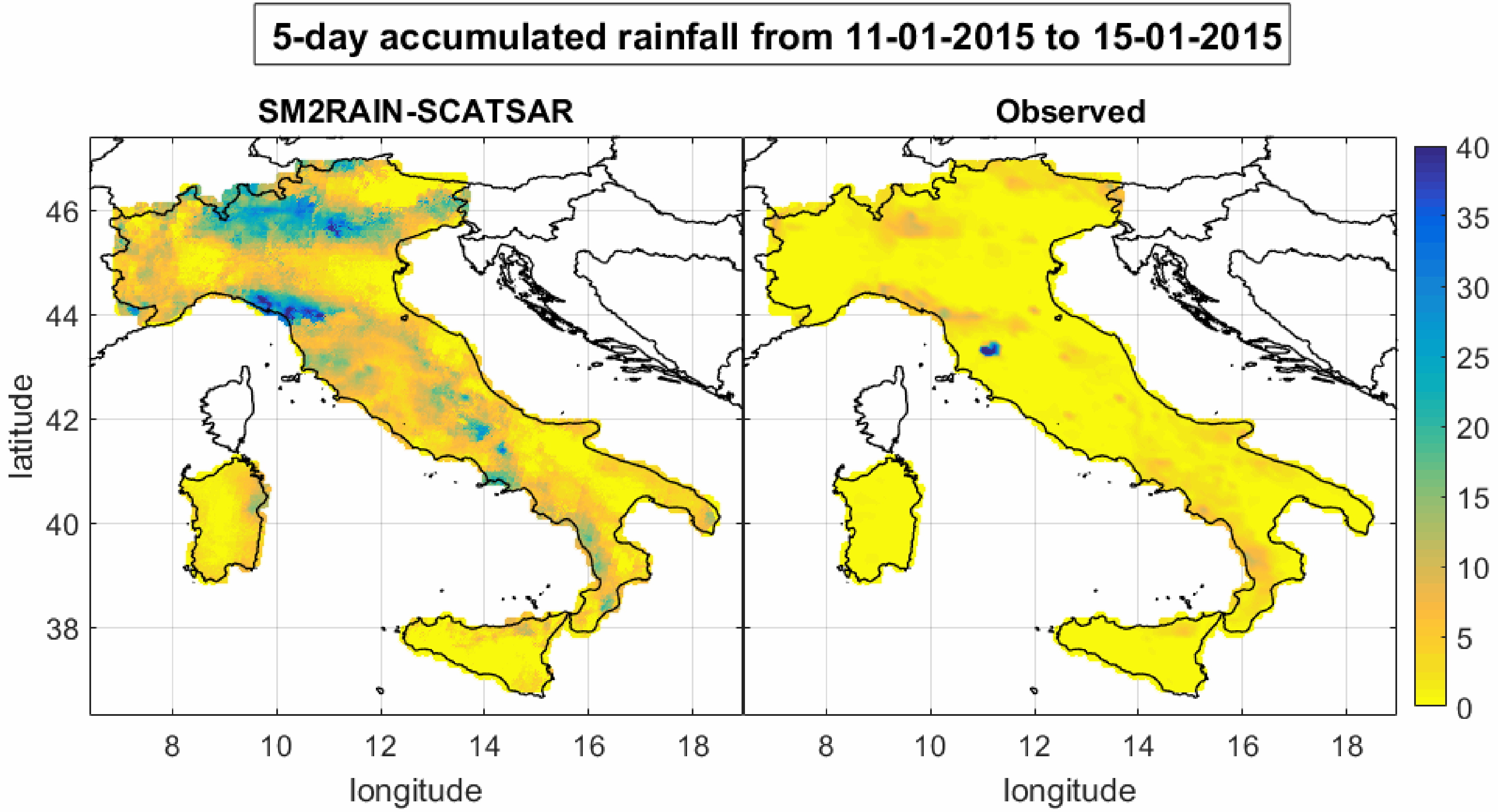
e ... evapotranspiration

g ... drainage

$$\Rightarrow \; p(t) \cong Z\ ds(t)/dt + a\,s(t)^b$$

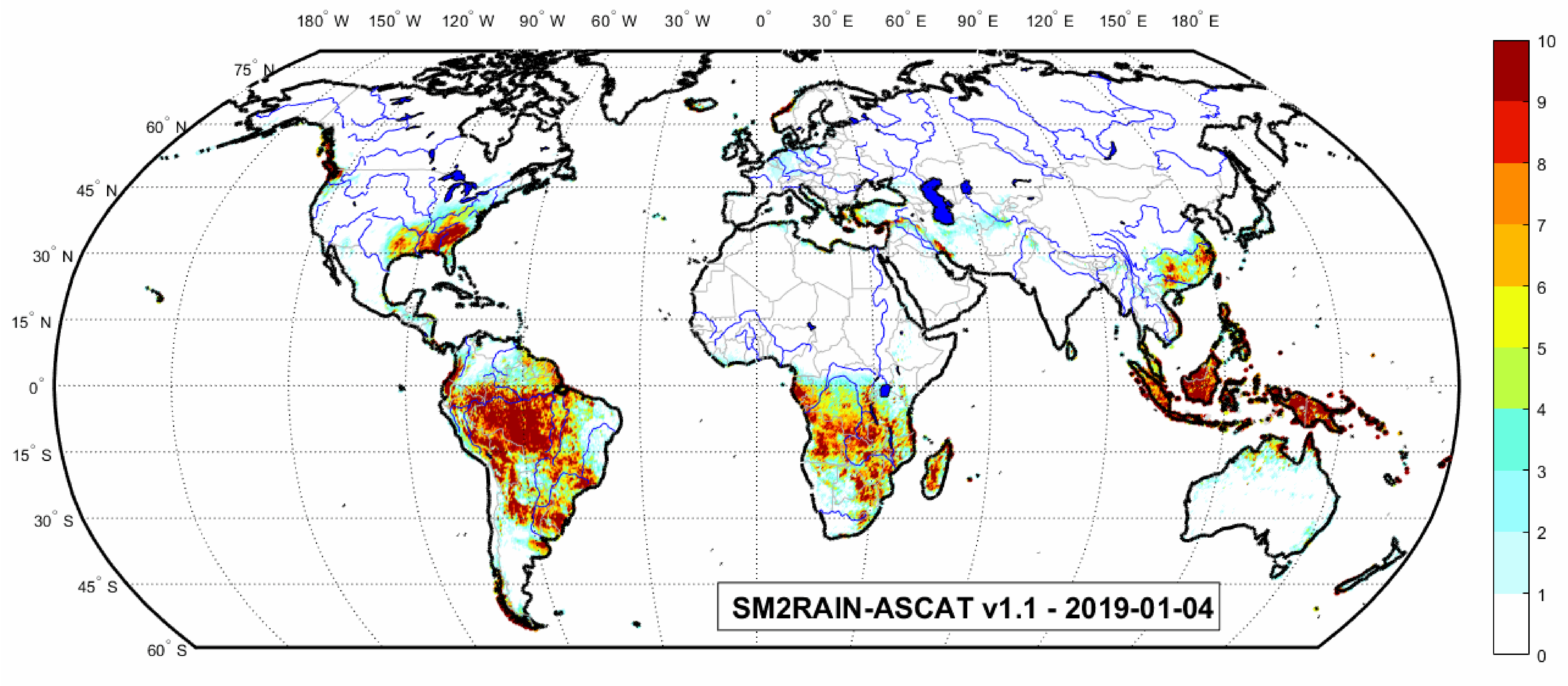
Brocca et al. (2014) Soil as a natural rain gauge: Estimating global rainfall from satellite soil moisture data. *Journal of Geophysical Research: Atmospheres*, *119*(9), 5128-5141.

SM2Rain Results for Italy



Istituto di Ricerca per la Protezione Idrogeologica

SM2Rain ASCAT Daily Rainfall Data



Brocca et al. (2019) SM2RAIN-ASCAT (2007–2018): global daily satellite rainfall from ASCAT soil moisture, Earth System Science Data, 11, 1583-1601.

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February 6, 2020

Dataset | Open Access

SM2RAIN-ASCAT (2007-2020): global daily satellite rainfall from ASCAT soil moisture

Luca Brocca; Paolo Filippucci; Sebastian Hahn; Luca Ciabatta; Christian Massari; Stefania Camici; Lothar Schüller; Bojan Bojkov; Wolfgang Wagner

SM2RAIN-ASCAT is a new global scale rainfall product obtained from ASCAT satellite soil moisture data through the SM2RAIN algorithm (*Brocca et al., 2014; 2019*). The SM2RAIN-ASCAT rainfall dataset (in mm/day) is provided over a regular grid at 0.1-degree sampling (3600x1801) on a global scale. The product represents the accumulated rainfall between the 00:00 and the 23:59 UTC of the indicated day. The SM2RAIN method was applied to the ASCAT soil moisture product (*Wagner et al., 2013*) for the period from January 2007 to December 2020 (14 years), for version 1.4.

The rainfall dataset is provided in NetCDF format. A total of 14 NetCDF files, one per year, are provided. The quality flag provided with the dataset has been used to mask out low quality data, as well as the areas characterised by complex topographic, frozen soil, and presence of tropical forests. In addition to the daily accumulated rainfall value, also the rainfall noise (mm/day) is provided for every day.

Three new feature of version 1.4 with respect to version 1.3 is only the extension to the end of 2020.

A GeoTIFF version of the dataset (v1.2) is available here (to be updated): https://zenodo.org/record/3520620

A monthly version at 0.25- and 0.5-degree resolution is available here: https://doi.org/10.5281/zenodo.4570191

A sample dataset that can be used for testing SM2RAIN algorithm is available here: https://zenodo.org/record/2580285

Details on the dataset development and its assessment with ground and reanalysis observations are provided as:

Brocca, L., Filippucci, P., Hahn, S., Ciabatta, L., Massari, C., Camici, S., Schüller, L., Bojkov, B., Wagner, W. (2019). SM2RAIN-ASCAT (2007-2018): global daily satellite rainfall from ASCAT soil moisture. *Earth System Science Data*, 11, 1583–1601, doi:10.5194/essd-11-1583-2019. https://doi.org/10.5194/essd-11-1583-2019.

