European High-Resolution Soil Moisture Analysis (EHRSOMA)

Jasmin Vural

EUMETSAT Fellow Day, 05.03.2018

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Goals:

- **Error estimation and implementation**
- **Improve spatial resolution of data assimilation**
- **Performance of data assimilation**

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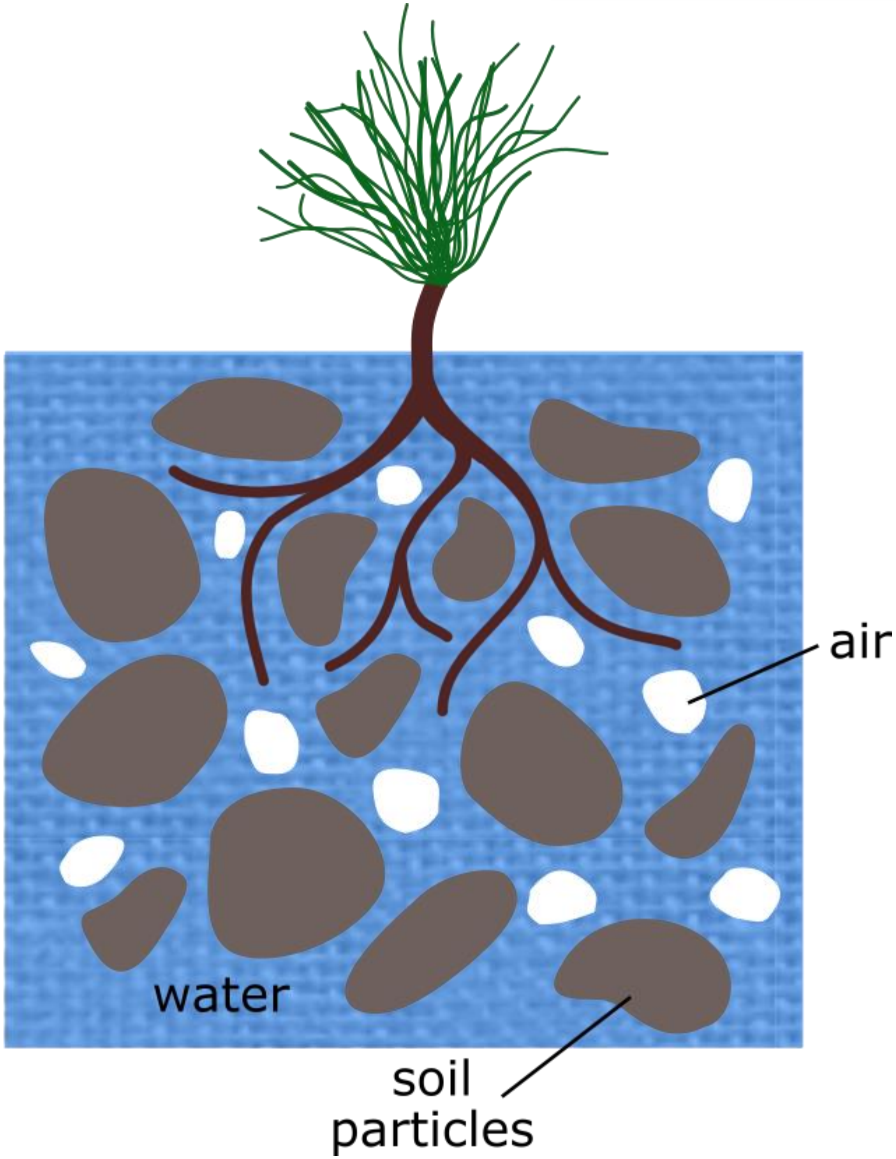
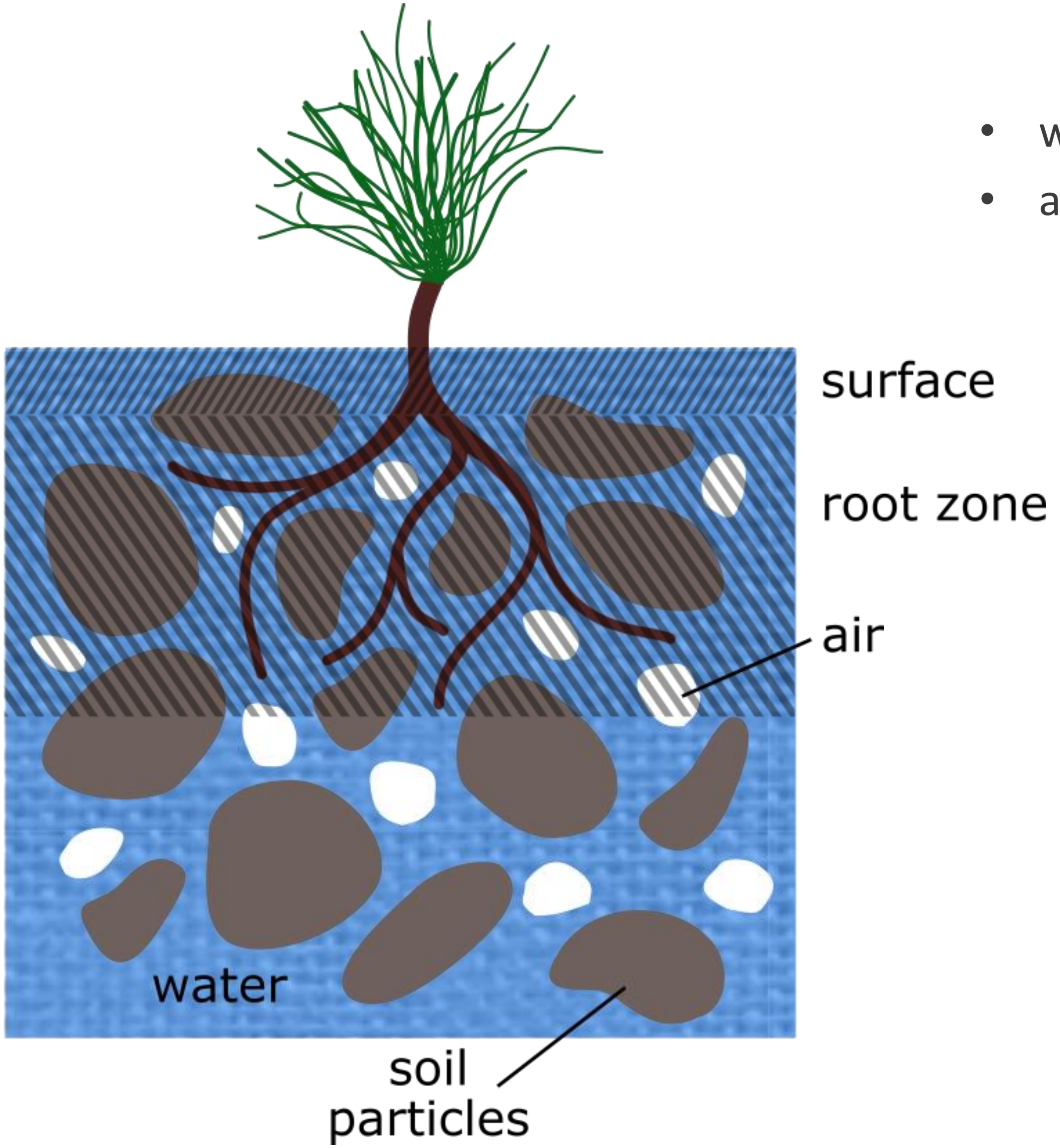
Soil moisture



- water content of unit of soil
- approx. 0.005% of terrestrial water

Soil moisture



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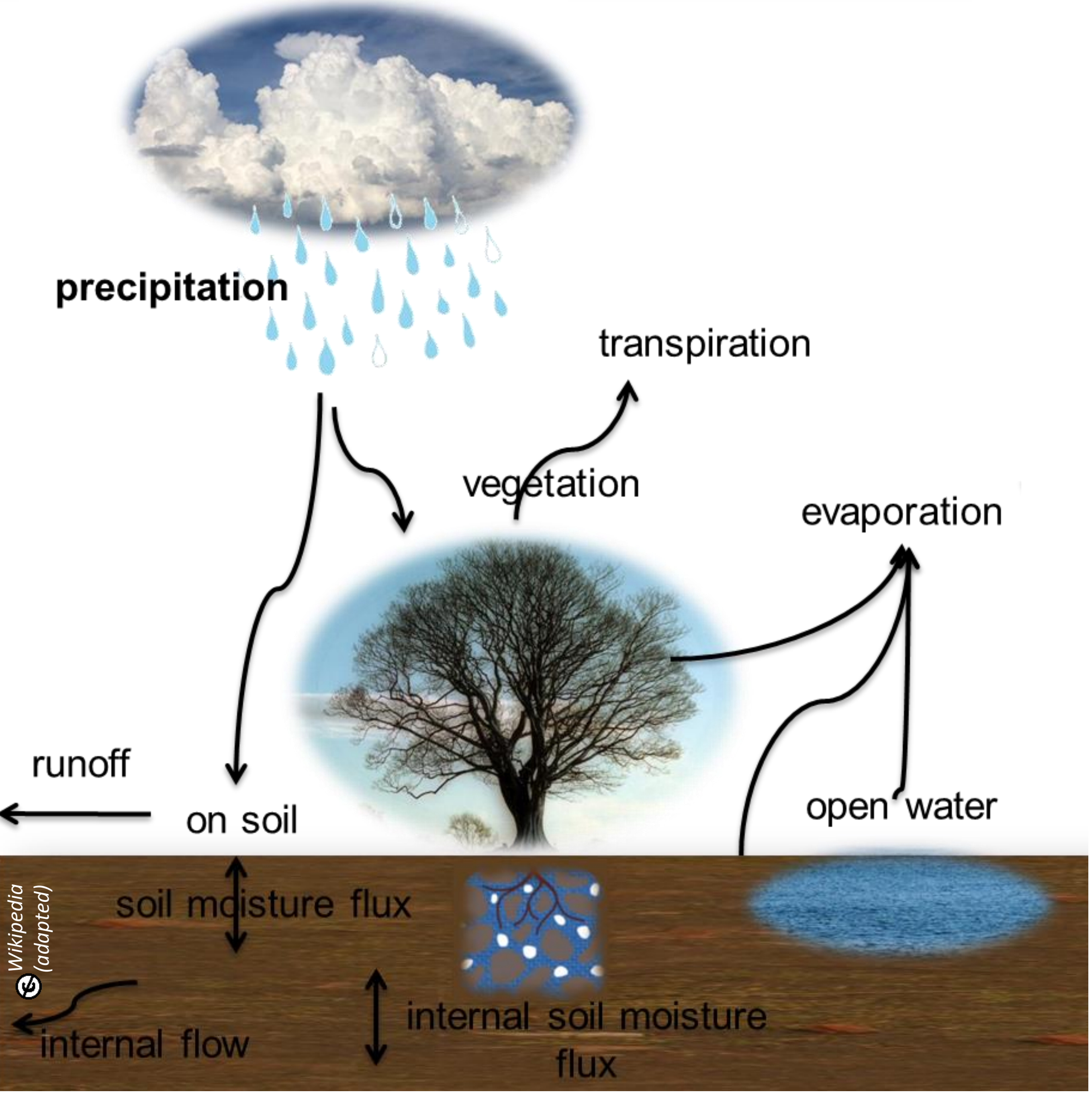
→ soil water index

