Using Light-Band Sensors for Stress Evaluation in Rainfed Maize Agricultural Crop

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***Abstract*- Sensors have become essential in farming. They have been allowing to climatically monitor not only plants, but also soil, in order to support decision making to greater yields, as well as allowing rational use of inputs. Based on sensors, it is possible to develop efficient tools for the dynamics evaluating of crops directly in situ, including real-time analyzes. In this study, based on the use of sensors for red and the near-infrared lights spectra, the stress of rainfed maize crop was evaluated as a function of both Nitrogen dose and water availability. In fact, for validation, a true crop dynamics stress was evaluated using the normalized difference vegetation index weighted by the value of the near infrared reflectance for each specific region of the agricultural field. Results have shown its relationship with both plant water and Nitrogen availability. Furthermore, positive correlation with the plant stress and the modified vegetation index has been found, i.e., leading to an adequate indicator for plant stress and yield evaluation.**

Keywords—light-band sensor; crop stress; agricultural sensor; intelligent instrumentation; yield analysis.

I. INTRODUCTION

Currently, agricultural farms make use of advanced sciences and technologies, which include orbital monitoring for land occupation planning, agricultural soil quality care, assessment of plant vigor in cultivation areas, intelligent climate monitoring, as well as safety of the rural properties.

Precision Agriculture, for example, is based on the observation, monitoring and management of all inputs, necessary to obtain an adequate relationship between costs and benefits [1]. The new technologies used in this segment came to meet demands and achieve favorable results, that is, productivity gains and building resilience in the agroecosystems, in order to reach sustainability. The breakthrough to such a new agricultural paradigm has occurred with the introduction of the Global Positioning System (GPS), which enabled the entry of other technologies such as the use of new machines guided by computers and satellites.

GPS-guided tractors for planting seeds, applying pesticides, and especially for harvesting, have been enabling performance gains and reduced downtime. The use of integrated systems was another major innovation in recent years. The possibility of accessing soil, plant and climate data in real time has brought new opportunities for improving practically all the processes involved in food, fiber and energy from biomass production. The use of technologies has been making it possible to use the minimum quantity required in each specific area, as well as, when necessary, treating each plant in a unique and differentiated way. All these innovations used in the sector make use of sensors. In fact, sensor technology involves measuring, quantifying and transmitting signals used in decision support systems [2]. In modern agricultural automation systems, sensors are present [3]. Likewise, the Internet of Things (IoT) technologies are also present and have contributed to expand the scale related to the use of sensors in agriculture, as well as occurred in industry [4].

In fact, in agriculture, there are a series of systems that involve automation, which combine different sensors, control systems and actuators to operate equipment such as spraying machines for pest control, planters, and harvesters, among others. This level of automation makes it possible to increase efficiency, to improve consistency, to increase quality, to bring gains in effectiveness and to reduce human errors [5].

Furthermore, such a context it is often associated with an increase in productivity, and consequently production rate.

Additionally, with the advancement of sensor-based technologies, embedded automation also helps to optimize the use of the agricultural inputs, as well as to minimize losses in agricultural production. In fact, there are known relations in between crop stress and the presence of both biotic and abiotic factors, like those caused respectively by the presence of pests and due the absence of water, which affects healthy crop growth [6]-[9].

Sensors help to understand the relationship between climate and agriculture within a production process in a farming area, which is fundamental for food production.

Agriculture is an essential activity for the economy of many countries. The climate and the inputs, like nutrients, are the most important factors that affect agricultural production. In this sense, climate variations, such as rainfall and temperature, and nutrients availability should be carefully observed during the crop`s management process.

Historical records, current readings and forecasts can assist the agricultural management process considering statistics and data collected directly in the field.

The monitoring with sensors that operate in the Red (RED) and Near Infra-Red (NIR) light-bands have been promising for crop monitoring, and by using these bands it is possible to calculate the Normalized Difference Vegetation Index (NDVI). This index was established in 1974 [10] and later validated in 1979 [11] through linear combinations of the RED and NIR bands to monitor biomass density.

