Use of CRNS/in situ Data for Validation of Remote Sensing Soil Moisture Products

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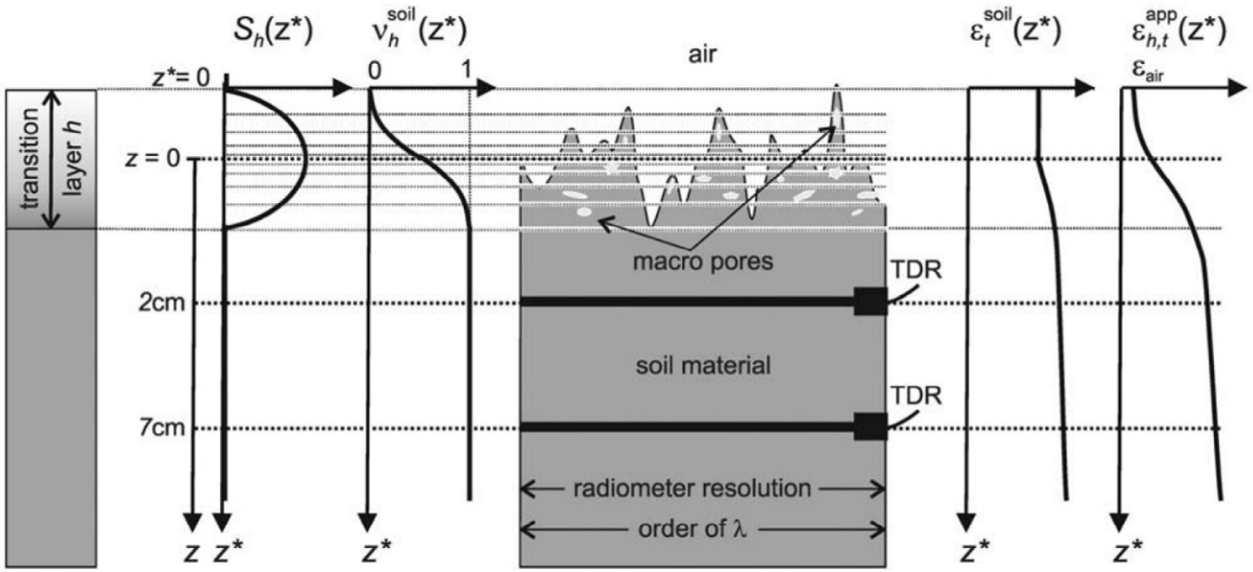
Topics

- Overview of Remote Sensing Soil Moisture Data Products Satellites and Sensors
  - Physical Basis
  - Microwave Satellites and Sensors
  - Soil Moisture Retrieval
  - Soil Moisture Data Products
  - Soil Water Index
- Use of CRNS/in situ Data for Validation of Remote Sensing Soil Moisture Products
  - Information Content of Satellite Data
  - Comparison to CRNS/in situ Data
- Applications of Remote Sensing Soil Moisture Data Products
  - Capturing Rainfall
  - Drought Monitoring
  - Other Applications

INFORMATION CONTENT OF SATELLITE DATA

Information Content of Soil Moisture Retrievals

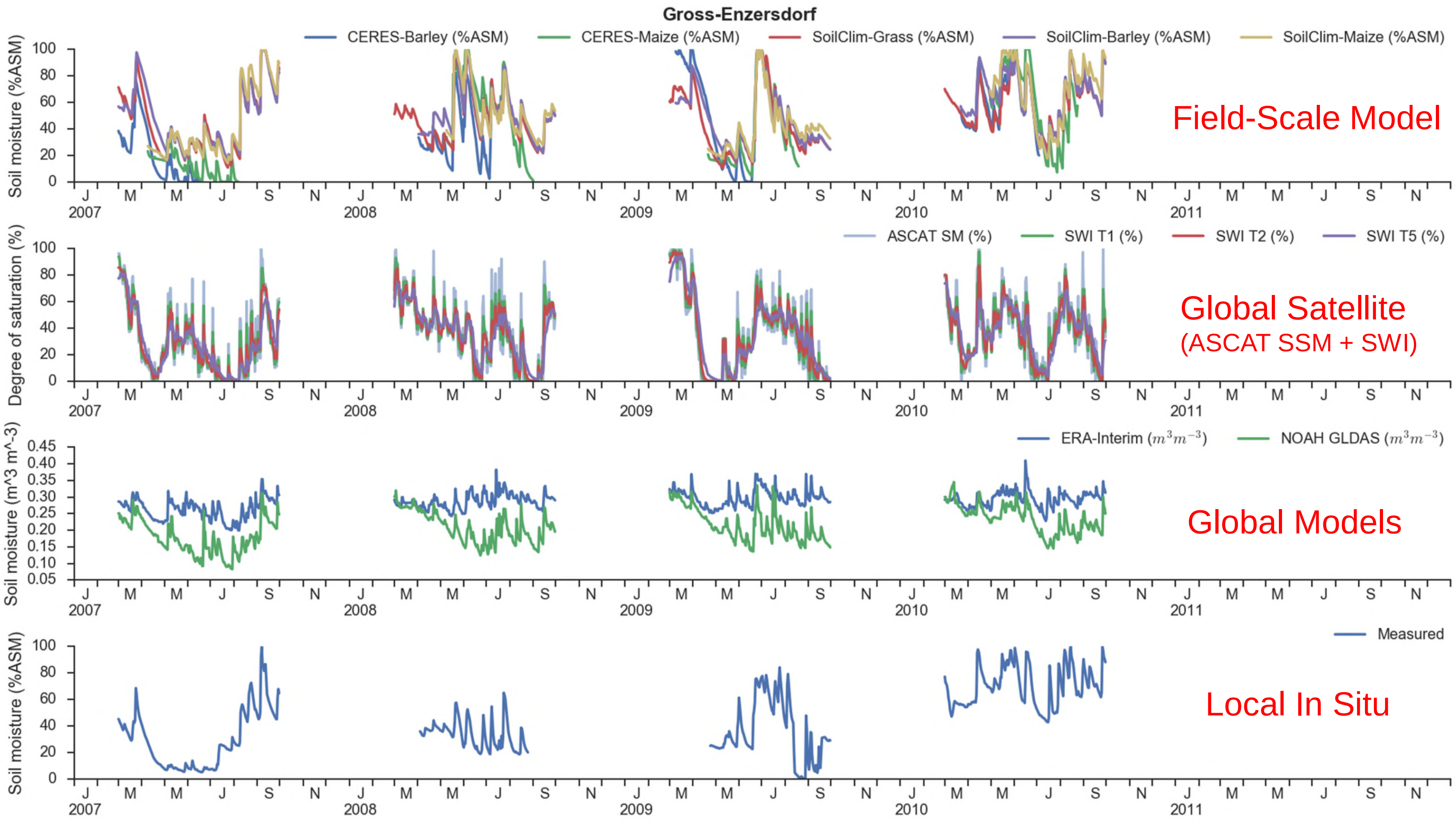
- Microwave sensors can provide information about spatio-temporal soil moisture trends
  - Information about absolute values comes from external data sets
- Absolute values in soil moisture retrievals driven strongly by
  - Available soil property maps
    - Soil porosity, texture, etc.
  - Surface roughness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



Air-to-Soil Transition Model

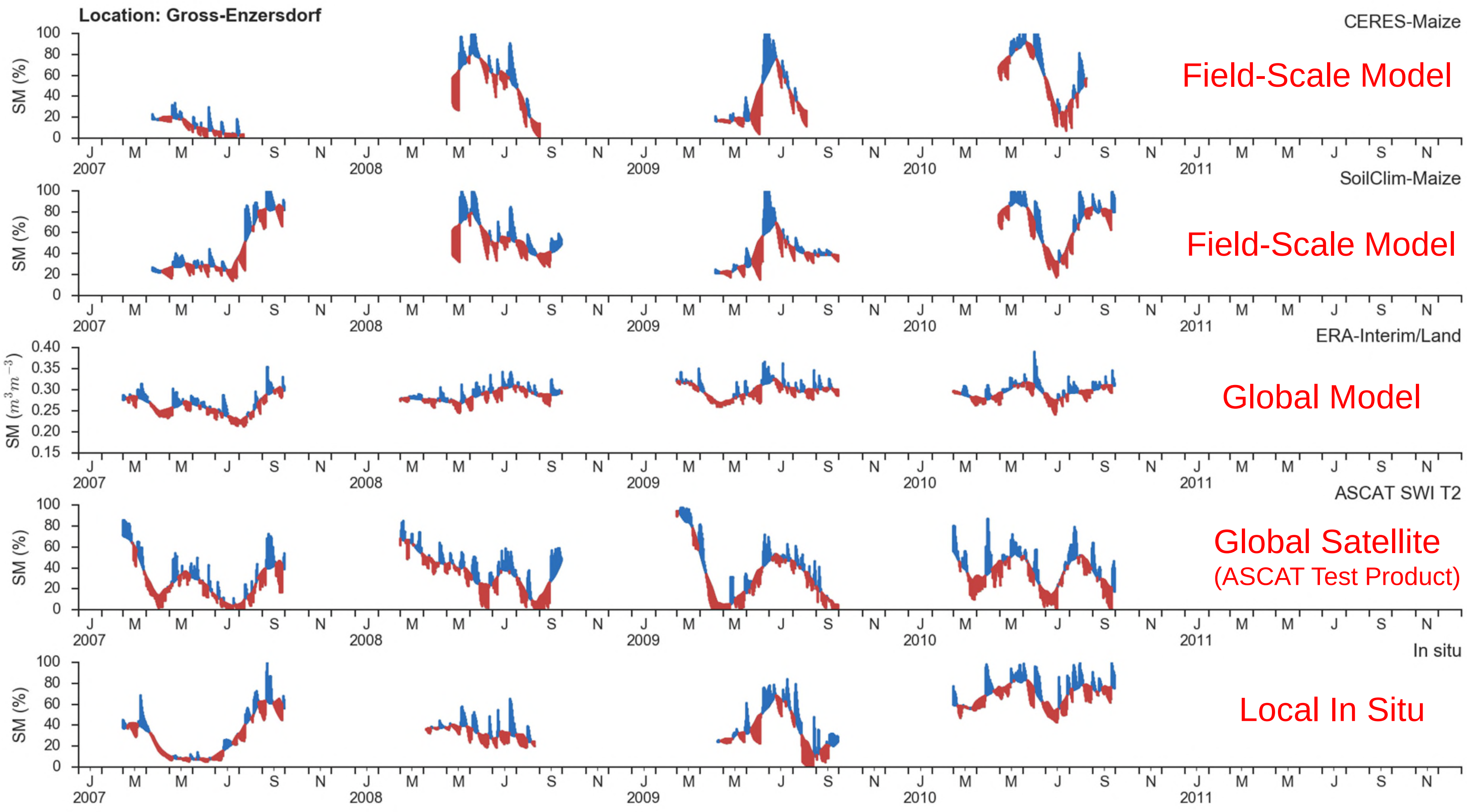
Schneeberger et al. (2004) Topsoil structure influencing soil water retrieval by microwave radiometry, Vadose Zone Journal, 3(4), 1169-1179.