$$SWI = \frac{w_{root} - w_{wilt}}{w_{fc} - w_{wilt}}$$

Soil moisture



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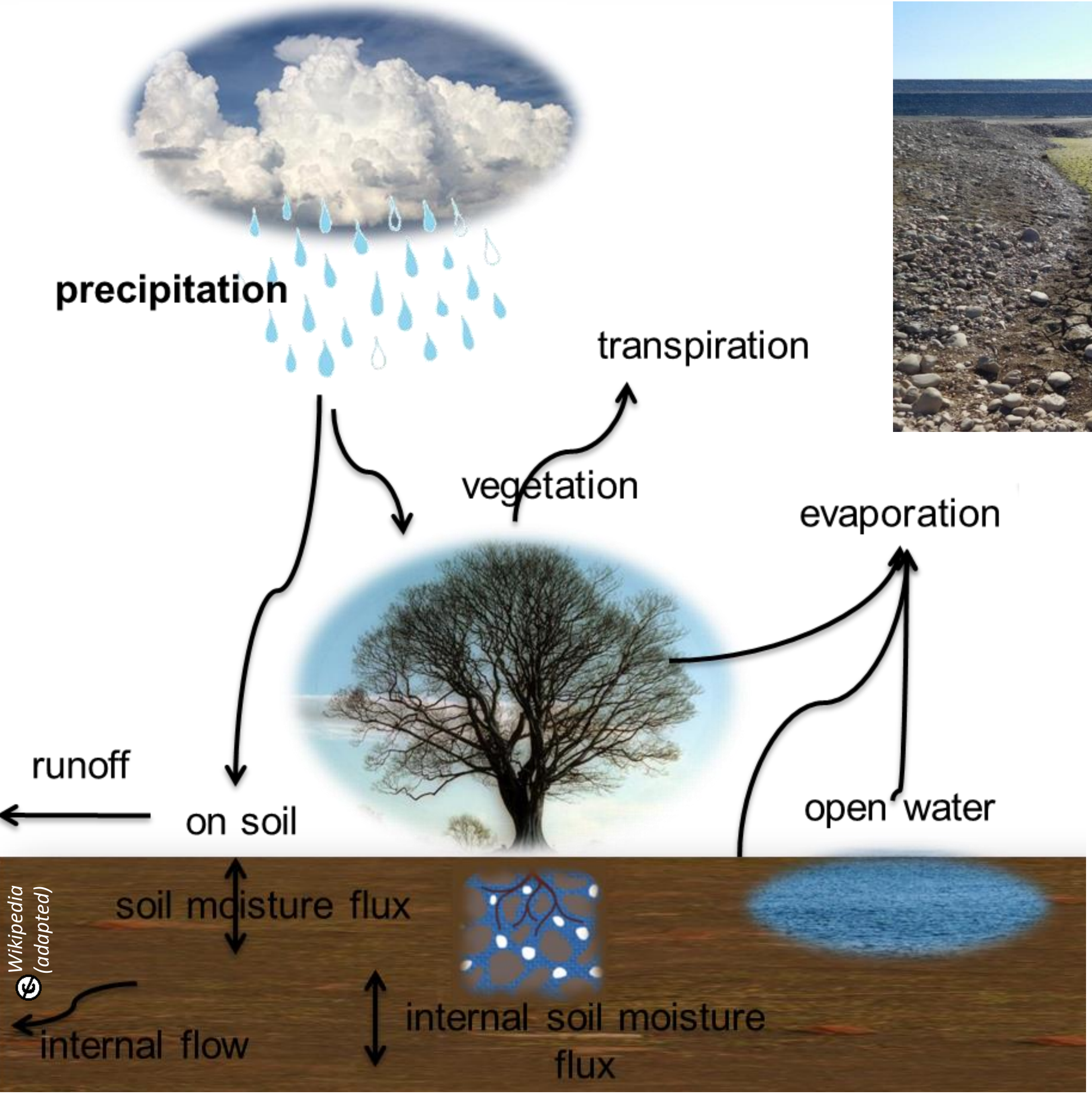
Soil moisture



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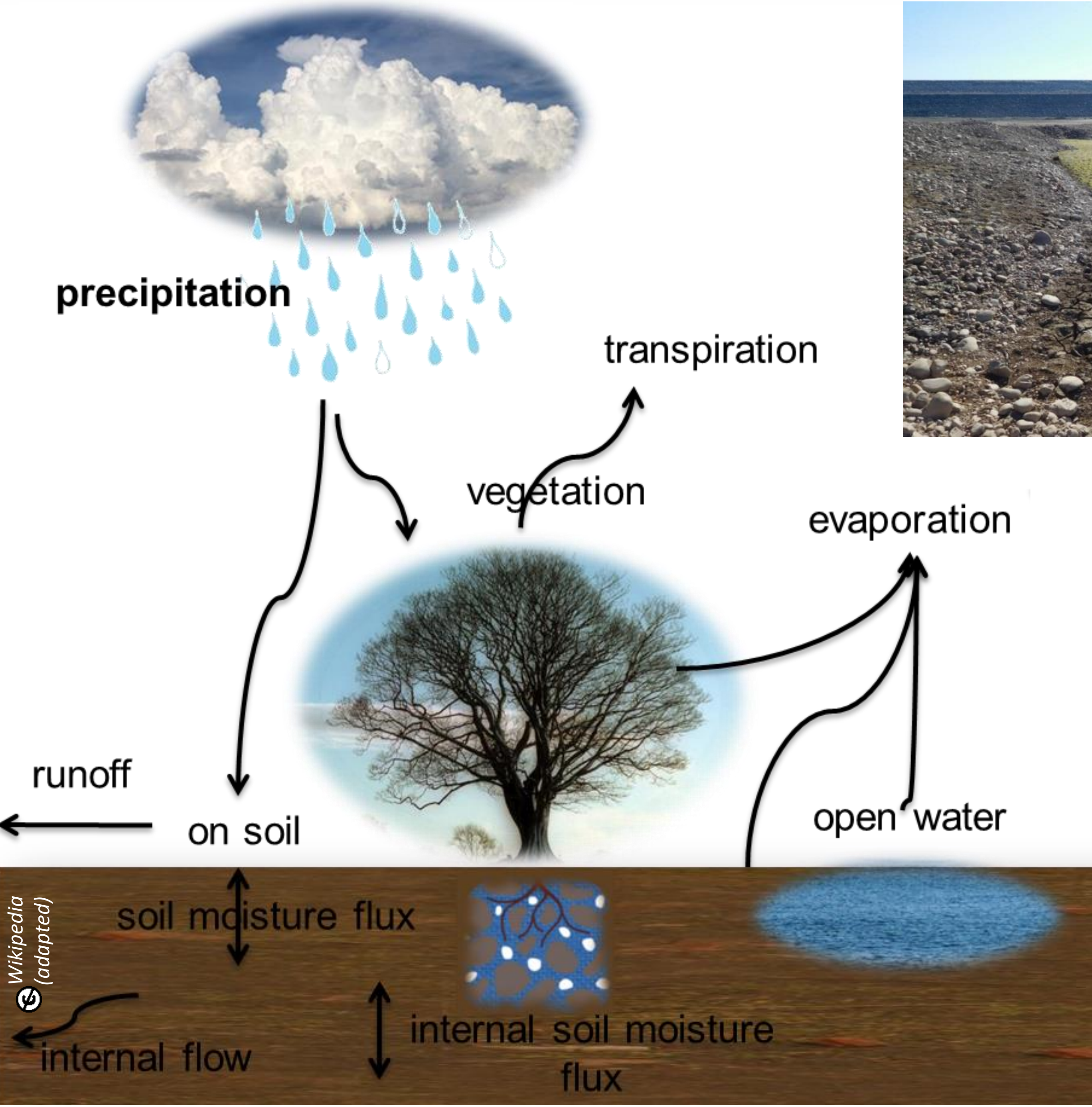

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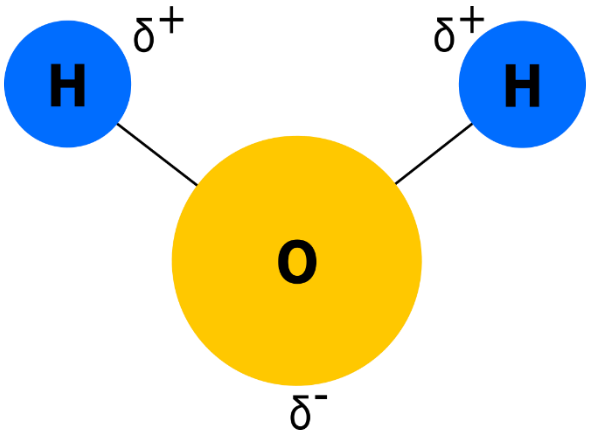
Measuring soil moisture

Basics

- Oriental polarisation of dipoles



- Orientation changes of applied electric field are followed below relaxation frequency f_r

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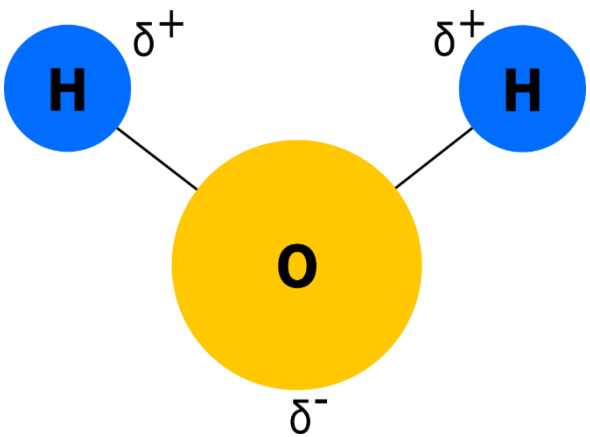

