Estimation of high-resolution soil moisture using machine learning, satellite observations and ground measurements

A case study in a hilly agricultural region

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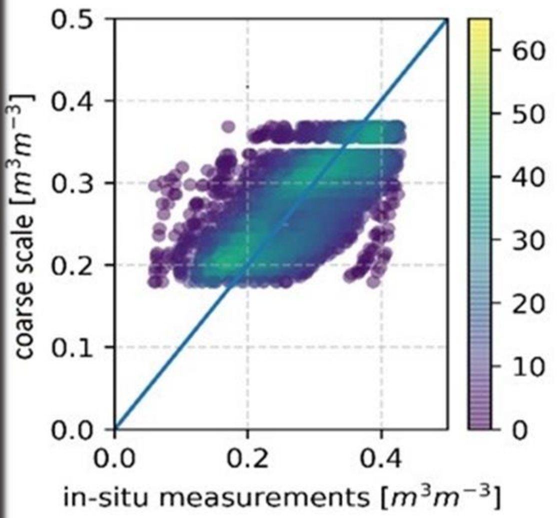
Background

- **High-resolution** (both in time and space) **soil moisture is needed** for a wide range of applications
- Currently, **no satellite-derived product** can **satisfy these requirements**
- Several (spatial) **downscaling methods** have been developed
- In the last decade, **Machine Learning** found wider use for downscaling
- Large amounts of **in-situ measurements** are required for **training**
- **Low-cost sensors** are an appealing solution

Overview

Predictors

- Coarse scale SM (25-36 km)



- Soil texture
- Topography
- Vegetation density

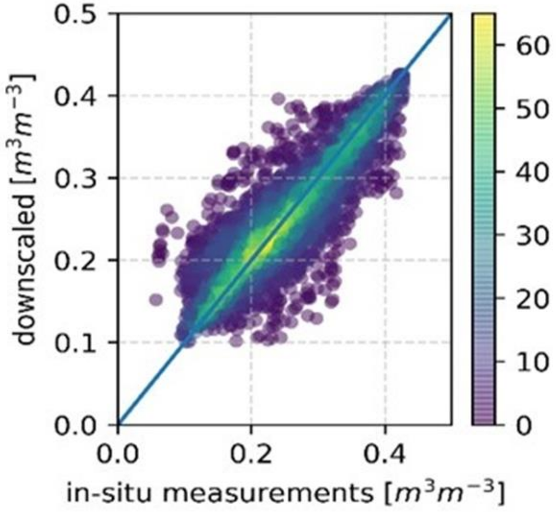
Training data

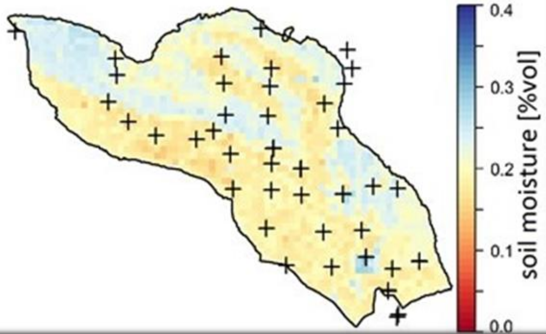
In-situ measurements

Random Forest

Output

High-resolution SM (30 m)

