# Radiative transfer model-based LAI retrieval from Sentinel-2 data through machine learning, adding phenological constraints and soil information

Sharing is encouraged

*Sélène Ledain[1,3], Felix Stumpf[2], Anina Gilgen[3], Helge Aasen[1]*

EOA Earth Observation of Agroecosystems team

*www.eoa-team.net*

## Motivation

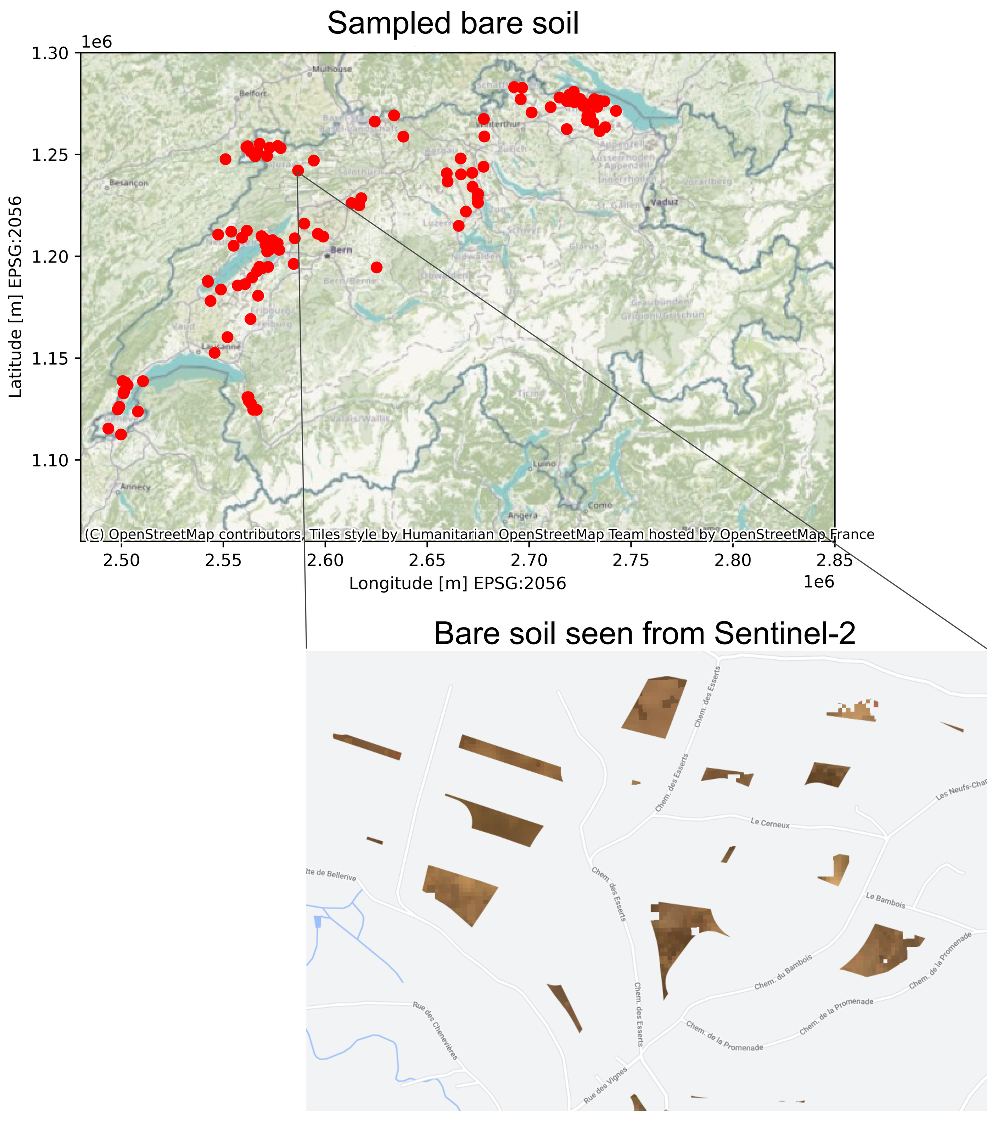
- **Soil erosion** of arable land can have important consequences on **crop production** and on the **environment** due to nutrient loss.
- **Cover crops** during fallow periods can help **protect the soil** from physical processes and maintain the topsoil fertility.
- We can assess **presence of cover crops** in fields by extracting **leaf area index (LAI)** from **satellite imagery**.
- LAI retrieval can be performed by **inversion of a mechanistic model** (Radiative Transfer Model = RTM), but is **computationally expensive**.