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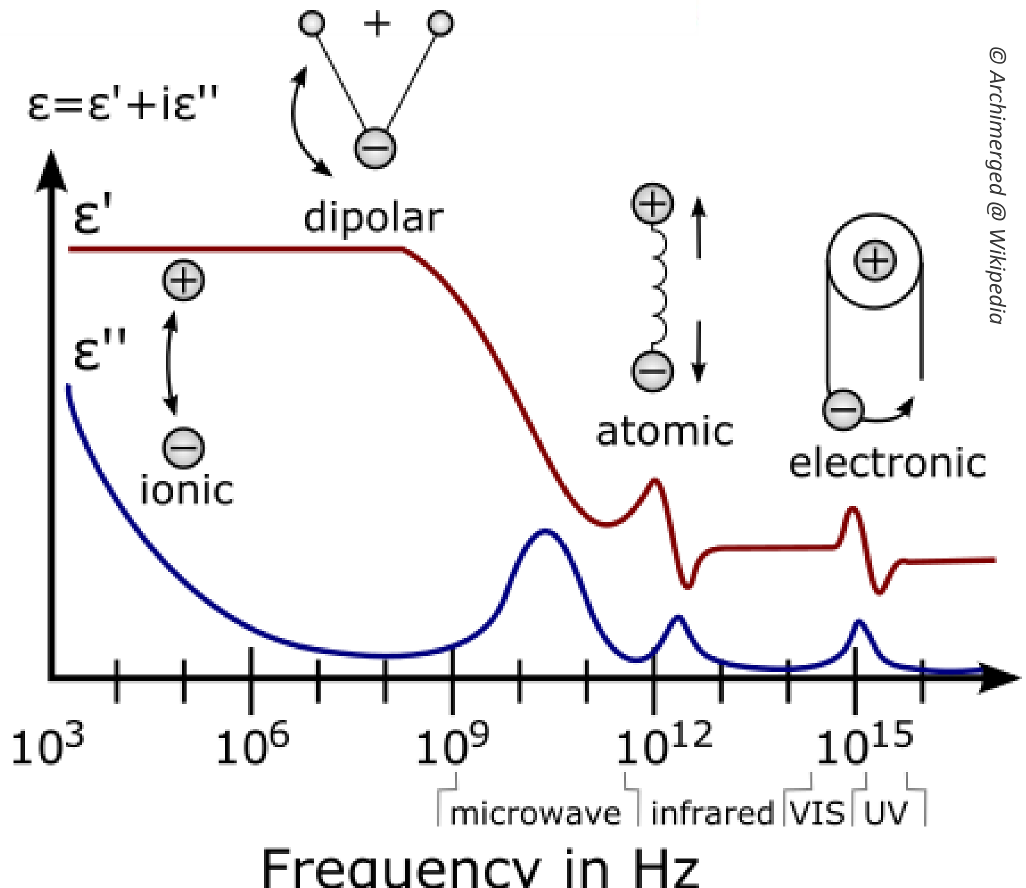

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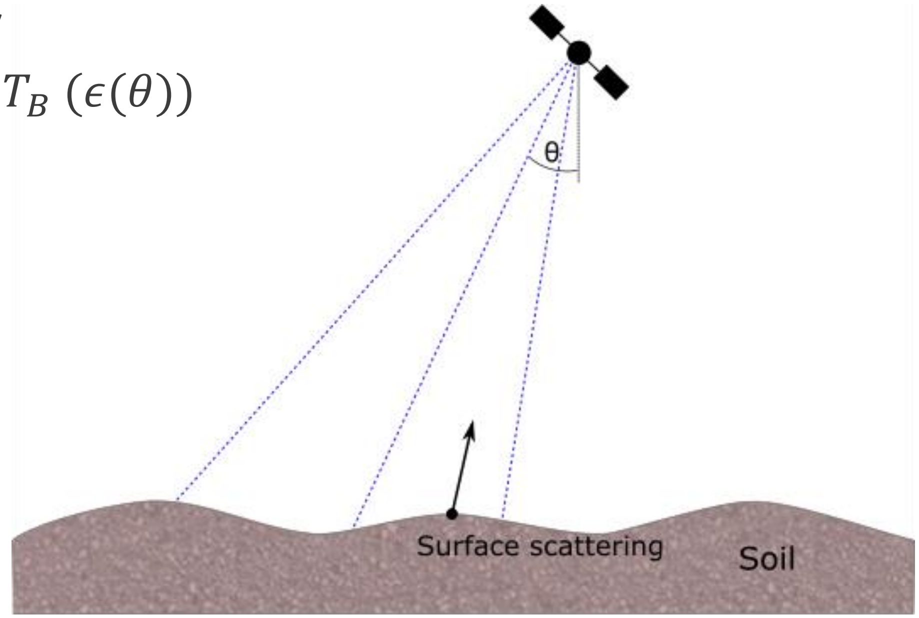
Measuring soil moisture

Remote sensing

- Backscatter coefficient measured remotely
  → brightness temperature of backscatter $T_B\ (\epsilon(\theta))$
  → properties of scattering objects



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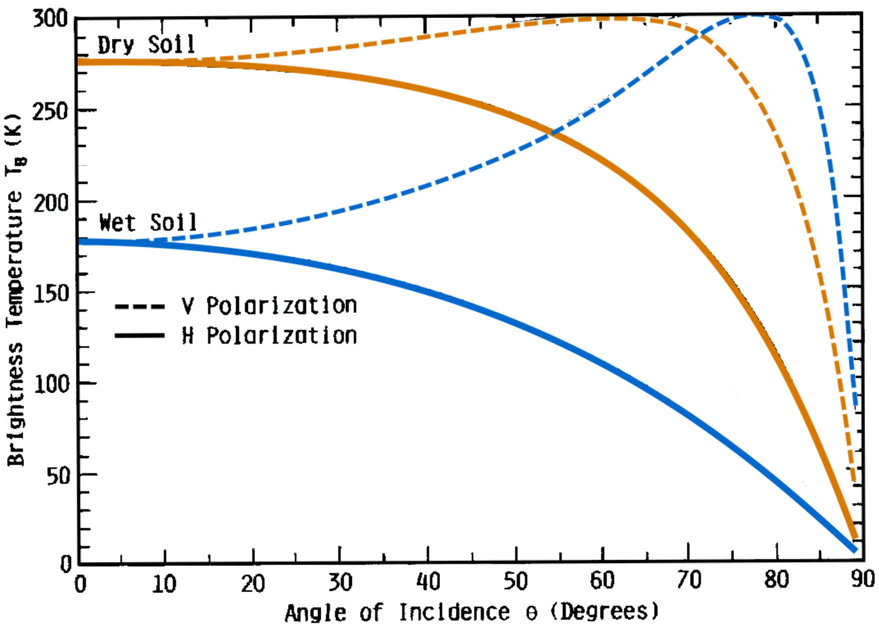
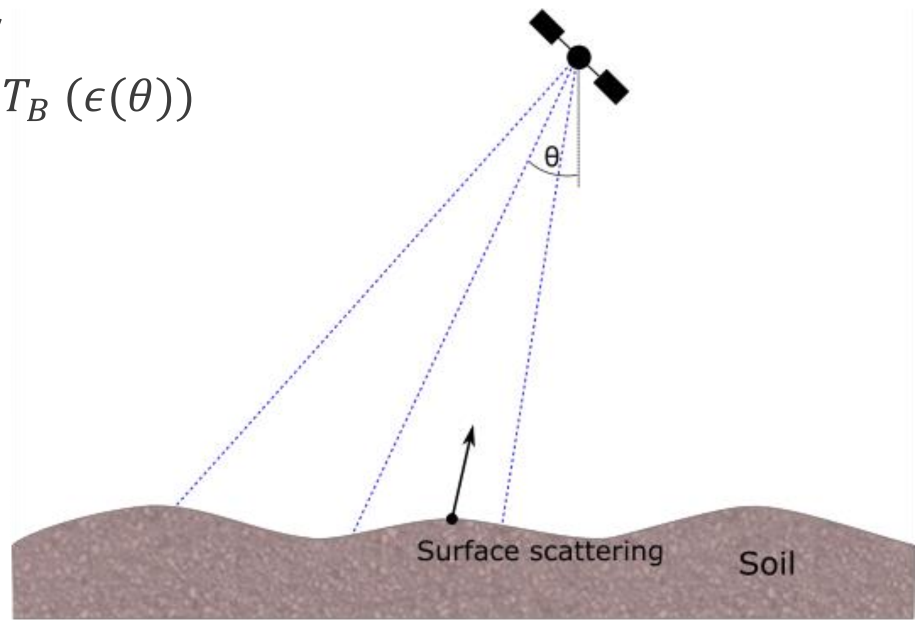


© Ulaby, Moore, Fung 1981; adapted



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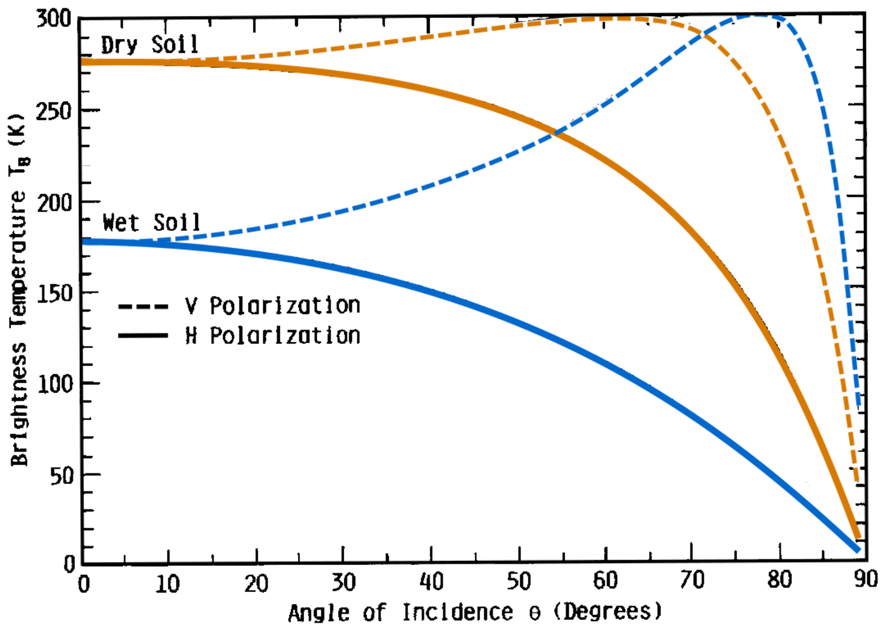
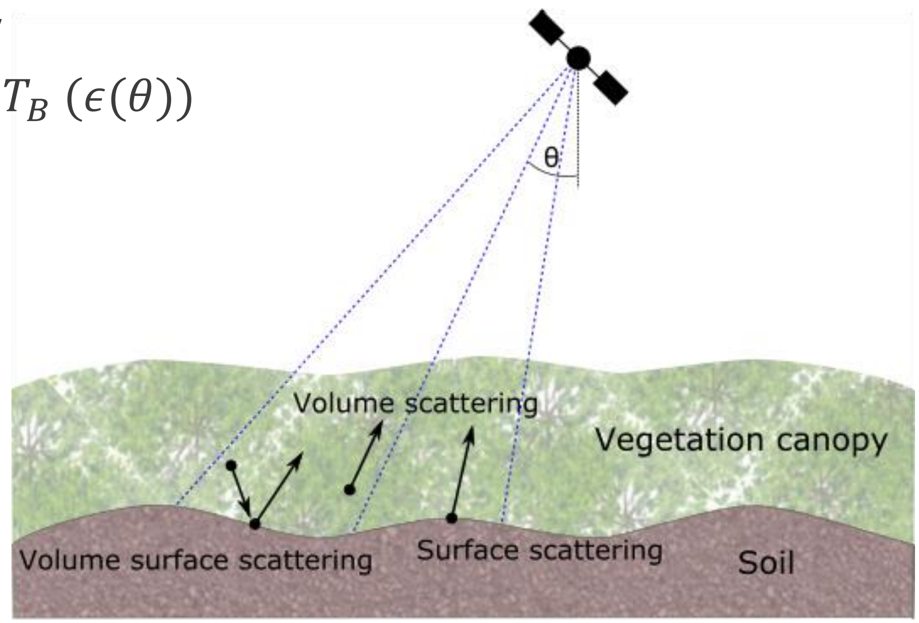
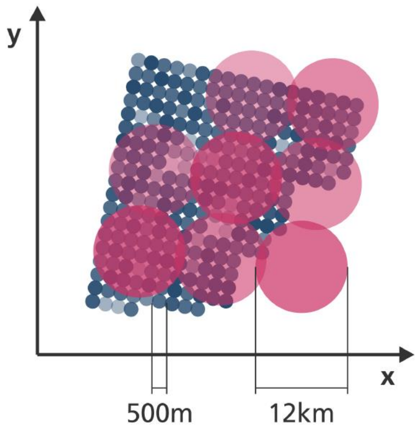