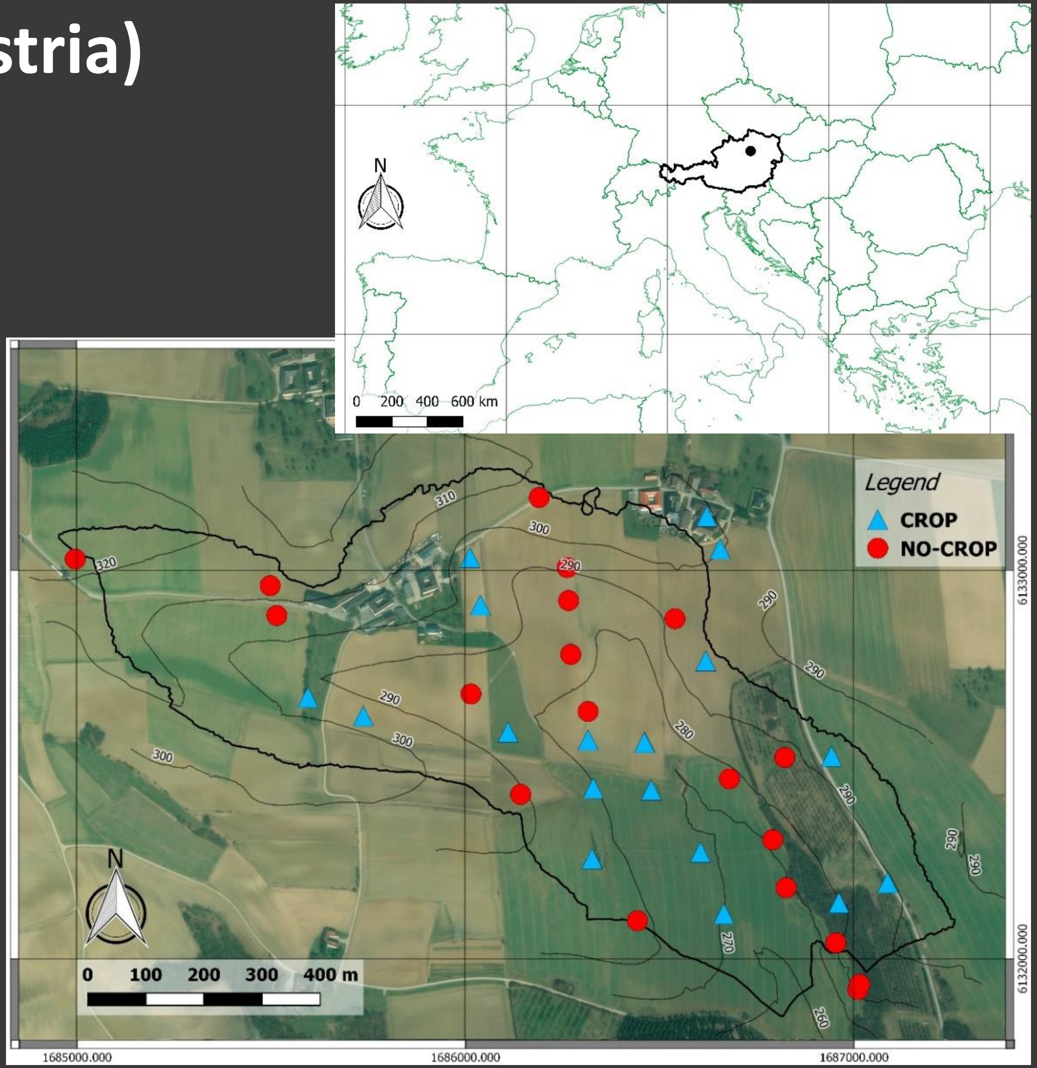




Data

- **Hydrological Open Air Laboratory – HOAL (Austria)**
  - **38 low-cost sensors**[1] measuring:
    - Soil moisture
    - Incoming solar radiation → Vegetation proxy (~fAPAR)
  - **Soil texture** (sand, silt, clay)
  - **DEM** (5 topographic indices)

- **ASCAT** and **SMAP** soil moisture products
- Average from in-situ sensors (AVG_insitu)



Location of the study area in Petzenkirchen, Austria (a) and distribution of the low-cost sensors within the study area (b). Map data ©2019 Bing.

[1] Xaver et al. 2020 (doi.org/10.5194/gi-9-117-2020)

Methods

- Downscaling using **Random Forest regression**

$$SSM_{HR} = RF(SSM, Soil\ Texture, Topography, Vegetation)$$

- Model **combinations**

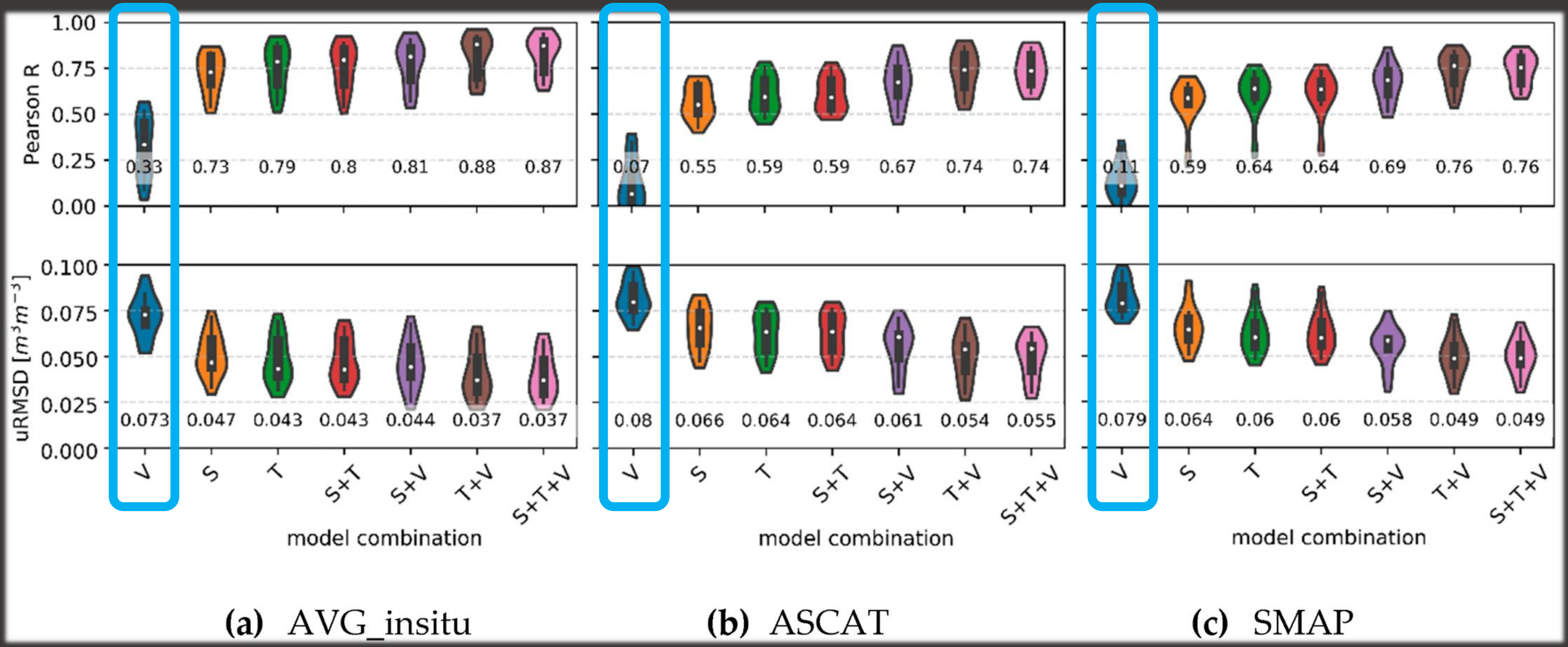
		Predictors			
		Coarse Scale Surface Soil Moisture (SSM)	**Soil Texture (S)**	**Topography (T)**	**Vegetation (V)**
	Variables	AVG_insitu or ASCAT or SMAP	Clay, silt, sand	Slope, TWI, Upslope_area, Total_insolation, General_curvature	fAGR
Model combinations	**SSM+V**	✔			✔
	SSM+S	✔	✔		
	SSM+T	✔		✔	
	SSM+S+T	✔	✔	✔	
	SSM+S+V	✔	✔		✔
	SSM+T+V	✔		✔	✔
	SSM+S+T+V	✔	✔	✔	✔

- Model evaluation: **10 fold cross-validation** (Pearson R and uRMSD)
- Additional analysis: **Effect of training set size** on model accuracy

Results

- Which set of input variables should be used?