How can we use **machine learning** (ML) to accelerate and improve **LAI retrieval** in fields across a **large scale** like Switzerland, by incorporating soil data and phenological constraints?

## Methods

### 1 Extract soil information from the Swiss landscape

- Background soil becomes important in low LAI (low crop cover) settings
- Sample representative spectra of bare soil pixels in Switzerland



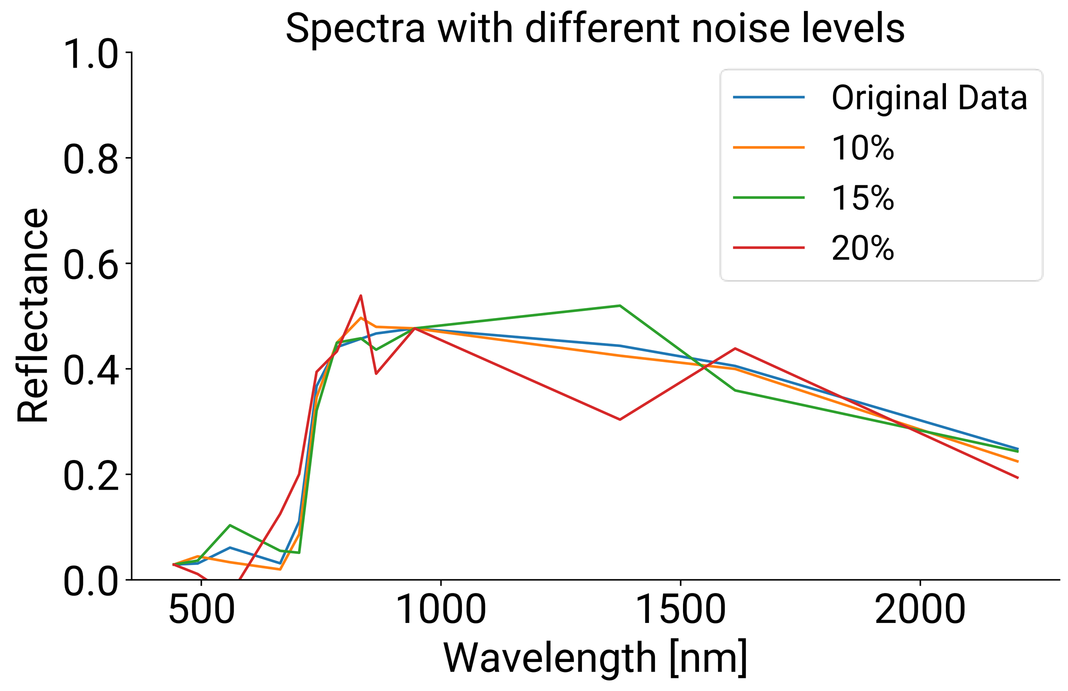

### 2 Generate a training dataset using a RTM model

- ProSAIL RTM simulates top-of-canopy reflectance of Copernicus' Sentinel-2 satellites
    - Takes in leaf and canopy variables (including LAI)
    - Uses background soil reflectance
- Simulate 50k reflectances using variable ranges for wheat as input
- Obtain pairs of simulated spectra and LAI

### 3 Add noise to make the data resemble satellite acquisitions

- Sentinel-2 data is atmospherically corrected, but can still contain noise and artifacts
- The simulated top-of-canopy reflectance doesn't account for residual atmospheric and sensor noise
- Add gaussian noise models to make simulated data more realistic

