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Retrieving crops' quantitative biophysical parameters through a newly developed multispectral sensor for UAV platforms

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Abstract. *Today's intensive agricultural production needs to increase its efficiency in order to keep its profitability in the current market of decreasing prices on one hand, and to reduce the environmental impact on the other. Crop growers are starting to adopt side dressing nitrogen fertilization as part of their fertilization programs, for which they need accurate information about biomass development and nitrogen condition in the crop. This information is usually acquired through ground sampling, missing the spatial variability, and therefore forcing an average field-base management.*

The Robin System has shown high capability for identifying spatial variability throughout a large range of crops and conditions. These results have established the basis to start developing algorithms for the retrieval of quantitative biophysical parameters. Synthetic data was used for establishing empirical relationships between crops' biophysical parameters and reflectance data. A large Look-Up-Table (LUT) was build, from which the most reliable and sensitive functions were selected for retrieving Chlorophyll content and Leaf Area Index (LAI) from the Robin Eye spectral bands.

The main objective of this study was to validate the crop biophysical parameters retrieved using the selected LUT functions from two Robin Eye images that were acquired over wheat crop in South Africa during the southern winter season of 2015. Between the two acquisition dates, ground sampling was performed for biomass and nitrogen content analysis. As the sampling was performed after the first image was acquired, the definition of the sampling points was performed from the first image so to characterize the spatial variability of the field. A coefficient of determination of 0.96 was *obtained for the LAI vs. Biomass relationship, while 0.97 for the Chlorophyll Content vs. Nitrogen concentration relationship. These results confirm that the combination of highly sensitive and accurate data together with robust theoretical models, can generate reliable and valuable information for the crop decision making process.*

Keywords. *Multispectral sensor, unmanned aerial systems, nutrient management.*

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Introduction

Today's main challenges for the remote sensing community in order to gain a larger place in leading agriculture, relies on its capability to deliver accurate information about crop condition, enabling the grower to improve the field's management decisions. Space- or air- borne images have been used in precision agriculture for almost two decades to map crop condition and define management zones so as to apply site specific management based on fields' spatial variability (Plant, 2001; Pinter et al., 2003). However, the real embracement of this technology by commercial field/industrial crops or fruit production industries has been limited to cutting edge growers. Stark (2014) untangle this limited technology adoption to some serious satellite or airborne drawbacks. In comparison to space- or air-borne images, Unmanned Aerial Vehicle (UAV) has the ability to provide data at a higher temporal resolution, lower economic cost, avoid cloud obstructions, and provide more flexible data acquisition, while keeping high accuracy potential.

The development of the aircraft itself among the UAV industry has grown by leaps and bounds during the last decade. However, despite the vital importance of data quality, development of UAV applications has been relegated by the industry to a secondary place of importance. This, lag behind the ability to turn the acquired images quickly into usable data. Under this scenario, Sensilize's *Robin System* was developed to fill this gap, following a careful design process that included system engineering, optical planning and application algorithms. This design was an application-driven process focused on agricultural and natural environments, selecting specific wavelengths for vegetation mapping and relevant optics to reach suitable spatial resolution. In addition to the discussed limitations of satellite images, the fact that most products that service providers and even researchers offer growers and field managers are still based on the well-known Normalized Difference Vegetation Index (NDVI), has not helped in the technology adoption. NDVI can be a good approach for estimating vegetation condition when low to medium biomass is present. However, it is limited at high biomass due to signal saturation (Aparicio et al., 2002; Hansen & Schjoerring, 2003; Pimstein et al., 2007; Gittelson, 2011). In this respect, during the last decade the high sensitivity of the optical range between red and near infrared wavelengths (i.e. the red-edge of the vegetation spectrum) even for high biomass conditions has been raised. Several indices based on this range have shown strong correlation with biomass, LAI and Chlorophyll content in various crops such as wheat, corn and soybean, among others (Viña et al., 2004; Schlemmer, et al. 2005; Pimstein et al., 2007).