→ Vegetation (V) alone is not enough

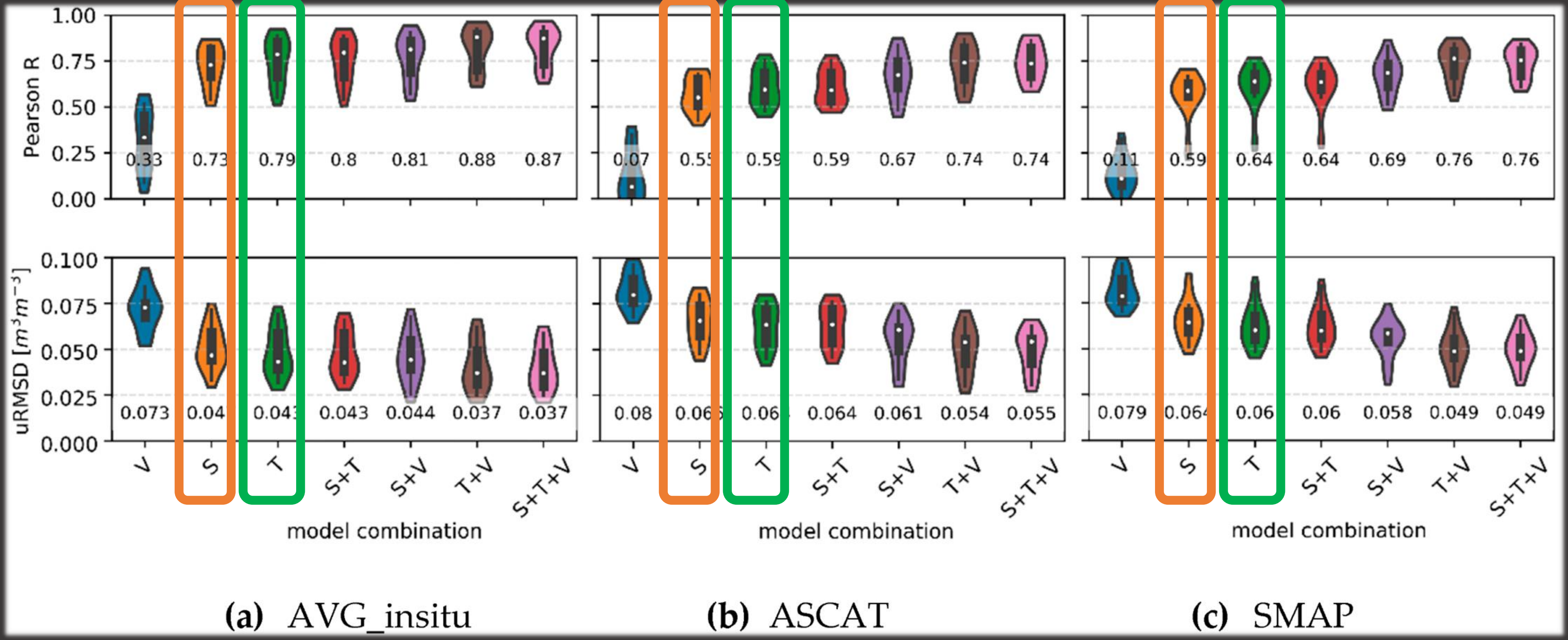


Pearson R and uRMSD between measured and predicted soil moisture. The soil moisture source used as predictor (AVG_insitu, ASCAT, SMAP) is displayed above each graph. The white dots indicate the median values (also reported below the violins)

Results

- Which set of input variables should be used?

→ Topography (T) has more predictive power than Soil texture (S)

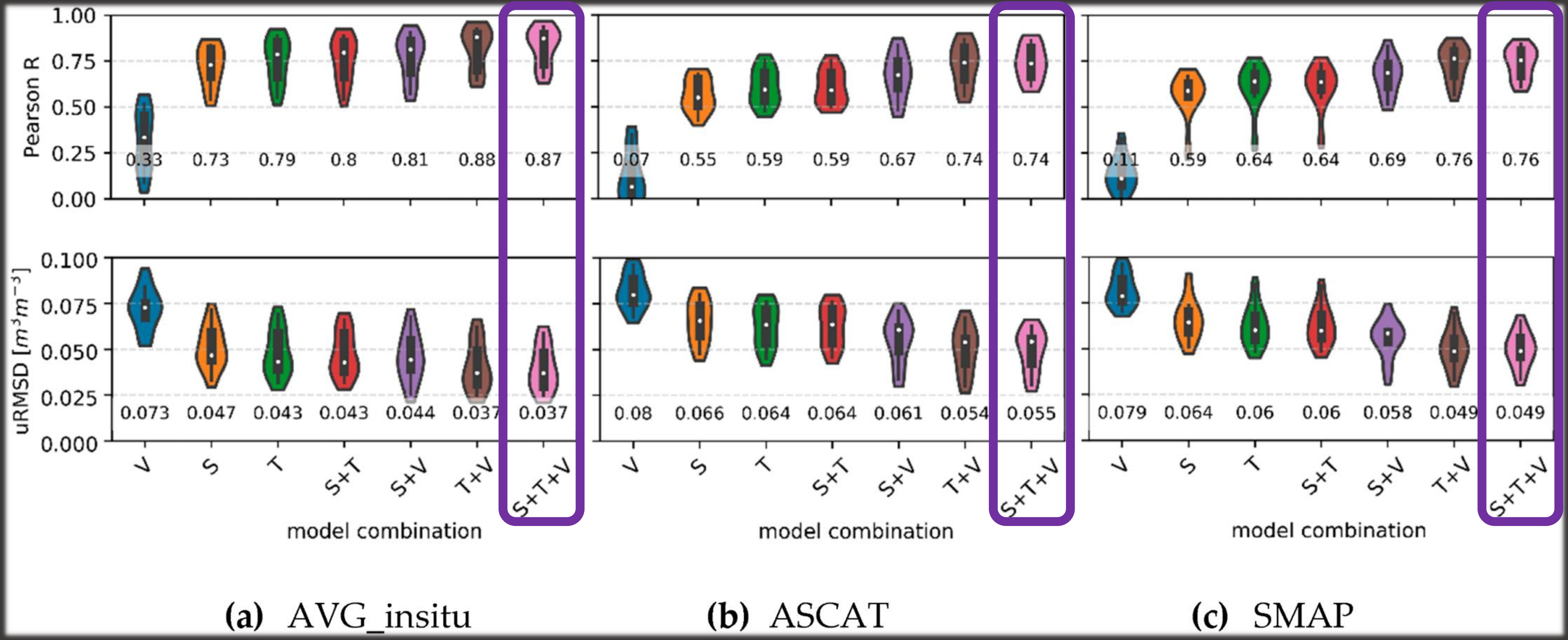


Pearson R and uRMSD between measured and predicted soil moisture. The soil moisture source used as predictor (AVG_insitu, ASCAT, SMAP) is displayed above each graph. The white dots indicate the median values (also reported below the violins)

Results

- Which set of input variables should be used?

