Use of Geomatics in Precision Agriculture

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Abstract

Nitrogen (N) is one of the major factor affecting canopy productivity and resistances to diseases or pests. Remote sensing and GIS technologies can be used for designing a precision agriculture system in order to allow N fertilization at a sub-plot level. There is then the need to relate crop N variables to remote sensing data acquired at a fine spectral resolution. Such a test has been made on potato fields subjected to two different irrigation regimes and four nitrogen (N) fertlization rates. Hyperspectral reflectances were shown to be suitable for discriminating between the N treatments, the difference between treatments being stronger for the non-irrigated plots than for the irrigared plots. A hyperspectral index ρ_{667}/ρ_{717} has been proposed, which gave the highest correlation with canopy biological variables, like biomass, N and chlorophyll content and ground cover. However, it was less correlated to leaf-level variables, like N and chlorophyll concentration and petiole nitrate than the SPAD leaf chlorophyll index and λ_0. Whatever the level, the red-edge inflection point (λ_{RE}) was poorly correlated to the biological variables. There is the need to calibrate more complex models to retrieve leaf variables from the canopy reflectance spectra.

Résumé

L'azote (N) est un des facteurs affectant la productivité des cultures. La télédétection et le SIG peuvent être utilisés pour concevoir un système d'agriculture de précision permettant la fertilisation azotée à un niveau sous-parcellaire. Il faut alors pouvoir relier les variables azotées du couvert aux données de télédétection acquises avec une résolution spectrale fine. Un tel test a été fait sur des parcelles de pommes de terre soumises à deux régimes d'irrigation et à quatre niveaux de fertilisation azotée. Les réflectances hyperspectrales sont adéquates pour discriminer entre les traitements N, la différence entre taitements étant plus importante pour les parcelles non-irriguées que pour les parcelles irriguées. Un index hyperspectral ρ_{667}/ρ_{717} est proposé qui donne la plus forte corrélation avec les variables biologiques du couvert, telles que la biomasse, le contenu en N et en chlorophylle et le taux de couverture. Mais, cet indice est moins bien corrélé aux variables biologiques foliaires, telles que la concentration en N et en chlorophylle ainsi que le contenu en nitrate du pétiole. Au niveau foliaire, ce sont l'indice chlorophyllien foliaire SPAD et λ_0 qui donnent les meilleures corrélations. Quel que soit le niveau, le point d'inflection du red-edge (λ_{RE}) est corrélé faibnlement aux variables biologiques. Il est nécessaire de calibrer des modèles plus complexes pour estimer les variables biologiques foliaires à partir des spectres de réflectance du couvert.

1. Introduction

Nitrogen (N) is one of the major factor affecting canopy productivity and resistances to diseases or pests. Nitrogen (N) fertilization needs to be optimized, to avoid the leaching and run-off of nitrogen from soil and to reduce the productivity costs. An accurate monitoring of the crop N status requires the determination of leaf N variables, which can be done using ground-based destructive measurements. These measurements are however time- and labor-consuming as well as limited to small sampling areas and numbers. A promising alternative would use remotely sensed measurements, that offers the advantage of larger sampling areas, lack of destruction of the studied resource, data easier to process and representing, in essence, the integrated response of crops to fertilization. Remote sensing technology was used since many years by airborne or spaceborne sensors, but now with the development of precision farming practices, there is a need to develop "smart" sprayers which can use remote sensing for detecting N deficiencies and correct them in real-time. In both cases, remote sensing of crop N status requires to estimate the relationships between spectral data recorded by the remote sensor and leaf N status. Relationship between leaf N status and remote sensing data can be either direct or indirect, through the chlorophyll status. Broad-band vegetation indices acquired on various crops were well related to N variables (Walburg et al. 1982, Fernandez et al. 1995, Stone et al. 1997, Vouillot et al. 1998) and to chlorophyll variables (Gitelson et al. 1996a, Gitelson and Kaufman 1998, Blackburn 1999).

