Use of Near Infrared Hyperspectral Imaging (NIR-HSI) and chemometric tools to dicriminate wheat roots and straws in soil.

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Introduction:

In agricultural research studying the effect of tillage, quantification of roots and straw residues in soil is very important in order to **monitor the development of root systems and the decomposition of crop residues.** Current methods need to wash the soil cores to extract individual elements (roots and straws), then to manually separate and to weight them (Cheng & al., 1990; Picon-Cochard & al., 2008). These methods are time consuming and dependent of the operator. **The aim of this work is the development of a complete procedure based on the use of Near Infrared (NIR) combined with Hyperspectral Imaging and chemometric tools** in order to cope with such problems. Hyperspectral Imaging provides simultaneously spectral and spatial information. Appropriate chemometric tools allow predictions of key parameters based on infrared spectra of each pixel of the image. NIR spectra can be directly linked to chemical nature of sample constituents (Dale & al., 2012; Fernández Pierna & al., 2012).

Material and methods:

Sample treatment and spectra selection

In this work, particular interest is put in the discrimination of wheat roots and straws in soil. A spectral library has been built including samples of background (conveyor belt and sieve on which samples were laid), soil, wheat roots and straw. In total, 16 samples of straw, 12 of roots, 5 of soil and 5 different sieves were used. Roots and straw were washed and dried before image acquisition. Soils samples were dried and grinded with mortar and pestle. A library including thousands of spectra has been built and a reduced data set of 1000 spectra was selected in each class taking into account spectral variability and was used for calibration.

NIR hyperspectral imaging system

NIR hyperspectral images were collected using a hyperspectral line scan instrument combined with a conveyor belt (Burgermetrics). The images consisted of lines of 320 pixels acquired at 209 wavelength channels (1118-2425 nm) with a spectral resolution of 6.3 nm (Vermeulen & al., 2012)

Model construction

To separate the different constituents (soil, roots and straws), a dichotomist classification tree based on successive PLS-DA (Partial Least Squares Discriminant Analysis) models was constructed: the first model discriminates background (conveyor belt and sieve) from the rest; the second one separates soil from straws and roots and the last one discriminates straws from roots (Figure 1). All models have been constructed using the absorbances from 1432-2368 nm range in order to avoid noisy region.

Model validation

To test the individual dichotomist models, a second data set (test set) including 500 spectra of each class was created.

Predictions

Finally, the models were applied to images including mixtures of all classes. Thanks to the spatial information provided by the hyperspectral system, the predicted class of each pixel can be indicated by assigning one color by class.

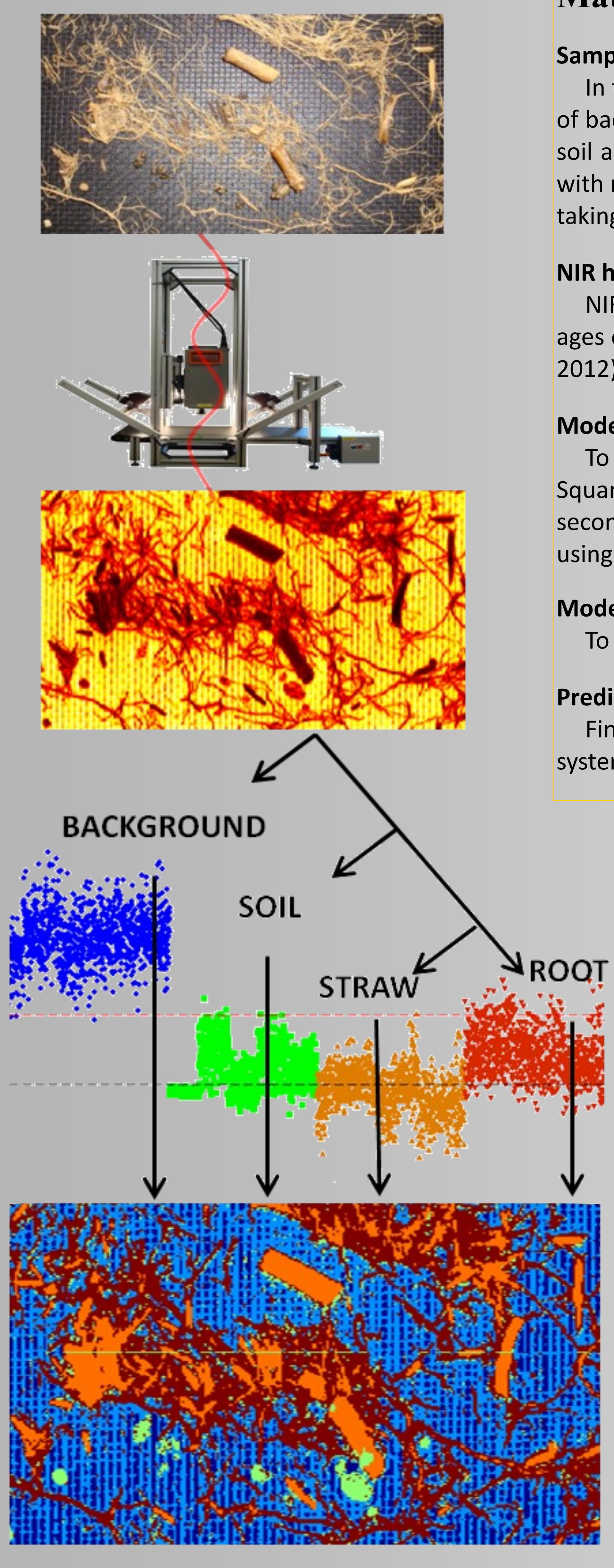

Figure 1: Path to follow in case of prediction on a new sample. From bottom to down: sample on conveyor belt, NIR acquisition by a hyperspectral system, NIR image, discrimination models and prediction on unknown images.

