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Research Paper

Airborne and ground level sensors for monitoring nitrogen status in a maize crop

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Remote sensing could improve fertilisation by monitoring crop nitrogen (N) status using non-invasive methods. The main goal of this experiment was to test the ability of proximal and airborne sensors to identify the nutritional N status of maize. We compared various indices and combination of indices to select those that provided the best estimation. As airborne images were acquired from different sensors and platforms (drone and airplane) we compared the effect of spatial resolution (SR) on the indices calculated. The study was conducted in a field maize experiment in Aranjuez (Madrid, Spain) during 2015. The experiment consisted of a complete randomized design with five fertiliser rates ranging from 0 to 220 kg N ha^{-1} and six replications. Readings at ground level were taken with proximal sensors (SPAD® and Dualex®), and airborne data were acquired by flying a multispectral camera and a hyperspectral sensor at 80 and 330 m above ground level, respectively. The aerial imagery was used to calculate N status indices for each plot. Proximal and airborne sensors provided useful information for the assessment of maize N nutritional status. Higher accuracy was obtained with indices combining chlorophyll estimation with canopy structure or with polyphenol indices. Combined indices improved the estimation compared to an individual index and mitigated its saturation at high N concentration values. Plant N concentration was strongly related with TCARI/OSAVI obtained from airborne imagery but not with NDVI. The SR did not affect the performance of structural indices whereas highly influenced the pigment indices.

1. Introduction

A key factor for improving N fertiliser efficiency and reducing input costs is to adjust N application to crop demand (Arregui & Quemada, 2008). In addition, matching N application and crop requirements decreases deleterious environmental effects of excessive fertilisation, either by nitrate pollution of water (Quemada, Baranski, de Lange, Vallejo, & Cooper, 2013) or by gaseous emissions (Snyder, Bruulsema, Jensen, & Fixen,

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2009). Some rapid and non-destructive ways to obtain multiple measurements are optical readings that can provide indicators of crop nutritional status. The greenness of plants is strongly related to leaf chlorophyll content and to N status, so it has been used as an indicator of N availability (Fox & Walthall, 2008; Hunt et al., 2013). The best variable to assess crop nutritional status is the N nutrient index, which is based on the critical N concentration (the minimum N concentration in the plant that allows maximizing growth; Greenwood et al., 1990). The strategy of some crops (as *Solanum tuberosum* L.) is to reduce leave development in order to maintain photosynthetic capacity per surface unit (Vos & van der Putten, 1998). However, maize (*Zea maize* L.) does not change leaves appearance rate nor the duration of leaf expansion and it does never reduce leaf area more than 30%. In this case, the leaf N concentration differed by at least a factor of 2 from the lowest to highest N supply, for a large range of N supply, presenting leaf N concentration as a good indicator of N status (Vos, van der Putten, & Birch, 2005). Moreover, along the crop cycle, the N concentration decreases with increasing crop biomass and for a given growth stage and biomass accumulation there is a critical level below which the crop yield would be reduced (Lemaire & Gastal, 1997). Therefore, determination of plant N concentration by destructive techniques (i.e. tissue analysis) is a recommended practice for improving fertiliser management (Plenet & Lemaire, 2000; Tei, Benincasa, & Guiducci, 2002), and a goal for application of remote sensing to improve N fertilisation should be monitoring crop N status by mean of non-invasive methods.

In the past decades, a tremendous progress on sensor technology for assessment of plant N status has been achieved. At the leave level, there are various commercial sensors to that estimate chlorophyll content and can be used to provide N fertilizer recommendations for farmers (Arregui et al., 2006; Piekielek, Fox, Toth, & Macneal, 1995). These chlorophyll leaf clip sensors ensure a good contact with the plant and show good relationships with N status, but may present some limitations as readings can be affected by water content, leaf structure, thickness changes or nutrient deficiencies other than N. Complementing chlorophyll measurements with polyphenol concentration in the leaf epidermis is a mean to overcome such constraints (Cerovic et al., 2002). The chlorophyll to polyphenol ratio has been reported to be more stable than the non-uniform leaf chlorophyll distribution (Cartelat et al., 2005).

On the other hand, remote sensing can cover large areas and reflect spatial variability of crop canopies. Remote sensors have being mounted in different platforms as: tractors, drones, airplanes and satellites, to provide information for precision farming (Fox & Walthall, 2008). There are several indices based on remote sensors that characterize plant canopy structure, soil cover, above-ground biomass, yield or water and nutrient-deficiency. The indices are calculated by combining reflectance on the wavelengths located in the visual, red-edge and near infrared range. The most commonly-used is the Normalized Difference Vegetation Index (NDVI) developed to identify areas covered by natural vegetation (Rouse, Haas, Schell, Deering, & Harlan, 1974). The NDVI and its variants (i.e. RDVI, Renormalized Difference Vegetation Index (Rougean & Breon, 1995)) characterize plant canopy structure and have been frequently used to analyze crop N performance and for fertiliser recommendation (Elazab, Ordóñez, Savin, Slafer, & Araus, 2016). More recently, researchers proposed other indices related to plants pigment concentration as a more accurate mean to estimate crop N status while minimizing the impact of canopy structure. Stroppiana, Boschetti, Brivio, and Bocchi (2009) showed that the optimal Normalized Difference Index (NDI_{opt}), based on the blue/green reflectance region, was less affected by leaf area index (LAI) and canopy structure of rice than NDVI, and was more sensitive to changes in plant N concentration. Chen et al. (2010) developed the Double-peak Canopy Nitrogen Index (DCNI) to estimate crop N status of wheat and maize and minimized the effect of canopy structure.

