Starlab
Living Science

TWIGA

H2020

EGU General Assembly 2020

Combining Sentinel-1 and -2 With In-Situ Data to provide Tim e Series of Soil Moisture Maps at Regional Scale in Ghana

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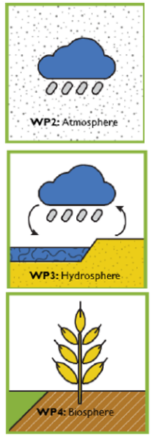
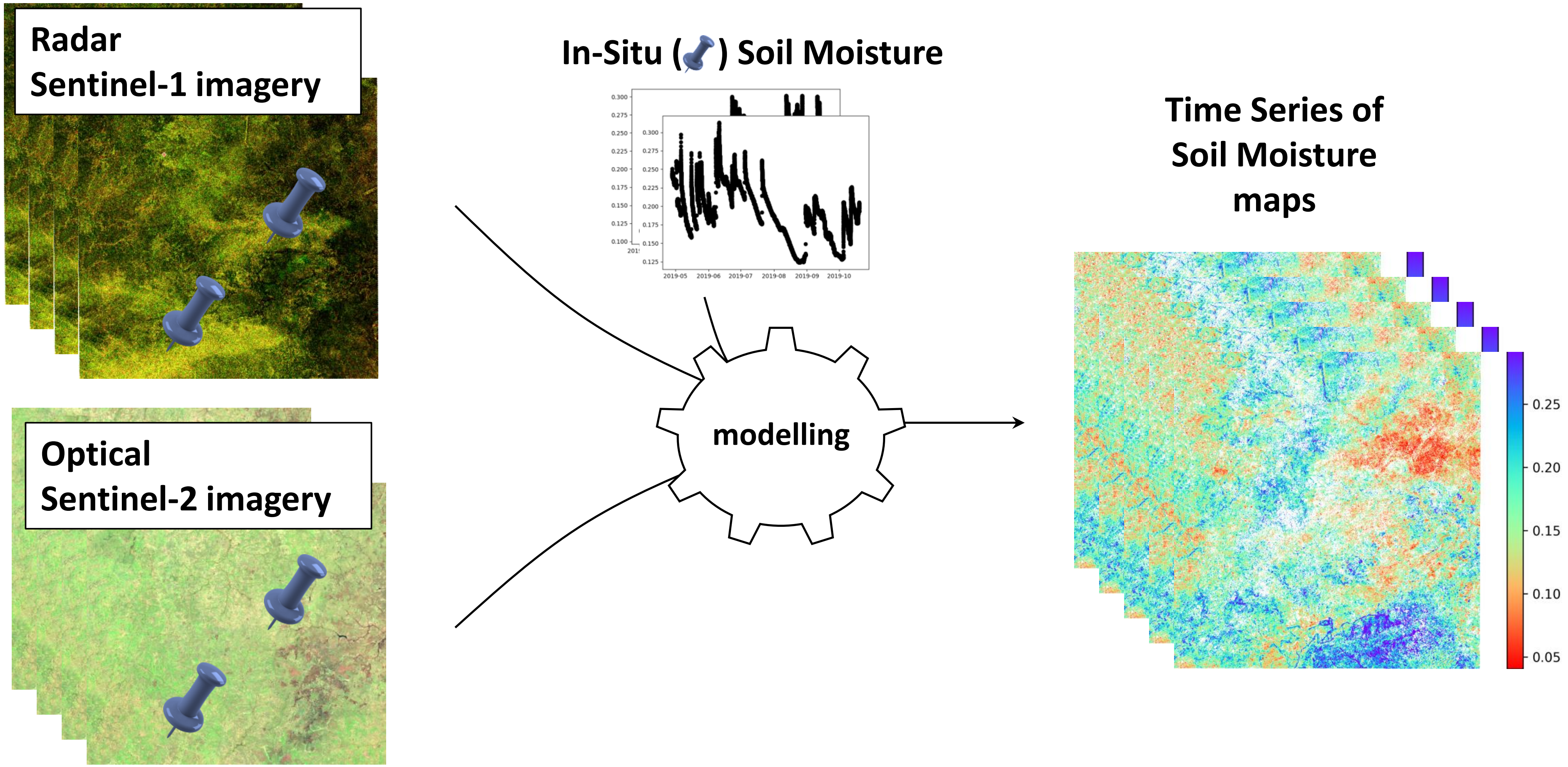
The TWIGA project

- Transforming Weather Water data into value-added Information services for sustainable Growth in Africa
- Developing market oriented services
- Value addition
  - Map integrated precipitable water vapour and tracking convective storm systems – **improve forecast in Africa**
  - Provide Calibrated high grade maps and time series of **<u>soil moisture</u>, surface energy fluxes, and floods**
  - Produce accurate maps of **land cover, land use and crop status**



Soil Moisture monitoring



Soil Moisture Modeling

- Combination of SAR and optical data
- Couple of Oh and Water Cloud Models (f)