Soil Moisture from Models, In Situ and Satellites



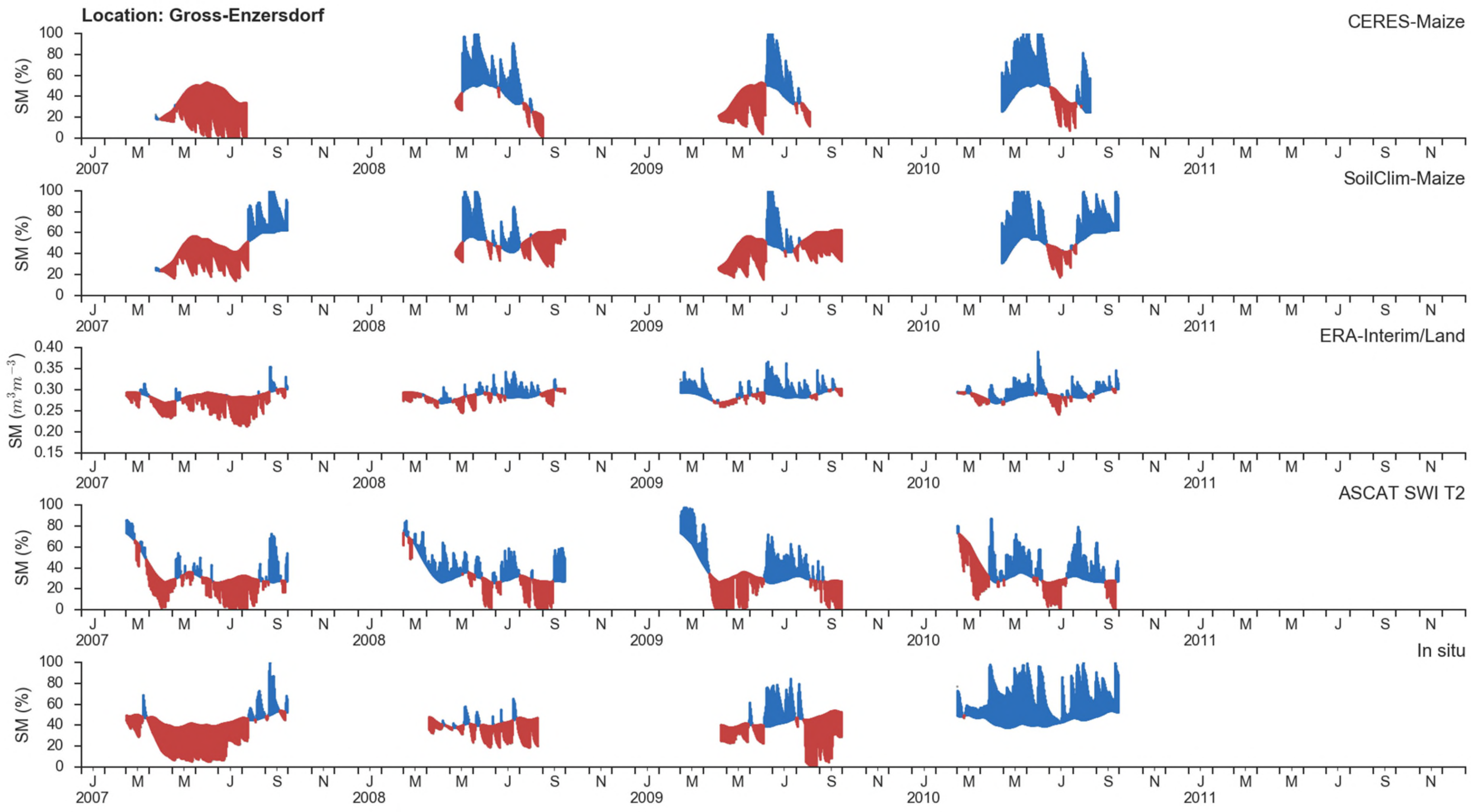
Thaler et al. (2018) The performance of Metop Advanced SCATterometer soil moisture data as a complementary source for the estimation of crop-soil water balance in Central Europe, The Journal of Agricultural Science, 156, 577-598.

Comparison of Short-Term Anomalies



Based upon Thaler at al. (2018)

Comparison Against Mean Seasonal Signals

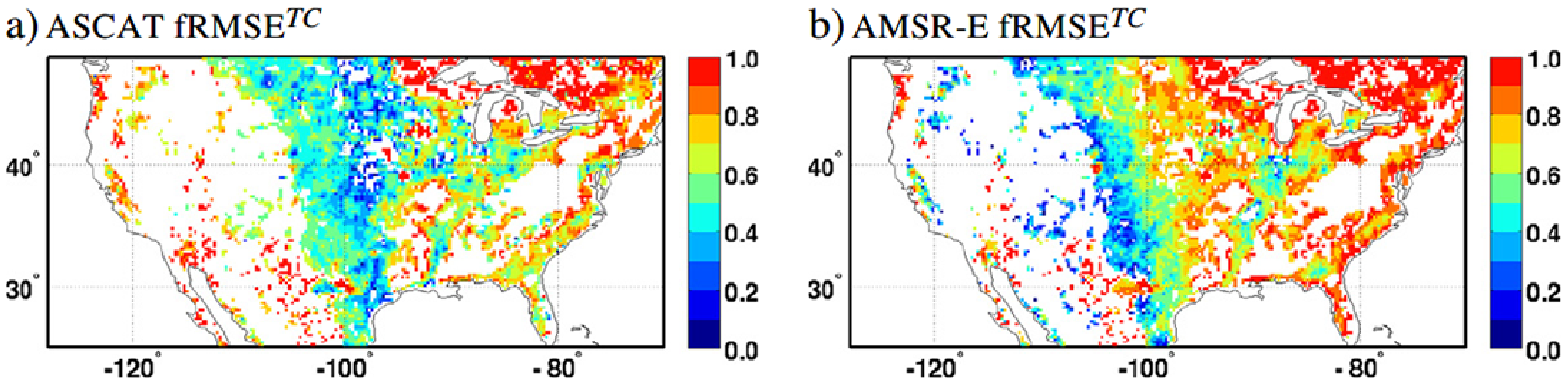


Based upon Thaler at al. (2018)

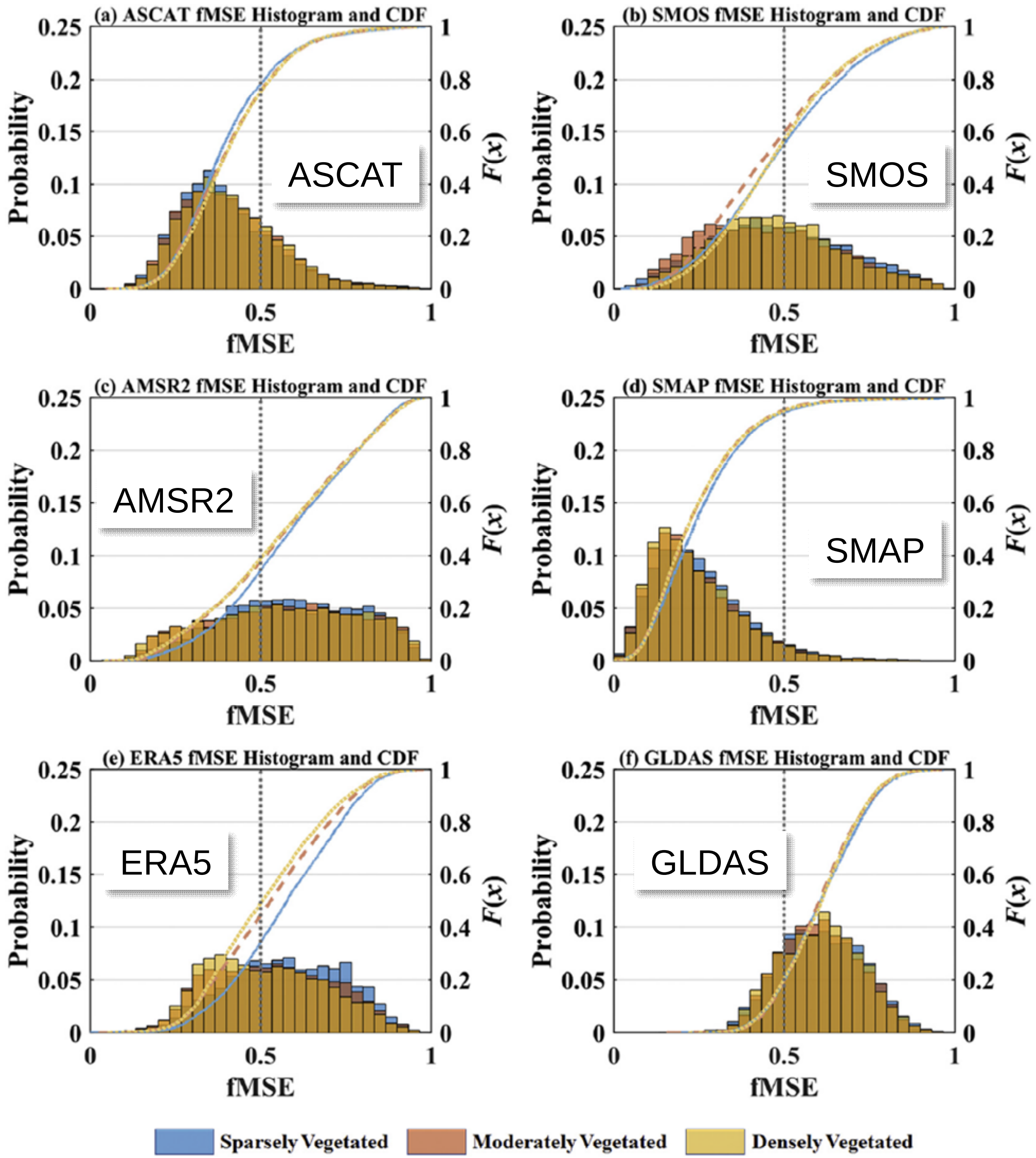
Fractional Root Mean Square Error

- Presents the uncertainty estimate of a given soil moisture data set X in relation to its standard deviation σ_X

$$fRMSE_X = \frac{RMSE_X(X)}{\sigma_X(X)}$$



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.



Cross-Comparison

- Cross-comparison of four satellite and two model data sets to determine the fractional mean square error (fMSE)
  - Satellite-based SSM estimates from ASCAT, SMAP, and SMOS showed fewer errors than ERA5 and GLDAS SSM products over vegetated conditions
  - Over irrigated areas, ASCAT, SMOS, and SMAP outperformed other SSM products

Kim et al. (2020) Global scale error assessments of soil moisture estimates from microwave-based active and passive satellites and land surface models over forest and mixed irrigated/dryland agriculture regions, Remote Sensing of Environment, 251, 112052, 21p.

