Applications of H SAF Soil Moisture Data

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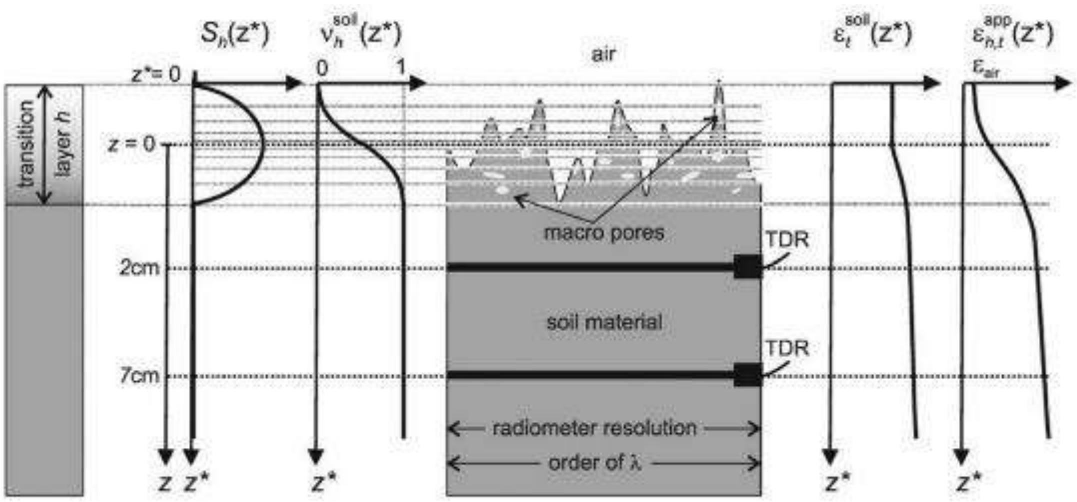
Information Content

Information Content of Soil Moisture Retrievals

- Microwave sensors can provide information about spatio-temporal soil moisture trends
  - Information about absolute values comes from external data sets
- Absolute values in soil moisture retrievals driven strongly by
  - Available soil property maps
    - Soil porosity, texture, etc.
  - Surface roughness parameterization
    - Not a geometric concept - use of “effective roughness” values - roughness depend on soil moisture



Air-to-Soil Transition Model

Schneeberger et al. (2004) Topsoil structure influencing soil water retrieval by microwave radiometry, Vadose Zone Journal, 3(4), 1169-1179.

Signal versus Noise

- The information content of soil moisture is best characterised by the **signal-to-noise ratio (SNR)**
  - Key criterion in data assimilation

- Signal is tied to a certain scale, hence
  - noise refers not only to random instrument noise and retrieval errors but also to representativity errors
  - SNR is scale dependent

- Soil moisture scaling approaches
  - Highly non-linear hydrological processes are assumed to linearize at coarse satellite scales
  - Standard error model

$$\hat{\Theta} = \alpha + \beta(\Theta + \varepsilon)$$

$\hat{\Theta}$ ... Satellite retrieval or model soil moisture

Θ ... "true" soil moisture state

α, β ... linear parameters

ε ... residual error

Triple Collocation

- Originally proposed to estimate **random error variances**
  - Covariance-formulation

Assumptions:

$$\hat{\Theta}_X = \alpha_X + \beta_X(\Theta + \varepsilon_X)$$
$$\hat{\Theta}_Y = \alpha_Y + \beta_Y(\Theta + \varepsilon_Y)$$
$$\hat{\Theta}_Z = \alpha_Z + \beta_Z(\Theta + \varepsilon_Z)$$

$$\xrightarrow[\substack{i, j \in \{X, Y, Z\} \\ i \neq j}]{\substack{\mathrm{Cov}(\Theta, \varepsilon_i) = 0 \\ \mathrm{Cov}(\varepsilon_i, \varepsilon_j) = 0}}$$

$$\mathrm{Var}(\hat{\Theta}_i) = \beta_i^2 \,\mathrm{Var}(\Theta) + \beta_i^2 \,\mathrm{Var}(\varepsilon_i)$$
$$\mathrm{Cov}(\hat{\Theta}_i, \hat{\Theta}_j) = \beta_i \beta_j \,\mathrm{Var}(\Theta)$$

Error variances:

$$\beta_X \,\mathrm{Var}(\varepsilon_X) = \mathrm{Var}(\hat{\Theta}_X) - \frac{\mathrm{Cov}(\hat{\Theta}_X, \hat{\Theta}_Y)\,\mathrm{Cov}(\hat{\Theta}_X, \hat{\Theta}_Z)}{\mathrm{Cov}(\hat{\Theta}_Y, \hat{\Theta}_Z)}$$

$$\beta_Y \,\mathrm{Var}(\varepsilon_Y) = \mathrm{Var}(\hat{\Theta}_Y) - \frac{\mathrm{Cov}(\hat{\Theta}_Y, \hat{\Theta}_X)\,\mathrm{Cov}(\hat{\Theta}_Y, \hat{\Theta}_Z)}{\mathrm{Cov}(\hat{\Theta}_X, \hat{\Theta}_Z)}$$

$$\beta_Z \,\mathrm{Var}(\varepsilon_Z) = \mathrm{Var}(\hat{\Theta}_Z) - \frac{\mathrm{Cov}(\hat{\Theta}_Z, \hat{\Theta}_X)\,\mathrm{Cov}(\hat{\Theta}_Z, \hat{\Theta}_Y)}{\mathrm{Cov}(\hat{\Theta}_X, \hat{\Theta}_Y)}$$

Scaling coefficients:

$$\beta_X = 1$$

$$\beta_Y^X = \frac{\mathrm{Cov}(\hat{\Theta}_X, \hat{\Theta}_Z)}{\mathrm{Cov}(\hat{\Theta}_Y, \hat{\Theta}_Z)}$$

$$\beta_Z^X = \frac{\mathrm{Cov}(\hat{\Theta}_X, \hat{\Theta}_Y)}{\mathrm{Cov}(\hat{\Theta}_Z, \hat{\Theta}_Y)}$$

Stoffelen, A. (1998). Toward the true near-surface wind speed: Error modeling and calibration using triple collocation. *Journal of Geophysical Research: Oceans* (1978–2012), 103(C4), 7755-7766.

Signal to Noise Ration (SNR)

- Recently extended to estimate the signal-to-noise ratio

$$\mathrm{SNR}_X = \frac{\mathrm{Var}(\Theta)}{\mathrm{Var}(\varepsilon_i)} = \frac{1}{\dfrac{\mathrm{Var}(\hat{\Theta}_X)\,\mathrm{Cov}(\hat{\Theta}_Y,\hat{\Theta}_Z)}{\mathrm{Cov}(\hat{\Theta}_X,\hat{\Theta}_Y)\,\mathrm{Cov}(\hat{\Theta}_X,\hat{\Theta}_Z)} - 1}$$

$$i, j, k \in \{X, Y, Z\}$$
$$i \neq j \neq k$$

- More easy interpretabilty when expressed in decibel units

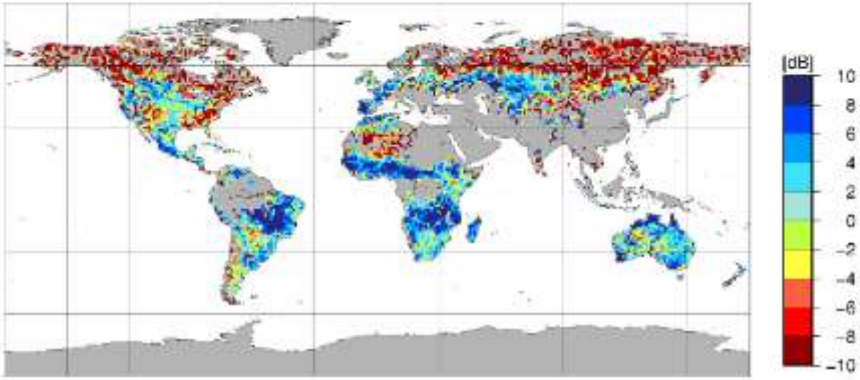
$$\mathrm{SNR}_i[\mathrm{dB}] = 10 \log \frac{\mathrm{Var}(\Theta)}{\mathrm{Var}(\varepsilon_i)}$$

0 dB: signal variance = noise variance
+/- 3 dB: signal variance = double / half noise variance

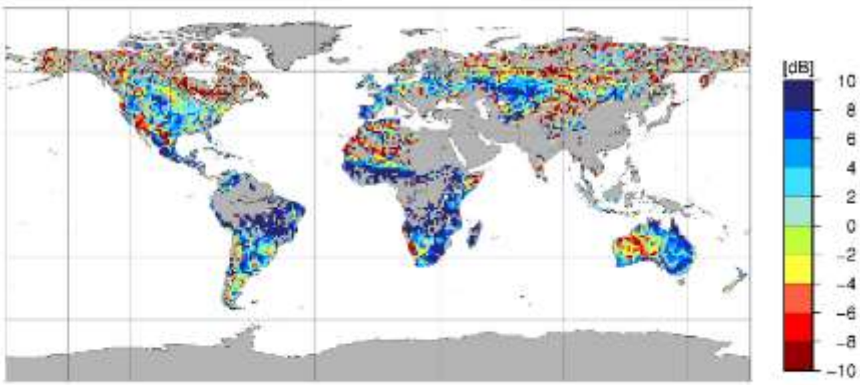
Draper, C., Reichle, R., de Jeu, R., Naeimi, V., Parinussa, R., & Wagner, W. (2013). Estimating root mean square errors in remotely sensed soil moisture over continental scale domains. Remote Sensing of Environment, 137, 288-298.

Gruber, A., C. H. Su, S. Zwieback, W. Crow, W. Dorigo, W. Wagner (2016) Recent advances in (soil moisture) triple collocation analysis, International Journal of Applied Earth Observation and Geoinformation, 45, 200-211.

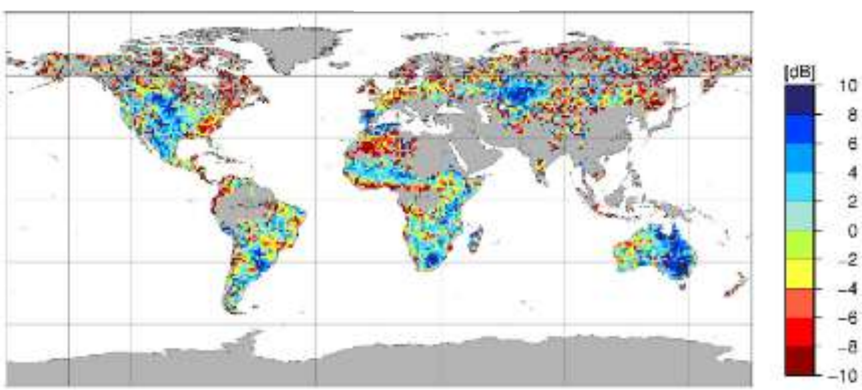
ERA-Interim



ASCAT



SMOS



SNR of ASCAT & SMOS

- Global triple collocation study using two different data triplets
  - JRA-55 – ASCAT – SMOS
  - ERA-Interim – ASCAT – SMOS
- SNR varies strongly depending on land cover
  - Spatial patterns of SNR of ASCAT and SMOS similar
- SNR shows where satellites may add value to models

Miyaoka et al (2017) Triple collocation analysis of soil moisture from Metop-A ASCAT and SMOS against JRA-55 and ERA-Interim, IEEE Journal of Selected Topics in Applied Earth Observation and Remote Sensing, 10(5), 2274-2284.