Simple Python and Matlab codes for the extraction of SM2RAIN-ASCAT rainfall at one and multiple station(s)\location(s) are available at (note that reader for versions <1.3 are not usable for version 1.3 and 1.4): https://github.com/IRPIhydrology/SM2RAIN_ASCAT_reader

The SM2RAIN code in Python is available here: https://github.com/IRPIhydrology/sm2rain
The SM2RAIN code in Matlab is available here: https://github.com/IRPIhydrology/SM2RAIN_Matlab
The SM2RAIN code in R is available here: https://github.com/IRPIhydrology/sm2rainR

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Keyword(s):
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Related identifiers:
Referenced by
10.5194/essd-2019-48

Communities:
Remote sensing

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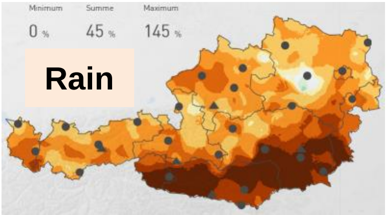
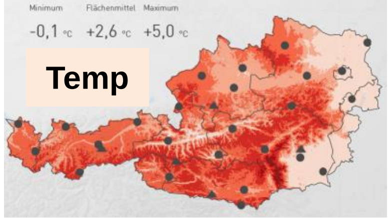
DROUGHT MONITORING

Upper Austria in August 2015

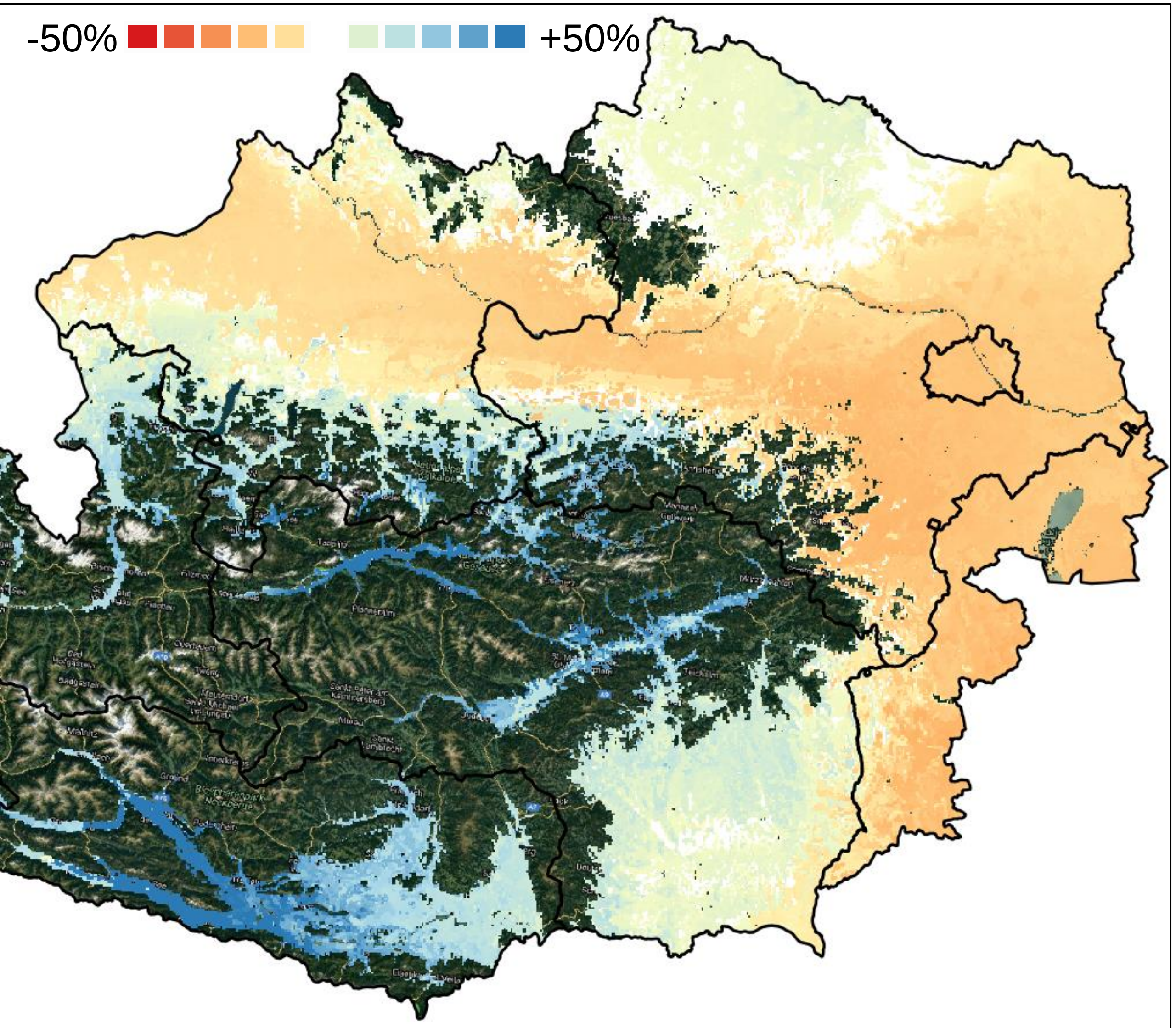
Upper Austria in August 2018

January 2020

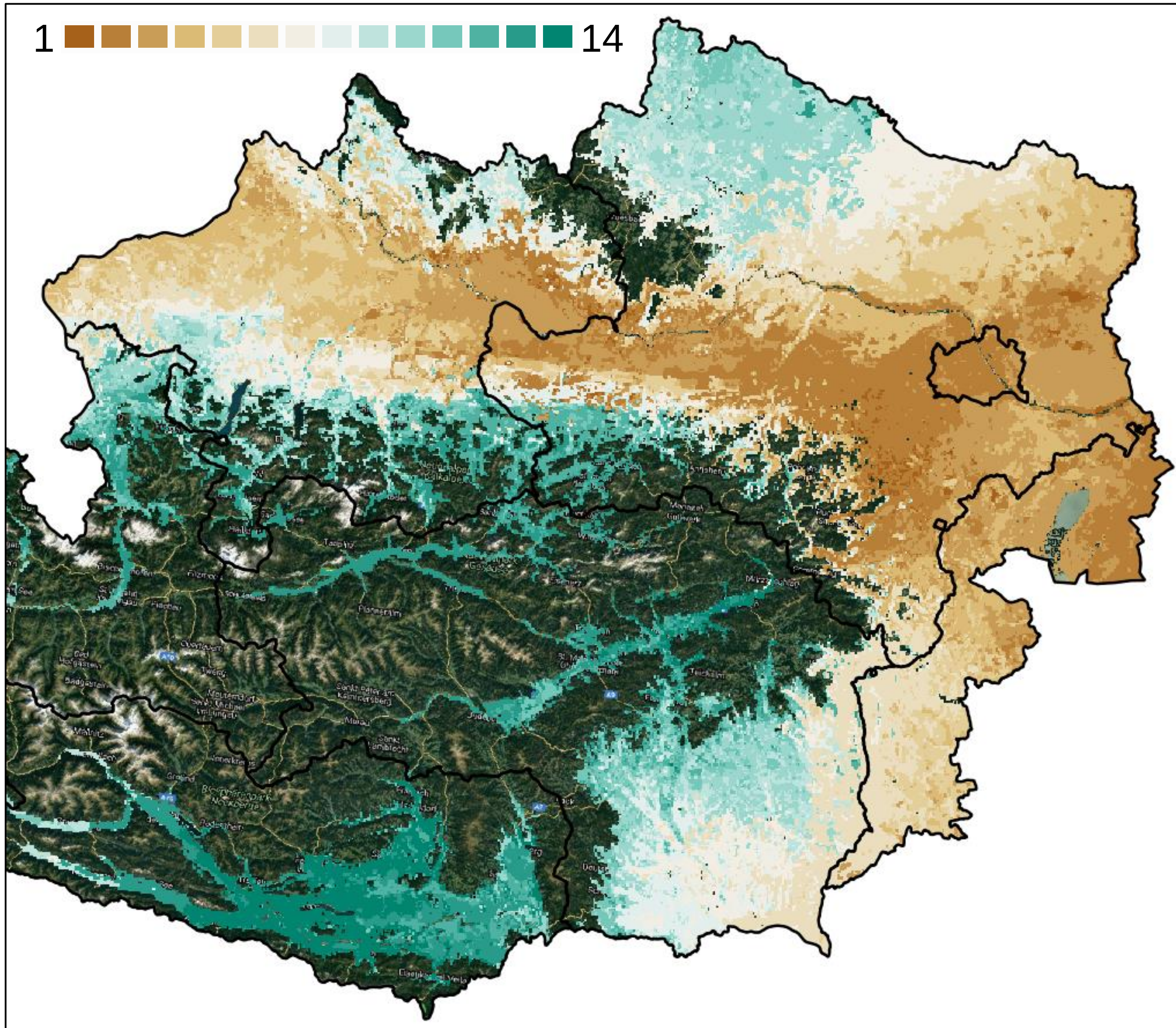




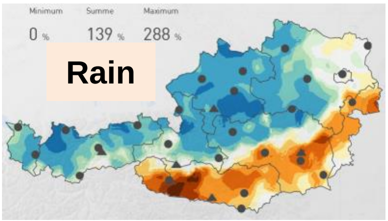
S1ASCAT SWI – Deviation from monthly mean 2007-2020

