

# Hyperspectral imaging for high-resolution mapping of soil profile organic carbon distribution in an Austrian Alpine landscape

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## Introduction

- ❖ Alpine mountainous regions are characterized by high **soil organic carbon (SOC)** content (Prietz et al., 2016).
- ❖ **Subsoils store 30 to 63%** of the SOC stocks (Rumpel and Kögel-Knabner, 2011).
- ❖ Topography **affects spatial variability of SOC** content, not only in topsoils but also in subsoils (Chen et al., 2016 ; Zhu et al., 2019).
- ❖ **Hyperspectral imaging** (Vis-NIR spectroscopy) can reveal the SOC hotspots at micro-scale (Hobley et al., 2018; Nawar and Mouazen, 2019).
- ❖ **Random forests (RF)** as a combination of tree predictors have been successfully used for modelling soil profile OC from spectral information of intact soil cores (Jia et al., 2017; Hobley et al., 2018; Sorenson et al., 2020).

## Objectives

- ❖ Test the use of **hyperspectral imaging** coupled with the RF machine learning for mapping of the soil profile OC distribution in an alpine mountainous landscape.
- ❖ Investigate the **effects of topographical factors** on SOC distribution in soil profiles.

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## Study area

- ❖ **Lungau Valley**, South of Salzburg, Austria.
- ❖ Mountainous region with **Alpine climatic conditions**.
- ❖ Characterized by **grassland farming** and **forest**.
- ❖ Soil types, mainly **Cambisol** and **Regosol**.