$$R_{ns}(\lambda) = 1 - \{[1 - R(\lambda)] * [1 + \chi(0, \sigma(\lambda))]\}$$



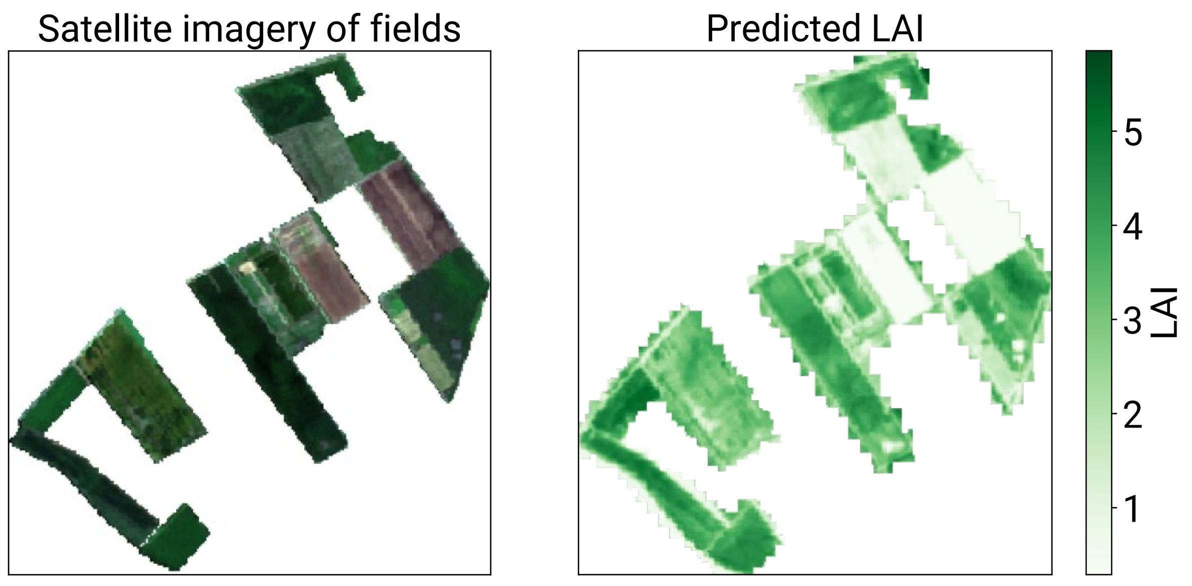

### 4 Train the ML model

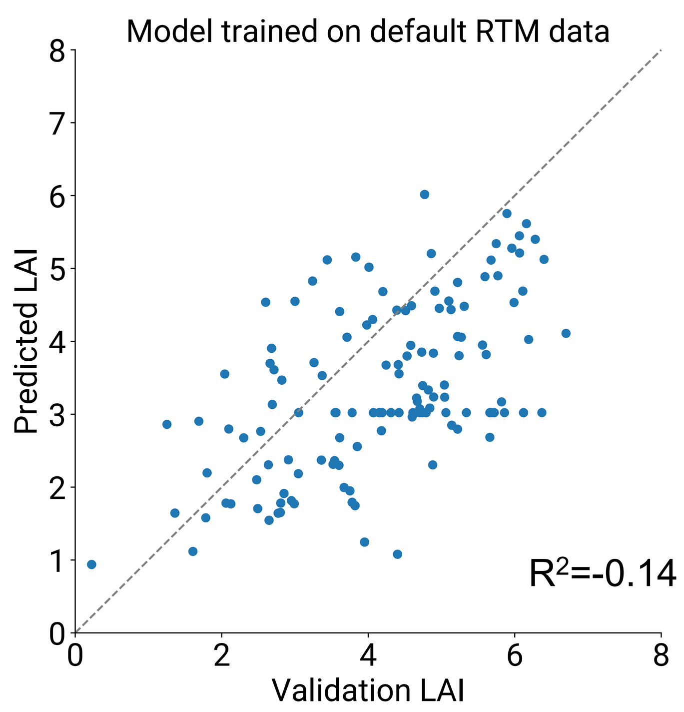
- Train a neural network on the data generated with the RTM, with added noise
- Predict LAI from a pixel's spectral response
- Validate on in-situ LAI measurements around Switzerland

