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# CORRELATIONS AMONG VEGETATION INDICES AND PEANUT TRAITS DURING DIFFERENT CROP DEVELOPMENT STAGES

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**KEYWORDS**

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control charts,
precision agriculture.

**ABSTRACT**

Active optical sensors have been widely used for the spatial and temporal monitoring of peanut culture because they are accurate, non-destructive methods for rapidly obtaining data. The objective of this study was to determine the optimal stage of crop growth for collecting sensor readings based on correlations between quality indicators. In addition, we compared vegetation indices (Normalized Difference Vegetation Index [NDVI], Normalized Difference Red-Edge Index, [NDRE], and Inverse Ratio Vegetation Index, [IRVI]) by monitoring temporal variability in the peanut crop in order to determine which of them obtained the best reading quality throughout the process. The experiment was performed on the 2016/17 crop in the agricultural area of the municipality of Dumont in the state of São Paulo, Brazil. The experimental design was based on the basic assumptions of statistical quality control and contained 63 sample points in a 30 × 30 m grid. The parameters were evaluated at 30, 45, 60, 75, and 119 days after sowing (DAS) using proximal sensing with GreenSeeker and OptRX sensors. We found that 45 and 60 DAS were the optimal times for monitoring peanut crop variability. For spatiotemporal monitoring of the culture with control charts, NDRE showed the best readings throughout the process when compared to NDVI and IRVI.

## INTRODUCTION

The largest peanut-producing state in Brazil is São Paulo. Production is concentrated in the region of Ribeirão Preto, where cultivation is usually done in rented areas using rotation schemes and crop succession, often to facilitate the renewal of sugarcane plantations (Barbosa et al., 2014).

Peanut is considered one of the most important legumes, not only for its economic value but also nutritionally. Additionally, it is widely used in crop rotation and succession, particularly in sugarcane and pasture reforestation areas, because it is a short-cycle crop and its operations are fully mechanized (Grotta et al., 2008).

Considering the economic significance of this crop, it is important to increase its productivity. This can be achieved through the use of modern techniques and methods that allow greater knowledge of crop status by providing accurate temporal monitoring. According to Grohs et al. (2009), within a given crop there are areas with different productivity potentials that need different types of management.

Owing to population growth, agricultural production is expected to double by 2050 in order to meet the food demand. Precision agriculture (PA) is the key to improve resource efficiency and productivity in order to help achieve this goal under the various constraints encountered in agriculture, such as soil degradation, rising costs, climate change, lack of labor, and limited availability of arable land. To overcome these challenges, PA develops and uses sensing methodologies to provide information on crop health indicators and stages of growth (Narvaez et al., 2017).

Remote-sensing techniques appear to have a high potential for both data processing and collection in agricultural areas. These data can be obtained by field radiometry, aerial photographs, and satellite images, and can accurately provide information on field variability (Motomiya et al., 2012). According to Amaral et al. (2015a), many active optical sensors can be found, but there is little research comparing the efficiency of these devices for the determination of the parameters of cultures. Using terrestrial remote-sensing with the Normalized Difference Vegetation

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Index (NDVI) associated with agronomic characteristics of the peanut crop, it was previously verified that results obtained with the GreenSeeker sensor can be used to determine the population characteristics of plant cover and yield estimates, and as an additional tool for farmers to detect crop potential (Zerbato et al., 2016).

This study addresses a subject of current relevance in the academic area of peanut crops, as it uses different vegetation indices with active or canopy sensors to monitor plants during their development and provide increased accuracy in data collection. Statistical Quality Control (SQC) was also used to study the growth stages of peanut, a statistic that has shown good results but is "not usually applied" in precision agriculture. This statistic is being used in the area of agricultural mechanization and has yielded good results in monitoring operational quality, as observed by Carneiro et al. (2017b), Cassia et al. (2015), Menezes et al. (2018), Ormond et al. (2016), Tavares et al. (2015), Voltarelli et al. (2015), and others.

The objective of this study was to investigate which stage of crop growth is optimal for collecting sensor readings, applying the best correlations between the evaluated quality indicators (vegetation indices, fresh biomass (*in natura*) and dry matter, canopy width, chlorophyll index, yield, and maturation). In addition, vegetation index readings (NDVI, NDRE, and IRVI) were compared by monitoring temporal variability in peanut crops and observing which of them obtained the best reading quality throughout the process.