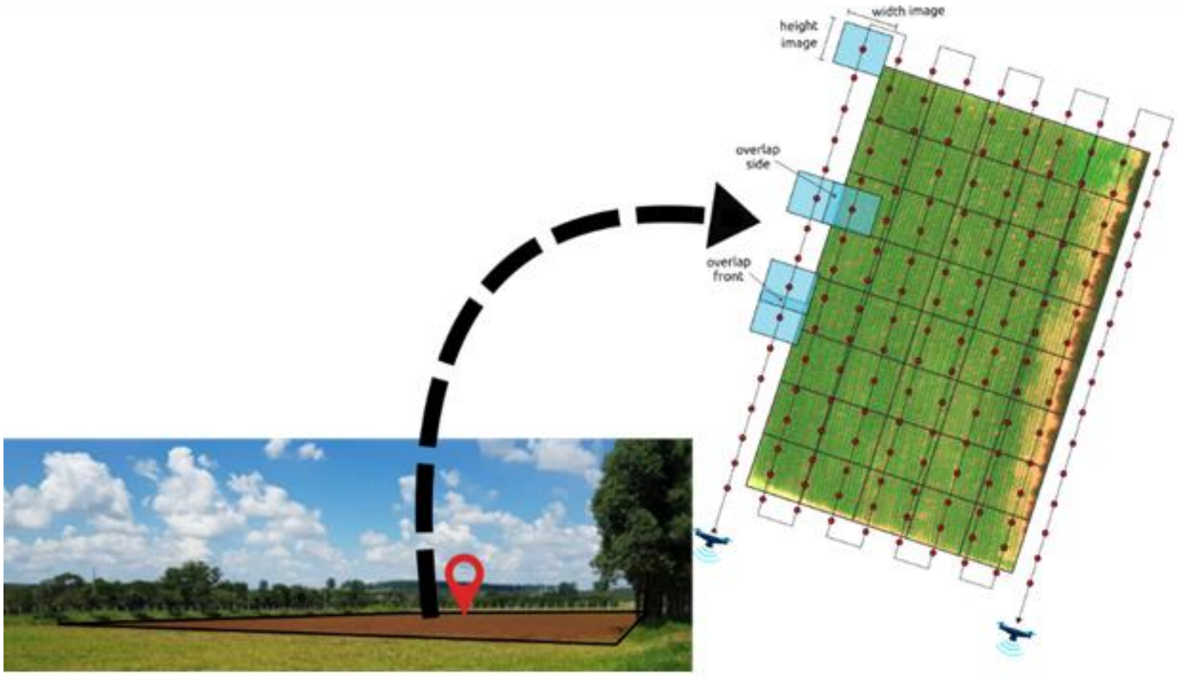

Figure 1. Experimental agricultural field`s view, having a grid for site-specific management.

NDVI has values between -1.0 and 1.0 and, in such a context, values between -1.0 and 0.0 correspond to non-plant surfaces that have RED reflectance greater than NIR. The soil has an NDVI value close to zero. With substantial reflectance in the NIR, plants have an NDVI value between 0.1 and 1.0, the higher the value, the greater the plant density. Also, the healthiest plants correspondent to a value equal to 1.0 and the least healthy plants to a value of 0.0. In fact, as a structural index, it is widely used for agricultural monitoring as it has a strong linear correlation with crop growth. However, NDVI has several limitations and challenges that need to be considered, such as sensitivity to external factors, variability among crops and cultivars, need for calibration and validation.

In addition, calibration and validation should be done using ground truth data and complementary indicators such as crop productivity.

This work presents a study to minimize the limitations when using the NDVI to evaluate stress regions in tropical agricultural crops due to lack of water and nutrients based on image sensors that respond to RED (668 nm ±10 nm) and NIR (840 nm±40 nm) wavelengths to aid the agricultural management process.

After this introduction in Section I, this paper is structured as follows. Section II presents the materials and methods, including the agricultural experiments for validation and the sensor`s system description, as well as the embedded board specifications. Section III presents the results of the validation of the use of the RED and NIR sensors and the evaluation of stress into a productive rainfed maize crop. The final conclusions are presented in Section IV.

