Sugarcane canopy structure temporal analysis considering phenological stages and the temporal dynamics of NDVI values

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Abstract. *This research aims to perform an exploratory analysis about the components of sugarcane canopy in each phenological stage. For this purpose, a methodology for field data sampling using an optical active sensor was proposed to obtain Normalized difference vegetation index (NDVI) values. Also, supervised classifications were conducted based on UAV images in order to measure the percentage of each component, in each phenological stage. As a result, the methodology had a satisfactory performance, further, the classification results demonstrated the temporal heterogeneity in sugarcane canopies.*

INTRODUCTION

Fundamental remote sensing of vegetation studies focusses on the characteristics and the dynamic of individual leaves reflectance, considering its causes and alterations. Individual properties of leaves reflectance are essential for the understanding of reflectance concerning the whole plants and the canopy. However, the measures made by remote sensors could not be actually explained exclusively for leaves characteristics, even with an interpretation directly associated to an ideal spectral behavior of an isolated leave (Goel and Strebel, 1984). Thus, it is not appropriated to extrapolate spectral data from an individual leave to a canopy without proper adjustment and comprehension. This, due to the fact that the canopies spectral behaviors are not composed exclusively by leaves (Bauer et al., 1981).

In this context, Meneses and Madeira Neto (2001) indicated that for canopies remote sensing, a complex interaction should be considered, by virtue of the many environmental parameters and factors described by Rosa (2009) and Jensen et al.(2009), that influence in the image(aerial or orbital) composition. The most cited parameters are atmospheric condition, illumination geometry and scene sight elements, sensor model, soils (substrate), leaf (shape, position, water content, pigmentation, internal structure), biomass (vegetation total density), canopy cover, canopy aspects in terms of vegetation/planting density and leaf area index (Ponzoni et al., 2012). Further, it should be weighed that all those cited parameters have spatial and temporal variation associated with vegetation type, development stage and crop conditions (Kimes and Kirchner, 1983).

Knipling (1970) analyzed vegetation interactions in remote sensing into aspects related to canopy, indicating that each canopy has a characteristic geometrical/structural, determined by plants size, shape and orientation, for both horizontal and vertical dimensions. Still, the same author emphasizes that crop management practices and growing environmental conditions also influence spectral behaviors, promote radiation attenuation (considering shadows and non-foliar background surfaces), also, it was observed that the reflectance in canopy is considerably lower than an individual leaf.

In terms of canopy structure, it could be mathematically described by physical parameters, such as plants disposal, leaf area index (LAI), leaves spatial distribution and inclination angles (Ponzoni et al. 2012). The same authors highlighted the clear distinctions made between complete agricultural canopies featured by homogeneity, complete soil cover and the incomplete ones, where plant lines and bare soil among lines could be clearly noted, this due to the incomplete canopy cover. Accordingly, Ranson et al. (1985) demonstrated spectral row crops complexity, since the scene obtained by the sensor is composed by vegetation and bare soil, in varying proportions as a consequence of crop cycle conditions. Likewise, the shadow produced by crops into bare soils rows should be considered.

Hence, as stated by Meneses and Madeira Netto (2001), the effectiveness of remote sensing of vegetation made by aerial and orbital platforms is directly depending on the capacity of relate the canopy spectral behaviors with its composition, this only could be achieved by the complete understanding of this relationship (field composition versus spectral reflectance) and its sources. The same authors also suggest the recognition of different spectral targets and their contributions for reflectance, based on repetitive field observations, in order to obtain the percentage of soil cover or LAI, shadows and vegetation. This comprehension could support many crop remote sensing studies, especially those related with crop yield for row crops, such as sugarcane.

Many sugarcane yield studies based on remote sensing use only values from the Normalized Vegetation Index (NDVI) (Mulianga et al., 2013). However, the use of NDVI for biomass and productivity estimation could cause inaccuracy, considering the composition of sugarcane canopies. The canopies in sugarcane lands are composed by a diverse vegetation condition with significant temporal dynamics (Bengué et al., 2010). Based on this framework, it is meaningful to figure out the sugarcane canopy particularities that contribute for spectral reflectance, especially for vegetation indexes such as NDVI and how they vary through time.

On account of this, the present work aimed the characterization (*in situ*) of sugarcane canopy and its dynamic change through phenological stages, based on the vegetative composition (green and dry leaves), shadow, substrate (soil and straw), correlated with NDVI values obtained by field sensor.

MATERIAL AND METHODS

This study was performed in partnership with a sugarcane mill, which provided data and environment for analyses, in Ribeirão Preto municipality, São Paulo state, Brazil.