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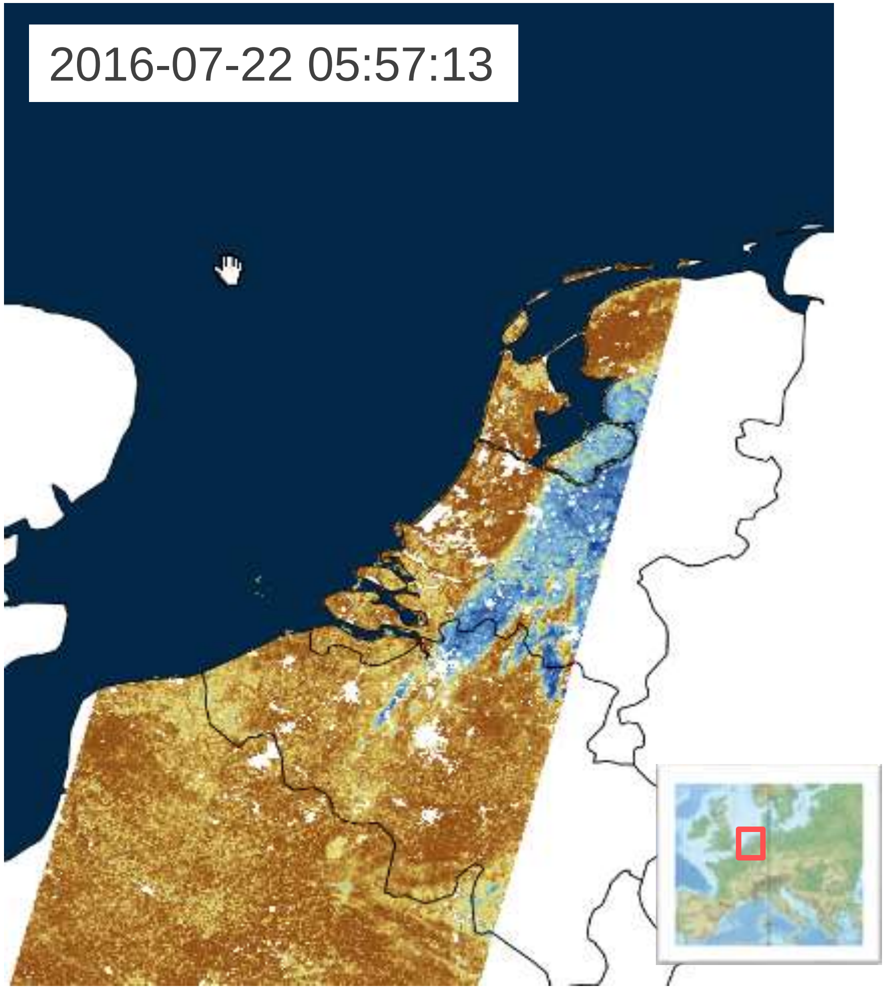
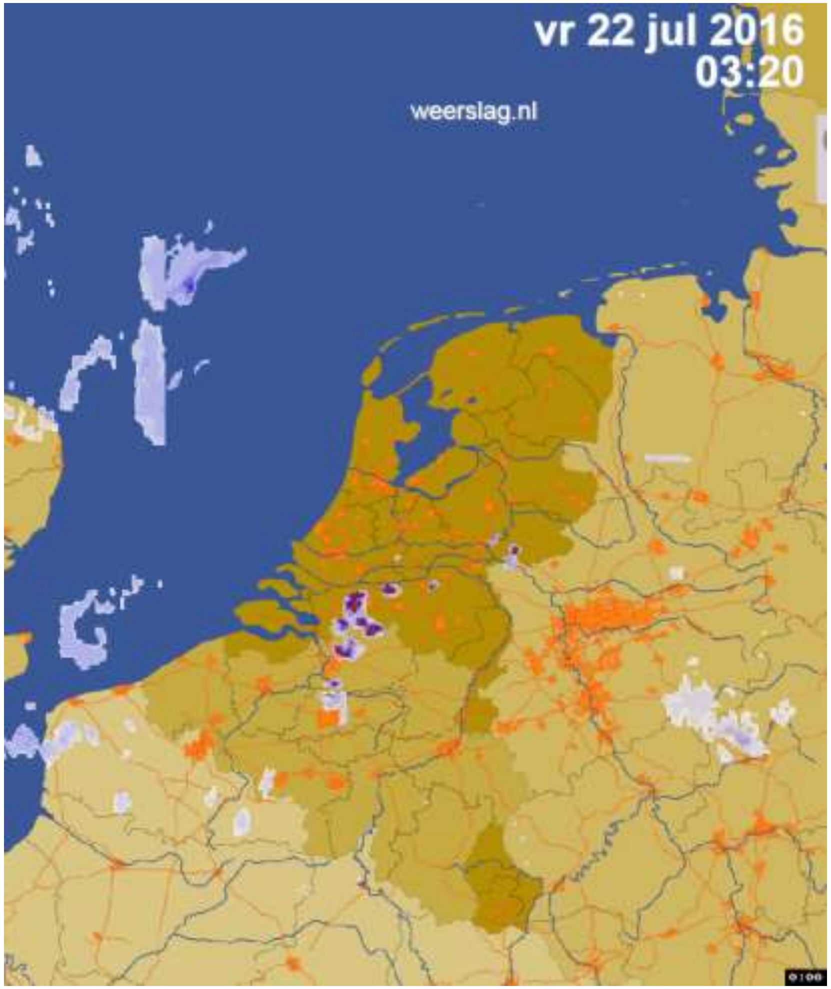
Capturing Rainfall

Sentinel-1 Soil Moisture vs Rainfall-Radar





Rainfall derived from satellite soil moisture: SM2Rain

Water balance model:

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

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

s ... relative saturation

p ... precipitat ion

r ... surface runoff

e ... evapotrans piration

g ... drainage

Inverting for *p(t):*

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

Assuming during rainfall:

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

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

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.

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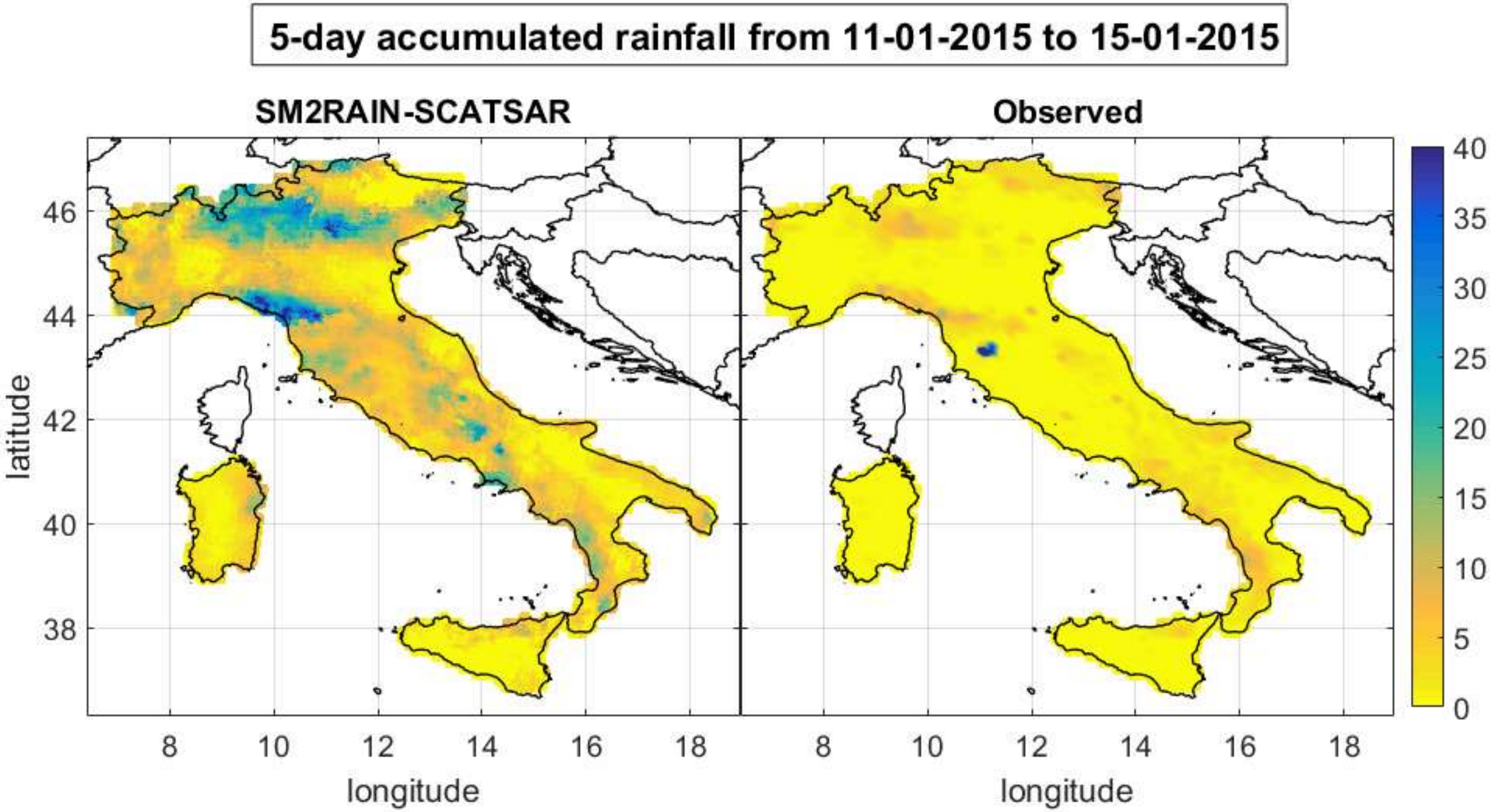
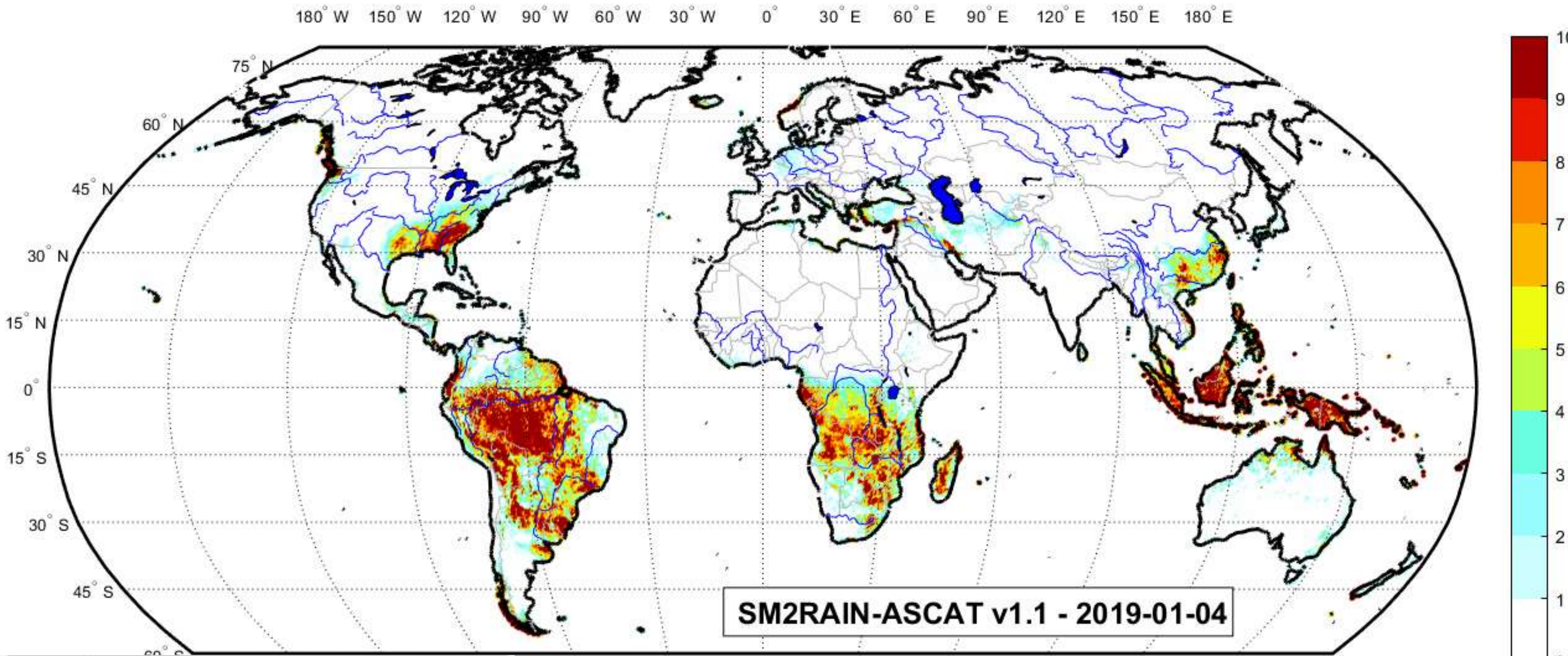
SM2Rain Results for Italy



Istituto di Ricerca per la Protezione Idrogeologica

SM2Rain ASCAT Daily Rainfall Data

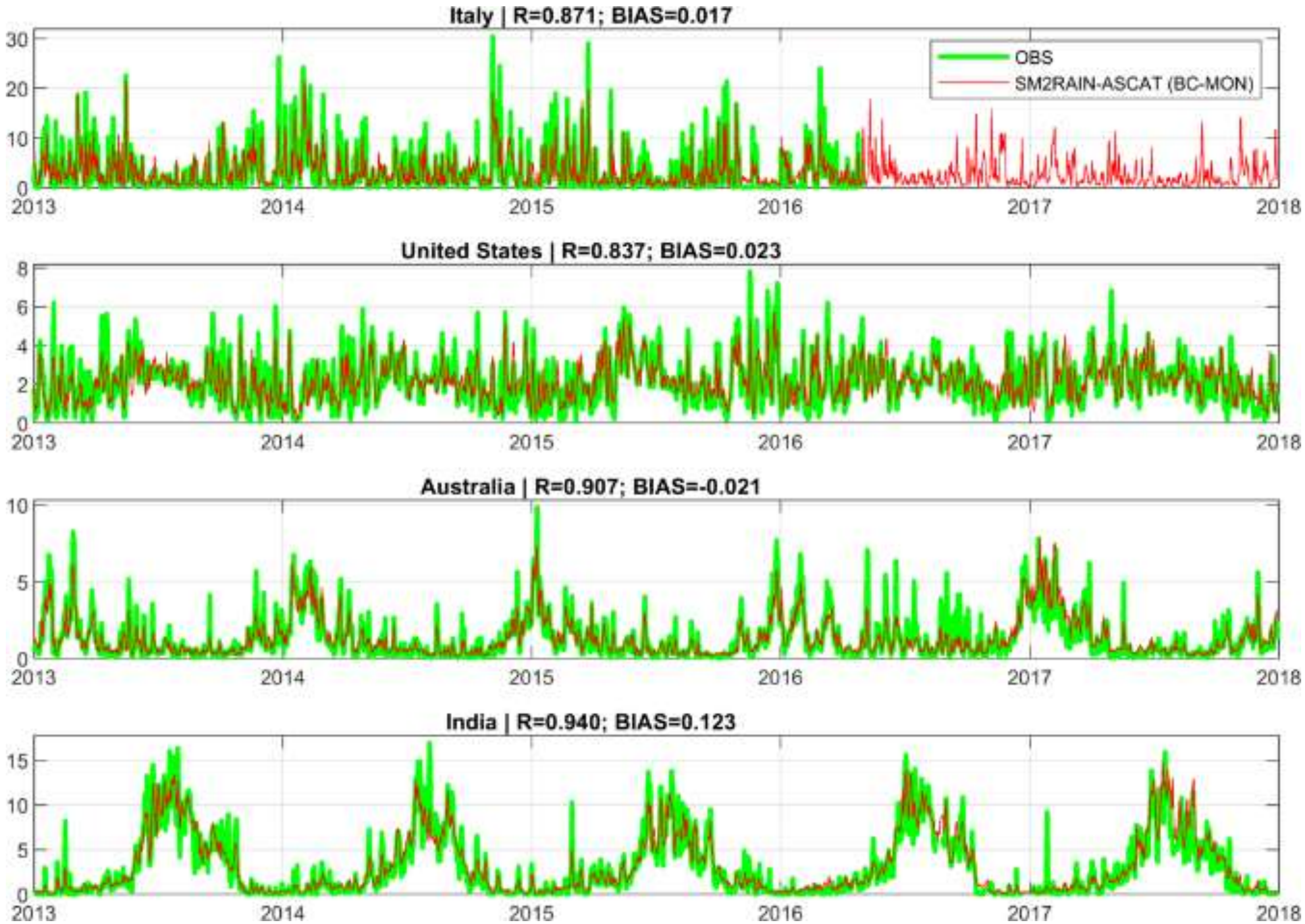
Freely available @ Zenodo
https://zenodo.org/record/2591215



