Insuring mountain grasslands against drought losses by Sentinel-2

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CONDIFESA TRENTO CODIPRA CONSORZIO DIFESA PRODUTTORI AGRICOLI

Background

Increasing frequency of drought threatening the "Water Towers" of Europe

- Snow depth shows a clear decreasing trend of -8.4% on average[1]
- Temperature is increasing fast, 1 to 1.4 °C on average during the 20th century[2]
- Climate projections show that the Alps will see an increase in summer droughts by more than 50%. This means that droughts could occur more than every second summer [3,4]

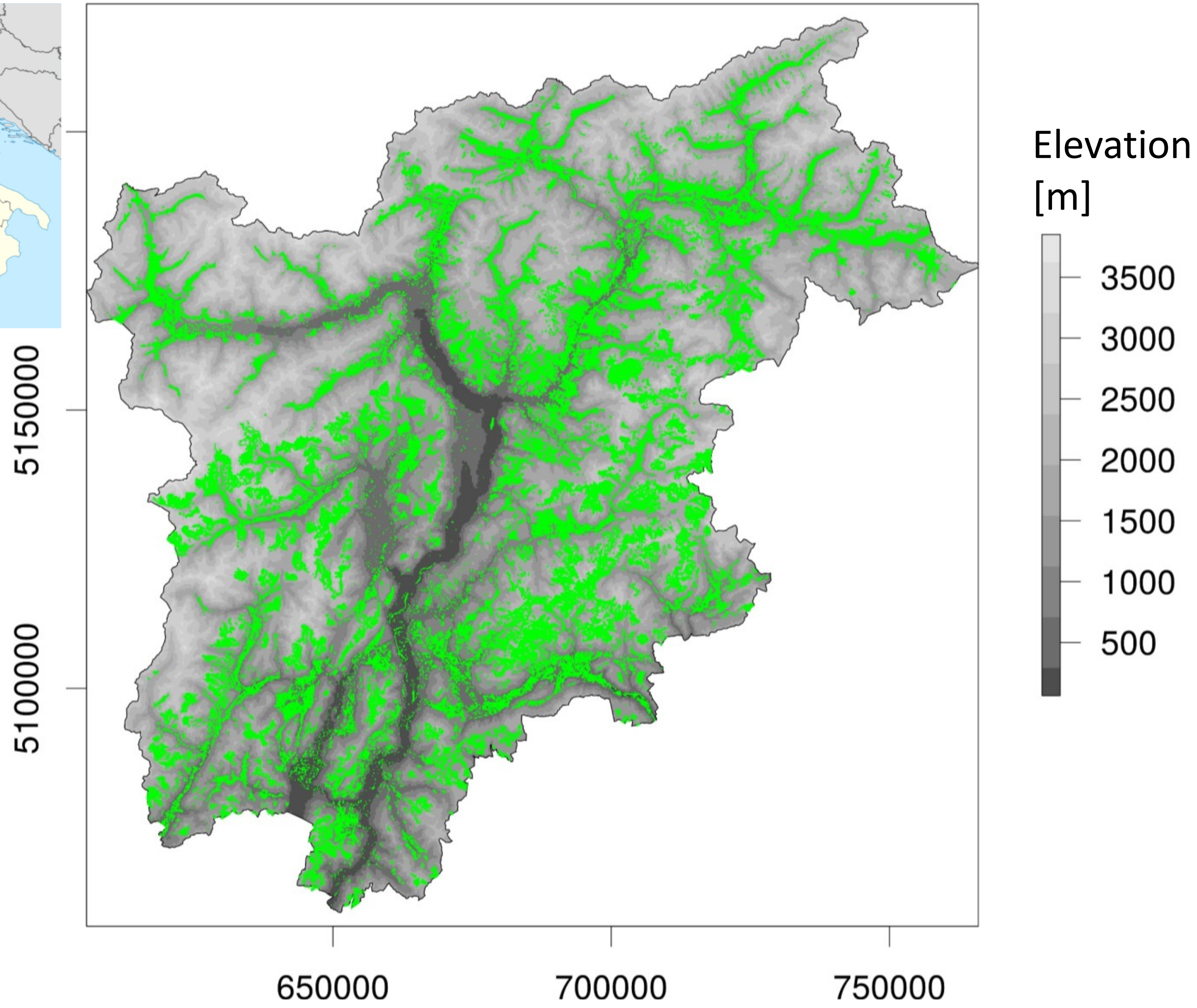
[1]Matiu et al. (2019). Evaluating snow in EURO-CORDEX regional climate models with observations for the European Alps: biases and their relationship to orography, temperature, and precipitation mismatches. Atmosphere, 11(1), 46.

[2]Auer et al. (2007). HISTALP—historical instrumental climatological surface time series of the Greater Alpine Region. International Journal of Climatology: A Journal of the Royal Meteorological Society, 27(1), 17-46.

[3]Böhnisch et al. (2021). Hot Spots and Climate Trends of Meteorological Droughts in Europe–Assessing the Percent of Normal Index in a Single-Model Initial-Condition Large Ensemble. Frontiers in Water, 107.

[4]Spinoni et al. (2018). Will drought events become more frequent and severe in Europe?. International Journal of Climatology, 38(4), 1718-1736.

Study area



Meadows primarily aimed at forage production in the province of Bolzano + meadows and pastures in the province of Trento

9.6% of the total area of the region

17697 farms
231439 parcels

"Agriculture Risk Management Plan, 2022", Italian Ministry of Agricultural, Food and Forestry Policies:
public support up to **65%**
yield losses **>30%**
automatic system to identify losses

1st pilot insurance for the growing season of year 2022 for 8 farms where we collect ground measurements.

Aim of the project

Develop and validate a combined meteorological/biophysical index to identify yield losses due to drought in mountain grasslands in the provinces of Bolzano and Trento

$$FPI_n = \sum_{i=SOS}^{i=EOS} \left(\overset{\text{bio}}{\boxed{LAI}}_{grassland\ i} \times \overset{\text{meteo}}{\boxed{WS}} \right)$$

$$\Delta FPI_n = \frac{FPI_n}{Olympic\ average(FPI_{n-1}; \dots; FPI_{n-5})}$$

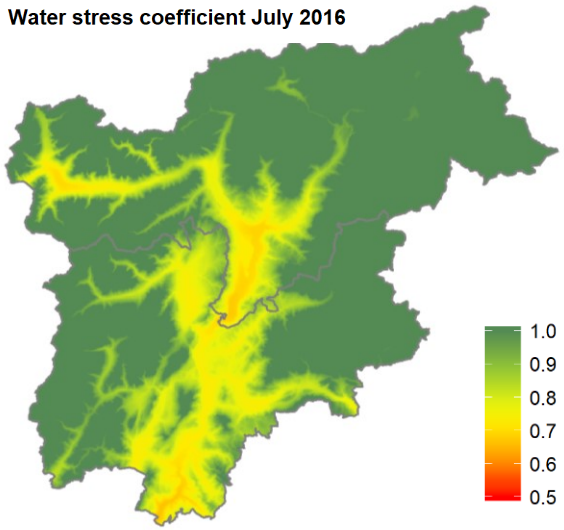
- **FPI**: growing season cumulative of the daily product between **LAI** e lo **water stress**
- FPI deviations from the long-term average allow to identify drought events
- Water stress and LAI anomalies correspond to the cause and the impact of drought