Field data sampling

Twenty sampling points, in a ratio of 20 km, were defined over similar sugarcane varieties (considering architecture and canopy) and different development crop stages. The sampling occurred systematically during 12 months (2018-08-23 up to 2019-08-26) with intervals ranging from 30 up to 45 days.

For NDVI values collection the active optical sensor Trimble GreenSeeker Handhelt was used. This sensor emits a range of electromagnetic waves in two wavelengths, being, red (660nm) and near infrared (770nm), those that once achieve the target are reflected and collected by the sensor. Further, reflectance values are converted to NDVI (Tucker, 1979), accordingly to equation 1.

$$NDVI = \frac{(\mathrm{NIR-RED})}{(\mathrm{NIR+RED})} \qquad \text{equation 1}$$

Where NDVI is Normalized vegetation index, NIR is the target reflectance in the near infrared wavelength and RED is the reflectance in the red wavelength.

The data acquisition was made using a vertical distance ranging from 60 up to 90 centimeters from the target. Each sampling point was composed by four samplings (Figure 1), and for each one, five NDVI measurements were performed. Then, the final NDVI value for each one of the four samplings is composed by the mean value considering the five measurements. This procedure was implemented in order to obtain most representative NDVI values for each area, besides the sampling standardization.

Figure 1.Schematization of field procedure performed to obtaining of NDVI values in Ribeirão Preto, São Paulo state, Brazil.

Moreover, to each sampling point, images from unmanned aerial vehicle (UAV) were obtained. A Mavic Pro from DJI was utilized, which is battery-powered and has a maximum flight autonomy of 27 min at 25 km/h or a maximum flight distance of thirteen kilometers. The UAV has a ½ 3” (CMOS) sensor and FOV 78.8 26mm lens. Four images were taken into each sampling point, in different altitudes, depending on sugarcane heights. Thus, for sugarcanes lower than 1 meter of heigh, the UAV imagery were obtained at flight altitudes of 3,10, 50 and 100 meters. In addition, for sugarcane plants taller than 1 meter, the flight altitudes were 5, 10, 50 and 100 meters. Those acquisitions were made aiming at broader imagery observation (DANDOIS et al., 2020).

Data classification

The three meters of altitude images were adopted to determine the percentage of green and dry leaves, shadow and soil, in order to characterize the canopy structure, sampling point conditions and NDVI values. The first step of this characterization was made in GIS environment using the software ArcGis 10.5 for image classification. The supervised classification was performed employing the Maximum likelihood algorithm (MAXVER), which is based on the Bayes optimization strategy, minimizing classification errors (Swain and Davis, 1978). This algorithm assumes that all the inputs attributes have a normal distribution, from this point, the probability of each pixel belong to a specific class is calculated.

The supervised classifiers are not usually recommended for high resolution images especially due to the fact that the classification could generate many isolated pixels. However, this limitation was attenuated increasing the number of samples for each class (50 samples) in addition to the methodology of sample collection, generating larger segments, thus, better representing a large variability of values for the same class.

Then, as a first step, five image classes were identified and designed as “green leaf”, “dry leaf”, “shadow”, “straw” and “soil” as demonstrated in Figure 2. Further, for feature training, 50 samplings were taken for each class such as illustrated in Figure 2.

Figure 2. Example of targets adopted as classes in UAV images, in Ribeirão Preto, São Paulo state, Brazil.

The sugarcane mill provided the last harvest date for the sampled areas, thus it was possible to determine how many days were passed from the last harvest until the sampling day. Using this information, based on literature review, the phenological stages were determined as described into Table 2 (EMBRAPA, 2012).

Table 1. Description of standard values used to estimate phenological stages accordingly to days after harvest (DAH)/days after planting (DAP).

DAH	Phenological stages
0 - 30	Germination
30 - 120	Tillering
120 - 360	Vegetative
360 - 500	Maturing

Data analysis

For data analysis, the NDVI values obtained in field and the results generated by the classification were structured, filtered and organized based on an individual id (ID_TA) attributed to each plot plus the data collection date(date_camp). According to Dasu and Jhonson (2003) the dataset cleaning and structuration is essential in order to conduct consistent data analysis. Further, the attribute “DAH” was generated, indicating the days after the last harvest. From this attribute, the dataset was ordered as “DAH” equal 0 up to the last registered one (500), aiming at a temporal analysis.

In sequence, an exploratory analysis and a linear regression were performed among plots containing the same sugarcane variety “DAH” and the classification results (percentage of “Green leaf”, “Dry leaf”, “Shadow”,” Straw” and “Soil”). Also, the same procedure was adopted for the comparison between NDVI values and classification results. All statistical analyses were conducted in python environment, using the libraries Pandas, Numpy, Statsmodels, Seaborn, Matplotlib and scikit_learn (Lemenkova, 2020).