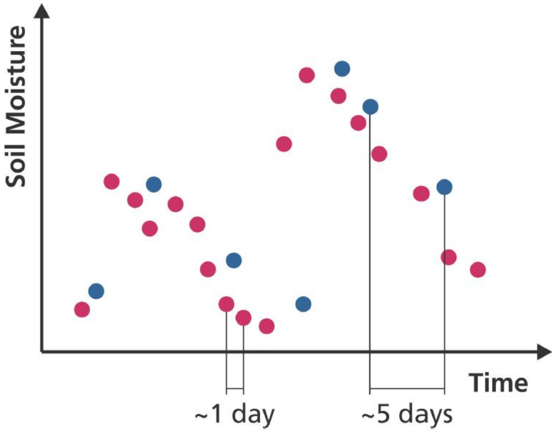
Measuring soil moisture

MetOp/ASCAT + Sentinel-1/SAR = SCATSAR

Spatial Match



Temporal Match



● MetOp ASCAT Observation
● Sentinel-1 SAR Observation

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Measuring soil moisture

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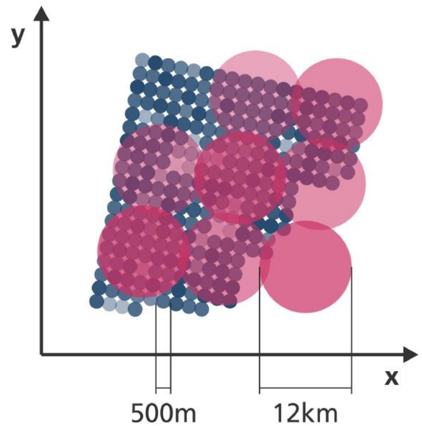

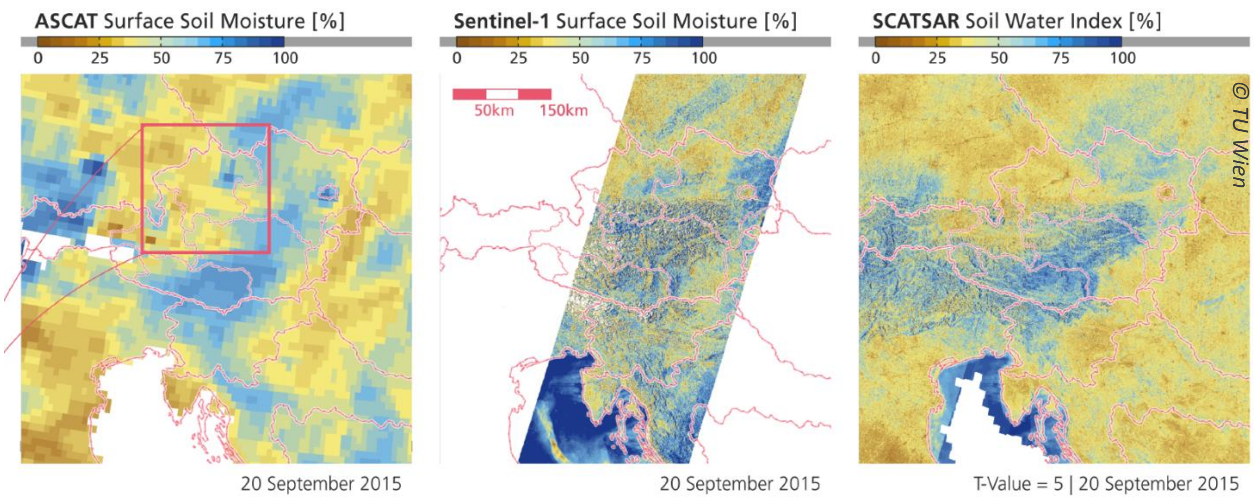

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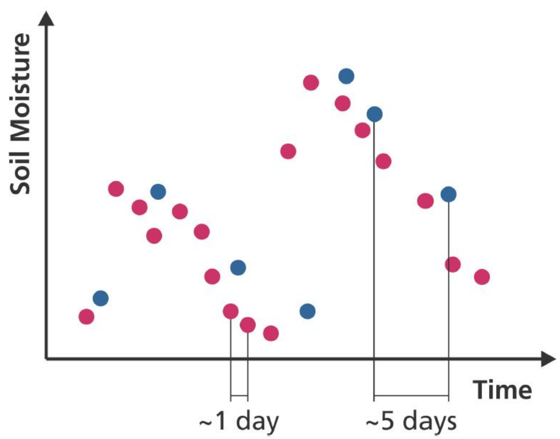

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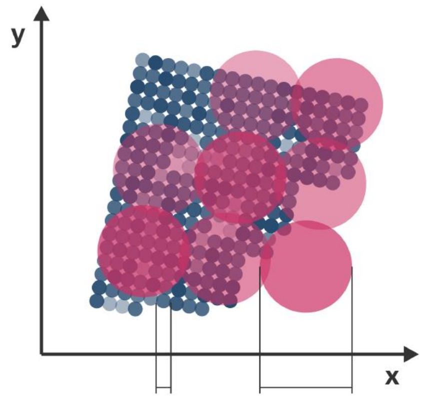

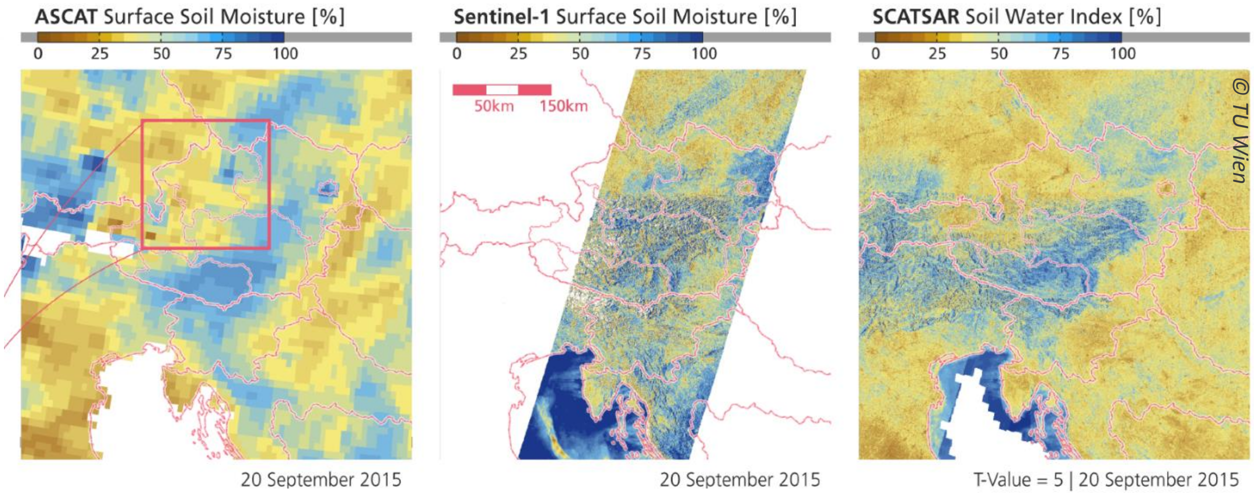

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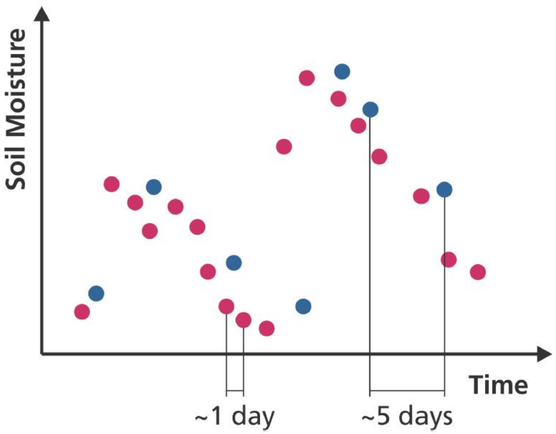