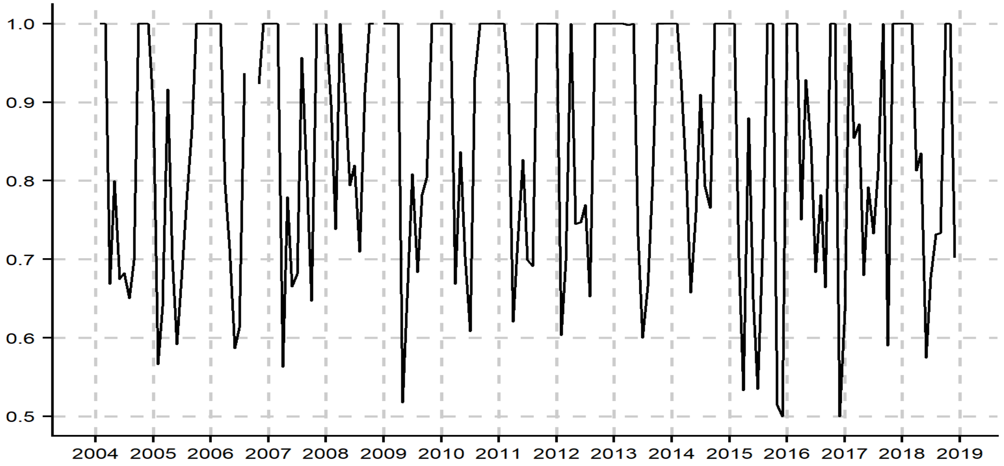
Meteorological index: Water Stress

- Daily reference evapotranspiration (ET_0) from Jensen-Haise equation over the 250-m grid

$$ET_0 = (0.0252 \cdot T_{mean} + 0.078) \cdot Rad_s \cdot 0.408$$

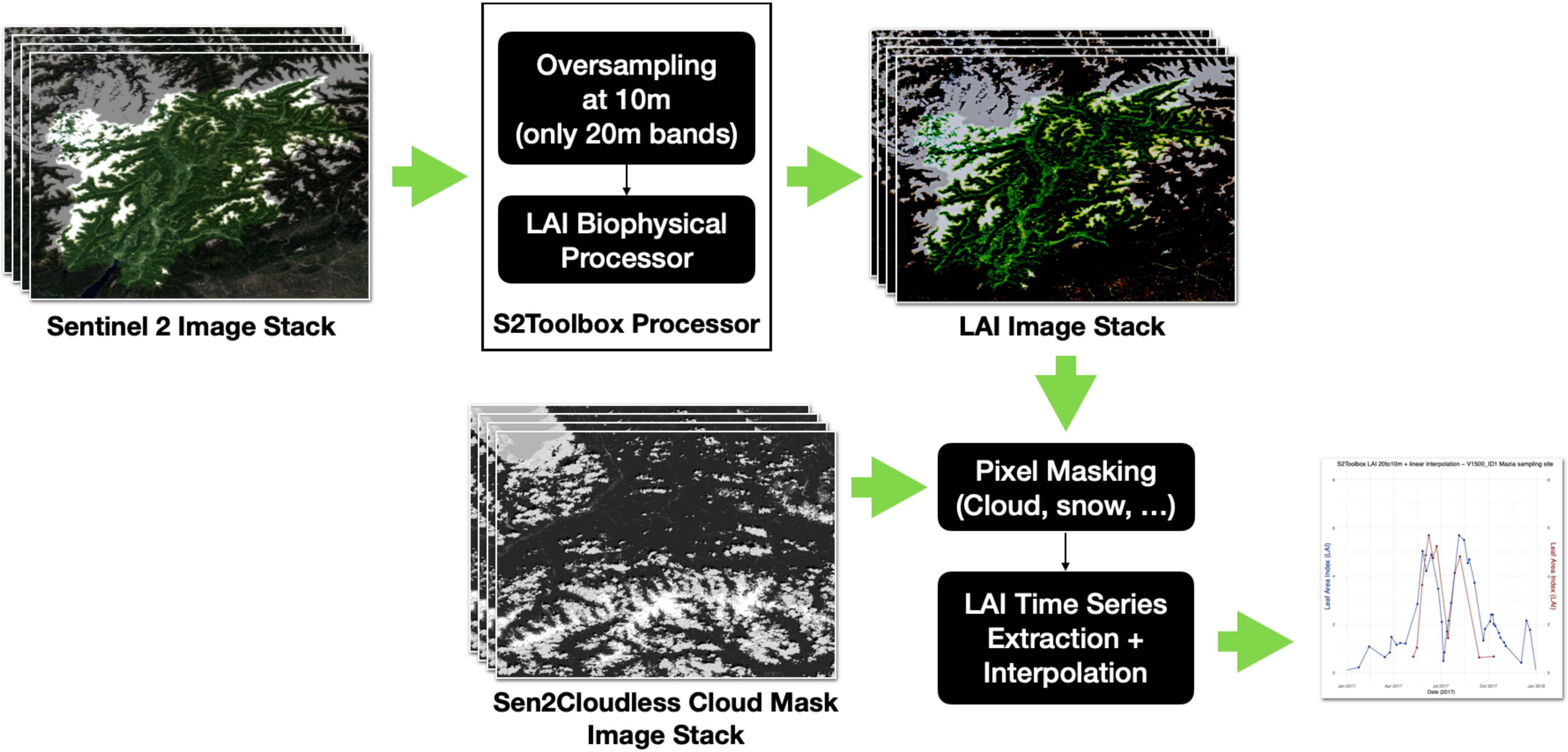
- Cws * $= \begin{cases} 0.5 + 0.5 \cdot \frac{P}{ET_0} & P \leq ET_0 \\ 1 & P > ET_0 \end{cases}$
- Cws is computed daily for 1-month accumulation periods from February to October





*Roumiguié, A., Jacquin, A., Sigel, G., Poilvé, H., Hagolle, O., & Daydé, J. (2015). Validation of a forage production index (FPI) derived from MODIS fCover time-series using high-resolution satellite imagery: methodology, results and opportunities. *Remote Sensing*, *7*(9), 11525-11550.

Biophysical index: LAI



Design - test sites

AG = autumn grazing

10 km

Mazia (M) 1450-1550 m a.s.l.