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

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

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

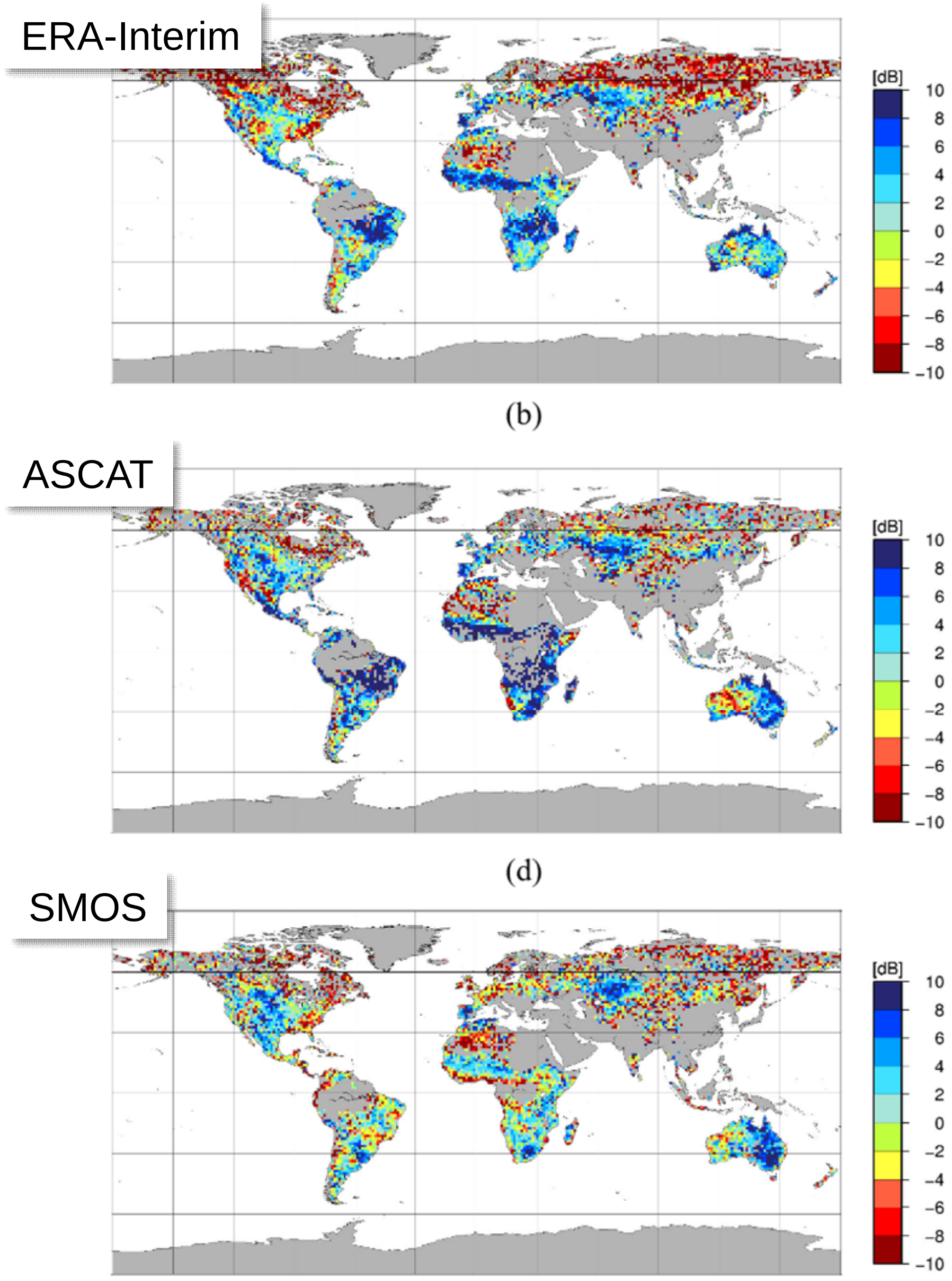
- More easy interpretabilty when expressed in decibel units

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

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

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.

Gruber, A., G. De Lannoy, C. Albergel, A. Al-Yaari, L. Brocca, J.-C. Calvet, A. Colliander, M. Cosh, W. Crow, W. Dorigo, C. Draper, M. Hirschi, Y. Kerr, A. Konings, W. Lahoz, K. McColl, C. Montzka, J. Munoz-Sabater, J. Peng, R. Reichle, P. Richaume, C. Rüdiger, T. Scanlon, R. van der Schalie, J.-P. Wigneron, W. Wagner (2020) Validation practices for satellite soil moisture retrievals: What are (the) errors?, Remote Sensing of Environment, 244, 111806, 34p.

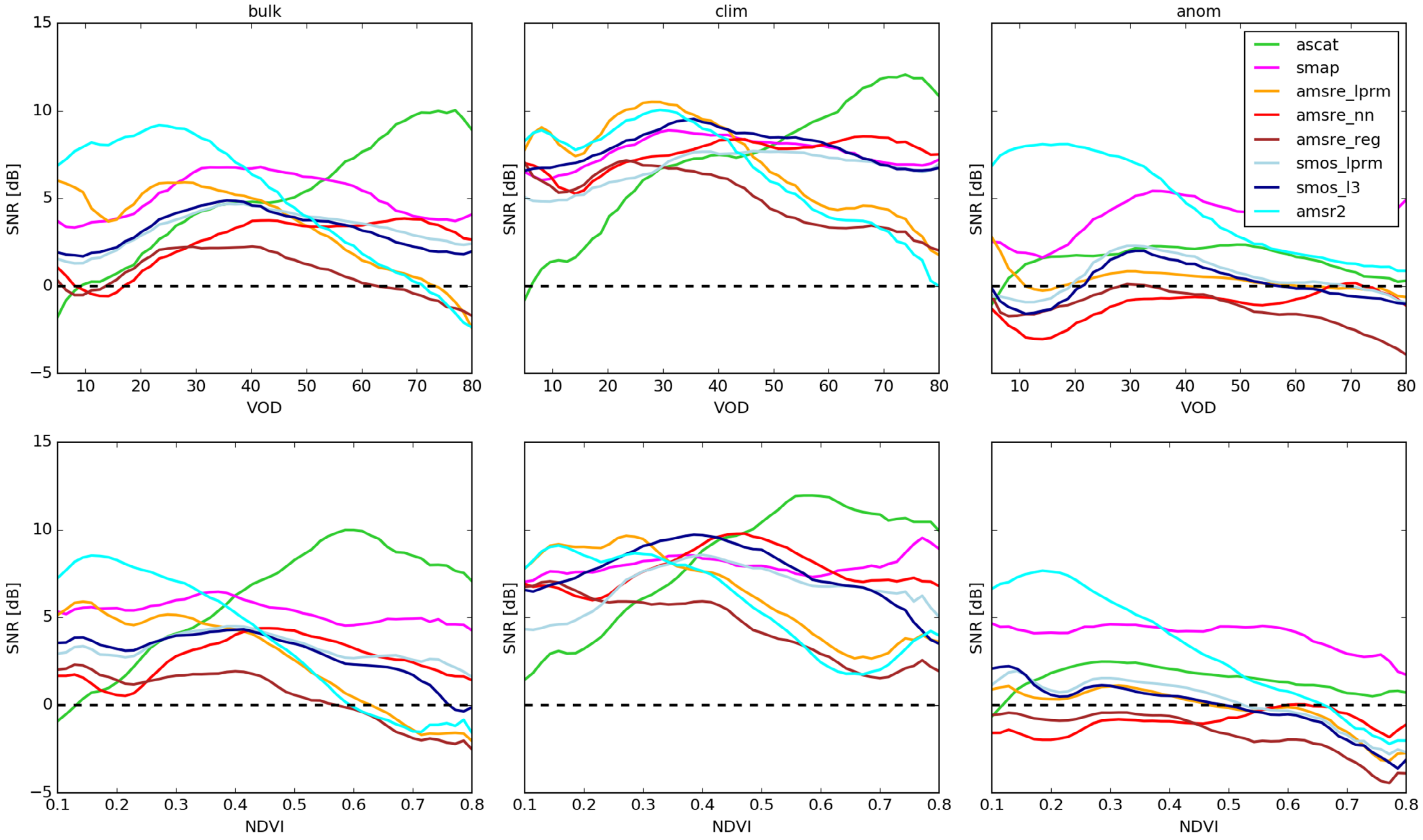


SNR of ASCAT & SMOS

- 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.

SNR as a Function of Vegetation

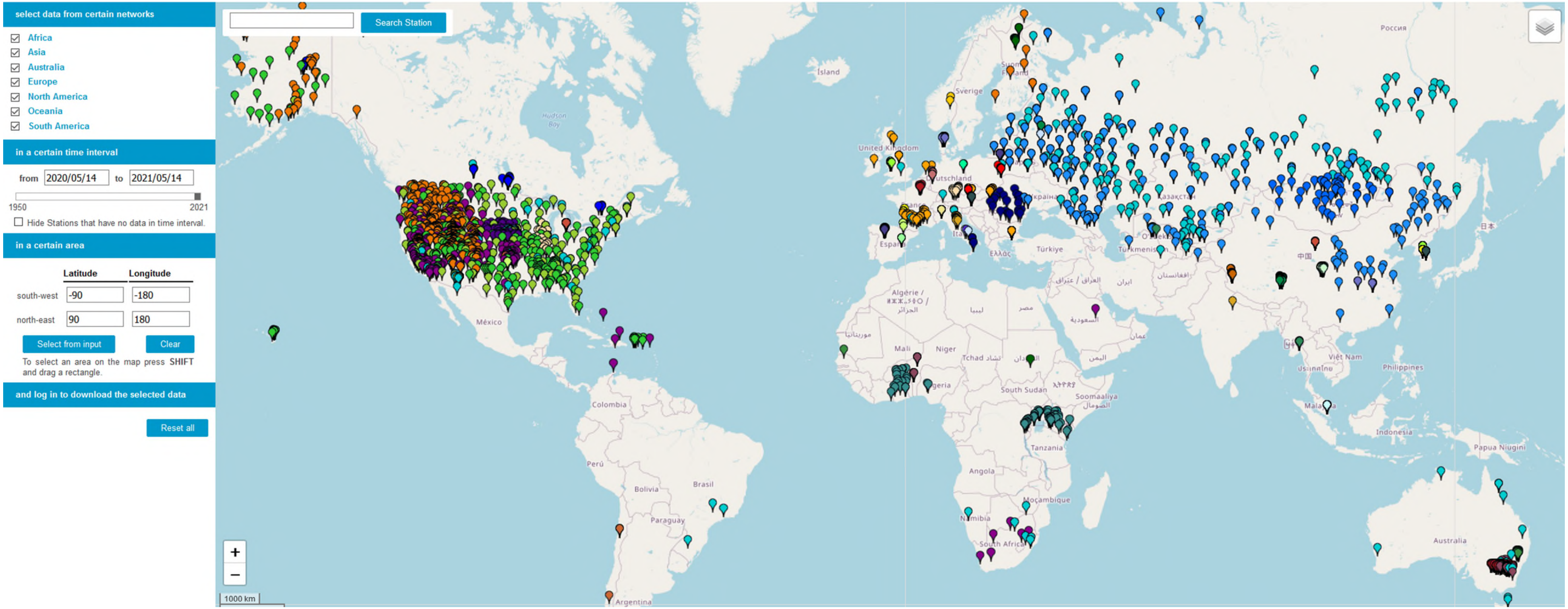


Comparison of SNR for original soil moisture data sets (left), their climatology (middle) and anomalies (right). Unpublished results prepared by Alexander Gruber.

