Towards Precision Agriculture for Oil Palm Mineral Nutrition Management: Relationships between the Reflectance Spectrum of Oil Palm Leaves and Nutrient Deficiencies.

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ABSTRACT

This study aims at determining if the reflectance spectra of oil palm leaves can provide an alternative measurement tool to expensive and time-consuming foliar chemical analysis to get information about any deficiencies of the trees. We focus here on the relationships between the reflectance spectra of oil-palm leaves and their deficiencies in five elements: nitrogen (N), phosphorus (P), potassium (K), magnesium (Mg), and iron (Fe). We carried out statistical analyses over a database that we built on palm trees measured in Sumatra (Indonesia), combining leaves reflectance in the visible and near-infrared domain (450-900 nm), leaves chemical composition, and observations of deficiencies visual symptoms on the tree. We obtained insignificant results on nutrient concentration prediction due to error rates above the stress detection threshold. At least we were able to discriminate the extreme situations of stress with an acceptable precision. We discuss here the results in terms of different sources of noise and errors in methodology, and we give prospective ways of improving the analysis.

1. INTRODUCTION

Nutrient stress detection is a major issue for the management of mineral nutrition and fertiliser regime in oil palm plantations. Foliar chemical analysis has been for a long time the main tool used to get information about any deficiencies of the trees. However, it is quite expansive and time demanding. In addition, the space and time sampling scales are

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not compatible with the concept of precision agriculture. This study aims at determining if the reflectance spectra of oil palm leaves can provide an alternative measurement tool to these chemical analyses.

For years, multispectral remote sensing has been widely used to detect crop stress, providing results of varying reliability (see for instance (Chaerle and Van Der Straeten, 2000), (Thenkabail et al., 2000),(Boegh et al., 2002), (Haboudane et al., 2002), (Huang et al., 2004), (Huang et al., 2007), and references within). This lays on the commonly accepted notion that strong relationships exist between the visible and near infrared reflectance of leaves and their pigment and mineral content.

Big advances in this field have been made for several simple crop covers (e.g. (Curran et al., 2001), (Sims and Gamon, 2002), (Christensen et al., 2004), (Zhao et al., 2005a), (Zhao et al., 2005b), (Bélanger, 2005), (Bélanger et al., submitted in 2005), (Nguyen and Lee, 2006)) and can now be used for precision farming. Although, this studies have pointed out many limits of reflectance-based estimations and in particular the non-generic property of any estimated relationship.

Moreover, some types of crops, like tree crops for instance, have not benefited from this work yet and one cannot find much documentation on their optical properties. Due to complex architecture and physiology, remote estimation of stress seems to be very difficult in this case and raises many questions while it solves few problems.

With multispectral imaging for instance, many different contributions to the observed signal might blur the compositional information. The spectral contrast between stressed and unstressed trees is insufficient and cannot be correctly interpreted. It is even more risky because functional models and understanding of the optical properties of tree leaves are very poor, when they exist. Actually, this information has even not been proven yet to reside within this type of signal. We propose here to analyse, in the case of oil palm trees and at the leaf level, the possible relationships between the leaves spectral signature and their nitrogen (N), phosphorus (P), potassium (K), magnesium (Mg), and iron (Fe) content. We will also study the means how the leaves reflectance can indicate factors of tree stress or deficiency.

2. FIELD MEASUREMENTS

We set up one month of survey in may 2006 in different oil palm plantations, owned by P.T. SMART, and located in the province of Riau in Sumatra (Indonesia). Hyperspectral field measurements were made with a UNISPEC-2001 from PP-Systems. This device allows the reflectance measurement at the leaf level, using a leaf clip and a fibre optics integrating the signal on a surface of about 5 square millimetres, in 256 spectral channels

between 303.6 and 1131.4 nm. The leaf-clip enables sensing the bidirectional reflectance of a circular spot of about 5 mm^2 in diameter. Reflectance was calibrated thanks to repeated measurements of a barium sulphate standard disk. Due to strong instrumental noise outside this domain, only the 450-900 nm domain was retained for analysis.
Two kinds of oil palm trees were sampled in the fields, up to a final number of 47 trees:

- Trees showing visual symptoms of a specific nutriment deficiency, which could be easily detected on leaves,
- Trees growing inside nutrition practices trials, putting in balance in one hand nitrogen (N) and phosphorus (P), and, in the other hand, magnesium (Mg) and potassium (K). These ones did not show clear symptoms of any deficiency on their leaves.