## MATERIAL AND METHODS

The study of the temporal variability of vegetation indices in the peanut crop was carried out on the 2016/17 crop, in the agricultural area of the municipality of Dumont located near the coordinates 21°15′22.05″S and 47°58′15.00″W in the state of São Paulo, Brazil.

The soil in the experimental area has a claylike texture and is classified as Red Latosol. According to the Köppen climatic classification, the climate of this region is tropical with dry winter (Aw; Alvares et al., 2013).

The experimental design was based on SQC. Sixty-three sampling points in a 30 × 30 m mesh grid were used for greater representativity of data collected regarding the biophysical characteristics of peanuts associated with NDVI, NDRE, and IRVI (Fig. 1). The behavior of the quality indicators, which were fresh and dry biomass, canopy width, chlorophyll index, maturation, yield, and productivity, was evaluated at 30, 45, 60, 75, and 119 days after sowing (DAS) using NDVI, NDRE, and IRVI by means of control charts to monitor the quality of readings of the vegetation indices for the peanut crop; this correlation was obtained from the best correlations between the quality indicators or parameters evaluated.

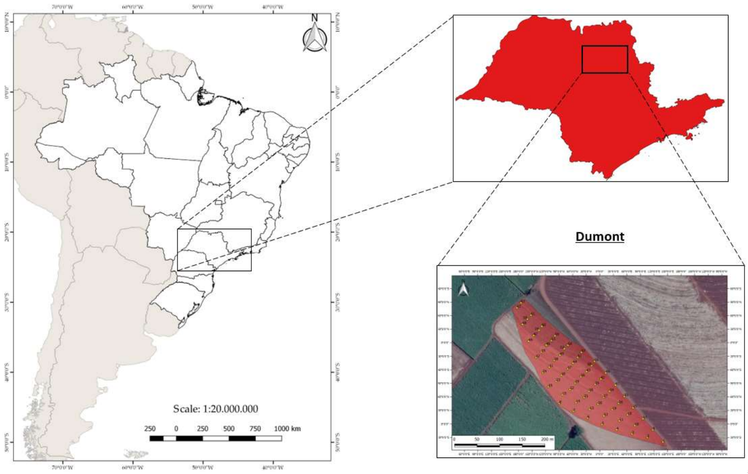



FIGURE 1. Location of the experimental area containing in total 63 sampling points in the municipality of Dumont, state of São Paulo, Brazil. Also, the sample points used in the experiment, spaced with a 30 × 30 m mesh.

Each sampling point was composed of two rows of 5 m in length with 0.90 m spacing between rows, comprising 9 m² of useful area per point. All evaluations were carried out at all points or plots to monitor the temporal variability of the peanut crop.

Remote-sensing evaluations were performed using GreenSeeker® (Trimble, Sunnyvale, CA) and OptRX® (Ag Leader, 2202 South Riverside Drive, Ames, IA 50010, USA) active optical sensors. Fig. 2 shows the evaluated periods in relation to the peanut growth stages. The vegetation index readings were taken in the canopy of the plant (Grohs et al., 2011) between 8:00 a.m. and 12:00 p.m. For the productivity and maturation parameters, only one evaluation was performed after peanut ripening. At 119 DAS, only NDVI, IRVI, and NDRE were collected because this evaluation was performed one day before peanut ripening (120 DAS).

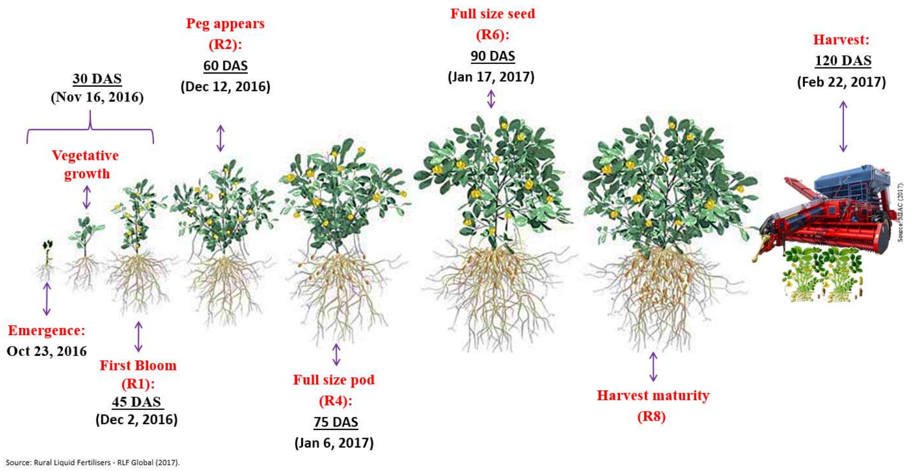



FIGURE 2. Growth stage of peanuts with evaluation dates. Source: Rural Liquid Fertilizers - RLF Global (2017), adapted from Carneiro (2018).