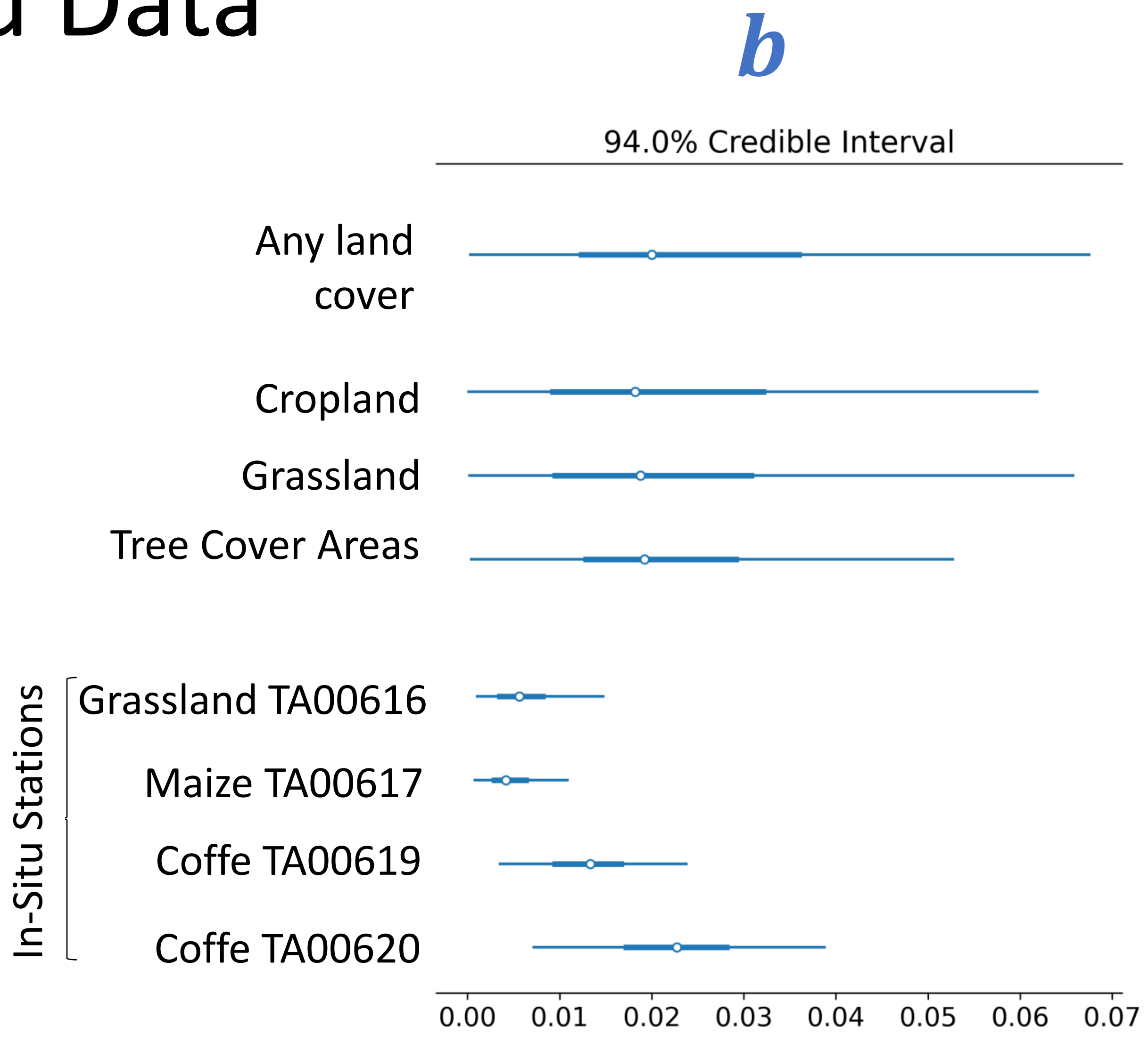
$$(\boldsymbol{\sigma_{VV}}, \boldsymbol{\sigma_{HV}}) = f(\boldsymbol{\theta}, \boldsymbol{NDVI}, \boldsymbol{a}, \boldsymbol{b}, \boldsymbol{ks}, \boldsymbol{M})$$

- **Observations**
  - $\boldsymbol{\sigma_{VV}}, \boldsymbol{\sigma_{HV}}$: **Radar backscatter coefficients**
  - $\boldsymbol{\theta}$: **Incidence angle**
  - **NDVI:** **Normalized Difference Vegetation Index** ($\frac{\rho_{NIR}-\rho_{red}}{\rho_{NIR}+\rho_{red}}$)
- **Empirical parameters**
  - **a:** **Vegetation's radar albedo**
  - **b:** **Vegetation's radar attenuation**
  - **ks:** **Soil roughness**
- **Parameter to be estimated**
  - **M:** **Surface soil moisture**

Calibration with In-Situ Data

$$(\boldsymbol{\sigma_{VV}}, \boldsymbol{\sigma_{HV}}) = f(\boldsymbol{\theta}, \boldsymbol{NDVI}, \boldsymbol{a}, \boldsymbol{b}, \boldsymbol{ks}, \boldsymbol{M})$$

- **In-situ soil moisture** at 10 cm depth
  - four stations in Ghana, every 30 minutes, May – Oct. 2019
- Hierarchical Bayesian regression
- Posterior distributions for each Land Cover (ESA-CCI-LCv1) type (with an in-situ station)

