Session 4

Integrating Radiative Transfer and Hybrid Deep Learning for the Modeling of Disturbing Factors and Advancing EO-based Soil Organic Carbon Retrievals

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ESA Symposium on Earth Observation for Soil Protection and Restoration

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Motivation: From laboratory to EO scale

- Increasing availability of large Soil Spectral Libraries (SSL)

➢ Basis for accurate estimation of soil parameters

OSSL

- However: Dynamic surface conditions at the EO scale

(1) Young emerging crops

(2) After harvest residues

(3) Soil moisture

Surface roughness & crusting

de Jong et al., 2011

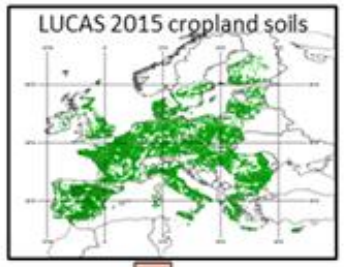
- Aim: Simulation of “landscape-like” reflectance spectra (Spatially Upscaled Soil Spectral Libraries: SUSSL) → Improve data basis for spectral soil modelling

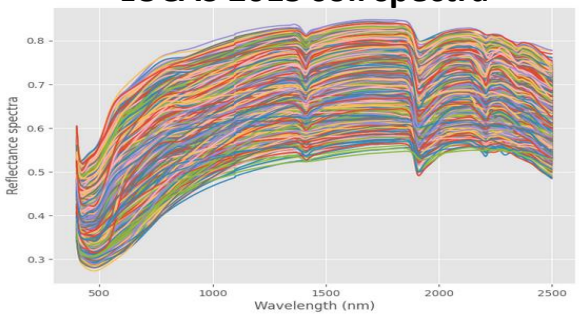
Modelling of dynamic surface conditions

Bare Soil

Full Lucas 2015

LUCAS Soil Spectral Library

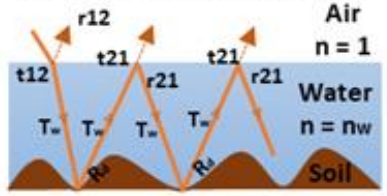


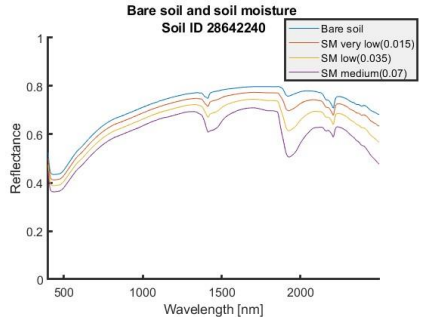


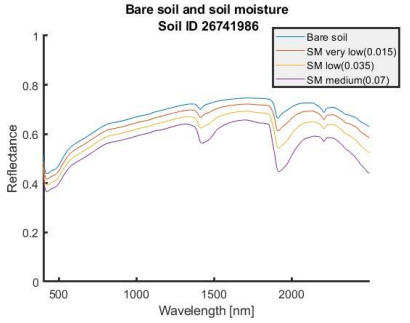
Surface Soil Moisture Model

MARMIT 2.0

Multilayer Radiative Transfer Model of Soil Reflectance

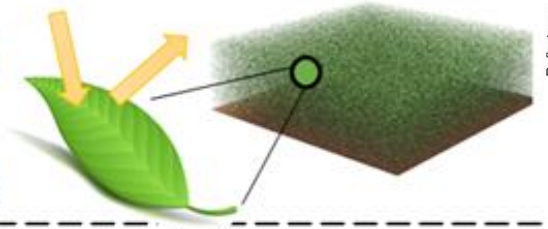


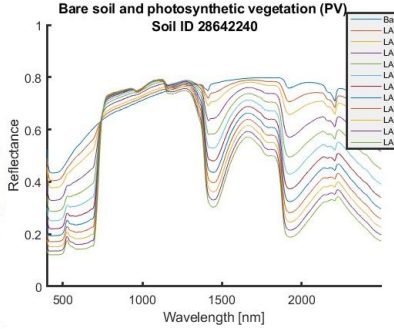


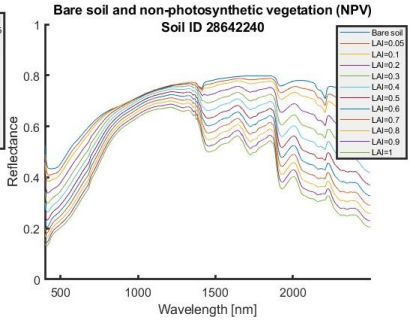


Leaf-Canopy Model

PROSPECT-4 & 4SAIL2







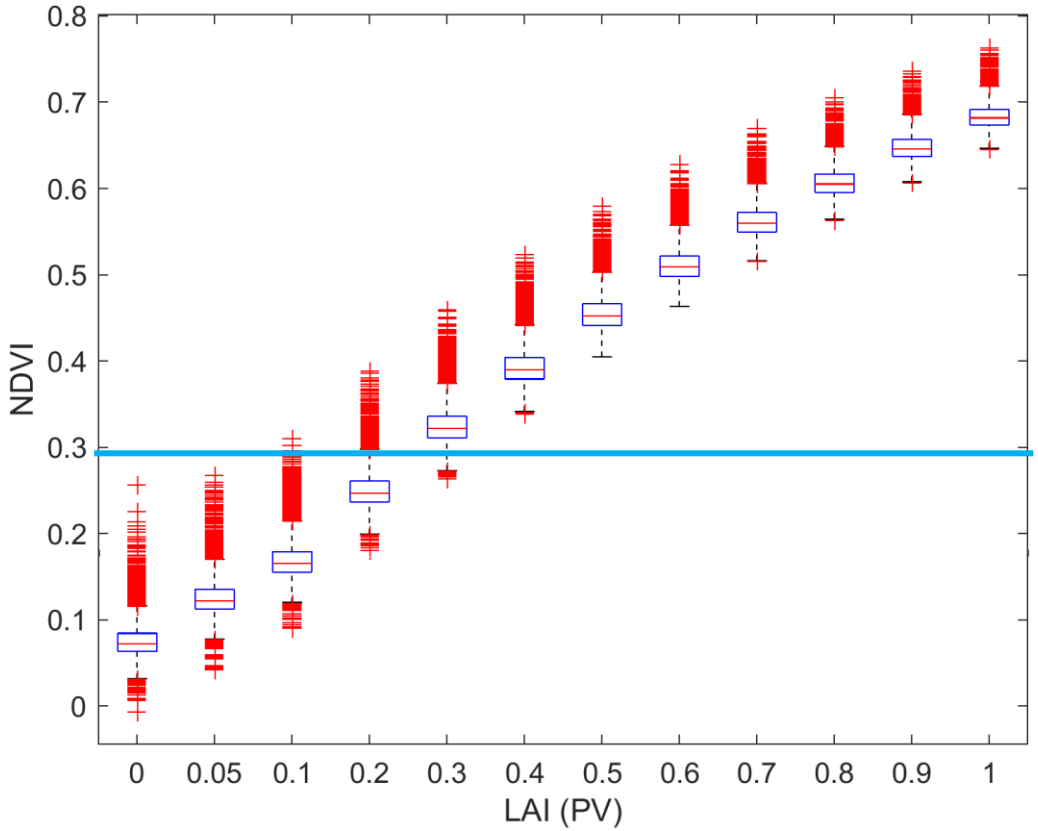
- LUCAS 2015 SSL for croplands: 8,869 soils
- Coupling of radiative transfer models (RTM)
  - MARMIT 2.0
  - PROSPECT-4 & 4SAIL2

