Information Content of ASCAT Soil Moisture Data

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Mission Goal of SMOS and SMAP

Launch 2009

Launch 2015

The mission goal of SMOS and SMAP is to provide absolute soil moisture retrievals with an accuracy of 0.04 m^3m^{-3}.

Targeted information: absolute soil moisture

Accuracy metric: root mean square error (RMSE) in m^3m^{-3}

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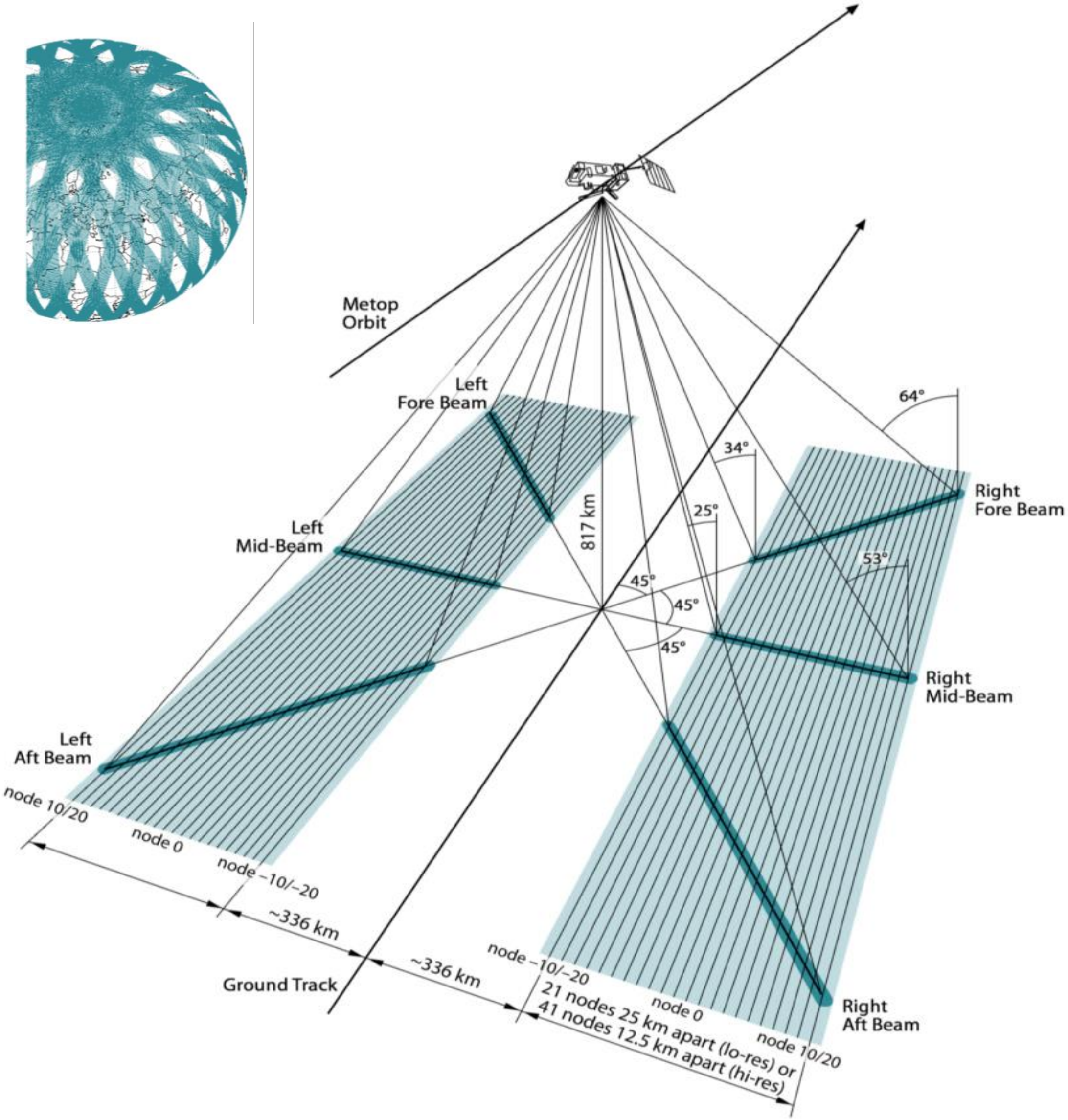
ASCAT on board of METOP-A/B