More recently, hyperspectral reflectances were shown to be more efficient than broad-band indices for plant biochemistry analysis, because physiological changes are mostly detectable at specific wavelengths (Penuelas et al. 1994) and because hyperspectral data allow derivative analysis. This analysis has the advantage of (i) increasing the spectral effect of absorbers, like N compounds (Peterson and Hubbard, 1992), (ii) removing the spectral effect of leaf structure (Danson et al. 1992) and of background (Demetriades-Shah et al. 1990), and (iii) of resolving overlapping spectra (Demetriades-Shah et al. 1990). Hyperspectral indices have been mainly used for chlorophyll estimations. These indices used reflectances in the visible bands (Benedict and Swidler 1961, Thomas and Gaussman 1977, Tsay et al. 1982, Carter et al. 1989, Andrieu et al. 1992, Bracher and Murtha 1993, Penuelas et al. 1994, Filella et al. 1995, Lichtenthaler et al. 1996, Gitelson et al. 1996a, Gitelson and Kaufman 1998, Datt 1998), in the near-infrared bands (Malthus et al. 1995, Gitelson et al. 1996b,c, Lichtenthaler et al. 1996, Luther and Caroll 1999, Blackburn 1999, Gitelson et al. 1999) or in both band types (Chappelle et al. 1992, Buschmann and Nagel 1993, Gitelson and Merzylak 1994, 1996, McMurtrey III et al. 1994, Gitelson et al. 1996b, Lichtenthaler et al. 1996, Schepers et al. 1996, Datt 1998, Blackburn 1998a,b, Blackburn 1999). Several derivative-type indices have also been proposed, like red-edge indices (Horler et al. 1983, Ustin et al. 1989; Curran et al. 1990, 1991, 1995; Demetriades-Shah et al. 1990, Buschman and Nagel 1993, Vogelman et al. 1993, Filella and Penuelas 1994, Munden et al. 1994, Matson et al. 1994; Bélanger et al. 1995, Filella et al. 1995, Lichtenthaler et al. 1996, Pinar and Curran 1996, Blackburn 1998b, Jago et al. 1999) and several others (e.g., Vogelman et al. 1993, Penuelas et al. 1994, Rollin and Milton 1998, Blackburn 1998b, Blackburn 1999, Adams et al. 1999). There are only a few studies, which proposed hyperspectral indices for direct N variable estimation (Schepers et al. 1996, Blackmer et al. 1996, Sembiring et al. 1998). N variables were mostly retrieved using stepwise multiple regressions, as in NIRS protocols (see the review in Leblon et al. (1997))

Our paper presents preliminary results of a study on potato crops which has, as first objective, to analyze, during the growing season, the effect of nitrogen fertilization rates and the effect of irrigation regimes on ground-measured hyperspectral reflectances. In the study, hyperspectral indices will be defined based on the method of Carter (1994). The operational use of hyperspectral data for detecting nitrogen crop deficiencies during the early growth will also be assessed. Our results were acquired from hyperspectral and biological data measured, during four week in Summer 1997, on thirthy-two experimental plots, corresponding to four replications of Russett Burbank, growing under four levels of nitrogen fertilization and two irrigation regimes. Spectral assessment of crop N variables is more difficult on potato than on cereal crops, because first, N exists in the plant, not only under the form of protein and chlorophyll, but also under the form of nitrate and second, potatoes are typically row crops for which soil background could have an effect over a long time before canopy closure.

2. Materials and methods

An experiment was conducted in Summer 1997 on 32 plots of Russet Burbank cut seed potatoes. The plots were located on sandy soils at the NB Horticultural Centre at Hoyt, NB. On each individual plot, the seeds were planted 41 cm apart on the rows and at a depth of 0.91 cm on May 15, 1997. A split-plot arrangement of the experimental treatments was used in a randomized complete block design with four replications. The main plots were four N rates combined with two irrgiation regimes and the subplots were the populations. The plots were under two irrigation regimes: one half of the plots have the soil moisture content that was maintained at 21% by a drip irrigation treatment system, while the other half did not get any irrigation. Priot to planting, 100 kg. ha^{-1} of ammonium nitrate (0-20-20) were surface-broadcast. At planting, the plots were fertilized with four N rates (heavily stress: 0, low stress: 75; sub-optimal: 150 and excessive: 225 kg N ha^{-1}).