The GreenSeeker is an active optical sensor (Trimble brand model 500) with a reading time between 1 and 2 s. This sensor emits electromagnetic radiation with a wavelength in the red (660 nm) and near-infrared (NIR; 770 nm) bands, and the light reflected by the plant is captured by the sensor. GreenSeeker automatically calculates the NDVI (Motomiya et al., 2014; Amaral *et al*., 2015a). The other obtained index along with the NDVI was the IRVI, which is still rarely used in research.

For a more accurate reading, the manufacturer recommends the working height of this sensor to be between 0.6 and 1.2 m from the target, in this case, the plant. The sensor readings were maintained at a working height of 0.6 to 0.7 m.

The OptRX is an active optical sensor (Ag Leader, model ACS430) with a reading time of 5 Hz (five readings per second). The reading height above the canopy was 0.6 to 0.7 m, with an image reading range (0.36 to 0.42 m) of 60% of the reading height. Two sensors were used to perform the average reading in real time.

According to the manufacturer (Ag Leader), in the United States, where OptRx was created, readings of vegetation indices are usually performed in real time in conjunction with product applications, using a sensor installed in a sprayer to allow the simultaneous realization of these operations. With this sensor, it is possible to obtain NDRE and NDVI. However, for this experiment, NDRE chosen as NDVI was collected with GreenSeeker.

The Laboratory of Machines and Agricultural Mechanization (LAMMA) built the support for transportation of the OptRx sensor during the field experiments, enabling the monitoring of the entire phenological cycle of the crop, from sowing to harvest. This support took into account the model developed by Professor Brenda V. Ortiz, University of Auburn (Alabama, USA). The study used a bicycle as a support, providing transport of two active optical sensors (GreenSeeker and Crop Circle) for field evaluations (Carneiro et al., 2017a).

Table 1 shows the calculations related to each index. The evaluated vegetation indices in this study were the NDVI and IRVI, obtained by GreenSeeker, and the NDRE, obtained by OptRX.

TABLE 1. Vegetation indices.

| Vegetation indices | Calculation index | Source |
|---|---|---|
| NDVI | $NDVI = \frac{F_{NIR} - F_{Red}}{F_{NIR} + F_{Red}}$ | Rouse *et al.* (1973) |
| NDRE | $NDRE = \frac{NIR - RE}{NIR + RE}$ | Buschmann & Nagel (1993) |
| IRVI | $IRVI = \frac{R_{650}}{R_{770}}$ | Kapp Júnior *et al.* (2016) |

*NDVI* - Normalized Differential Vegetation Index, *NIR* - fractions of near-infrared emission, *Red* - fractions of red emission, *NDRE* - Normalized Difference Red Edge, *RE* - ratio of red edge indices, *IRVI* - Inverse Ratio Vegetation Index. *NIR* - 774 nm, *Red* - 656 nm, *RE* - 720 nm

The evaluated parameters were as follows:

- Vegetation indices were acquired using GreenSeeker and OptRX sensors, which obtained NDVI, IRVI, and NDRE.

- Fresh and dry biomass were collected only from the aerial part of the plant. The samples were obtained utilizing a 0.25 m² (0.5 × 0.5 m) frame. Sampling was performed per row (5 m in length), 1 m per point, in the two adjacent rows at the same time. After placing the frames in each of the two rows on both sides of the sample point, the plants were cut to the ground with the aid of a knife. The aerial part of the peanut plant was taken and the roots were discarded. The collected plants were placed in paper bags and then weighed to obtain the wet mass (fresh biomass, Fig. 3a). After that, the samples were placed in a greenhouse with air circulation at 65 °C for 72 h (Gobbi et al., 2009; Grohs et al., 2009) to dry them (dry biomass, Fig. 3b). Finally, the dried samples were weighed with a semi-analytical balance (model BL 3200H) to obtain the dry mass.

Fresh Biomass (a) Dry Biomass (b)


FIGURE 3. Fresh (a) and dry (b) biomass per sample.