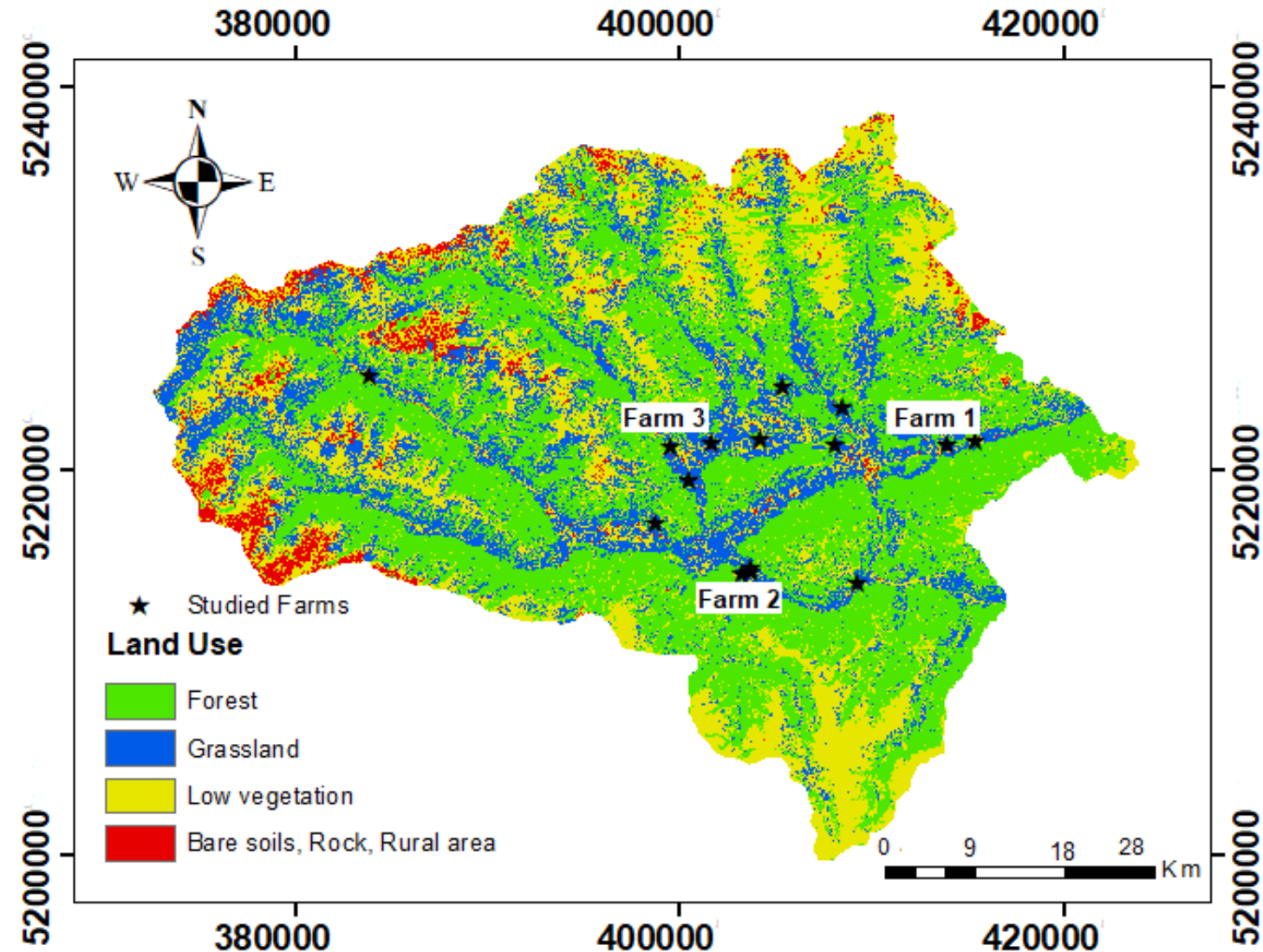


Figure 1. Land use map of the study site and 3 selected farms



## Soil sampling

- ❖ **60 core-samples** from 15 organic farms by using a hydraulic corer to a depth of 1 m.
- ❖ One **un-disturbed** half of the **cores** for hyperspectral imaging.
- ❖ Another half of the cores for laboratory bulk analyses.
- ❖ Five depth intervals: 0-10 cm, 10-20 cm, 20-40 cm, 40-80 cm and 80-100 cm.



## Laboratory analyses

- ❖ **Classical bulk physico-chemical analyses:** bulk density, soil texture, organic and inorganic C and total N.
- ❖ State-of-the-art **imaging technique:** hyperspectral imaging to reveal the hotspots of C and N in the soil profile (Hobley et al., 2018).