Defining a robust measurement protocol to get a representative signature of one tree at the leaf level was difficult due to a strong gradient of chemical components inside a single leaflet, from one leaflet to the other on a single palm leaf, and from one leaf to the other inside the palm tree canopy. Moreover, we observed that not all the different deficiencies we were looking about provoke symptoms on the same level of leaves. We thus decided to get a signature that always corresponds to the same location in the gradient pattern of the leaf to let them be comparable. Therefore, we cut 4 to 5 leaves per palm, that are representative of the different canopy stratus and that are still visible from the top of the canopy. This latter condition was set in the long-term goal of precision agriculture based on aerial or satellite remote sensing, that only reaches the top of the tree canopy.
On each leaf, we made concurrently two distinct samplings

1) 5 leaflets were regularly cut, one every fifteen to twenty leaflets from the end extremity of the leaf. On each one, we reproduced a set of 10 spectral measurements, on each of the two squares of 2 cm^2 symmetrically located at each side of the leaflet central vein, and at each of the 1/3 and 2/3 of the leaflet length (see *Figure 1*). This means that we measured a whole set of 40 spots per leaflet. These acquisitions were then averaged so that we get a mean spectral signature at 1/3 and one at 2/3 of the leaflet length.

2) A dozen of leaflets were also cut around the 40^{th} to 55^{th} position on each palm leaf, and sent to laboratory for chemical analysis. This foliar diagnostic was made by SMARTRI, research laboratory of P.T. SMART in Pekanbaru (Sumatra). They used an atomic absorption spectrometer providing the chemical composition determination in 6 macro-elements: Nitrogen (N), Phosphorus (P), Potassium (K), Magnesium (Mg), Calcium (Ca), and Chloral (Cl), and 5 olio-elements: Bore (B), Copper (Cu), Zinc (Zn), Manganese (Mn), and Iron (Fe).

Finally, the spectral database gives, in one hand, the representative chemical composition of the leaf in 11 elements and, in the other hand, several spectral signatures on different locations in the leaf.

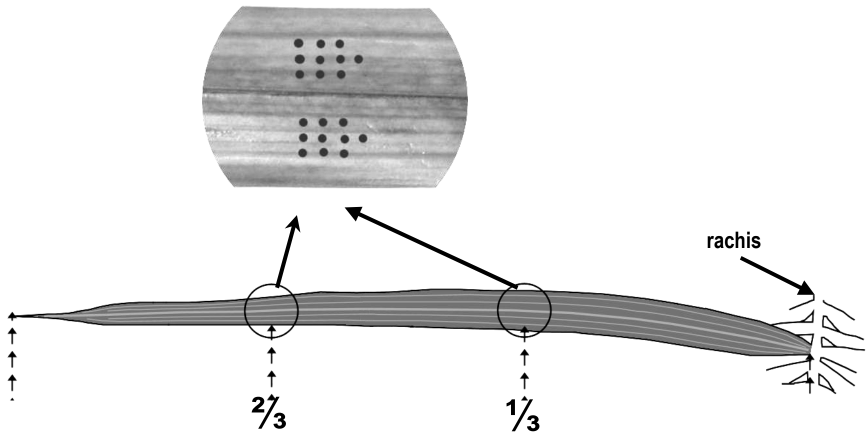

Figure 1 : Location of the spectral measurements on each leaf: Two areas were considered, at 1/3 and 2/3 of the leaf length; For each, the two 2 cm^2-spots located on each side of the central vein were sampled respectively by ten measurements of 5 mm^2 in diameter.