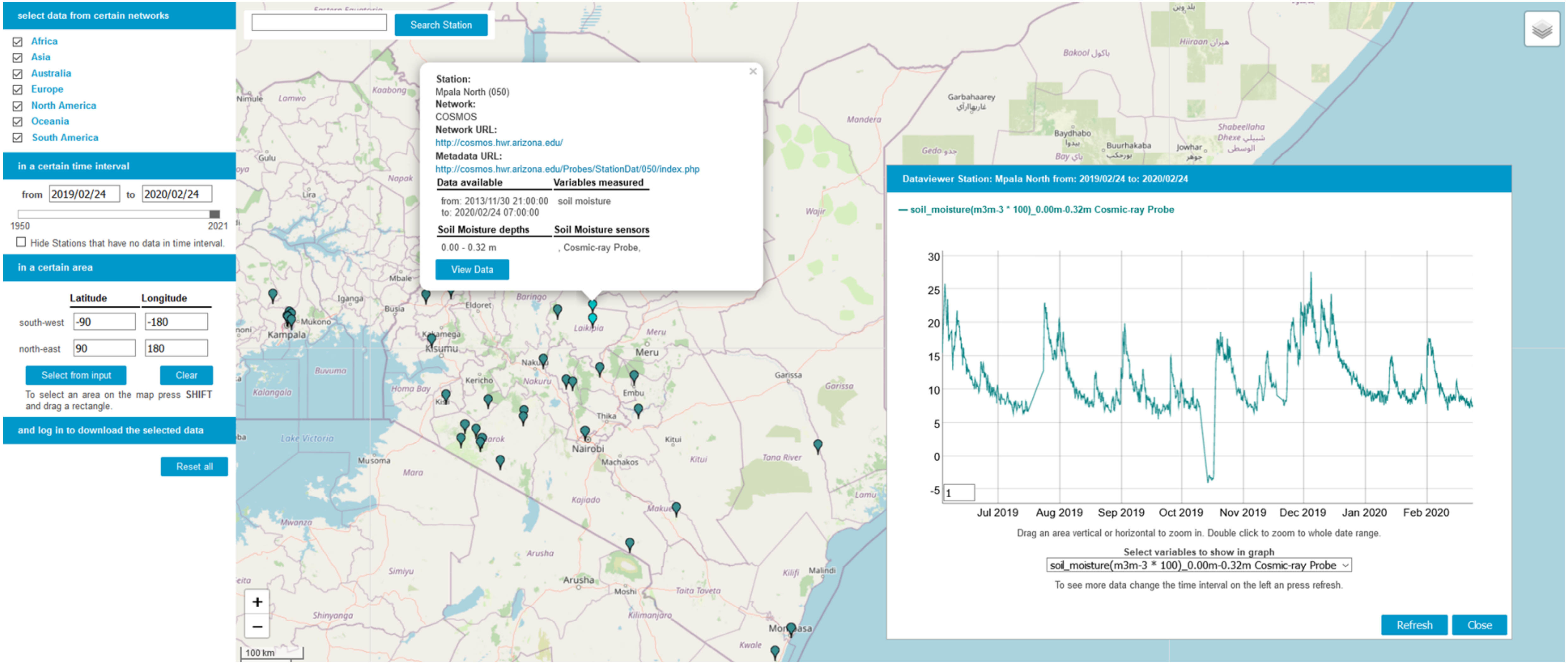
COMPARISON TO CRNS/IN SITU DATA

International Soil Moisture Network

https://ismn.earth/

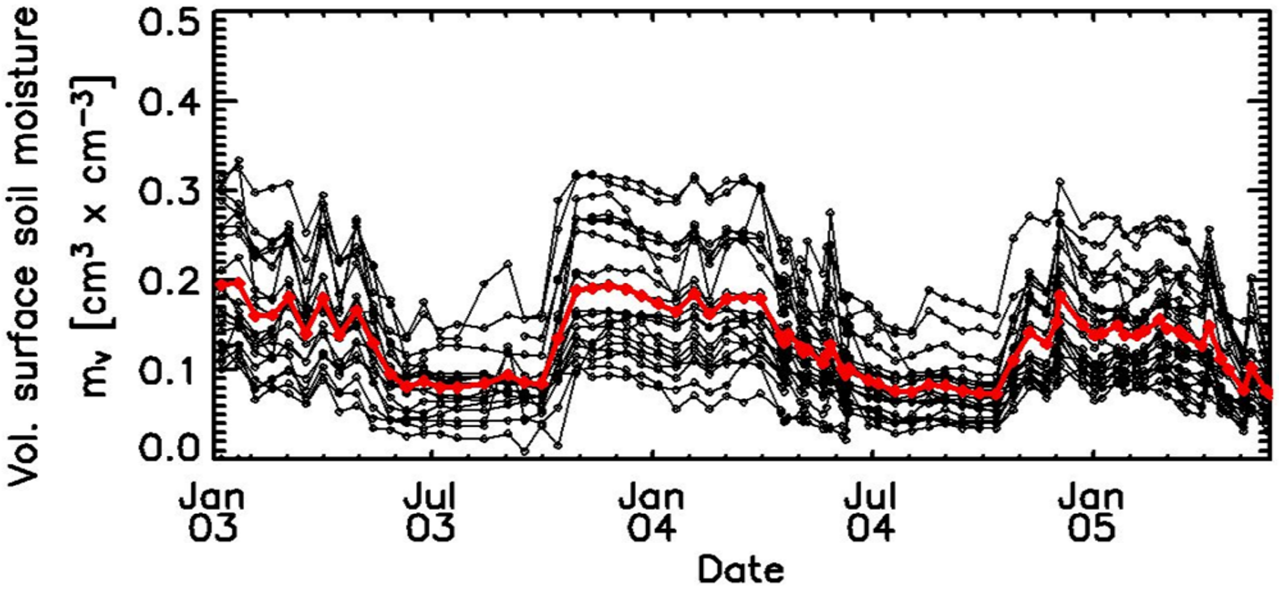


Dorigo, W.A., W. Wagner, R. Hohensinn, S. Hahn, C. Paulik, A. Xaver, A. Gruber, M. Drusch, S. Mecklenburg, P. van Oevelen, A. Robock, T. Jackson (2011) The International Soil Moisture Network: a data hosting facility for global in situ soil moisture measurements, Hydrology and Earth System Sciences, 15(6), 1675-1698.



select data from certain networks
Africa
Asia
Australia
Europe
North America
Oceania
South America
in a certain time interval
from 2019/02/24 to 2020/02/24
1950
2021
Hide Stations that have no data in time interval.
in a certain area
Latitude
Longitude
south-west -90 -180
north-east 90 180
Select from input
Clear
To select an area on the map press SHIFT and drag a rectangle.
and log in to download the selected data
Reset all
Search Station
Station:
Mpala North (050)
Network:
COSMOS
Network URL:
http://cosmos.hwr.arizona.edu/
Metadata URL:
http://cosmos.hwr.arizona.edu/Probes/StationDat/050/index.php
Data available
Variables measured
from: 2013/11/30 21:00:00
to: 2020/02/24 07:00:00
soil moisture
Soil Moisture depths
Soil Moisture sensors
0.00 - 0.32 m
, Cosmic-ray Probe,
View Data
Dataviewer Station: Mpala North from: 2019/02/24 to: 2020/02/24
soil_moisture(m3m-3 * 100)_0.00m-0.32m Cosmic-ray Probe
30
25
20
15
10
5
0
-5
Jul 2019
Aug 2019
Sep 2019
Oct 2019
Nov 2019
Dec 2019
Jan 2020
Feb 2020
Drag an area vertical or horizontal to zoom in. Double click to zoom to whole date range.
Select variables to show in graph
soil_moisture(m3m-3 * 100)_0.00m-0.32m Cosmic-ray Probe
To see more data change the time interval on the left an press refresh.
Refresh
Close
Kampala
Kisumu
Nairobi
Meru
Embu
Thika
Nakuru
Kericho
Eldoret
Arusha
Moshi
Mombasa
Garissa
Lake Victoria
100 km

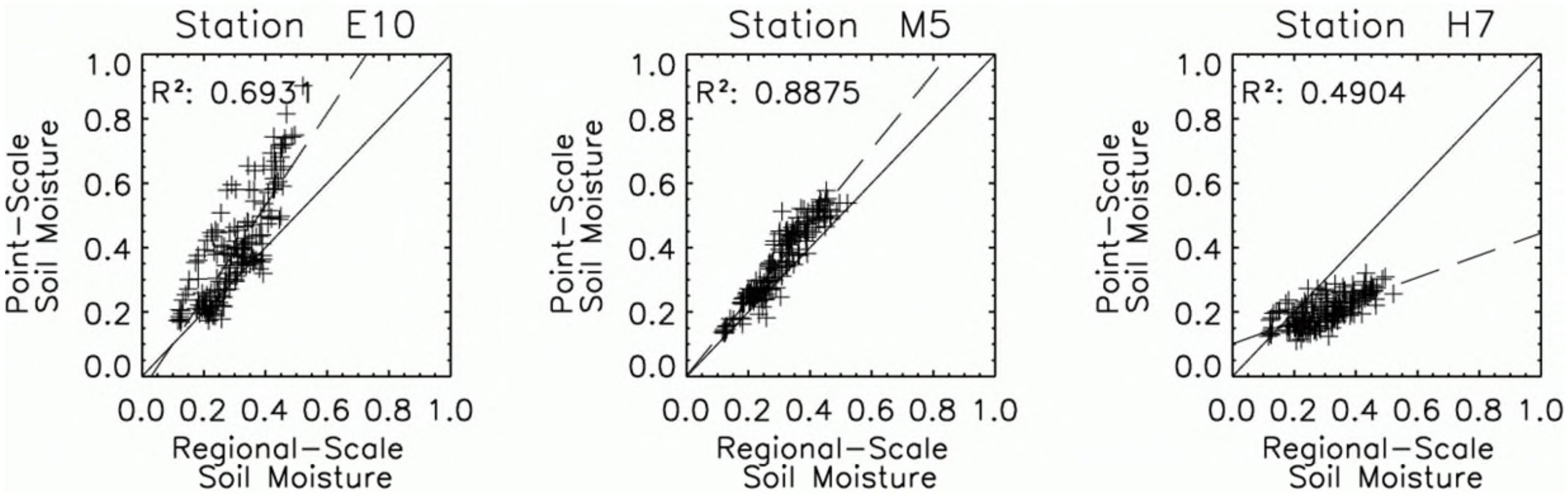
Variation of in situ Soil Moisture Data within Individual Networks



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

Ceballos, A., K. Scipal, W. Wagner, J. Martínez-Fernández (2005) Validation of ERS scatterometer-derived soil moisture data over the central part of the Duero Basin, Spain, Hydrological Processes, 19, 1549-1566.

Time-Invariant Linear Relationship



Regional scale soil moisture

$$\theta_r(t) = \frac{1}{A_r}\iint_P \theta_p(x',y',t)\,dx'dy' = c_{rp}(x,y) + d_{rp}(x,y)\,\theta_p(x,y,t)$$

Local scale soil moisture

Linear scaling coefficients

Model Error ≅ 5 %

Wagner, W., C. Pathe, M. Doubkova, D. Sabel, A. Bartsch, S. Hasenauer, G. Blöschl, K. Scipal, J. Martínez-Fernández, A. Löw (2008) Temporal stability of soil moisture and radar backscatter observed by the Advanced Synthetic Aperture Radar (ASAR), Sensors, 8(2), 1174-1197.