- Chlorophyll content was obtained using a Marcone chlorophyll Meter, model CCM-200 Plus. The readings were performed by randomly collecting three leaves per plot, and three readings were taken from each leaf to achieve greater accuracy.
- Canopy width and the height of the plants were measured using a scale graded in centimeters. The height of the plants was measured from the ground level to the highest point of the plant, and the width of the canopy was measured from one end of the plant to the other.
- The productivity of the plants was measured with a frame of 2 $m^2$. The plants were collected in raffia bags and later taken to be trodden off manually to obtain the pods, which were then weighed. The data were transformed into kg $ha^{-1}$.
- The maturation of the pods was determined by the hull-scrape method, in which the exocarp of the pods was scrubbed, exposing the staining of the mesocarp. The classification of the pods was performed by color according to the Peanut Maturation Classification Table, which was developed by the University of Georgia, USA (Williams & Drexler, 1981). In this experiment, 100 random pods were collected per sampling point to determine their maturation, and the area of maturation percentage was determined using black, brown, and orange classes (Santos et al., 2013).

The quality indicators were analyzed through SQC using individual value control charts, which are one of the most commonly used statistical process control tools among researchers because they allow the monitoring of data behavior over time.

The control charts for individual values are composed of the arithmetic mean of the sample and the Upper (UCL) and Lower Control (LCL) Limits, obtained from the mean and standard deviation of the values analyzed per parameter. The LCL equals the mean minus three times the standard deviation, while the UCL equals the mean plus three times the standard deviation (Toledo et al., 2008).

Correlation analysis of quality indicators (vegetation indices, fresh and dry biomass, chlorophyll index, canopy width, maturation, and yield) was also performed in this study. These analyses were used to verify the relationship between the variables and the indicators, as well as whether there were any differences between them.

Galarça et al. (2010) and Figueiredo Filho & Silva Júnior (2009) stated that the Pearson correlation coefficient (r) has values ranging from -1 to 1 and that its value suggests the strength of the relationship between the variables. A perfectly positive correlation between two variables is represented by values close to 1 (r = 1), whereas a perfectly negative correlation is represented by values close to -1 (r = -1), indicating that when one variable increases, the other decreases.

Dancey & Reidy (2006) proposed a classification for the Pearson correlation coefficient as r = 0.10 to 0.30 (weak), r = 0.40 to 0.6 (moderate), and r = 0.70 to 1 (strong). According to Figueiredo Filho & Silva Júnior (2009), the degree of linear statistical dependence between the variables is greater when the value is closer to 1 (independent of the signal), but the strength of this relationship is lower when the value is closer to zero.

All the analyses presented in this study were performed using the Minitab 16 statistical software.

## RESULTS AND DISCUSSION

The correlation graphs were obtained using the Pearson coefficient in order to determine the behavior and relationships of indicators and the evaluated qualities (vegetation indices, fresh and dry biomass, chlorophyll index, canopy width, maturation, and productivity). In Table 2, the highest values of the correlation coefficient for the majority of the evaluated parameters are shown at 45 and 60 DAS, which correspond to development stages R1 and R2 of the peanut, respectively (Fig. 2). This correlation is especially strong at 45 DAS (R1 stage). As observed in Table 2, according to the Dancey & Reidy (2006) classification, the highest correlation values were moderate (r = 0.40 to 0.60) at 45 and 60 DAS (stages R1 and R2).

TABLE 2. Pearson correlation coefficients (r) for NDVI, NDRE, and IRVI in relation to fresh and dry biomass, canopy width, yield, chlorophyll index, and maturity at 30, 45, 60, 75, and 119 DAS (n = 63).