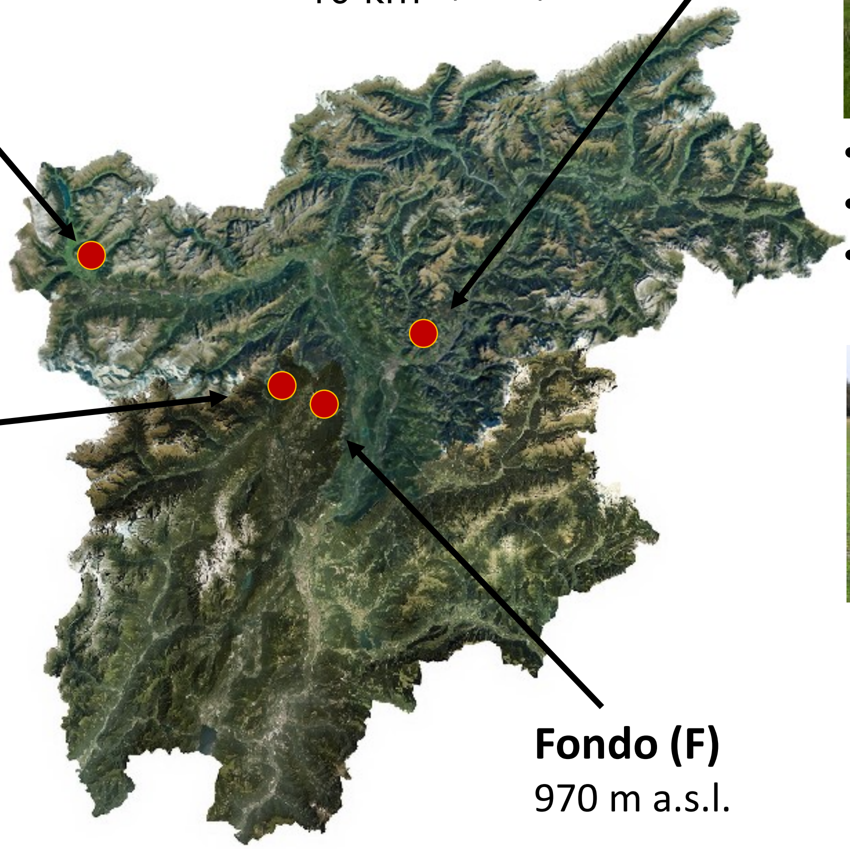
- 4 ha
- 2 cuts year^{-1}

- 1.1 ha
- grazed only

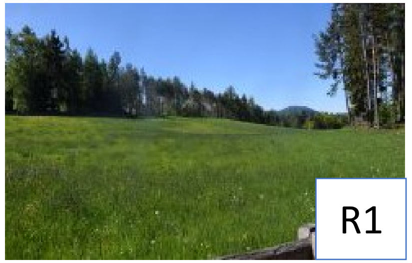
Laurein (L) 1330-1340 m a.s.l.

- 0.5 ha
- 2 cuts year^{-1} + AG
- N-input 167 kg ha^{-1} year^{-1}

- 0.37 ha
- 3 cuts year^{-1}
- N-input 167 kg ha^{-1} year^{-1}



Ritten (R)
1250-1270 m a.s.l.



- 0.77 ha
- 3 cuts year^{-1} + AG
- N-input 209 kg ha^{-1} year^{-1}

- 1.58 ha
- 3 cuts year^{-1} + AG
- N-input 209 kg ha^{-1} year^{-1}

- 0.99 ha
- 4 cuts year^{-1}
- N-input 162 kg ha^{-1} year^{-1}

- 0.5 ha
- 4 cuts year^{-1}
- N-input 162 kg ha^{-1} year^{-1}

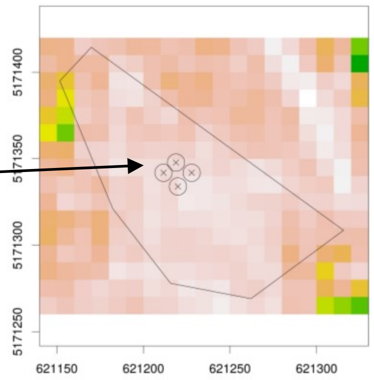
Fondo (F)
970 m a.s.l.