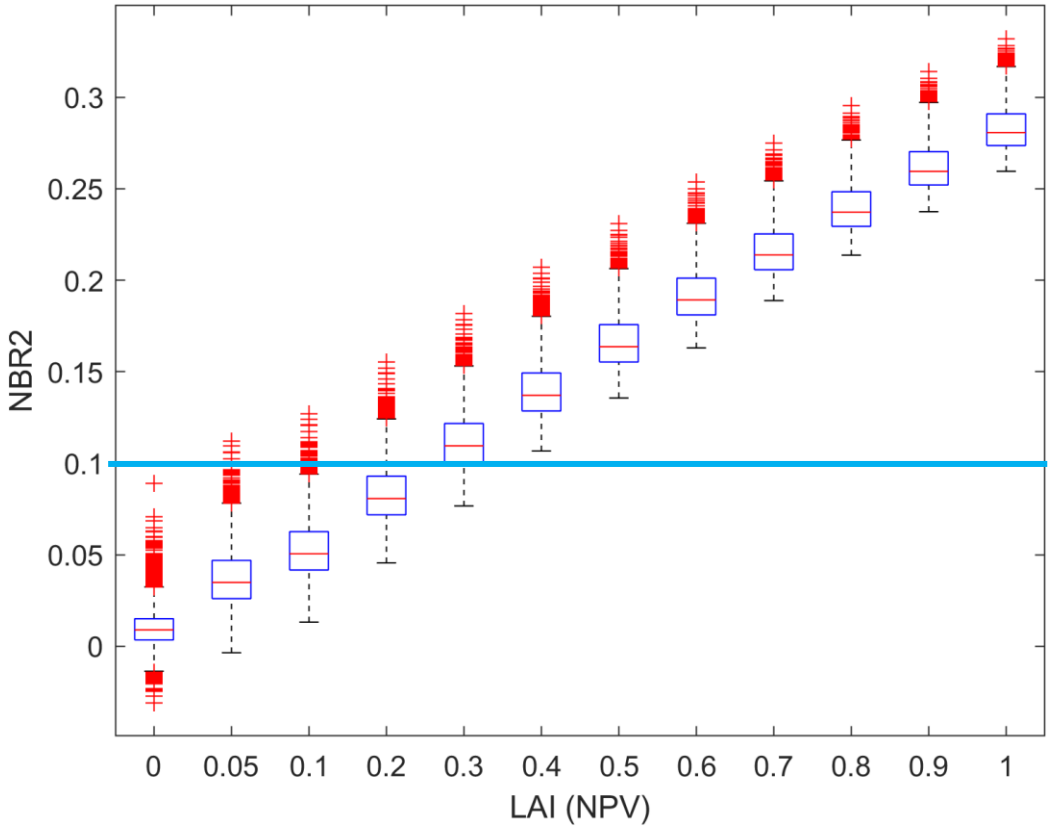
➢ Simulate wet soils and mixed soil-vegetation scenarios
822,572 spectra