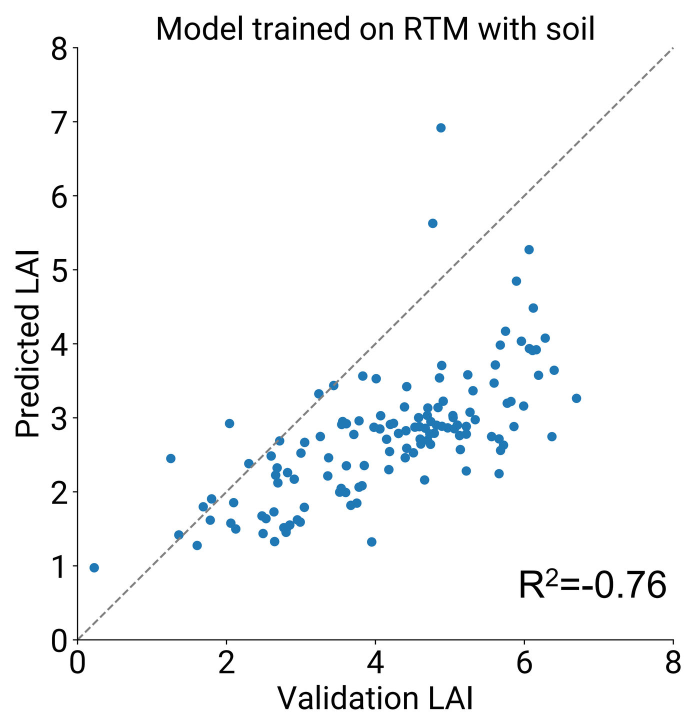
## Results

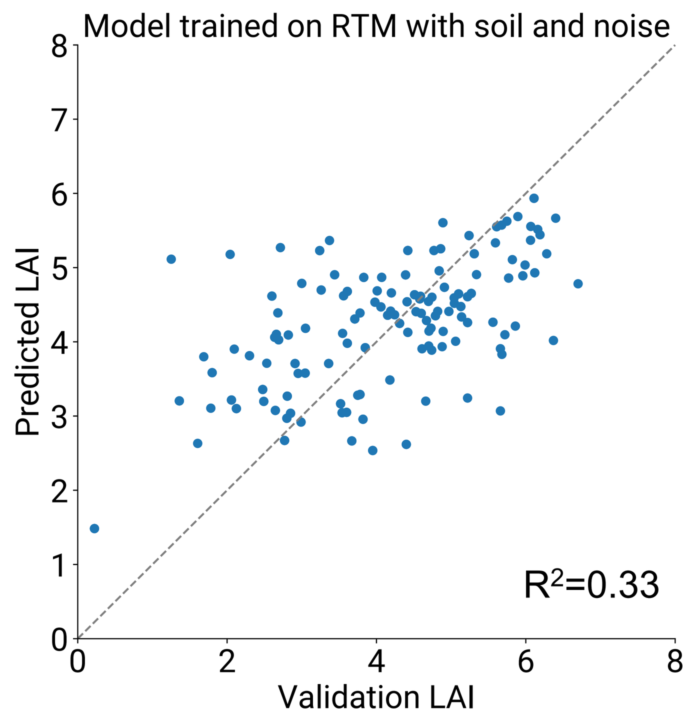
Adding environmental data and phenological constraints to the RTM, as well as noise to the generated dataset, has shown improvement in the LAI-retrieval model.

| Setup | RMSE for LAI<3 | Overall RMSE |
|---|---|---|
| Default RTM data | 0.916 | 1.35 |
| RTM with added soil data | 0.845 | 1.65 |
| RTM with added soil data and noise | 1.42 | 1.03 |




**Default RTM data** → RMSE improves by 8% in low LAI (<3) → **RTM with soil observations** → Overall RMSE improves by 37% → **RTM with soil observations + 10% inverse gaussian noise**

### What's next?

- Adjust noise model so that it does not negatively impact predictions for low LAI
- Further optimize the model hyperparameters
- Inference on fields across Switzerland

Let's Chat!

[1] *Water Protection and Substance Flows, Division Agroecology and Environment, Agroscope, Reckenholzstrasse 191, 8046 Zurich, Switzerland.*

[2] *Competence Center for Soil, Berne University of Applied Sciences, Länggasse 85, 3052 Zollikofen, Switzerland.*

[3] *Integrative Agroecology, Division Agroecology and Environment, Agroscope, Reckenholzstrasse 191, 8046 Zurich, Switzerland.*

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