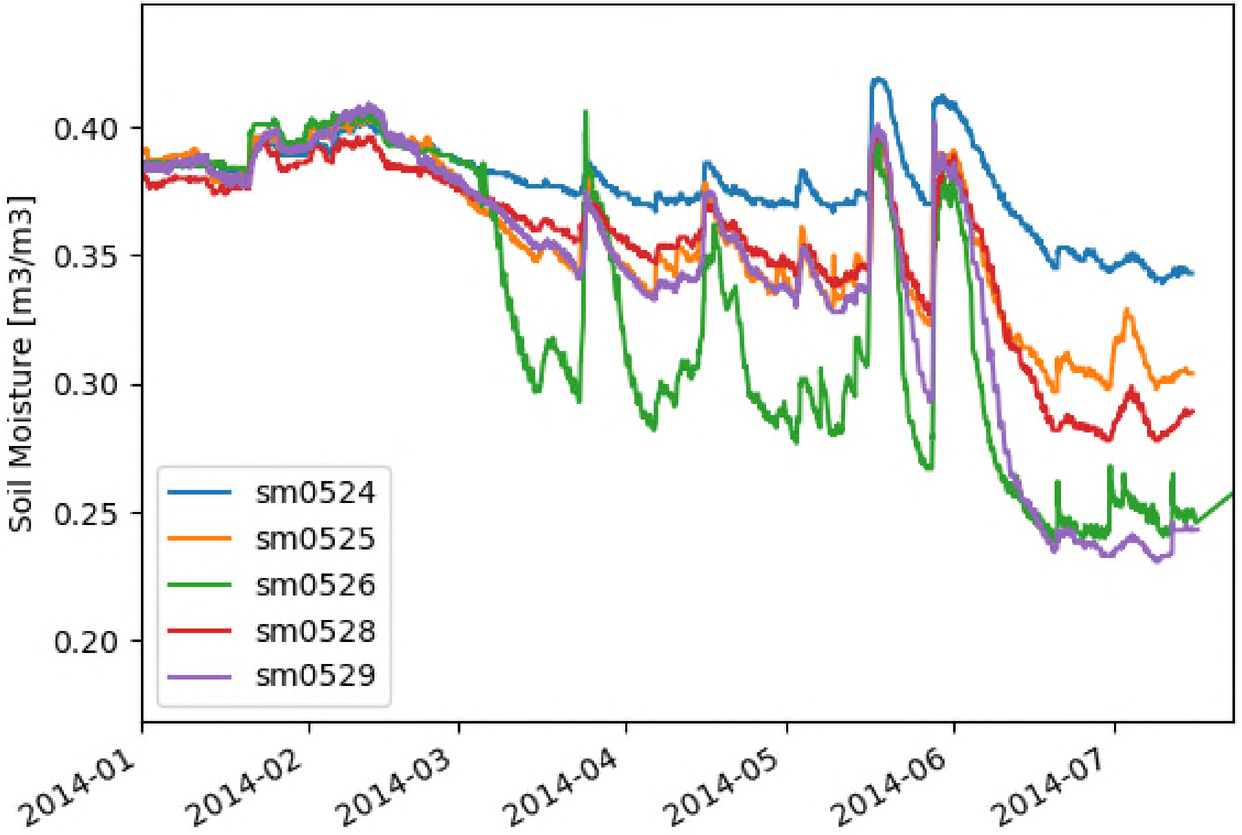
Hydrological Open Air Laboratory (HOAL)

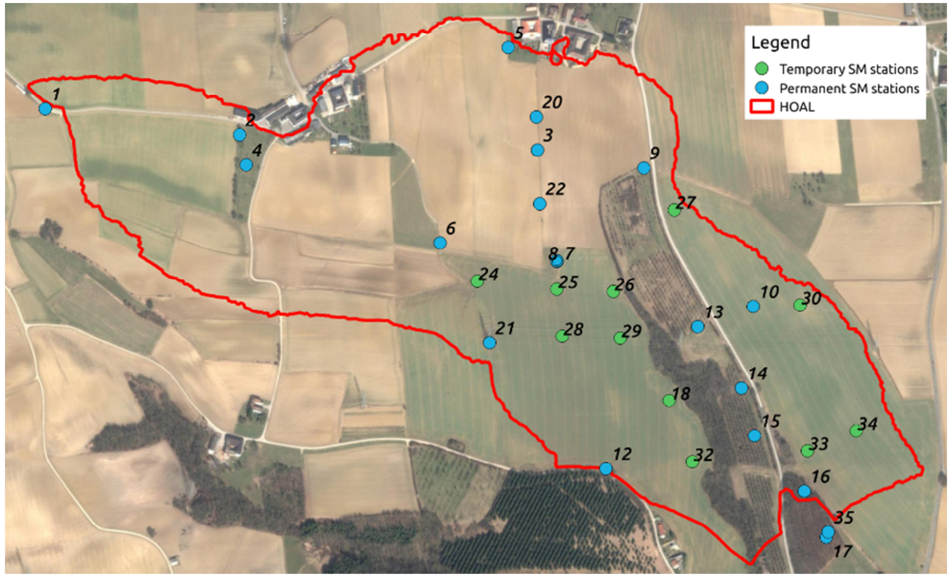
Vienna Doctoral Programme on
Water Resource Systems

A hydrological observatory for interdisciplinary research in Petzenkirchen, Austria.
Aerial picture of the HOAL viewing North, courtesy of Alexander Eder.

Variation of Soil Moisture Data within Individual Fields

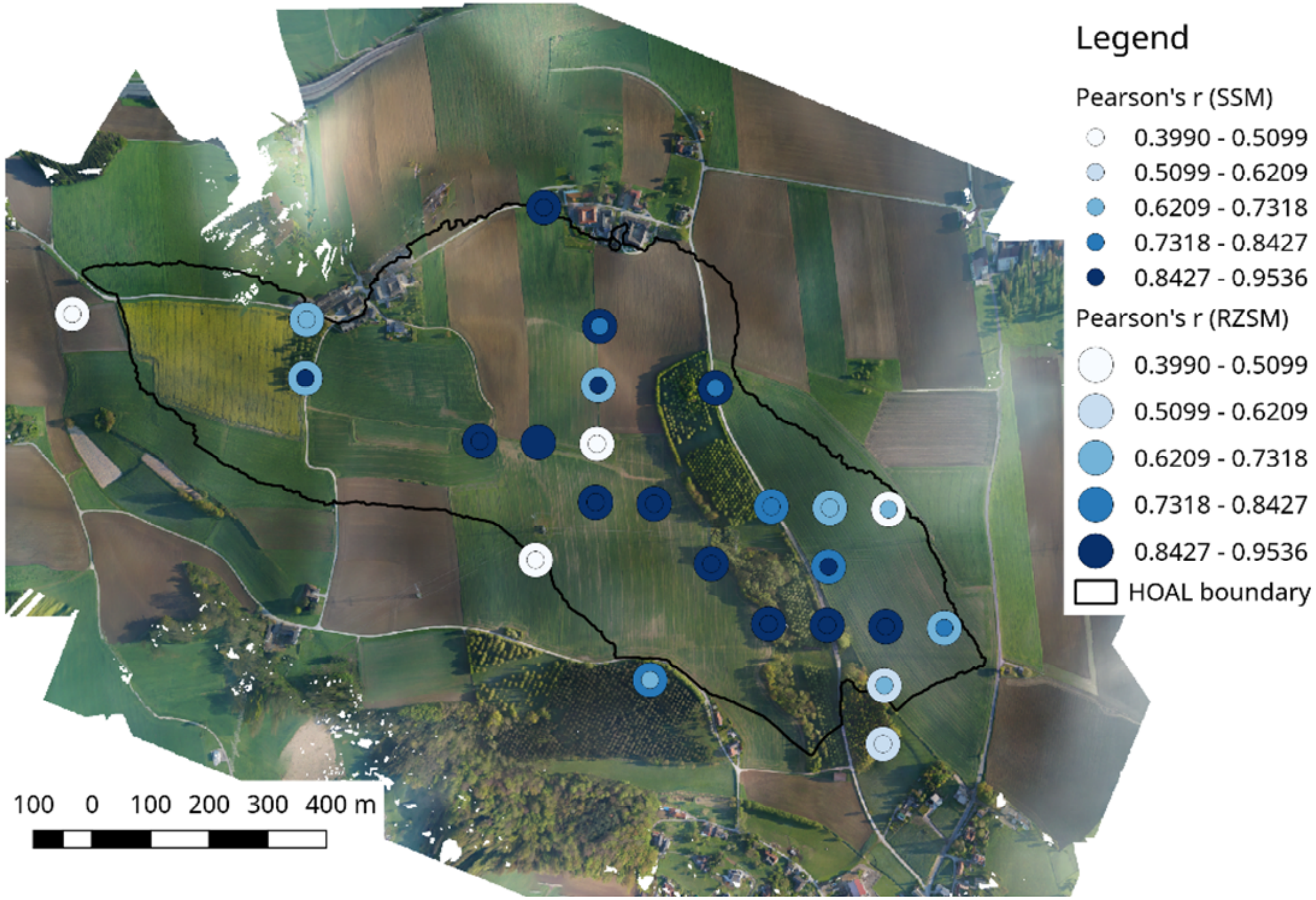
- In situ oil moisture data can vary significantly within one field with the same land cover





HOAL Soil Moisture Network,
Petzenkirchen, Austria

Spatial Variability of Temporal Correlations



Spatial distribution of Pearson correlations over the HOAL catchment.
Small circles: Surface SM - Large circles: Root-zone SM

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

17

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

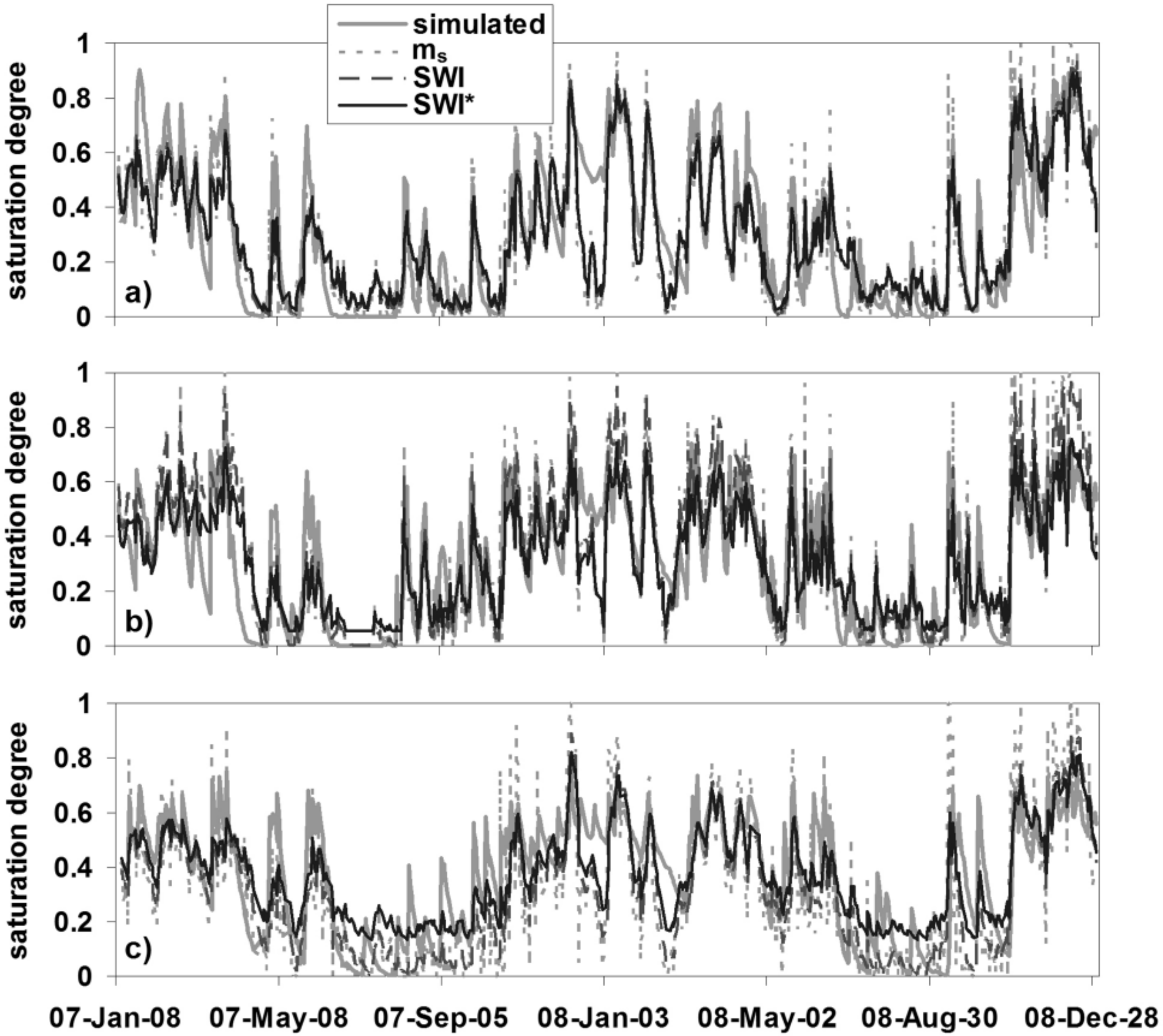
Luca Brocca, Florisa Melone, Tommaso Moramarco,
Wolfgang Wagner, and Clement Albergel