- Since 2006
- Frequency
  - 5.255 GHz (C-band)
- Polarisation
  - VV
- Spatial Resolution
  - 25 km/ 50 km
- Swath
  - 2 x 500 km
- Multi-incidence
  - 25-65°
- Daily global coverage
  - 82 %

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H-SAF Downstream Services

- ESA Climate Change Initiative
  - Inputs
    - Data Records H25+
  - Output
    - ECV Soil Moisture Data Record (daily, 0.25°)
  - Perspective
    - CCI Phase 2, Copernicus Climate Services
- Copernicus Global Land Service
  - Inputs
    - NRT product H16
    - For reprocessing H16 and/or H25 have been used
  - Output
    - NRT Soil Water Index (daily, 0.25°)
    - SWI Archive
  - Perspective
    - Inclusion of Sentinel-1 to improve spatial resolution to 1 km

soil moisture cci

> 1300 Users

Copernicus The European Earth Observation Programme

> 500 Users
(entire distribution history of SWI)

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ASCAT Calibration

- Radiometric calibration of ASCAT
  - Internal calibration
    - Remove drifts in transmitter power and receiver gain
  - External calibration
    - Estimation of antenna gain pattern
- External calibration is performed by means of three transponders
  - Located in Turkey
  - Acting as artificial point targets
  - Well-known radar cross-section
- Verification of calibration over natural targets
  - Rainforest
  - Sea Ice and
  - Ocean
- Rainforest verification
  - Instrument stability within ~0.2 dB

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Working Hypothesis for ASCAT Soil Moisture Retrieval

- Information about <u>absolute</u> soil moisture content comes from <u>soil maps</u>, not the satellite
- ASCAT data are not fundamentally different to SMOS or SMAP. Nonetheless, for ASCAT we have always stressed that the information content lies in the <u>relative variation</u> of the observations
  - This has resulted in a disparate treatment of ASCAT and SMOS data in the literature
    - ASCAT data have often been referred to as soil moisture index
    - ASCAT users approached the problem with less expectations
- ASCAT soil moisture data are represented in <u>degree of saturation</u>
  - Unit 0-1 or 0-100 %
  - Dry and wet reference values are extracted from multi-year time series
  - Conversion to absolute values possible if soil porosity and soil moisture residual content are known

ASCAT Information Content

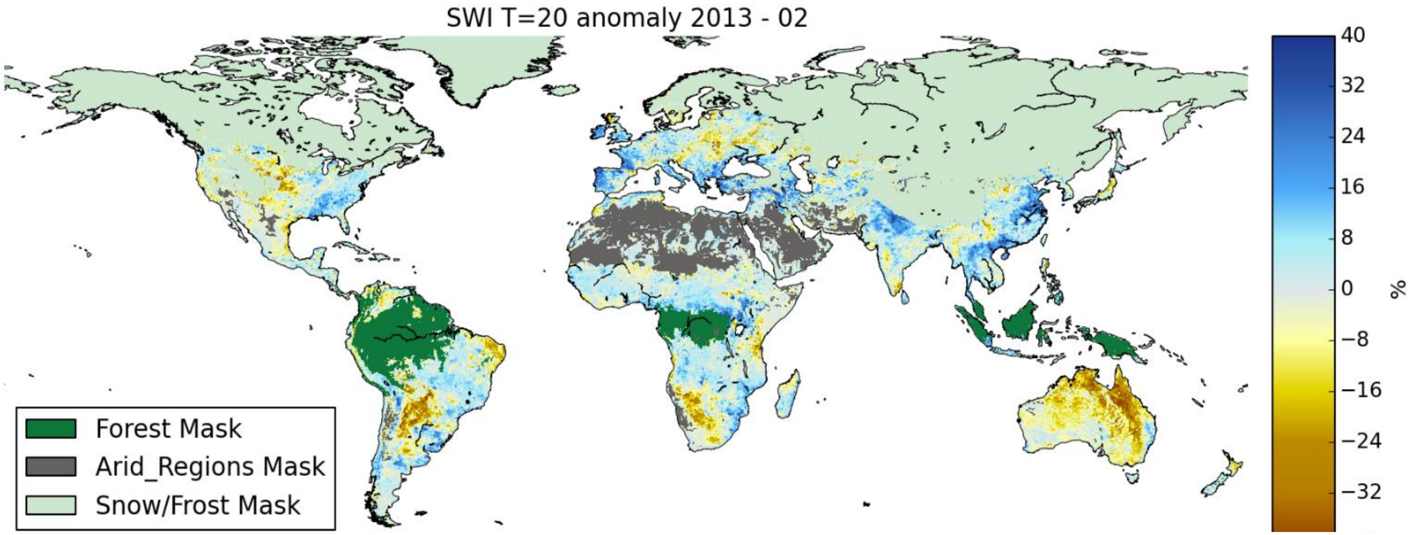
- ASCAT captures soil moisture changes
  - Good at short (1-3 days) and long (>years) time scales
  - Seasonal biases over some areas
    - Working on optimisation of model parameters