In field-scale images, the canopy reflectance spectrum is affected by both, canopy structure and N concentration. Remote sensors are carried at different altitudes above the ground level depending on specific application and the platform used. Sensors spatial resolution (SR) depends on the altitude and the sensor specifications. The SR at which the image is captured might affect the relative weight of canopy structure on the actual value of a particular index due to the angular effects of shadows and background at each specific resolution. Therefore, there is a need to evaluate the effect of image SR on the indices designed to estimate crop N status.

Nitrogen only constitutes 2–4% of the maize dry matter but is considered the most important factor in grain maize production together with water availability (Elazab et al., 2016). In addition, when low crop growth is attained, the canopy only covers the ground partially. During this period, the N deficiency may be affected by both, canopy structure and pigment concentration. The FAO (United Nations Food and Agriculture Organization) has identified the maize as the second most cultivated cereal worldwide in terms of land area and the first in production (FAO, 2016). The world production in 2014 was over a thousand million Mg and is continuously increasing.

The main goal of this experiment was to test the ability of proximal and airborne sensors to identify the nutritional N status of maize. We specifically compared various indices or combination of indices to select those that provided the best estimation. As airborne images were acquired from different sensors and platforms (drone and airplane) we compared the effect of SR on the indices calculated.

2. Material and methods

2.1. Experimental site and crop management

The study was conducted at La Chimenea field station (40°03′N, 03°31′W, 550 m a.s.l.), which is located in the central Tajo river basin near Aranjuez (Madrid, Spain) during 2015. The soil at the field site is a *Typic Calcixerept* (Soil Survey Staff, 2014), alkaline, rich in organic matter, silty clay loam texture and low stone content throughout the soil profile. The soil mineral N at planting in the first 1 m depth was 25 kg N ha^{-1}. The climatic conditions in the area are Mediterranean semi-arid. Mean annual temperature is 14.2 °C with an average annual rainfall of 350 mm, most of it during autumn and spring. Details on soil and climate conditions are described in

Gabriel, Lizaso, and Quemada (2010) and Gabriel and Quemada (2011). The experiment consisted in a complete randomized design with five fertiliser treatments and six replications. The plot size was 6 × 6 m^2 and the measurements, either at ground or remote level, were taken in the central 3 × 3 m^2 central square. Treatments consisted of various N fertiliser rates 0, 70, 120, 170 and 220 kg N ha^{-1}. The site was sown with maize (*Zea mays* L., Pioneer P1574, cycle 700) in early spring (14 April 2015) in rows separated by 0.74 m and 0.17 m within rows, resulting in a plant population density of 80,000 plants ha^{-1}.

Water was uniformly applied with a sprinkler irrigation system (12 m × 12 m, 9.5 mm/h) during the whole cropping season. According to FAO, crop water requirements were calculated based on the crop evapotranspiration (ETc). The reference evapotranspiration (ETo) was calculated using the Penman–Monteith model, and the crop coefficient was obtained using the ratio for maize in semiarid conditions (Martínez-Cob, 2008). This resulted in 558 mm of irrigation, added to the 65.7 mm of rainfall accumulated during the cropping season. The N applied with the irrigation water was 6 kg N ha^{-1}.

Before sowing the maize, 30 kg P ha^{-1} (triple superphosphate) and 100 kg K ha^{-1} (potassium chloride) were applied to all plots to ensure P and K availability. Nitrogen fertiliser (calcium ammonium nitrate, 27%) was hand broadcast to plots when the maize had six leaves (27 May 2015). The experiment was conducted in a field that had been left fallow in the previous year and had not received organic amendments or N fertiliser during four years prior to the beginning of the trial.

2.2. Ground-level optical determinations

The SPAD-502® chlorophyll meter (Konica Minolta Inc., Japan) is a leaf clip sensor that measures the light transmitted by a plant leaf when a red LED (650 nm) and an infrared LED (940 nm) provide illumination in a small (~1 cm^2) dark chamber. The instrument processes the ratio of the light transmitted at these wavelengths and the ratio determined in the absence of a sample to produce a digital reading that is highly correlated with leaf chlorophyll content (Yadava, 1986). The dimensionless index obtained will be called SPAD index throughout the manuscript.

The Dualex® Scientific (Force-A, Orsay, France) is also a leaf clip sensor that estimates chlorophyll content as the difference between the light transmitted at the red and infrared wavelengths (Chl). However, this device also measures leaf polyphenols concentration as flavonol (Flav), which is directly related to the optical absorption of the leaf epidermis under UV light. Chlorophyll fluorescence is induced by a UV (375 nm) and a red LED. Since the epidermis absorbs UV-induced fluorescence, but transmits red light induced fluorescence, epidermis absorbance can be determined by comparing both. The Nitrogen Balance Index (NBI), calculated as the ratio between Chl and Flav content, has been used to assess N nutritional status in wheat and corn (Cartelat et al., 2005; Tremblay, Wang, & Cerovic, 2011).