Additionally, growers and agronomist are now demanding for more actionable information than the regularly accepted spatial variability maps (e.g. zone managements). Nellis et al. (2009) raised the importance of the role that this technology is capable to bring into crop management by providing quantitative information as vegetation cover, chlorophyll content and LAI. The most common approach for retrieving crop biophysical characteristics (BPCs) is to relate them to one or more vegetation indices (VIs) through an empirical relationship that can be later applied to crops that were grown under similar conditions. On this regard, Hatfield et al. (2008) concluded that this approach is valid only under conditions similar to those at the time the correlation was established, so the relationship is broken when the BPCs values escape from the calibration. In addition, in order to obtain significant variability in the calibration of this relationship, complex field trials with combined factors are required.

An additional approach refers to the inversion of synthetic reflectance data (SRD), which retrieve the BPCs that define the SRD directly from the image reflectance value for each pixel (Verhoef & Bach, 2003). This approach is based on the comparison of simulated images with actual remotely sensed images so to retrieve the crop's parameter by means of a feedback loop. For doing so, strong computation resources are needed, which limits its application for an operational service for growers. Alternatively, SRD's are used for simulating reflectance at different vegetation conditions, and later building empirical relationships between VIs and BPCs from these simulations. This combined approach have been tested in several field crops and open tree crops showing high accuracy on the retrieval of LAI and chlorophyll content from hyperspectral images (Haboudane et al., 2004; Zarco-

Tejada et al., 2004).

Moreover, among growers all over the globe there is a constant request that beyond the characterization of the field spatial variability, it is needed to develop algorithms that incorporate both spectral and agronomic parameters to provide economically viable, practical products. According to Nellis et al. (2009), in order to make use of the biophysical properties in a practical manner and to see remote sensing gaining wide acceptance and use, the remotely sensed products must be linked to a set of ‘agronomic indicators’.

The main objective of this study was to validate the crop biophysical parameters retrieved using the selected LUT functions from two Robin Eye images that were acquired over wheat crop in South Africa during the southern winter season of 2015.

Materials and Methods

The present work was based on previous development of Look-Up-Tables (LUT) functions for the retrieval of biophysical crop characteristics (BPCs) from multispectral images. These LUT considered a wide range of vegetation conditions, varying the different model’s input parameters so to evaluate vegetation algorithms and establish the most robust empirical function for the different BPCs. The main factors that are considered in the used canopy synthetic reflectance data are Leaf Area Index (LAI), Leaf Angle Distribution (LAD) and soil and leaf reflectance. During 2015 growing season, two Robin Eye flights were performed over a wheat field in South Africa from where crop samples were obtained to validate the results of the developed algorithms.

In order to test the LAI and Chlorophyll algorithms, two flights were performed over a pivot irrigated wheat field in the Northern Cape South Africa, on 08-Sep-15 and 06-Oct-15. Because large areas of the field that had poor emergence, the grower decided to reseed almost 75% of the field. Only a center strip of 130 m width showed good emergence and was therefore left with no reseeding. The first flight happened about 5 days after the emergence of the reseeded area. By the time of the second flight, the whole field had reached homogeneous full coverage. Flying height was about 100 m above ground (~10 cm ground pixel size) with an overlapping of at least 70%, both along- and cross-track. Pre-processing correction and mosaic building was performed using Sensilize proprietary Local Robin Processor (LRP) software. More details about LRP characteristics and capabilities can be found in Sensilize newsletter (http://sensilize.com/wp-content/uploads/2015/01/newsletter-sensilize-Jan16.pdf). LRP output correspond to a geo corrected and geo referenced reflectance multispectral mosaic, ready for computing any VI and/or alternate algorithm. All this post-processing was performed with Sensilize automatic processing routine that is written in IDL.

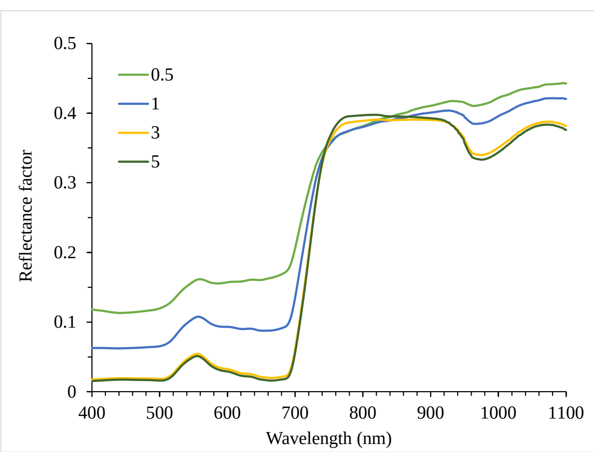


Figure 1. LAI sensitivity analysis – Reflectance at different LAI levels.