3. SPECTRAL ANALYSIS

The database was first analysed trying to compare different spectra obtained in several contexts in order to detect any actual variations in the spectral signature of stress leaves compared to unstressed ones. As an example, the Figure 2 shows the spectra of 4 leaves obviously showing apparent symptoms of different deficiencies, along with the spectrum of a sane leaf. The first observation is that all stress leaves have a lower reflectance in the near infrared plateau (750-900 nm) than the unstressed one but no clear tendency is seen to discriminate the different deficiencies. Nevertheless, in the visible part of the spectrum (450-675 nm) the reflectance variations seem to be reproducible for each respective deficiency with the following overall characteristics:

- Green (~550nm) and red (~660m) absorptions intensity decreases,
- Location of the green reflectance maximum (~550nm) is shifted to higher wavelengths,

- Green “peak” widens and changes in shape. N and Fe deficiencies in one hand and Mg and K deficiencies in the other hand correspond to almost the same spectral shape with different intensities.

It thus seems possible to detect a stress by means of visible and infrared spectrometry. However, at this stage, it seems complex to discriminate between different deficiencies only based on visual spectral analysis because of the various observed trends.

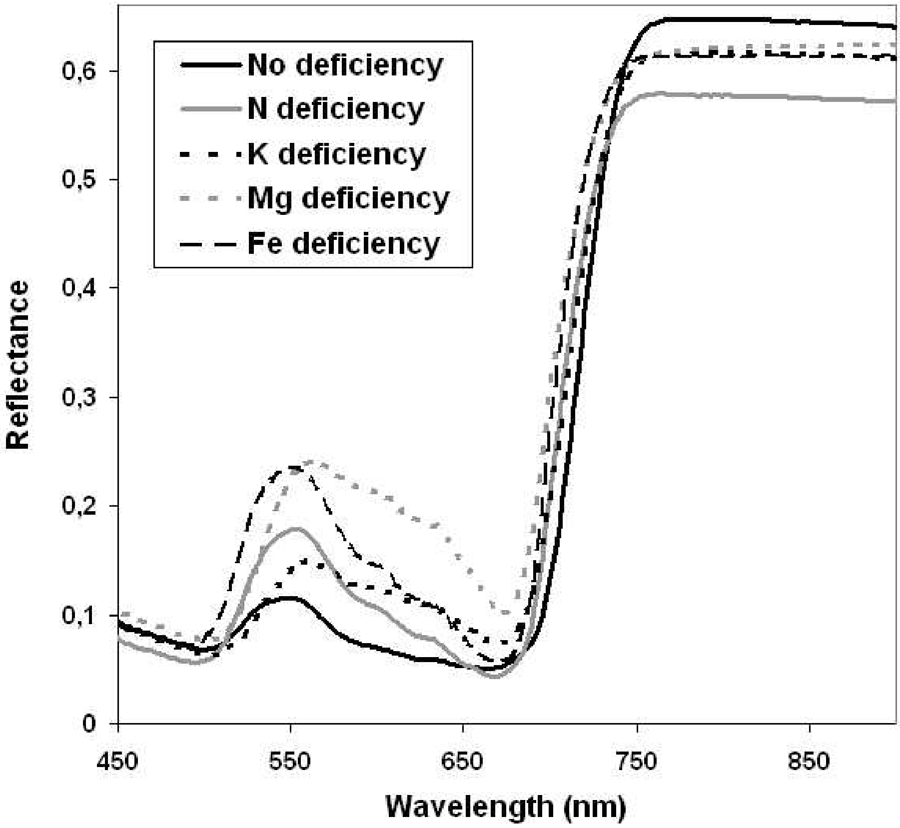

Figure 2 : Measured reflectance spectra between 450nm and 900nm for 4 deficient leaves (N in grey line, K in black dots, Mg in grey dots, and Fe in black discontinuous line) and on a standard leaf (black line).

In order to extract the more objective information out of the huge built spectral database, we selected a set of 27 analytic parameters describing both the spectrum shape and intensity (see *Figure 3* and *TABLE 1*). These indexes are for instance levels of reflectance, wavelengths of the local maxima, minima or inflection points, or some areas of spectral features like peaks and valleys. They are illustrated on the spectrum of an Mg-deficient leaf at ***Figure 3***.