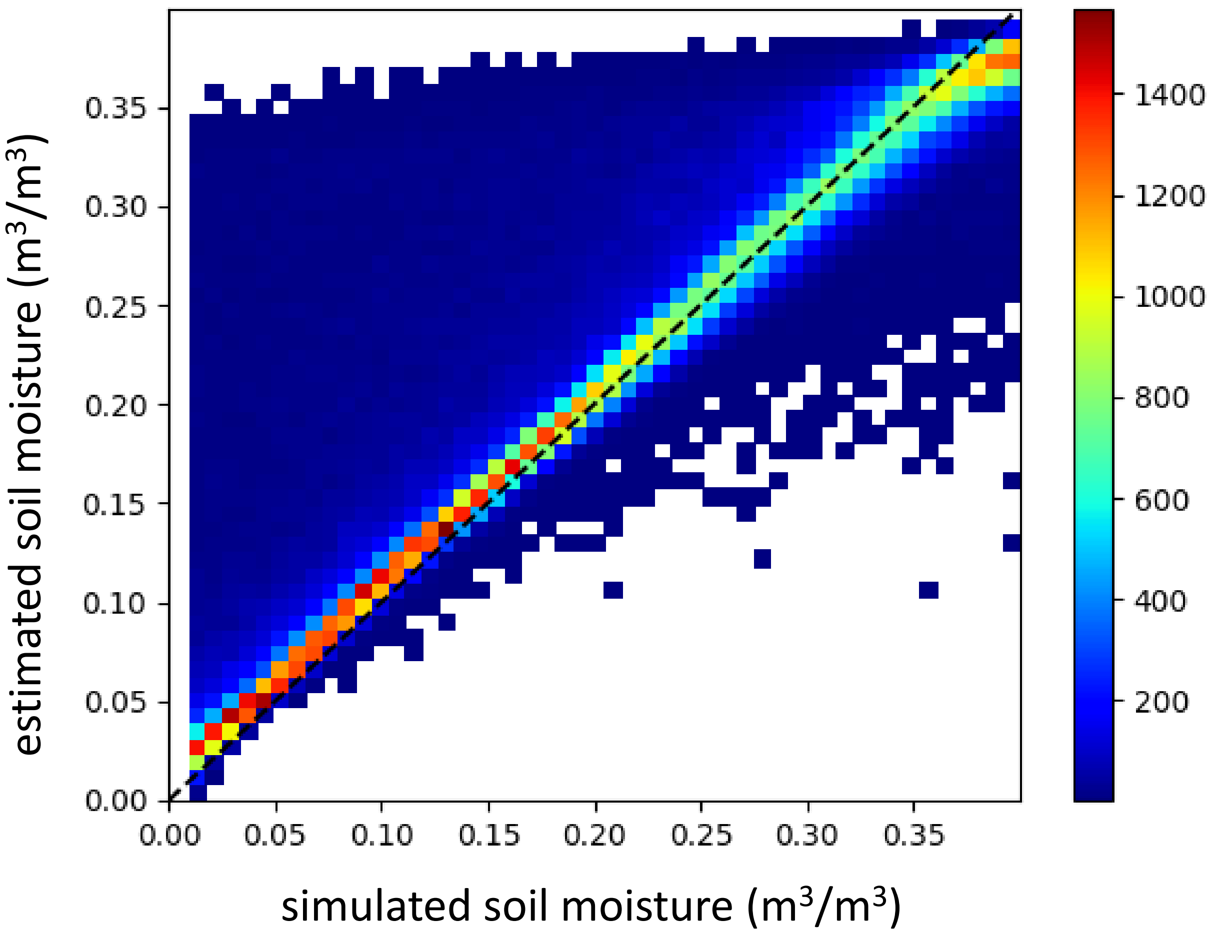


Mapping Algorithm

- $\boldsymbol{M} = m(\boldsymbol{\sigma_{VV}}, \boldsymbol{\sigma_{HV}}, \boldsymbol{\theta}, \boldsymbol{NDVI}, \boldsymbol{a}, \boldsymbol{b}, \boldsymbol{ks})$
- Neural Network
  - Synthetical dataset (with *f*)

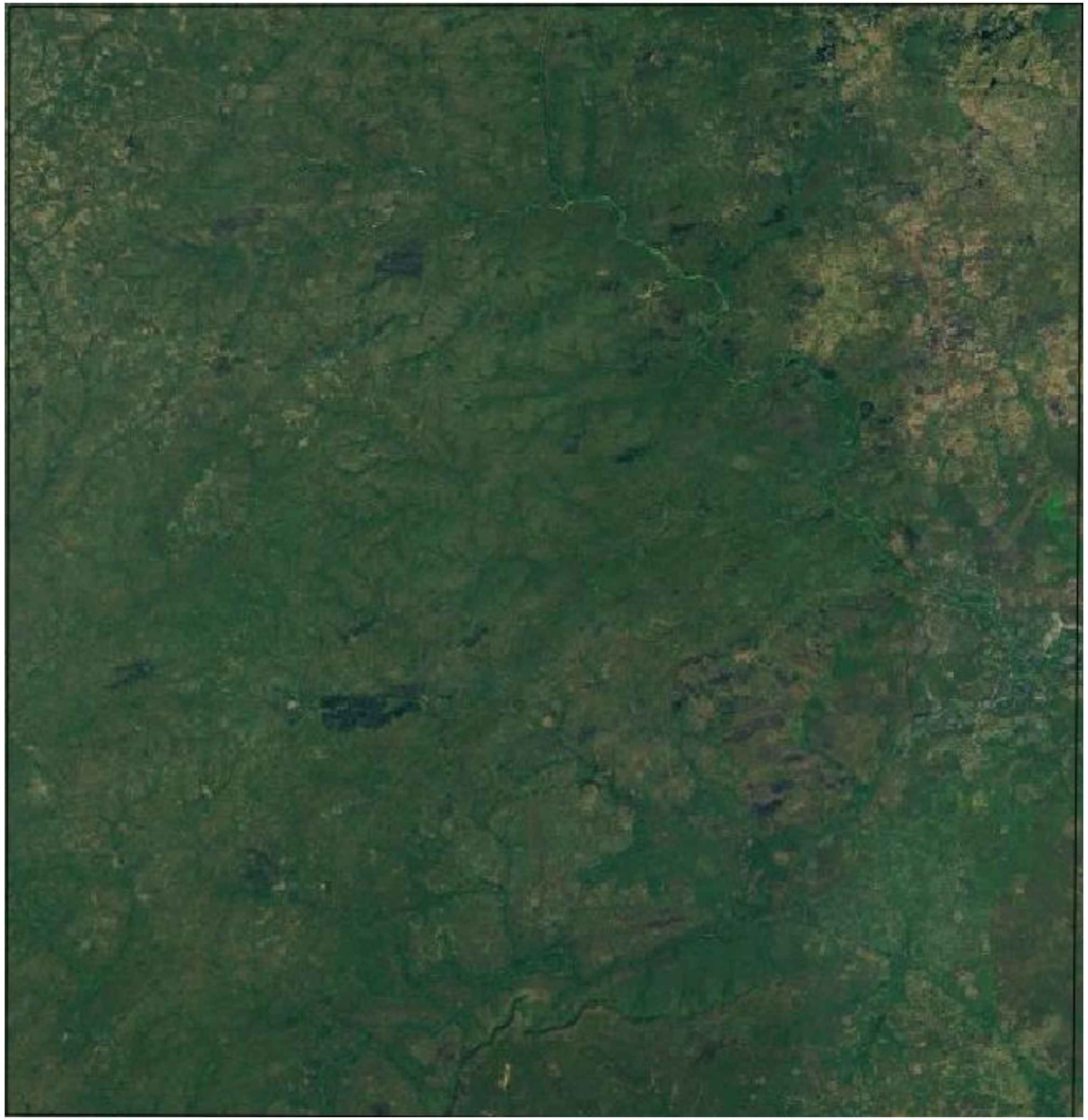
M	σ_{VV}	σ_{HV}	θ	$NDVI$	a	b	ks
0.289	0.767	0.386	40.748	0.060	0.361	0.092	3.867
0.067	0.446	0.281	34.673	0.024	0.303	0.061	3.583
…	…	…	…	…	…	…	…