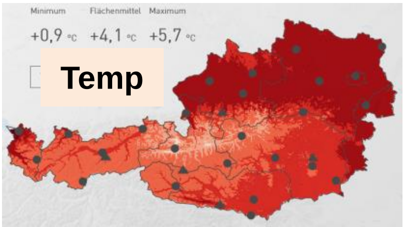


ASCAT/S1 SWI Wetness Ranking in the period 2007-2020



February 2020





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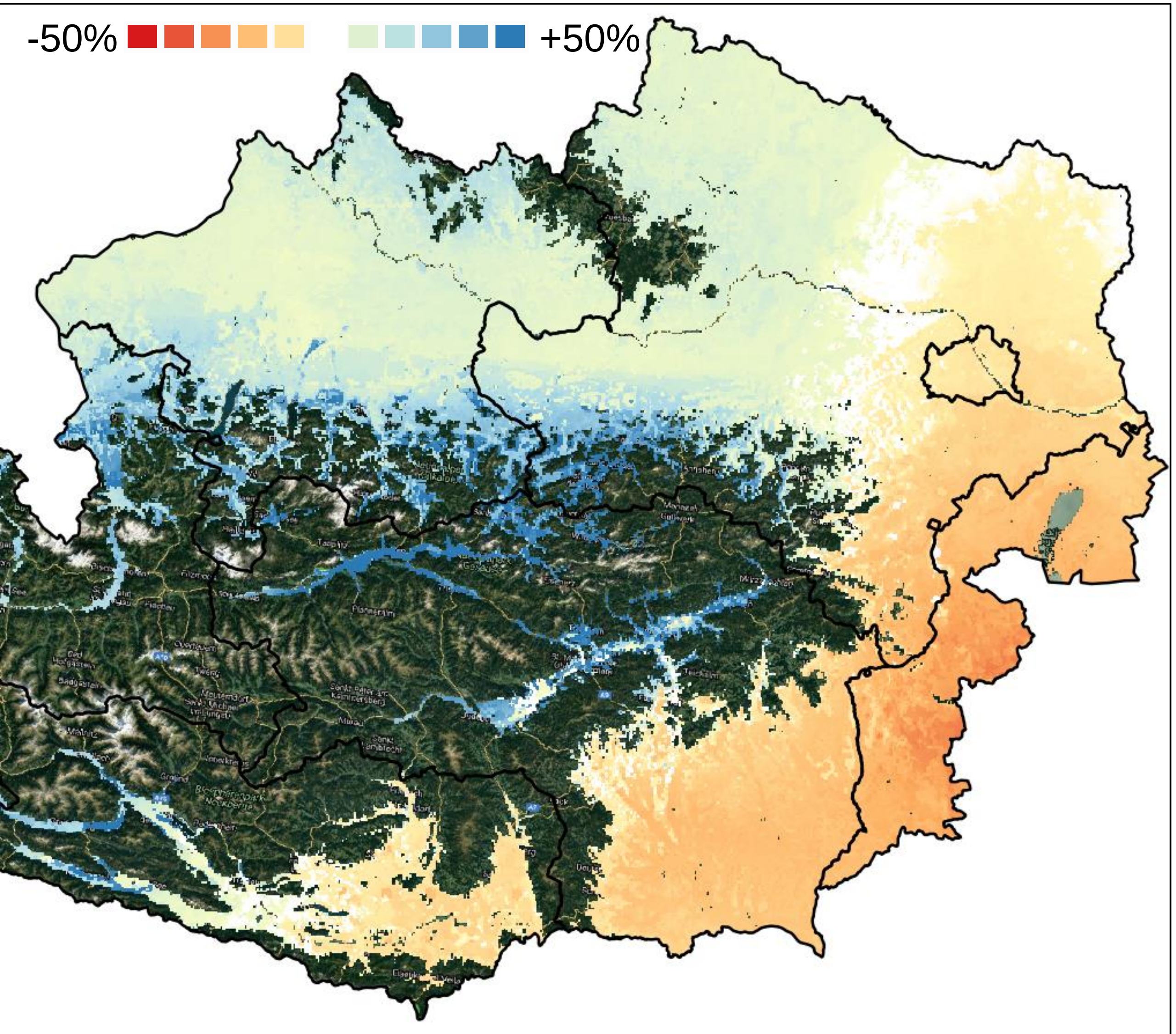
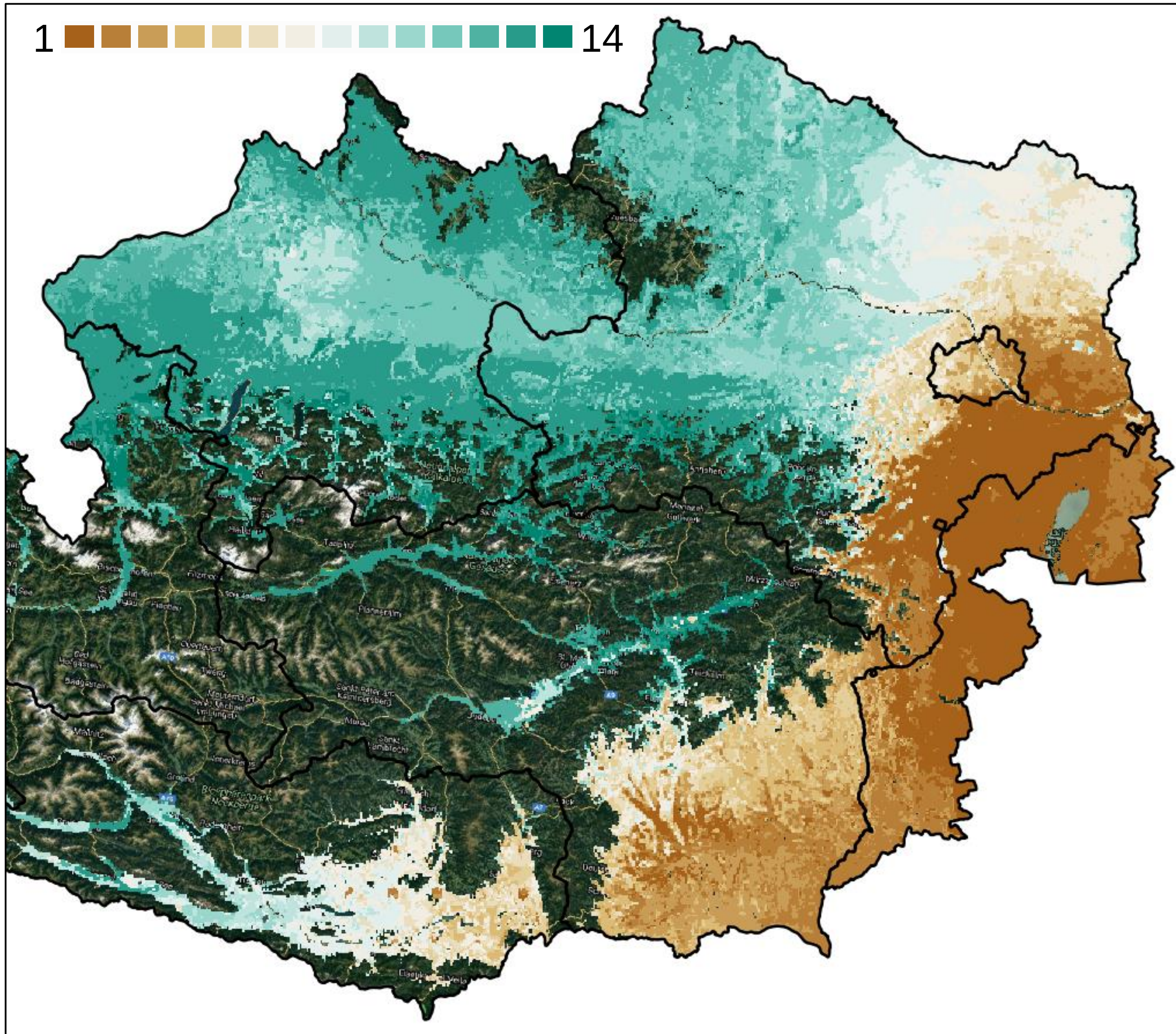
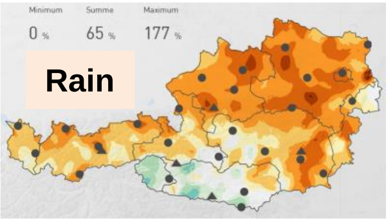
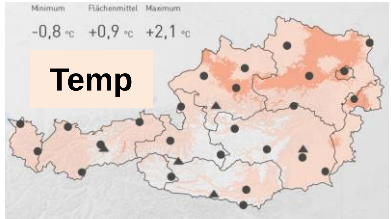