Results and discussion:

Model validation

Results of the validation step in terms of sensitivity and specificity are given for the models in Table 1. Good results were obtained for the first model (background vs rest) and the second one (soil vs rest). However, a more precise analysis of results (each constituent predicted by each model; not show on this poster) shows that roots are less well predicted (16% of misclassification) in the first model. In the third model (straw vs root), discrimination of constituents is more difficult: 25% of straws and 16% of roots are not well predicted.

Table 1 : Performances of the models applied to the test set in terms of sensitivity and specificity.

Model	Sensitivity*	Specificity**
Background vs Rest	Background	Rest
	0.992	0.935
Soil vs Rest	Soil	Rest
	0.930	0.962
Straw vs Root	Straw	Root
	0.754	0.838

* 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

Predictions

When the equation was used to predict, at pixel level, new NIR images including all constituents, most of the pixels are well predicted (Figure 2). As observed during the validation, the separation between straw and root is not perfect, which could be quite easily explained by the very close chemical composition of these constituents. There is also confusion between roots, sieve and edge of straw. Most roots being thin, quite a few spectra selected for the library as root must be probably spectra coming from the shadow, which can explain this prediction error.

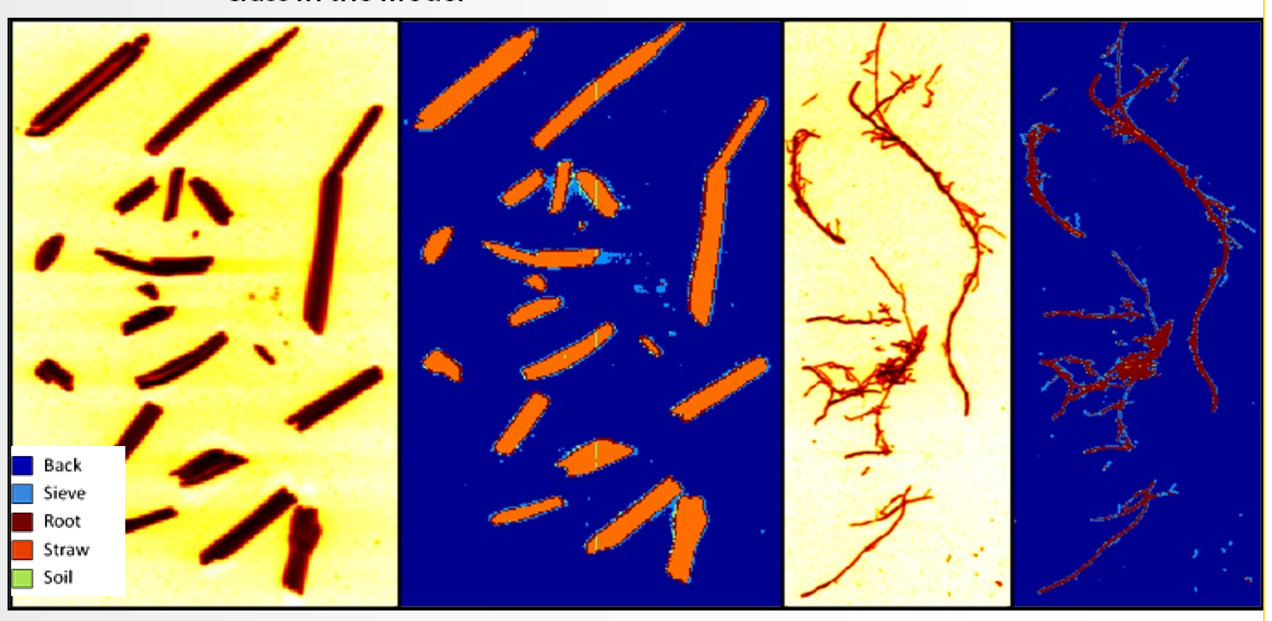

Figure 2: NIR images and predictions of wheat straws and roots

Conclusion:

This preliminary work has permitted to detect, based on the NIR spectra, the presence of the different constituents (roots and straws) in a sample of soil, which is the first step before a possible quantification of each of them. In order to quantify these constituents in a sample of soil, further research has to be done to link the number of pixels detected on the NIR images as belonging to a certain class to the corresponding weight of the constituent in the sample. **This work is an important step in order to easily follow root development and organic matter decomposition in soil.**

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