DOI 10.5281/zenodo.2591215

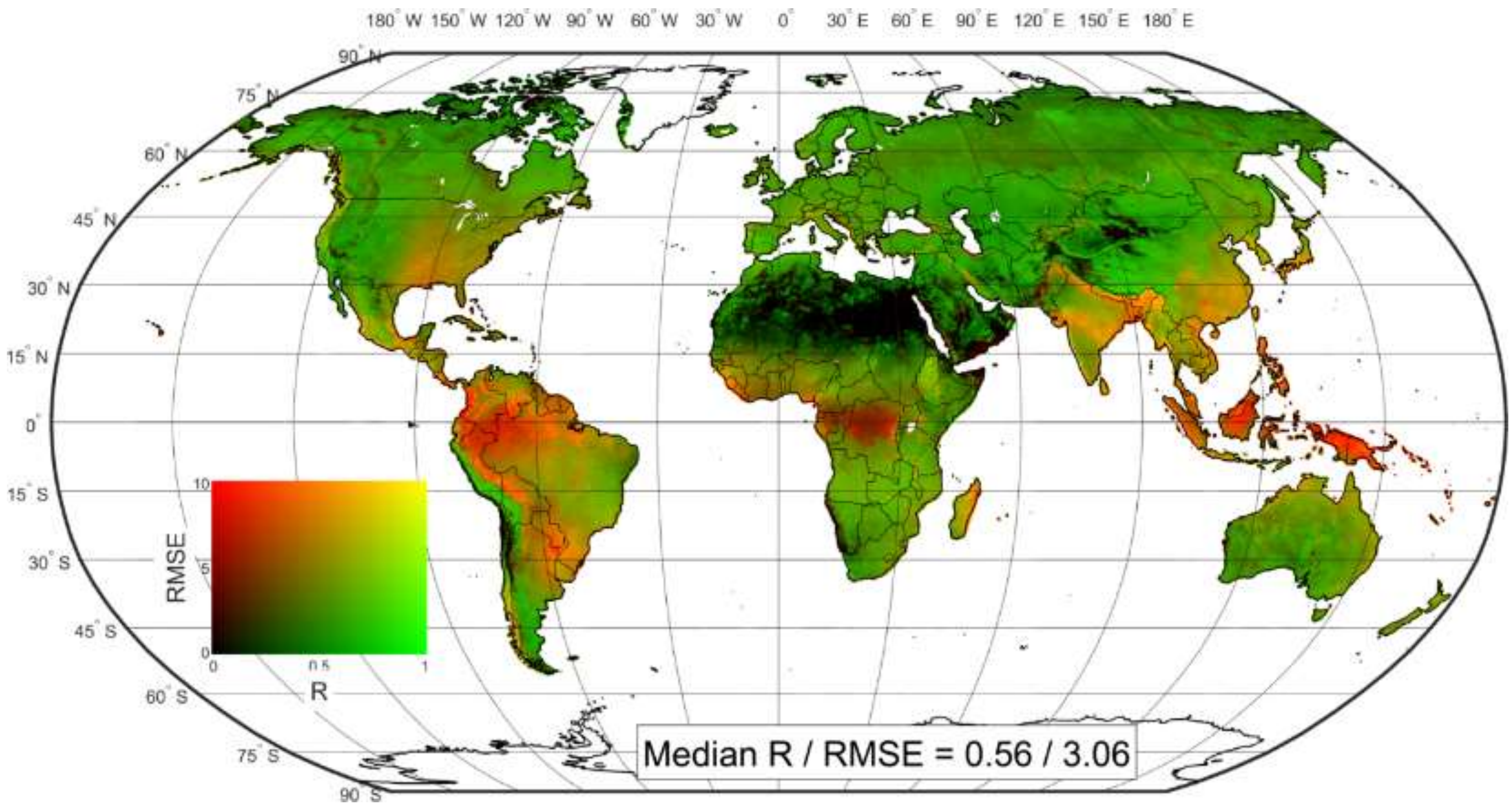
Brocca et al. (2019) SM2RAIN-ASCAT (2007–2018): global daily satellite rainfall from ASCAT soil moisture, Earth Syst. Sci. Data, in press.

SM2Rain ASCAT Rainfall Time Series



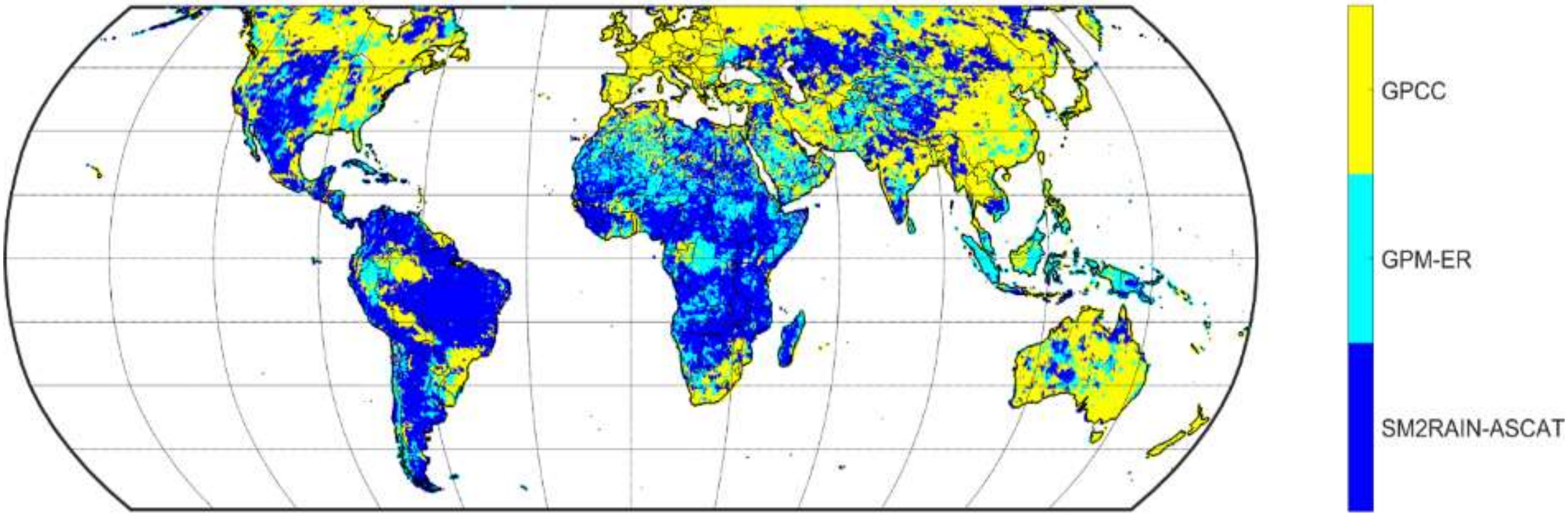
Time series of mean areal rainfall for the four regions for observed data, OBS, and SM2RAIN-ASCAT data record. From Brocca et al. (2019).

SM2Rain ASCAT Rainfall versus ERA5 Rainfall



Pearson's correlation, R, and root mean square error, RMSE, map of SM2RAIN-ASCAT data record compared with ERA5 reanalysis dataset used as benchmark (period 2007-2018). From Brocca et al. (2019).

AM2Rain ASCAT vs GPM vs GPCC



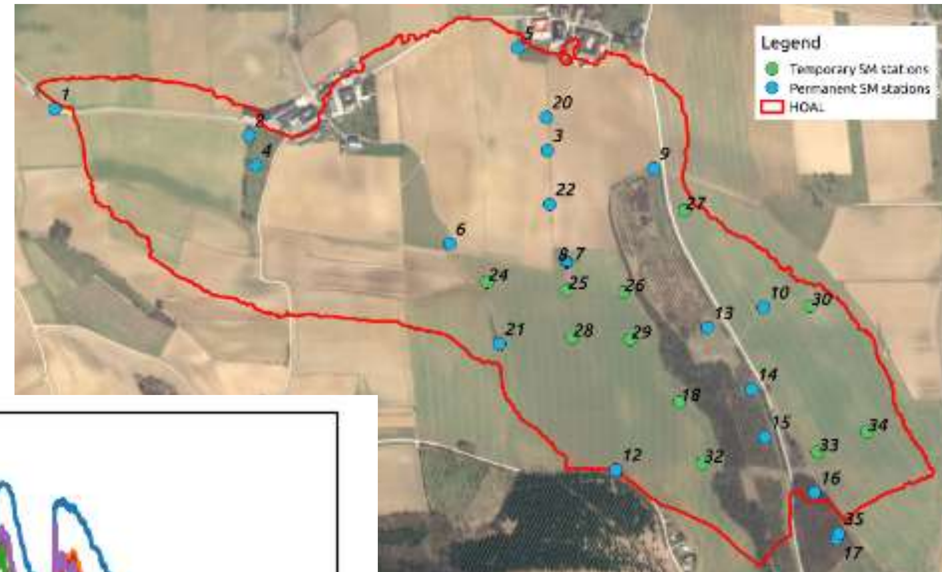
Best performing rainfall product based on the results of a triple collocation analysis according to Brocca et al. (2019).

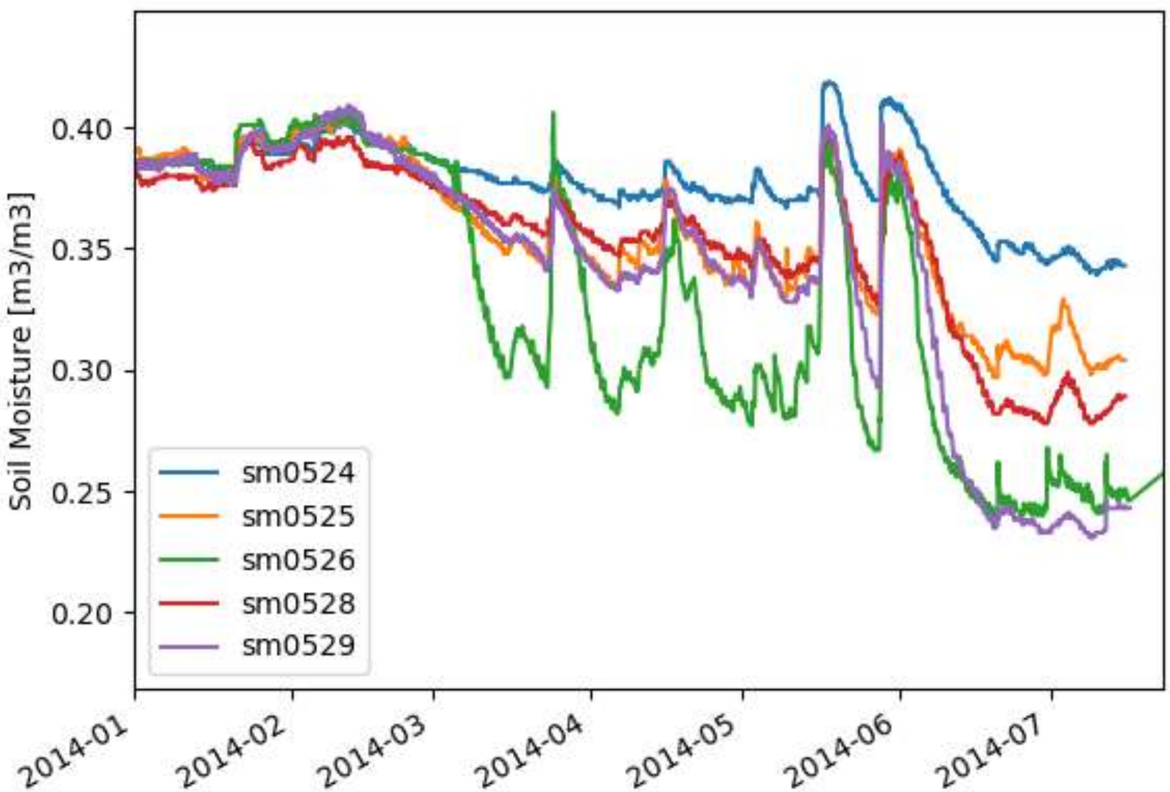
- GPCC = gauge-based Global Precipitation Climatology Centre data set
- GPM = Integrated Multi-Satellite Retrievals for Global Precipitation Measurement

Comparison with in situ and model data

Representativeness of In Situ Data?