Results and Discussion

In order to be able to generate accurate functions that suits crops conditions at critical phenological stages, it is needed to limit the range of alternatives to generate the synthetic data. The data was designed for comparing the sensitivity to different LAI and canopy architecture. Figure 1 shows the sensitivity to biomass development up to LAI=3, noticing a reduction in red range and increase in the NIR range while increasing LAI.

VIs vs LAI

The relationship between the analyzed VIs and LAI followed an exponential curve with lack of sensitivity after LAI of 4, matching what has been reported by several authors (Aparicio et al., 2002; Hansen & Schjoerring, 2003; Pimstein et al., 2007; Gittelson, 2011). Figure 2 shows the relationship between LAI and VI for Sensilize's red edge index and for NDVI that is the most commonly used VI for monitoring biomass development. As can be seen, Sensilize's red edge index shows a higher sensitivity than NDVI given by the wider value range and the fact that Red Edge saturates only at LAI 4, while NDVI at LAI 3 does not show non variability. All this resulted in a higher coefficient of determination between the index and LAI.

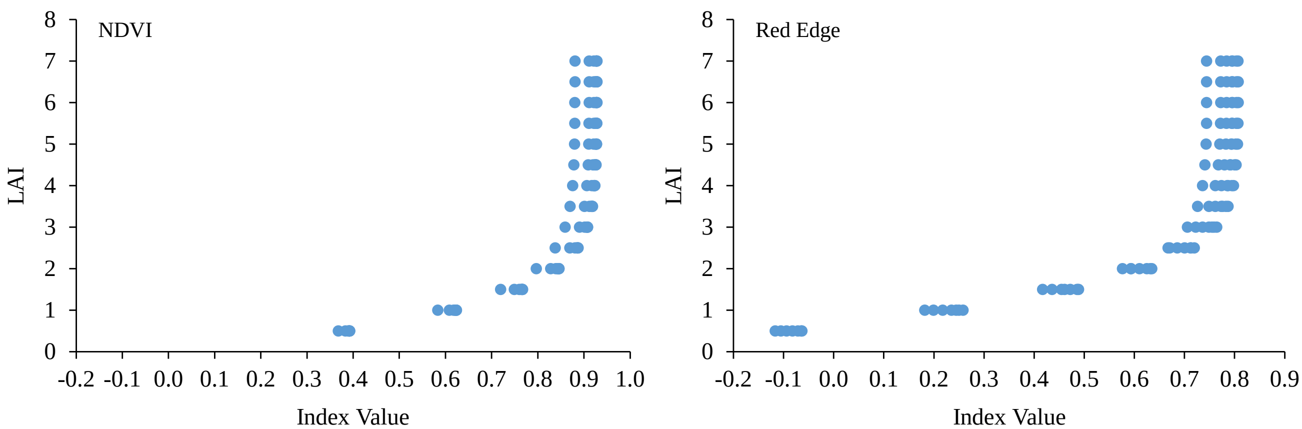


Figure 2. LAI vs. VI relationship. The horizontal variability of the VI values at a certain LAI shows the sensitivity to variability of leaf parameters (e.g. LMA and Cab)

Using only the data with LAI between 0 and 4, empirical functions were created for vegetation indices, which were applied into a new synthetic data for validation purposes. As can be seen in Figure 3 (left), both NDVI and Red Edge indices shows high level of accuracy for LAI 0 to 4, showing that NDVI reached saturation slightly before the Red Edge. This was confirmed when analyzing the slope of these relationships, clearly showing that NDVI reached slope zero (saturation) at LAI 3, while Red Edge index did not reach slope zero.