In July 1997, spectral and biological data were collected on the plots, once a week, during four weeks, until flowering, with the sampling scheme detailed in Table 1. Biological data consisted of shoot and tuber biomass, shoot and tuber nitrogen concentration (in %) and chlorophlylll a and b concentration (in µg. mg^{-1} dry weigth). Shoot sand tubers collected in the field were weighed fresh and dried at 55°C for determination of biomass. The dried subsamples of shoot and tuber biomass were ground to pass a 1-mm screen and stored prior to laboratory analyses. The N concentration in plant tissue was determined by dry combustion using a LECO CNS-1000 elemental analyzer (*LECO Corp*., Michigan, USA). Leaf chlorophyll a+b concentration was estimated from calibrated field measurements done with a *Chlorophyll Meter SPAD-502* (*MINOLTA Camera Corp. Ltd*, Japan). The calibration was done in the laboratory with the samples taken on each plot in the middle of the experiment, i.e., 14 July. Chlorophyll was extracted using dimethyl sulfoxide (DMSO) and absorbances at 645 nm and at 663 nm were measured with a *LKB Ultrospec Model 4050* (*LKB Biochrom*

Ltd., Cambridge, U.K.) spectrophotometer. These absorbances were used in Bruinsma (1963)'s equations to estimate leaf chlorophyll a+b concentration (in µg. mg^{-1} dry weight). Ground coverage was assessed from vertical normal color photographs taken over each plot, as described in McRobert (2001).

Table 1 Timing and tools used to measure the different biological variables

Variable (1)	Dates	Tool	Sampling
ADW (g/m^2)	6/30, 7/7, 7/14, 7/21	Oven	2 plants
RDW (g/m^2)	6/30, 7/7, 7/14, 7/21	Oven	2 plants
TDW (g/m^2)	6/30, 7/7, 7/14, 7/21	Oven	2 plants
%Naerial (%)	7/3, 7/8, 7/15, 7/29	LECO CNS-1000	2 plants
%Ntuber (%)	7/3, 7/8, 7/15, 7/29	LECO CNS-1000	2 plants
%Ntotal (%)	7/3, 7/8, 7/15, 7/29	LECO CNS-1000	2 plants
Chla+b (ug/mg dw)	6/30, 7/7, 7/14, 7/21	SPAD 502	2 leaves
Ground Coverage (%)	1/7, 7/7, 7/15, 23/7	35mm Camera	1 Inter-row 1 Row
ρ (%) (400nm - 1000nm)	1/7, 7/7, 7/15, 23/7	Spectron SE -590	1 Inter-row 1 Row

(1) ADW = Above-ground biomasss, RDW = Tuber biomasss, TDW = Total biomass, %Naerial = Above-ground nitrogen concentration (%) , %Ntuber = Tuber nitrogen concentration (%), %Ntotal = Total nitrogen concentration (%), ρ = reflectance in the 400-1000 nm range

Biological measurements were used to fit models for estimating the biological variables at the time of spectral measurements. These estimated values have also the advantage of being less variables than the original measurements. As detailed in McRobert (2001) the model used for the biomass is the classical logistic model. The model was fitted for the above-ground biomass and for the total biomass, separately, the tuber biomass being computed as the difference between total and above-ground biomass. The model used for both the N concentration and the chlorohyll concentration is a cubic, quadratic, linear or logarithmic fucntion, depending on the plot. Ground coverages were not used to fit models because they were acquired the same date as the spectral measurements. Canopy N and chl a+b contents (g. m^2) were computed as the product of the biomass by leaf concentration.

Spectral data consisted of ground-measured whole reflectance spectra acquired, between 400 and 1000 nm, at the canopy level, with a *Spectron SE-590* spectroradiometer, having a 15^{o} FOV. The sensor was positionned always at 1.67 m from the ground, so that the viewed ground surface was 0.15 m^2. Spectral measurements were performed as follow: one radiance measurement on a *SPECTRALON* reference panel (*Spectralon, Labsphere Inc.*, New Hampshire, USA) (measure of irradiance), one radiance measurement per plot over a row of eight plots, one radiance measurement on a *SPECTRALON* reference panel (measure of the irradiance variation during radiance measurements). For each plot, radiances were measured separately over the row and inter-row and a mean spectra was computed. Reflectance spectrum was calculated as the ratio between radiance and irradiance spectra corrected for irradiance variations, assuming a linear change in irradiance over time. In addition, reflectance spectrum was acquired on wet and dry bare soils. The spectral measurements were made at noon time and under clear sky conditions. Each reflectance spectrum was smoothed using a three point weighted mean to suppress instrumental and environmental noise in the data, as in Danson et al. (1992). Smoothed individual plot reflectance spectra were averaged for each of the four N fertilization rates to assess effect of N fertilization on reflectance spectra.