- Soil moisture can vary within one field with the same land cover
- Temporal stability concept

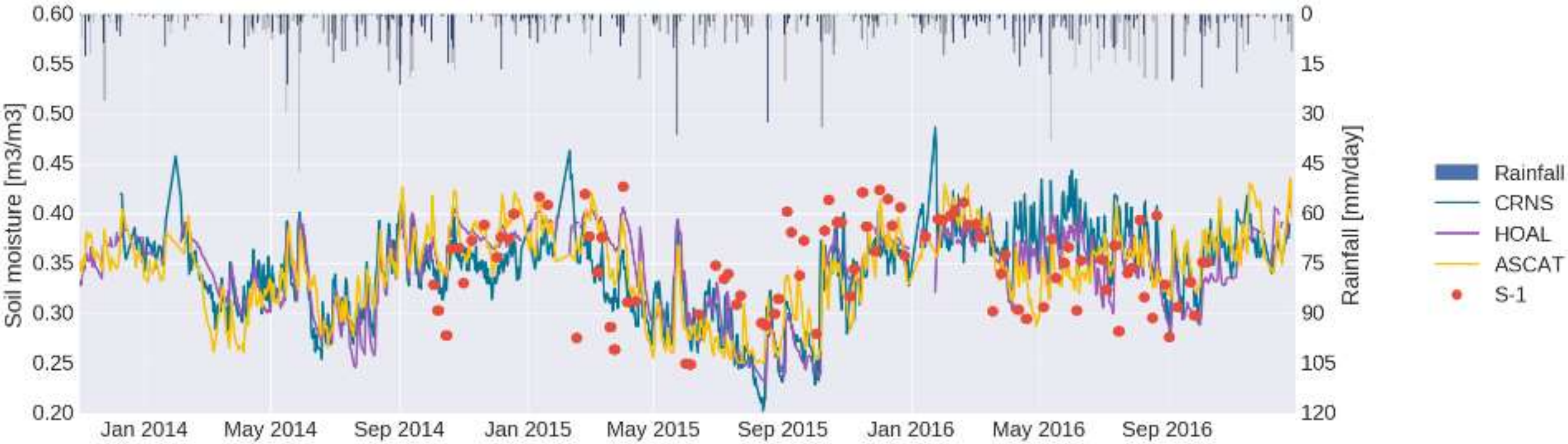




HOAL Soil Moisture Network, Petzenkirchen, Austria

Vienna Doctoral Programme on Water Resource Systems

Satellite versus In Situ Soil Moisture Data over HOAL



CRNS: Cosmic Ray Neutron Sensor

HOAL: Catchment average of 31 TDT measurements

ASCAT: 25 km ASCAT soil moisture retrievals

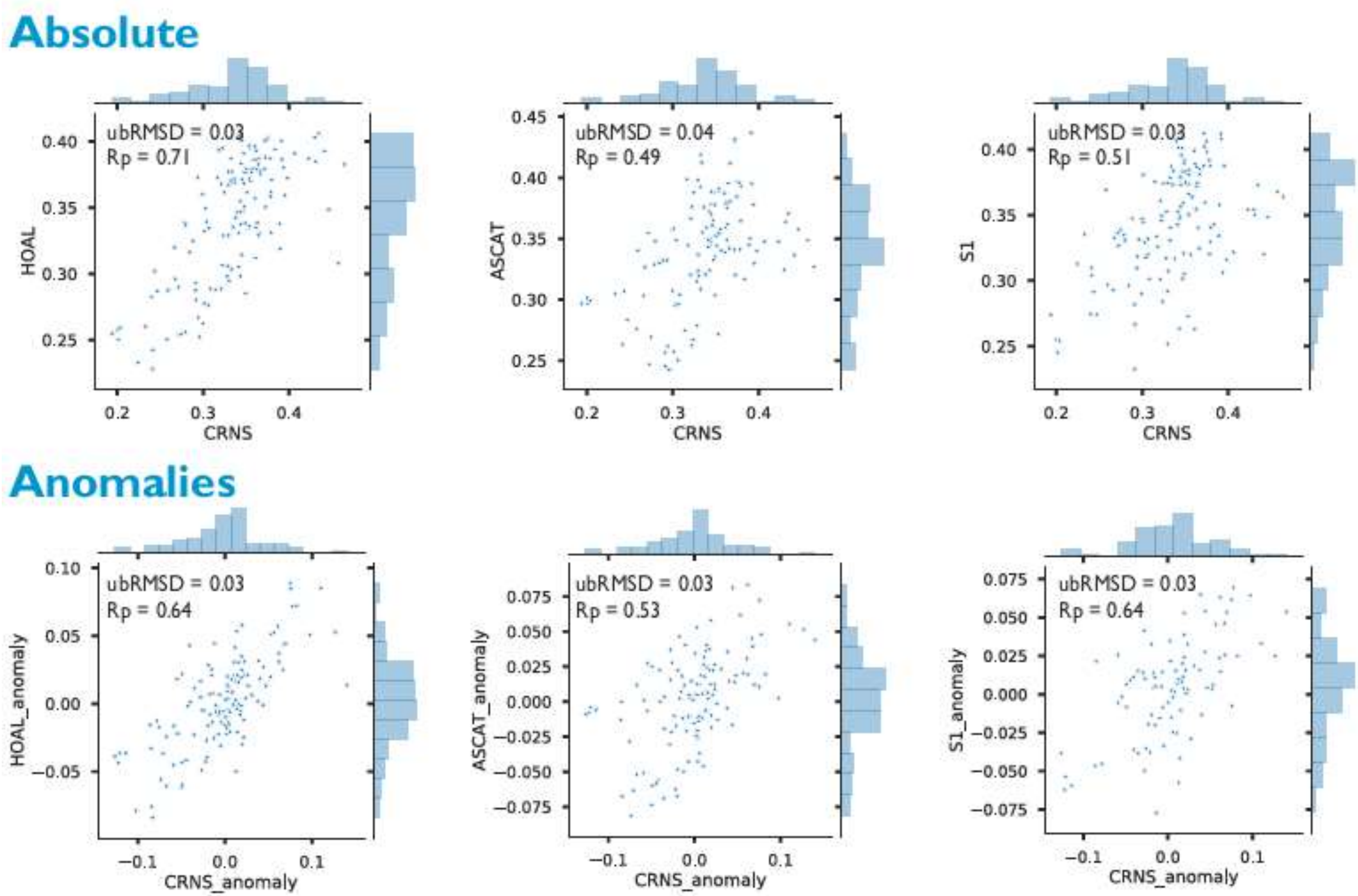
S-1: 1 km Sentinel-1 soil moisture retrievals

Hydrological Open Air Laboratory (HOAL) in Petzenkirchen, Austria

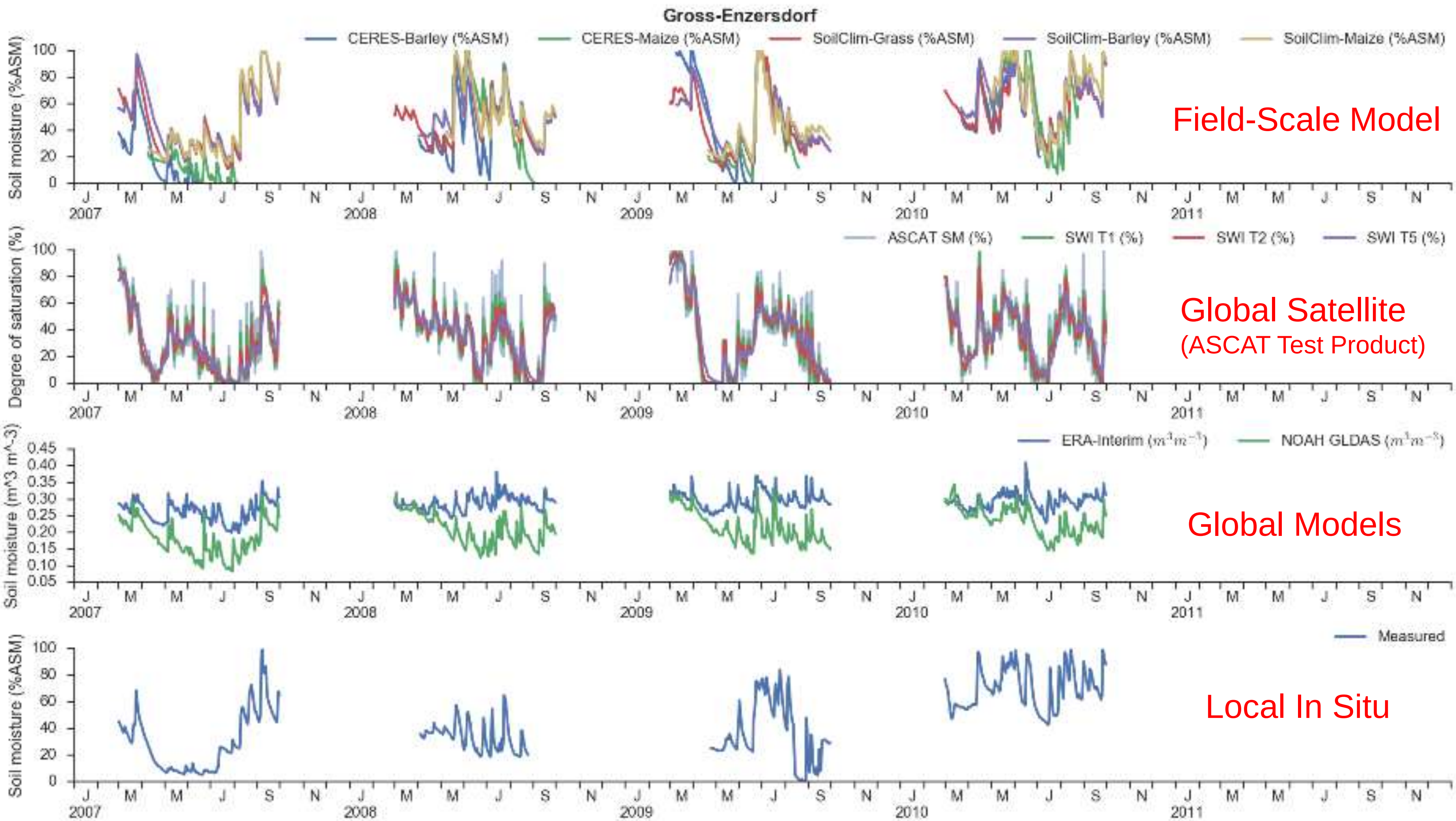
Vienna Doctoral Programme on Water Resource Systems