  - Calibration
    - $r^2 = 0.890$
    - RMSE = 0.042 m^3/m^3



Time series of soil moisture maps

- 80km x 80km in Ghana



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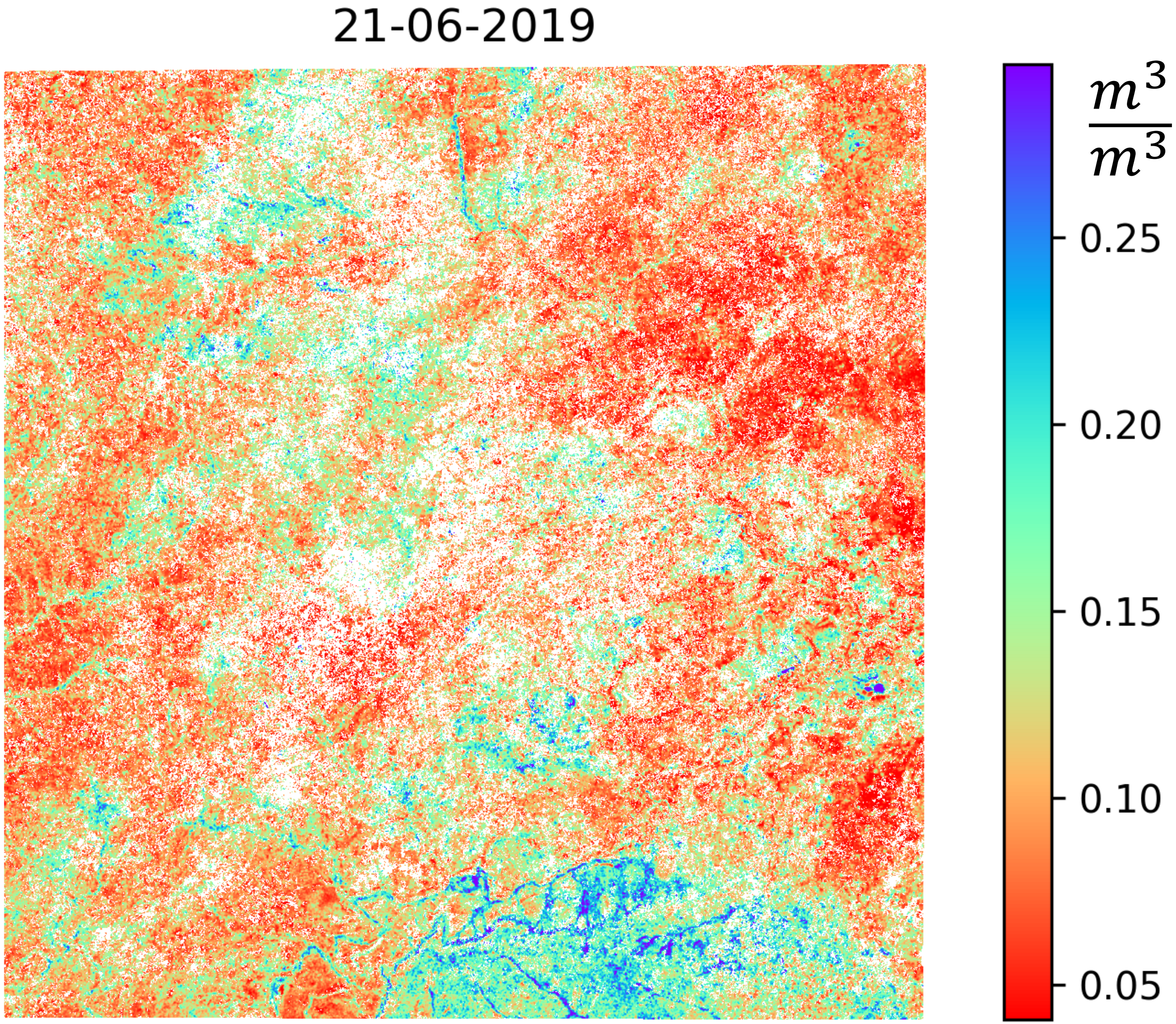