Impact of dynamic surface conditions

- Limitation of spectral indices for detection of ‘bare soil’ conditions

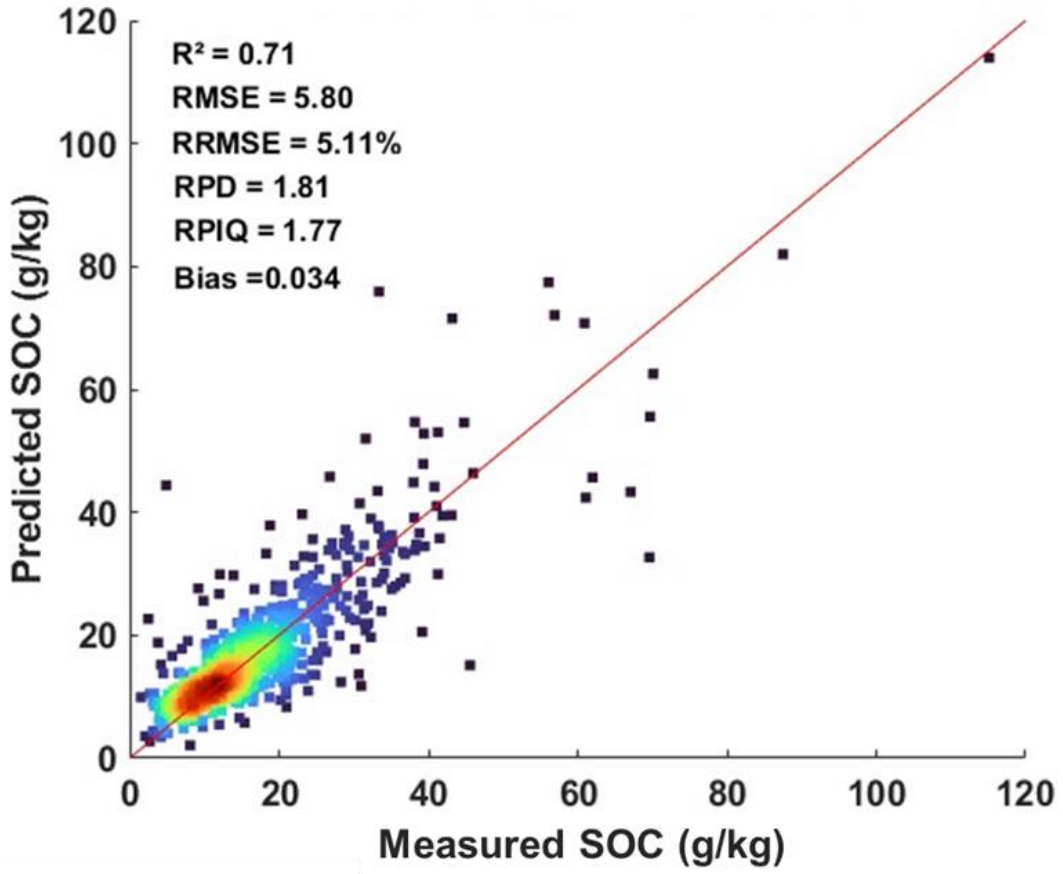
➢ Mixed spectral information remain at the EO scale





Estimation of SOC using 1-D CNN

- Baseline 1D-CNN trained on LUCAS 2015 bare soil spectra



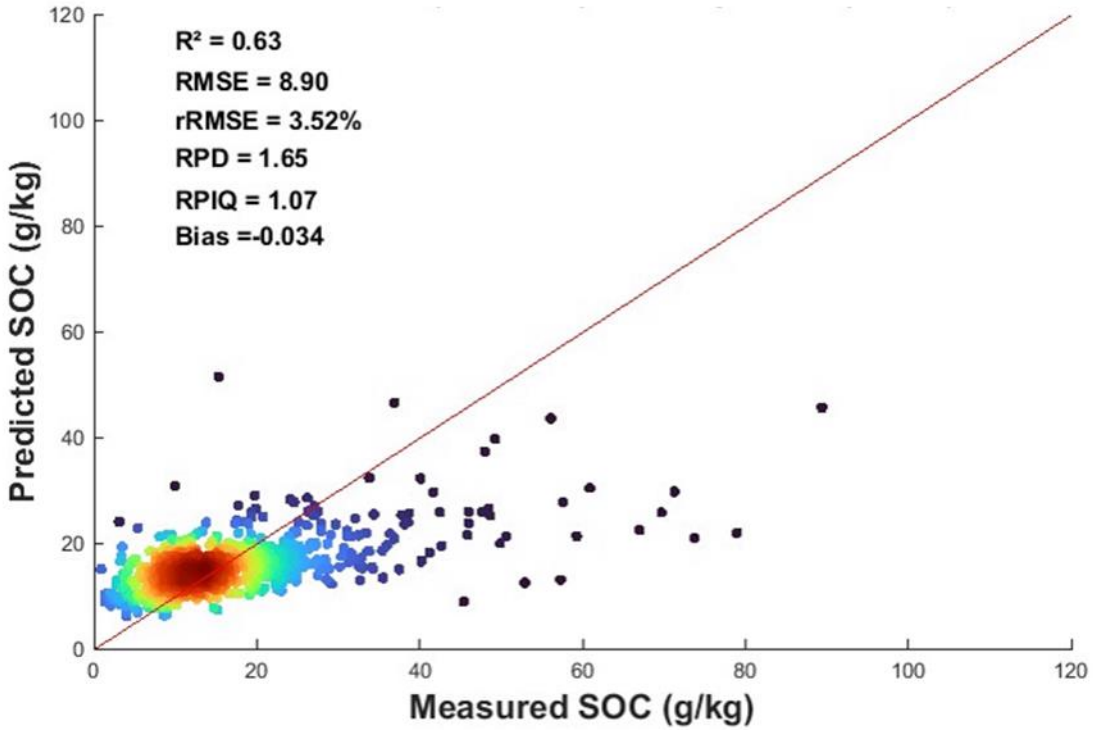
- 1-D convolutional neural network (CNN)
  - 3 convolutional layers and 3 fully connected layers (after Tsakiridis et al., 2020)
  - Single input (soil reflectance, 1 nm resolution)
  - No systematic hyperparameters optimization
- Cal/Val/Test Split: 80/10/10
- Trained in 1,000 epochs
- Accuracy in line with Deep Learning of other large SSL, e.g., USDA RaCA SLL (Wang et al,. 2022)