- 1.36 ha
- 3 cuts year^{-1}
- N-input 186 kg ha^{-1} year^{-1}

- 0.55 ha
- 2 cuts year^{-1}
- N-input 186 kg ha^{-1} year^{-1}

Validation of LAI

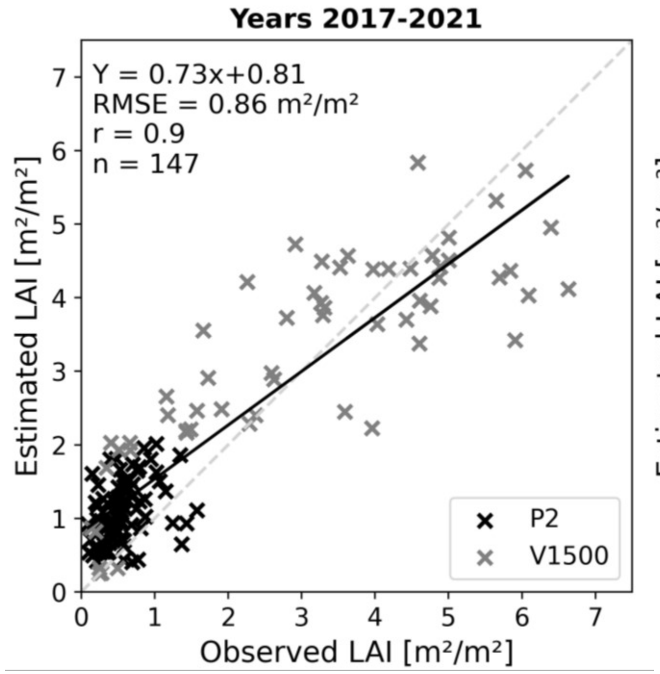
5 m buffer



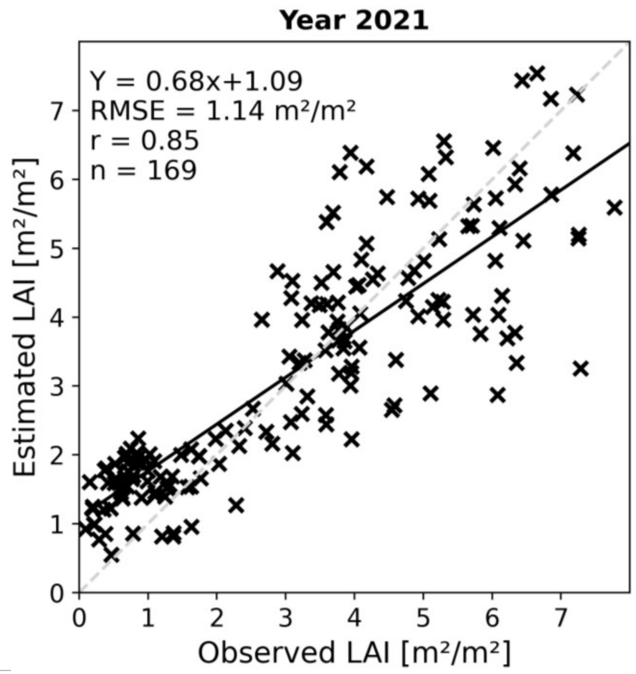
Parcel	Years	MSE	RMSE	MB	r	n
F1	2021	0.51	0.71	-0.39	0.94	21
F2	2021	0.75	0.87	-0.69	0.93	8
L1	2021	4.22	2.05	-0.89	0.81	16
L2	2021	1.12	1.06	-0.31	0.85	12
R1	2021	1.02	1.01	0.08	0.92	25
R2	2021	1.43	1.2	0.81	0.86	19
R3	2021	0.96	0.98	0.20	0.71	25
R4	2021	0.90	0.95	0.68	0.92	21
V1500	2017-2021	1.19	1.09	0.17	0.83	58
P2	2017-2021	0.45	0.67	0.53	0.36	89
V1500, P2	2017-2021	0.74	0.86	0.39	0.90	147
All	2021	1.29	1.13	0.07	0.85	170

Global comparison for all the parcels

2 parcels, 5 years



10 parcels, 1 year

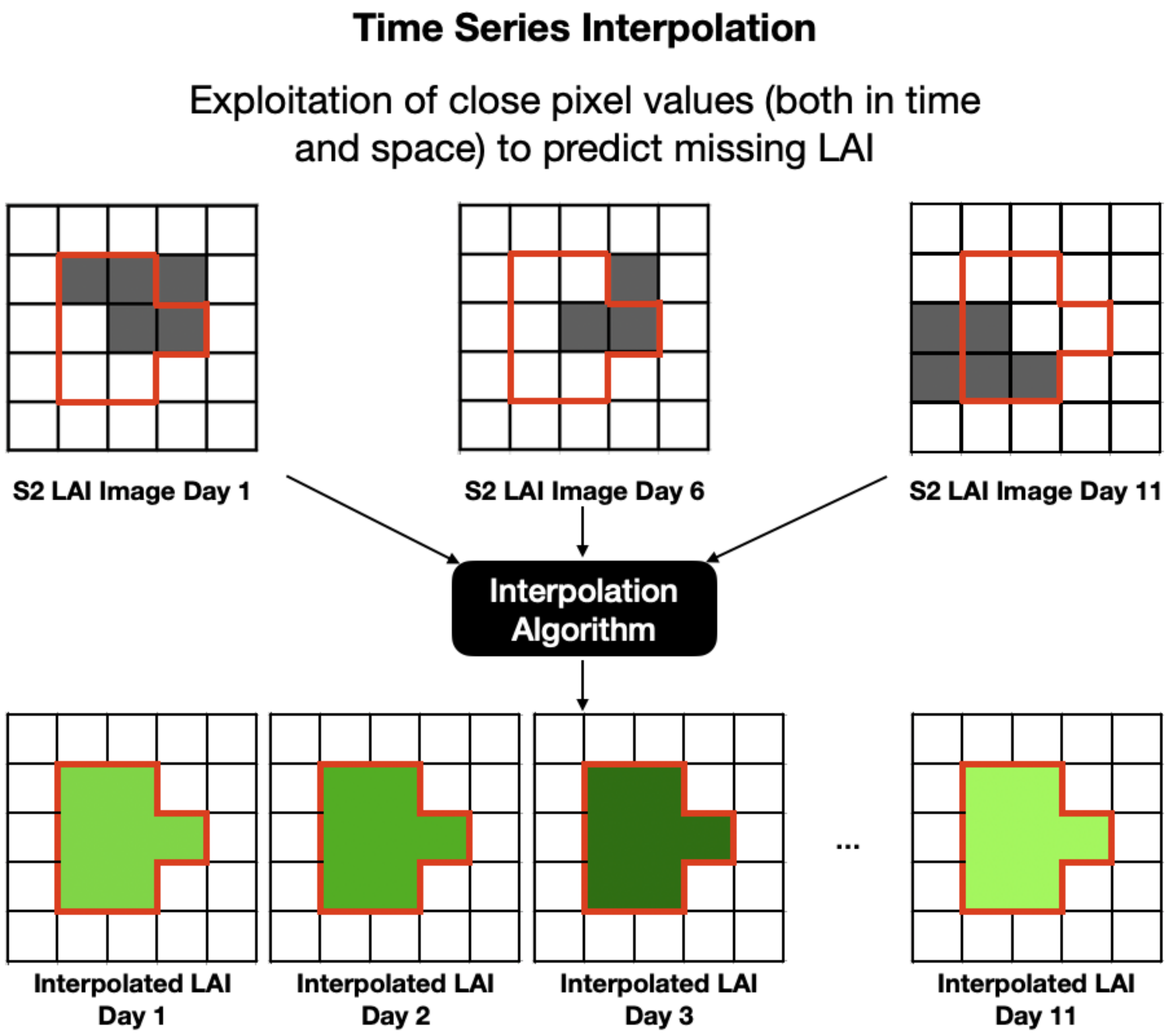


Sentinel-2 LAI Gap-filling

Method 1:
timeseries interpolation by
- Linear model at pixel level
- Linear model at parcel level
- Gaussian Process Regression model at parcel level

Input:
Raster stack of LAI timeseries derived from Sentinel-2

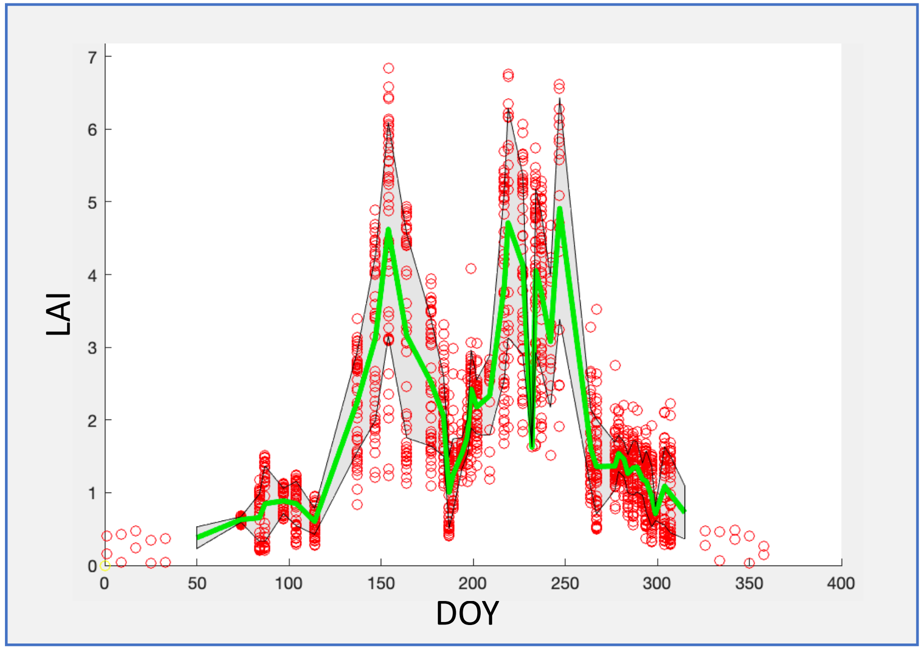
Output:
Daily LAI timeseries for each parcel, without gaps