- Information content at longer time scales
  - Extreme conditions (drought, floods) can be well recognised
- Information content at short time scales
  - Rainfall can be derived from surface soil moisture time series

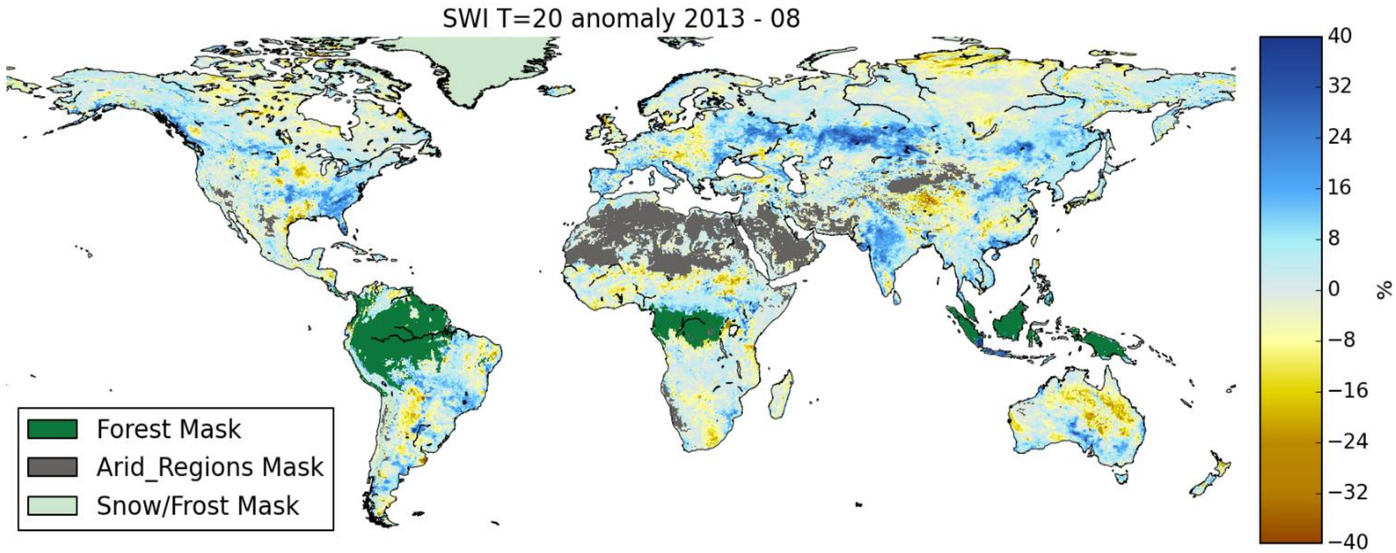
- Advanced error characterisation methods needed to characterise ASCAT information content
  - Spectral analysis
  - Triple collocation