II. MATERIAL AND METHODS

Figure 1 shows the experimental agricultural area that has been used for validation, i.e., following the study standards of Embrapa Instrumentation. It is located 860 m from the geographic coordinates: 21°57’3.9” S and 47°51’10.9” W at the National Reference Laboratory for Precision Agriculture (LANAPRE) in São Carlos, SP, Brazil.

The experiment for the evaluation of the crop stress was organized in an agricultural area with maize (*Zea mays L.*), having 4000 m^2, and sampling grid equal to 10 m × 10 m [12]. Also, Figure 1 shows such an arrangement for specific management, i.e., divided into 40 blocks (from B1 to B40).

An important point to be noted is that the respective area was divided into four plots of 1000 m^2 (20 m × 50 m) aiming to manage Nitrogen with surface and broadcast fertilization, thus being associated with fertilization of soil that was initially carried out before planting in the experimental agricultural area.

Soil chemical analyzes were carried out from composite samples collected in horizon A (root zone) at specific sites on the sampling grid. Soil fertilization occurred once and scaled applications of Nitrogen (top-dressing fertilization) were also considered, i.e., using the 0, 18, 36 and 72 kg/ha, respectively 0%, 50%, 100%, and 200% in relation to agronomic recommended dose [13].

Figure 2 illustrates the electromagnetic spectrum for the frequency`s bands that have been used in this work. In the light spectrum, it has been considered a Region Of Interest (ROI) comprised by the visible and near infrared spectra.

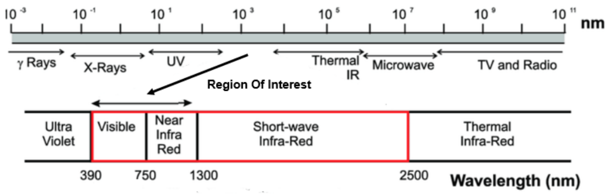

Figure 2. Electromagnetic spectrum and the ROI related to the visible and infrared bands.

In addition, eight flight missions were considered, all of them based on the use of a multirotor Unmanned Aircraft System (UAS), DJI Matrice 100 (Figure 3).

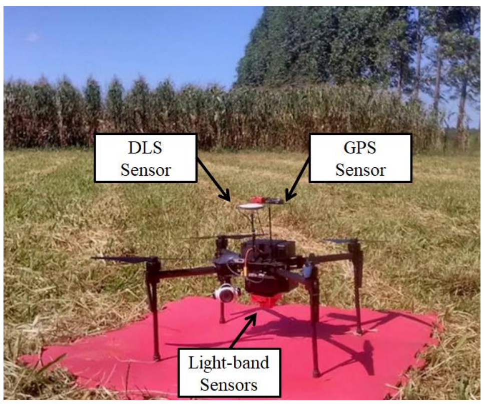

Figure 3. The UAS and hardware setup for the RGB, RED, and NIR images acquisition.

For imaging, a Micasense RedEdge-M multispectral camera was embedded, and provided onboard. The specifications of the sensors located at the Micasense camera are detailed in Table I [14].

TABLE I. TECHNICAL SPECIFICATIONS FOR MICASENCE REDEDGE-M

Parameters	Specifications
Weigth	170 g (Including DLS)
Dimensions	9.4 cm × 6.3 cm × 4.6 cm (3.7" × 2.5" × 1.8")
External Power	4.2V−15.8V, 4W nominal, 8W peak
Spectral Bands	Narrowband: Blue, Green, Red, Near-IR
Capture Rate	1 capture per second (per band), 12−bit RAW
Ground Sample Distance (GSD)	5.95 cm/pixel (per band)
Wavelength	Blue (475 nm center ± 20 nm) Green (560 nm ± 20 nm) Red (668 nm center ± 10 nm) Near-IR (840 nm ± 40 nm)

The flights missions were carried out considering the timeline related to the phenomenological state of the maize culture [15]. For the RED, GREEN, BLUE, and NIR measurements, the acquisition process used the Ground Control Points (GCP). They were collected by high-precision GPS in conjunction with a Real-Time Kinematic (RTK) receiver that recorded their geographic coordinates to an accuracy of ± 1 cm. In this way, the GCPs were used as input to control the flight missions. Additionally, the imaging equipment includes to a Downwelling Light Sensor (DLS) for measuring the influences of the sun's brightness, or changes in contrast due to superimposition of clouds in the sky, thus providing the capacity to correct global changes in light.