RESULTS AND DISCUSSION

The results obtained by a supervised classification are illustrated in Figure 3, where it is possible to see how each pre-defined class was classified in each phenological stage. Based on Figure 3 observation, it is possible to argue that the pre-defined targets where identified in a satisfactory manner.

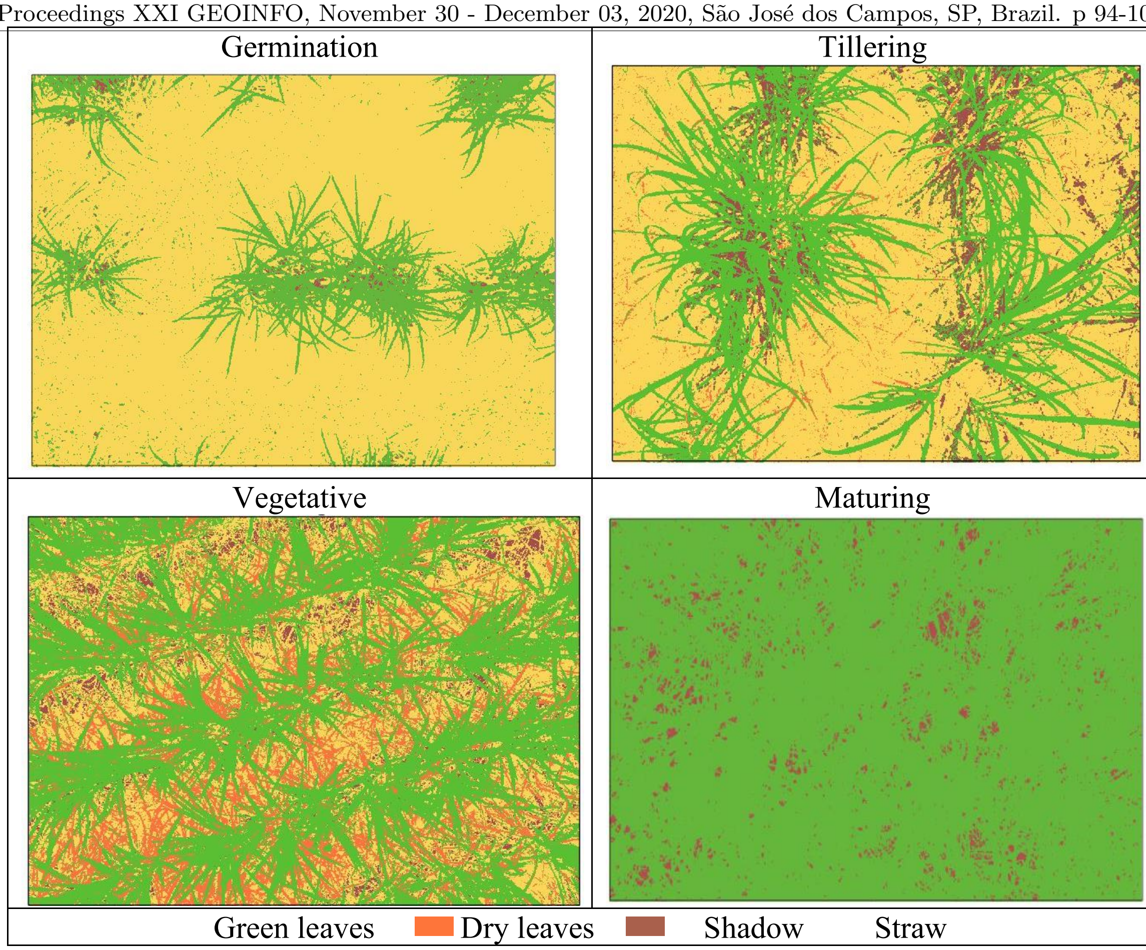

Figure 3. Example of classification results obtained based on UAV images for sugarcane canopy in each phenological stage, in Ribeirão Preto, São Paulo state, Brazil.

Further, in Figure 4 it is possible to see the classification results demonstrating the contribution (area - %) of each vegetative component (green and dry leaves), shadow and substrate (soil/straw), for all collected samples and how they evolve through each phenological stage.