ASCAT/S1 SWI Wetness Ranking in the period 2007-2020

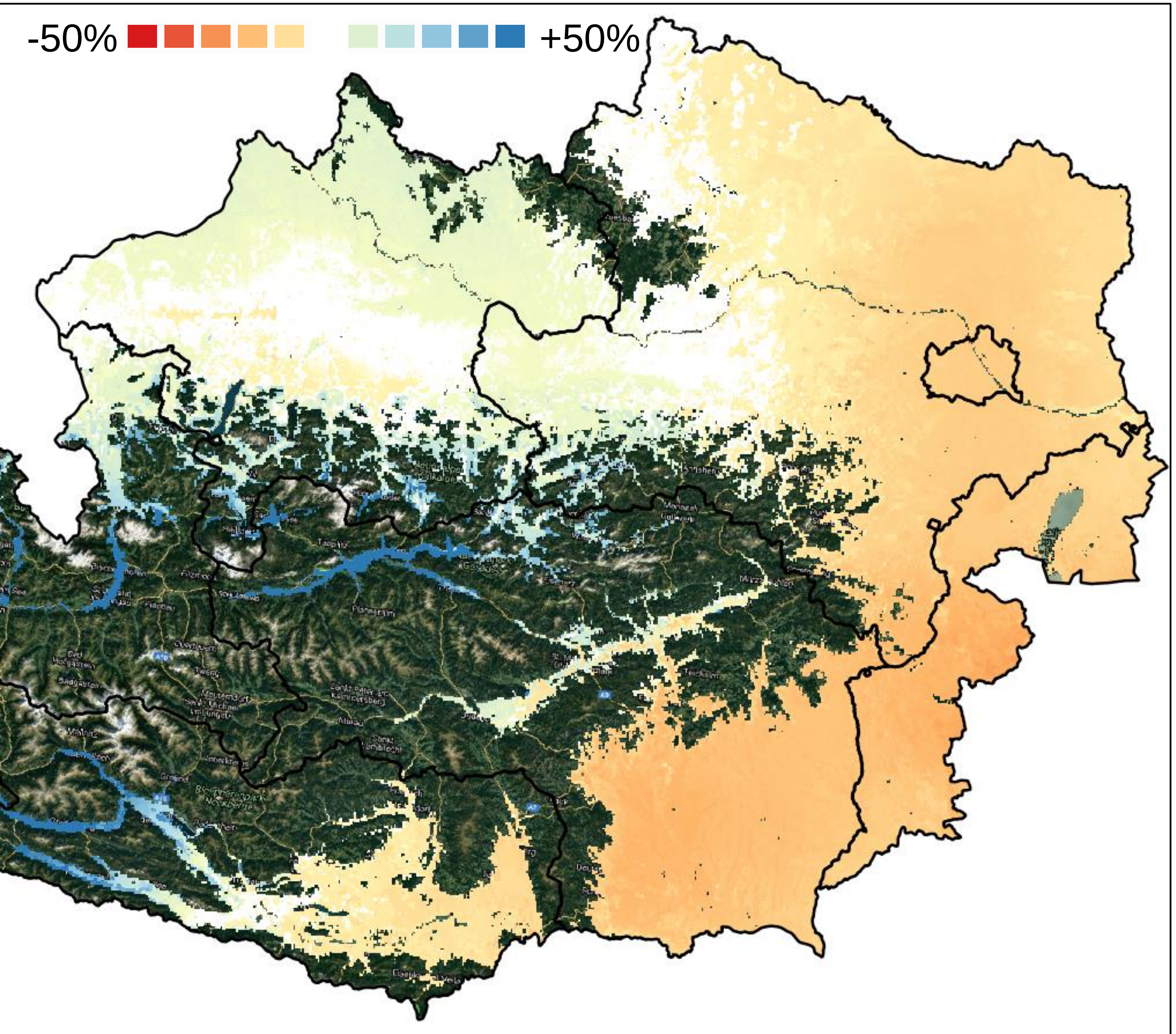


March 2020

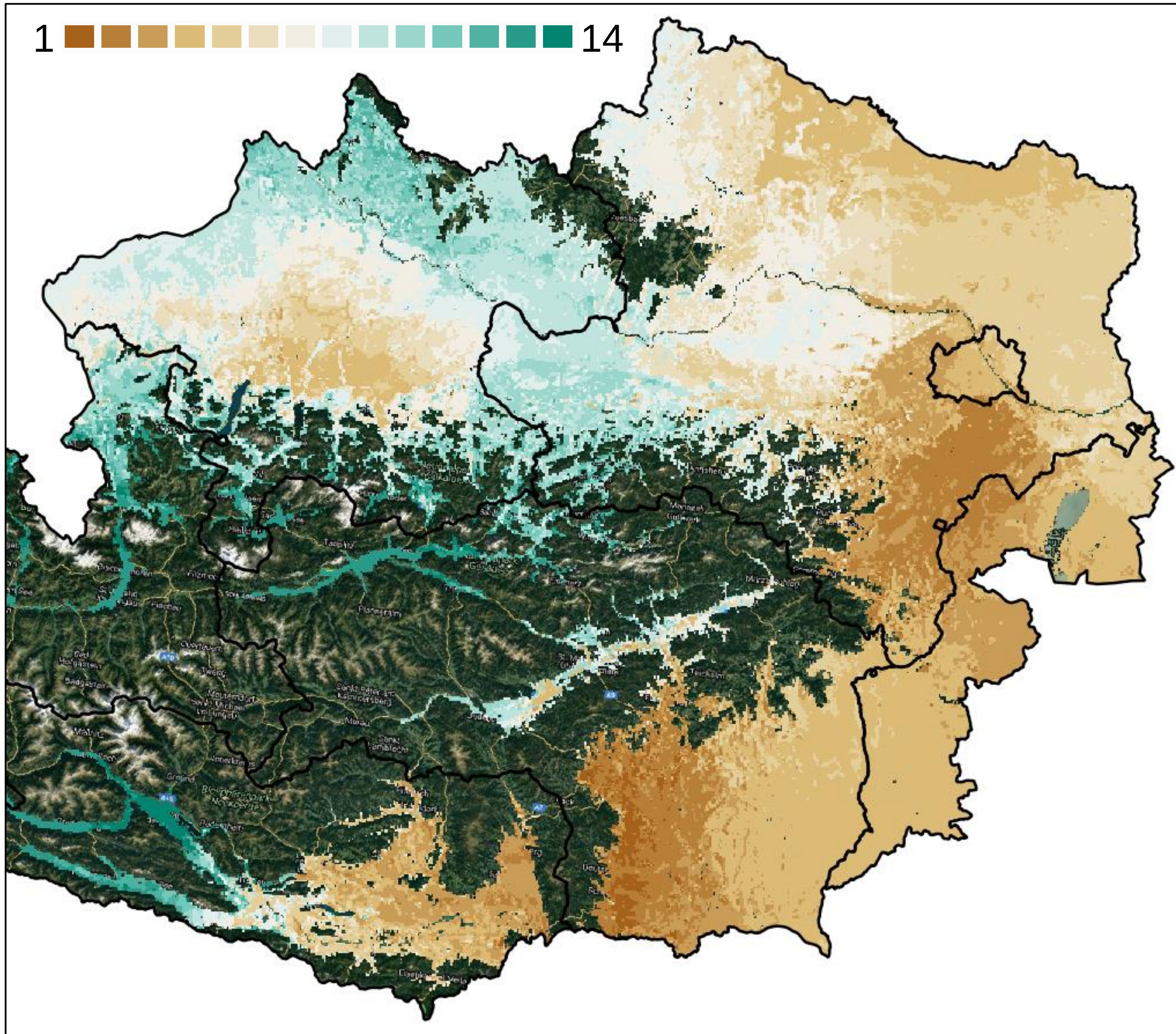




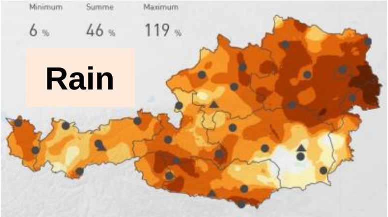
S1ASCAT SWI – Deviation from monthly mean 2007-2020