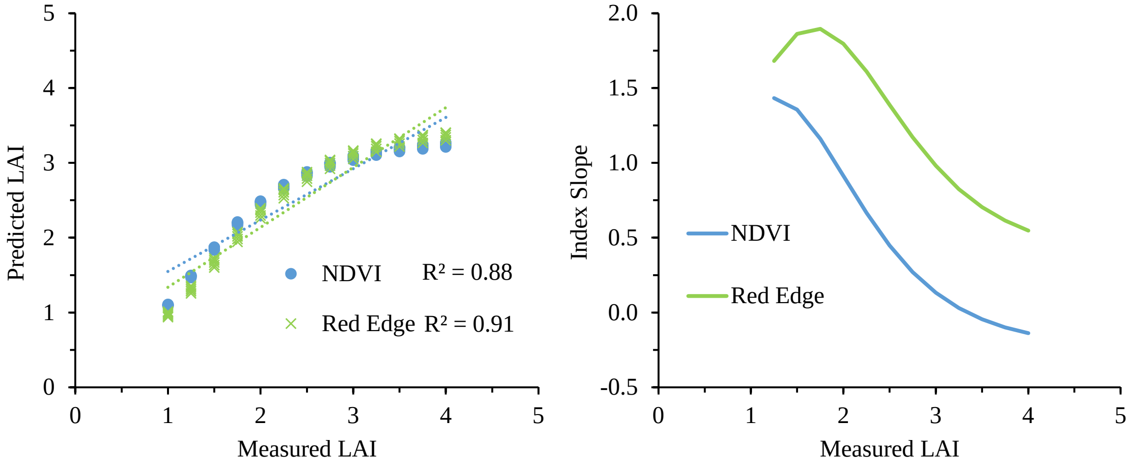


Figure 3. Measured vs. Predicted LAI validation of NDVI and Sensilize's Red Edge (left). Measured/Predicted slope for both indices for increasing LAI (right)

VIs vs Chlorophyll

Synthetic data was used for analyzing the relationships between the VI's and the Chlorophyll content. All the VIs showed a linear relationship with Chlorophyll content. However, this relationship is strongly affected by variable LAI, decreasing the slope until reaching a constant value for LAI larger than 3. This is explained by the fact that the Chlorophyll energy absorption is mainly located in the blue and red range of the spectrum that reach maximum absorption levels at those LAI values. As can be seen from Figure 4, a differentiated function should be applied for variable LAI until 3, while a unique function applies for conditions of higher biomass development. This approach suits the previously discussed capabilities of Sensilize's Red Edge index for monitoring high levels of LAI.

As can be seen from Figure 4 (left), when selecting all the data with LAI bigger or equal than 3, it can be generated a general formula that precisely fit all the data (R^2 = 0.98). This Cab/VI function was applied to an independent validation dataset (different set of the model parameters). Considering that Chlorophyll content of field crops with LAI between 3 and 7 is relatively constant around 45 μg cm-2 (Gandia et al. 2007), the validation of this function was limited to narrower range (35 – 65 μg cm-2). As can be seen from Figure 4 (right), the use of Sensilize's Red Edge for LAI bigger than 3, showed high levels of accuracy and low error.