→ A combination of S, T, and V provides the most accurate results

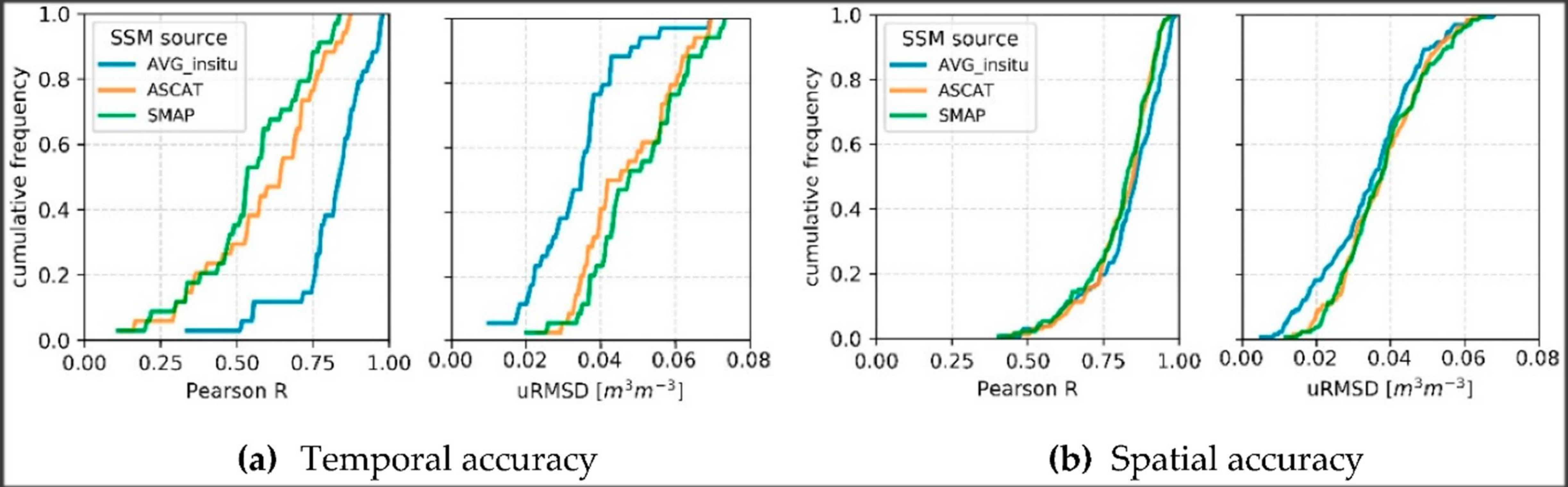


Pearson R and uRMSD between measured and predicted soil moisture. The soil moisture source used as predictor (AVG_insitu, ASCAT, SMAP) is displayed above each graph. The white dots indicate the median values (also reported below the violins)

Results

- Are both the temporal dynamics and the spatial patterns captured?

  → Quality of temporal dynamics strongly related to input (coarse scale) soil moisture product

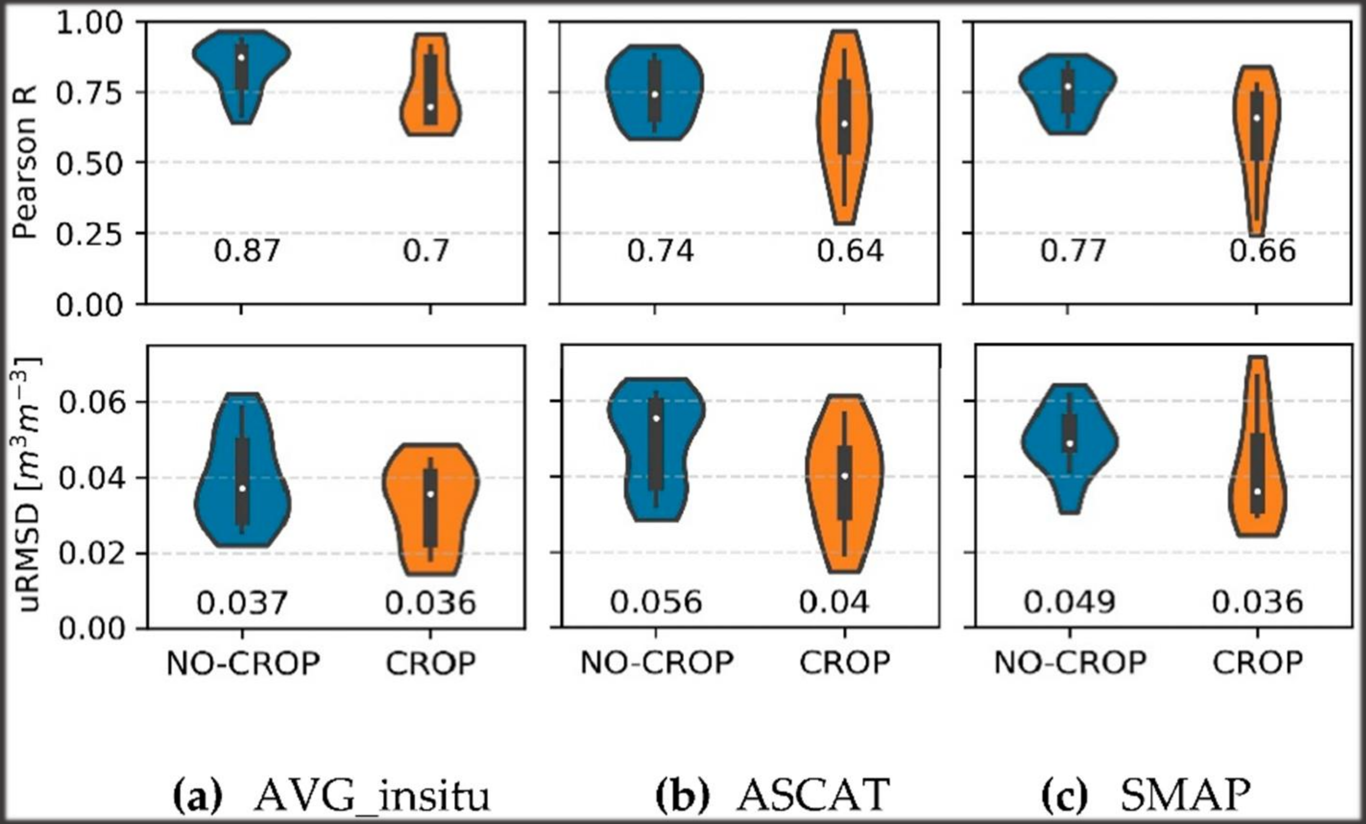


Cumulative frequency of Pearson R and uRMSD between measured and predicted soil moisture (model combination SSM+S+T+V). The statistical metrics were calculated for each sensor location, thus representing the ability of the model to capture temporal dynamics (a), and for each time-step, accounting for the model skill to reproduce spatial patterns (b).