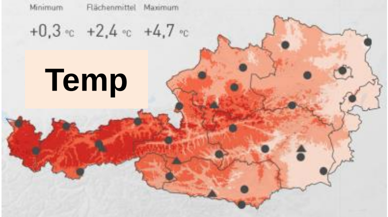


ASCAT/S1 SWI Wetness Ranking in the period 2007-2020

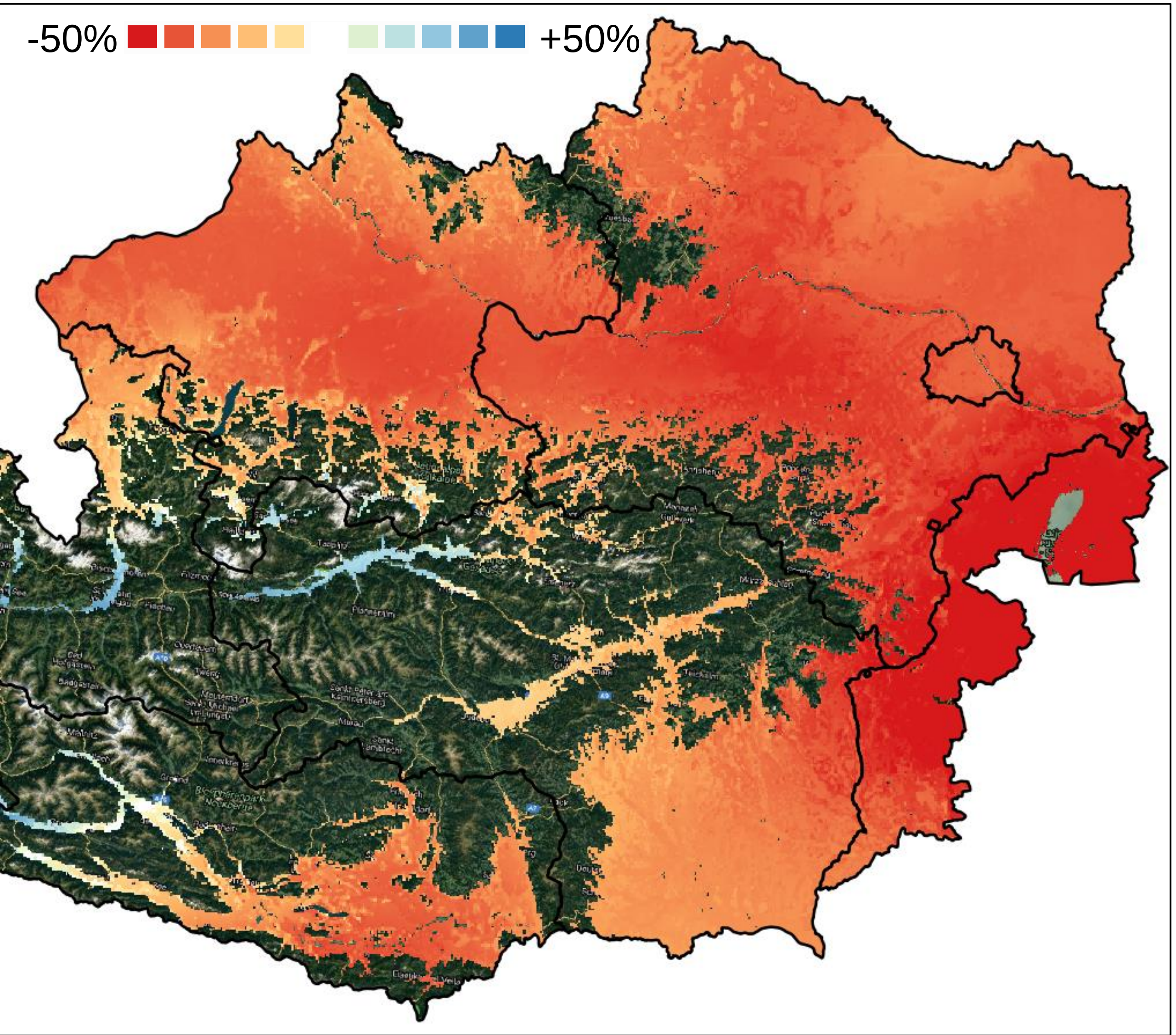


April 2020

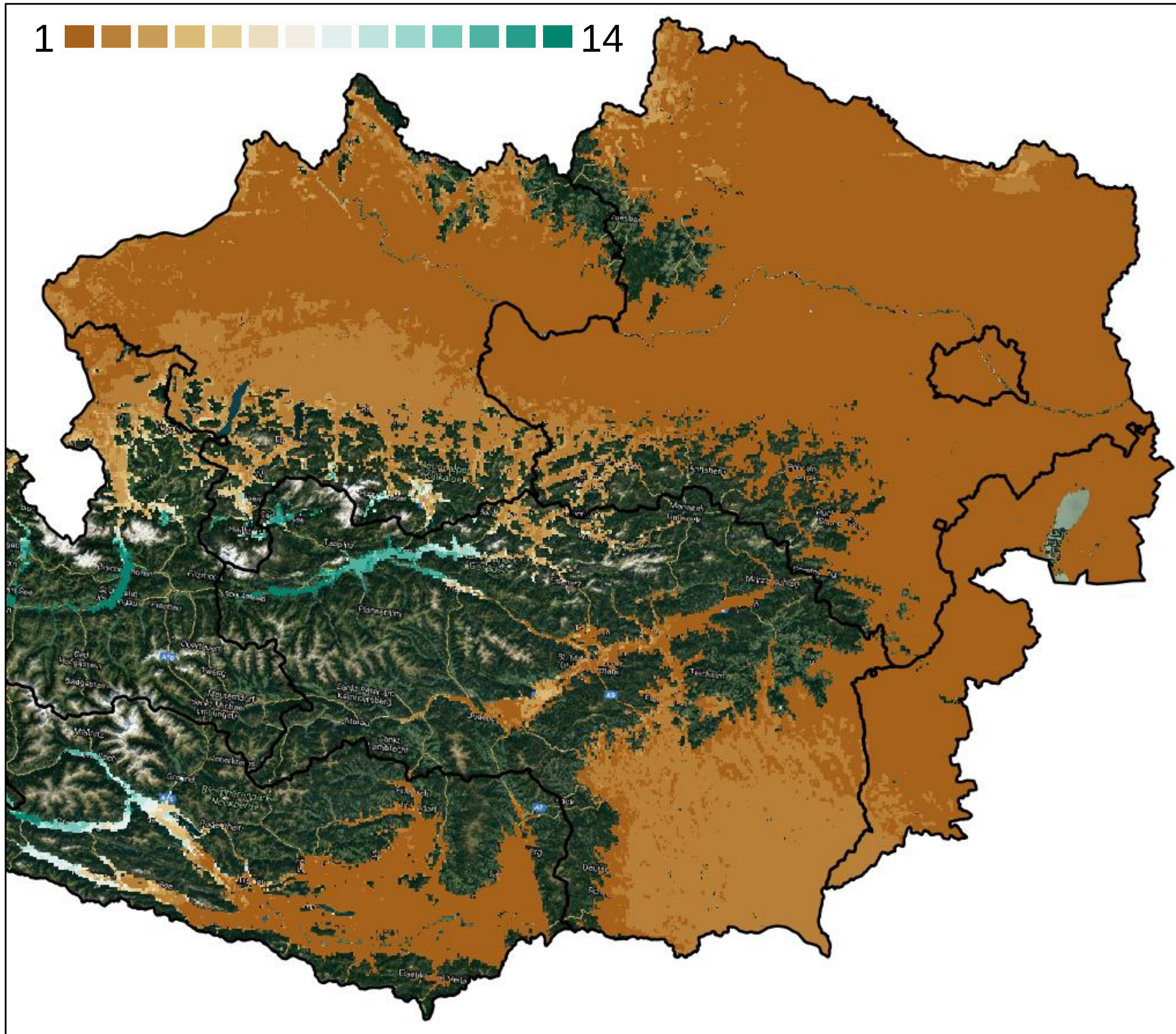




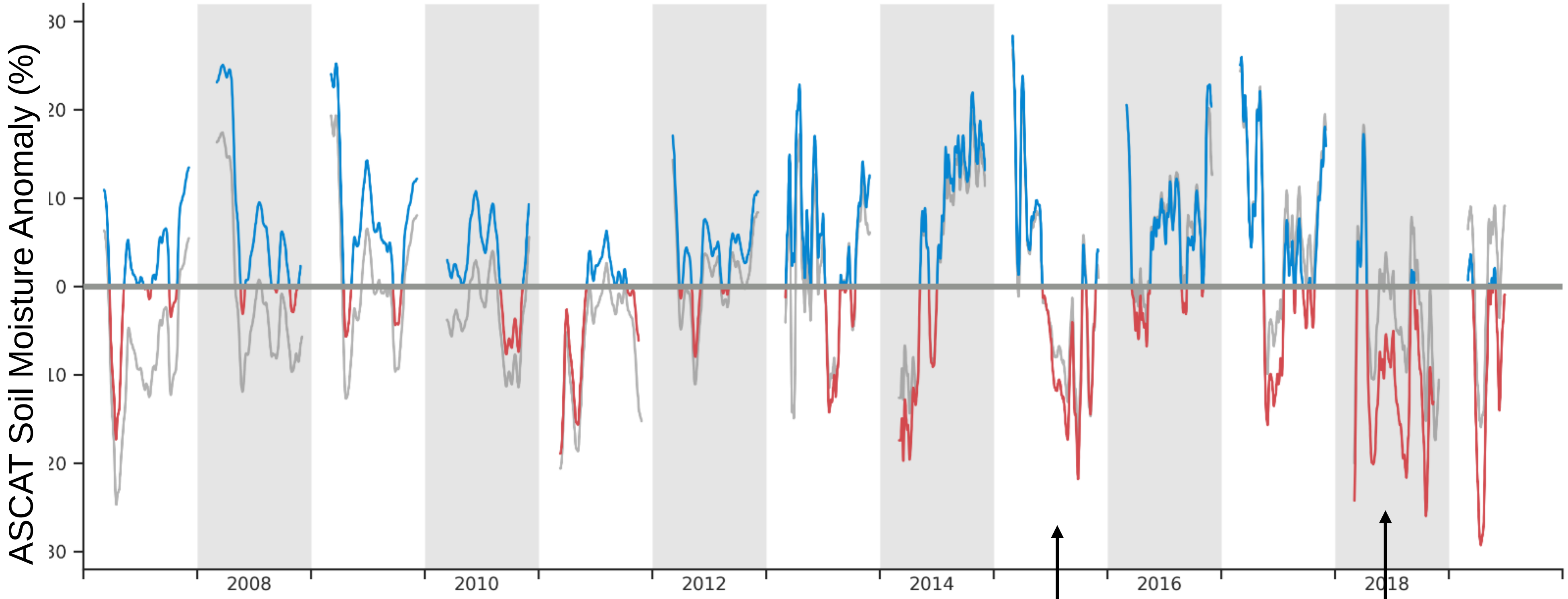
S1ASCAT SWI – Deviation from monthly mean 2007-2020



ASCAT/S1 SWI Wetness Ranking in the period 2007-2020



Drought Monitoring with Satellite Soil Moisture Data



Drought-index derived from ASCAT soil moisture data over Offenhausen, Upper Austria. Grey line: without correcting for land cover changes and RFI.