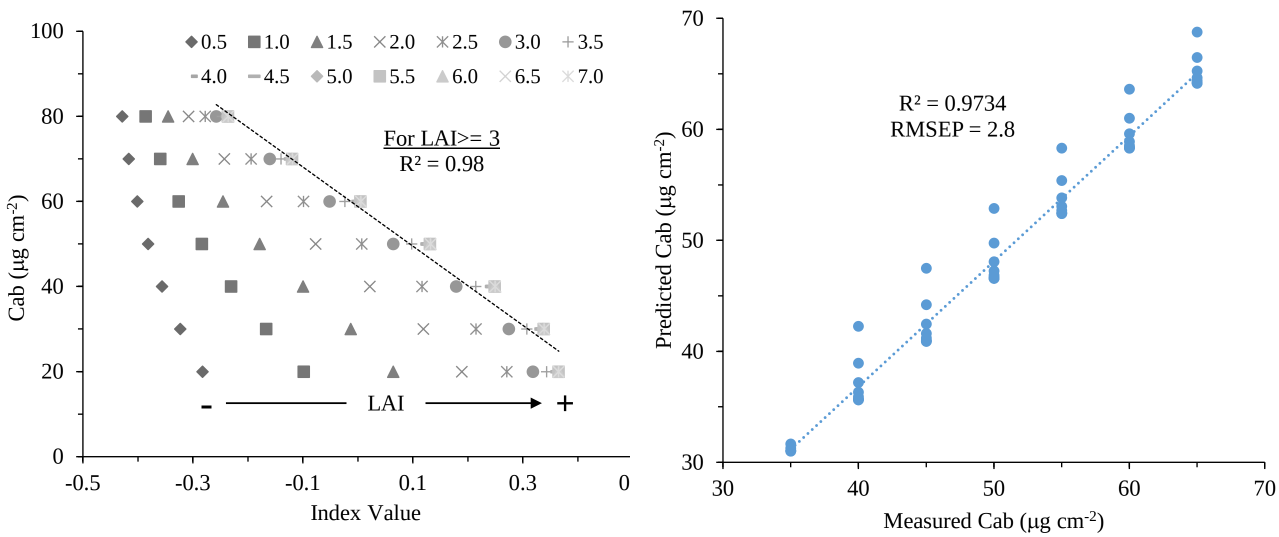
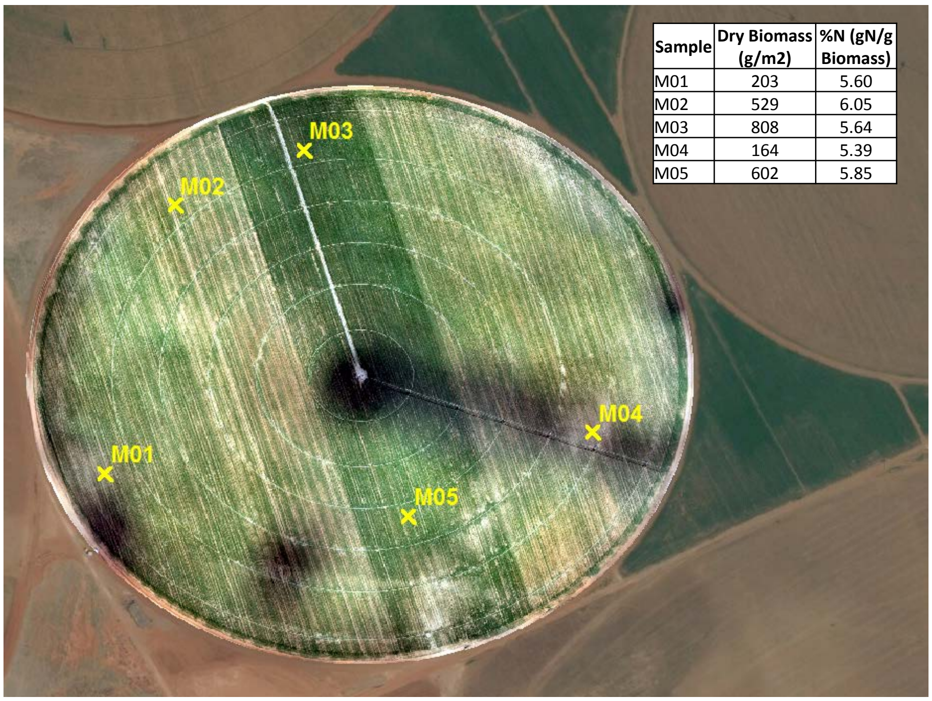


Figure 4.(Right) Chlorophyll content (Cab) vs. VI calibration. The presented VI Cab function is based on all the data of LAI >= 3. (Left) Validation of Sensilize's Red Edge function for predicting Chlorophyll content

LAI and Chlorophyll Validation on Robin Eye image

For the retrieval of LAI and Chlorophyll content, the developed algorithms were applied to the resulting reflectance mosaic of the wheat field.

For validating these products, 5 samples were collected from the field on September 14th 2015 for Nitrogen concentration and dry biomass. As mentioned, the field showed lack of homogeneity during emergence, so the location for collecting the samples was defined before reseeding by the field managers so to try to understand the source of this non-uniformity. Figure 5 shows the samples distribution among the field over the RGB mosaic acquired on 08-Sep-15 over an archive satellite image of the area. As can be seen, samples M03 and M05 shows the highest biomass because they were acquired from the central strip that was not reseeded. On the other hand, the nitrogen concentration does not show significant fluctuation between the samples.