Interpolation at parcel level

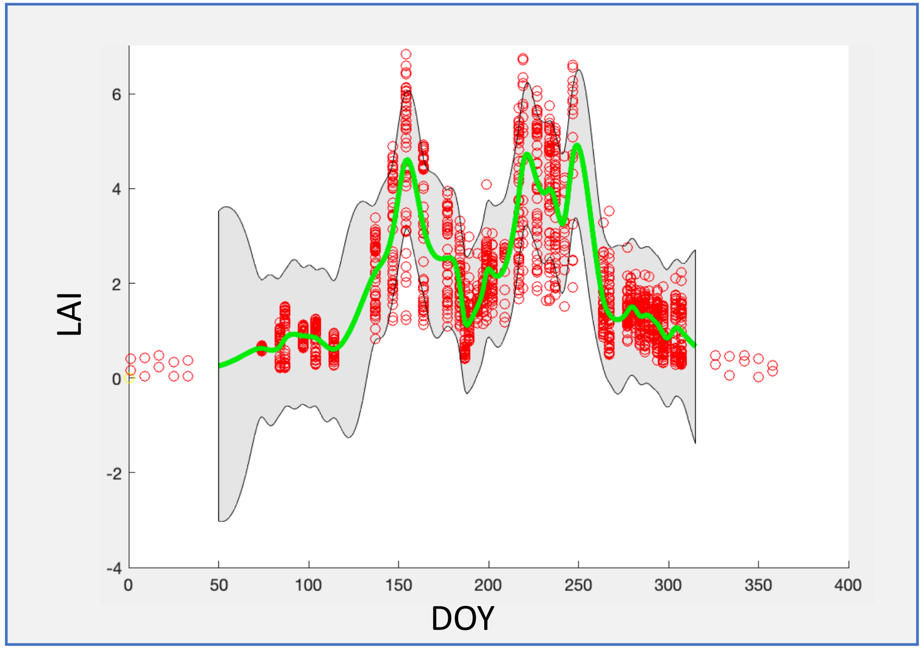
Linear model

Parametric model:
We assume that an analytical linear model fits the data

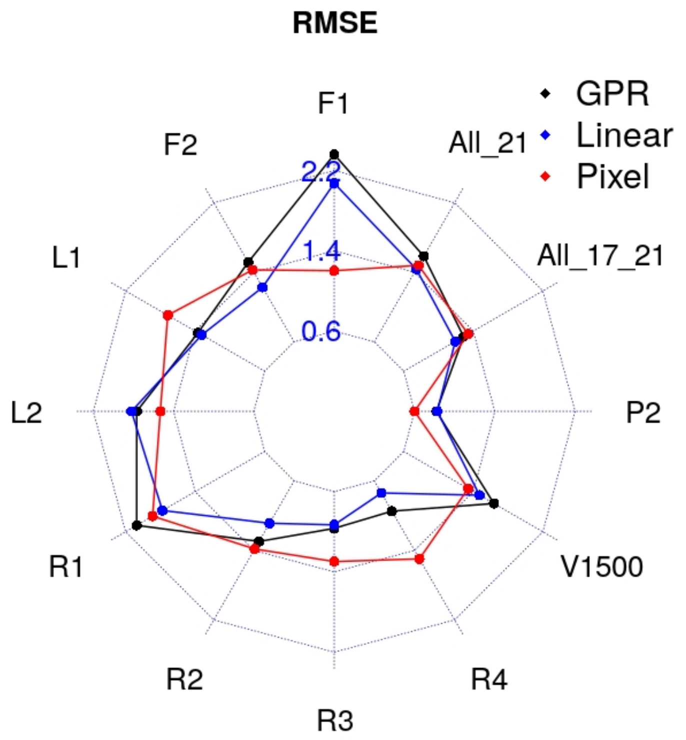


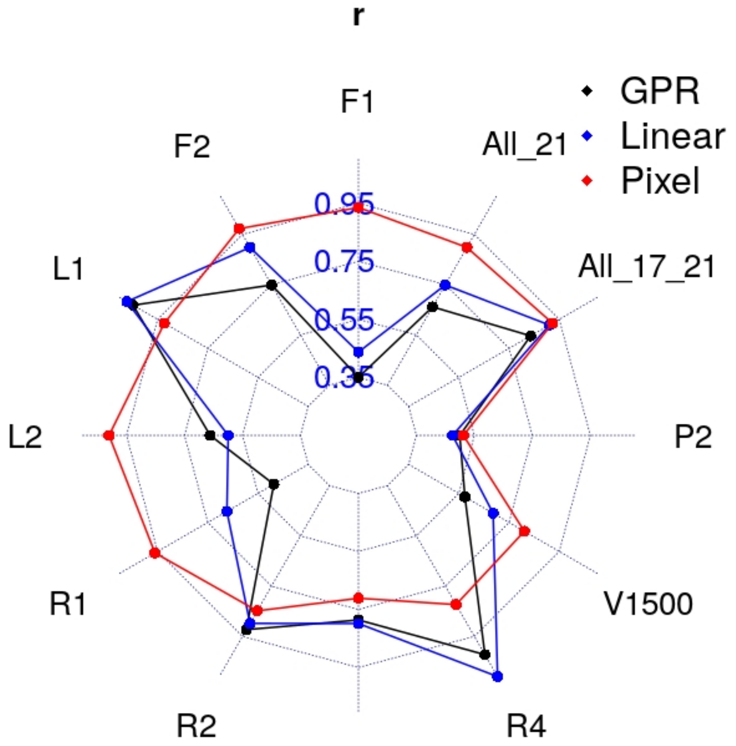
Gaussian Process Regression model

Non-parametric model:
We exploit observations to infer the best fitting model, without an analytical formulation



Results: Timeseries interpolation





Pixel-based linear interpolation performs better.

Comparison between gap-filled LAI and measurements averaged at parcel level.