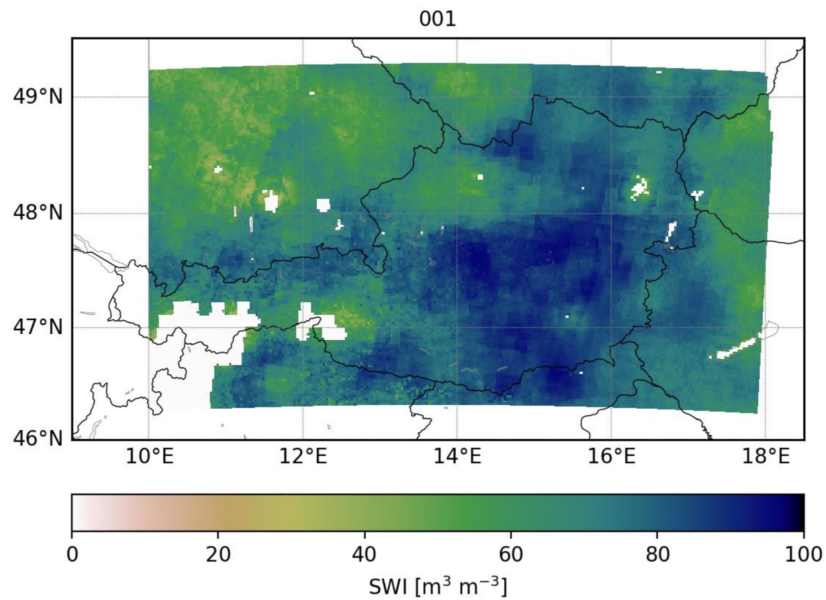

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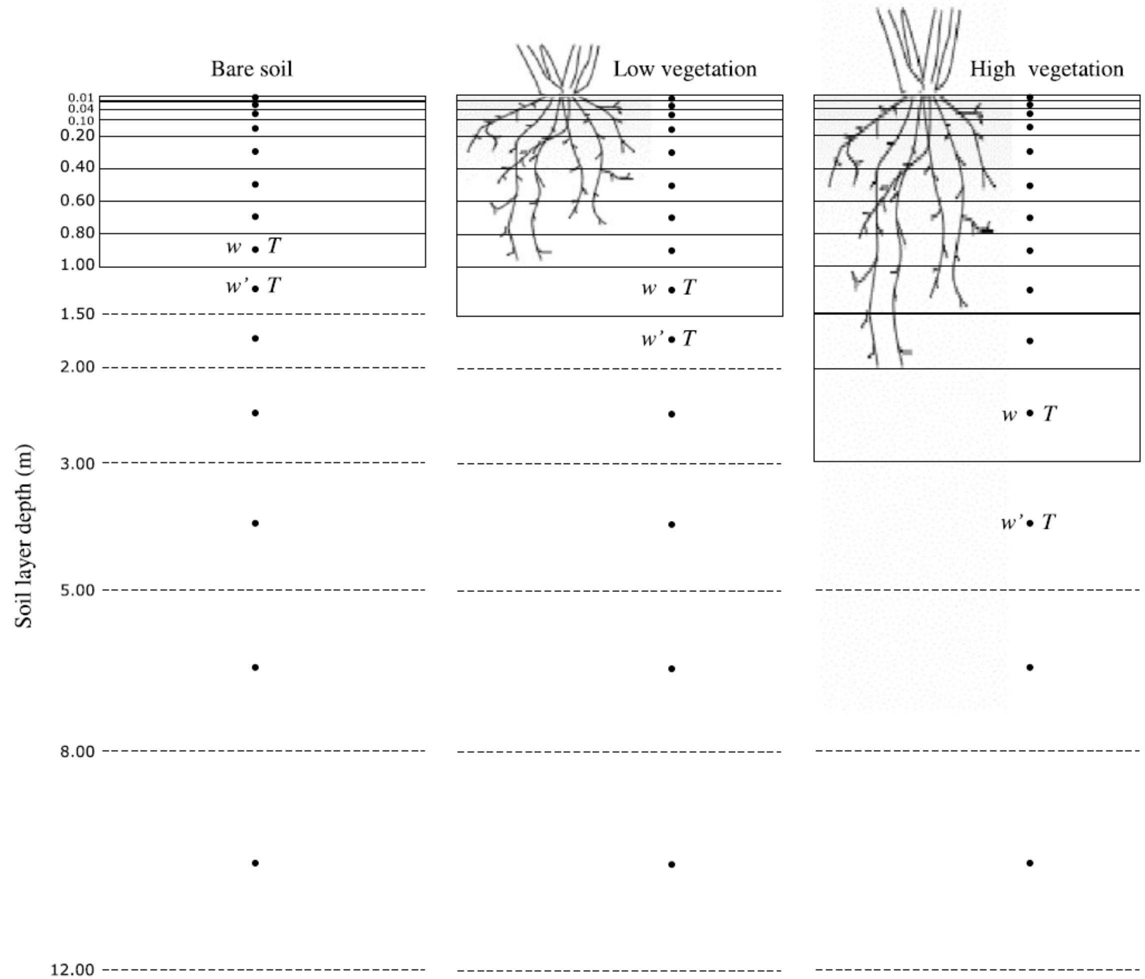
Data assimilation

Land surface model

Interaction Soil Biosphere Atmosphere (ISBA)

- 14 vertical levels
- only vertical exchange



© Decharme et al. 2013

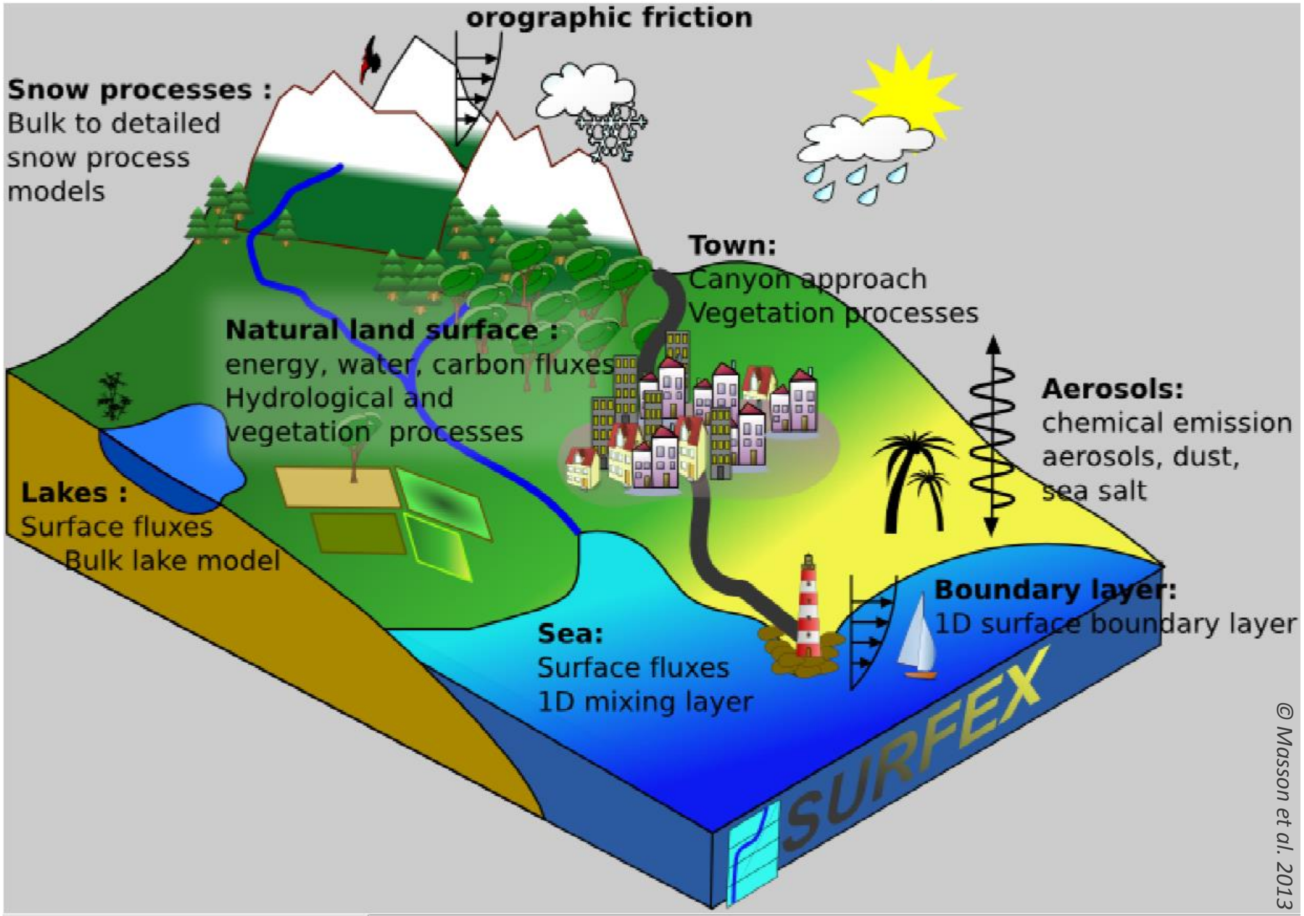
Data assimilation

Land surface model

SURFEX 8.1

- 259 x 133 grid points
- 2.5km resolution

- SURFEX Offline Data Assimilation (SODA)
- atmospheric forcing by AROME



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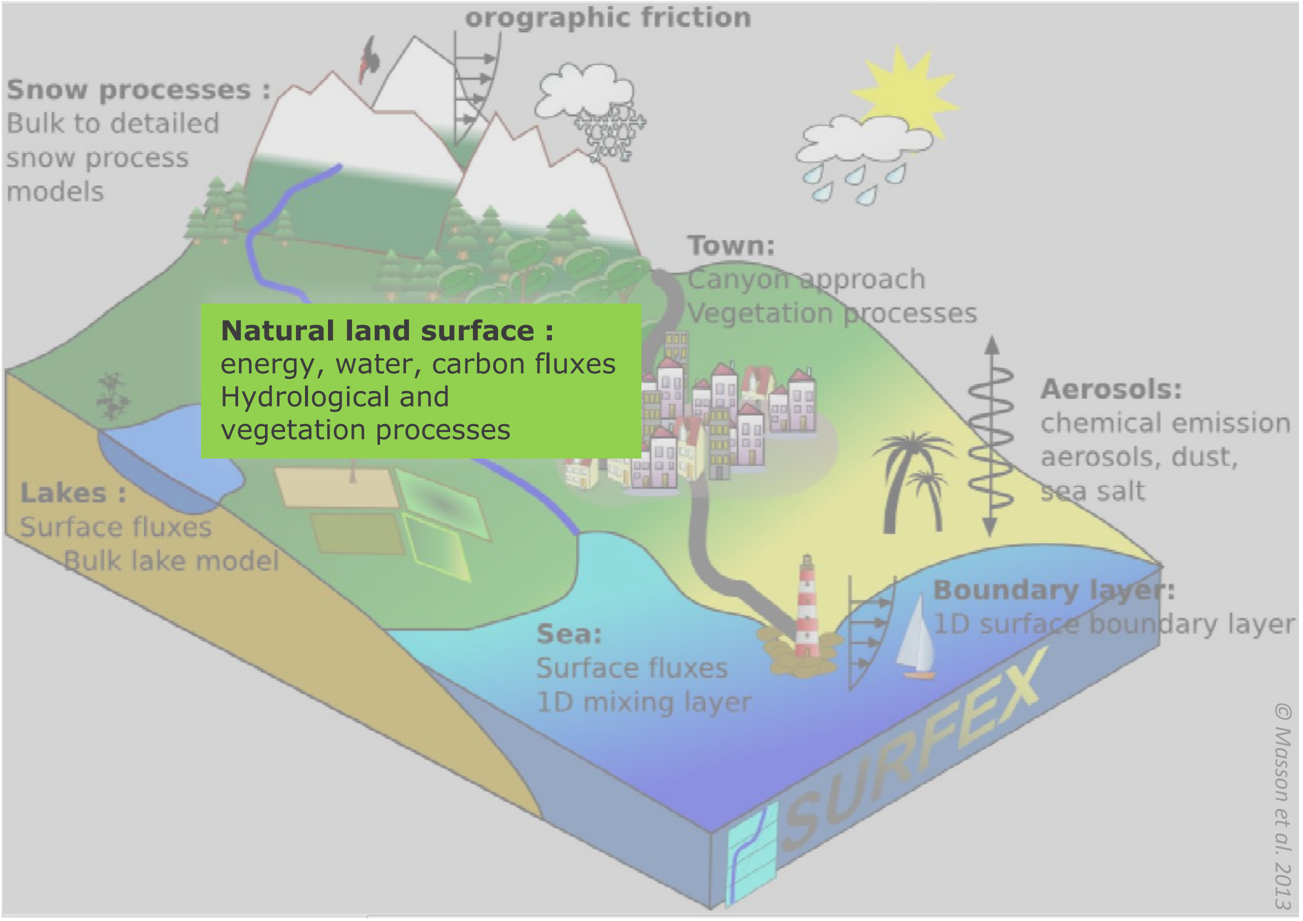