Readings with both different optical sensors were taken at ground level in 22 July 2015. The crop was at flowering (full tassel in flower and female stigma emerged; 65 in the Lancashire et al. (1991) decimal code), when the difference between the N applied to the various treatments was expected to be most evident (Kyveryga, Blackmer, & Pearson, 2012). Two measurements were taken from the uppermost fully developed leaf of 15 representative plants in the two central rows of each plot using the SPAD and Dualex® optical sensors. The readings average for each plot was obtained as the representative value.

2.3. Remote-level optical determinations

Field crop measurements and multispectral (drone) and hyperspectral (airplane) imagery acquisition were conducted concurrently at 22 July. Hyperspectral imagery was taken onboard of a Cessna airplane, 330 m over the experimental plots on the solar plane at 9:00 GMT using a VNIR micro hyperspectral imager (Micro Hyperspec VNIR model, Headwall Photonics, Fitchburg, MA, USA). The micro hyperspec VNIR was set up with a configuration of 260 spectral bands acquired at 8 nm/pixel and 12-bit radiometric resolution in the 400–885 nm spectral region, yielding a 6.4 nm Full Width at Half Maximum (FWHM) with a 25-μm slit. The storage rate was 50 frames per second, with an integration time of 18 ms. The 8-mm focal length lens yielded a 30 × 30-cm pixel resolution at the 330-m altitude and a 75 km/h ground speed. The micro-hyperspectral sensor was radiometrically calibrated in the laboratory and ortho-rectificated (Zarco-Tejada, González-Dugo, & Berni, 2012).

Hyperspectral indices were calculated for each experimental plot with regard to structural (or greenness) indices, chlorophyll a + b concentration, epoxidation state of the xanthophylls cycle, blue/green/red ratio indices and fluorescence. Sixty four indices were estimated from the airplane hyperspectral imagery. Table 1 shows a selection of the most relevant indices, either because of the importance in the literature or because their good adjustment in this experiment.

The drone images were acquired with a multispectral sensor (MCA-6, Tetracam, Inc., California, USA), 80 m over the experimental plots, on the solar plane at 8:00 GMT. The flight was conducted optimizing the path of the drone through parallel past, with automatic pilot function according to the project planned, with a ground sampling distance (GSD) of 2.16 cm. The drone quadcopters used a system GPS of double frequency and differential corrections RTK, as an inertial system for the positioning of the photo-centers and the parameters of tilt at the time of taking the image. Twenty control points were positioned on the ground with a GPS in order to ensure an ortho-image rectified of the plots, providing a 2.1 × 2.1-cm pixel resolution. This cinematic support was contrasted with the captures in Earth, obtaining a precision of 2.7 cm in planimetry and 3.1 cm in altimetry, which corresponded to an error of 1.05 pixels. The camera had six independent image sensors that captured narrow wavelength bands center at 530, 550, 570, 670, 700 and 800 nm and a bandwidth of 10.0 ± 2 nm. The sensors provided images made up of 1280 × 1024 pixels. The ortho-image was used to extract five different vegetation indices (NDVI, RDVI, OSAVI, TCARI, TCARI/OSAVI) for each experimental plot using equations in Table 1.

Table 1 – Indexes calculated from either the hyper-spectral imager on-board the airplane or from the multi-spectral camera carry on the drone (**).

Index	Equation	Reference
Structural indices		
**Normalized difference vegetation index (NDVI)	$NDVI = (R_{800} - R_{670})/(R_{800} + R_{670})$	Rouse et al., 1974
**Renormalized difference vegetation index (RDVI)	$RDVI = (R_{800} - R_{670})/(R_{800} + R_{670})^{0.5}$	Rougean & Breon, 1995
**Optimized soil-adjusted vegetation index (OSAVI)	$OSAVI = (1 + 0.16) \times (R_{800} - R_{670})/(R_{800} + R_{670} + 0.16)$	Rondeaux, Steven, & Baret, 1996
Chlorophyll indices		
Red edge reflectance index	R_{750}/R_{710}	Zarco-Tejada, Miller, Mohammed, Noland, & Sampson, 2001
Double peak canopy nitrogen index (DCNI)	$(R_{720}\text{-}R_{700})/(R_{700}\text{-}R_{670})/(R_{720}\text{-}R_{760}+0.16)$	Chen et al., 2010
**Transformed Chlorophyll absorption in reflectance index (TCARI)	$TCARI = 3\ [(R_{700} - R_{670}) - 0.2\ (R_{700} - R_{550})/(R_{700}/R_{670})]$	Kim, Daughtry, Chappelle, & McMurtrey Walthall, 1994
**Combined TCARI/OSAVI	TCARI/OSAVI	Haboudane, Miller, Tremblay, Zarco-Tejada, & Dextraze, 2002
Xanthophyll indices		
Photochemical reflectance index (PRI)	$PRI = (R_{570} - R_{539})/(R_{570} + R_{539})$	Gamon, Peñuelas, & Field, 1992
Normalized photochemical reflectance Index (PRI norm)	$PRI\ norm = (R_{515} - R_{531})/(R_{515} + R_{531})$	Zarco-Tejada, Morales, Testi, & Villalobos, 2013
Blue/green/red ratio índices		
BGI1	$BGI_1 = R_{400}/R_{550}$	Zarco-Tejada et al., 2012
BGI2	$BGI_2 = R_{450}/R_{550}$	Zarco-Tejada et al., 2005
Fluorescence retrieval		
Fluorescence (SIF760)	FLD3 method using 2 reference bands (750; 762; 780)	Plascyk & Gabriel, 1975 Zarco-Tejada et al., 2013