ASCAT Soil Water Index Anomalies for 2013

- Contribution to the WMO State of the Climate Report 2013



February 2013



August 2013

Information Content at Short Time Scales

- 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 ... precipitation

r ... surface runoff

e ... evapotranspiration

g ... drainage

Inverting for *p(t):*

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

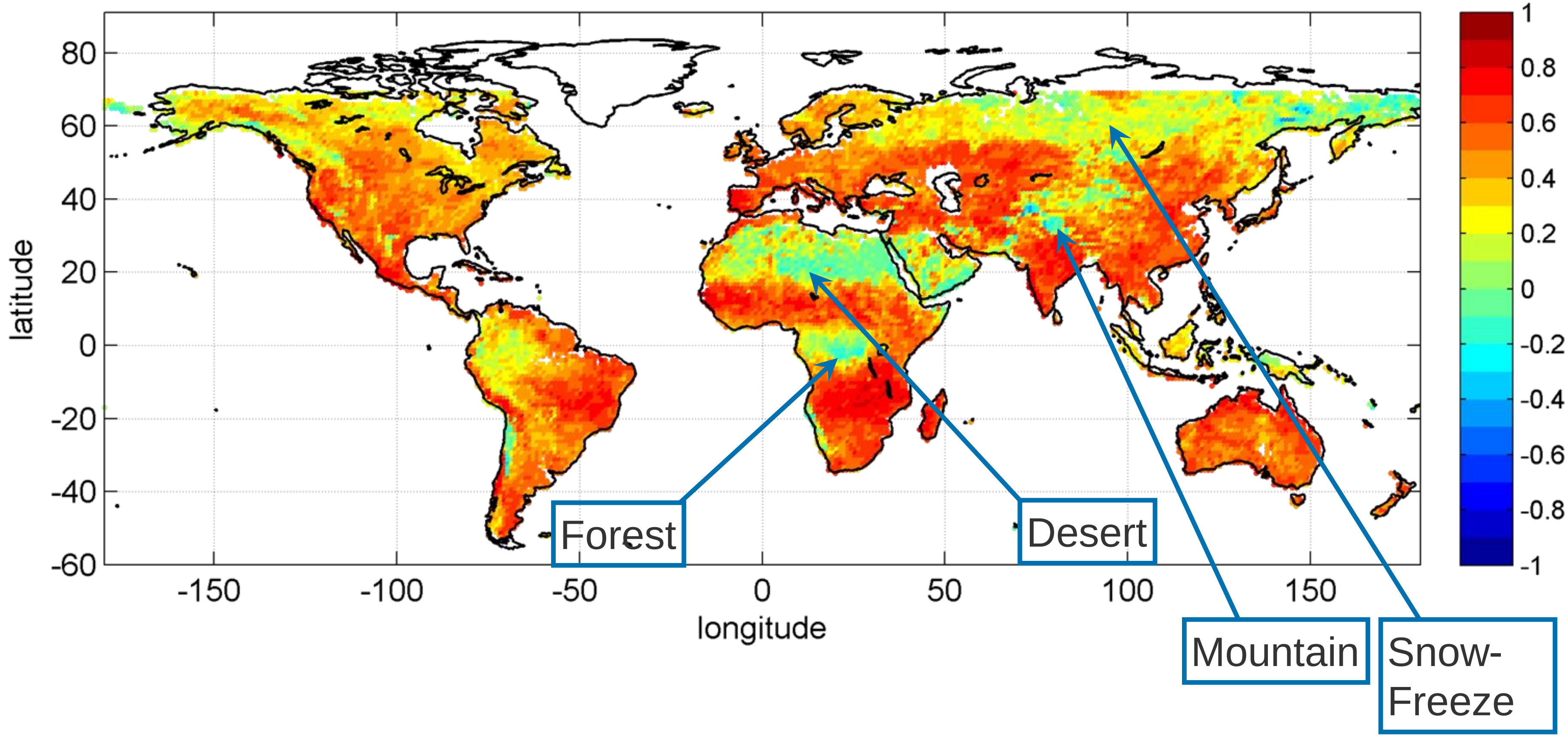
Assuming during rainfall:

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

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

Brocca, L., Ciabatta, L., Massari, C., Moramarco, T., Hahn, S., Hasenauer, S., Kidd, R., Dorigo, W., Wagner, W., & Levizzani, V. (2014). Soil as a natural rain gauge: Estimating global rainfall from satellite soil moisture data. *Journal of Geophysical Research: Atmospheres*, *119*(9), 5128-5141.