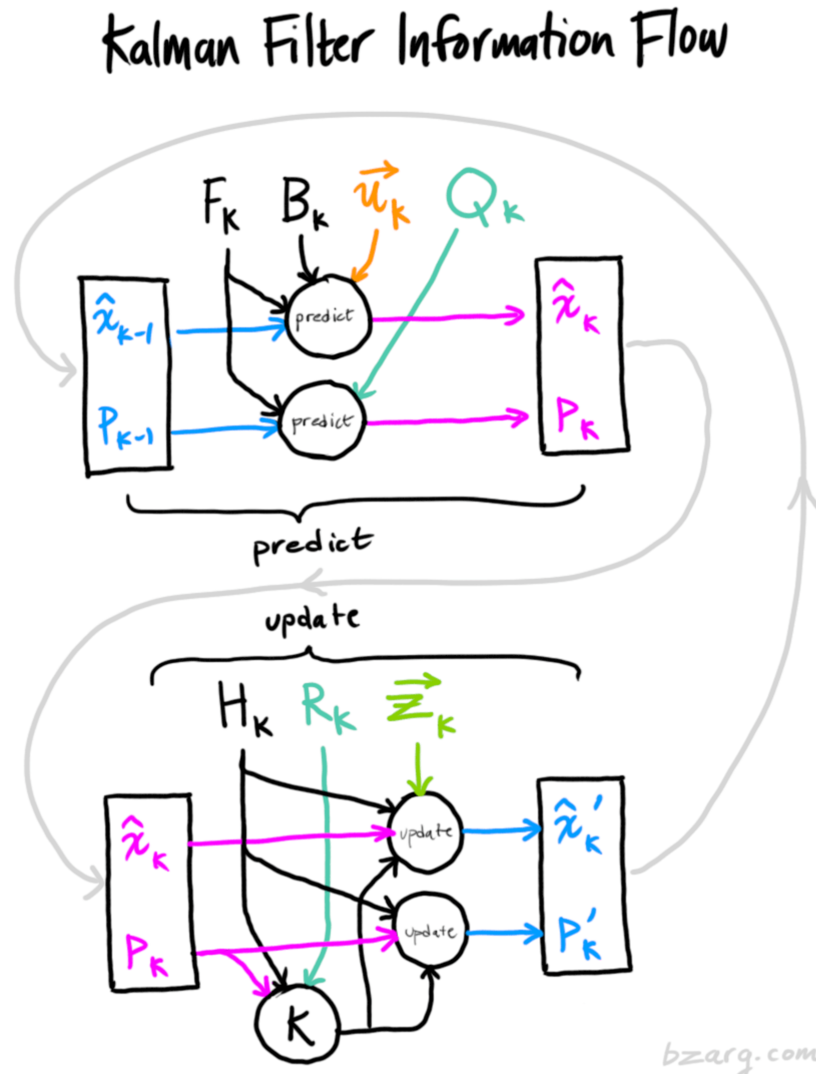
Data assimilation

Kalman Filter

Forecasting $\hat{x}_k = F_k \hat{x}_{k-1} + B_k \vec{u}_k$

Update $\hat{x}'_k = \hat{x}_k + K'(\vec{z}_k - H_k \hat{x}_k)$

Kalman gain $K' = P_k H_k^T \, (H_k P_k H_k^T + R_k)^{-1}$



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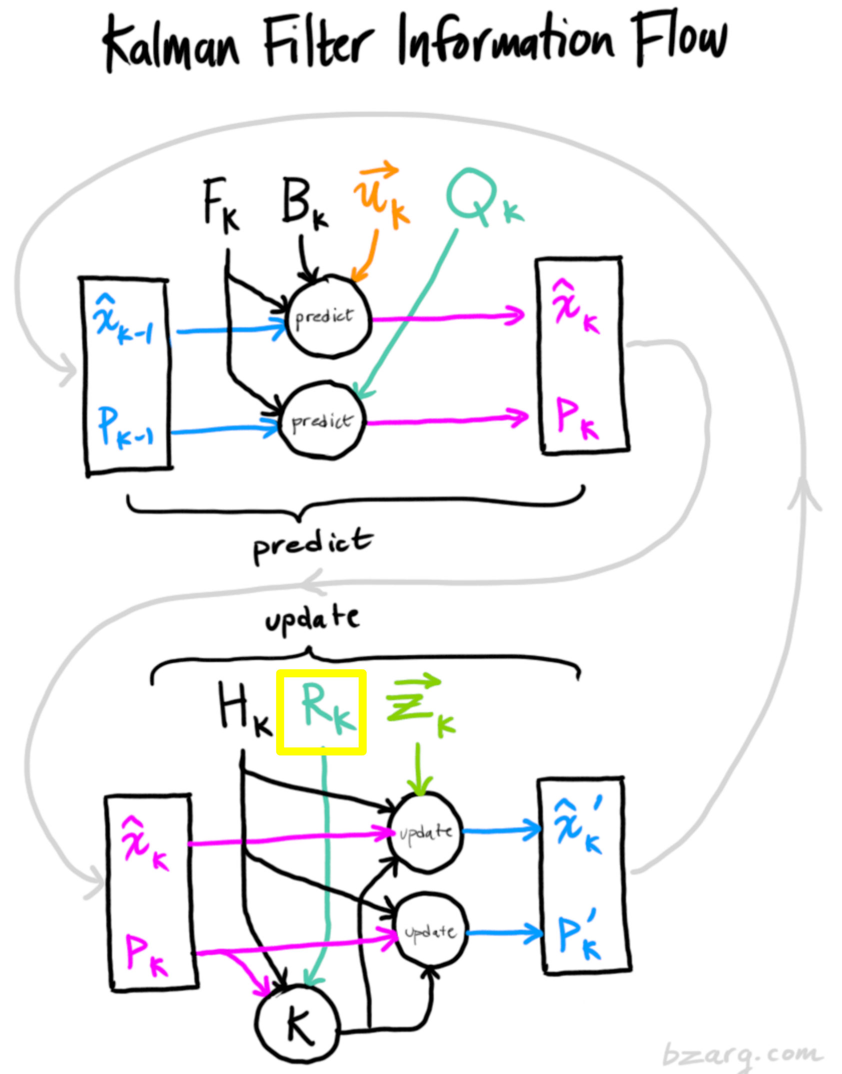
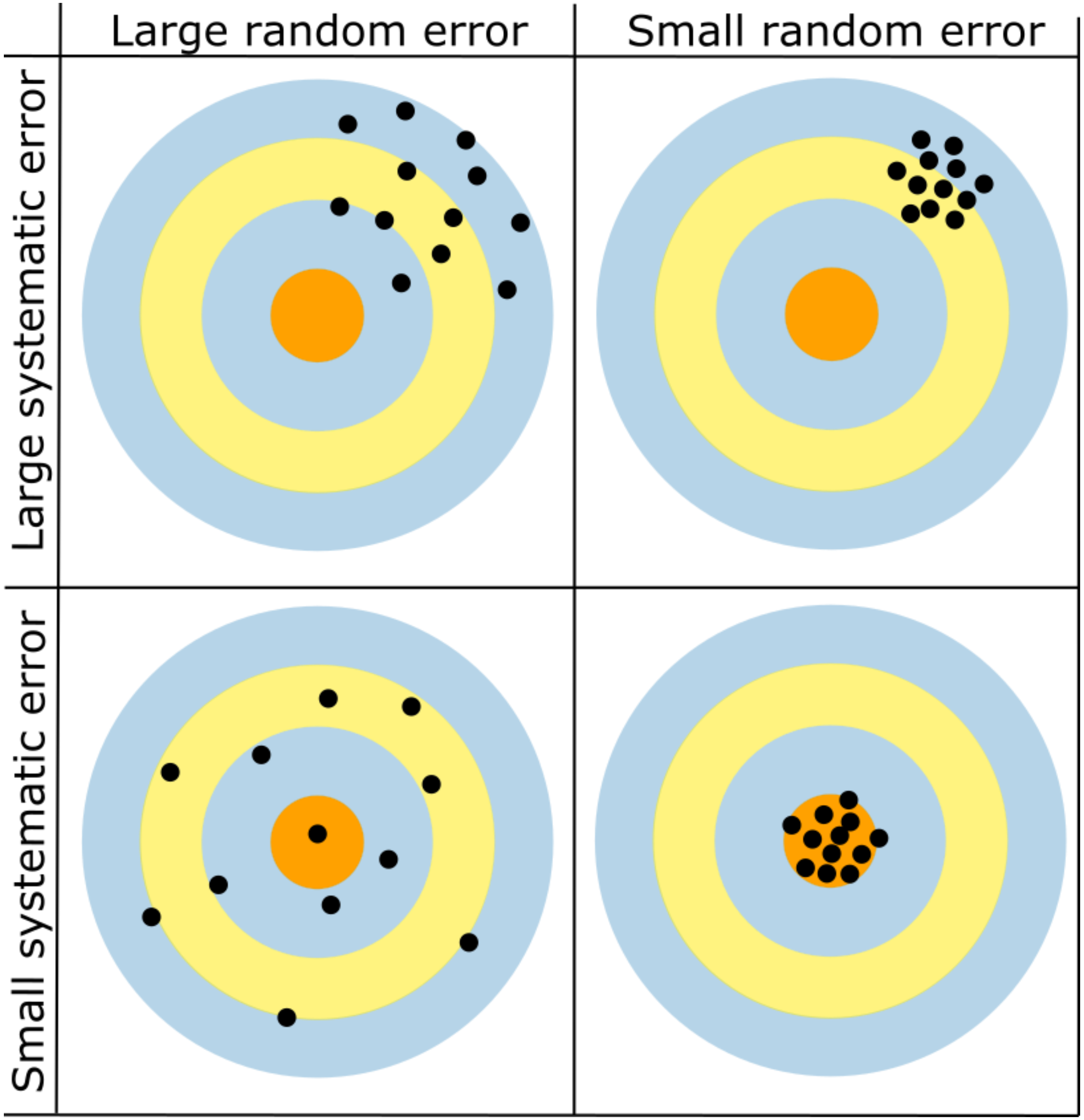
Measurement uncertainty $R_{ii} = \sigma^2_{obs,i}$