Results

- Is the model accuracy consistent between crops and natural vegetation?

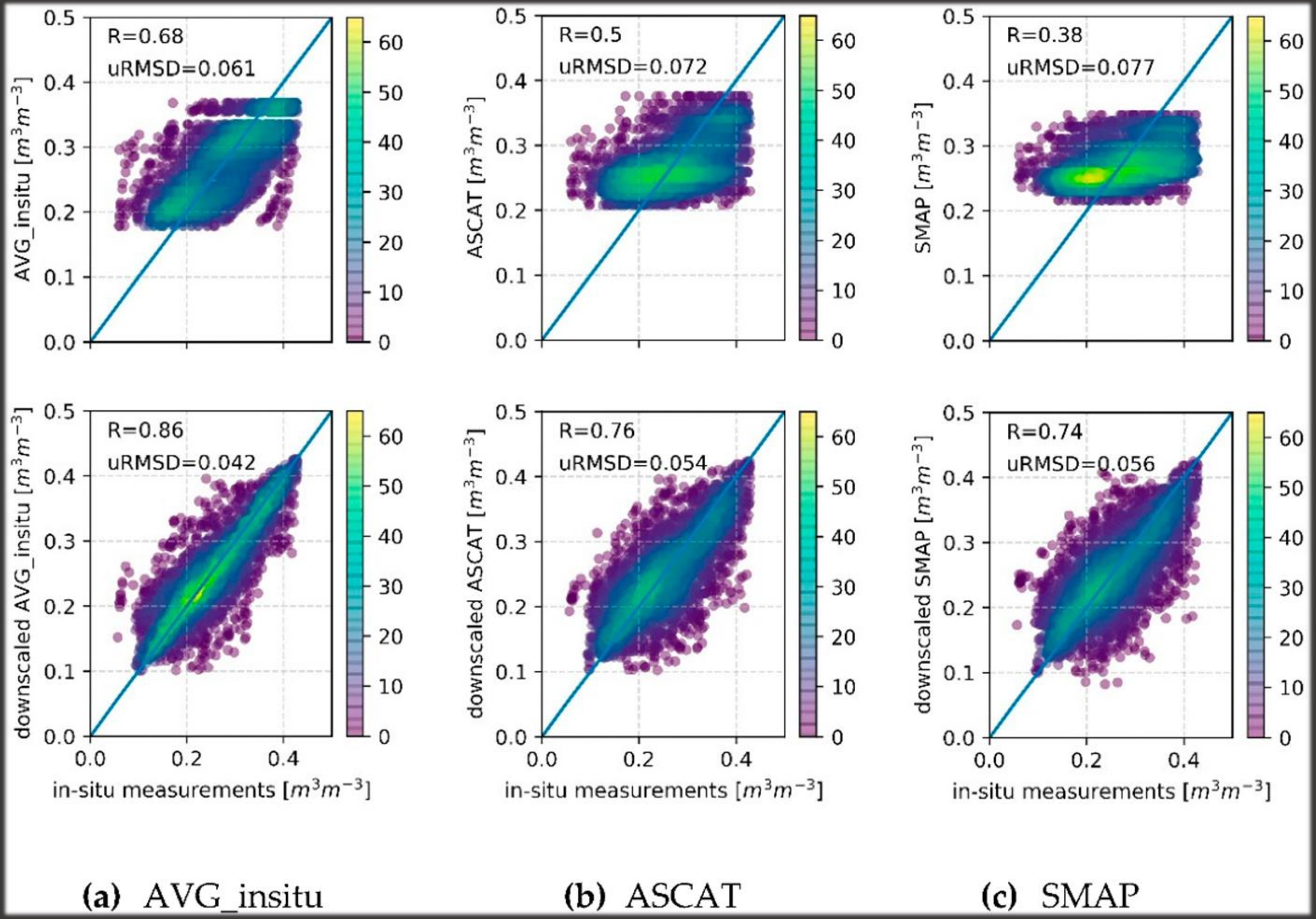
→ Higher accuracy observed for non-agricultural locations