Sample	Dry Biomass (g/m2)	%N (gN/g Biomass)
M01	203	5.60
M02	529	6.05
M03	808	5.64
M04	164	5.39
M05	602	5.85

Figure 5. RGB Robin Eye mosaic acquired on 08-Sep-15. Inset present the lab analysis of the samples that were acquired on 14-Sep-15

After computing reflectance for each flight, the selected algorithms for LAI and Chlorophyll content were applied to each image. Figure 6 shows the Chlorophyll and LAI products for each acquired image. As can be seen, the field completely recovered after re-seeding, showing no differences between the central strip and the rest of the field during the second acquisition image. Interesting to see in the second image the weaker development around the center of the pivot, suggesting a strong lack of homogeneity in the water distribution along the pivot. For validating these algorithms a buffer of 600 pixels (~1.5 m radius) was selected around the location of the ground samples. The importance of this is to reduce GPS errors between the one used during ground sampling and one on board the UAV. The LAI and Chlorophyll content values were retrieved from each of the images and the average of the buffer was computed for each sample. Figure 7 shows the relationship between lab samples and the retrieved data from the first image (closest to the date when the lab samples were collected). From this figure, it can be seen an almost perfect match between biomass and LAI, confirming that the LAI product it is a reliable product for early stages of development. In order to match the units of the nutritional analyses and the retrieved biophysical parameters, the total nitrogen content was computed. This way, the overall nitrogen available per surface unit is compared to the total chlorophyll content per surface area that it is retrieved from the canopy reflectance models. As can be observed in Figure 7, the total nitrogen content and the Chlorophyll content shows an almost perfect fit with the data from the first image. This explains the fact that for this flight the LAI and Chlorophyll content show a very similar distribution pattern, making it very clear here that the main limiting factor is more related to biomass development and not to nutrient condition. For this reason, the field managers decided to undergo a deep review of the pivot homogeneity, but not to apply additional nitrogen as side dressing. The importance in the retrieval of these biophysical parameters is the fact that more and more researchers and growers are adopting local agronomical models as integral part of their operational decision process, optimizing the economical results of a certain field along the season. One example is a Decision Support System that is currently being applied among wheat growers of the northern Negev desert in Israel (Bonfil et al., 2004). Depending on the water and nitrogen plant condition during expansion of flag leaf (before heading), plus rain forecast for the following weeks, this DSS recommends whether to apply more nitrogen or not so to improve grain quality and yield, or to interrupt earlier the crop for hay. Similar approach is starting to be applied in Corn management, were nitrogen side dressing is being applied at the end of the vegetative stages in order to ensure a good nitrogen availability in the soil towards grain filling stages (Mulvaney et al., 2006). Therefore, identifying those areas among the field with different nutrient condition is crucial for defining a variable rate side dressing application.