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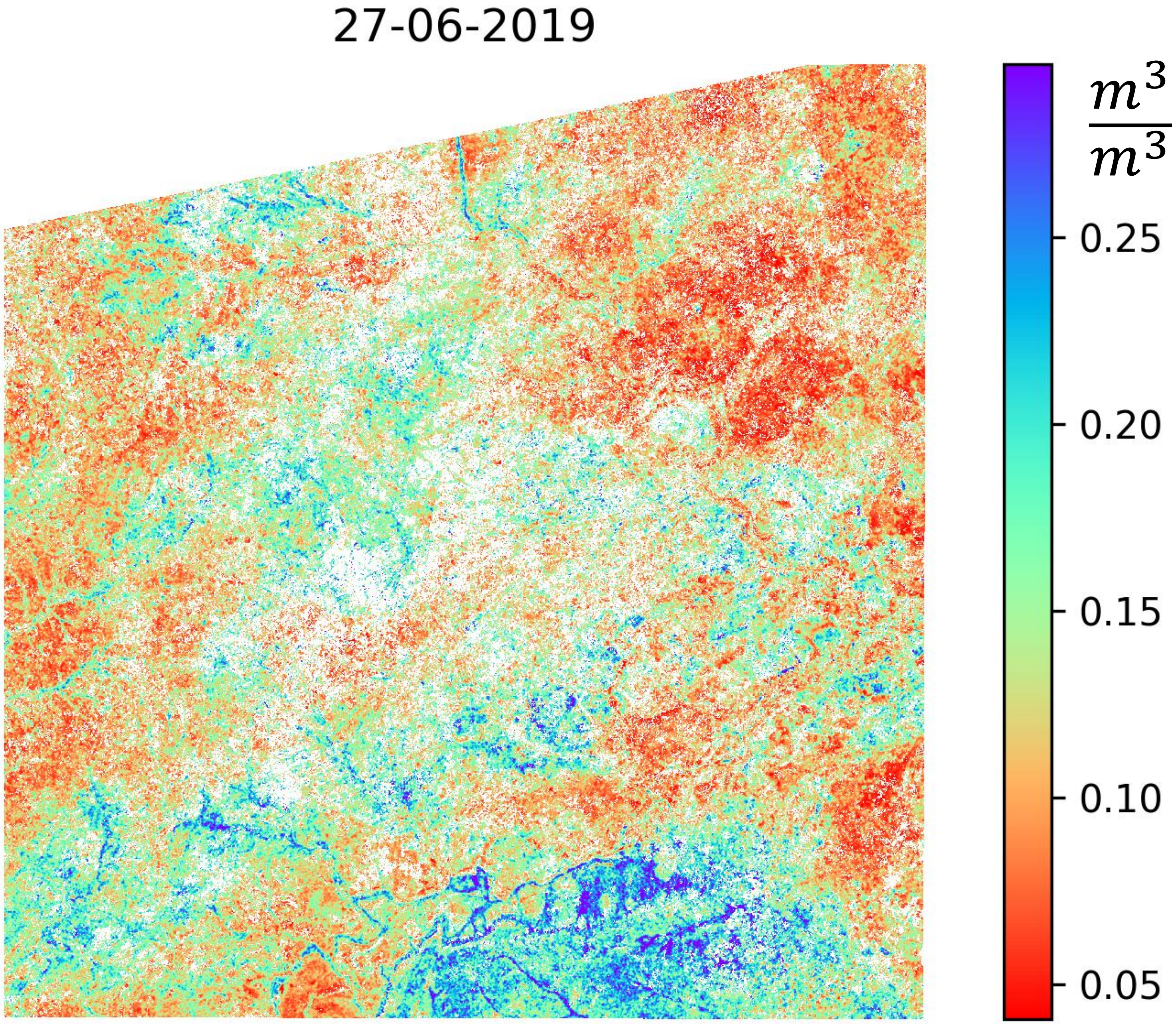