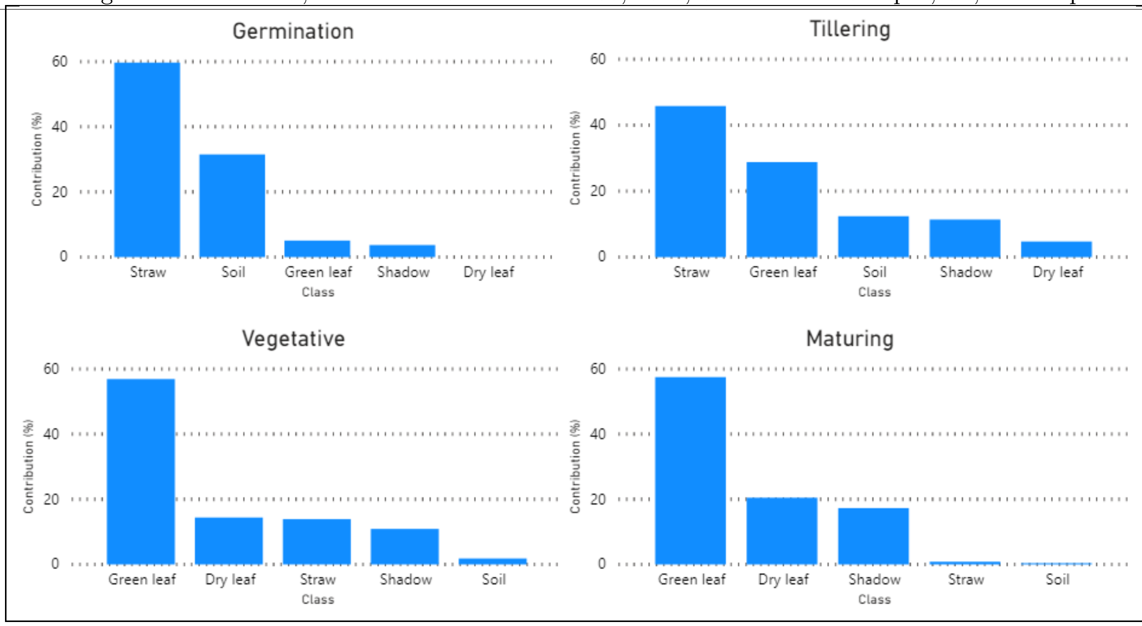

Figure 4. Distribution of vegetative components (green and dry leaves), soil, shadow and straw through phenological stages in Ribeirão Preto, São Paulo state, Brazil.

The first consideration about Figure 2 is the noticed high variability among classes even after grouped through phenological stages. This result reinforces the necessity of consider individual sugarcane management practices in order to perform precise analyses.

However, one constant could be observed, that is the high occurrence of straw in canopy cover until the tiller stage, followed by green leaves in vegetative and maturing stages (Figure 4). The dry leaves start to be more representative during vegetative and maturing stages. Other relevant observed result is the shadow occurrence that was constant through all phenological stages, with high occurrence in the maturing stage (17%) (Figure 4).

Further, as previously discussed, it is important to relate the canopy cover targets occurrence with NDVI values measured in field. Then, Figure 5 present the NDVI values variability, considering all the collected samples, through all phenological stages.

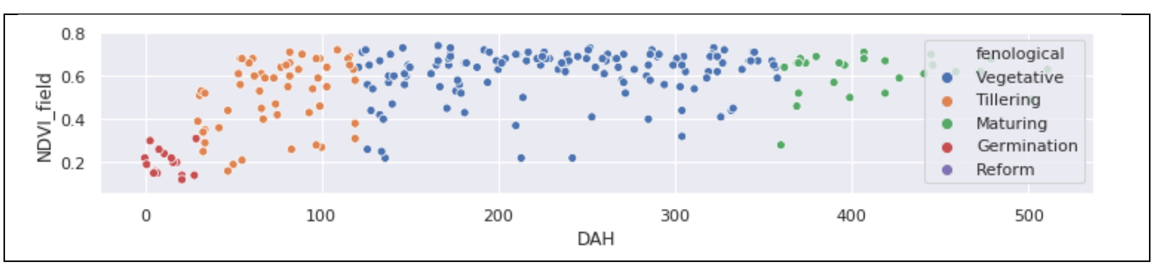

Figure 5. Distribution of NDVI values through phenological stages and days after harvest (DAH), in Ribeirão Preto, São Paulo state, Brazil.

In Figure 5, it is possible to see the increase of NDVI values through the DAH variable, thus if we consider the sugarcane development in field, low values of NDVI (<0.2) could be associated with bare soil, and the value increases following the sugarcane development until sugarcane maturity (NDVI>0.71). This temporal behavior is accordingly to related in literature (Fernandes et al., 2017; Gonçalves et al., 2012). The statistical values presenting the overall tendency for each target class, considering phenological stages and NDVI values are presented in Table 2. Those measures were obtained using the zonal statistics tool in GIS environment through the software ArcGis 10.5.