| IV | **Fresh Biomass** (kg ha$^{-1}$) | | | | | **Dry Biomass** (kg ha$^{-1}$) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 30 | 45 | 60 | 75 | 119 | 30 | 45 | 60 | 75 | 119 |
| | --- DAS --- | | | | | --- DAS --- | | | | |
| NDVI | $0.39^{**}$ | $0.59^{**}$ | $0.27^{*}$ | $0.05^{ns}$ | - | $0.30^{*}$ | $0.45^{**}$ | $0.26^{*}$ | $0.05^{ns}$ | - |
| NDRE | $0.25^{*}$ | $0.68^{**}$ | $0.40^{**}$ | $-0.15^{ns}$ | - | $0.29^{*}$ | $0.63^{**}$ | $0.38^{**}$ | $-0.06^{ns}$ | - |
| IRVI | $-0.35^{**}$ | $-0.49^{**}$ | $-0.23^{ns}$ | $-0.07^{ns}$ | - | $-0.28^{*}$ | $-0.39^{**}$ | $-0.21^{ns}$ | $-0.05^{ns}$ | - |
| | **Canopy Width** (cm) | | | | | **Chlorophyll Index** (CCI) | | | | |
| NDVI | $-0.08^{ns}$ | $0.47^{**}$ | $0.34^{**}$ | $-0.03^{ns}$ | - | $0,07^{ns}$ | $0.23^{ns}$ | $0.11^{ns}$ | $-0.03^{ns}$ | - |
| NDRE | $0.06^{ns}$ | $0.48^{**}$ | $0.48^{**}$ | $0.15^{ns}$ | - | $0,18^{ns}$ | $0.57^{**}$ | $-0.11^{ns}$ | $0.05^{ns}$ | - |
| IRVI | $0.11^{ns}$ | $-0.42^{**}$ | $-0.25^{*}$ | $0.03^{ns}$ | - | $-0,06^{ns}$ | $-0.18^{ns}$ | $-0.11^{ns}$ | $0.00^{ns}$ | - |
| | **Maturation** (%) | | | | | **Yield** (kg ha$^{-1}$) | | | | |
| NDVI | $-0.14^{ns}$ | $0.36^{**}$ | $0.18^{ns}$ | $-0.20^{ns}$ | $0.17^{ns}$ | $0.11^{ns}$ | $0.29^{*}$ | $0.35^{**}$ | $0.07^{ns}$ | $0.35^{**}$ |
| NDRE | $0.22^{ns}$ | $0.26^{*}$ | $0.19^{ns}$ | $0.18^{ns}$ | $0.15^{ns}$ | $0.30^{*}$ | $0.26^{*}$ | $0.26^{*}$ | $0.36^{**}$ | $0.26^{*}$ |
| IRVI | $-0.13^{ns}$ | $-0.37^{**}$ | $-0.14^{ns}$ | $0.22^{ns}$ | $-0.16^{ns}$ | $-0.13^{ns}$ | $-0.26^{*}$ | $-0.29^{*}$ | $-0.04^{ns}$ | $-0.34^{**}$ |

IV: Vegetation index; ** Significant at $p < 0.01$; * Significant at $p < 0.05$; ns, Not significant at $p > 0.05$.

The fresh and dry biomass provided the highest correlation values with vegetation indices when compared with the other parameters, especially the correlation between NDRE and biomass (Table 2). The biomass was the parameter that most influenced the readings of the active optical sensors, corroborating the results obtained by Amaral et al. (2015b).

Regarding the vegetation indices, NDRE presented the highest correlations when compared to the other indices for the parameters under analysis. On sugarcane, Amaral et al. (2015a) and Taubinger et al. (2012) found that NDRE had less influence on the plant canopy and was more efficient at predicting biomass when compared to NDVI.