2.4. *Maize analysis*

Maize plants were also sampled at the same date than the sensor sampling. Leaf tissue samples were obtained from the same 15 plants and leaves in which ground-optical sensors were measured. These samples were dried in a 65 °C oven and ground for determining total N concentration, applying the Dumas combustion method (LECO FP-428 analyzer, St. Joseph, MI, USA). The LAI was measured in representative maize plants from each plot using the CI-203 handheld laser leaf area meter (CID Bio-Science, Camas, WA, USA). The fraction of intercepted photosynthetically active radiation (FIPAR), defined as the fraction of the total incident PAR over the sampling area intercepted by the vegetation, was calculated as the complementary of the ratio between transmitted and incident PAR. PAR measurements were obtained with a Sunfleck ceptometer (Delta-T Services, Cambridge, UK). The transmitted PAR was the average of four measurements taken at ground level below the vegetal cover and the incident PAR was measured over the crop, with the sensors looking up at the sky.

At harvest (7 October 2015), two 4 m central rows of each plot were harvested with an experimental combined harvester and the maize yield was recorded. En each plot, 1 m stripe next to the central row was harvested by hand and separated into plant components (grain vs. rest of above-ground biomass), dried in a 65 °C oven, weighed, and ground. The harvest index (=grain/(grain + rest of aboveground biomass)) was obtained and the average used to calculate the rest of aboveground biomass from the yield recorded in the experimental combined harvester. Total N concentration was determined in grain subsamples from the combined harvester and in the rest of the biomass for each plot by the Dumas combustion method. For each plot, the N content of each crop component was calculated by multiplying its dry biomass by its N concentration and adding up both to obtain crop N uptake. The available N was calculated as the addition of crop N uptake in the control plus the fertiliser application to each treatment.

2.5. *Statistical analysis*

To quantify the degree of correlation between data from sensors (either ground or airborne) and agronomic measurements, the Pearson correlation coefficient was calculated between the indices obtained in each measurement campaign and the agronomic parameters (available N, leaf N concentration). Linear and polynomic models were fitted between indices and the agronomic parameters, and the root mean square error (RMSE) and the coefficient of determination (R^2) calculated to analyze goodness of fit. Statistical analyses were conducted with IBM® SPSS® statistics software.

3. Results and discussion

3.1. *Fertilisation effect on crop N uptake*

In the non-fertilised treatment, the mean N leaf concentration was 2.2% and the crop N uptake by the above ground biomass at harvest was ≈56 kg N ha^{-1}. The N fertiliser rate increment resulted in an increase of the N concentration observed in the leaves and in the crop N uptake by the plant (Fig. 1). The maximum concentration (around 3.5%) was obtained at

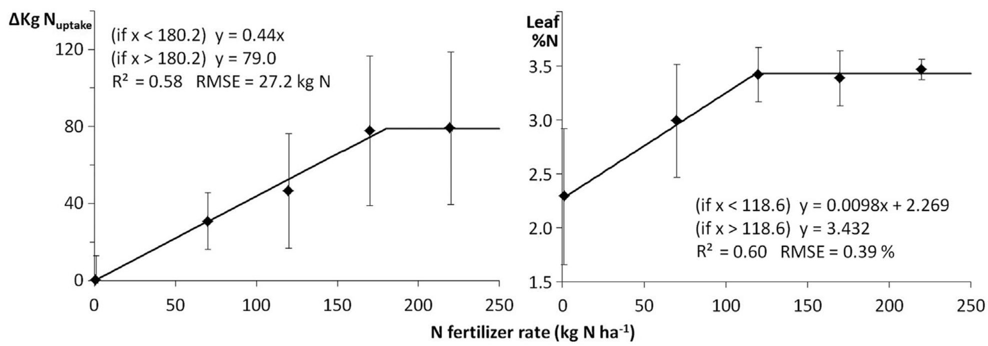

Fig. 1 – Crop N uptake at harvest relative to the non-fertiliser control (Δkg N_{uptake} = crop N uptake in the fertilised treatment – crop N uptake by the control) and leaf N concentration (%N) at the time the images and samples were acquired for the various N fertiliser treatments. In the control, the mean crop N uptake was 56 kg N ha^{-1}. Vertical lines represent ±1 standard error.