In addition, we selected in the literature 21 spectral indices often used in remote sensing for crops nutrient status characterisation (see *TABLE 2*) to test them in the case of oil palm.

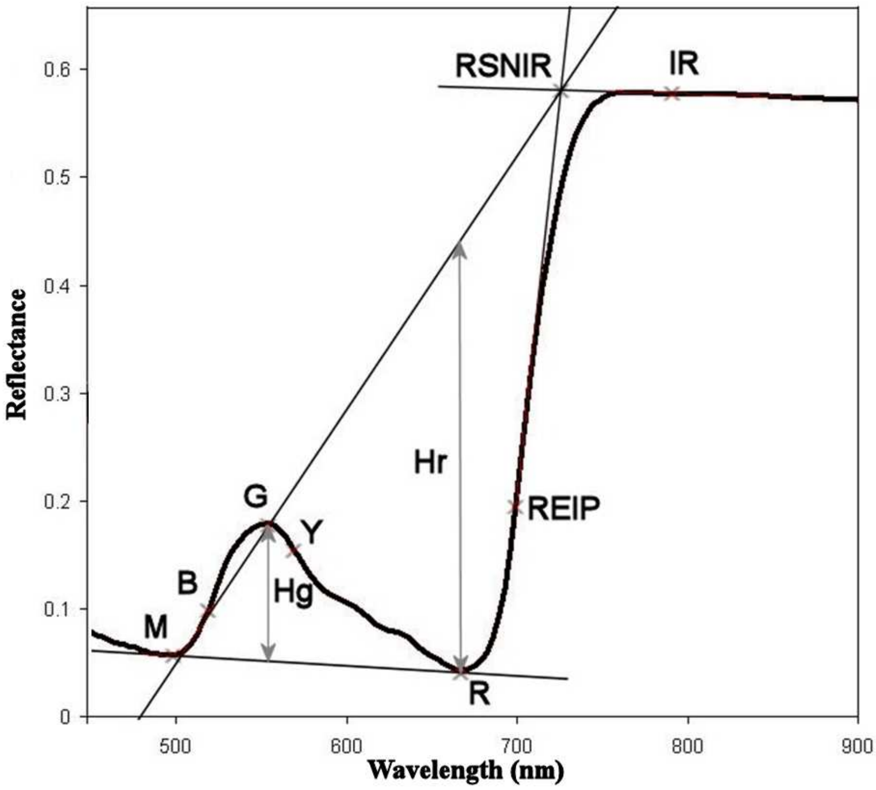

Figure 3: Schematic definition of main analytic spectral indexes (see TABLE 1 for analytic definition) M, B, G, Y, R, REIP, RSNIR, IR, Hr, and Hg

TABLE 1: ANALYTIC DEFINITION OF THE 27 SPECTRAL INDEXES SELECTED FOR THE OIL-PALM SPECTRUM DESCRIPTION	
Index	**Definition**
M (λ_M, R_M)	minimum in the blue domain (380-550 nm)
B (λ_B, R_B)	blue edge: inflection point between blue (450 nm) and green (550 nm)
G (λ_G, R_G)	maximum in the green domain (500-650 nm)
Y (λ_Y, R_Y)	yellow edge: inflection point between green (500 nm) and yellow (650 nm)
R (λ_R, R_R)	minimum in the red domain (550-750 nm)
REIP (λ_{REIP}, R_{REIP})	Red Edge Inflection Point: inflexion point between red (550 nm) and near IR (800 nm)
RSNIR (λ_{RSNIR}, R_{RSNIR})	Red Slope-Near Infra Red: intersection point between the tangent at REIP and the near infrared plateau line
IR	mean reflectance of the near infrared plateau (780-900 nm)
SB	Slope of Blue edge: mean value of the slope between M and G
SY	Slope of Yellow edge: mean value of the slope between G and R
SV	slope of red-IR: mean value of the slope between RSNIR and R
SC	Slope of Continuum: mean value of the slope between RSNIR and G
HG	net height of the green peak
HR	net absorption depth
HI	net height of the near infrared plateau
λ_{wG}	green peak width ($\lambda_Y - \lambda_B$)
λ_{wR}	red valley width ($\lambda_{REIP} - \lambda_Y$)
AG	total area of green peak
Agn	net area of green peak
AR	net area of red absorption