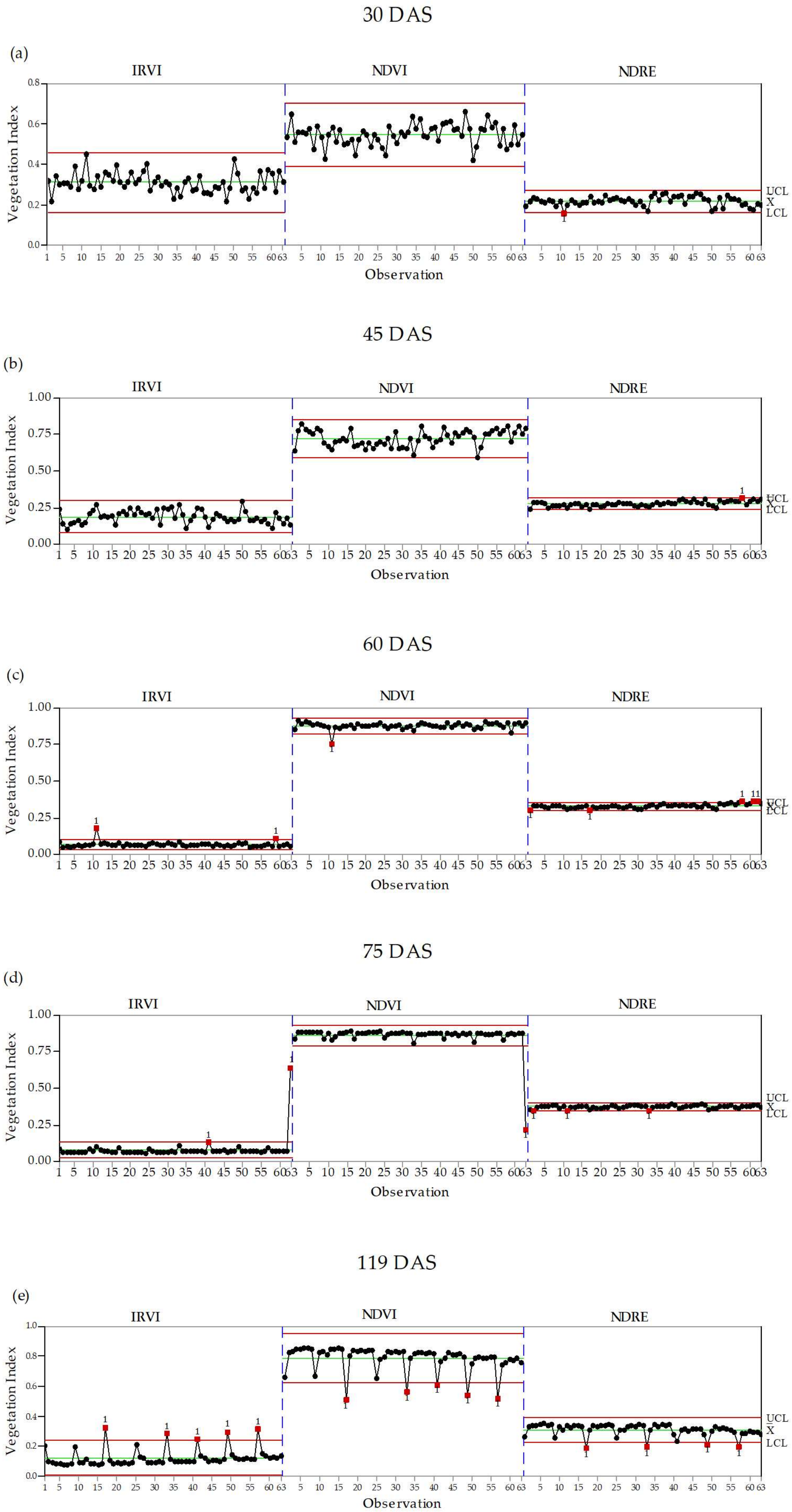
One limitation of NDVI that could explain these results is the saturation of the red electromagnetic wave band. This is due to the high absorption of chlorophyll pigments, which causes saturation in this band by the canopy of the culture. Furthermore, NDVI also presents a nonlinear relationship between the biophysical parameters (Baret & Guyot, 1991). In most of the evaluated parameters at 60 and 75 DAS (R2 and R4 stages, respectively), the NDVI values were probably lower due to saturation.

Regarding the width of the canopy and the chlorophyll index, the highest correlations between the indices were at 45 DAS (stage R1), mainly in the NDRE readings. Steven et al. (1990) explained that the red-edge spectrum is one of the best descriptors for the remote sensing of chlorophyll concentration because this wavelength represents the maximum slope of the vegetation reflectance spectra. The same authors mentioned that this occurs in the 680 to 750 nm bands, where the reflectance changes from very high to very low (in the region of red absorption by chlorophyll) NIR because of canopy and leaf growth.

Regarding the productivity and maturation parameters, the highest correlations were at 45 and 60 DAS (stage R1 and R2, respectively). As NDRE at 60 DAS presented a higher correlation between productivity values, it should be preferred for predicting productivity compared to other indices such as NDVI (Amaral et al., 2015b).

Thus, given these results, the most feasible period to begin monitoring of productivity and maturation using NDRE would be 45 DAS (stage R1), because of the physiological potential of the plant. This stage is at the beginning of flowering, with high translocation of peanut fluids and nutrients to flower formation. At 30 DAS (emergence stage until the beginning of flowering), most of the parameters showed low correlations, particularly the canopy width as the plant was still small and had not yet covered the area between the rows of the crop, leaving the soil exposed. Feng et al. (2016) noted that the spectral reflectance of the plant canopy is affected by the crop canopy, soil, biophysical properties of the vegetation, and factors that affect the accuracy of agronomic index readings.