Observation errors



Systematic errors

- dependent on instrument

Random errors

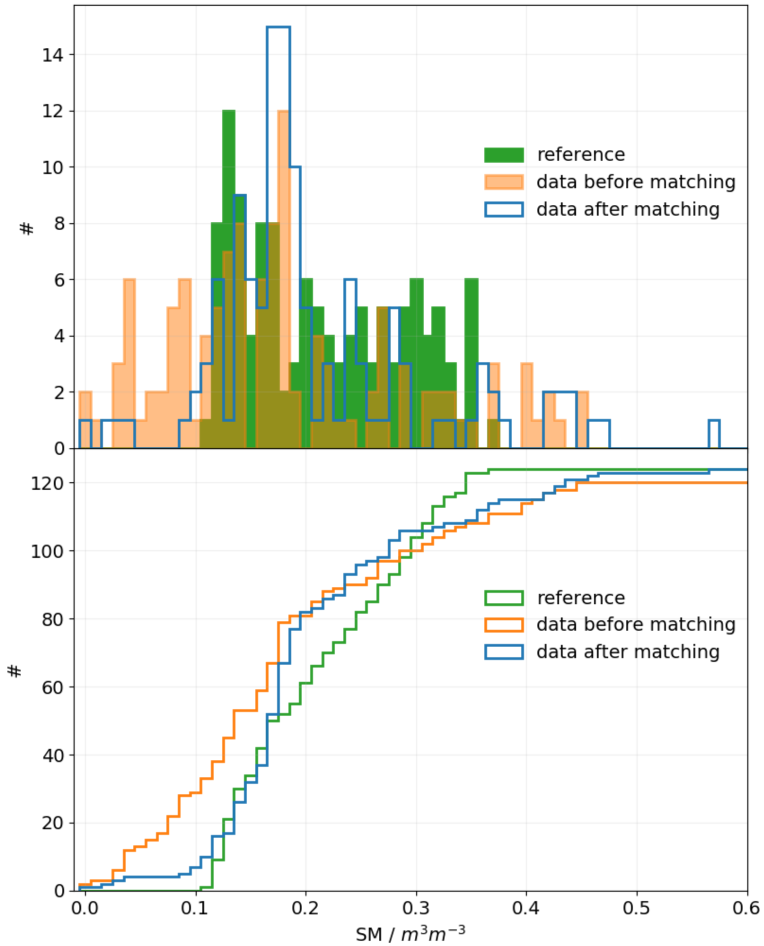
- noise
- assumed to be normally distributed

Observation errors

Systematic errors

Bias correction

- data set (SCATSAR) + reference (SURFEX)
- match cumulative density functions
- apply fit parameters to actual data



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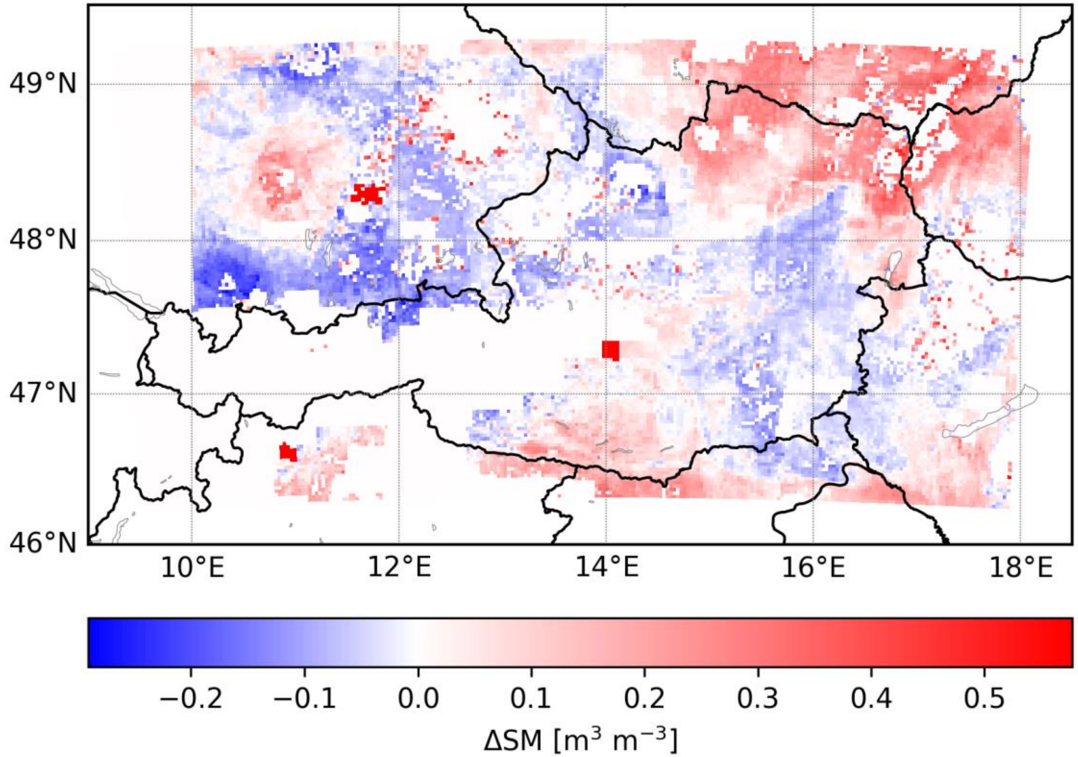

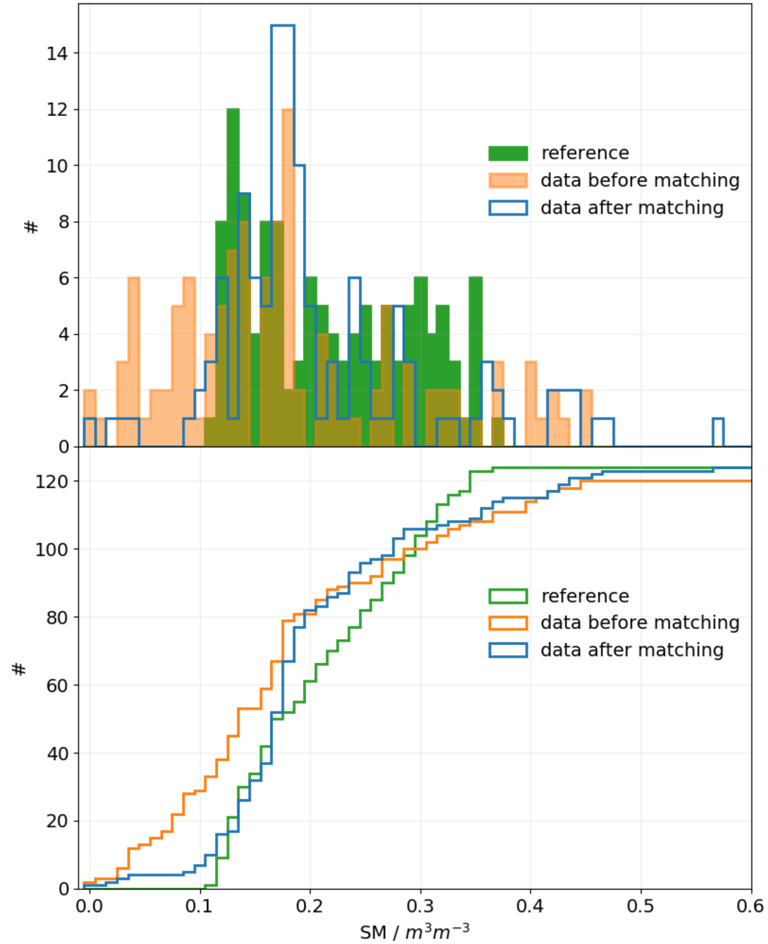

Observation errors

Random errors

Triple Collocation

- error model:

$$\Theta_i = \alpha_i + \beta_i \Theta + \varepsilon_i$$

i: active & passive data sets & reference

SCATSAR AMSR2 SURFEX

Observation errors

Random errors

Triple Collocation

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SCATSAR AMSR2 SURFEX

- assumptions:
  - linearity of error model
  - signal stationarity → same climatology for all data sets
  - error stationarity → dependent on length of time period (seasons!)
  - independency between Θ_i and ε_i (error orthogonality) → negligible
  - independency between errors (zero error cross-correlation)
    → different type of observations

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→ Python Toolbox for the Evaluation of Soil Moisture Observations (pytesmo) of TU Wien http://pytesmo.readthedocs.io

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Observation errors

Random errors

bias corrected data → time series → correlation? point # ? → Triple Collocation

Observation errors

Random errors

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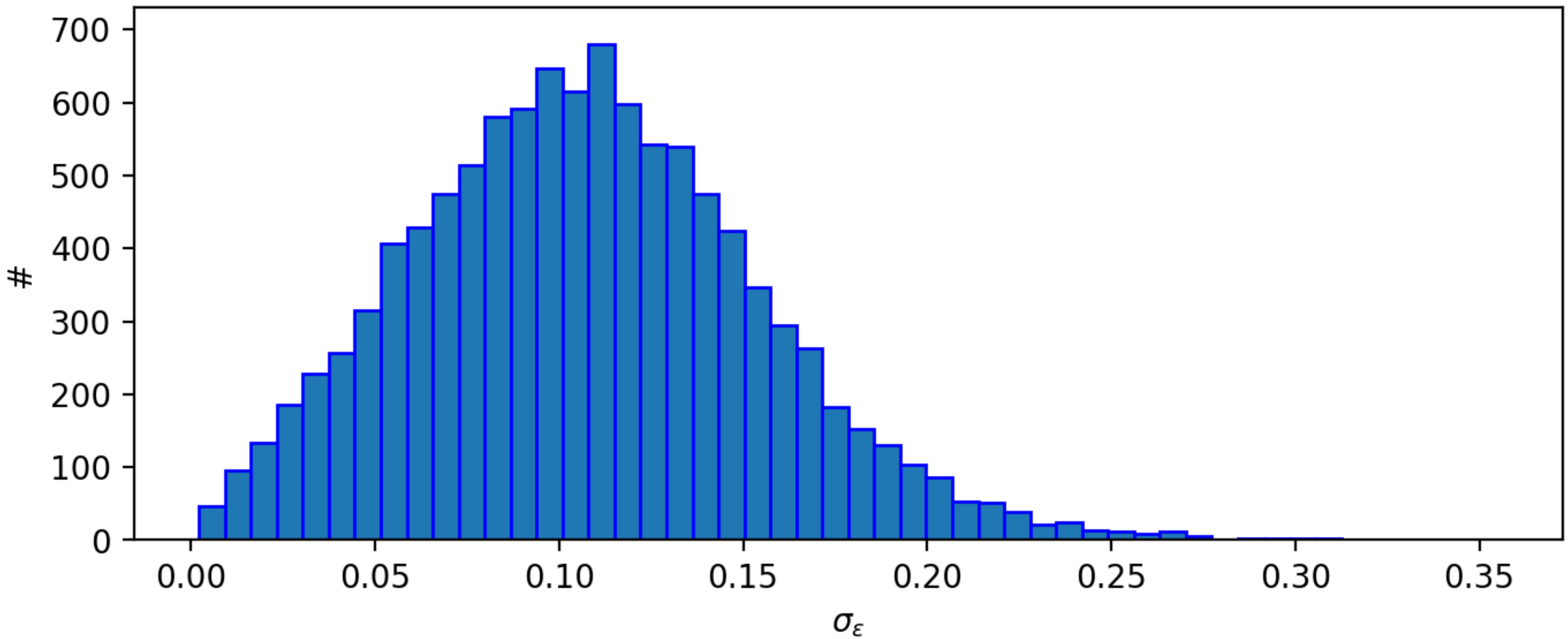