To represent more clearly the reflectance vs wavelength difference between the control and stress plots, a reflectance difference spectrum was computed, as in Carter (1991), by substracting each individual plot reflectance spectra to the mean reflectance spectrum for the N-150 plots of the corresponding date and irrigation treatment. N-150 plots were used as reference, because among all the fertilization rates, 150 kg/ha can be considered as a suboptimal rate (Zebarth, pers. comm.), although it could be lower than usual fertilization rates. The computed differences were first used into a Dunnett's test to assess which wavelength gave a significant (at $\alpha = 0.05$) difference between each individual plot and the mean N-150 reflectance. These differences were then divided by the mean N-150 reflectance spectrum in order to compute reflectance sensitivities, as in Carter (1991). Sensitivity maxima and minima determined the wavelengths from which numerator and denominator reflectances should be selected for computation of hyperspectral ratioing indices, as in Carter (1994). These indices were compared to other spectral variables, because of their links with chlorophyll variables. They included the SPAD leaf chlorophyll index, the position of the red-edge inflection point (λ_{RE}) computed using both the inverted-Gaussian model of Miller et al. (1990) and the Lagrangian method of Dawson and Curran (1998) and the peak absorption wavelenmgth (λ_o), which corresponds to the wavelength of the red absorption band around 670 nm and which was computed using the inverted-Gaussian model of Miller et al. (1990). Correlations between each spectral index and each biological variable were then computed.

3. Results

3.1. Biological variables

A F-test of an analysis of variance with three factors of classification was applied to each estimated biological variable for testing the effect of the date, the N fertilization rate and of the irrigation regime and their interaction on these variables (Table 2). The date had a significant effect on all of the biological variables except the tuber nitrogen concentration. The N rate had a significant effect on all biological variables. The irrigation regime (referenced hereafter as “irr”) only has an effect on the above-ground and total biomass. The interaction between the factors generally had a lower effect than the individual variables.

Table 2. Values (1) of a Fisher-Snedecor test for a analysis of variance with three factors of classification and their interactions (all plots) (df=127, except for the ground coverage, df =102)

Biological variables (2)	Date	Nrate	Irr	Date * N	Date * Irr	N * Irr.	Date * N * Irr.
Total biomass (g/m^2)	127.27	48.22	6.19	9.52	3.28	3.24	1.09
Above-ground biomass (g/m^2)	128.42	39.97	4.61	8.20	2.67	2.40	0.98
Tuber biomass (g/m^2)	60.89	10.45	0.68	4.11	0.76	1.01	0.96
Total N cc (%)	23.68	70.62	0.64	4.68	0.98	2.48	2.37
Above-ground N cc (%)	9.37	36.34	0.21	2.16	0.98	3.00	2.08
Tuber N cc (%)	1.24	5.17	0.00	0.77	0.50	1.81	1.26
Chl a+b cc (µg/mg dw)	10.47	69.43	2.41	1.38	1.05	2.03	0.27
Ground Coverage (%)	109.09	4.10	0.08	0.70	1.64	1.88	1.87

(1) Underlined coefficients are significant at α =0.05; (2) cc=concentration

These overall results did not show that date and N rate and their interaction had both a stronger effect for the irrigated plots than for the non-irrigated plots (Table 3). Bélanger (pers. comm.) already reported a different N efficiency over irrigated and non-irrigated plots. Thereby, the analysis on the reflectance spectra will be further be carried out on each irrigation regime, separately.

Table 3. Values (1) of a Fisher-Snedecor test for an analysis of variance with two factors of classification (Date and Nrate) amd their interaction for both irrigation regimes (df=63, except for the ground coverage = 51)

Biological variables (2)	Non-irrigated plots			Irrigated plots		
	Date	Nrate	Date * Nrate	Date	Nrate	Date * Nrate
Total biomass (g/m^2)	39.02	14.36	2.17	102.94	42.04	9.80
Above-ground biomass (g/m^2)	33.02	10.84	1.59	146.78	47.01	12.08
Tuber biomass (g/m^2)	17.83	3.90	0.93	61.28	10.02	6.29
Total N cc (%)	7.10	37.60	2.90	20.67	34.87	4.52
Above-ground N cc (%)	3.07	29.08	2.75	6.98	11.63	1.59
Tuber N cc (%)	0.70	8.26	1.87	0.96	1.09	0.58
Chl a+b cc (µg/mg dw)	4.71	29.25	0.55	6.71	41.65	1.07
Ground Coverage (%)	38.59	2.38	0.84	76.54	4.87	1.63

