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Does remote and proximal optical sensing successfully estimate maize variables? A review

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ABSTRACT

Mapping the within-field variability of crop status is of great interest in precision agriculture that seeks to match agronomic inputs to crop demand, both spatially and temporally. In this context, nitrogen (N) management plays a key role that must balance its importance in crop production with its potential to be a source of environmental pollution. Remote and proximal sensing techniques are widely studied to assess the dynamics of crop status during the growing season. While many experiments were conducted to prove the feasibility of optical sensors to estimate N management-linked variables, a summary evaluation of their performance in maize is lacking. This review considers studies of ground-measured maize variables with remote and proximal optical sensor measurements under varying N levels to inform the feasibility of using sensors for N management. We collected 66 papers published between 1992 and May 2017 that reported 647 regressions between vegetation indices and maize variables (chlorophyll content, N concentration, leaf area index, above ground biomass, crop N uptake, crop yield, and optimum N rate). Regression tree analysis was applied to understand the roles of seven factors on the performance of estimation of maize variables with vegetation indices: crop development stage, sensor type, acquisition mode, sensed target, spatial resolution, type of vegetation index, and standardisation of sensor readings. Our results indicate that the factors have different effects accordingly to the different maize variables. Furthermore, regression parameters are specific for location, year, and cultivar. As empiricism severely limits practical application of these highly specific regressions, estimation of optimal N rates for delivery to the soil-crop system should take into account N budgets in soil that could be derived by chemical analysis or soil sensors as well as by more complex mechanistic simulation models.

1. Introduction

Optical sensing employs electromagnetic energy to detect and measure characteristics of its target. It is defined as the science of acquiring, processing, and interpreting data that record interactions between matter and electromagnetic radiation (Sabins, 2007). Interactions include reflection, absorption, and transmission of solar or artificial radiation by the target matter (crop), in addition to emission of radiation and fluorescence.

Reflection measured at high spectral resolution allows the reflected radiation to be plotted as a function of wavelength. In turn, a reflectance spectrum can be constructed for each material, including vegetation (Fig. 1). Visible range leaf reflectance properties are closely related to leaf pigment contents, and chlorophyll in particular. Chlorophyll causes greater reflectance in the green portion of the electromagnetic radiation spectrum (centered at 550 nm, G) than in the red (650–690 nm, R) and blue (430–490 nm, B) absorption bands (Barnes et al., 1996). In the 725–1000 nm portion of the near-infrared (NIR) region, reflectance is greater than in the visible region, due to light scattering caused by complex interactions between the incident radiation and leaf internal physical structure (cell walls, mesophyll cells, and air cavities) (Bauer, 1985; Knipling, 1970; Peñuelas et al., 1993). The "Red-Edge" (centered around 750 nm, RE) is the narrow portion of the curve between R and NIR regions where vegetation uniquely causes reflectance to spike because R light is mostly absorbed by chlorophyll and NIR radiation is reflected (Scotford and Miller, 2005), whereas the

Abbreviations: AGB, above ground biomass; CC, chlorophyll content; COMP, index based on more than two reflectance bands; DVS, development stage; G, green; GDD, Growing Degree Days; GY, grain yield; INSEY, in-season estimate of yield; LAI, leaf area index; MSE, mean-squared error; Nc, nitrogen concentration; NDVI, Normalised Difference Vegetation Index; NIR, near-infrared; NNI, Nitrogen Nutrition Index; Nu, nitrogen uptake; ONr, optimum nitrogen rate; R, red; RE, red-edge; SI, Sufficiency Index; VI, vegetation index; VIS, visible; VT, tasseling; TOT, analysis based on all reflectance bands recorded by the sensor

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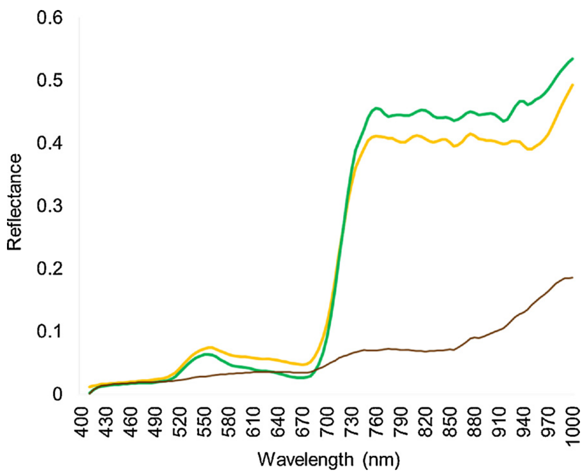

Fig. 1. Reflectance curve from 400 to 1000 nm of a crop canopy under optimal (green line) and insufficient (yellow line) nitrogen availability and from soil (brown line) (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.).

reflectance increase in the RE region of soils and other terrestrial objects is much smaller (Fig. 1).

Optical sensors that record radiation reflected or absorbed by vegetation in the visible and NIR regions of the electromagnetic spectrum are used to estimate variables associated with N management, such as, crop N uptake and concentration, yield, optimum N rate. Indeed, the N contained in chlorophyll of leaves and canopies can be remotely sensed thanks to its high correlation with chlorophyll (Samborski et al., 2009), especially if N is limiting (Schut et al., 2003). Leaf N is contained not only in chlorophyll, but also in proteins where radiation interaction occurs mainly at wavelengths above 1450 nm.