TABLE 2: MATHEMATICAL DEFINITION OF THE 21 SPECTRAL INDEXES FOUND IN THE LITERATURE SELECTED FOR THIS STUDY.	
Index (reference)	**Definition**
SIPI (Penuelas et al., 1995)	$\frac{(R_{800} - R_{445})}{(R_{800} - R_{680})}$
PSRI (Merzlyak et al., 1999)	$\frac{(R_{680} - R_{500})}{R_{750}}$
PRI (Gamon et al., 1997)	$\frac{(R_{531} - R_{570})}{(R_{531} + R_{570})}$
SR680 (Sims and Gamon, 2002)	R_{800}/R_{680}
SR705 (Gitelson and Merzlyak, 1994a)	R_{750}/R_{705}
ND680 (Sims and Gamon, 2002)	$\frac{R_{800} - R_{680}}{R_{800} + R_{680}}$
ND705 (Sims and Gamon, 2002)	$\frac{R_{750} - R_{705}}{R_{750} + R_{705}}$
mSR705 (Sims and Gamon, 2002)	$\frac{R_{750} - R_{445}}{R_{705} - R_{445}}$
mND705 (Sims and Gamon, 2002)	$\frac{R_{750} - R_{705}}{(R_{750} + R_{705} - 2R_{445})}$
CI (Zarco-Tejada et al., 2002)	$\frac{(R_{675} - R_{690})}{R^2_{683}}$
TCARI / OSAVI (Haboudane et al., 2002)	$\frac{R_{700}-R_{670}) - 0.2(R_{700} - R_{550}) \cdot \frac{(R_{700})}{(R_{670})}}{\frac{(1 + 0.16).(R_{800} - R_{670})}{(R_{800} + R_{670} + 0.16)}}$
R1 (Read et al., 2002)	R_{705}/R_{715}
R2 (Read et al., 2002)	R_{705}/R_{930}
R3 (Merzlyak et al., 1999)	R_{750}/R_{700}
R4 (Bélanger, 2005)	R_{450}/R_{762}
R5 (Bélanger, 2005)	R_{550}/R_{430}
NDVI	$\frac{MOY(700{:}979nm) - MOY(600{:}700nm)}{MOY(700{:}979nm) + MOY(600{:}700nm)}$
R6 (Carter et al., 1996)	R_{550}/R_{450}
R7 (Carter et al., 1996)	R_{694}/R_{760}
R8 (Carter et al., 1996)	R_{694}/R_{420}
R9 (Carter et al., 1996)	R_{750}/R_{650}

4. STATISTICAL ANALYSIS

We followed two statistical approaches to decipher the information collected in the database.

1) Establishment of a predictive model for the chemical elements concentrations [N], [P], [K], [Mg], [Fe].
2) Discrimination of 5 pre-defined classes of specific deficiencies: in N, in P, in K, in Mg and in Fe.

For the first one, we applied a multiple linear regression (MLR) on the 48 indexes described at *TABLE 1* and *TABLE 2* as the explicative variables, with the 5 element concentrations as the expected results. This regression was combined with a stepwise procedure, which determined the most significant parameters to be used in the model.
For the second one, we used a partial least square regression (PLS) (Preda and Saporta, 2005) followed by a factorial discriminative analysis (DFA) on the set of the 130 couples (wavelength; reflectance value) that compose the leaf reflectance spectrum in the 450-900 nm domain. This can be called the PLS-DA approach (Roger et al., 2005).
A cross-validation was used in both algorithms.

This analysis main difficulty lies in the best model selection based on the function of the quadratic error vs. the number of predictive or latent variables selected by the stepwise procedure. Indeed, this curve shows no absolute minimum, but only local minima that do not constitute ideal solutions. Finally, a four-variables-based model was selected for the MLR application, while the model chosen for the PLS-DA was based on four axes and six variables.