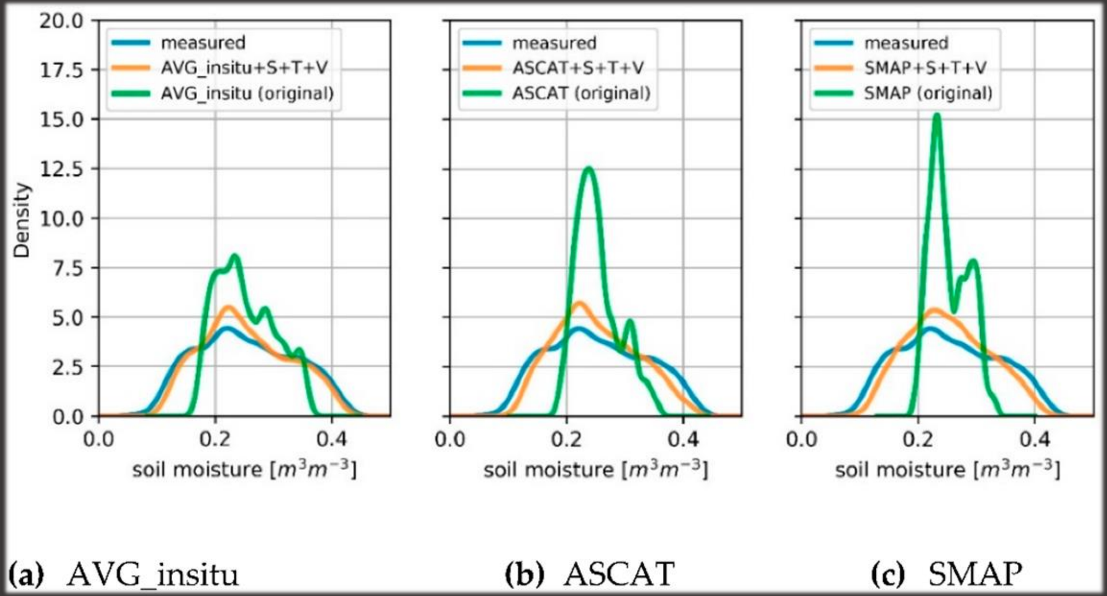


Violin plots of Pearson R (top) and uRMSD (bottom) between measured and predicted soil moisture (model combination SSM+S+T+V) depending on the vegetation type. CROP indicates agricultural fields, while NO-CROP includes grassland, forest, and field edges. The boxplots within the violins indicate quartiles and the white dots depict the median values (also reported below the violins).

Results

- What is the improvement compared to the input (coarse scale) soil moisture?



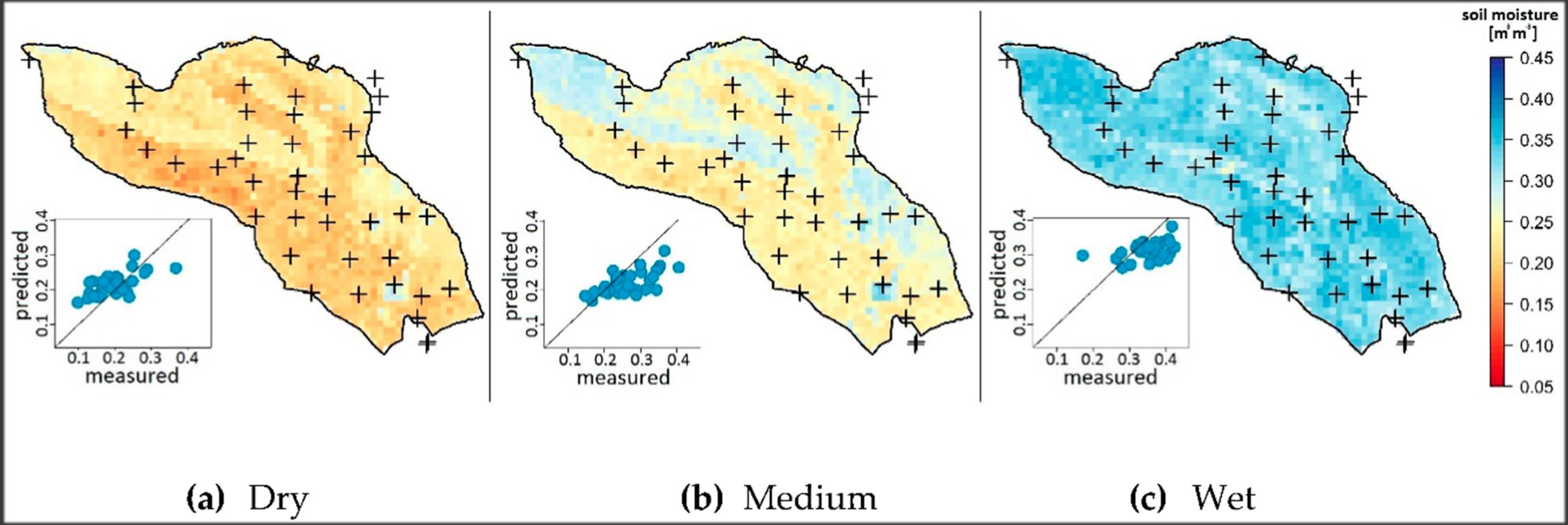


Density distributions of soil moisture obtained for in-situ measurements (blue lines), downscaled soil moisture from the model combination SSM+S+T+V (orange lines), and the original coarse-scale SSM products (green lines).

Scatterplots between measured soil moisture and original coarse-scale SSM products (top) and between measured and downscaled soil moisture (model combination SSM+S+T+V) (bottom). The color indicates the number of observations