(1) Underlined coefficients are significant at α =0.05; (2) cc = concentration

3.2. Reflectance spectra

The comparison presented in Figure 1 between mean reflectance spectra corresponding to the four N fertilization rates for each irrigation regime show that N-0 plots are well discriminated from the other N-rate plots. N-0 plots have a lower near-infrared reflectance than the other plots, but a higher visible one. Spectral discrimination between the different N levels was better achieved for non-irrigated plots than for irrigated plots. Except for the N-0 plots, near-infrared wavelengths were the most discriminating ones. On well-developed winter wheat canopies, discrimination between N fertilization levels was also better in near-infrared bands than in the visible ones (Filella et al. 1995). Signiifcant differences between N treatments were reported in the 550 nm and 700 nm band areas of the spectrum corn canopies

(McMurtrey et al. 1994, Blackmer et al. 1996). McMurtrey et al. (1994) explained the difference in 550 nm, by the maximum reflectance and the minimum absorption of chlorophyll and the one in 700 nm, by the chlorophyll concentration effects on the red-edge shift.

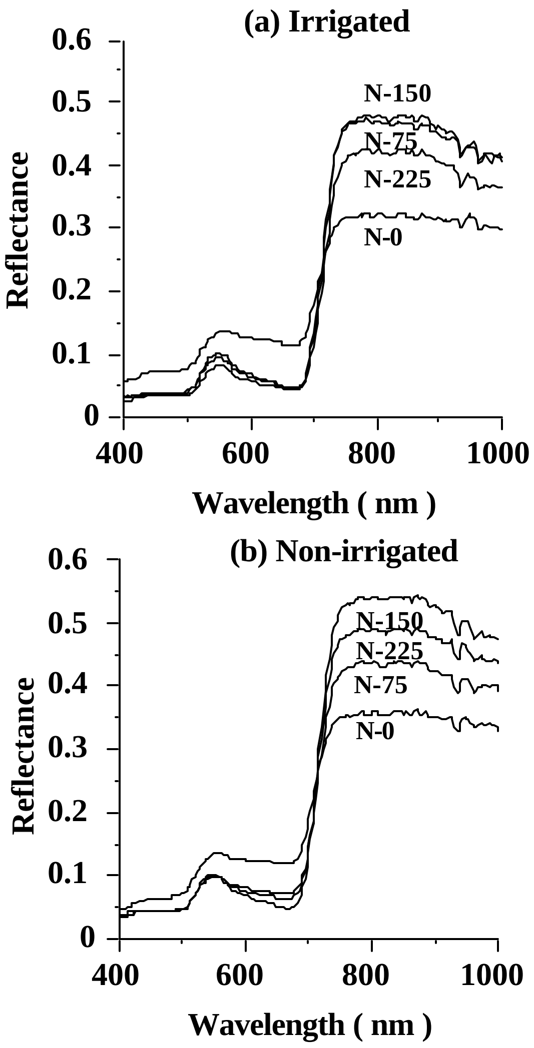


Figure 1. An example of mean reflectance spectra for the different N-rate plots for Day 54

To represent more clearly the reflectance vs wavelength difference between the control and stress plots, a reflectance difference spectrum was computed, as in Carter (1991), by substracting each individual plot reflectance spectra to the mean reflectance spectrum for the N-150 plots of the corresponding date and irrigation treatment. The computed differences were first used into a Dunnett's test to assess which wavelength gave a significant (at α=0.05) reflectance difference between each individual plot and the mean N-150. As in Carter (1994), difference maxima and minima determined the wavelengths from which numerator and denominator reflectances are selected into hyperspectral ratioing indice computation (Table 4). These differences were also divided by the corresponding mean N-150 reflectance spectrum in order to compute reflectance sensitivities, as in Carter (1991) (Figure 2).