CONTENTS

17.1 Introduction 411
17.2 Scaling and Filtering Techniques Methods: Overview 412
17.2.1 Scaling Techniques 413
17.2.1.1 Linear Regression 413
17.2.1.2 CDF Matching 413
17.2.1.3 Linear Rescaling 413
17.2.1.4 Min/Max Correction 414
17.2.2 Filtering Techniques 414
17.2.2.1 Exponential Filter 414
17.2.2.2 Nonlinear Exponential Filter 415
17.2.2.3 Moving Average 415
17.3 Case Studies Datasets 415
17.3.1 *In situ* Soil Moisture Observations 415
17.3.2 Satellite Soil Moisture Observations 416
17.4 Results and Discussions 417
17.4.1 Scaling Techniques 417
17.4.2 Filtering Techniques 421
17.5 Conclusions 423
References 423

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.

ASCAT versus Modelled Soil Moisture

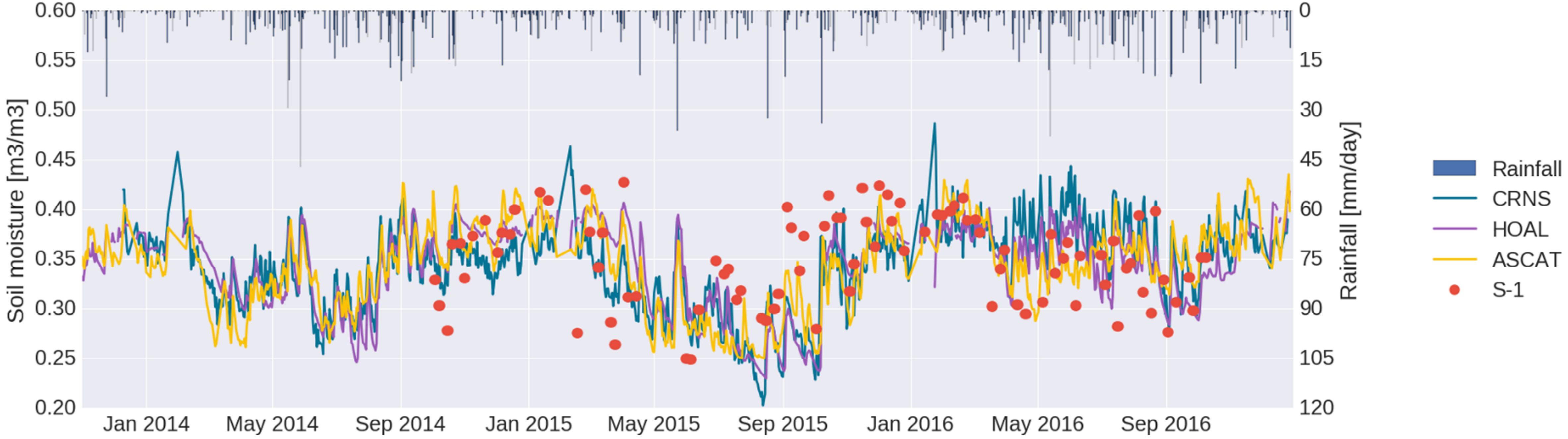


ASCAT versus 3 cm simulated degree of saturation for products, ms, SWI, and SWI* and investigated sites:

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.

Satellite versus In Situ Soil Moisture Data over HOAL

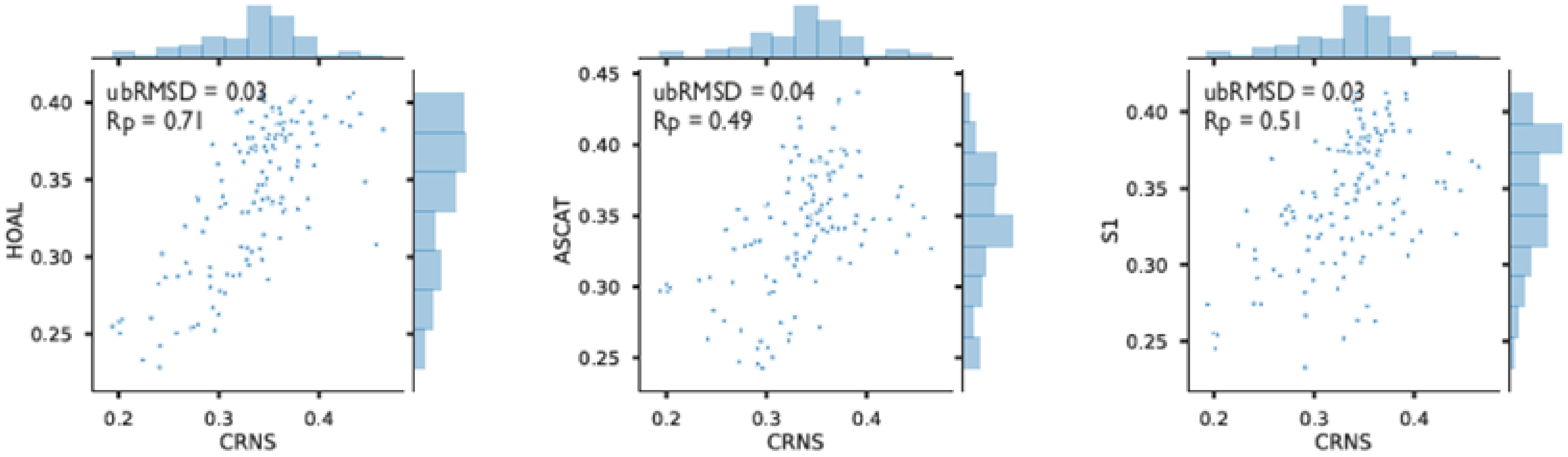


CRNS: Cosmic Ray Neutron Sensor
HOAL: Catchment average of 31 TDT measurements
ASCAT: 25 km ASCAT soil moisture retrievals
S-1: 1 km Sentinel-1 soil moisture retrievals

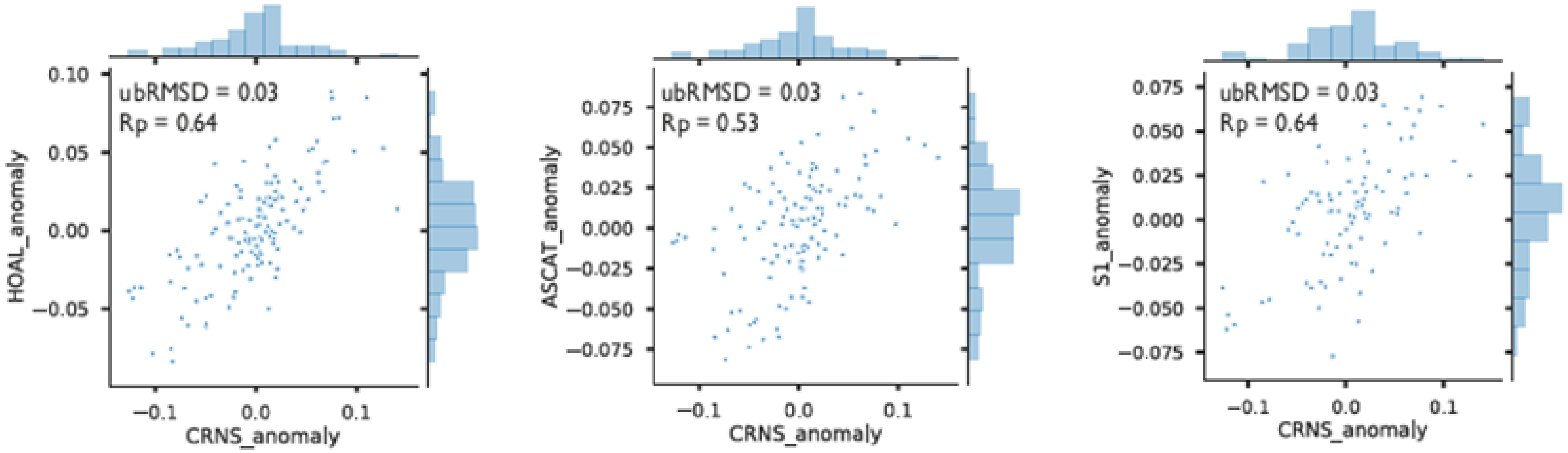
Joint FAO/IAEA Programme
Nuclear Techniques in Food and Agriculture