5. RESULTS AND DISCUSSION

In one hand, it seems that we can not derive any model for the concentration predictions of P, K, Mg or Fe. MLR algorithm found a very faint model for [N], following the E*quation 1*:

$$[\mathbf{N}]=(61.6\boldsymbol{\lambda_M} + 4375.9\boldsymbol{R_B} + 60.2\boldsymbol{SR_{680}} - 7.4m\boldsymbol{SR_{705}} + 5228.8).10^{-3} \qquad \textbf{\textit{(Equation 1)}}$$

This model allows to estimate the concentration [N] with an accuracy of 44% only and an error bin of ±0.44% . Considering that an optimal [N] is about 2.5% and a critical [N] about 2.3%, it is obvious that this bin is out of the admissible range and that any nitrogen stress will not be detected.

This unsatisfying result can come from different origins that we try to explain in the following.
1) There may be no relationship between the nitrogen or the minerals and the reflectance spectra in these wavelengths. Considering the large amount of publications in this field, applied to many other crops as different as barley (Jorgensen et al., 2007), rice (Nguyen and Lee, 2006), sorghum (Zhao et al., 2005a), eucalypt (Huang et al., 2007), chestnut tree or maple (Gitelson and Merzlyak, 1994b), it would be such an exception if oil palm would not drive any rule.

2) Such a relationship exists, but is not linear. In our study we only used the MLR method, which only seeks linear combinations of the explicative variables. Even though this method had proven to be powerful in a wide range of applications, it would be of large interest to test now other types of regressions that allows other types of combinations.

3) The uncertainty on the reflectance measurements (due to protocol, instrumental noise, etc…), summed to chemical diagnostic uncertainty, might be higher than the detection threshold of this relationship. This is the biggest constraint of the problem, because this study was lead in the most rigorous way, with devices that provides some of the richest spectral information available in the fields, at the smaller scale that remote detection can afford to reach. Thus, it seriously embeds future applications in the field of precision farming, where the conditions can only be worse than experimental surveys. Unfortunately, we have no means to estimate the total amount of noise that our protocol implies and to validate this assumption, except testing all the other possibilities of failure.

In the other hand, we could not establish a sharp and reliable discrimination of the 5 deficiency classes by means of the PLS-DA. Indeed, in the selected solution with 4 axes and 6 variables, the error committed on the test sample is 27% while the error in cross-validation is 28%. A solution based on 3 axes and 11 variables gives lower errors, neither very satisfying (25% on the test sample, 18% in cross validation), but the system looses strongly in stability, providing very noisy discriminative vectors. Looking at the projections of the database population in the planes defined by the two first discriminative vector (cf. ***Figure 4***), it is obvious that the great majority of points are concentrated near the barycentre. Such population has intrinsically little chance to be classified in different separable groups. Nevertheless, it seems also that several "branches" move aside this barycentre, and that these trends correspond to single classes of deficiencies.