Table 4. Wavelengths at which the difference with the N-150 plots reflectance is maximal and minimal

Date	Nrate	Maximum λ	 Diff. (1)	Minimum λ	 Diff.	Index
Irrigated plots						
48	0	670	1.39	720	0.05	ρ_{670}/ρ_{720}
54	0	661	1.48	717	0.11	ρ_{661}/ρ_{717}
62	0	656	0.50	717	0.10	ρ_{656}/ρ_{717}
70	0	641	0.83	723	0.09	ρ_{641}/ρ_{723}
70	75	597	0.23	717	0.02	ρ_{597}/ρ_{717}
70	225	447	0.17	756	0.12	ρ_{447}/ρ_{756}
Non-irrigated plots						
48	75	667	0.48	723	0.28	ρ_{667}/ρ_{723}
54	0	667	1.46	712	0.04	ρ_{667}/ρ_{712}
62	0	667	1.58	717	0.09	ρ_{667}/ρ_{717}
62	75	402	0.32	982	0.05	ρ_{402}/ρ_{982}
62	225	405	0.33	673	0.09	ρ_{405}/ρ_{673}
70	0	658	1.91	726	0.08	ρ_{658}/ρ_{726}
70	75	667	0.33	723	0.04	ρ_{663}/ρ_{723}
70	225	407	0.33	906	0.11	ρ_{407}/ρ_{906}

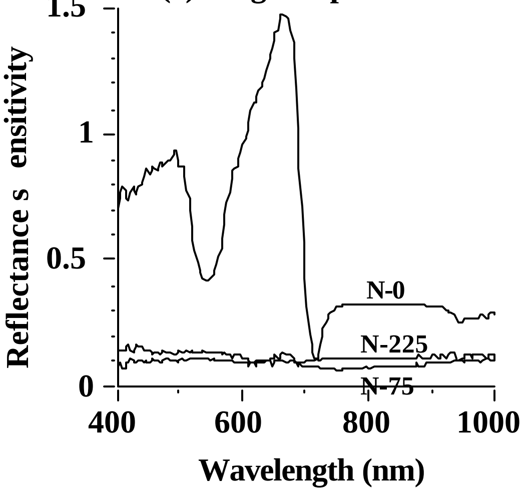
(1) significant at $\alpha = 0.05$

3.3. Correlation with the biological variables

Each biological variable was correlated to the hyperspectral indices, which were defined in the previous paragraph using a Dunnett's test and which are listed in Table 4. Among all the cosidered indices, the one which gave the highest correlation in most of the cases, was the one defined for day#62 and N-0 plots, i.e., ρ_{667}/ρ_{717} (Table 5). For comparison, correlations with the SPAD leaf chlorophyll index and with three red-edge indices were also computed (Table 5).

The proposed index ρ_{667}/ρ_{717} used similar wavelengths as the hyperspectral index RARSa proposed by Chappelle et al. (1992) for estimating leaf chlorophyll a concentration, but not as the hyperspectral index proposed by Carter (1994), for detecting stressed vegetation.

(a) Irrigated plots



(b) Non-irrigated plots

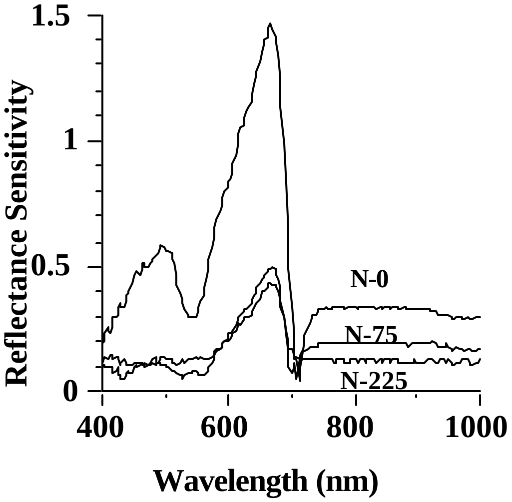


Figure 2. Reflectance sensitivities for day 54

This difference is not due to the method, because we used the same Dunnett's test-based method as Carter (1994). It may explain by the fact that we focussed only on one type of stresses, both in a positive (excessive N) or negative (N deficient) way, whereas Carter (1994) dealt with eight different stress factors, from chlorosis to water stress, but exclusively in the negative way, i.e., the stressed plants have a chemical status lower than the control plants.