Joint FAO/IAEA Programme

CRNS versus In Situ, ASCAT and S-1 over HOAL

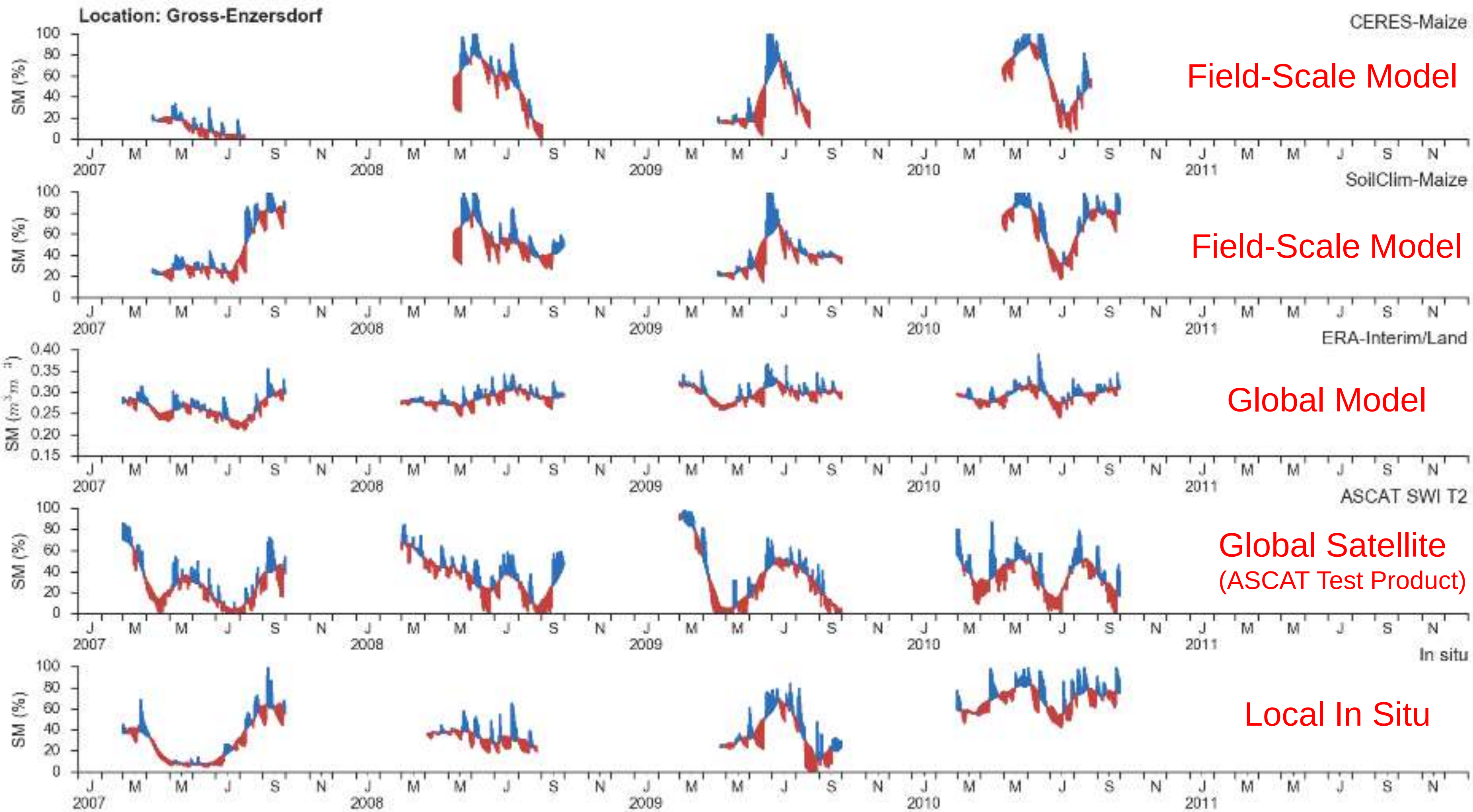


Soil Moisture from Models, In Situ and Satellites



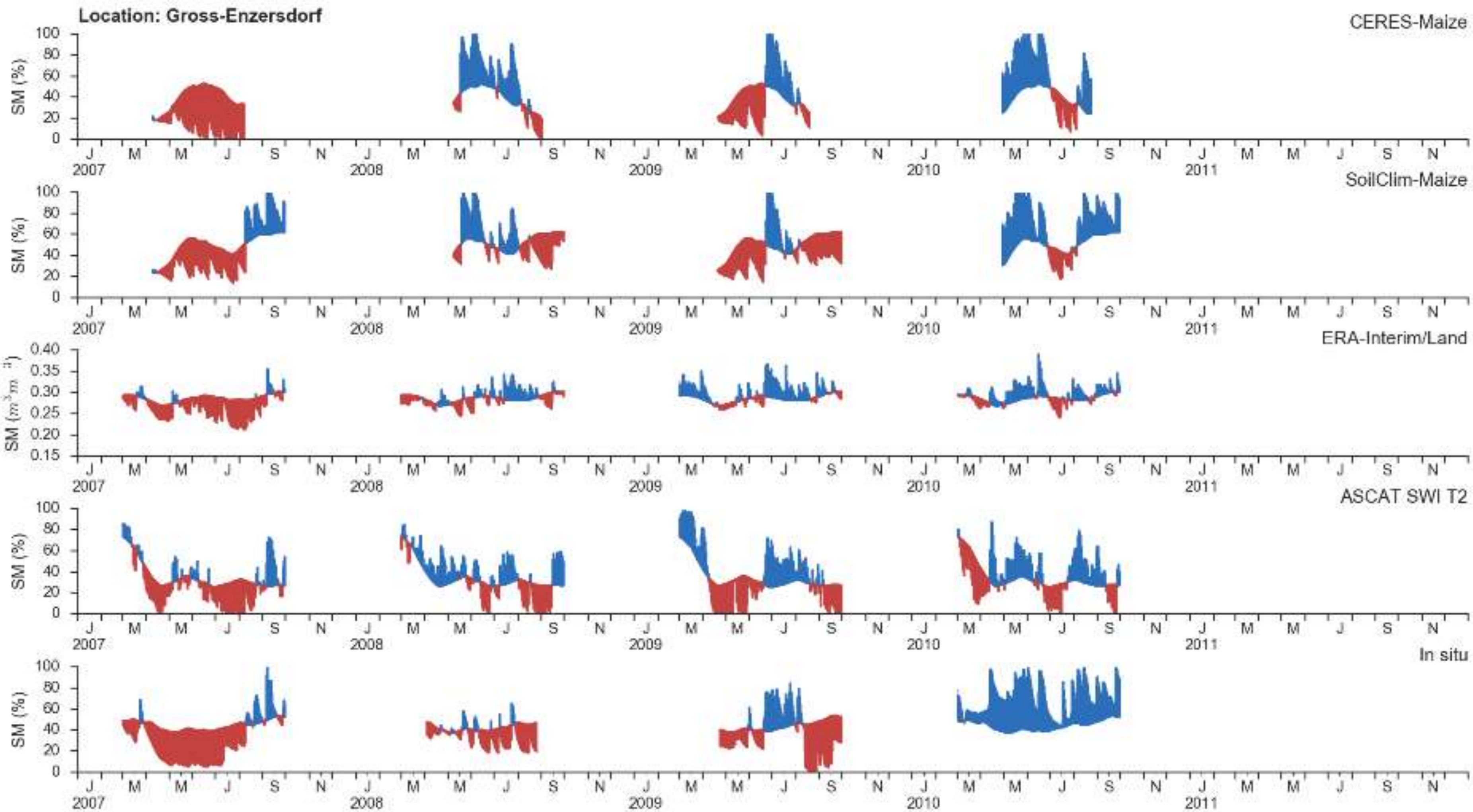
Thaler et al. (2018) The performance of Metop Advanced SCATterometer soil moisture data as a complementary source for the estimation of crop-soil water balance in Central Europe, The Journal of Agricultural Science, 156, 577-598.

Comparison of Short-Term Anomalies



Based upon Thaler at al. (2018)

Comparison Against Mean Seasonal Signals



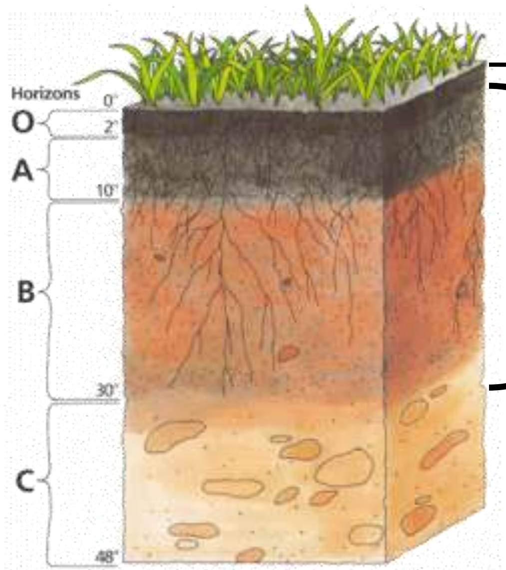
Based upon Thaler at al. (2018)

Soil Water Index

Soil Water Index

- The SWI is an indicator of the profile soil moisture content
- 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

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



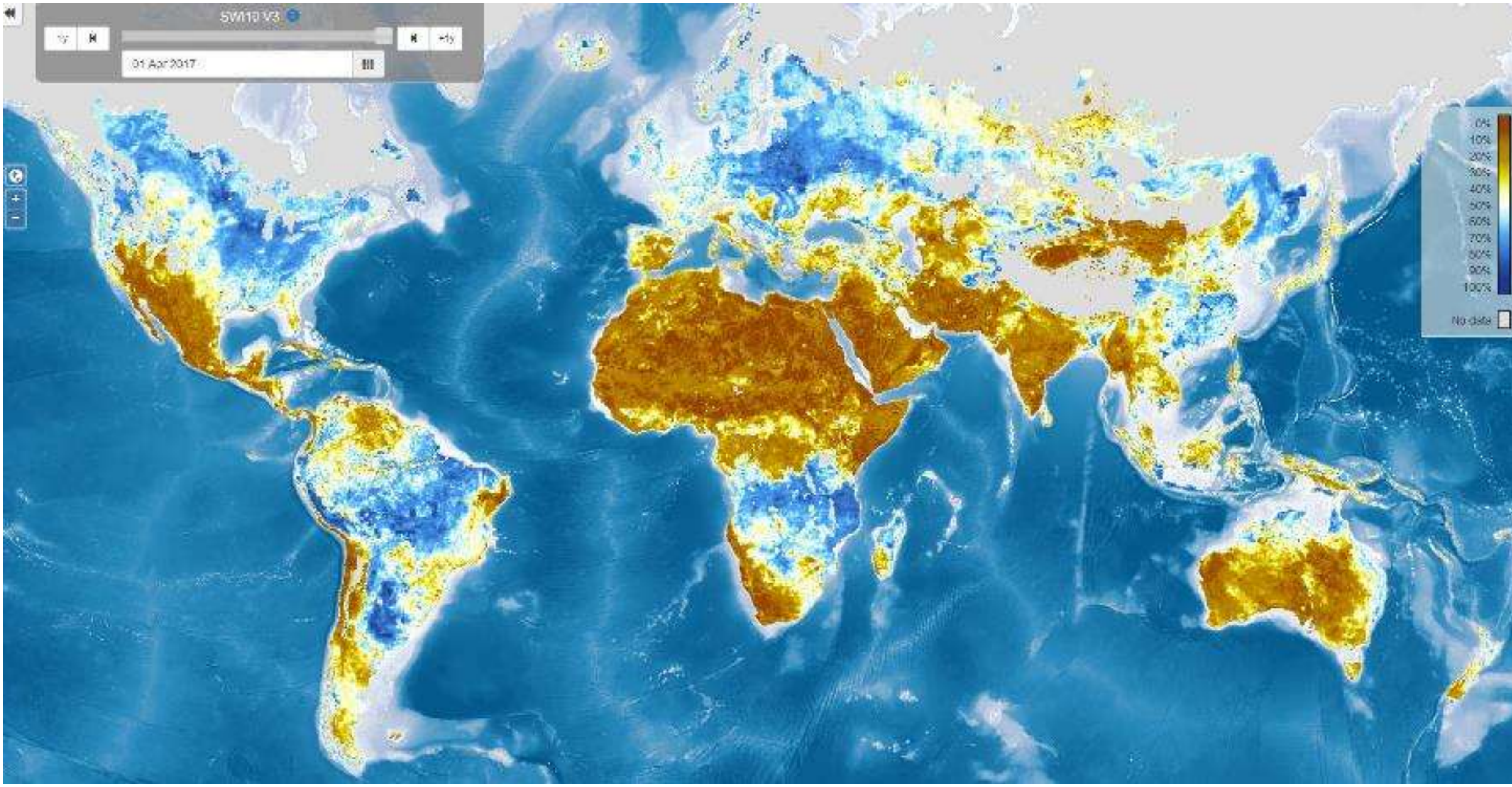
Thin, remotely sensed soil layer with Θ_s

Root zone with Θ : layer of interest for most applications

Soil profile

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.

ASCAT Soil Water Index

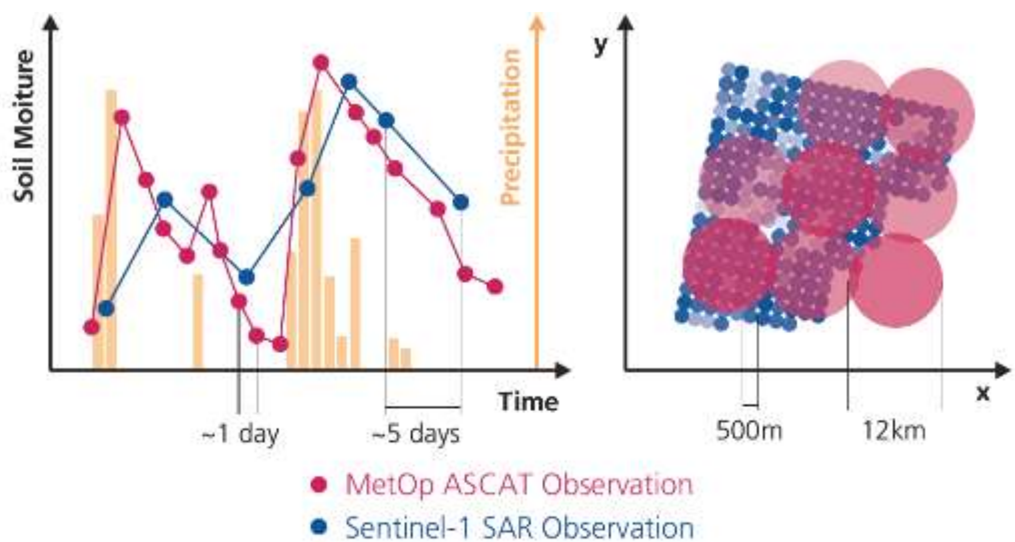


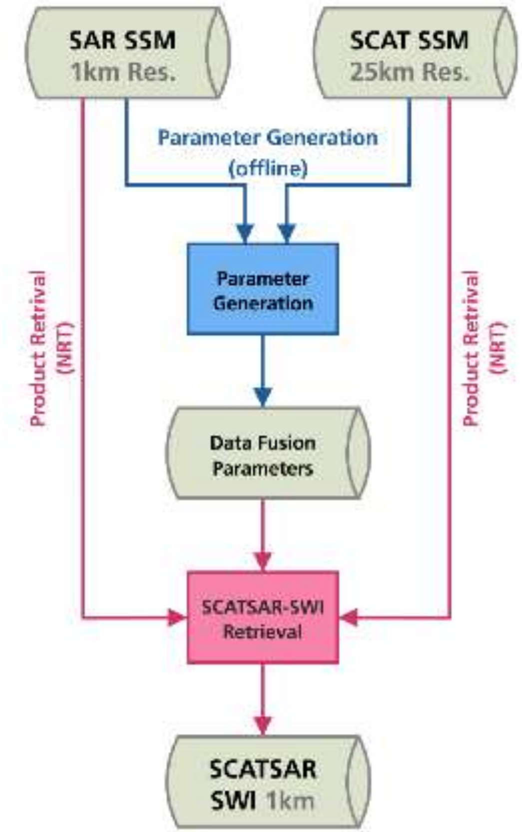
remote sensing

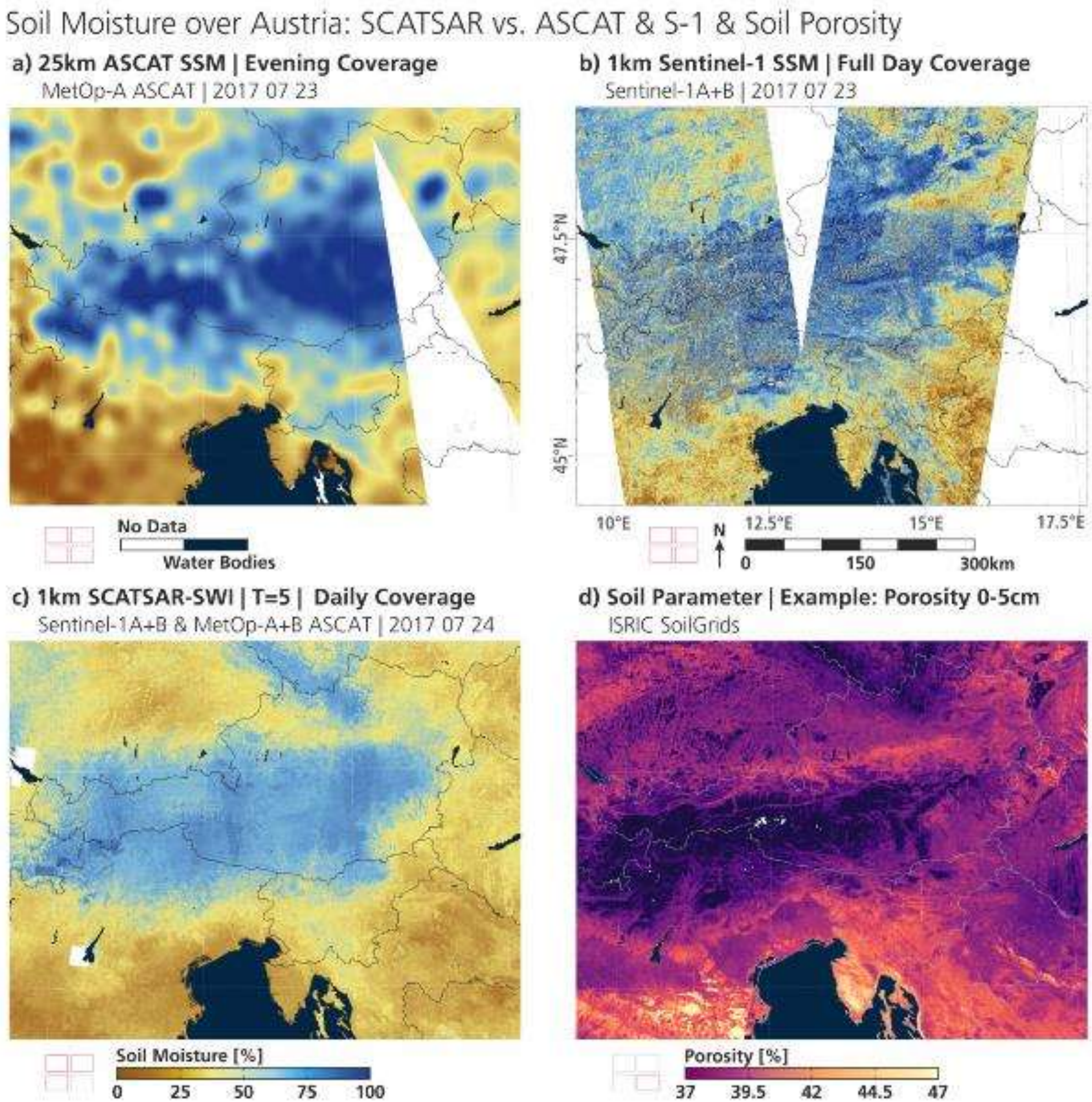
Article

Soil Moisture from Fusion of Scatterometer and SAR: Closing the Scale Gap with Temporal Filtering