Estimation of SOC using spatially upscaled SSL

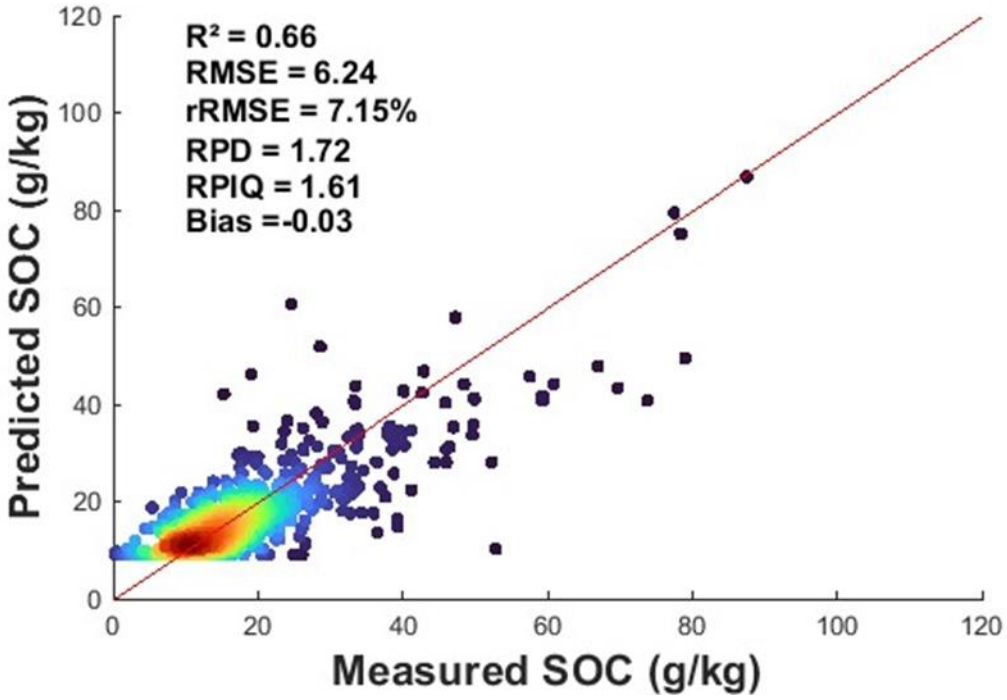
- Training of 1D-CNN of ‘disturbed’ soil spectra (SUSSL)

➢ 1D-CNN is able to model SOC even in strongly disturbed cases with acceptable loss in accuracy

CNN – high PV (LAI=1) and SM (~7%)



CNN – high NPV (LAI=1) and SM (~7%)



Conclusion & Outlook

- Challenging surface conditions at the EO scale are an essential factor for the decrease in SOC prediction accuracy
- Filtering approaches using spectral indices can only differentiate the most heavily disturbed cases
- Development of “landscape like” SSL provides test ground for testing of correction methods → Improvement of soil spectral models

Outlook:

- Application of the hybrid modelling approach to hyperspectral EO data (e.g., EnMAP)
- Including further “disturbances”, e.g., soil roughness and crusting
- Comparison with spectral unmixing based approaches

Thank you!

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Impact of dynamic surface conditions

- NBR2 shows slightly higher potential for filtering NPV affected soil spectra