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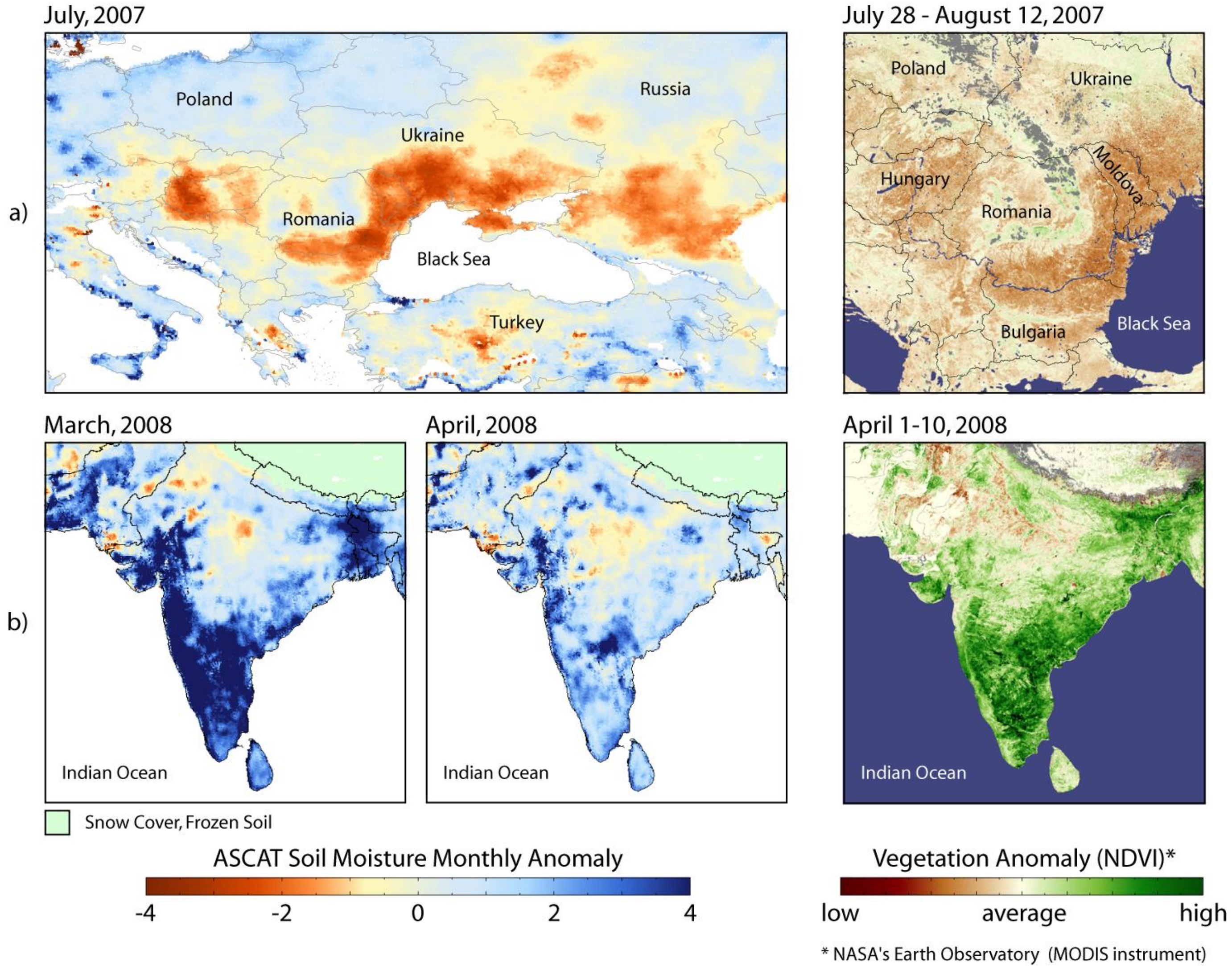
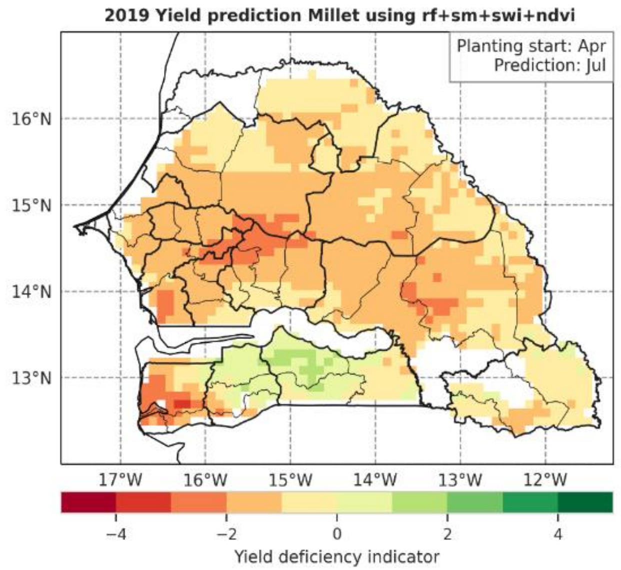
Soil Moisture and Vegetation



Naeimi, V., W. 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.

Satellite soil Moisture and Rainfall Testing for Drought Risk Insurance (SMART-DRI)

- Disaster risk financing instruments, and especially parametric drought risk financing instruments, rely on drought risk indices for financial applications
  - A useful, cost-efficient, and sustainable drought risk financing instrument, **reliability and performance of these drought risk indices is pivotal**.
  - Indices are often based on precipitation, temperature and vegetation greenness
  - Satellite-based **soil moisture measurements can help to improve parametric drought risk assessment**
- Main project analysis
  - Convergence-of-evidence of rainfall deficits through the hydrological cycle, resulting in drought hazard indicators
  - Yield deficiency analysis which relates to drought indicators and number of people affected
  - The skill of satellite-based soil moisture for predicting vegetation state in addition to classic indicators such as temperature and precipitation



Yield deficiency map for millet in Senegal for the drought 2019.

- Use case
  - Moroccan drought in 2015/2016
  - Senegal drought in 2014 and 2019

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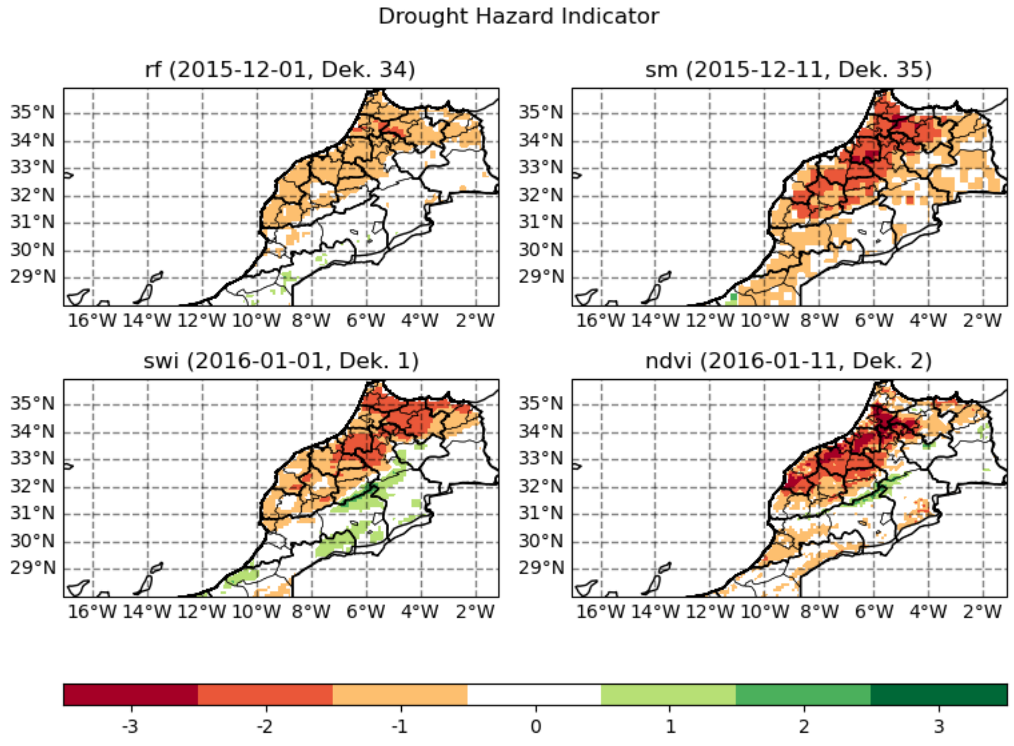
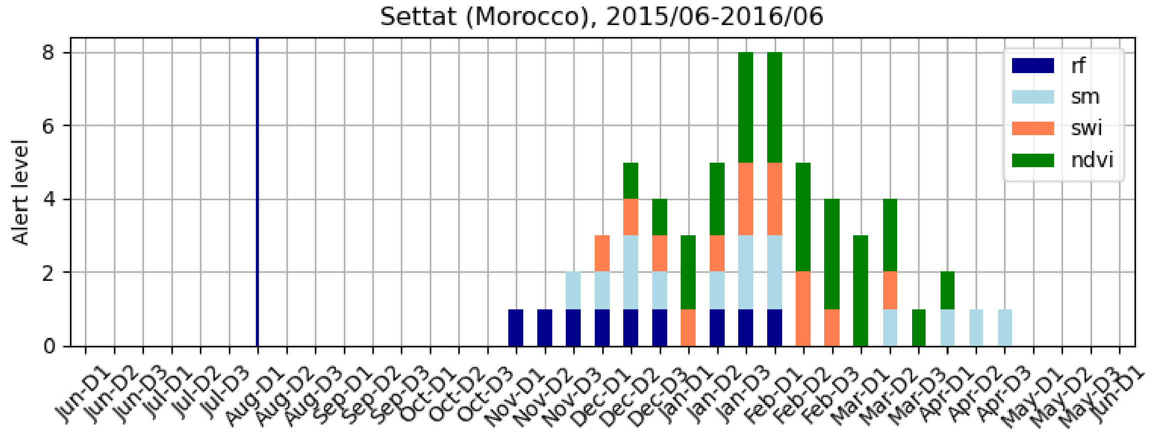
Satellite soil Moisture and Rainfall Testing for Drought Risk Insurance (SMART-DRI)



Rainfall-, surface SM-, SWI- and NDVI-based drought hazard indicators for Morocco, December 2015-January 2016