Results

- Example of downscaled ASCAT

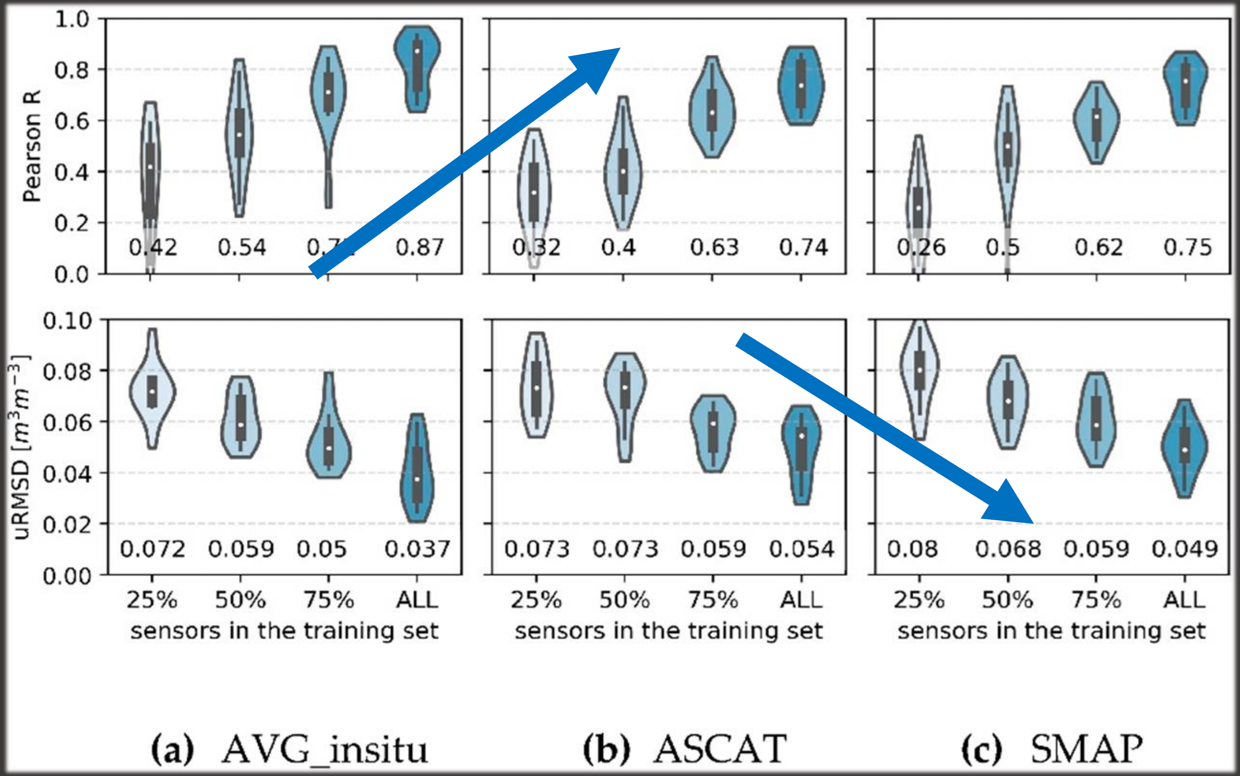


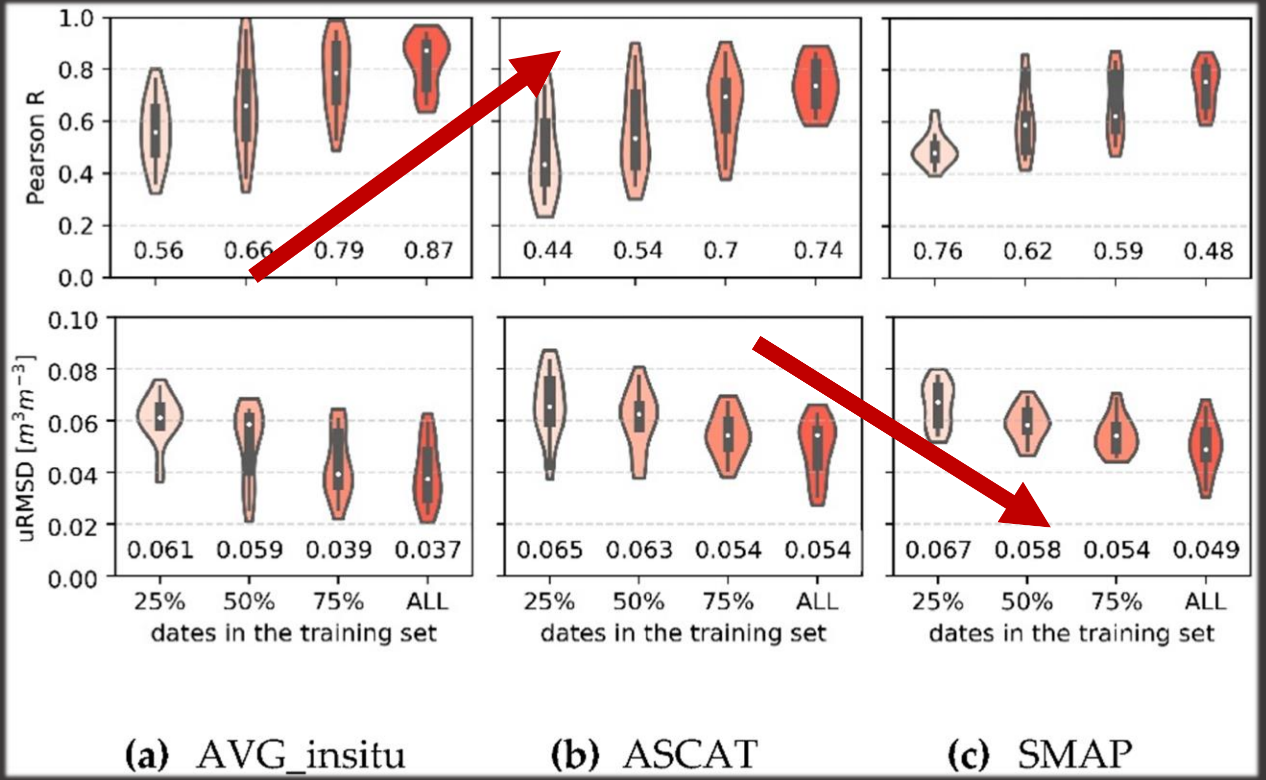
Spatial patterns of soil moisture over the study site for three days with varying moisture conditions. Each graph shows also the scatterplot between measured and predicted soil moisture for the same day. Soil moisture was obtained from the sub-optimal model combination ASCAT+S+T (similar patterns were found for the SMAP+S+T combination, not shown). Note that a proxy of vegetation cover "V"nwas not included because it was available only for the sensor locations (depicted with the cross) but not for the entire study area.

Results

- What is the effect of training set size on downscaling accuracy?