ASCAT Rainfall



Correlation between 5-day rainfall from GPCC and the rainfall extracted from ASCAT data through SM2RAIN

Signal versus Noise

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

- Signal is tied to a certain scale
  - Noise refers to random instrument noise as well as representativeness 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

Spectral Fitting Method

- Assuming a simple relationship between satellite soil moisture estimates and the true signal through additive noise and systematic errors

$$\theta_{true} = f(S_{trend}, S_{seasonal}, S_{events})$$

$$\theta_{sat} = f(S_{trend}, S_{seasonal}, S_{events}, E_W, E_R)$$

$$= \theta_{true} + E_W + E_R$$

E_W: stochastic white-noise

E_R: false resonances (systematic errors)

E_W and E_R are additive errors

S_{trend}: trend in the soil moisture signal

S_{trend}: seasonality in the soil moisture signal

S_{trend}: soil moisture events

Su, C. H., Ryu, D., Crow, W. T., & Western, A. W. (2014). Stand-alone error characterisation of microwave satellite soil moisture using a Fourier method. *Remote Sensing of Environment*, 154, 115-126.

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Spectral Fitting Method

- Fitting of a simple water balance model with and without noise to the satellite observations and estimating noise through their difference.

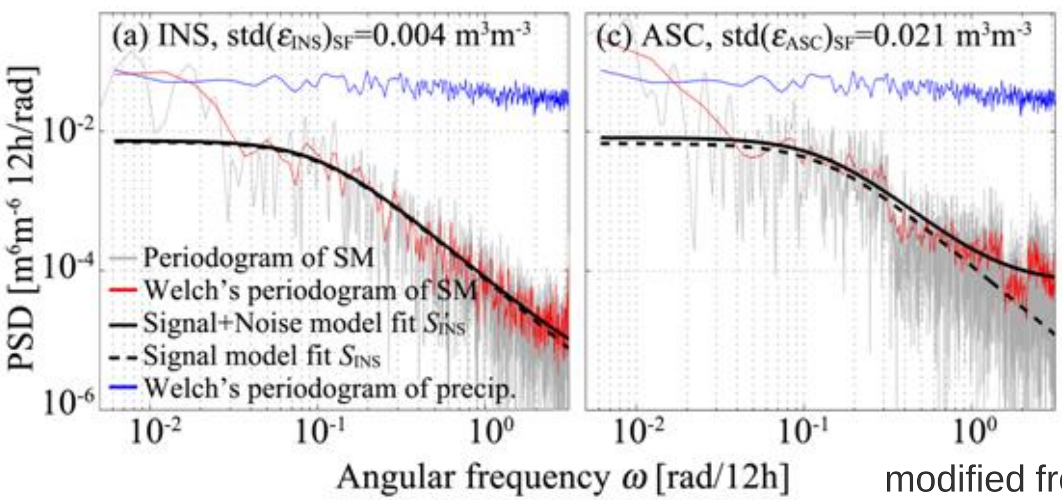
• Linear 1D model of soil moisture driven by precipitation (p) and attenuated by loss rate η

• Poisson process for rainfall forcing $|P(\omega)|=P$ for $\omega>0$, and add the stochastic white-noise noise $|E_{\omega}(\omega)|=E$ and resonances at ω_k

$$\frac{d}{dt}\theta_{true}(t) = p(t) - \eta\theta_{true}(t) \xrightarrow{\text{FT}} \Theta(\omega) = \frac{P(\omega)}{\eta + i\omega}$$

$$\Theta'(\omega) = \Theta(\omega) + E + \sum_k \delta(\omega - \omega_k)$$

$$|\Theta'(\omega)|^2 = \frac{(P+\eta E)^2 + \omega^2 E^2}{\eta^2 + \omega^2} + \sum_k \delta(\omega - \omega_k)$$



$$E^2 = \Delta t \sigma_N^2$$

where Δt =12h is the sampling interval

modified from Su et al. (2014)

Triple Collocation

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

Assumptions:

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

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

$$\longrightarrow$$

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

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.

Triple Collocation

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

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

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

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.