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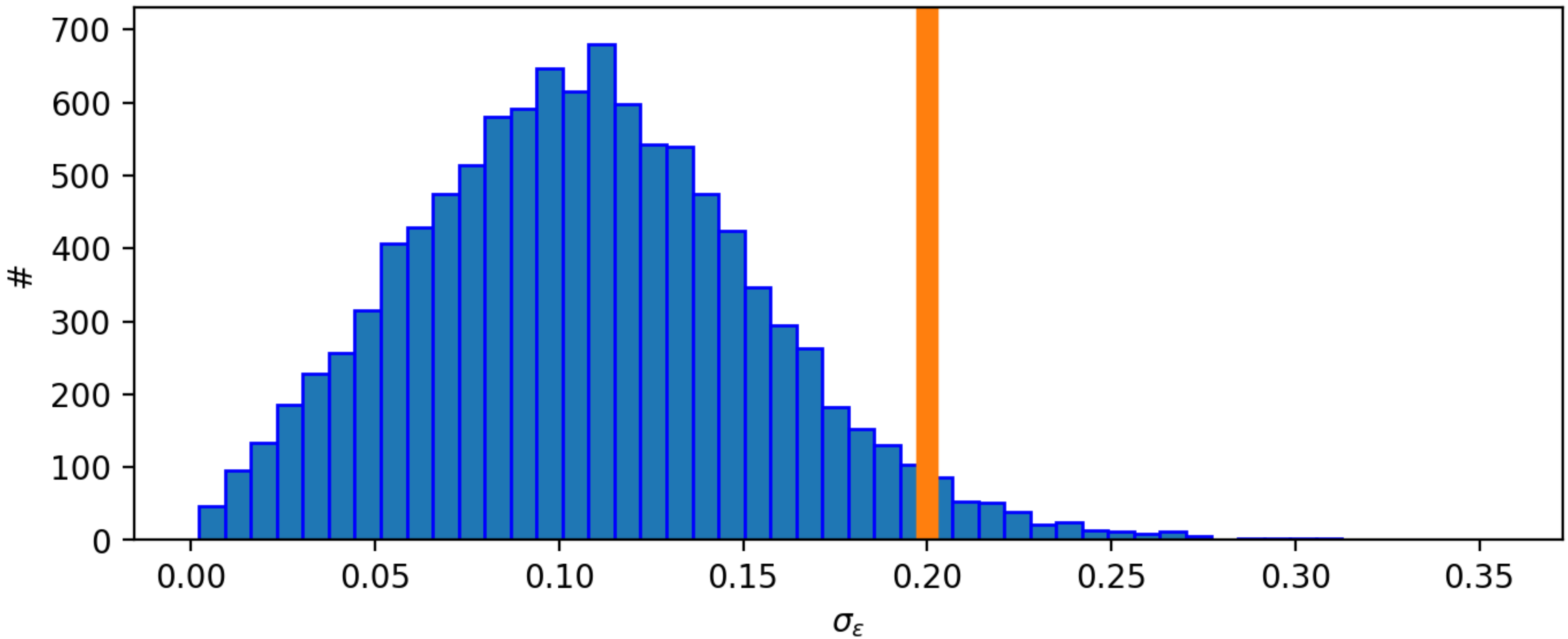

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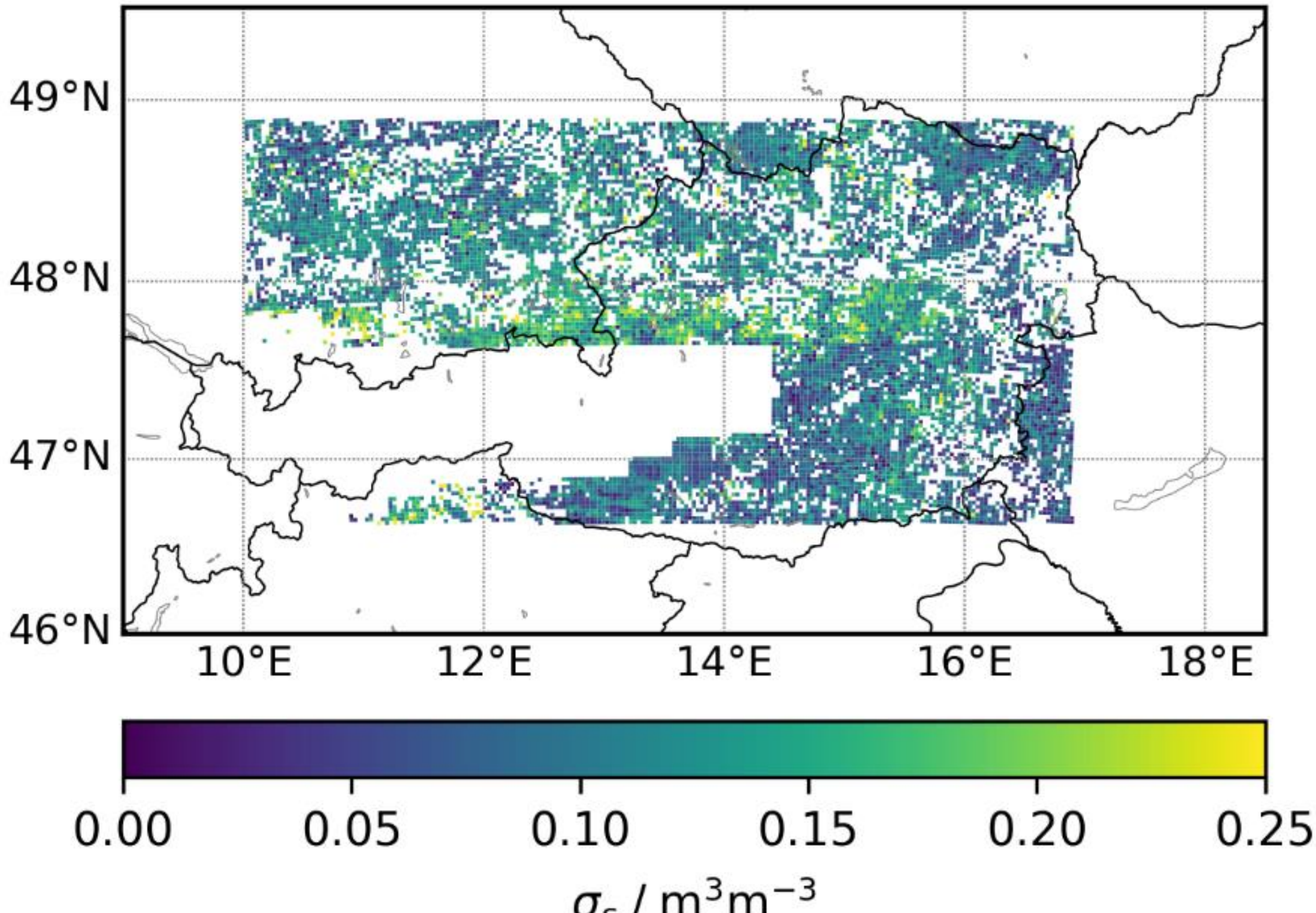

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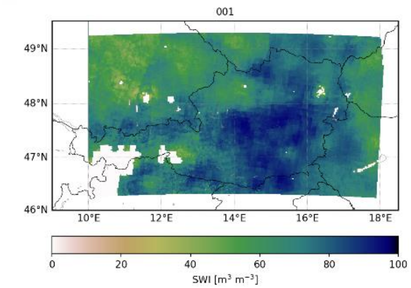
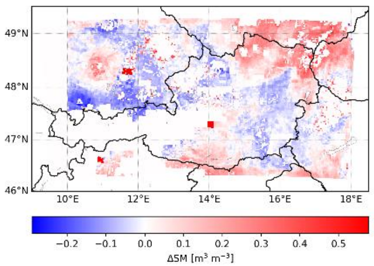
Summary

- SCATSAR data → high spatial & temporal resolution



- Bias correction → systematic error



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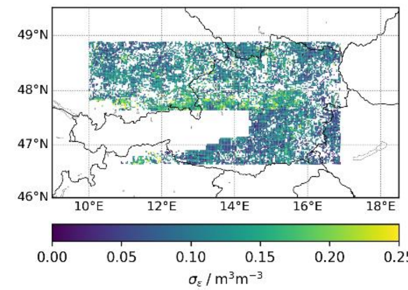
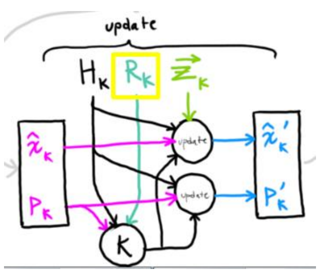


- Covariance matrix of observation error → data assimilation



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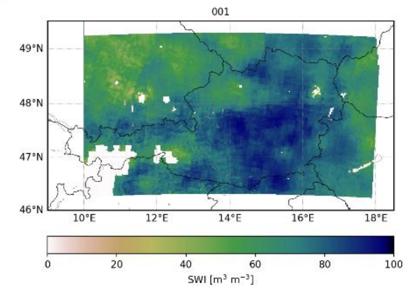

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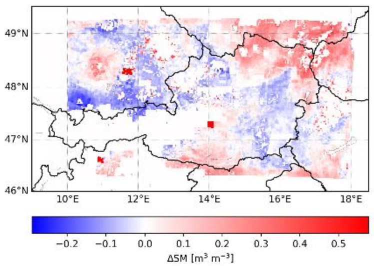

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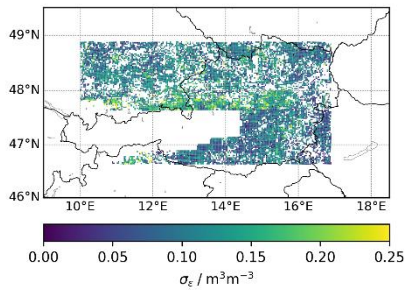

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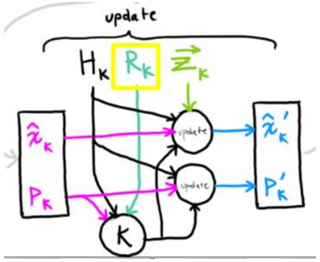

Thanks to

Stefan Schneider (ZAMG)

Alexander Gruber (TU Wien)

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