DETECTION OF WHEAT ROOT AND STRAW IN SOIL BY USE OF NIR HYPERSPECTRAL IMAGING SPECTROSCOPY AND PARTIAL LEAST SQUARE DISCRIMINANT ANALYSIS

Damien EYLENBOSCH [1] *– Juan Antonio FERNÁNDEZ PIERNA* [2] *– Vincent BAETEN* [2] *– Bernard BODSON* [1]

[1] Crop Science Unit, Gembloux Agro-Bio Tech, University of Liège, Gembloux, Passage des déportés 2, 5030 Gembloux, Belgium, d.eylenbosch@ulg.ac.be

[2] Valorisation of Agricultural Products Department, Walloon Agricultural Research Centre (CRA-W), Gembloux, Belgium

Introduction

In studies on tillage, monitoring of root systems development and crop residues decomposition is very important. However, it is only possible if these different constituents can be discriminated from soil and then quantified. Current methods, based on soil coring, need to wash cores to extract individual elements (roots and straws), then to manually separate and to weight them (Gao-Bao et al., 2012). These methods are time consuming and dependent of the operator. In this work, we propose the use of Near Infrared combined with Hyperspectral Imaging (NIR-HSI) and chemometric tools (Partial Least Square Discriminant Analysis - PLS-DA) as a new rapid and reliable procedure to discriminate soil, roots and straws after wheat crop (*Triticum aestivum* L.). NIR-HSI provides simultaneously spectral and spatial information and PLS-DA allows discrimination between classes based on spectra of each pixel linked to chemical nature of sample constituents on the image (Dale et al., 2012; Fernández Pierna et al., 2012).

Materials and Methods

In a first step, a spectral library comprising thousands of spectra of the different materials (soil, wheat roots and straws) as well as background (conveyor belt and sieve on which samples were laid) has been built. Roots and straws collected in soil cores were washed and dried before image acquisition. Soil samples were dried and grinded with mortar and pestle. NIR-HSI images were collected using a hyperspectral line scan instrument combined with a conveyor belt as described by Vermeulen et al. (2012). Then, in a second step, and in order to isolate the different constituents (soil, roots and straws), a dichotomist classification tree based on successive PLS-DA models was constructed; the first model discriminates background from the rest; the second one separates soil from straws and roots and the last one discriminates straws from roots. A reduced data set of 1000 spectra was selected in each class for model construction and a second one of 500 spectra per class was created to validate the models. All models have been constructed with data preprocessed by autoscale and the reduced wavelength range of 1432-2368 nm in order to avoid noisy areas. Cross-validation was used in models construction. After validation, the models were applied on images including mixtures of all classes. The spatial information provided by the NIR-HSI allows assigning different colours for the prediction of individual pixels in the images.

Results and Discussion

The first model (background vs rest) allows discriminating the background from the rest of the samples (99.2% of sensitivity for the independent validation set) as well as correct detection is obtained with the second equation (soil vs rest) with 93.5% of correct classification (Table 1). However, a more precise analysis of results (each constituent predicted separately by each model) shows that roots are less well predicted (15.8% of misclassification) in the first model. In the third model (straw vs root), discrimination of constituents became more difficult: 24.6% of straws and 16.2% of roots are not well predicted. When the equation is used to predict, at pixel level, new NIR-HSI images including all constituents, most of the pixels are well predicted. As observed during the prediction on the independent validation set, the separation between straw and root is not an easy task, which could be 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 as root for the library must be probably spectra coming from the shadow, which can explain this prediction error. Additional researches are presently done to explain these results and improve discrimination between constituents.

Table 1. Performances of the PLS-DA models calibration, cross-validation and when applied to the independent test set in terms of sensitivity (proportion of spectra detected as positive for the positive class in the model) and specificity (proportion of spectra detected as negative for the negative class in the model)

	Calibration		**Cross-validation**		**Prediction**	
Model	**Sensitivity**	**Specificity**	**Sensitivity**	**Specificity**	**Sensitivity**	**Specificity**
Background vs Rest	0.971	0.977	0.971	0.976	0.992	0.935
Soil vs Rest	0.990	0.985	0.989	0.986	0.930	0.962
Straw vs Root	0.917	0.879	0.916	0.877	0.754	0.838

Conclusions

This preliminary work has permitted to detect, based on the NIR-HSI spectra, the presence of wheat roots and straws in a sample of soil, avoiding cumbersome visual observation. This is the first step before a possible quantification of each material present in soil, but for this, further research is needed to link the number of individual pixels detected on the NIR-HSI 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.

References

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