120 kg N ha^{-1} rate, reaching a plateau at higher fertiliser rates. However, the crop N uptake reached the plateau at the rate of 180 kg N ha^{-1}. This effect suggested that once the leaves reach the maximum N concentration, the plant tend to increase size and biomass instead of increasing N concentration. The N fertiliser efficiency based on the N increase with respect to the non-fertilised treatment was ≈45% up to the recommended rate (170 kg N ha^{-1}), but decreased to 31% for the 220 kg N ha^{-1} treatment. The recommended rate is in agreement with previous recommendations made for maize crop in this region (Gabriel, Alonso-Ayuso,García-González, Hontoria, Quemada, 2016; Gabriel & Quemada, 2011).

The relationship of crop available N with some indices obtained with both ground and remote-level sensors was significant (Fig. 2). The tendency was similar to the N concentration, reaching the plateau closer to 175 kg N ha^{-1} (corresponding to a fertiliser rate of 120 kg N ha^{-1}) than to 225. The adjustment was slightly lower, being the Dualex NBI the most accurate (R^2 = 0.57), followed by Dualex/SPAD Chl (R^2 = 0.55) and TCARI/OSAVI (R^2 = 0.48). The better performance of NBI with respect to Chl readings or to Dualex Flav alone as an indicator of available N was already reported (Tremblay et al., 2011). The strength of combined indices is also obvious when comparing TCARI or OSAVI analyzed independently (R^2 of the quadratic model = 0.22 and 0.17 respectively) with the TCARI/OSAVI index. Under these conditions, the indices obtained from the ground-level sensors performed better predicting the crop available N, followed by the plane indices and finally by the indices from the Tetracam drone. Similar results were obtained by Quemada, Gabriel, and Zarco-Tejada (2014) when hand sensors and plane indices were compared. This is mostly due to

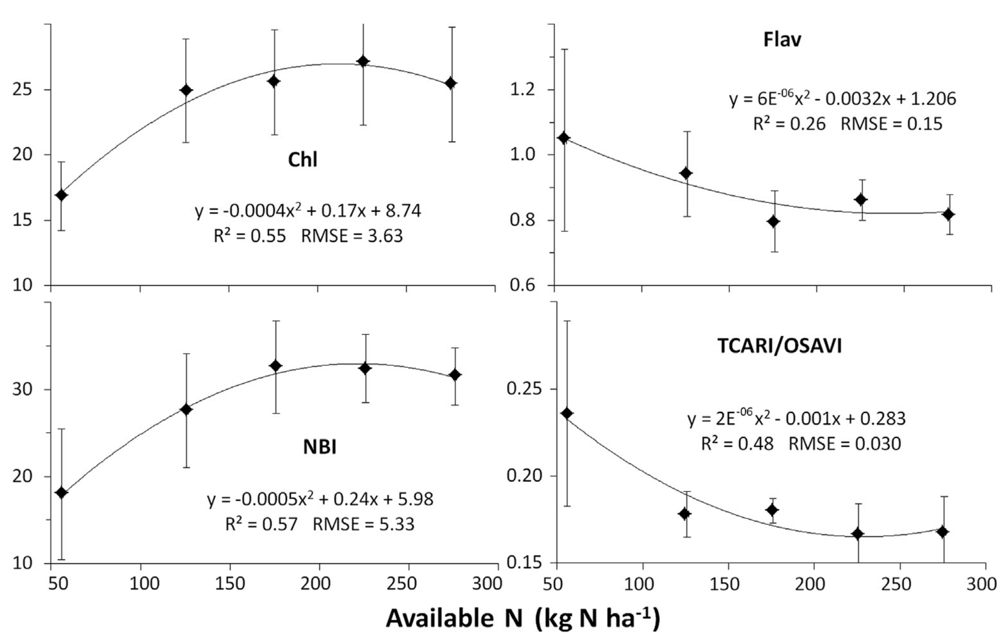

Fig. 2 – Relationship between relevant leaf clip and remote indices calculated from the hyper spectral sensor with available N for the various N fertiliser treatments. The available N was calculated as the addition of crop N uptake in the control (56 kg N ha^{-1}) plus the fertiliser application to each treatment. Vertical lines represent ±1 standard error.