Bernhard Bauer-Marschallinger [1,*], Christoph Paulik [1], Simon Hochstöger [1], Thomas Mistelbauer [2], Sara Modanesi [3], Luca Ciabatta [3], Christian Massari [3], Luca Brocca [3] and Wolfgang Wagner [1]





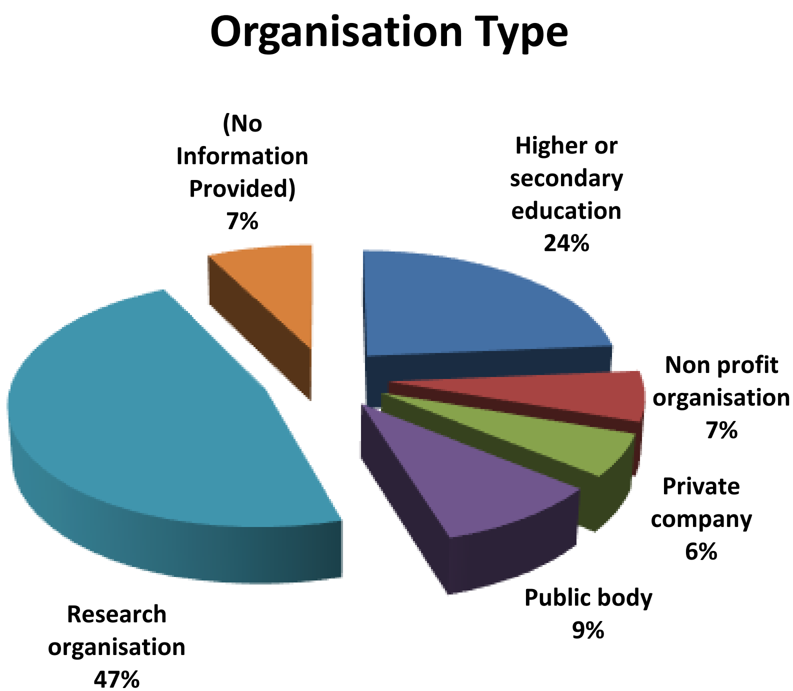


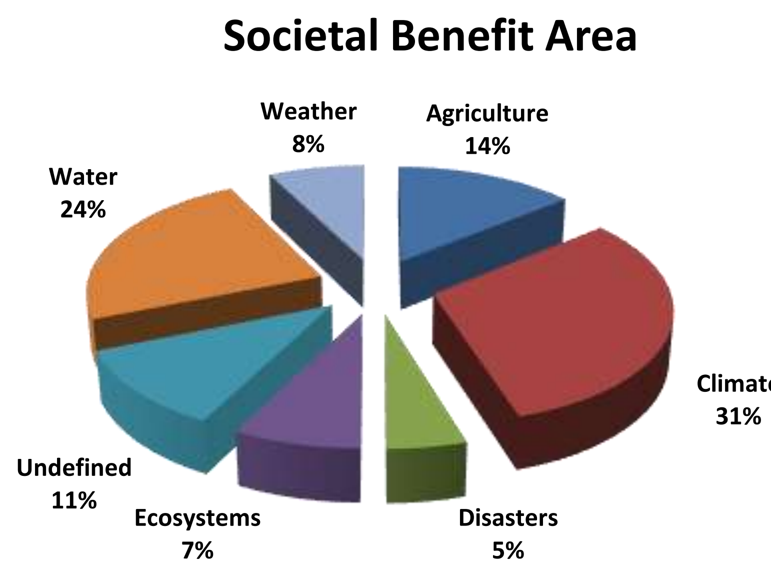
Bauer-Marschallinger et al. (2018) Soil moisture from fusion of scatterometer and SAR: Closing the scale gap with temporal filtering, Remote Sensing, 10(7), 1030, 26 p.

Applications

A Review of the Applications of ASCAT Soil Moisture Products

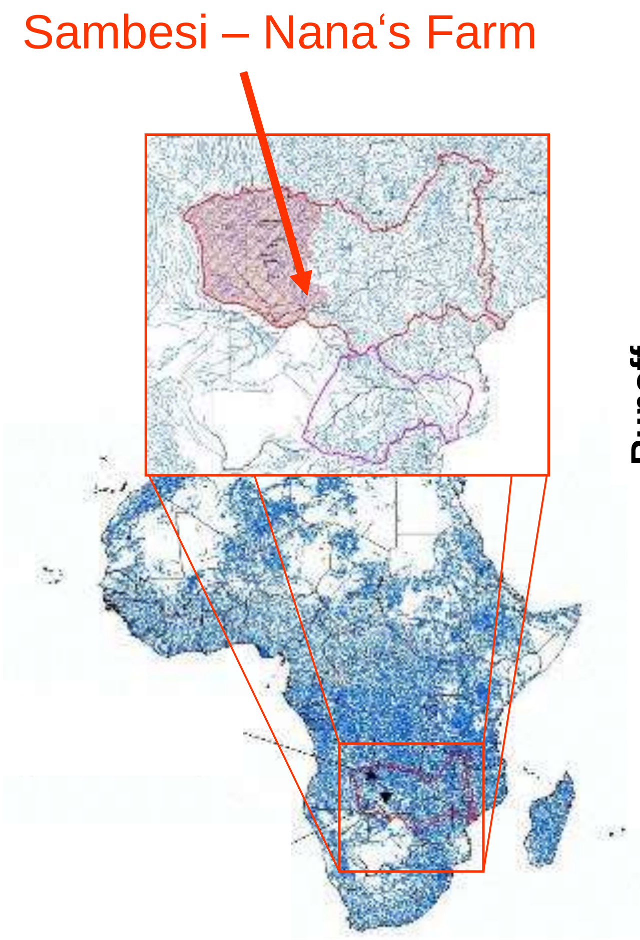
Luca Brocca, Wade T. Crow, Luca Ciabatta, Christian Massari, Patricia de Rosnay, Markus Enenkel, Sebastian Hahn, Giriraj Amarnath, Stefania Camici, Angelica Tarpanelli, and Wolfgang Wagner, *Senior Member, IEEE*

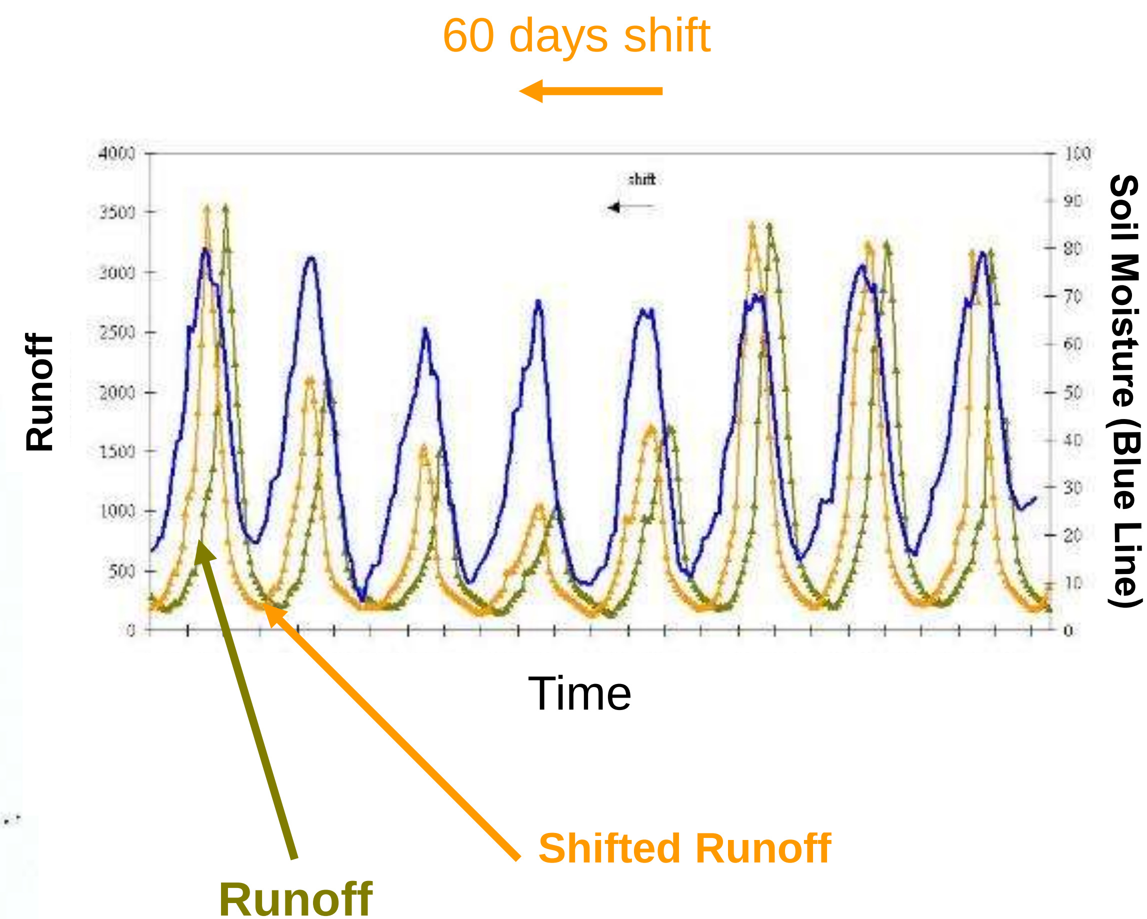




Users of first Climate Change Initiative (CCI) soil moisture data set release (2012)