Time series of soil moisture maps

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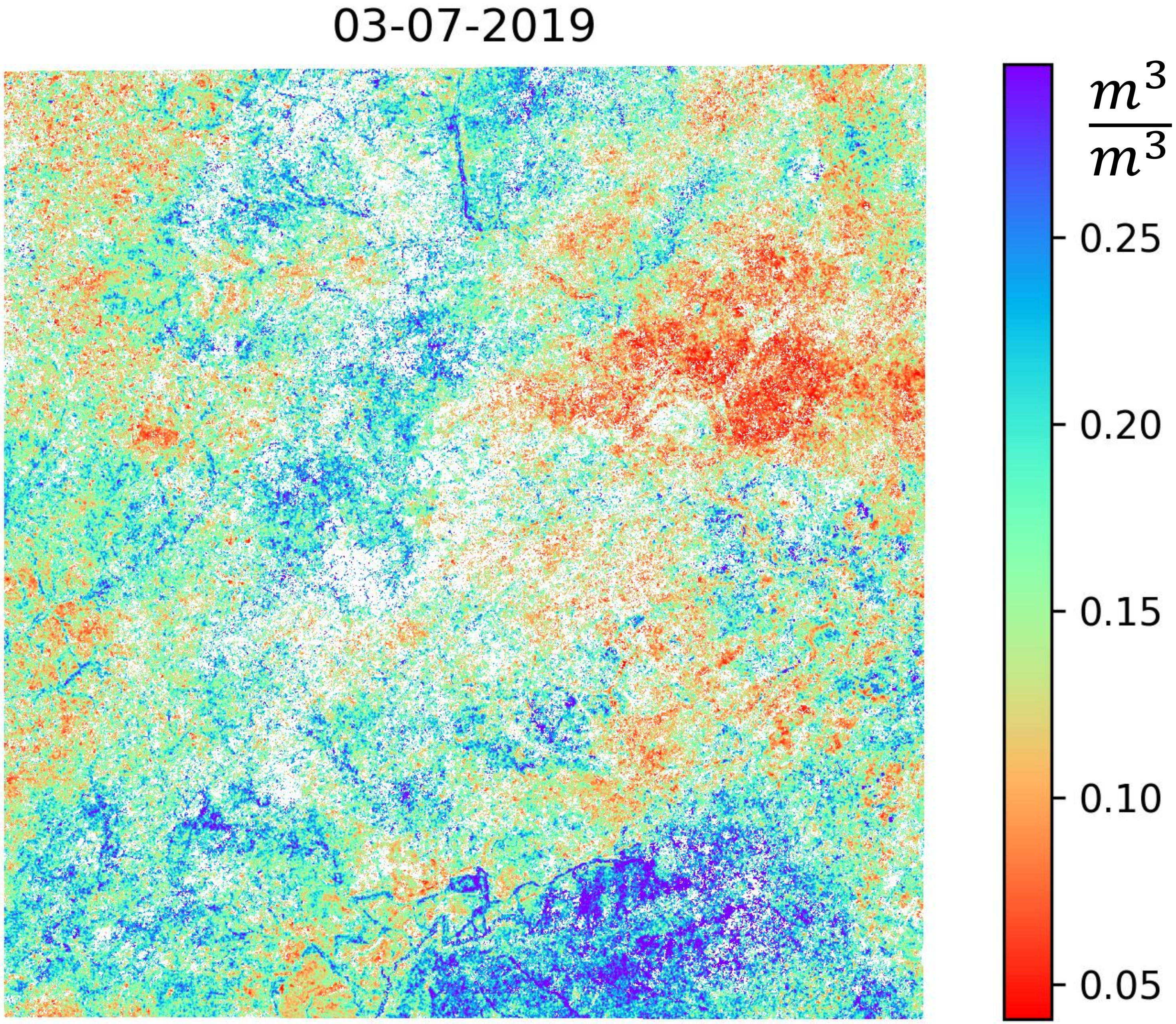
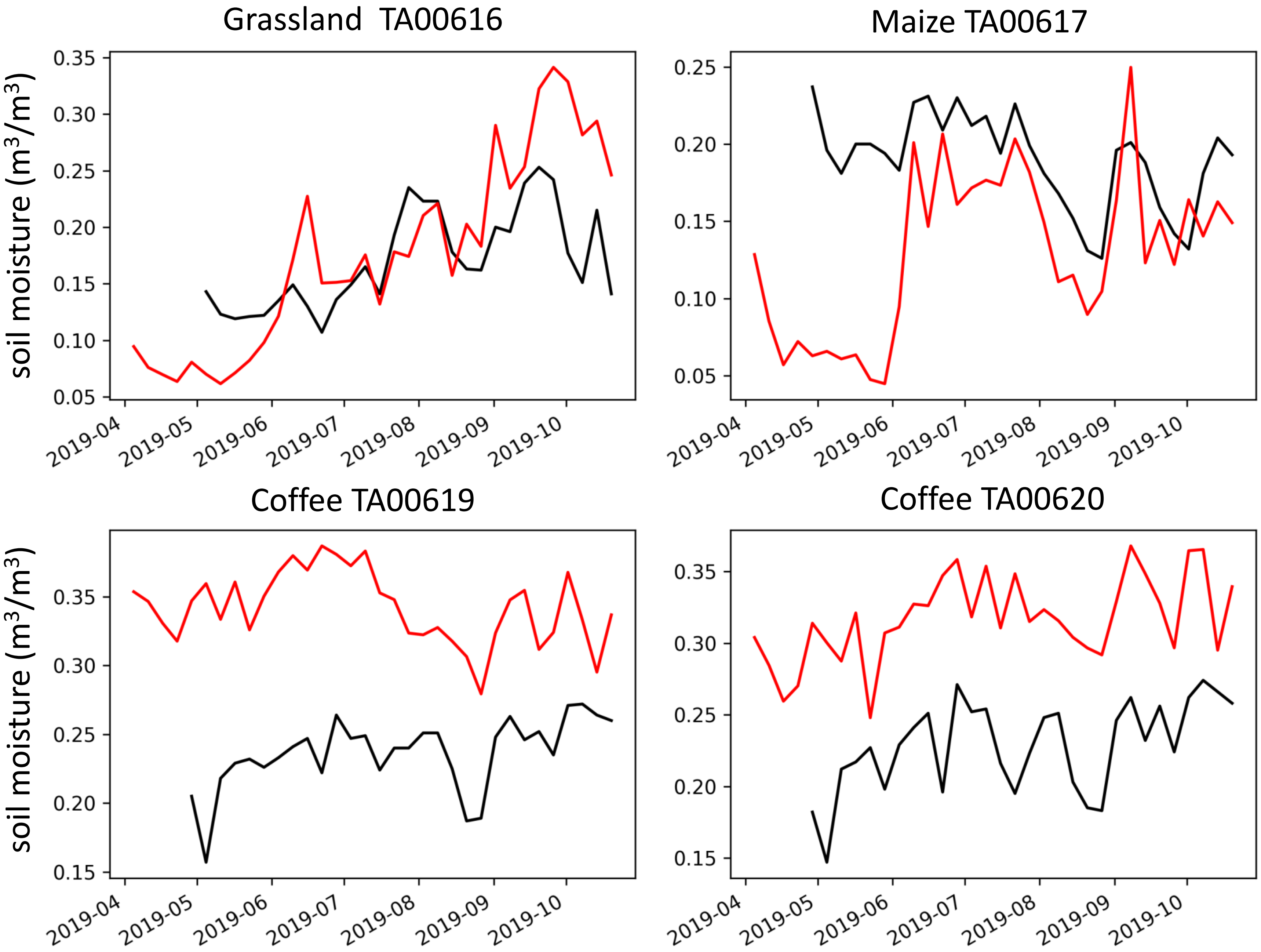


Validation

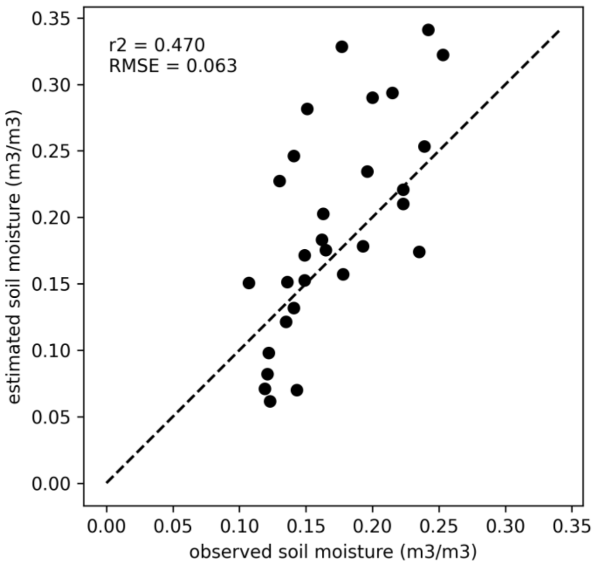
- **Estimation**
  Observation
- Leave-One-Out Cross validation