The proposed index worked better for the biological variables measured at the canopy level , i.e., biomass, N and chl a+b content, and ground cover, whereas the SPAD leaf chlorophyll index worked better for biological variables measured at the plant or leaf level, i.e., petiole nitrate and N or chl a+b concentration. Changes in reflectances as detected by the proposed index shoudl thus be more related to plant growth, i.e., LAI change, rather than to plant biochemistry variations. There is therefore the need to validate more analytical methods, like near-infrared spectroscopy methods. This method was already tested successfully over forage crops (Leblon et al. 1997). Other analytical approaches use physical models, like the PROSPECT+SAIL model, which was successfully tested on sugar beets (Jacquemoud 1993),. Both approaches will be tested in a further study with the data acquired for this study.

Table 5. Pearson's correlation (1) between biological and spectral indices for all the plots together

Biol.Var.(2)	SPAD	ρ_{667} / ρ_{717}	l_0	l_{RE} Gaus.	l_{RE} Lagr.
Total biomass (g/m^2)	-0.02	-0.76	0.39	-0.14	0.01
Above ground biomass (g/m^2)	0.03	-0.76	0.41	-0.14	-0.00
Tuber biomass (g/m^2)	-0.15	-0.63	0.27	-0.10	0.02
Total N cc (%)	0.66	0.11	0.38	0.12	0.21
Above-ground N cc (%)	0.73	0.15	0.40	0.05	0.16
Tuber N cc (%)	0.33	0.00	0.18	0.18	0.21
Total N ct (g/m^2)	0.12	-0.69	0.44	-0.13	0.02
Above-ground N ct (g/m^2)	0.18	-0.67	0.46	-0.13	0.01
Tuber N ct (g/m^2)	0.05	-0.66	0.39	-0.12	0.03
Chl a+b cc(µg/mg dw)	0.96	-0.10	0.49	0.03	0.18
Chl a+b ct (g/m^2)	0.24	-0.69	0.45	-0.11	0.02
Ground Cover(%)	-0.06	-0.61	0.35	-0.20	-0.01
Petiole Nitrate (ppm)	0.80	0.02	0.43	0.04	0.09
Number of obs.	128	103	102	102	102

(1) Underlined coefficients are significant at α =0.05
(2) ct = content and cc = concentration

Whatever the level, among all the red-edge indices, λ_0 works the best, particularly for both chlorophyll variables. By contrast, the red-edge inflection point (λ_{RE}) is poorly correlated to the biological variables, even with those related to chlorophyll. Matson et al. (1994) already reported consistently higher correlations with λ_0 than with λ_{RE}, retrieved from CASI and AVIRIS images, which were acquired over coniferous forests. Similarly, canopy λ_{RE}, was found to be a poor indicator of chlorophyll, because of spectral influence of the background (Currran et al. 1990, Demetriades-Shah et al. 1990) or in the case of low range in chlorophyll (Filella and Penuelas 1994). In fact, most of the good correlations between λ_{RE} and chlorophyll variables which were reported in the literature were acquired at the leaf level. Those acquired at the canopy level are questionable because they were established over a small number of observations (Filella and Penuelas 1994, Filella et al. 1995, Munden et al. 1994, Pinar and Curran 1996) or over special canopies, i.e., those having spatially-invariant biomass or being optically thick (Blackburn 1998b, Jago et al. 1999). In our case, the studied canopies were not optically thick or did not have spatially variable biomass, owing to the raw canopy structure of potatoe fields.

4. Conclusions

We analyzed reflectance spectra acquired between 400 and 1000 nm at fine spectral resolution on potato fields subjected to two different irrigation regimes and four nitrogen (N) fertlization rates. Hyperspectral reflectances were shown to be suitable for discriminating between the N treatments, the difference between treatments being stronger for the non-irrigated plots than for the irrigared plots. A hyperspectral index ρ_{667}/ρ_{717} has been proposed, which gave the highest correlation with canoopy biological variables, like biomass, N and chlorophyll content and ground cover. However, it was less correlated to leaf-level variables, like N and chlorophyll concentration and petiole nitrate than the SPAD leaf chlorophyll index and λ_0. Whatever the level, the red-edge inflection point (λ_{RE}) was poorly correlated to the biological variables. There is the need to calibrate more complex approaches to retrieve leaf variables from the canopy reflectance spectra, for example those used in near-infrared spectroscopy or through more analytical reflectance models, like the PROSPECT+SAIL model of Jacquemoud (1993).

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