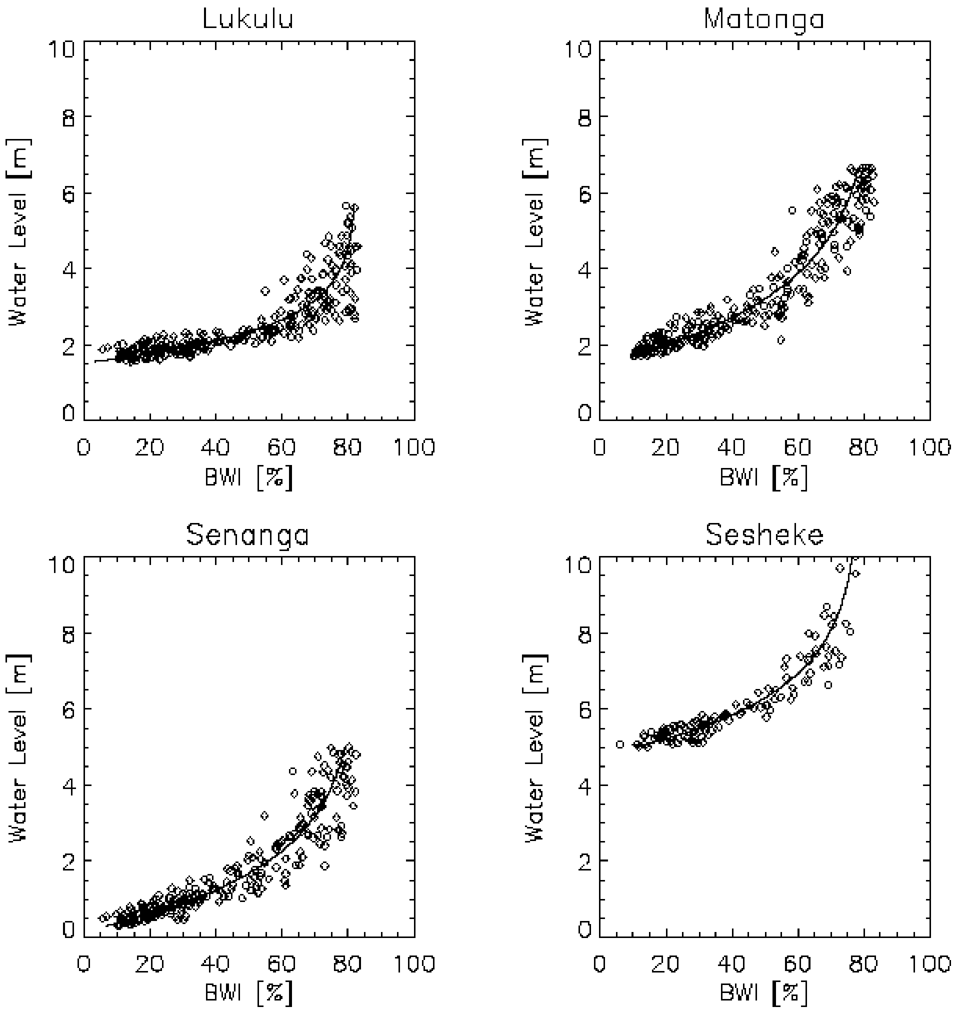
SCAT Soil Moisture versus River Runoff

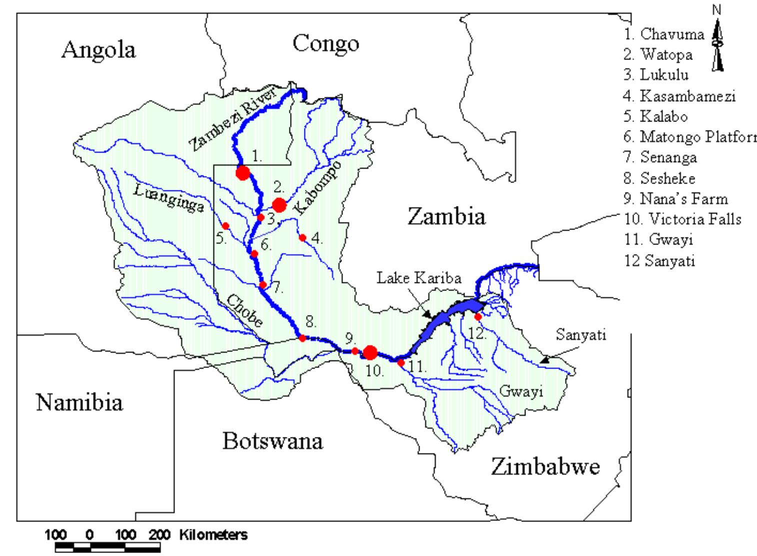


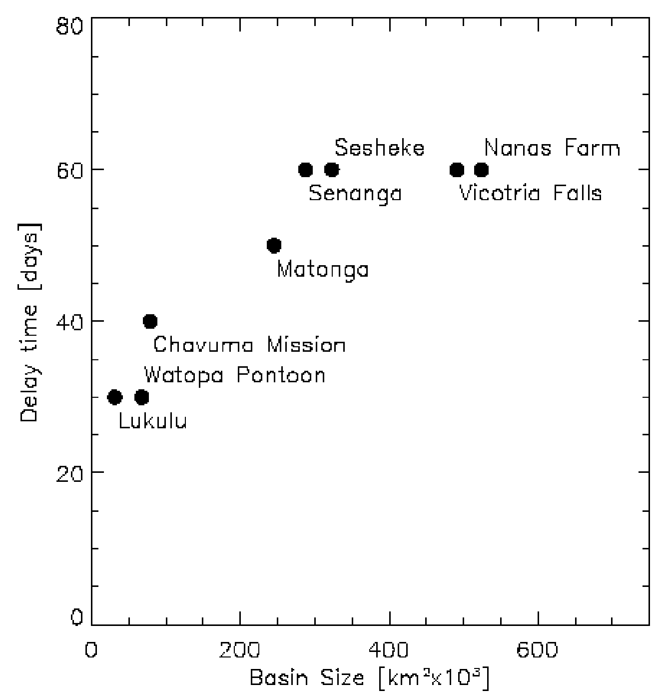


Scipal et al. (2005) Soil moisture-runoff relation at the catchment scale as observed with coarse resolution microwave remote sensing, Hydrology and Earth System Sciences, 9(3), 173-183.

Time Shift and Catchment Size





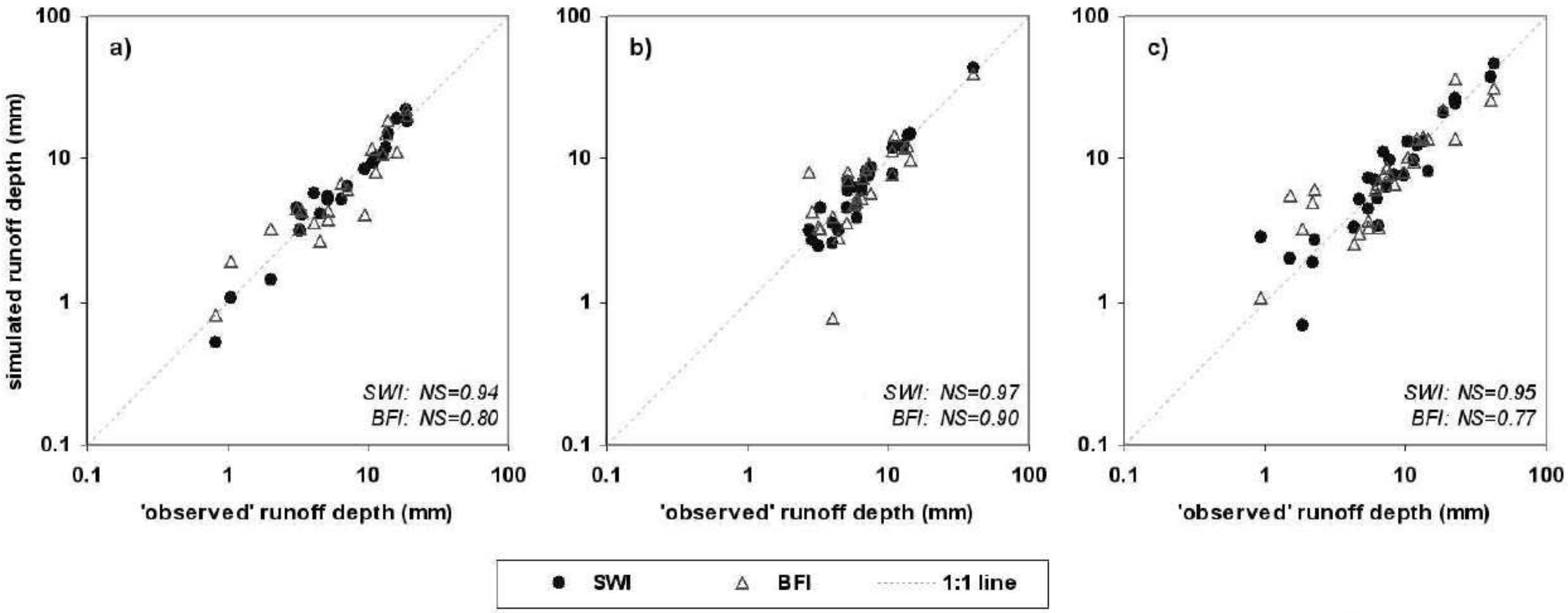


Event-based Rainfall-Runoff Modelling

- "Curve Number Method"

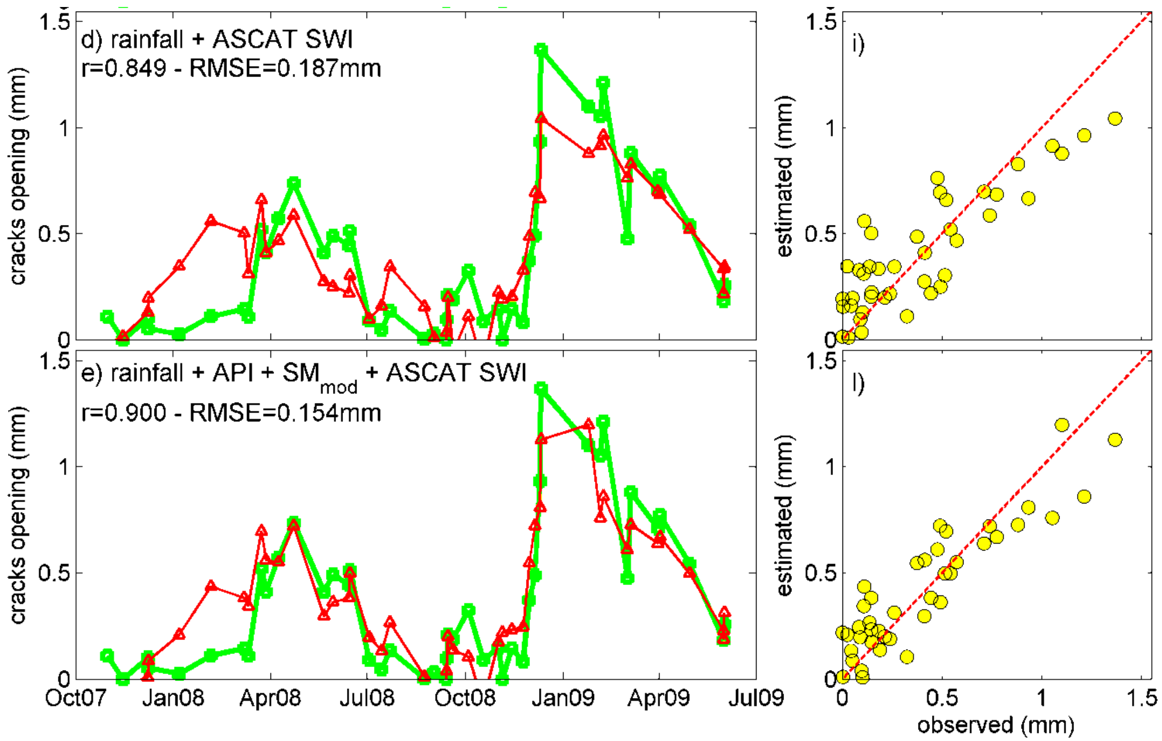
$$Q = \frac{(P - 0.2S)^2}{P + 0.8S} \quad \text{with} \quad S = c + d \cdot SWI$$

Q … runoff
P … precipitation
S … retention
SWI … Soil Water Index



Brocca et al. (2009) Antecedent wetness conditions based on ERS scatterometer data, Journal of Hydrology, 364(1-2), 73-87.

Landslide Monitoring



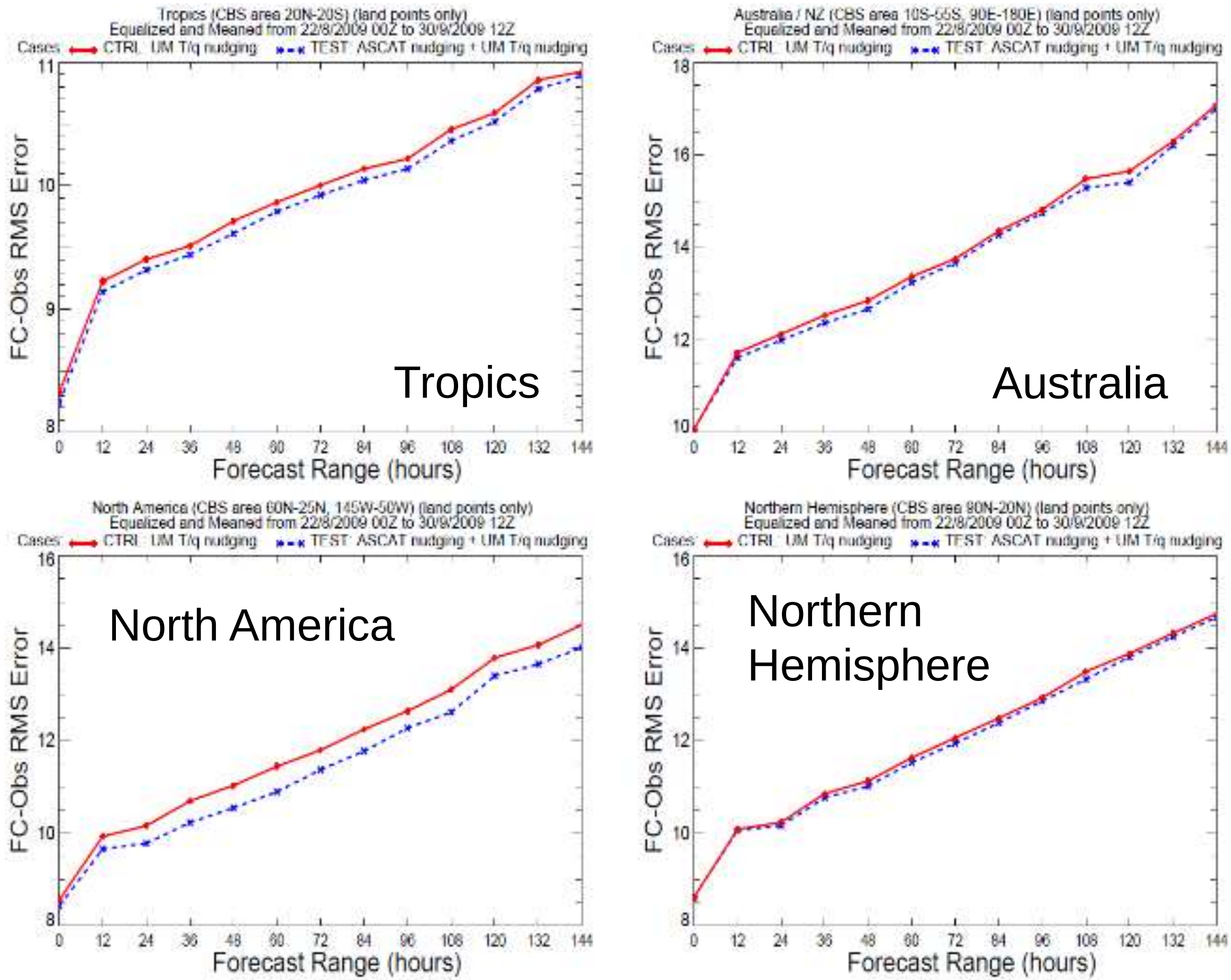
Comparison between observed (circles) and estimated (triangles) crack aperture of the Torgiovannetto Landslide in Central Italy from the beginning to the end of the selected rainfall events.

Brocca et al. (2012) Improving Landslide Forecasting Using ASCAT-Derived Soil Moisture Data: A Case Study of the Torgiovannetto Landslide in Central Italy, Remote Sensing, 4(5), 1232-1244.