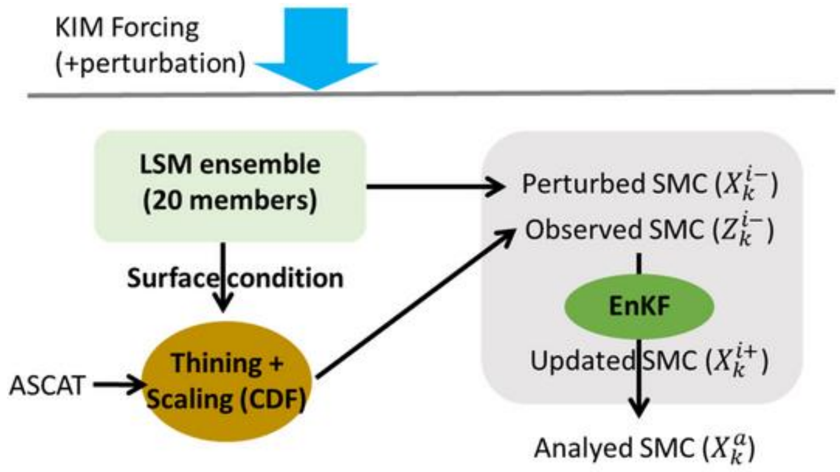


Alert levels during the 2015/2016 drought event in the Settat department, Morocco. The blue vertical line indicates the start of the rainy season (derived from SM2RAIN-ASCAT)

OTHER RECENT STUDIES

Soil moisture data assimilation

- A soil moisture data assimilation system has been developed and evaluated based on the Korea Integrated Model (GDAPS-KIM) to improve its weather forecast skill.
- ASCAT soil moisture observations were assimilated every six hours using EnKF to improve the initial land surface conditions of GDAPS-KIM.
- Two experiments with and without soil moisture data assimilation for the period of July 2019 to 10 August 2019.
- Results show that incorporating the soil moisture assimilation contributes to improving the initial surface condition and predictability of GDAPS-KIM during the boreal summertime (in particular, the soil moisture data assimilation alleviated the warm biases that are related to soil moisture and enhanced the weather forecasting).
- Based on these results, this assimilation system has been operational for the GDAPS-KIM at KMA since October 2020

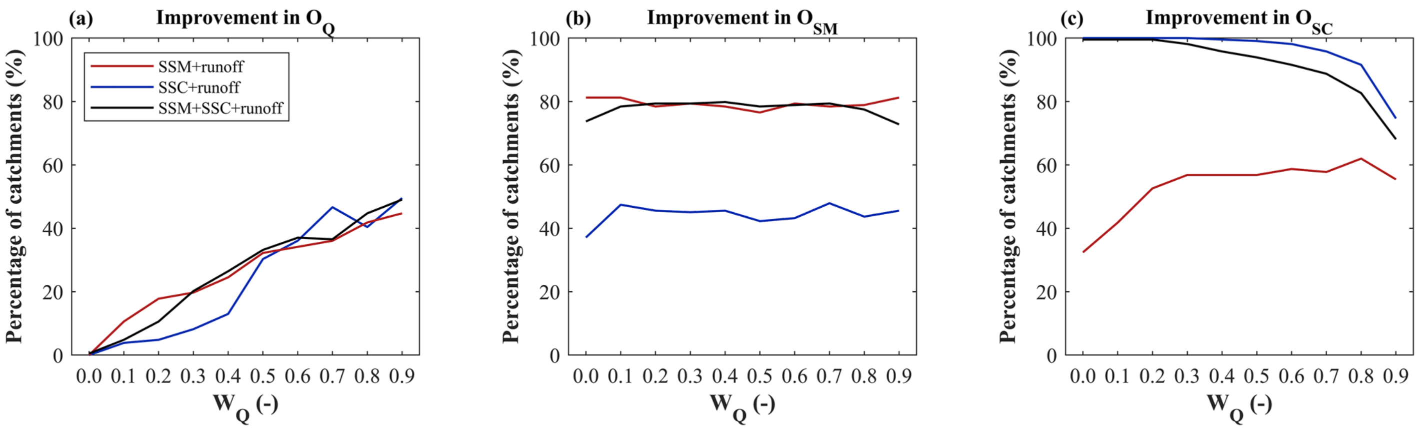


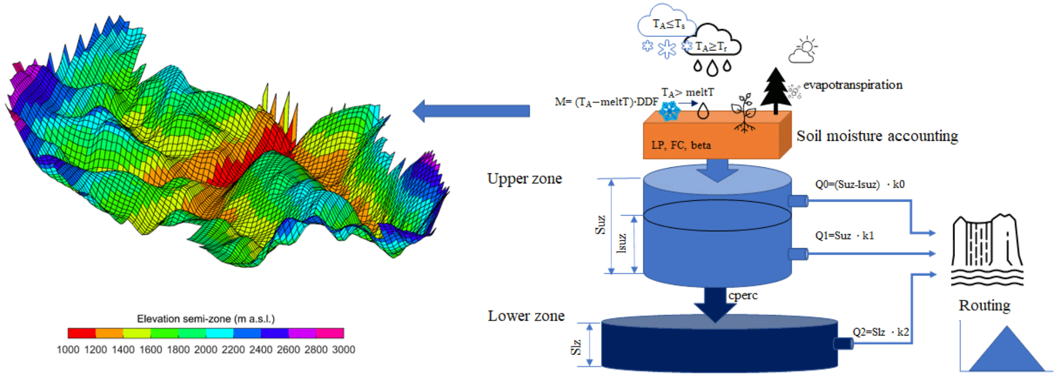
Jun et al. (2021) Impact of Soil Moisture Data Assimilation on Analysis and Medium-Range Forecasts in an Operational Global Data Assimilation and Prediction System. Atmosphere, 12, 1089.

Calibrating and validating a conceptual hydrologic model

- Three multiple calibration variants have been tested using runoff data along with ASCAT soil moisture and MODIS snow cover data

- The hydrologic model used in this study is a semi-distributed version of TUWmodel, following the structure of the HBV.





(a) *For up to 40 % of catchments, the validation runoff efficiency is improved by using multiple objective calibration as compared to calibration to runoff alone.*

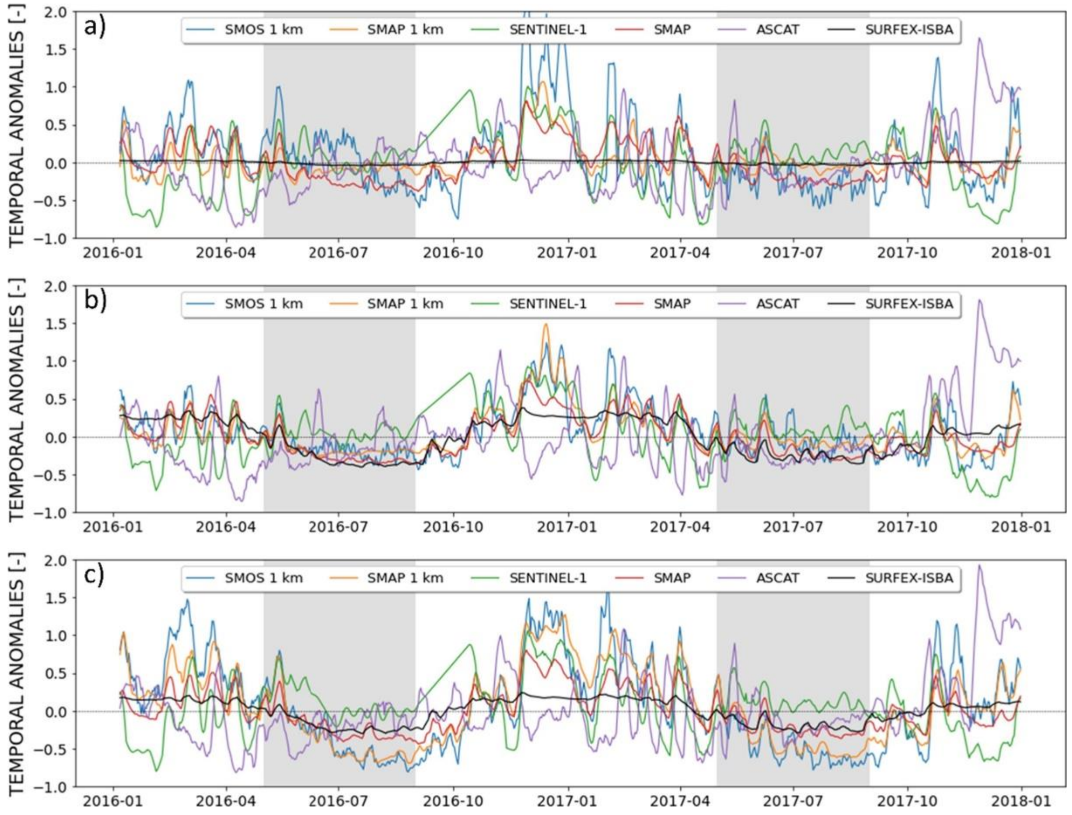
(b) *The calibration variants that use SSM data improve soil moisture simulations in more than 80 % of the catchments for all weights, and the addition of snow data does not change the performance.*

(c) *The snow model efficiency is vastly improved by the inclusion of the SSC data for w_Q <0.6 in almost all catchments, and the inclusion of soil moisture (in the variant that uses all variables) still has a very big improvement in snow simulations as compared to the case when only runoff is used in the calibration.*

Tong et al. (2021) The value of ASCAT soil moisture and MODIS snow cover data for calibrating a conceptual hydrologic model, HESS, 25(3), 1389–1410.

Detecting and mapping irrigated areas

- This study investigates the capability of five remotely sensed soil moisture products to detect the irrigation signal over an intensely irrigated area located in the North East of Spain
- The evaluation of detecting irrigated areas has been addressed by looking at the spatial and temporal dynamics of soil moisture through normalized indices derived from the temporal stability theory.
- The coarser resolution products adopted in this study, ASCAT and SMAP, do not show promising results in detecting irrigation over the pilot area (attributed to the scale of the irrigated land and to the complexity of the surrounding).
- However, ASCAT and SMOS proved to be capable to detect irrigation signal over different wide irrigated areas in the continental United States (Kumar et al., 2015, Lawston et al., 2017).