Aerial mapping reproduces the phenomenon of stereoscopic vision, following a flight pattern of parallel lines, along specified routes with waypoints. Likewise, in accordance with the UAS settings and the onboard light-bands sensors, eight flights were conducted within a time interval from 11 A.M. to 12 A.M., i.e., during the morning periods.

Besides, to perform the analysis of stress into the crop having maize plants, an extraction of information from each site-specific or block has been considered. In fact, for each block has been considered a ROI and collected data from the multispectral light-bands. In addition, the collected images have been filtering by means of a Gaussian filter (Equation 1). Likewise, for each ROI the rotation angle has been found by calculation, using Equation 2.

$$G_\sigma(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{1}$$

where the Gaussian function $G_\sigma(x, y)$ is controlled by the variance σ^2, and mean equal to zero.

$$Rotation = \begin{bmatrix} 1 & 0 & t_x \\ 0 & 1 & t_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \cos\theta & -\sin\theta & 0 \\ \sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & -t_x \\ 0 & 1 & -t_y \\ 0 & 0 & 1 \end{bmatrix} \tag{2}$$

where $-t_x$, and $-t_y$ correspond to the translation of the ROI to the origin, whereas t_x, and t_y shift it back to its original position.

Furthermore, for the NDVI index (Equation 3), it has been considered adjustments based on the reuse of the NIR light-band, i.e., in order to allow information beyond the biomass evaluation and plant growth only. Such an arrangement has been considered in order to figure out plant`s stress due external abiotic factors like water and nutrients availability in the crop area (Equation 4).

$$NDVI = (\frac{NIR-RED}{NIR+RED}) \tag{3}$$

$$\widehat{NDVI} = (\frac{NIR-RED}{NIR+RED})\overline{NIR} \tag{4}$$

where $\overline{NIR}$ correspond to the mean value of the NIR pixels values for each site-specific. The $\widehat{NDVI}$ represents the modified NDVI value, that means, taking emphasis on the plant stress into a specific crop region.

For data analysis it has been used descriptive statistics method, i.e., a boxplot, which is a type of chart often used in explanatory data analysis. Box plots visually show the distribution of numerical data and skewness by displaying the data quartiles (or percentiles) and averages. Also, it shows the five-number summary of a set of data: including the minimum score, first (lower) quartile, median, third (upper) quartile, and maximum score [16].

III. RESULTS AND DISCUSSION

For multispectral image acquisition, it was necessary to perform radiometric calibration to convert the metadata of the digital image to a physical scale. On the other hand, the geometry of the aerial image was established by the size of the sensor, the focal length, and height of the UAS flight, which together determine its Ground Sample Distance (GSD) (Table II). The GSD provides the corresponding measure for the pixels of the surface of the experimental area or the area covered by the image. It was necessary to establish the percentages of lateral and frontal overlapping of the aerial images, which were equal to 80% respectively.

The number of registered images for all the realized flight was equal to 300 for each spectral band, i.e., leading to a total amount of 9600 images. In such a context, the total required storage capacity was equal to 29.52 GB (gigabyte), because the surface width and height were equal to 27 m × 20 m respectively, and the distances between each front and side capture were 4 m and 5 m, respectively.

TABLE II. PARAMETERS USED FOR DATA ACQUISITION

Description	Values	Units
Flying altitude	138	m
Mission flying time	12	min
Max. speed of flying	11	m/s
Front and side overlap	80	%
Ground sample distance	5.95	cm/pixel

Figure 4 shows examples of results obtained from the second and eighth flights respectively, i.e., considering the rotation of the images and Regions Of Interest (ROI) for analysis of block 25, in terms of the RGB and NIR light-bands.