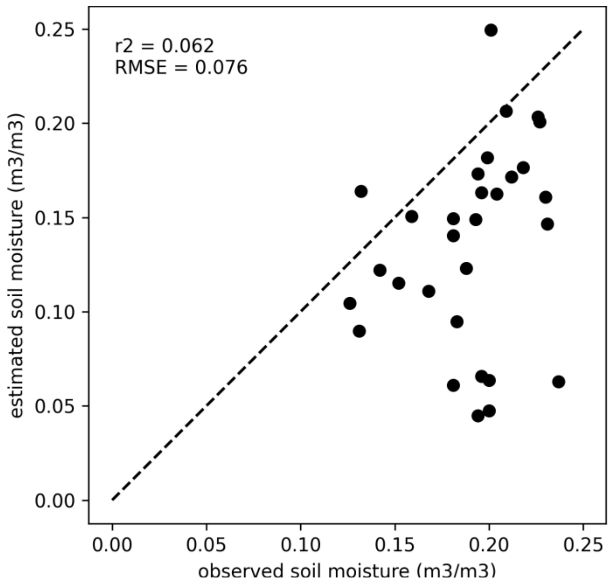
Validation

- High accuracy for specific time periods
- Sudden change in bias
- Systematic bias

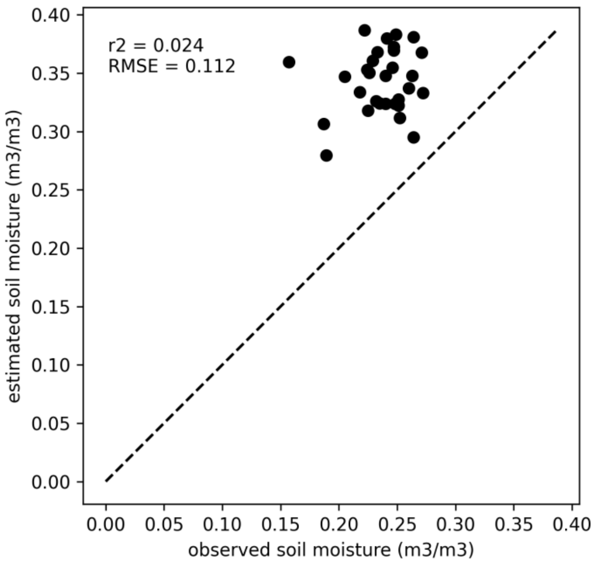
Grassland TA00616



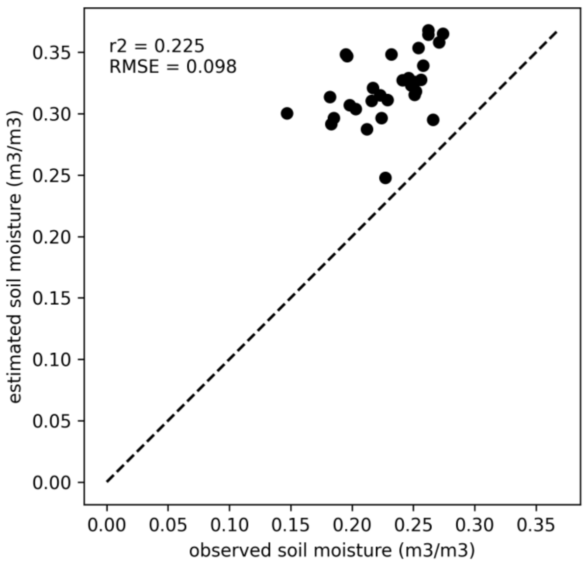
Maize TA00617



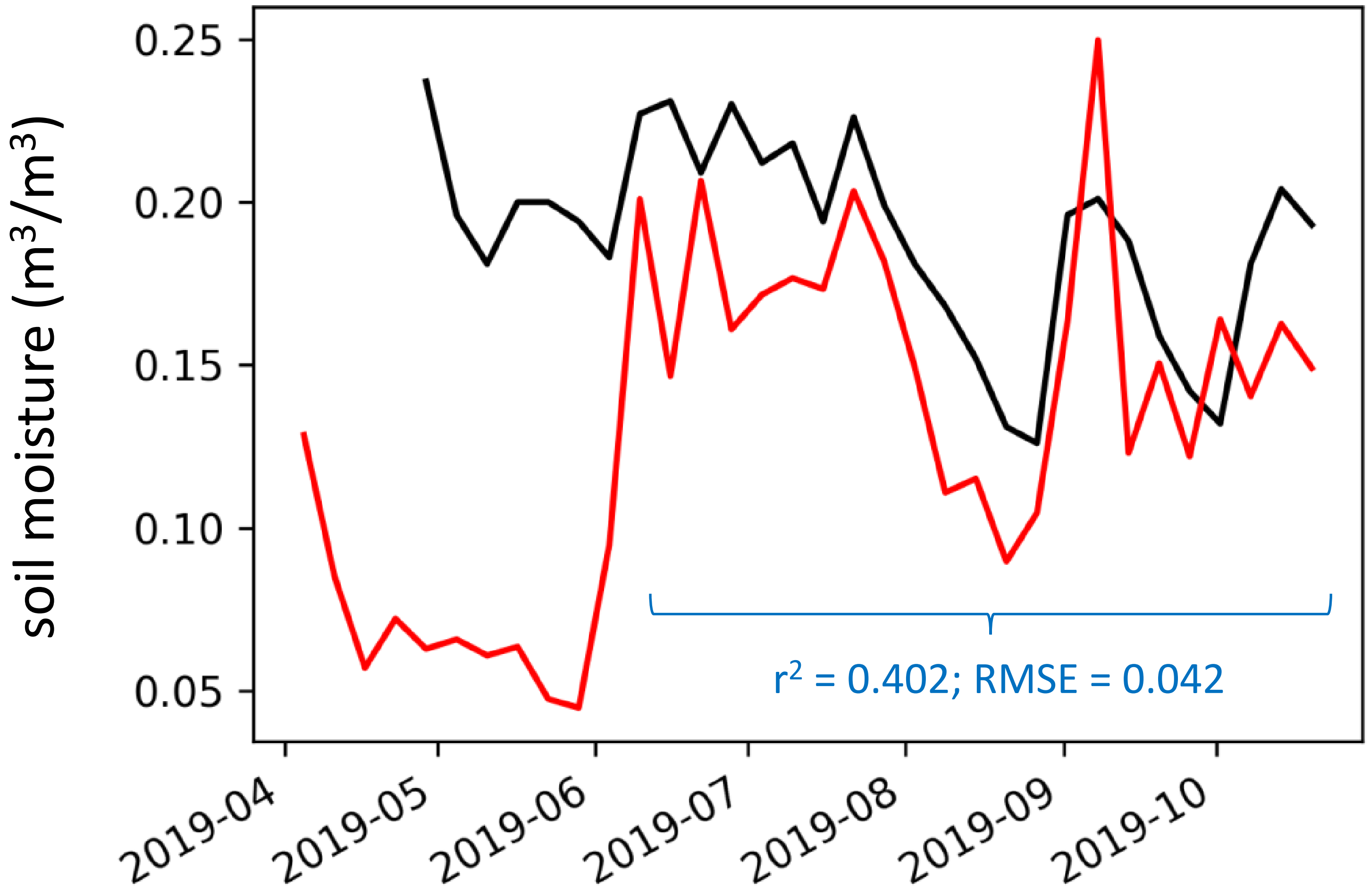
Coffee TA00619



Coffee TA00620



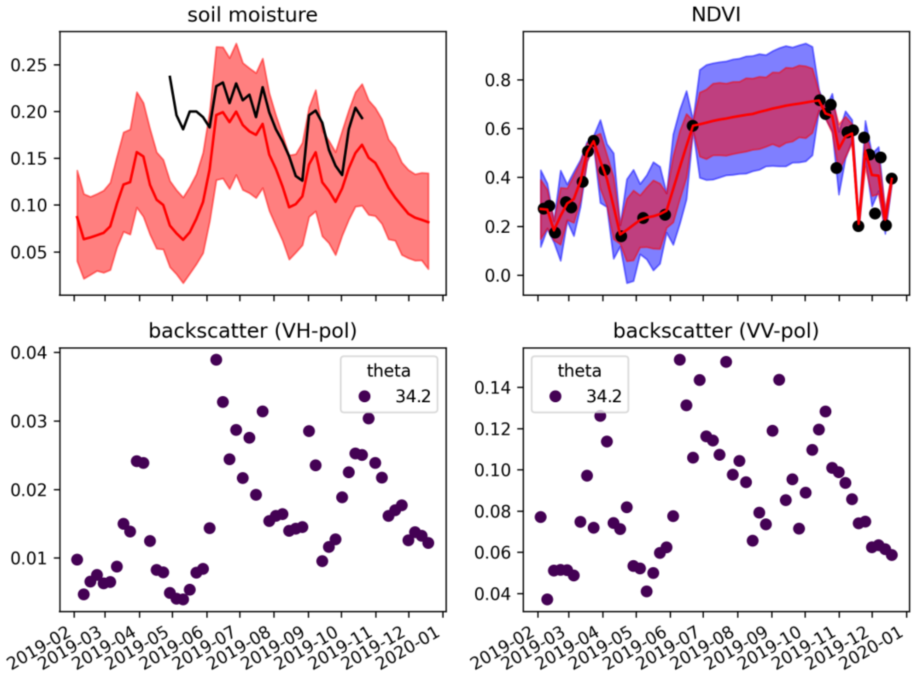
High accuracy for specific time periods



Possible causes of the sudden change in bias

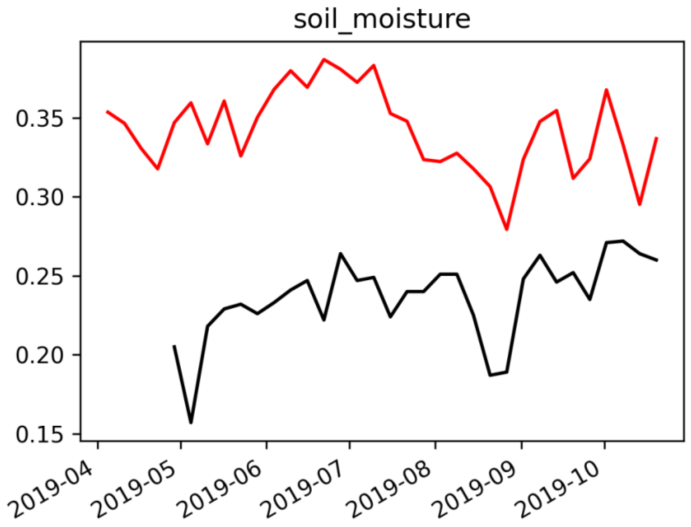
- Change in the vegetation? (NDVI increases ~3 weeks after the bias change)
- Change in the soil roughness

Maize TA00617
results from a Bayesian inversion



Possible causes of the sudden change in bias

- Small size of fields and forest nearby
- For Coffe TA00619 and Coffe TA00620



Conclusions

- Good accuracy of soil moisture estimates for homogeneous areas
- Sudden changes of accuracy, due to unmodelled changes in
  - Vegetation?
  - Land surface roughness?
- Systematic bias, due to
  - Landscape heterogeneity
- Further work needed
  - Increase calibration sample (e.g. with TAHMO stations)
  - Compare with other soil moisture products

Thank you!

For any question, please do not hesitate to ask in the chat