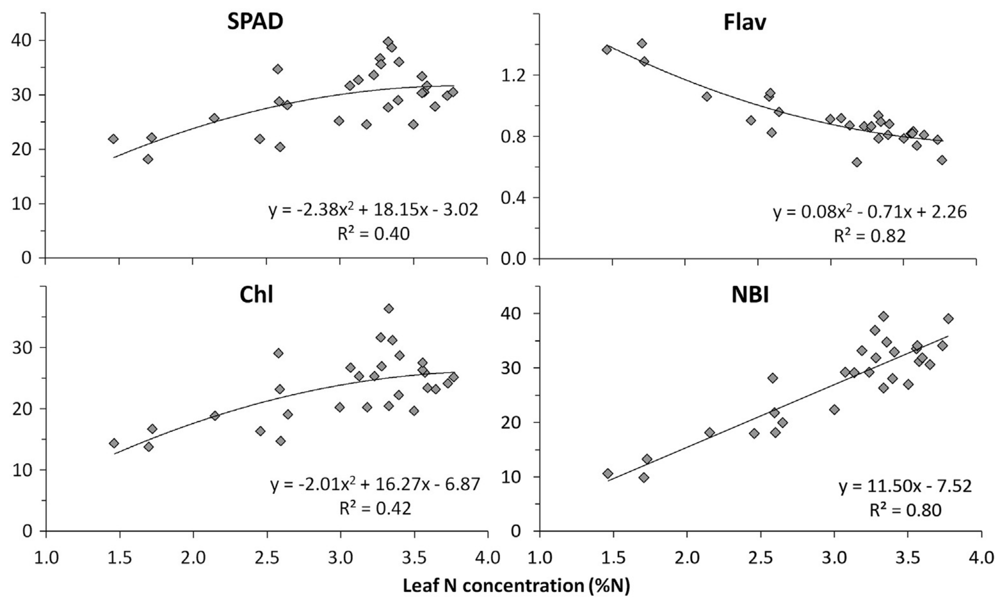

Fig. 3 – Polynomial relations between leaf clip indices and leaf N concentration (%N).

the plant architecture and the error included in the plane indices when some soil fractions are captured. Because of that, remote indices integrating structural and pigment information (*i.e.* TCARI/OSAVI) can provide better estimation of crop N uptake.

3.2. *N status prediction with sensors*

All indices were also compared with the actual leaf N concentration observed in the field (Fig. 3). Optical ground-level sensors resulted in good adjustments, but there were

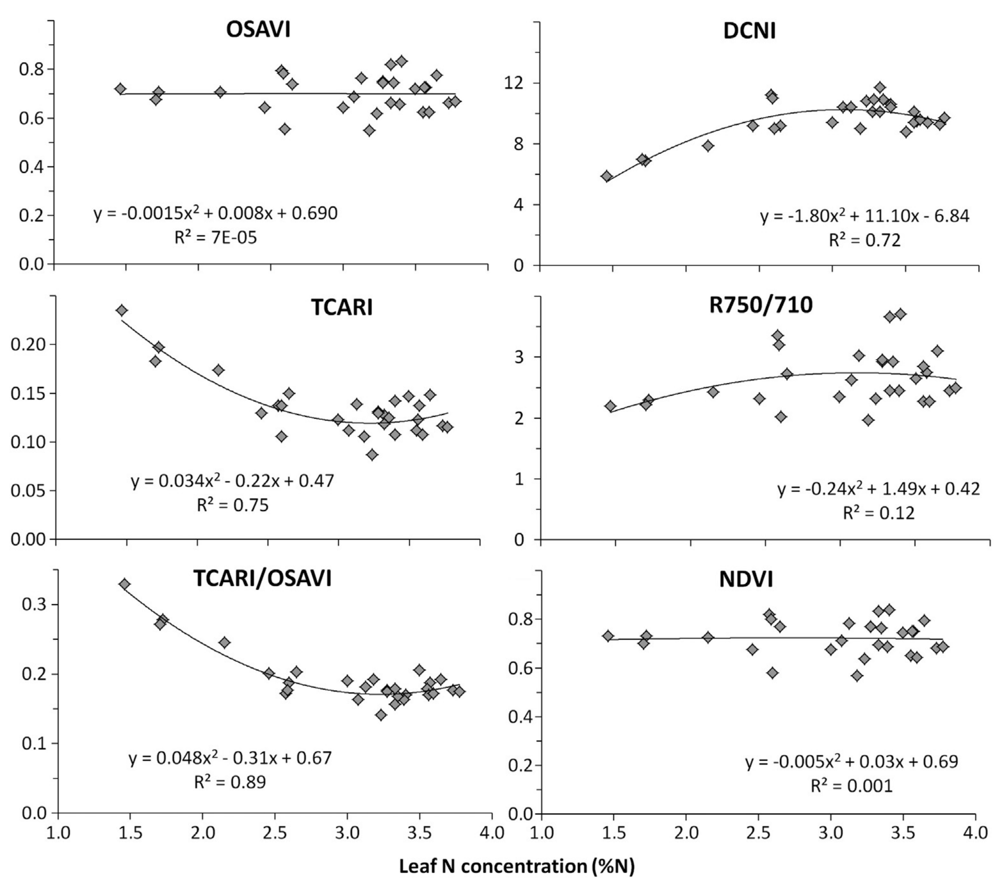

Fig. 4 – Polynomial relations between indices calculated from the hyper spectral sensor and leaf N concentration (%N).