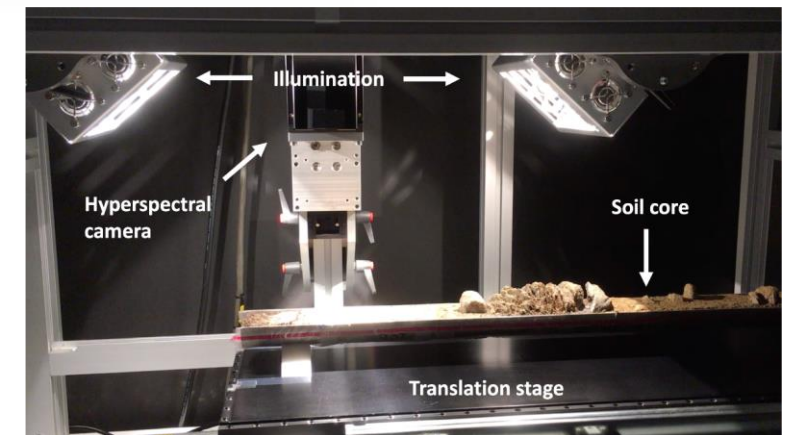


Figure 2. Hyperspectral imaging

## Hyperspectral imaging

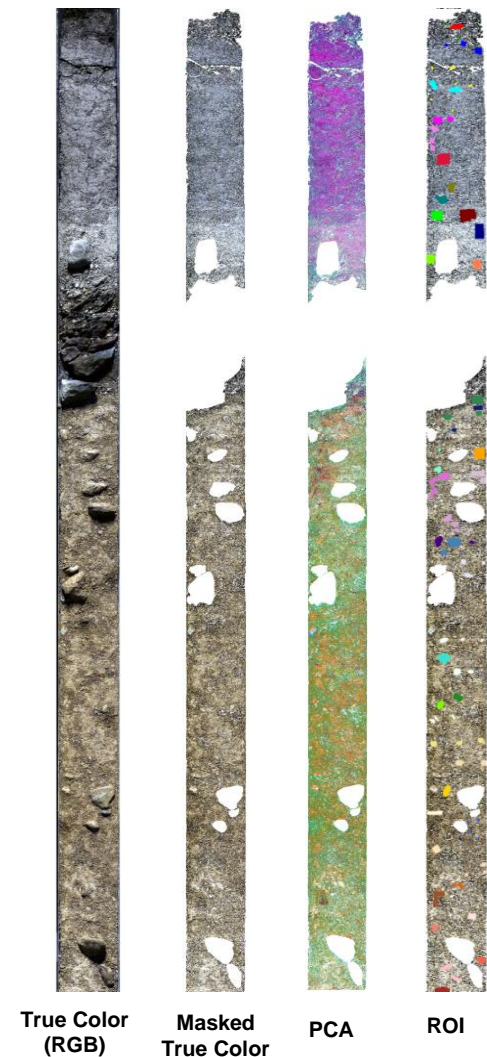


Figure 3. Scan of the selected core (Farm 2) and flowchart of the hyperspectral analysis

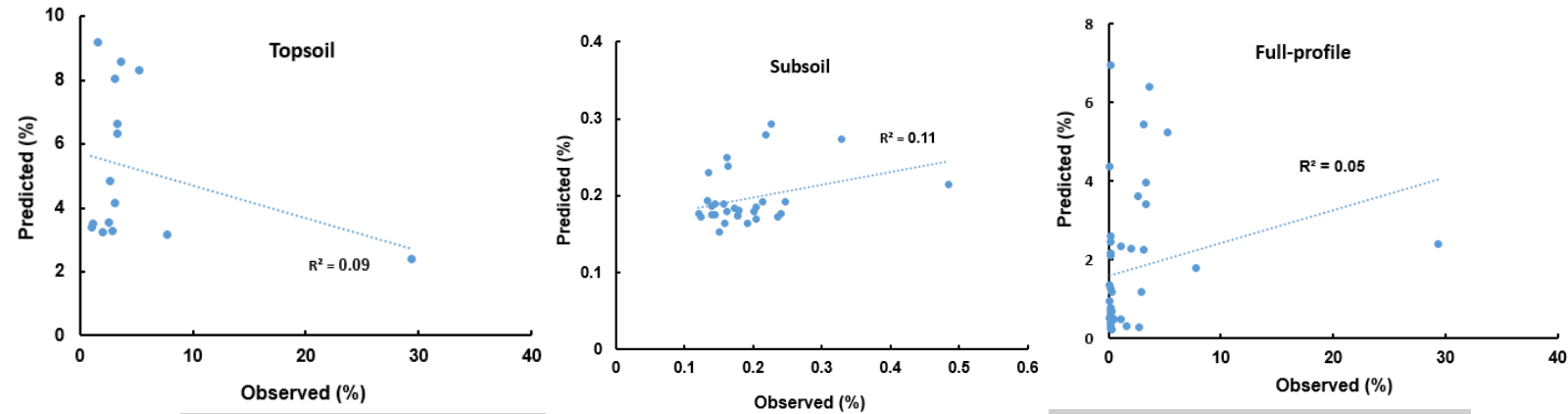
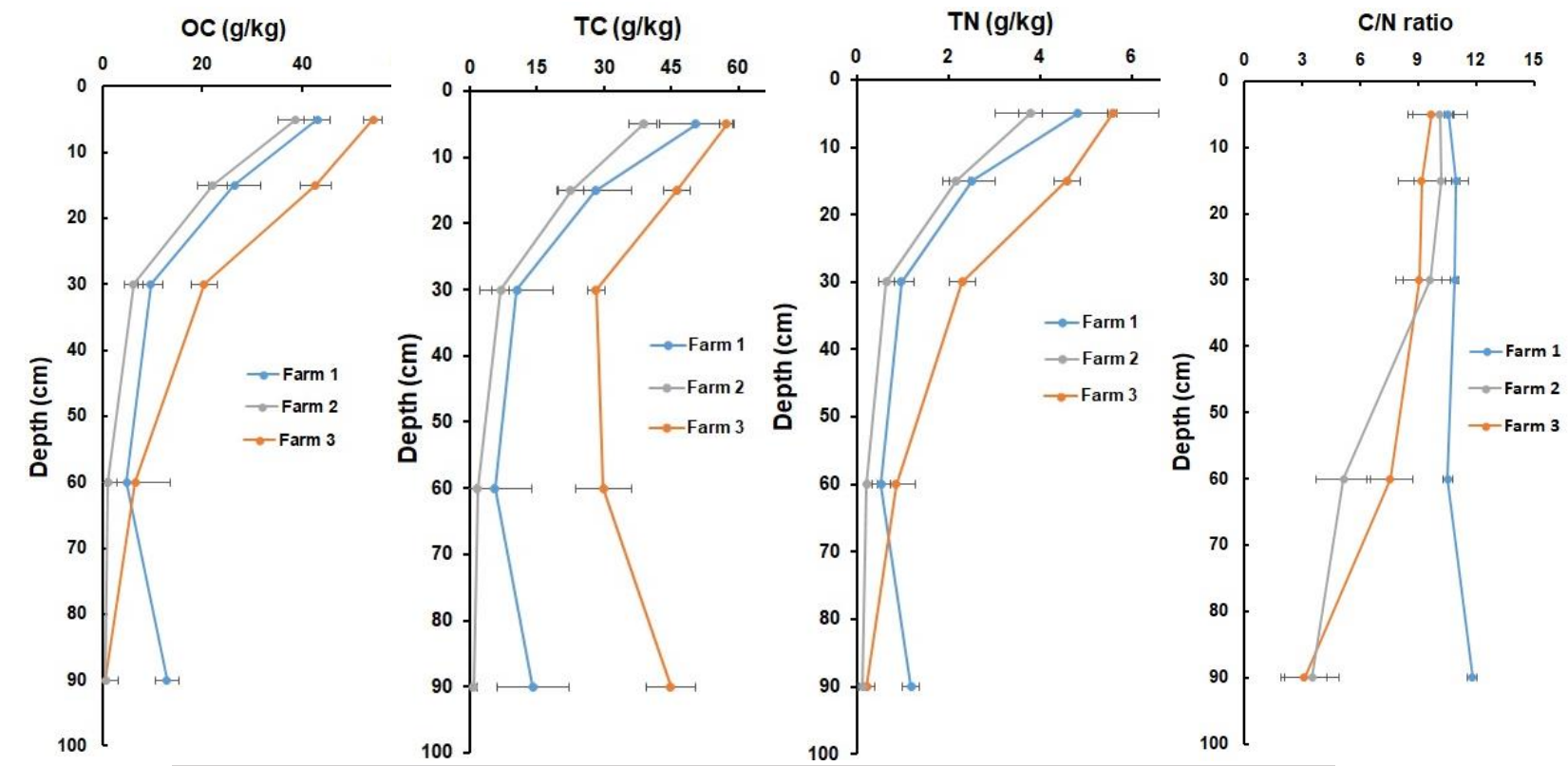