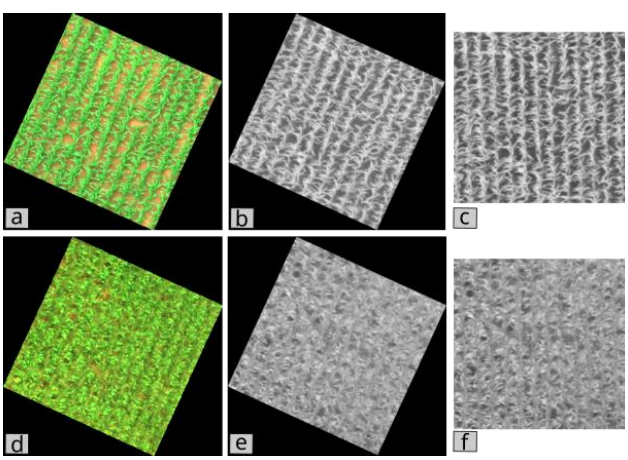

Figure 4. Sample of analysis for the block 25: from the second flight - (a) RGB, (b) NIR, and (c) ROI NIR; from the eighth flight - (d) RGB, (e) NIR and (f) ROI NIR.

Statistical analyzes for collected data were carried out for the eight flights, that is, considering the reflectance measurements for each site-specific in the culture area, i.e., based on both the RED and the NIR light-bands of the electromagnetic spectrum.

Thus, considering as an example of the obtained results, one may observe the carried-out data analysis for the eighth flight (Figure 5 and Figure 6).

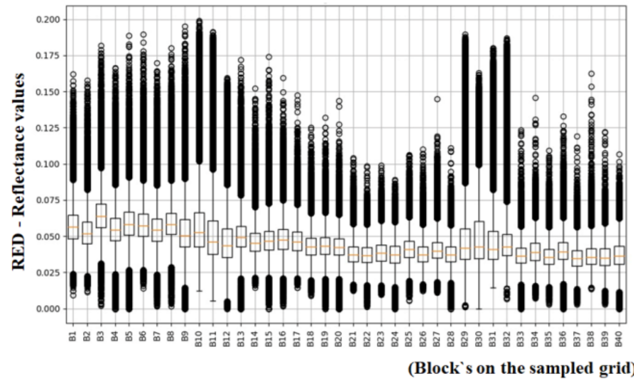

Figure 5. Statistical evaluation for the RED light-band reflectance in the specific-sites of the maize crop area, that means, considering all the experimental regions (from B1 to B40).

Such results were obtained by scanning with the RED and NIR sensors the 40 sites-specific of the maize production areas. In fact, such a UAS flight was programmed to occur during the phenological reproductive stage of the maize in the crop area, when the corn's seeds are being structured on the cobs to reach the known physiological maturity stage.

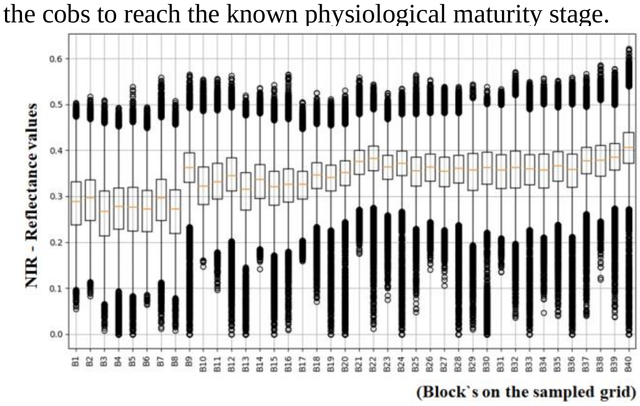

Figure 6. Statistical evaluation for the NIR light-band reflectance in the specific-sites of the maize crop area, that means, considering all the experimental regions (from B1 to B40).