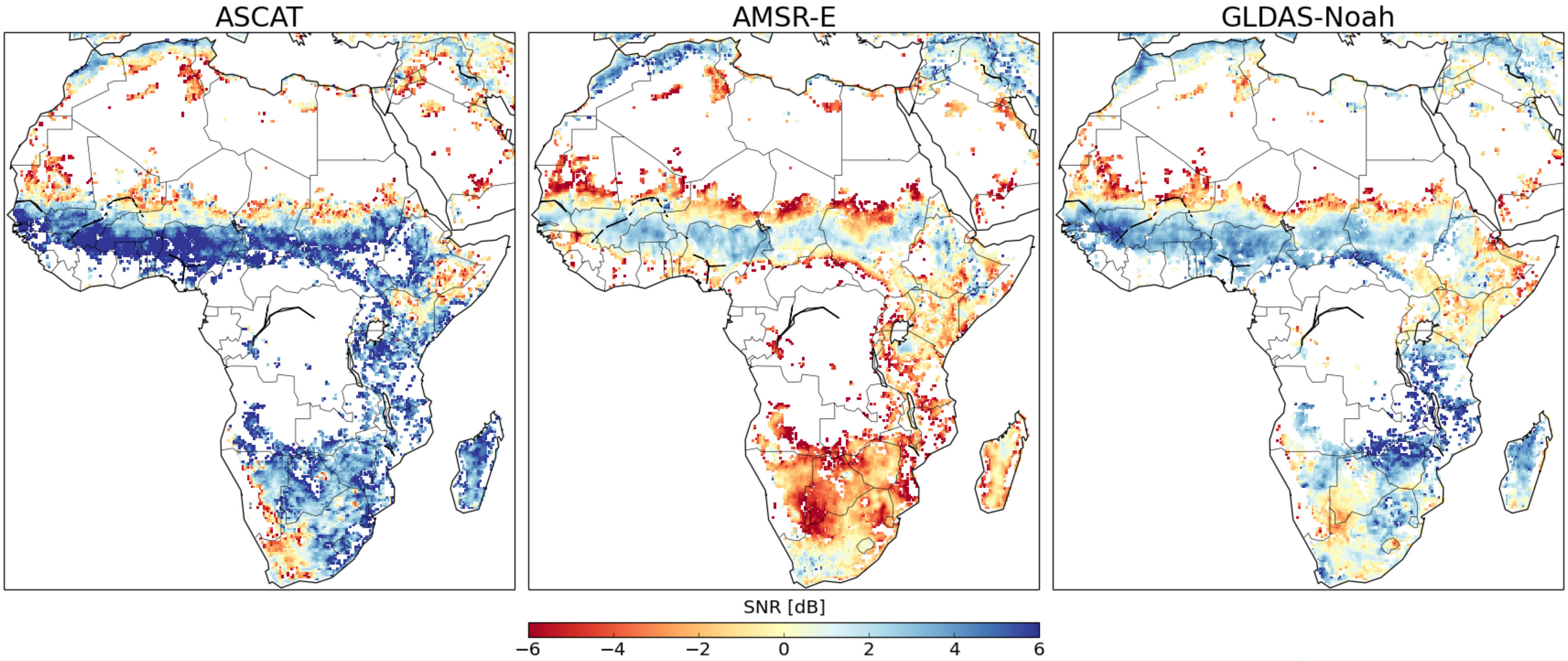
McColl, K. A., Vogelzang, J., Konings, A. G., Entekhabi, D., Piles, M., & Stoffelen, A. (2014). Extended triple collocation: Estimating errors and correlation coefficients with respect to an unknown target. Geophysical Research Letters.