Figure 4. Observed vs. predicted total C from spectra information by using the RF machine-learning

Results showed that model developed by using a combination of spectral data and RF provided weak predictions for total C (Fig. 4) along the soil profile. This could be due to:

- ❖ Large heterogeneity in color, texture and high reflectance along the soil profile of core 2 (Fig. 3).
- ❖ Existence of high amount of inorganic C in subsoil, influencing prediction of the SOC content by hyperspectral data.

For improving the SOC prediction by using the spectra data, we are still testing an approach, involving the removal of inorganic C with high reflectance.



Topography effects on soil OC and TN

Table . Topographical factors of the 3 test farms

Farms	Elevation (m)	Aspect	Slope %
1	1109	West	8.5
2	1124	East	4
3	1125	South	4.3

Fig. 5. Soil profile organic C, total C and N contents and C/N ratio of the 3 selected farms

- ❖ Elevation and slope do not play a significant role regarding SOC and TN contents in the 3 selected farms (see Table).
- ❖ Farm 3 located in south aspect (north-facing) has higher SOC and TN contents than Farms 1 and 2 (Fig. 5).
- ❖ In the northern hemisphere, soils in south aspects have generally higher moisture and lower temperatures in comparison with soils in other aspects, resulting in higher litter input and lower decomposition rates (Zhu et l., 2019).



## References

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**Thank you very much**