The stress evaluation in this phase of the maize production is essential since water and nutrients play a very important role. How much higher the plant stress in the crop sites-specific smaller will become the productivity, i.e., loss in maize production is increased. Furthermore, we observed that for the RED light-band the median values for the reflectance were between the 3.7 % and 6.3 %, while for NIR the median values were between 26.8 % and 40.9 %.

The lowest reflectance values indicate higher absorbance values for the RED light-band, which were produced by pigments present in corn leaves, while in the NIR light-band reflectance's resulted from the interaction of radiation with the superficial cellular structure of the maize leaves. In this context, it was possible to observe that the increase in reflectance in the NIR light-band was related to the physiological aspects of the leaf and varied with its water content in the cellular structure and the Nitrogen availability, thus being useful for characterizing the level of crop stress in all analyzed regions.

In addition, the NDVI values were calculated using Equation 3, as well as statistically evaluated (Figure 7).

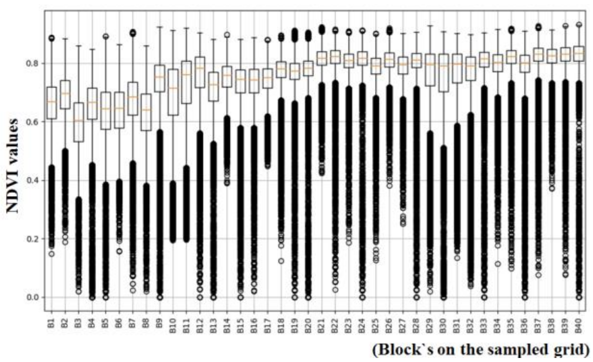

Figure 7. Statistical evaluation for the NDVI for all sites-specific of the maize crop area, that means, considering the experimental regions (from B1 to B40).

The yield (in kg) for the 40 specific sites were also evaluated. In such a result, it was possible to verify a great spatial variability in productivity.

In fact, as mentioned previously, while the NDVI can give information about the biomass density and crop growth, something else should be understand in relation to productivity. In fact, NDVI doesn't have a good sensitivity to external factors, like agricultural inputs. In fact, once soil fertilization with the application of scaled Nitrogen contents were considered for the rainfed maize crop area, it has become possible to evaluate its contribution in the crop stress.

The blocks B1 to B10, B11 to B20, B21 to B30, and B31 to B40 were evaluated in relation to Nitrogen`s application, following the percentage concentration equal to 0%, 50%, 100%, and 200% respectively. Likewise, it was possible to observe the yield values and their increments.

Then, to get such a better understanding it was considered Equation 4, to evaluate the variability occurrence due to agricultural inputs externalities, i.e., the stress response to both Nitrogen and the water from natural rains based on the correlation between productivity and the modified index.

Figure 8 shows the resultant statistical analysis for all sites-specific of the experimental maize crop area.

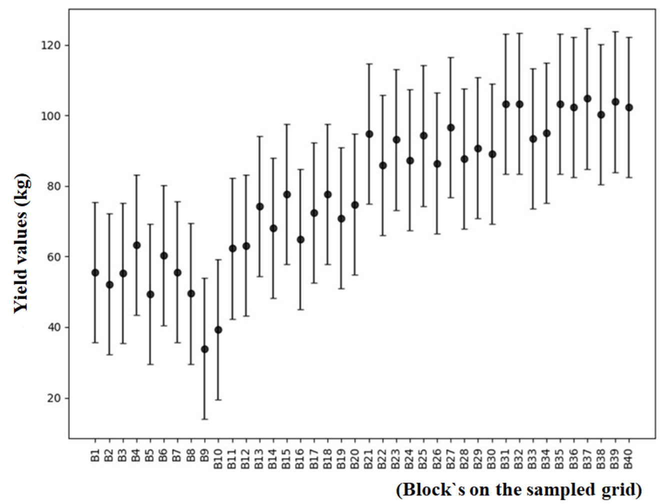

Figure 8. Productivity for each specific site from the maize crop area that means, considering the experimental regions (from B1 to B40).

In addition, based on such an analysis, it was possible to evaluate the yield variability in relation to the crop stress mainly as a function of the Nitrogen availability in each site-specific (Figure 9).