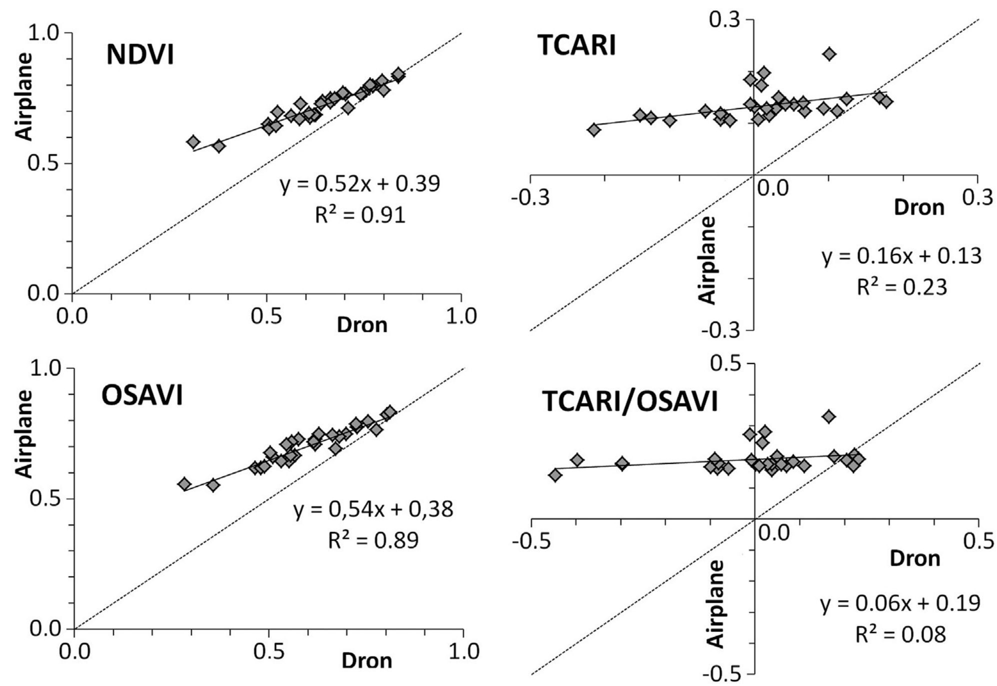

Fig. 5 – Differences in the spectral indices calculated from images acquired from either an airplane at 330 m over the ground or a drone at 80 m over the ground.

differences between indices. Both, chlorophyll estimations (Chl and SPAD) and NBI tended to increase with the leaf N concentration. On the other hand, Dualex Flav tended to decrease with increasing N concentration. These results are in agreement with Cerovic et al. (2002) and Tremblay et al. (2011), who observed that N deficiency reduced chlorophyll content and increased polyphenols. The better performance of NBI with respect to Chl readings alone as an indicator of crop N status was reported by Tremblay et al. (2011) and shows that the NBI overcomes the constraints derived from a non-uniform leaf Chl distribution. It is notable that while Chl and Flav indices presented some indications of saturation at high N content values, NBI showed a linear relationship without saturation at the concentration range observed. This could be a determining factor in order to define if a crop needs to be N fertilized or there is luxury supply when the farmer is moving close to potential yield. Padilla, Peña-Fleitas, Gallardo, and Thompson (2016) reported that NBI uses to be the most consistent index in order to get the N crop status throughout the cropping season. However, they also found that Chl and Flav indices were also strongly related with the N crop status during the initial and the latest growth stages, respectively. In our study, with measurements made at flowering (in the second half of the cropping season), the relation with N crop status has been also stronger with the Flav than with the Chl. Similar tendency was observed by Quemada et al. (2014) in maize, with better relation during the first stages for the Chl, but increasing for the Flav as the cropping season advanced.

The remote sensors presented more variability between indices when compared with the leaf N concentration (Fig. 4). There were indices as TCARI/OSAVI with better adjustment ($R^2 = 0.89$) than even the ground-level indices ($R^2 < 0.82$), but most of them resulted in lower accuracy, as expected. Again, most of the remote-level indices presented saturation at high N concentration, making difficult the recommendation of fertilisation when the crop is close to potential yield, but detecting crop N deficit. So, remote sensing can lead to identification of farm zones with higher nutrient demand, improving the adjustment of fertilizer rates in precision farming (Fox & Walthall, 2008). In addition, other remote-level indices related to pigments presented R^2 larger than 0.72, as BGI1, TCARI and DCNI.

On the other hand, remote sensing indices related to structural crop properties, as NDVI, RDVI or OSAVI, presented weak relations to leaf N concentration ($R^2 < 0.2$). This structural indices related better with the crop FIPAR measured with the ceptometer ($R^2 = 0.42$ for the airplane and $\approx$0.48 for the drone indices). These indices provided useful information about canopy structure, but were not able to predict accurately the crop N nutritional status. Nevertheless, canopy structure is used many times as the reference value for decision taking because it is the combination of various crop growth factors as water stress, pest attack,… (Boegh et al., 2002; Elazab et al., 2016; Vergara-D et al., 2016).

Xanthophylls indices resulted between chlorophyll and structural indices. In this case, indices as the PRI family provided R^2 adjustments between 0.42 and 0.47. The relation with structural crop properties was also low; however, they related with a $R^2 \approx 0.62$ with the Flav measurements.