Sensors that record vegetation diffuse reflection can be classified as passive or active, depending on their source of electromagnetic radiation. While passive sensors measure sunlight reflected by the canopy, active sensors standardise electromagnetic radiation by their own light source. Passive sensors can be ground-based, such as the FieldSpec spectroradiometer sensor (Analytical Spectral Devices, Inc., Boulder, CO, USA) and Cropscan multispectral radiometer (CROPSCAN, Inc., Rochester, MN) or mainly airborne- and satellite-based, such as the CASI-1500 (ITRES Research Limited, Alberta, Canada), AVIRIS (NASA JPL, Pasadena, CA), AISA Eagle (Specim, Spectral Imaging Ltd., Oulu, Finland) and Landsat, Sentinel-2, HYPERION satellites. On the other hand, the most commonly used active sensors for the leaf level is chlorophyll meter Minolta SPAD 502. In the case of active tractor-mounted systems, Yara N-Sensor (Yara International ASA, Oslo, Norway), GreenSeeker (NTech Industries, Inc., Ukiah, CA) and CropCircle ACS-470 (Holland Scientific, Lincoln, NE) sensors are employed the most. The GreenSeeker system records two broad bands (660 and 770 nm), while CropCircle records from two bands (590 and 880 nm) to six bands; the Yara N-Sensor records five bands (450–900 nm).

Among the bands available in the visible spectrum, R or G is extremely useful due to its correlation with chlorophyll. NIR (800–1000 nm) sensors are relatively cheap, so visible sensors are usually augmented with additional NIR and RE bands to ascertain chlorophyll (RE) and leaf structure (NIR) information. All four bands (R, G, RE, and NIR) are widely reported, and commercial sensors produce reflectance values, analysed alone or combined, for use as vegetation indices (VIs). Most of the applications for vegetation monitoring focus on a few VIs and typically include NIR and one or two bands from R, G, or RE, as seen with the Normalised Difference Vegetation Index (NDVI) and the Green Normalised Difference Vegetation Index (Gitelson et al., 1996). Table A1 (in Appendix A) lists and defines all VIs used in this work; for a comprehensive VI review, refer to Mulla (2013).

Optical sensors can be multispectral or hyperspectral, depending on the number and width of wavebands recorded. Hyperspectral sensors have high spectral resolution because they collect sets of 10–100 narrow (< 10 nm) and contiguous wavebands (Lan et al., 2010). Their make-up makes them powerful and versatile tools, albeit expensive and less suited to routine field applications. Conversely, the less expensive, but lower spectral resolution associated with multispectral sensors that record a maximum of 10 optimally chosen, non-contiguous broad bands (Lan et al., 2010) are potentially better-suited for in-field crop monitoring.

Hyperspectral sensors detect narrow wavebands to provide information on a selected set of vegetation properties (Hansen and Schjoerring, 2003). While these bands are normally used to formulate a new index, potentially useful information contained within the full spectrum is often lost. Multivariate data analysis techniques, however, can resolve this issue as it can consider data from the full spectrum to build prediction models that estimate a single or more crop variables.

Finally, multi- or hyper-spectral "imaging" sensors can register reflectance in tens or hundreds of wavebands for each image pixel, from which descriptive maps of reflectance spatial variability can be derived for the estimated variable. Such capability is highly relevant for field management in which precision agriculture is practised. If spatial resolution differentiates between vegetation and soil, it gives rise to the potential to retrieve information on the fraction of canopy cover and to separate the soil signal from that of the canopy.

Many experiments have been conducted to evaluate the performances of proximal and remote sensing in estimating variables connected to N management, such as crop N uptake, above ground biomass, grain yield and economically optimum N application rate. The main approach in the estimation of such crop variables is based on the study of empirical regressions, but other plant factors, not strictly dependent on leaf features, were found out to affect the reflectance of canopies *e.g.,* plant species, development stage (DVS), age, site, leaf orientation, presence of visible background (Shaver et al., 2011; Tremblay et al., 2009); sensor characteristics *e.g.,* sensor geometrical and its source of electromagnetic radiation and weather conditions during data acquisition (Blackmer et al., 1996a; Tremblay et al., 2009). For this reason, biophysical approaches were developed: it is the case of the use of inverted leaf or canopy reflectance models *e.g.,* PROSPECT and SAIL radiative transfer models (Jacquemoud et al., 2009). These models were designed to retrieve leaf or canopy reflectance spectra from biophysical leaf and canopy descriptors (*e.g.,* leaf area index, average leaf inclination angle, the hot spot parameter as the ratio between leaf horizontal correlation length and canopy height but also the leaf chlorophyll, dry matter and water contents). Model inversion techniques enable to estimate crop leaf area index (LAI) and chlorophyll content (CC) from canopy reflectance as input, by taking into account canopy structure and its effects on the reflected light (Weiss et al., 2000).

A lot of work has been carried out on the estimation of crop variables from their optical properties and it was summarised in specific reviews of the methods (Muñoz-Huerta et al., 2013) or of the applications on winter cereals (Diacono et al., 2013) that are more suitable for optical N-monitoring due to no (or low) limitations caused by water stress. For maize, no comprehensive summary exists that describes the performance of multispectral and hyperspectral sensors in relation to factors affecting crop N-status. This lack of summarised knowledge limits the establishment of generalized rules to translate spectral information acquired with these tools into N management decisions in maize.

This review summarises the state of the art in optical sensing applied to N management in maize cropping-systems to broaden the understanding of sensor feasibility for this use. To this end, we collected and summarised a large collection of published experiments describing empirical regressions between ground-measured maize variables and