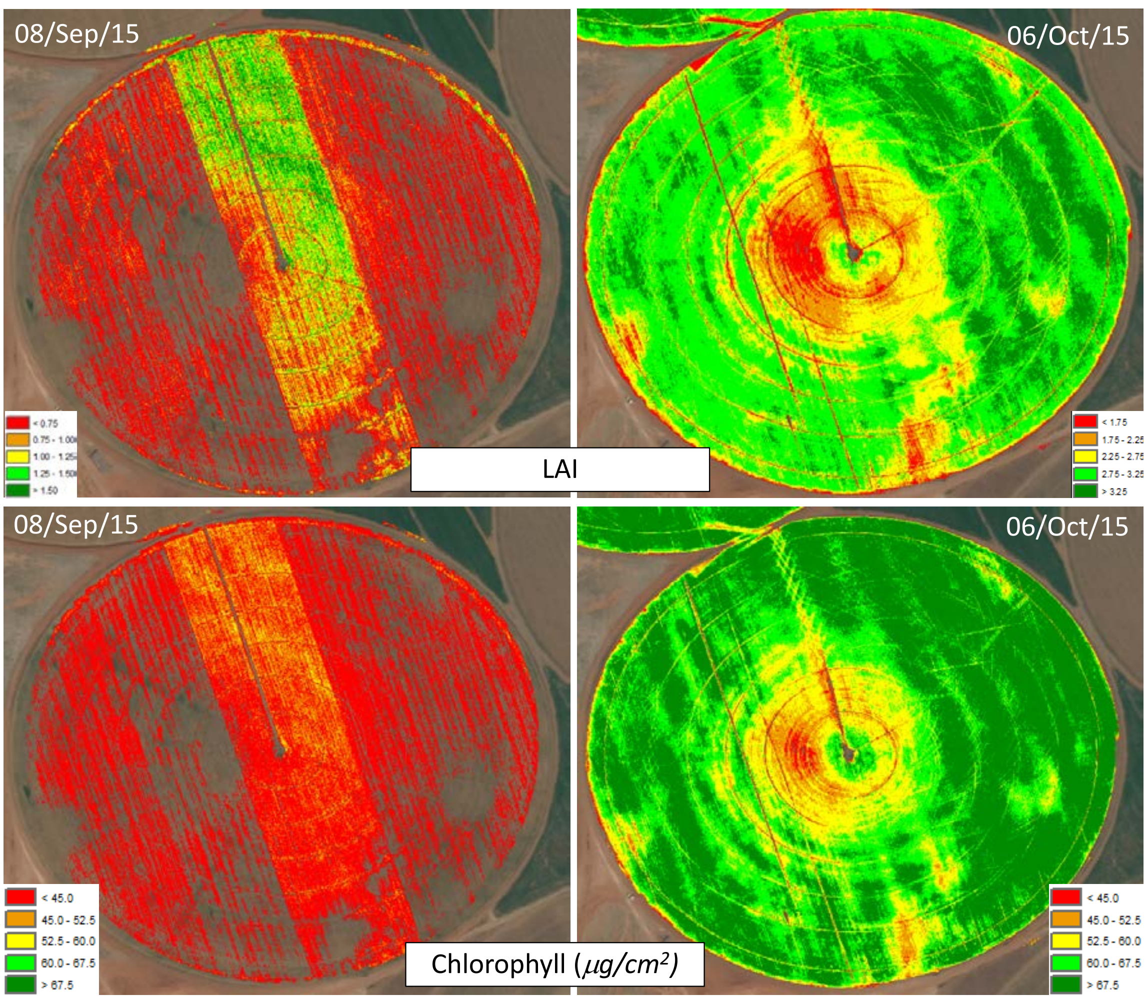


Figure 6. LAI and Chlorophyll content computed from developed algorithms onto both acquired Robin Eye images, North Cape, South Africa.

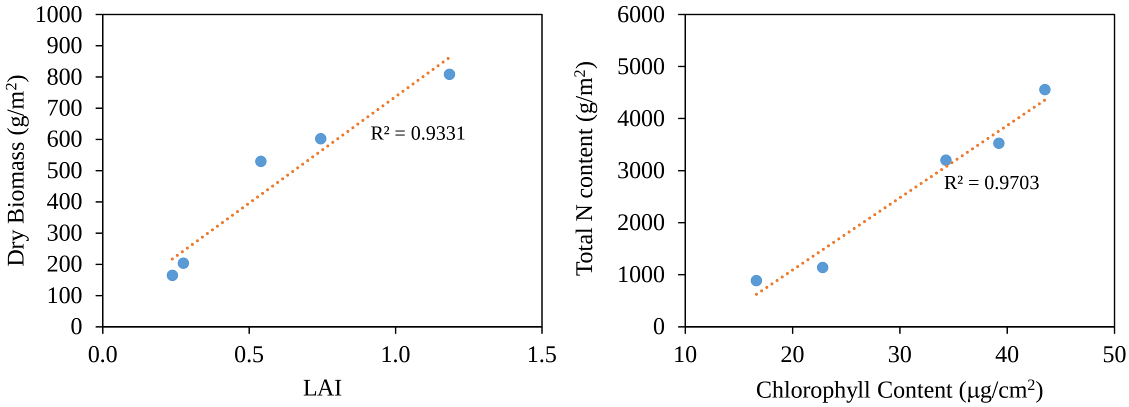


Figure 7. LAI and Chlorophyll content relationship with Biomass, Nitrogen concentration and total nitrogen content.

Conclusions

Spectral simulations of different crop canopy conditions through the use of synthetic data enabled the development of empirical functions for the retrieval of wheat Leaf Area Index and Chlorophyll content. In addition, this approach gives accurate information about the sensitivity and variability of the crop's condition and response without the need of running many field trails.

After applying these empirical functions to images acquired by *Robin System*, it is possible to generate accurate spatial information about the crop's condition through the models' quantitative parameters. These parameters are important crop's indicators for being applied in the decision making process during the growing season.

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