3.3. *The effect of the image SR on N indices*

The image SR affected indices on two different ways (Fig. 5). On the one hand, the structural indices NDVI, RDVI or OSAVI were only slightly influenced by the SR and the correlation between measurements from airplane and drone were very

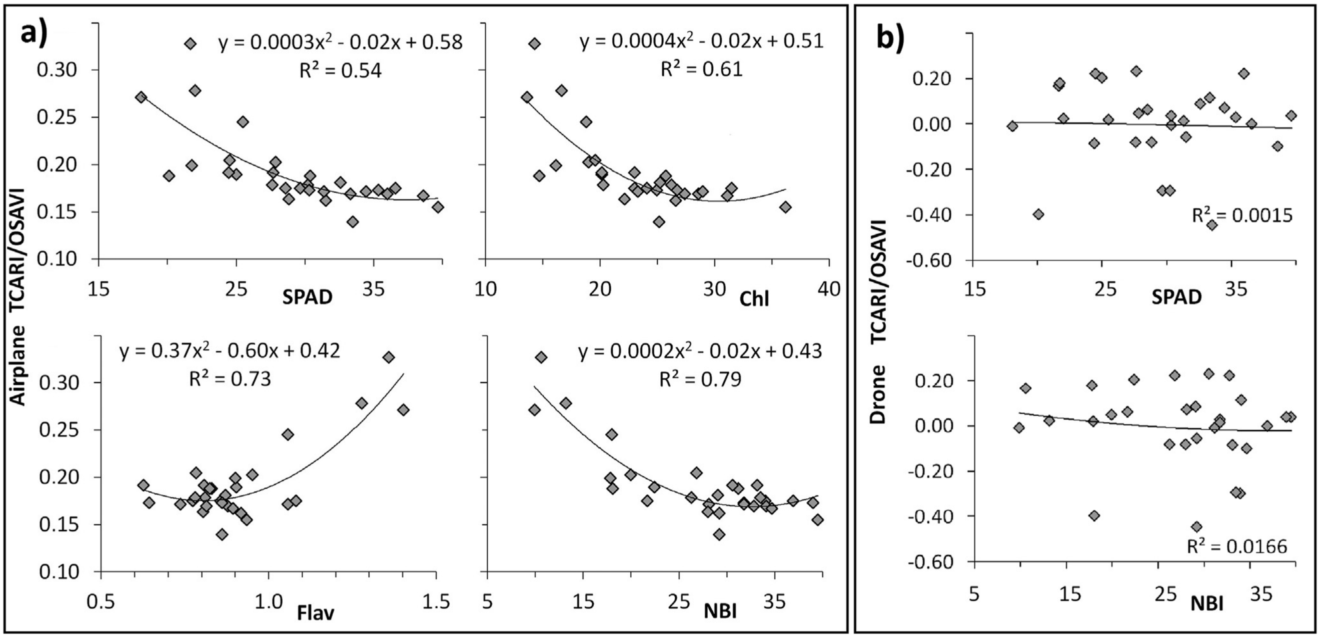

Fig. 6 – Polynomial relations between TCARI/OSAVI index calculated from images acquired from a) an airplane at 330 m over the ground, and b) a drone at 80 m over the ground, and various leaf clip indices.

high (r > 0.91 for the three indices). Indices at low values were more sensitive to SR when they were based on drone imagery, of higher SR, than on airplane images (i.e. NDVI values for the drone ranged from 0.311 to 0.840 and for the airplane from 0.566 to 0.840). Because of that, the correlation line between drone and airplane indices slightly differed from the one–one line (slope ≈ 0.50; residual value ≈ 0.35). The higher sensitivity of drone indices when the crop does not cover the ground completely (i.e. lowest index values) may be explained by a larger weight of ground-pixels on the index calculation when pictures are taken closer to the ground or SR is higher.

On the other hand, the pigment indices TCARI and TCARI/OSAVI, were highly influenced by the image SR. In this case, the relation between airplane and drone measurements was very weak ($R^2 < 0.25$ in both cases). The influence of ground-pixels on the index calculation was driving the differences. For all values, indices based on pigments were underestimated by the drone imagery of higher SR due to the larger weight of ground-pixels when comparing to the airplane pictures with lower SR. The good relationship between TCARI/OSAVI of the hyperspectral imagery and proximal sensors, reinforced the presence of the SR effect (Fig. 6). For instance, NBI was highly related with TCARI/OSAVI calculated from airborne sensors ($R^2 = 0.79$) but not from drone measurements ($R^2 = 0.02$). The practical importance of the SR effect might be mitigated in real situation fields were the probability of finding fields with yield losses >25% due to N deficiency is very low (Piekielek et al., 1995). Nevertheless, the effect of ground pixels may be relevant when airborne indices are used to identify responsive sites to N at topdressing at early development stages, when the LAI and ground cover is still low.

4. Conclusions

Proximal and airborne sensors provided useful information for the assessment of maize N nutritional status. Higher accuracy was obtained with indices combining chlorophyll estimation with canopy structure (i.e. TCARI/OSAVI for airborne sensors) or with polyphenol indices (NBI for proximal sensors). Combined indices yielded better performance than individual indices, while NBI mitigated the index saturation at high N concentration values. The relationship between leaf N concentration and TCARI/OSAVI obtained from airborne imagery was very strong, whereas NDVI was not significant.

The SR of the acquired image had an effect on the indices performance. Structural indices (NDVI, RDVI or OSAVI) presented low dependency of image SR, whereas pigment indices (such as TCARI) were highly influenced by SR because of the background and shadow effects. Further research will focus on the identification of robust indices across species and stress levels related to leaf N concentration for better monitoring crop N nutritional status.

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