ASCAT Assimilation at NWP Centres

- Impact on temperature and humidity
- Centres
  - ECMWF
  - Mete Office
  - Meteo France
  - ZAMG

Skill of relative humidity forecasts



Dharssi, I., Bovis, K.J., Macpherson, B., & Jones, C.P. (2011). Operational assimilation of ASCAT surface soil wetness at the Met Office. Hydrology and Earth System Sciences, 15, 2729-2746

Afternoon rain more likely over drier soils

Dark red = rain falls most likely over drier soils

Pink = rain falls likely over drier soils

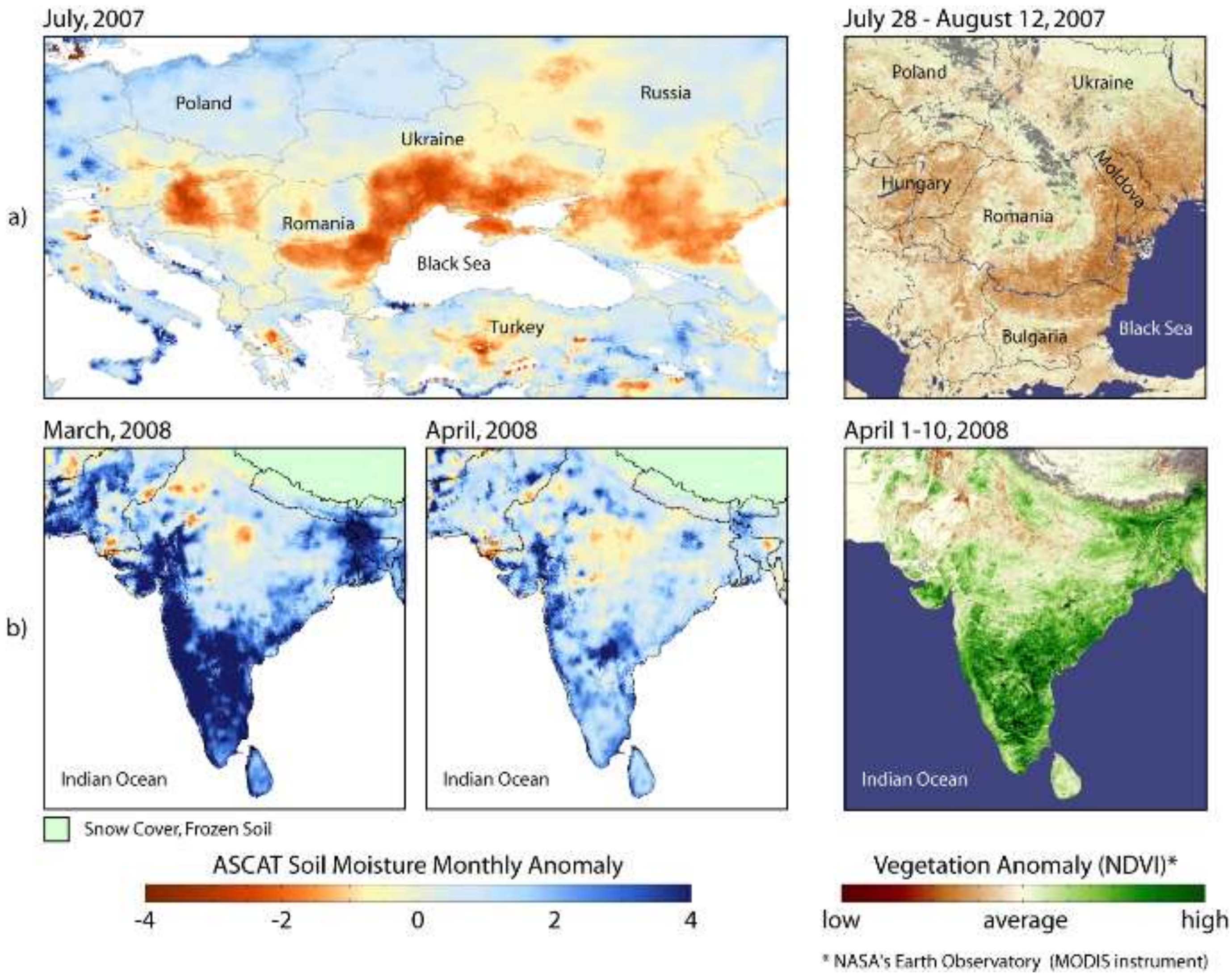
Blue = rain falls likely over wetter soils

Dark blue = rain most falls likely over wetter soils

	Observations								Models					
	AMSR-E CMORPH	ASCAT CMORPH	AMSR-E TRMM	ASCAT TRMM	AMSR-E PERSIANN	ASCAT PERSIANN	AMSR-E CMORPH 1°	ASCAT CMORPH 1°	HadGEM2	CNRM-CM5	MRI-AGCM3_2H	INMCM4	MERRA	ERA-Interim
Moist tropics	89.5 (587)	19.8 (196)	93.5 (911)	18.1 (304)	27.2 (777)	18.1 (255)	-	-	>99 (7852)	>99 (20457)	>99 (28578)	>99 (1154)	>99 (3514)	>99 (25462)
Savanna	1.13 (12937)	<0.01 (6666)	<0.1 (17898)	<0.1 (8243)	<0.1 (12490)	1.1 (6248)	0.03 (632)	1.61 (451)	>99 (12021)	>99 (23777)	>99 (26422)	>99 (3256)	>99 (9612)	>99 (33595)
Semi-arid	<0.1 (23453)	<0.1 (7880)	<0.1 (33668)	<0.1 (8302)	1.1 (19539)	0.5 (5773)	0.39 (1872)	0.3 (821)	>99 (3438)	>99 (9517)	>99 (8284)	>99 (643)	86 (4467)	>99 (9761)
Arid	<0.1 (18810)	<0.1 (3752)	<0.1 (23450)	<0.1 (2926)	<0.1 (13952)	<0.1 (2216)	<0.01 (2613)	0.67 (620)	>99 (907)	<1 (6931)	84 (2957)	>99 (186)	97 (2401)	>99 (2496)
Temperate	58.1 (6224)	0.12 (4721)	13.1 (7917)	<0.1 (4858)	50.5 (5565)	54.5 (3844)	38.69 (474)	10.02 (455)	>99 (1844)	>99 (7151)	>99 (7174)	>99 (376)	1 (4811)	>99 (6092)
Continental	9.5 (11612)	<0.01 (6514)	78.4 (5009)	<0.1 (1774)	64.3 (9617)	49.0 (4304)	32.79 (485)	34.17 (485)	45 (2981)	61 (5949)	>99 (10377)	>99 (206)	<1 (3692)	>99 (5963)

Taylor et al. (2012) Afternoon rain more likely over drier soils. Nature, 489, 423-426.

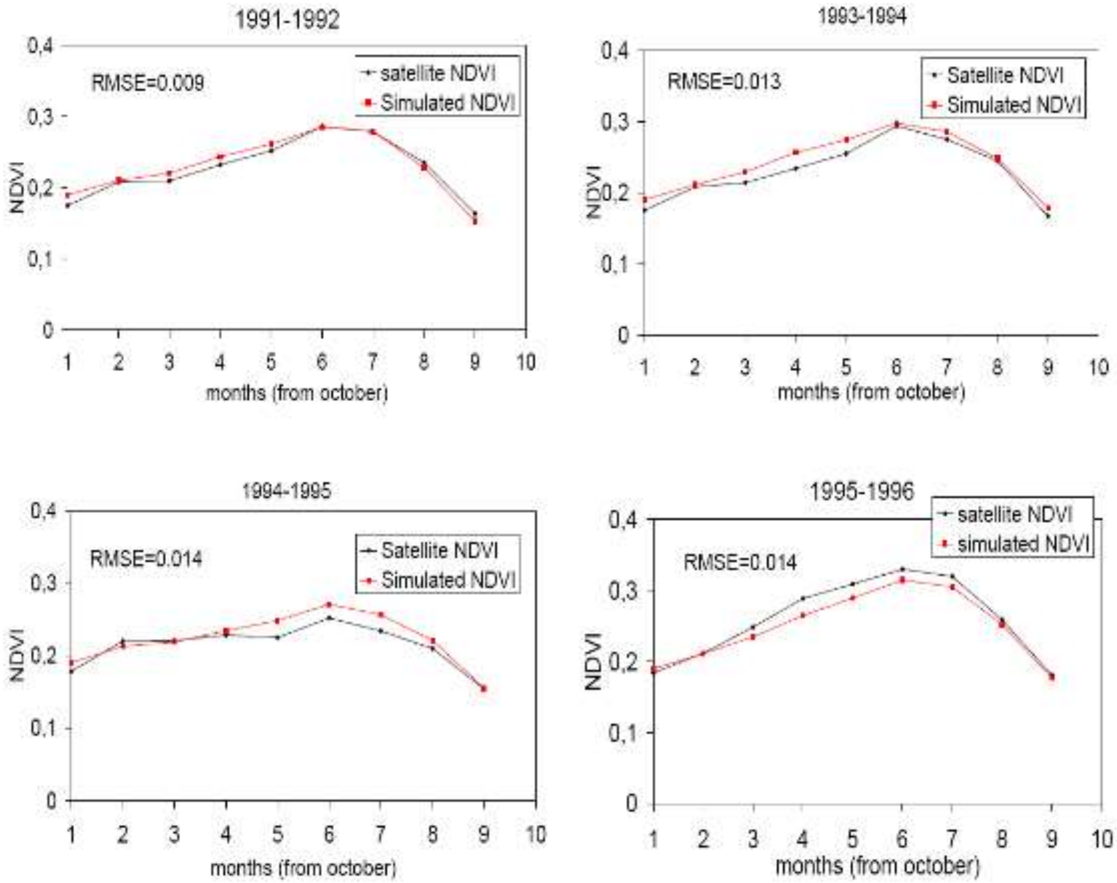
Soil Moisture and Vegetation



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.

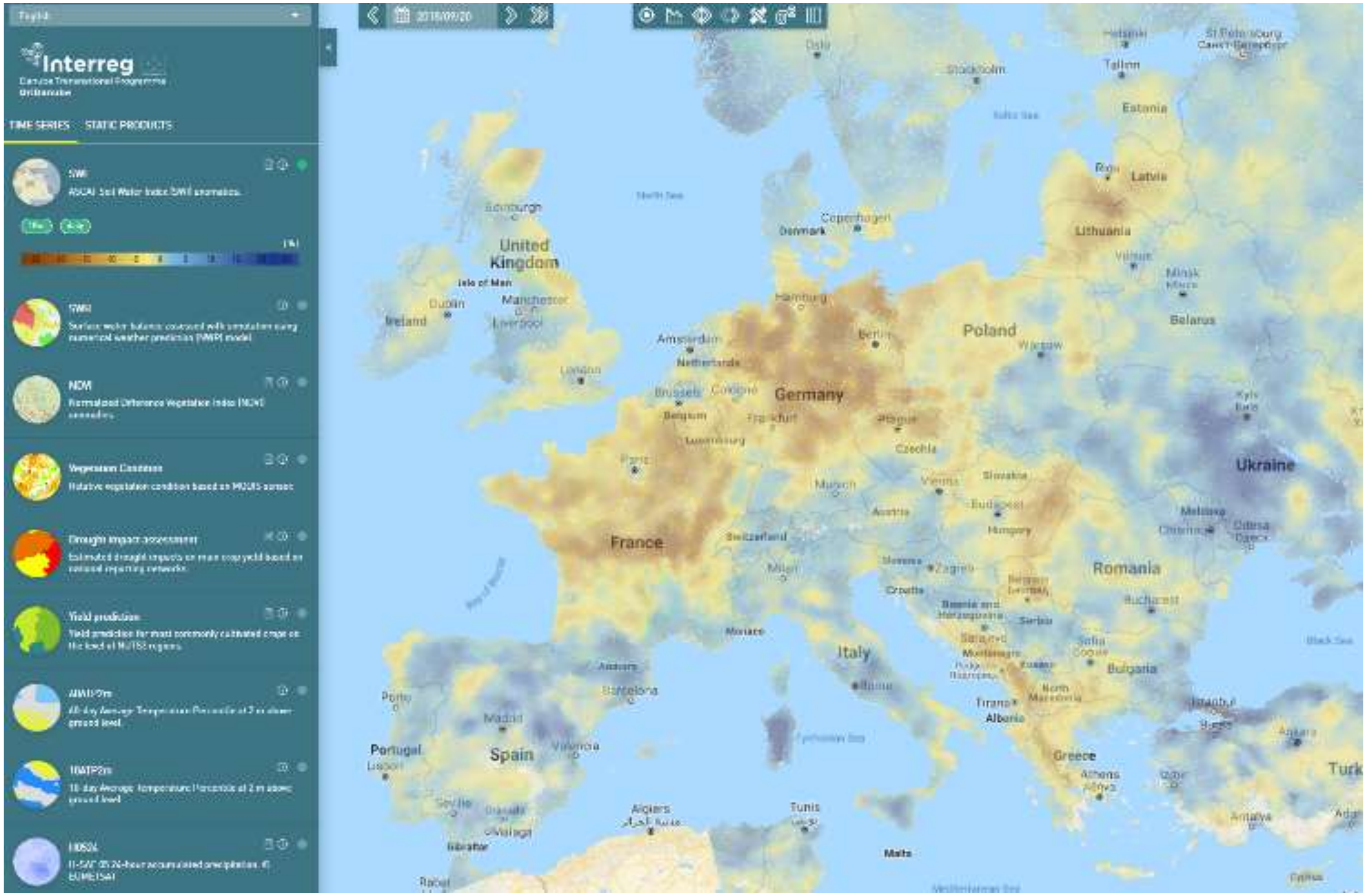
Prediction of NDVI using SWI

- Modelling next month's NDVI using SWI



Zribi et al. (2010) Relationship between soil moisture and vegetation in the Kairouan plain region of Tunisia using low spatial resolution satellite data, Water Resources Research, 46, W06508, 13 p.

Drought Monitoring



ASCAT based drought index for 20 September 2018. https://droughtwatch.eu/

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Final Thoughts

- Steadily increasing uptake by users despite ASCAT soil moisture data are not “plug and play”
  - Soil moisture is often not a direct input variable but a state variable
  - Many land surface models do not have a topsoil layer
  - Dealing with spatially and temporally varying uncertainties is challenging
  - Long time series needed for model calibration
  - Data are complex
- Increasing number of downstream data services
  - Value-added soil moisture data
  - Rainfall estimates
  - Drought indices
  - Etc.

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