USE OF NIR HYPERSPECTRAL IMAGING AND CHEMOMETRICS TO QUANTIFY ROOTS AND CROP RESIDUES IN SOIL

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Context: Monitoring of root development and crop residues decomposition in crop soils is important to understand the effects of agricultural practices and to improve them. In the fields studies on root system development, soil coring method allows multiple samplings but manual sorting of roots and crop residues extracted from soil samples before quantification is a tedious and time consuming step. Discrimination of roots and crop residues based on their Near Infrared (NIR) spectral signature and chemometrics was tested as a new rapid and reliable method.

Methodology

Sampling

1 **Field sampling** of soil cores

Extraction of roots and crop residues from soil with tap water

Drying of washed samples

2 Image acquisition

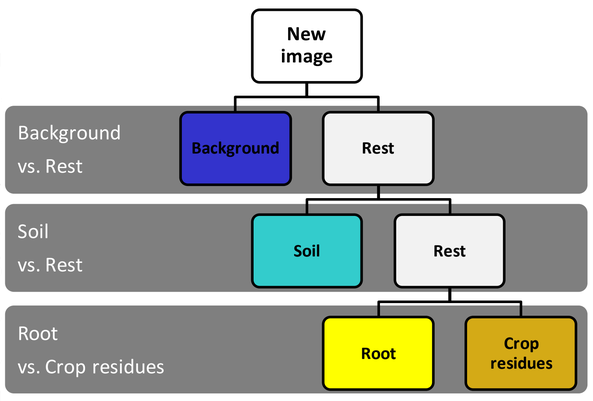
NIR images are acquired with a **NIR hyperspectral line scan** (= push-broom) and HyperProVB software (BurgerMetrics SIA, Riga, Latvia).

Samples are laid on a **conveyor belt** placed under the NIR camera. For each pixel of the NIR image, a complete spectrum including **209 wavelengths** (1100-2498 nm) is saved with a spectral resolution of 6.3 nm. Spatial resolution of images is 0.3 mm.

(Vermeulen et al., 2012)

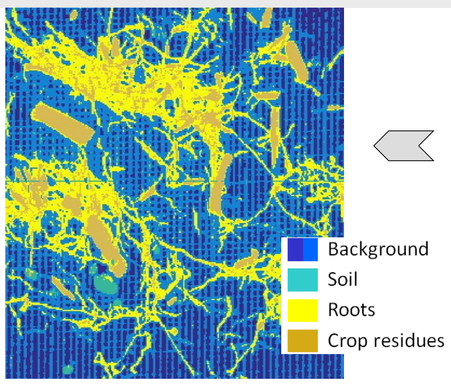
3 Spectra discrimination

A **dichotomist classification tree** based on successive **Support Vector Machine discriminant analysis models** is used to separate spectra into **4 distinct classes**: background, soil, roots and crop residues. These models were calibrated with PLS Toolbox 7.8 (Eigenvector Research, Inc., Wenatchee, WA, USA) working on Matlab (The MathWorks, Inc., Natick, MA, USA). At least 1000 spectra were used for each class. These spectra were selected by Duplex method in order to take into account maximum variability.



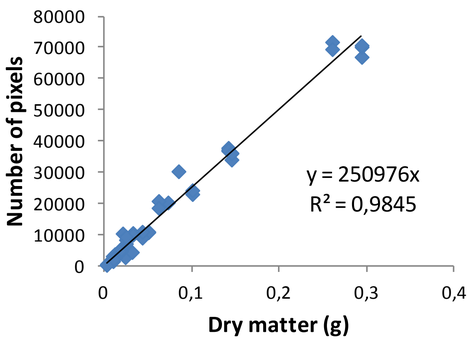
(Eylenbosch et al., 2014; Fernández Pierna et al., 2004; Snee, 1977)

4 Prediction and quantification



A color is assigned to each spectral class allowing the creation of **prediction images**.

Roots quantification is based on the number of pixels predicted as roots which is converted in an amount of dry matter thanks to a regression line.



Results and applications

Validation on spectral data

Good discrimination of spectral classes was observed during calibration and validation on independant set of spectra. The discrimination between root and crop residues spectra gived the lowest results with 86% of well classified spectra.

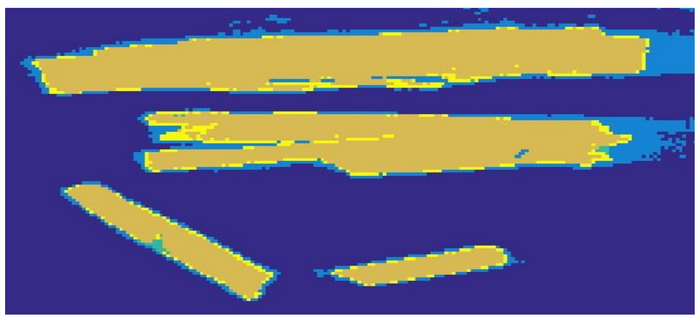
	Calibration		Validation	
	Sensitivity	Specificity	Sensitivity	Specificity
Background *vs.* **Rest**	0.997	0.999	0.999	0.999
Soil *vs.* **Rest**	0.994	0.997	0.992	0.991
Crop residues *vs.* Root	0.914	0.942	0.895	0.922

Sensitivity: proportion of spectra detected as positive for the positive class in the model.
Specificity: proportion of spectra detected as negative for the negative class in the model.

Models 14 bis FH

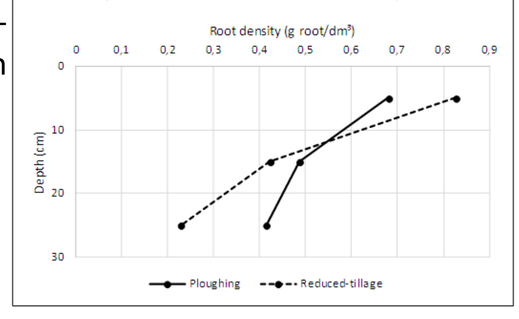
Validation on images

Applied on NIR images of roots and crop residues of winter wheat, models correctly discriminate 92.5% of roots and 79.4% of crop residues, some confusion appearing on the border of crop residues, in the shadow area.



Quantification of roots and crop residues of winter wheat under different tillage

The quantification method was applied on soil samples taken in a long term trial on tillage under winter wheat. It was clearly observed that root system had a higher development in the top soil horizon (0-10 cm) in reduced tillage and a deeper development with ploughing.



Advantages and limitations of discrimination and quantification based on analysis of NIR hyperspectral images

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- Quicker than manual sorting
- No operator subjectivity during sorting
- Possible discrimination of roots from different species
- No destruction of samples
- Spectral data can easily be re-analysed when models are improved

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- Time consuming steps (field sampling, washing of soil cores and acquisition of NIR images)
- Some spectral confusion between the elements of the samples in shadow areas
- Underestimation during quantification if elements overlap on images
- Models need to be regularly recalibrated

References:

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