All_21 <- all available parcels in year 2021

All_17_21 <- all available parcels in years 2017-2021

Sentinel-2 LAI gap-filling with Sentinel-1

Aim: enrichment of S2 LAI timeseries exploiting C band SAR data from Sentinel-1 A/B (S1), based on SAR sensitivity to vegetation structure

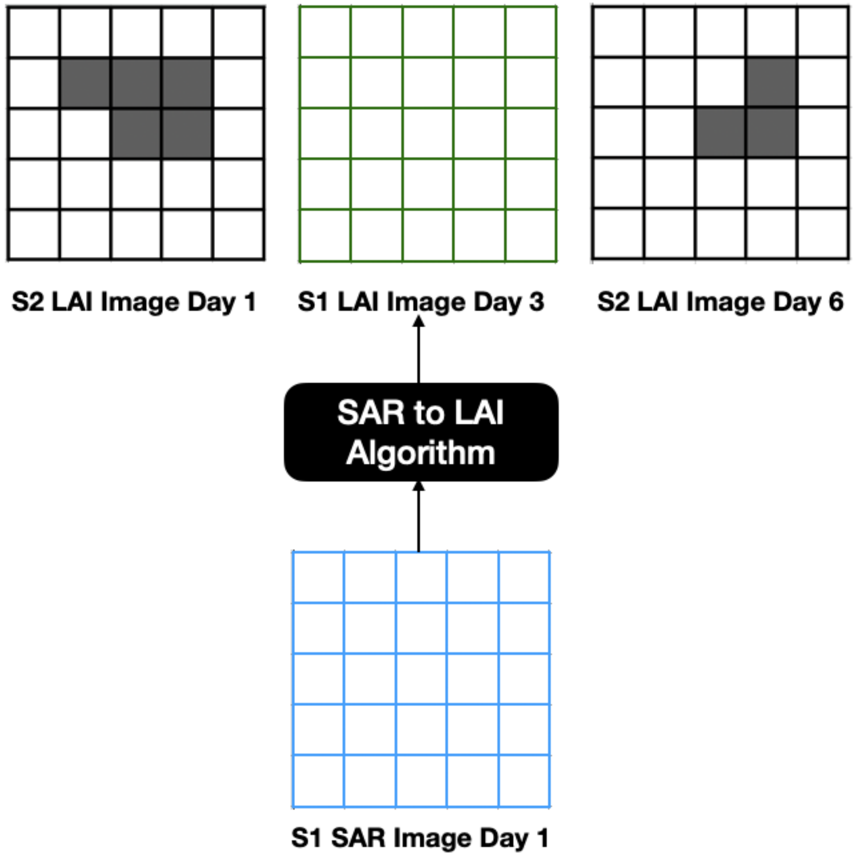
+

Challenge: SAR backscattering intensity is the combination of different interactions with soil and vegetation

Surface + Volume Scattering, Soil moisture, Vegetation water content, Surface roughness

$\rightarrow \sigma^0$

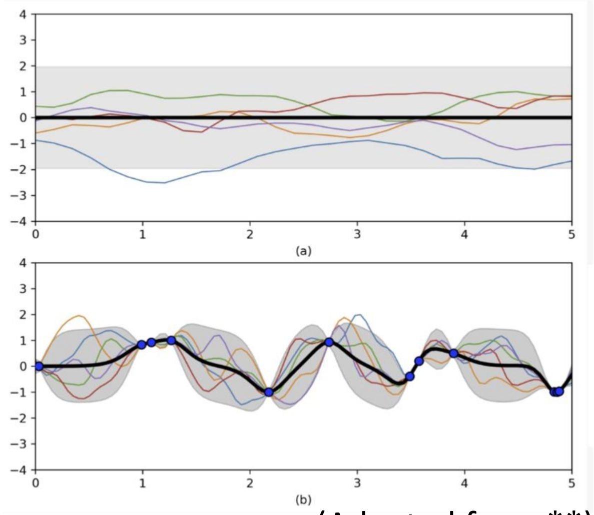
Solution: Non-linear machine learning regression to infer a generic non-parametric relationship between the SAR signal and the target variable (LAI)



Gap-filling with Sentinel-1

Gaussian Process Regression (GPR) model: predict Gaussian distributions of the target function at the test points $\boldsymbol{x}_* \in \mathbb{R}^D$, with *D* the number of input features

$$f(\boldsymbol{x}_*) = \boldsymbol{k}_*^T (K + \sigma_n^2 I_N)\, \boldsymbol{y}$$
$$\sigma_f^2(\boldsymbol{x}_*) = k(\boldsymbol{x}_*, \boldsymbol{x}_*) + \sigma_n^2 - \boldsymbol{k}_*^T (K + \sigma_n^2 I_N)^{-1} \boldsymbol{k}_*$$



(Adapted from **)

1) S1 pre-processing by SNAP S1 toolbox

2) Training: target -> S2, input features -> $\sigma_{VH}^0, \sigma_{VV}^0, ratio = \frac{\sigma_{VH}^0}{\sigma_{VV}^0}, RVI = \frac{4\,\sigma_{VH}}{\sigma_{VH}+\sigma_{VV}}$, *soil moisture**, *DOY*

3) Validation: leave-one-out -> GPR performances are calculated excluding one sample per time from the training

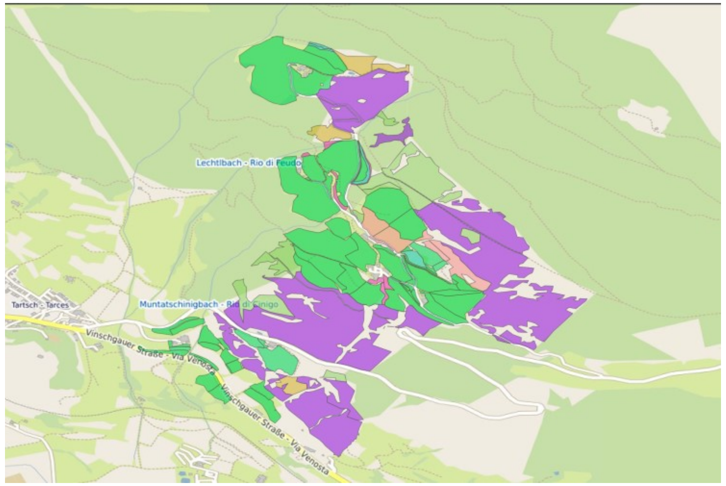
Best combination of input features: $\boldsymbol{\sigma_{VH}^0, RVI}$, ***soil moisture*, DOY***

*Greifeneder, F., Notarnicola, C., & Wagner, W. (2021). A machine learning-based approach for surface soil moisture estimations with google earth engine. *Remote Sensing*, *13*(11), 2099. https://gitlab.inf.unibz.it/Felix.Greifeneder/pysmm
** Rasmussen, C.E.,Williams, C.K.I. Gaussian Processes for Machine Learning; The MIT Press: New York, NY, USA (2006).