Signal to Noise Ratio

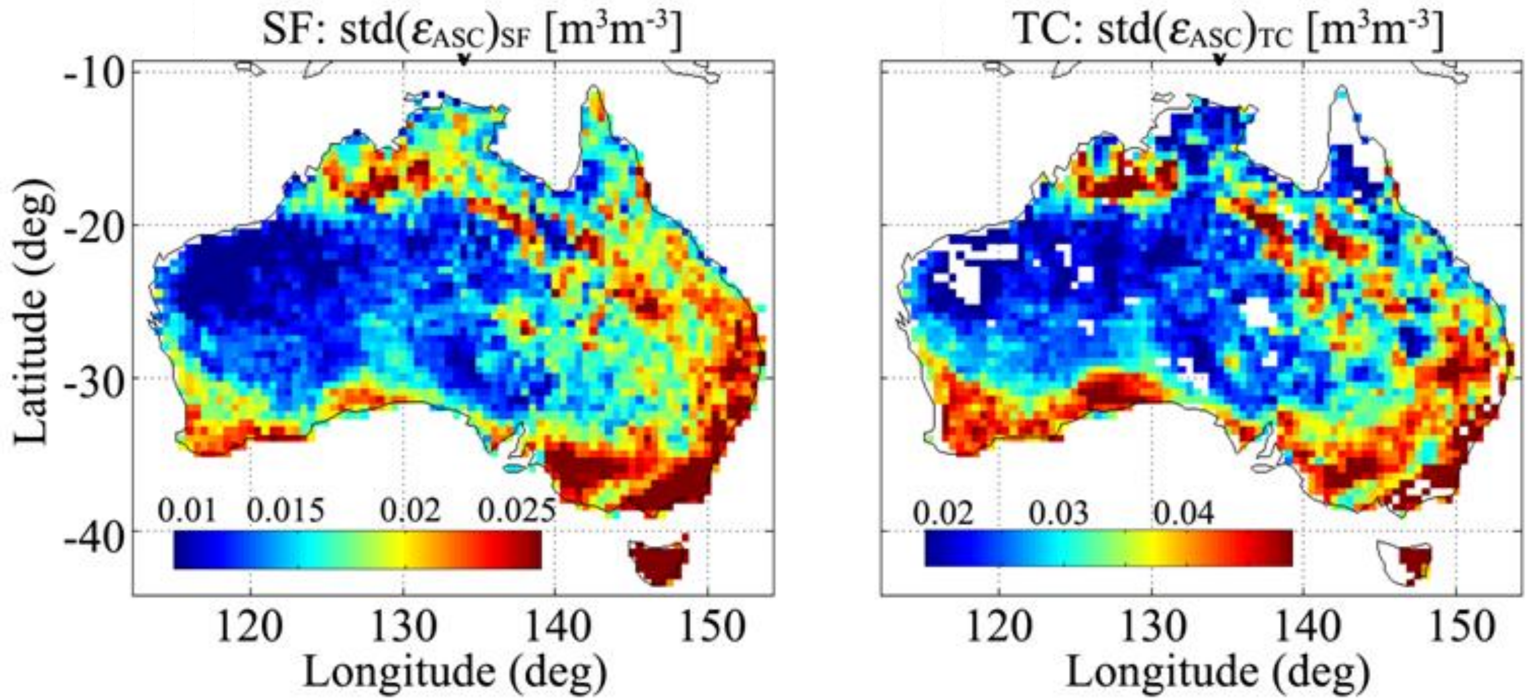
- **More easy interpretabilty** when expressed in **decibel** units

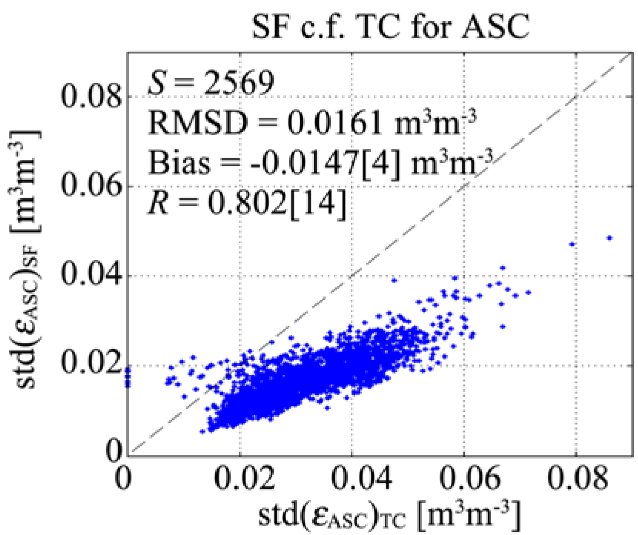
$$SNR_i[dB] = 10 \log \frac{Var(\Theta)}{Var(\varepsilon_i)}$$

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



Spectral Fitting versus Triple Collocation





Modified from Su, C. H., Ryu, D., Crow, W. T., & Western, A. W. (2014). Stand-alone error characterisation of microwave satellite soil moisture using a Fourier method. *Remote Sensing of Environment*, 154, 115-126.

Conclusions

- Our understanding of the information content of satellite soil moisture data has improved significantly over the past few years

- SNR estimated through triple collocation or spectral fitting is a more meaningful measure than the RMSE between satellite data and an assumed “truth”
  - When using SNR, the added value of satellite data over models becomes apparent

- High-quality of ASCAT soil moisture retrievals opens up new and unexpected applications
  - ASCAT rainfall estimates

- ASCAT soil moisture “product family” has already a few thousand users

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