The data in Table 2 show that at 45 and 60 DAS, higher correlations were obtained between the parameters. The values presented lower variabilities during these periods, which can be explained by the developmental stage of the plants. In the R1 and R2 reproductive stages, the plant demands greater physiological potential and greater translocation of fluids and nutrients in its interior. Moreover, the control charts verified that lower dispersion values were found in the NDRE, with lower variability indicating higher process quality, as seen in Fig. 4.




UCL: Upper Control Limit. LCL: Lower Control Limit. $\overline{X}$ : Average

FIGURE 4. Control chart of individual values for vegetation indices (NDVI, NDRE, and IRVI) at 30, 45, 60, 75, and 119 DAS.

The analysis regarding the temporal variability of the peanut crop was monitored using the control charts of individual values of the vegetation indices (NDVI, NDRE, and IRVI) at 30, 45, 60, 75, and 119 DAS, as shown in Fig. 4. For all the evaluated periods, NDRE presented higher process quality because of its lower variability.

Among the vegetation index readings, NDVI had the highest mean values because of the saturation problem related to biomass increase. Grohs et al. (2009) also observed that NDVI increased with increasing biomass up to the saturation value. In the present study, the mean saturation of NDVI was 0.89 between stages R2 and R4 (at 60 and 75 DAS), as shown in Fig. 4c and 4d.

Analyzing each vegetation index separately, NDVI readings at 60 and 75 DAS (stage R2 and R4) demonstrated saturation because data were constant and showed the same behavior, as shown in Fig. 4c and 4d. The control charts represented excellent tools for the temporal monitoring of the spectral behavior of the indices because they facilitated the visualization of the moment when the saturation of the NDVI reading occurred.

Similarly, Zanzarini et al. (2013) observed that this vegetation index has a limiting factor due to its rapid saturation at a certain stage of development due to the increase in biomass, and the consequent stability in the readings. However, at 119 DAS, one day before harvest, NDVI accurately collected the indices, probably owing to the decrease in biomass at this stage.

Regarding IRVI, Table 2 shows that its values were inversely proportional to those of NDVI. Kapp Júnior et al. (2016) verified that the concentration of chlorophyll in the leaf tissue affects the reflection of the wavelength in the visible range. This pattern is expected because the lower the chlorophyll level and application of nitrogen in the crop, the lower the absorption of solar radiation in the region, resulting in a decrease in NDVI and an increase in the IRVI.

There was temporal variability among the indices because of the stage of peanut development, bands of readings used in the indices, and size of the plant canopy. In the initial stages, the crop had an incomplete canopy and this influenced the sensor readings due to soil reflectance. The outlying points can be explained by factors influencing the vegetation indices, such as canopy width, leaf geometry, stage of development or age of the plant, leaf color, and sensor imaging range.

Our results show that the optimum time for the use of active optical sensing from a terrestrial platform was identified. Besides, the employed method allows the monitoring of the growing stages of the culture because of its non-destructive nature and provides knowledge regarding the spatial variability of the crop through vegetation indexes, specifically showing if plants are vigorous. This will facilitate the faster detection of the causes that could affect the development of crops and consequently the yield, such as pests, diseases, and nematodes, among others. This work is very relevant because it shows the optimal time for the use of these sensors, which could give farmers greater time-saving.

## CONCLUSIONS

Considering that the best correlations among the evaluated quality indicators were obtained at, 45 and 60 DAS (stage R1 and R2), particularly 45 DAS, these times should be considered the optimal time for the monitoring of peanut crop variability.

For the spatiotemporal monitoring of the culture through control charts, NDRE showed the best reading qualities throughout the process when compared with NDVI and IRVI.

The use of active optical sensors shows great potential for the detection of temporal variability in peanut crops. Furthermore, it was also possible to associate the biophysical characteristics of the crop with the vegetation indices. Through the use of Pearson correlation, it was possible to identify the parameters that best correlated with the vegetation indices.

The control charts applied in this study show promise for the temporal monitoring of vegetation index readings during the different stages of peanut growth.

This study will serve as a reference for future research regarding the use of remote sensing techniques at the terrestrial level. These approaches will also help both researchers and rural producers by identifying the optimal time for the use of active optical sensors in order to monitor peanut crop variability and verify plant vigor using a vegetation index. Finally, it also provides new knowledge in the area of physiology, irrigation with varied rate, and soil fertility application of fertilizers before and after the optimal time.

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