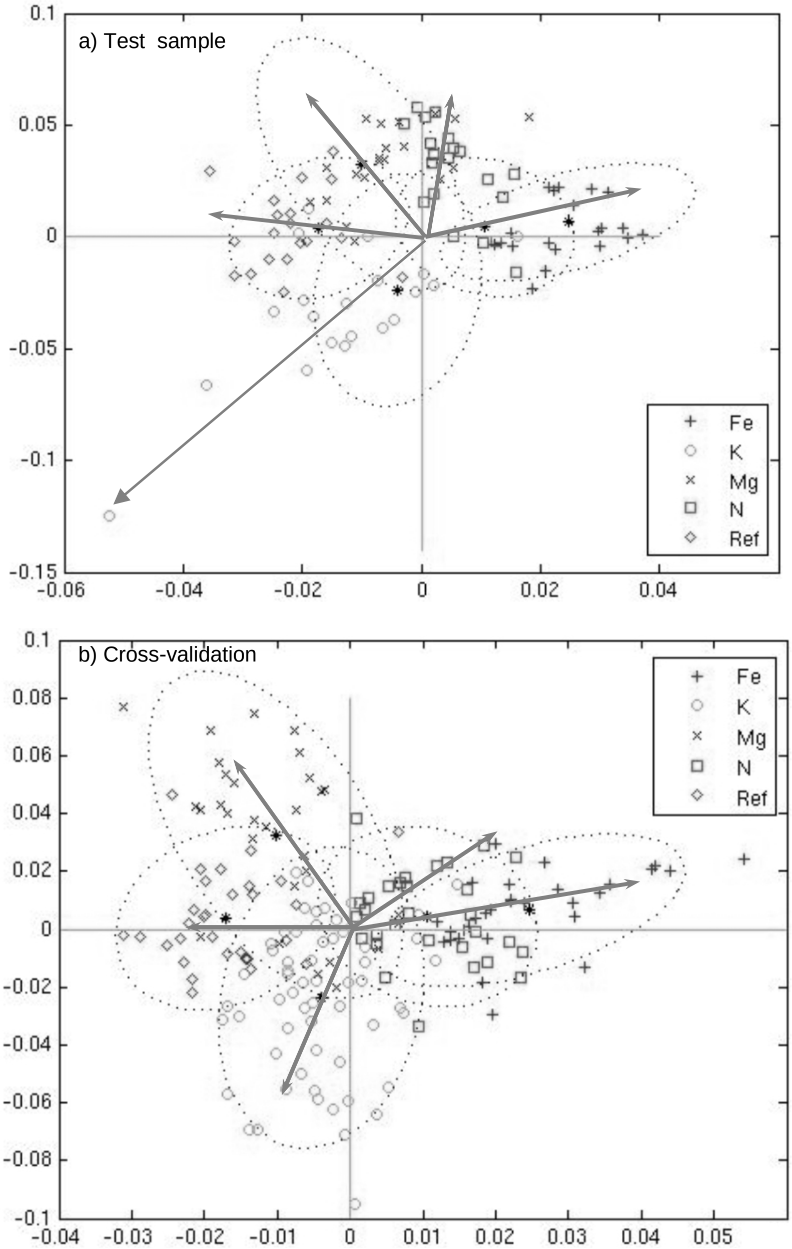

Figure 4: Representation of the spectral database population in the plane defined by the two first PLS-D discriminative vectors for: a) the test sample and b) the cross-validation.

We can thus be confident in the fact that strong tendencies exist for extreme individuals, namely highly deficient leaves. We suppose that the mathematical discrimination difficulty between the different deficiencies classes among our population comes from the population itself. In fact, a kind of "noise" may blur the classification trends, due to the possible sampling of poorly deficient leaves and leaves that are simultaneously deficient in two or more elements.

6. CONCLUSIONS AND PERSPECTIVES

A spectral database was constituted on leaves of oil-palm trees presenting apparent deficiencies in different elements (N, P, K, Mg, Fe). This base associates the reflectance spectrum between 450 and 900 nm, the chemical composition of the leaves in terms of constituent concentrations, and the list of deficiencies visible symptoms on the trees. Spectral shape and variations analysis led to the extraction of representative indexes describing the main reflectance features. A multiple regression analysis combined with a stepwise procedure and a cross validation (MLR) was applied to the indexes combined to the elements content values to establish a concentration predicting model. A mathematical model was found for [N] with 4 latent variables, but too faint to allow any stress detection. No model could be derived for the other elements. A partial least square regression, combined with a stepwise procedure and a cross validation, and followed by a discriminative factorial analysis (PLS-DA) was then applied to the spectra in the aim of discriminating the five deficiencies classes. It shows that it can separate only highly deficient leaves, the others being discriminated only with a high level of error.

To improve these results, we will now extract the more significant and "pure" individuals off the database to derive reliable linear and non-linear models of prediction or discrimination in the extreme/ideal cases. We will then analyse the possibilities of unmixing the remaining individuals on the basis of the extreme cases as endmembers.
Concurrently, we will quantitatively estimate the possible factors of “noise” coming from the spectral measurements, the chemical analysis or the way the database was built. We will then assess the exact potentiality of these models.

At this stage of the study, we are not able to propose recommendations on the use of hyperspectral data to detect and characterise oil palm nutrient stress. We have only showed that there is a potential in such measurements. Nevertheless, the next step in further analysis should establish the bases for this kind of sensing.

7. ACKNOWLEDGEMENTS

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