Preliminary Results: GPR model

Test at hillslope scale:

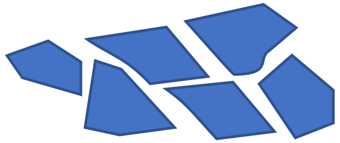
Derivation of the model at polygon scale, on 126 parcels with different land use, including pastures, meadows, and alpine summer pastures



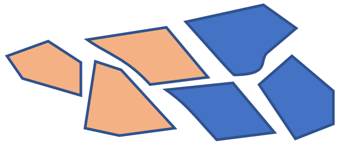
Monteschino, Venosta Valley (Bolzano), including measurement sites in parcels P2 and V1500.

Training strategies:

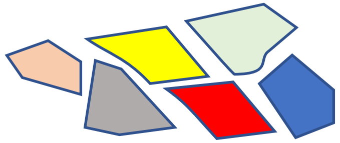
- Global model for any land use

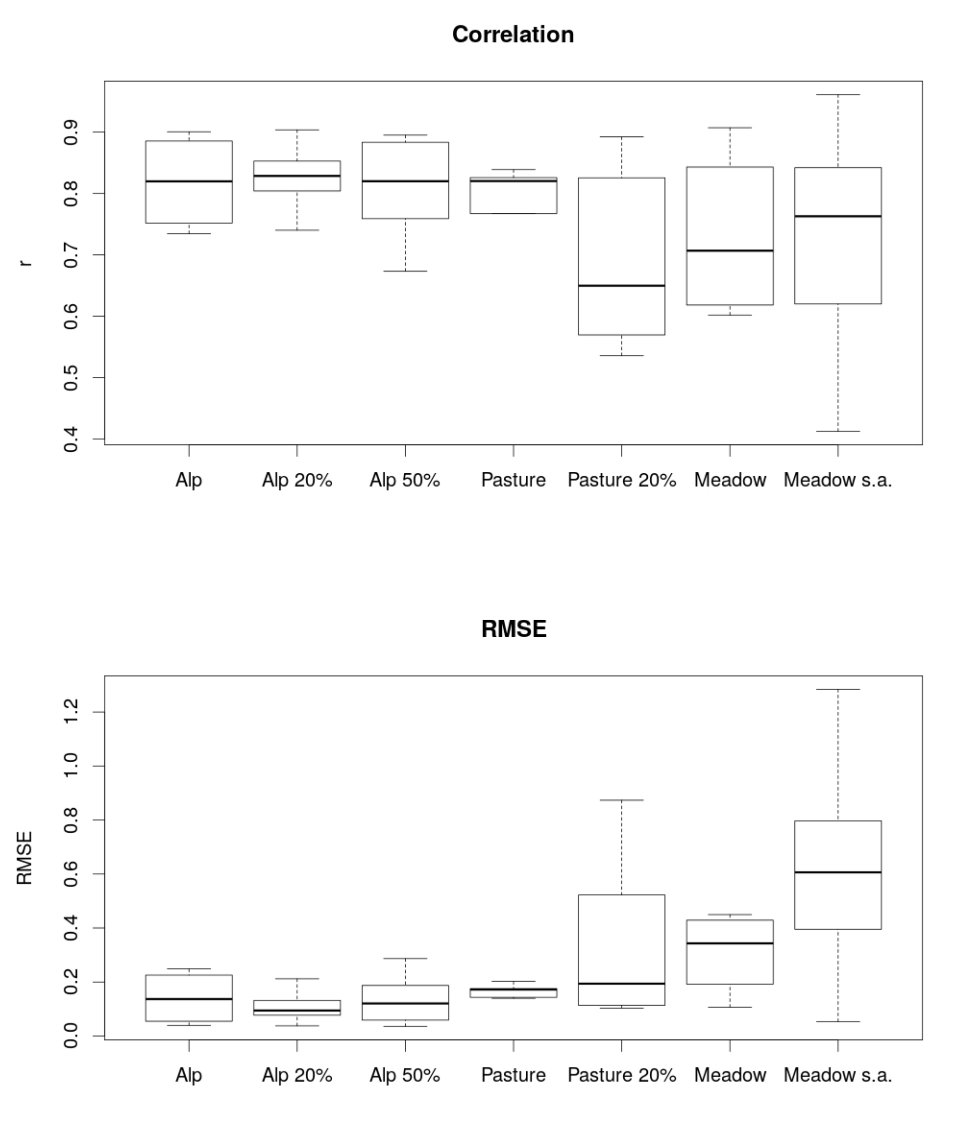


- Land use specific model



- **<u>Parcel Model</u>**



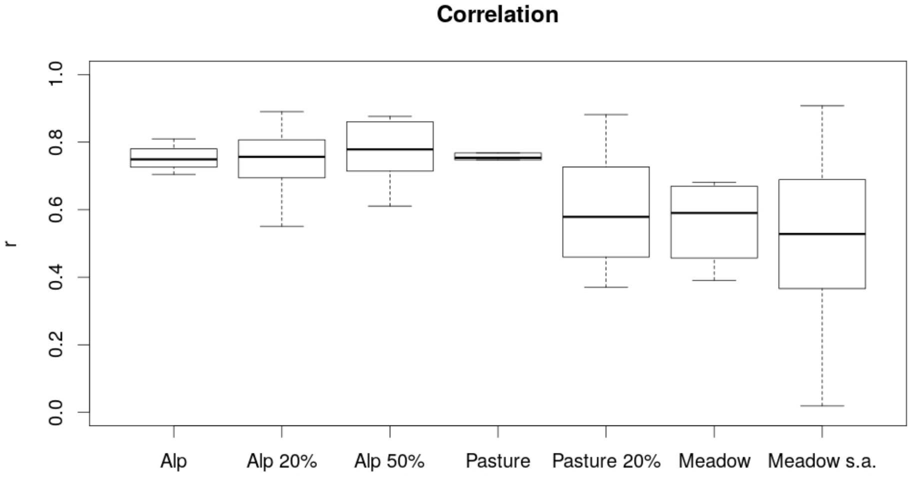


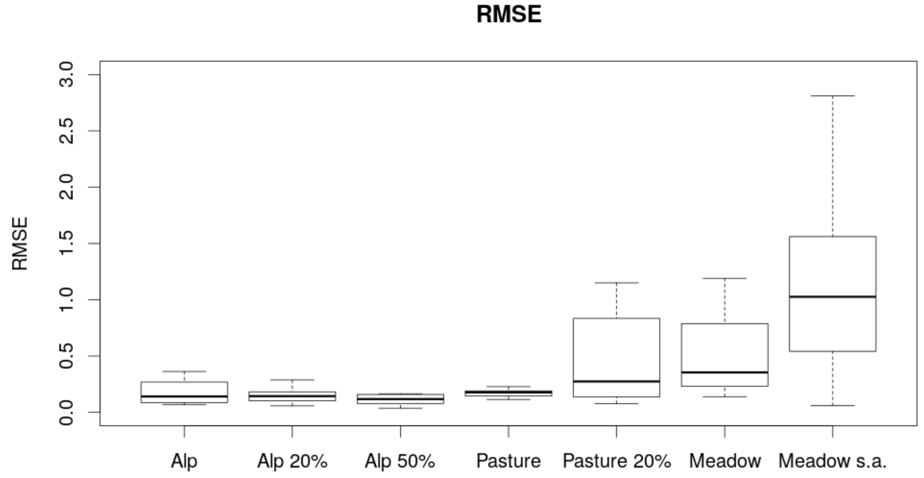
Preliminary Results: GPR model

Validation strategies:

- Temporal sampling:

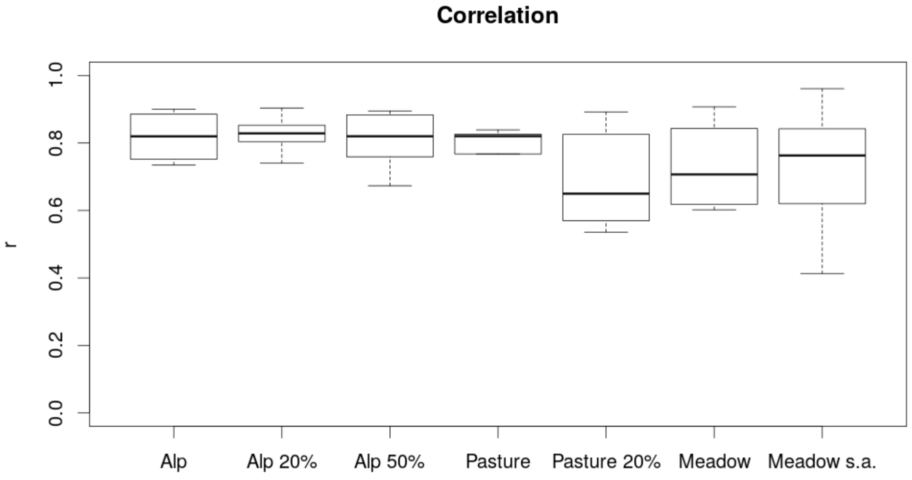
  Can the model predict missing overpasses?

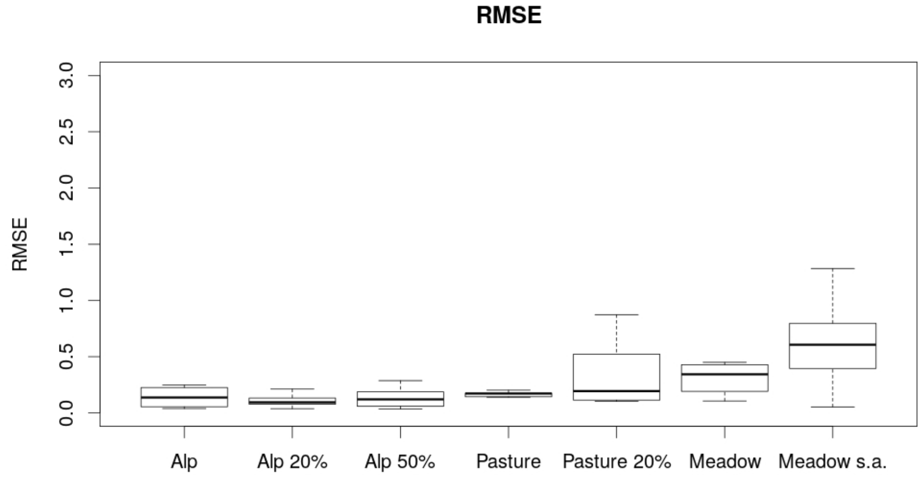




- **<u>Spatial sampling:</u>**

  Can the model predict missing pixels?





Conclusions

Sentinel-2 LAI:

- Good performances compared to ground data
- Overestimation of low values

Gap-Filling methods:

- Interpolation
  - ✓ Linear interpolation performs better than GPR interpolation

- GPR to estimate LAI from Sentinel-1:
  - ✓ Training: parcel scale models are more accurate due to homogeneity
  - ✓ Validation: the model is more performant to predict in space (missing pixels) than in time (missing overpass)

- Ideal combination:
  - ✓ Spatial gap-filling by GPR LAI estimation from S1 + linear temporal interpolation

Outlook

1) FPI evaluation: Compare FPI with biomass measurements

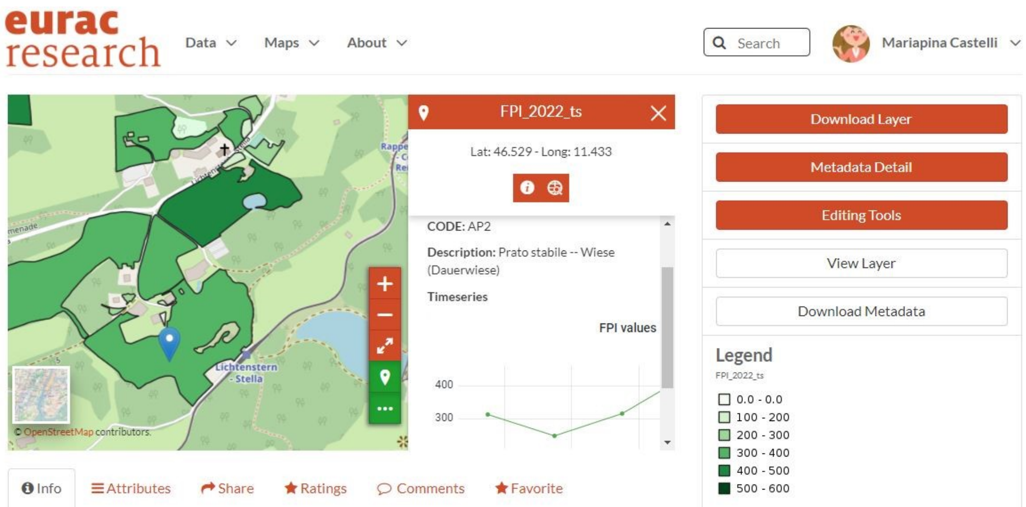
$$FPI_n = \sum_{i=SOS}^{i=EOS} (LAI_{grassland\ i} \times WS) \qquad vs\ \ ground\ measurements\ of\ biomass$$

2) ΔFPI exploitation for calculating 2022 payments for 8 insured test farms

$$\Delta FPI_n = \frac{FPI_n}{Olympic\ average(FPI_{n-1}; \dots ;\ FPI_{n-5})}$$

3) FPI and ΔFPI publication on the Eurac maps portal:

https://maps.eurac.edu/layers/edp_geonode_data:geonode:FPI_2022_ts



Thank you for your attention!

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