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

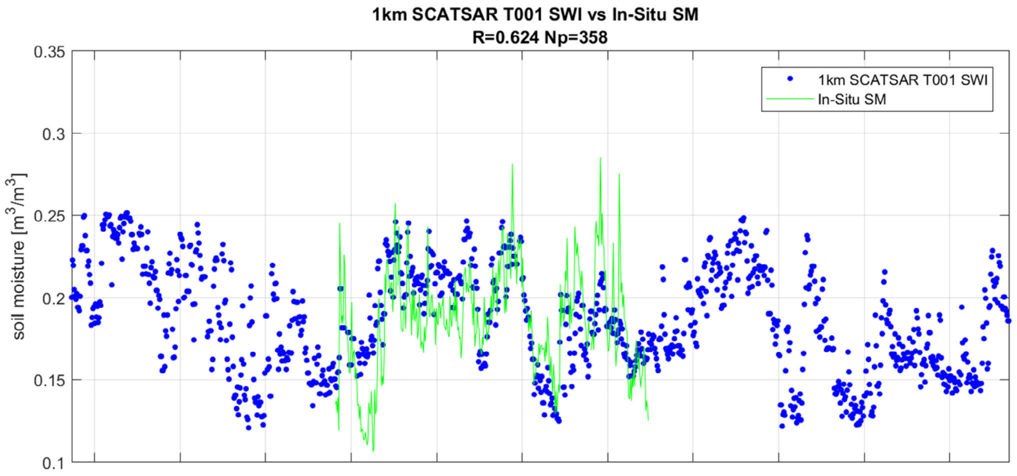
Absolute



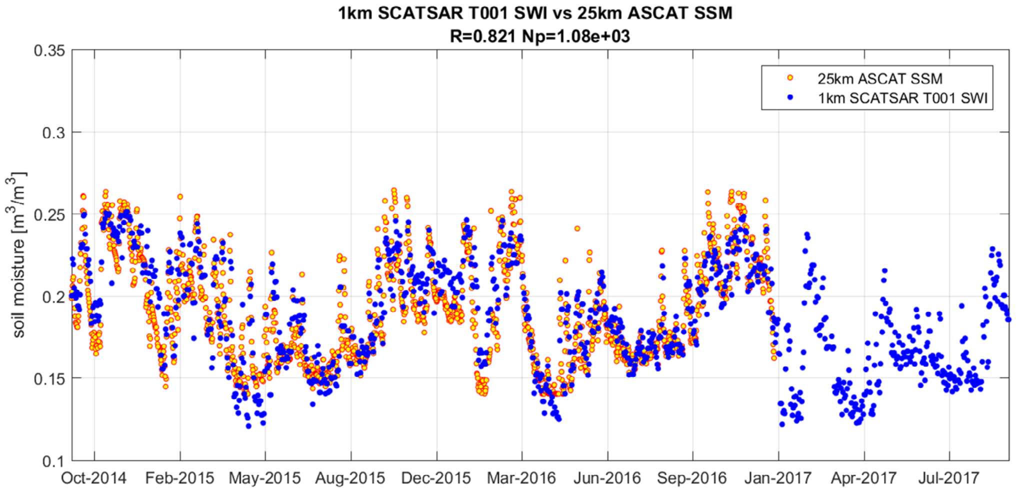
Anomalies



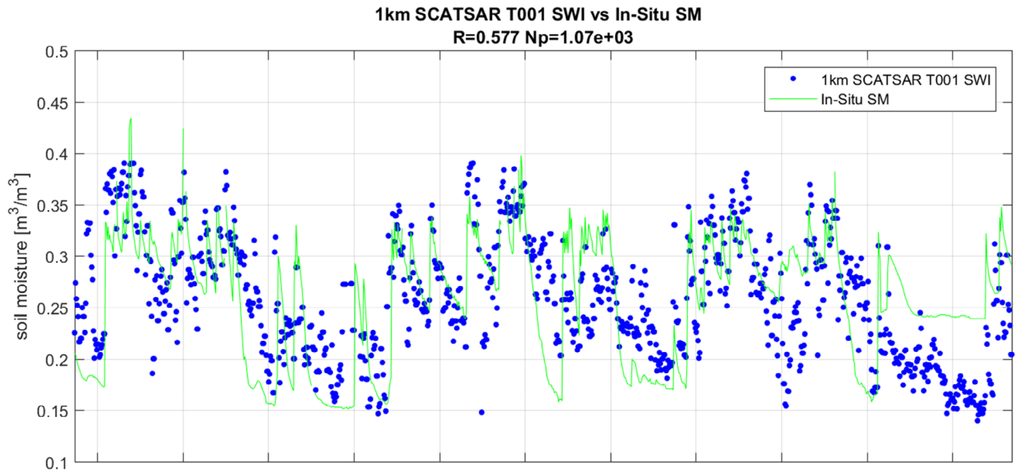
ASCAT and Sentinel-1 based SWI versus COMOS Data



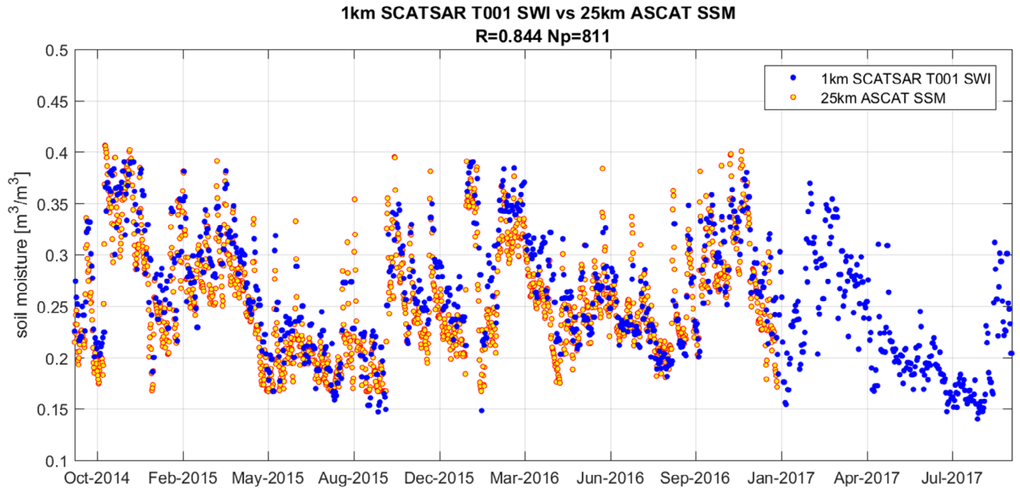
COSMOS-Station in Emilia-Romagna



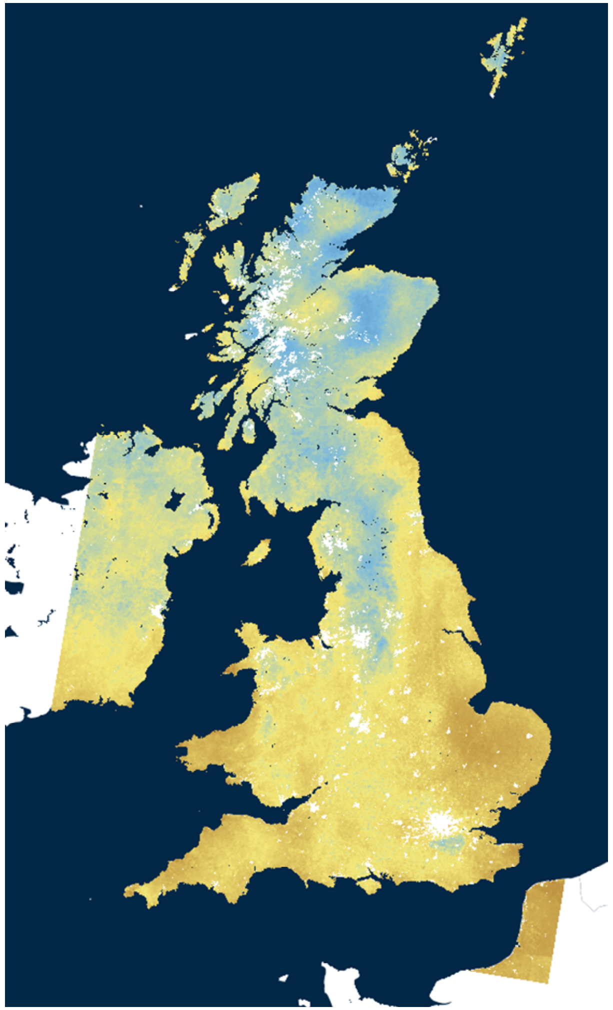
ASCAT and Sentinel-1 based SWI versus in situ Data