In such an analysis, since the linear correlation coefficient of determination was equal to 0.78 (Figure 10), it was possible to confirm the usefulness of the modified index to evaluate the yield dependency in relation to the crop stress.

Likewise, these results have illustrated that RED and NIR sensors-based imagery can provide information on the plants stress. Spectral measurements also reflect changes in nutritional deficiency in plants. In addition, with the advent of precision farming, there has been an interest not only in large-scale but also in small-scale application of light-band sensors for imagery acquired through UAS technologies.

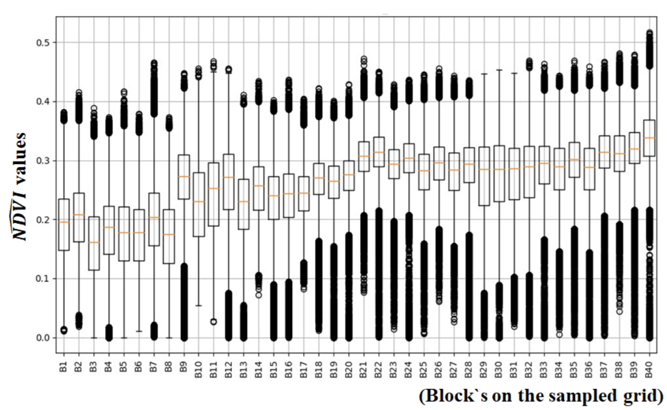

Figure 9. Statistical evaluation for the $\widehat{NDVI}$, i.e., considering all specific sites of the experimental maize crop area.

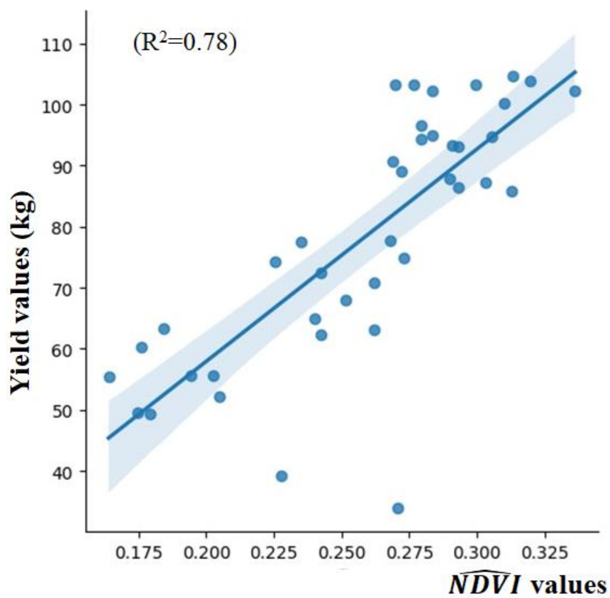

Figure 10. Correlation analysis ($\widehat{NDVI}$ and Yield), considering all sites-specific of the experimental rainfed maize crop area.

Moreover, Carbon and Hydrogen (C-H), Oxygen and Hydrogen (O-H), and Nitrogen and Hydrogen (N-H) absorbtion wavelengths fall in the NIR spectrum. NIR is suitable for use in agriculture mainly because in the living plants the organic compounds are the major components.

IV. CONCLUSION

The ability of $\widehat{NDVI}$ to evaluate crop stress based on physical and chemical externalities was studied through measurements and imaging at various phenological stages in an experimental agriculture rainfed maize crop. Besides, the information on the deficiency or excess of Nitrogen, one of the major plant nutrients, by detecting plant stress was useful to established alerts on crop production. In fact, the signature related to plants led to a new sensor-based index to support decision making related to crop stress and its relation to productivity improvement, which is an original contribution. If an analysis shows a deficiency of Nitrogen, a manager can provide timely nutritional supplements, i.e., by aggregating values in sustainability of the crop area, avoiding over-use of fertilizers, decreasing the resulting toxicity in plants, as well as decreasing the costs. Future research works will consider the development of customized agricultural sensors for smart and real-time crop stress evaluation.

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