→ considerable improvements with increasing training set sizes



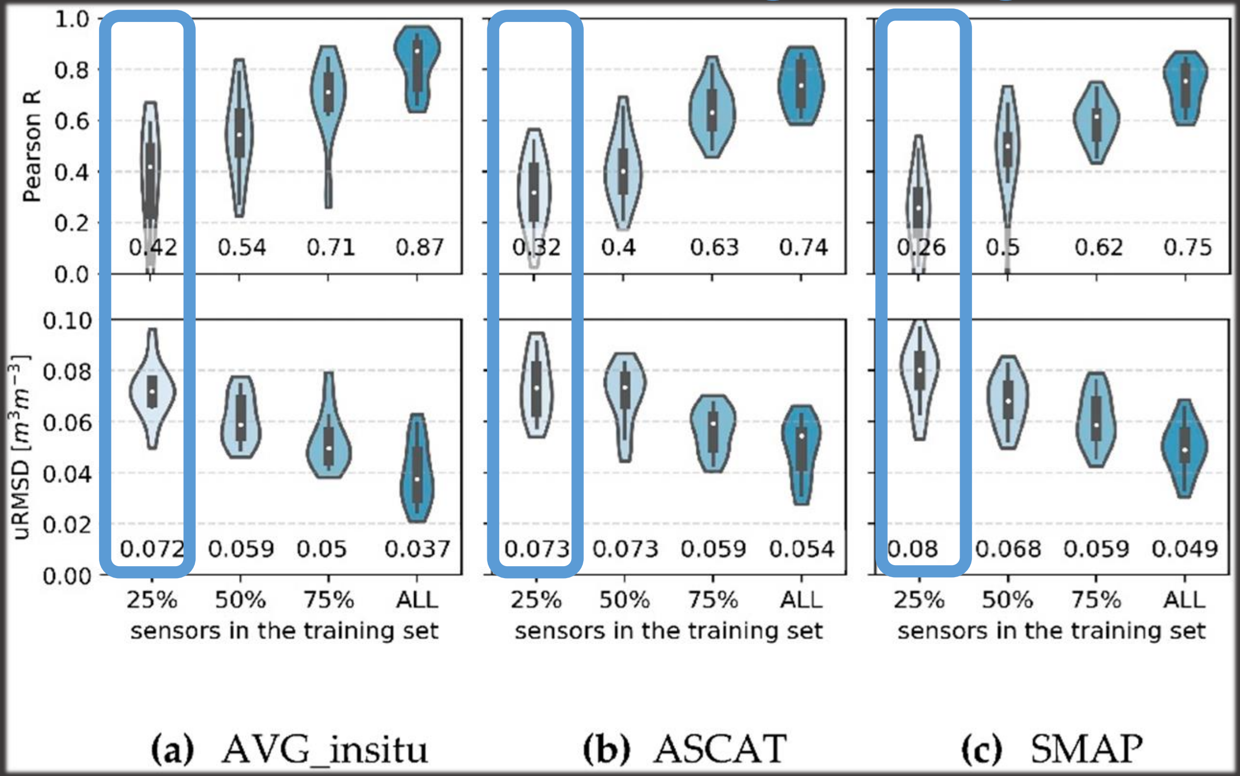


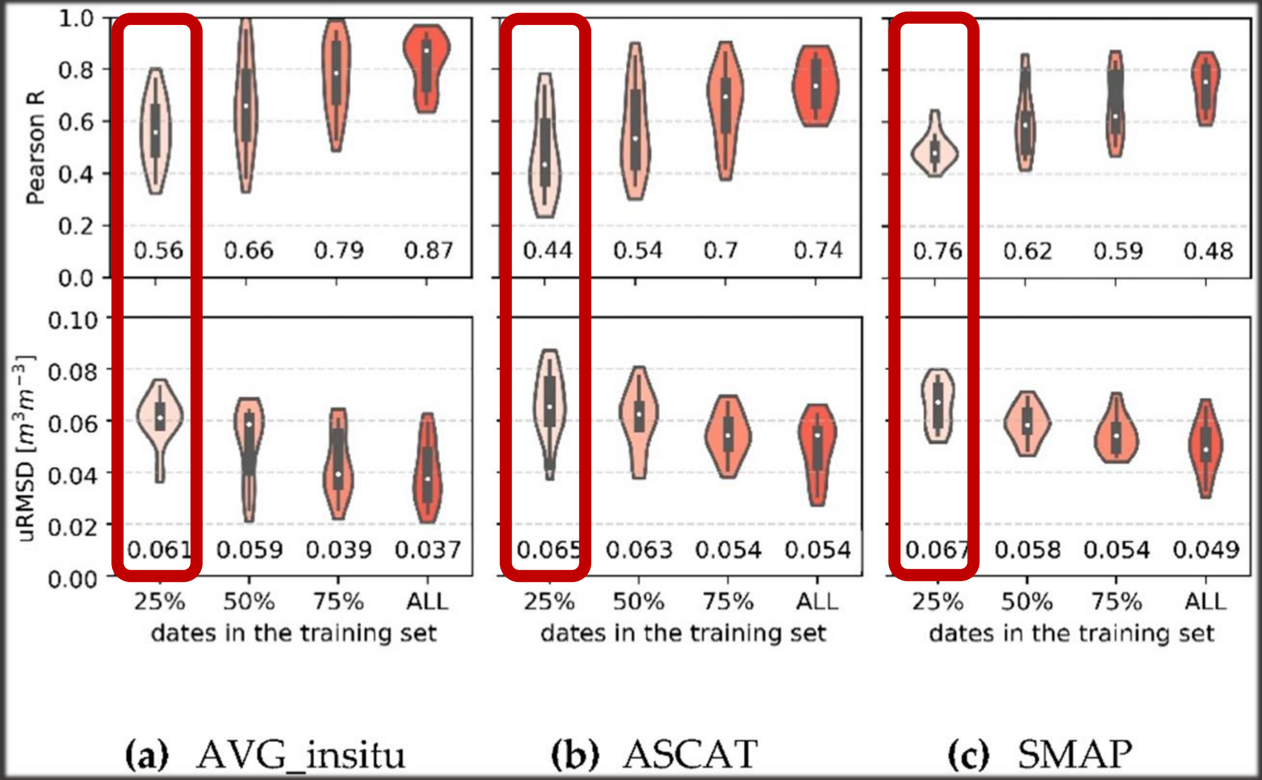
Pearson R and uRMSD between measured and predicted soil moisture (SSM+S+T+V) against the number of sensors used to train the models. Training sets consisted of 25%, 50%, and 75% of: (LEFT) all available sensors (38), (RIGHT) of contiguous observations sampled from the original training sets (ALL). For each training set size, we repeated the evaluation for 10 random permutations. The median values are reported below the violins.

Results

- What is the effect of training set size on downscaling accuracy?

→ Higher accuracy if data from more sensors and short period rather than few sensors measuring for longer





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Conclusions & *Outlook*

- The **accuracy** of the downscaled soil moisture is strongly related to the **quality of the model predictors**
- **Topography** has **higher predictive power** than **soil** texture (study site has hilly landscape)
- **Vegetation** plays a **key role** in organizing soil moisture spatial patterns, and **great accuracy improvement** is obtained if included as model predictor
- If limited training data, **priority** should be given to **increase the number of sensor locations** to adequately cover the spatial heterogeneity, rather than expanding the duration of the measurements
- *Improve the proposed framework by* ***including satellite-derived vegetation indices***
- ***Test the model*** *developed here in* ***regions*** *with* ***similar environmental conditions***