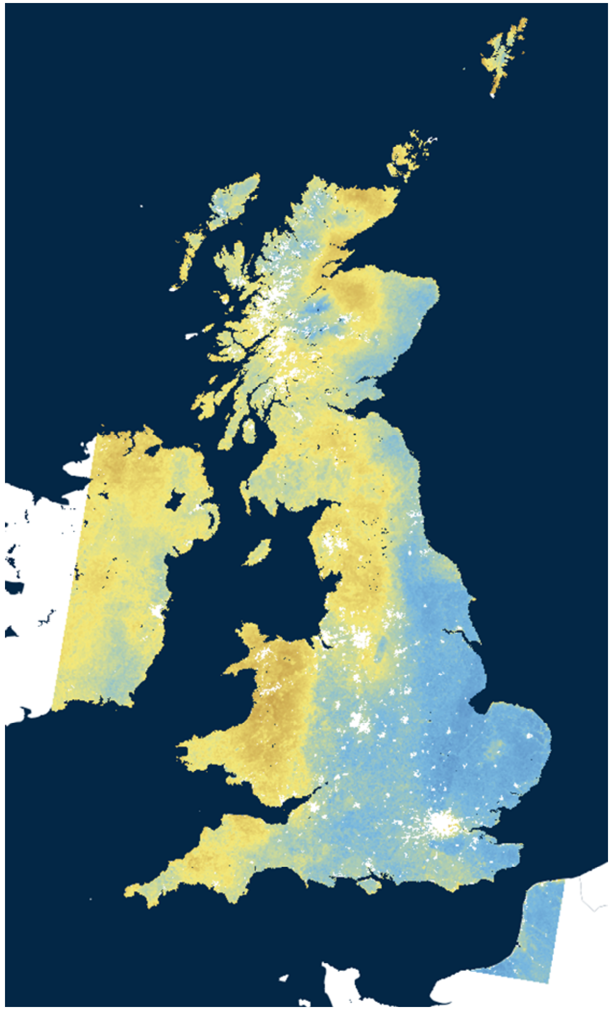
UMBRIA in-situ station „Petrelle“



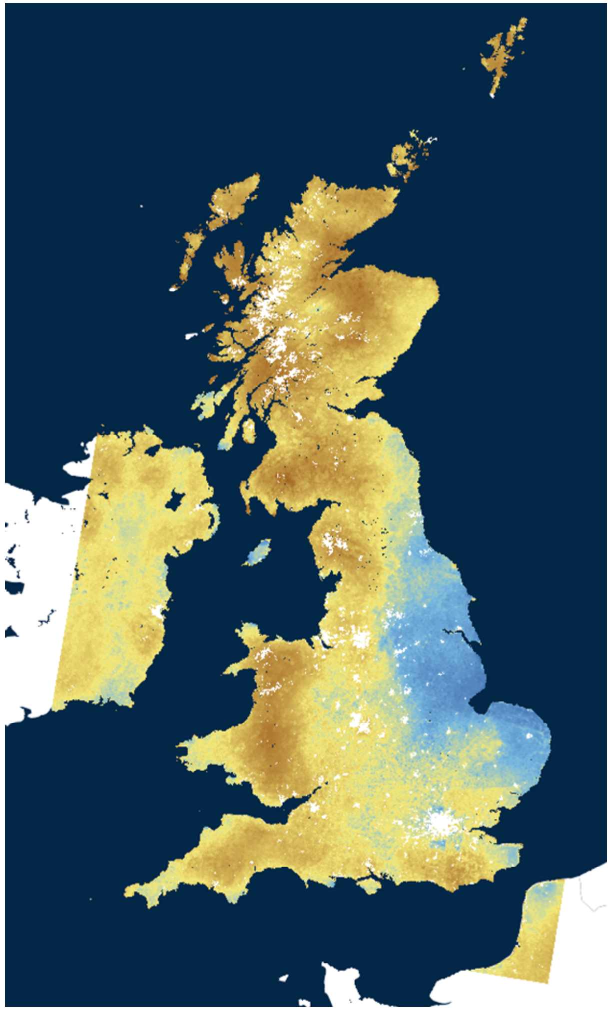
ASCAT and Sentinel-1 based SWI for UK



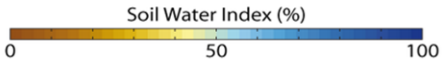
2015-05-04 | T020



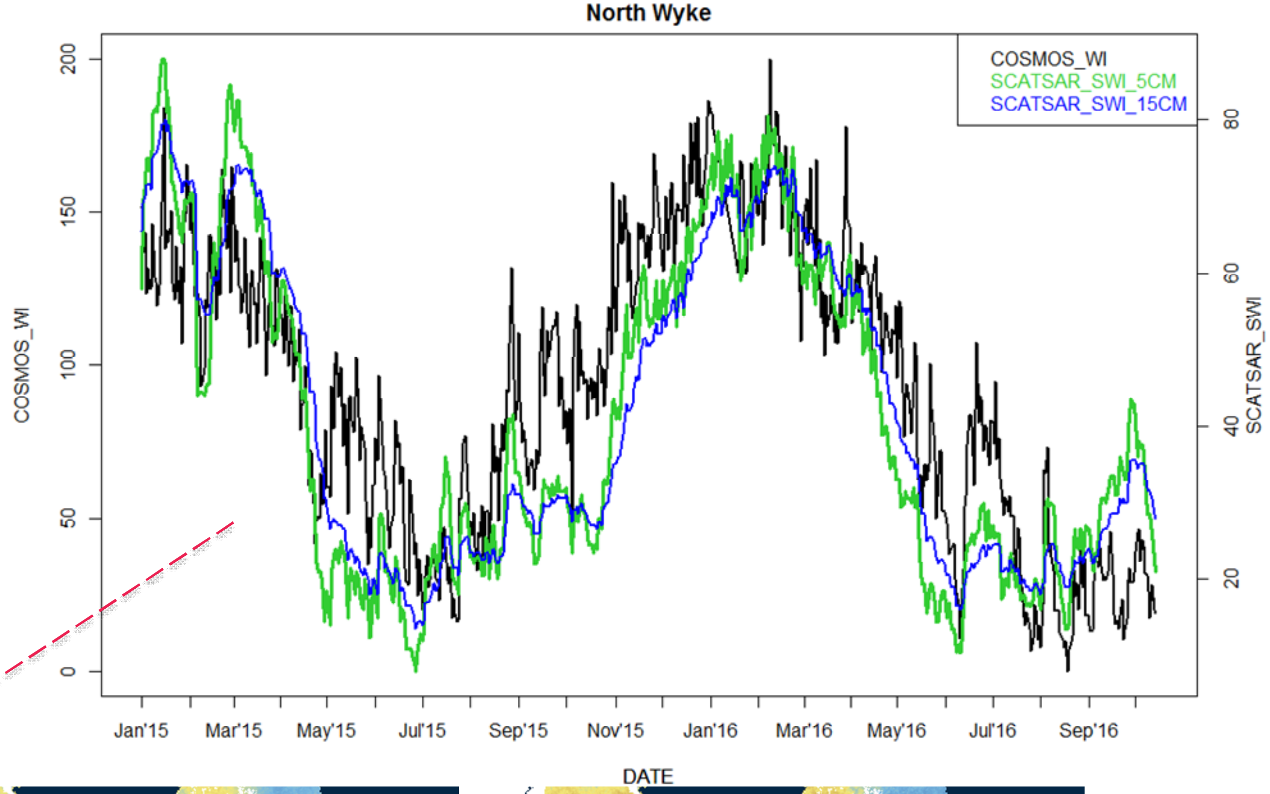
2015-11-07 | T020



2016-10-13 | T005



CEH UK
COSMOS Stations



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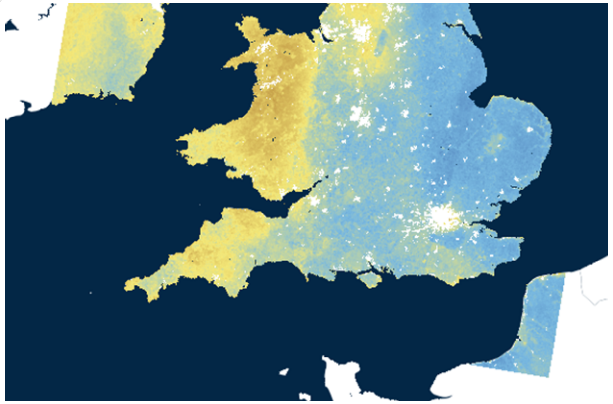
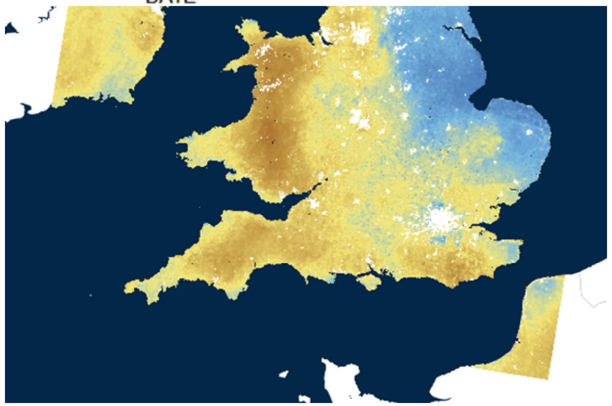
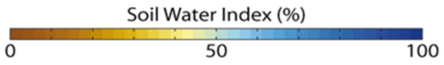


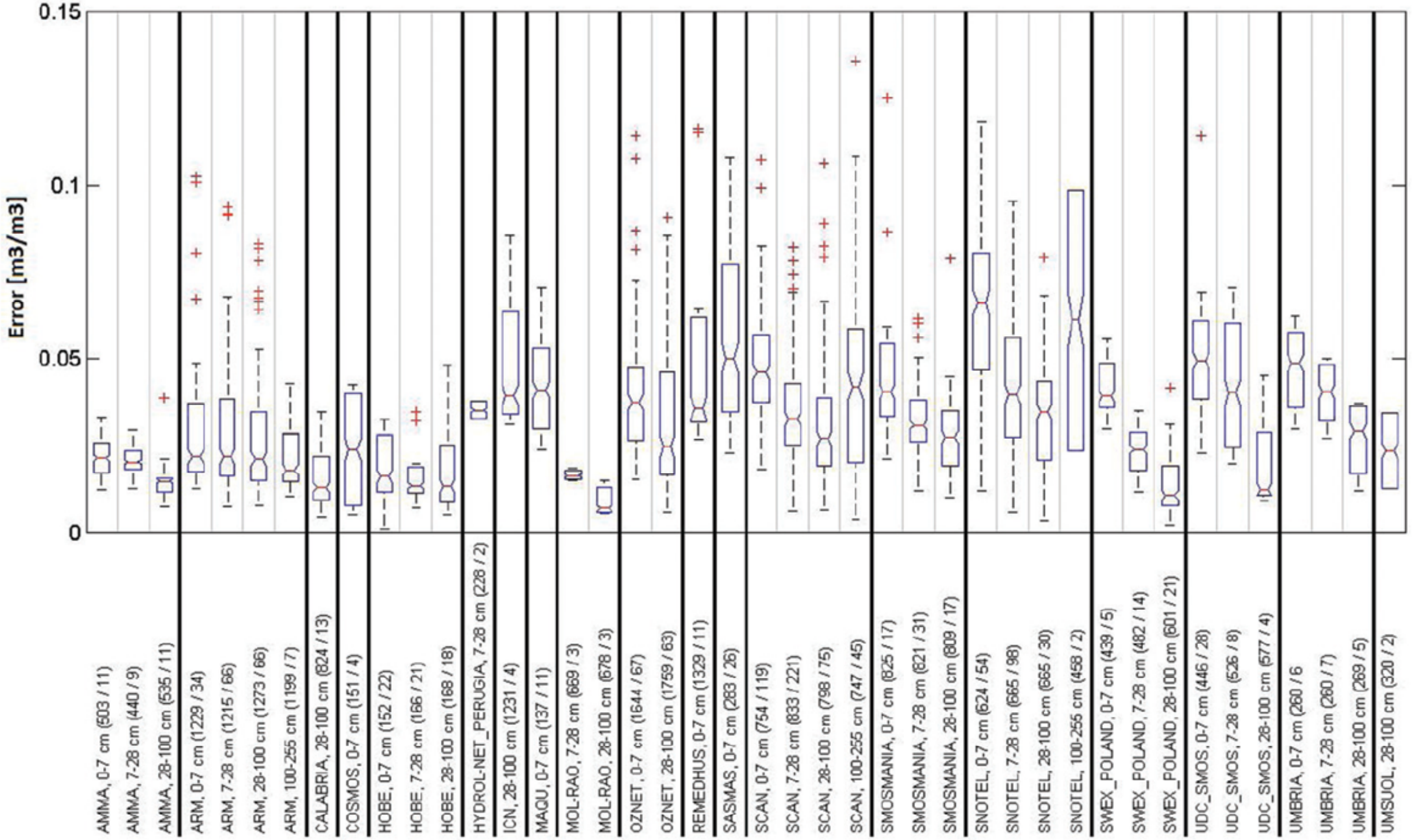
2015-11-07 | T020

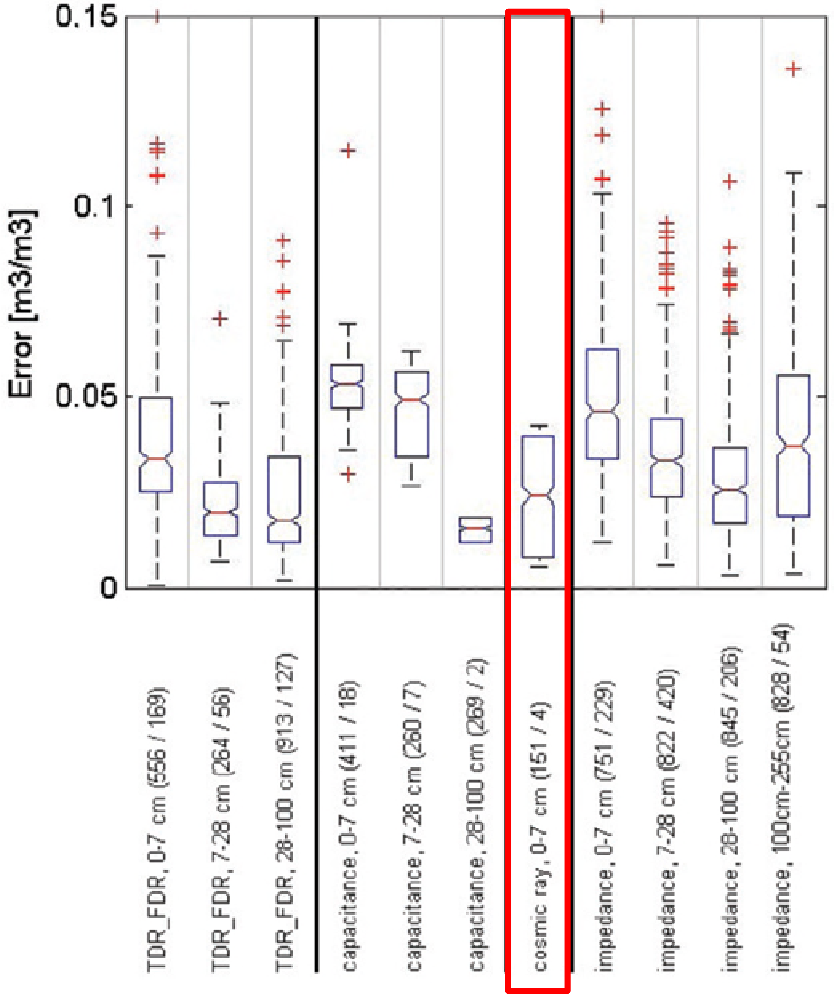


2016-10-13 | T005



How Representative are the CRNS/in situ Observations?





Gruber, A., W.A. Dorigo, S. Zwieback, A. Xaver, W. Wagner (2013) Characterizing coarse-scale representativeness of in-situ soil moisture measurements from the International Soil Moisture Network, Vadose Zone Journal, 12(2), 16 p.