Time series of the 7-days moving average of the mean temporal anomalies for each corresponding area: a) Urgell area, b) Catalan and Aragonese area, and c) dryland

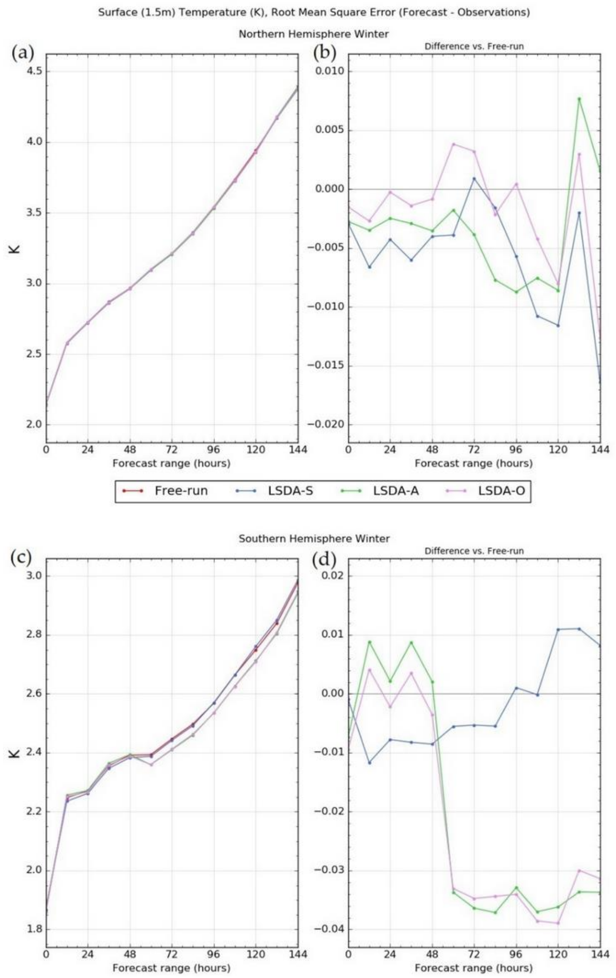
Dari et al. (2021) Detecting and mapping irrigated areas in a Mediterranean environment by using remote sensing soil moisture and a land surface model. Journal of Hydrology, 596(), 126129.

The Met Office Operational Soil Moisture Analysis System

- A Simplified Extended Kalman Filter is used to ingest pseudo-observations of screen temperature and humidity and satellite-derived soil wetness (ASCAT) in both the global and regional Land Surface Data Assimilation (LSDA) system to improve forecasts of surface air temperature and humidity

- Global model: running trials for two seasons, winter and summer, and assessing the results against two truth types using the root mean squared error show that LSDA provides an overall positive impact across hemispheres and seasons

- Regional model: Comparison against 1.5 m observations of temperature and humidity shows that LSDA provides a neutral impact over winter and a mixed result for summer, where temperature is degraded, and specific humidity is improved when compared to the free-run. However, when using the previous operational system as a benchmark (daily-update) the performance in temperature is comparable and the humidity is improved.



*Winter forecasts compared to observations. Root mean squared errors or RMSE (panels **a**, **c**) in surface (1.5 m) temperatures (Kelvin) computed for global forecasts against ground-based SYNOP observations for all forecast ranges up to T+144 h. Panels (**b**, **d**) show the RMSE difference between the control and the three experiments such that a negative result means improvement of the experiment over the control*

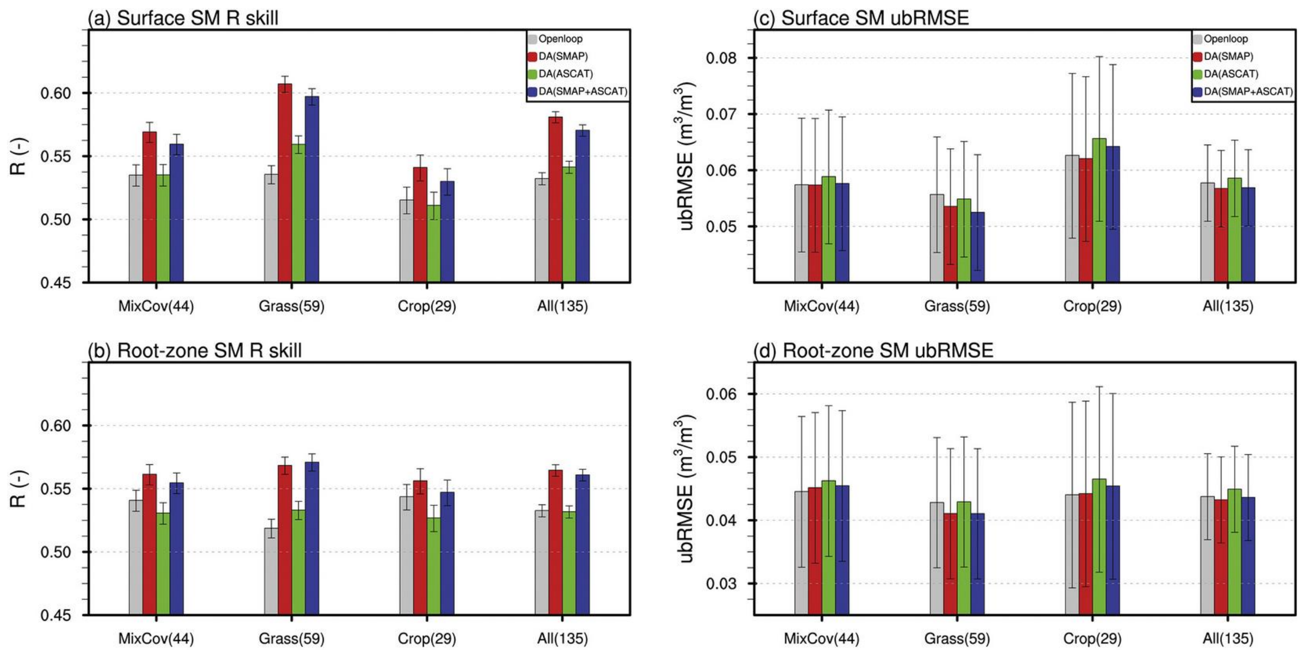
Gomez et al. (2020) The Met Office Operational Soil Moisture Analysis System. Remote Sensing, 12(22), 3691.

Assimilation of soil moisture retrievals into the JULES land surface model

- This study develops a data assimilation system based on the JULES land surface model and the Local Ensemble Transform Kalman Filter (LETKF) scheme assimilating soil moisture retrievals from L-band passive (SMAP) and C-band active (ASCAT) microwave remote sensing

- The results reveal that both sets of satellite retrievals provide added value in the representation of surface and root-zone soil moisture in the assimilation estimates over the continental U.S. The skill improvement is more pronounced in the relatively dry grasslands regions of the western U.S.

- SMAP assimilation estimates show relatively higher skill compared to the ASCAT assimilation estimates in the western U.S. than in the eastern U.S. (attributed mainly to the fact that relatively fewer ASCAT observations are assimilated in the western U.S).



R (a, b) skill and ubRMSE (c, d) of surface and root-zone soil moisture estimates from the open loop (gray), DA(SMAP) (red), DA(ASCAT) (green), and DA(SMAP+ASCAT) (blue). The soil moisture estimates are validated against in situ measurements over North America and averaged for each land cover class. Error bars represent 95% confidence intervals.

Seo et al. (2021) Assimilation of SMAP and ASCAT soil moisture retrievals into the JULES land surface model using the Local Ensemble Transform Kalman Filter. Remote Sensing of Environment, 253, 112222.

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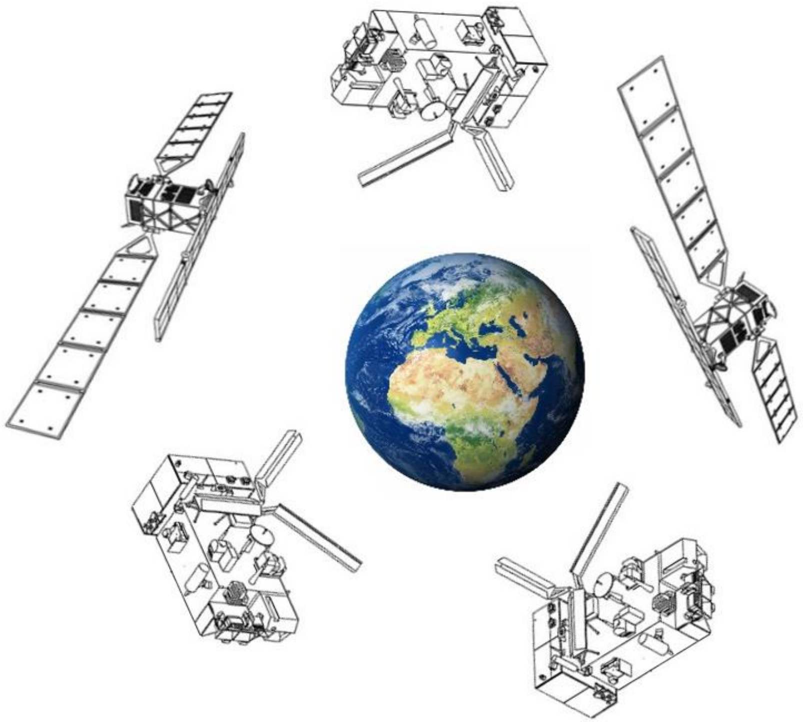
Final Remarks

- H SAF ASCAT + SCA soil moisture
  - Sub-daily temporal sampling
  - Well-calibrated and stable backscatter time series
  - Long-term perspective
- Many and diverse applications
- However, use of data requires expert knowledge
  - Complex data product with many data fields
  - Retrievals errors vary in space and time
  - Masking required for static (e.g. dense forest) and dynamic (e.g. snow and frost) effects
- Constellation with Sentinel-1



Acknowledgements

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