Table 2.Descriptive statistics for each target class, considering different phenological stages in Ribeirão Preto, São Paulo state, Brazil.

Target class occurrence (%)	Measure	Germination	Tillering	Vegetative	Maturing	Reform
Green_Leaf	count	16	55	134	26	9
	Mean	5.067	28.867	56.986	57.501	13.912
	Std	6.85	22.276	25.884	26.058	15.823
	Min	0	0	0	0	0
	Max	18.019	77.472	95.179	94.657	45.852
Dry_leaf	Count	16	55	134	26	9
	Mean	0	4.73	14.485	20.48	0
	Std	0	13.364	17.686	22.758	0
	Min	0	0	0	0	0
	Max	0	90.193	74.13	68.748	0
Shadow	Count	16	55	134	26	9
	Mean	3.698	11.482	10.999	17.297	4.049
	Std	5.343	10.214	10.29	12.296	3.857
	Min	0	0	0	0	0
	Max	16.795	47.971	67.138	42.201	10.792
Soil	Count	16	55	134	26	9
	Mean	31.514	12.492	1.829	0.05	54.345
	Std	42.237	24.855	7.493	0.253	32.21
	Min	0	0	0	0	1.007
	Max	100	100	52.488	1.29	100
Straw	Count	16	55	134	26	9
	Mean	59.721	45.887	13.924	0.825	27.695
	Std	38.822	33.794	23.991	4.209	26.374
	Min	0	0	0	0	0
	Max	100	100	88.768	21.46	72.213
NDVI	Count	16	55	133	26	9
	Mean	0.2	0.513	0.611	0.608	0.442
	Std	0.057	0.157	0.116	0.097	0.198
	Min	0.12	0.16	0.22	0.28	0.18
	Max	0.31	0.72	0.74	0.71	0.7

Based in Table 2 it is recognized that for the Germination stage soil and straw have larger mean values than other classes, this, due to the fact that in this phenological stage the sugarcane has a low number of leaves and it is starting its growing stage, further, for this stage the NDVI values are low, varying from 0.2 up to 0.31.

In sequence, in tillering stage, the cited mean values of soil and straw start to decrease, while green (28)/dry (4.7) leaves and shadow (11.4) begin to increase, as well as NDVI value. Furthermore, in this stage, the std values are high, many factors could cause this, such as sugarcane age, vegetative material, soil type, that were not considered in our evaluation, moreover this is a phenological stage where there is vertical and horizontal growing, which could increase the std values (Table 2).

In parallel with sugarcane development, in vegetative stage there is an increase of occurrence for green/dry leaves and shadow, as opposite of, the soil and straw occurrence, that decrease (Table 2).

Finally, in maturing stage, green leaves and NDVI achieve their maximum value of reflectance and occurrence, in the other hand, the increase in dry leaf and shadow is not so significant. This could be caused due to the canopy configuration of the selected varieties, that were developed to reduce the quantity of shadow between rows, in order to promote a better use of the area.

FINAL CONSIDERATIONS

The proposed methodology for collecting NDVI in field using an optical active sensor demonstrated to be effective, since the temporal NDVI values and patterns were similar to the ones found in literature.

The determined classes in order to represent the sugarcane canopy structure were effective. However, it was perceived that the analyses should be limited to agronomical specific groups, mainly by soil type (instead of production environment), specific varieties and ratoon number.

The high variance of NDVI during all the phenological stages, demonstrates the main difficulty in stablishing direct correlations among vegetation indexes with crop sanity, since the presence of dry leaves (as a vegetative component) and substrate (mainly due to straw presence) were observed in scene cover.

As a further step, we suggest the use of this methodology to verify the differences among sugarcane varieties. Also, we suggest a comparison between NDVI values obtained by the in-field sensor and satellite images.

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REFERENCES

BÉGUÉ. Agnes et al. Spatio-temporal variability of sugarcane fields and recommendations for yield forecast using NDVI. **International Journal of Remote Sensing**. v. 31. n. 20. p. 5391-5407. 2010.

BONNETT. Graham D. Developmental stages (phenology). **Sugarcane: physiology. biochemistry. and functional biology**. p. 35-53. 2013.

Bull. T.A. and Glasziou. K.T.. 1975. Sugarcane. In: L.T. Evans (Editor). Crop Physiology. Cambridge University Press. London. pp. 51-72.

DANDOIS. Jonathan P.; OLANO. Marc; ELLIS. Erle C. Optimal altitude. overlap. and weather conditions for computer vision UAV estimates of forest structure. **Remote Sensing**. v. 7. n. 10. p. 13895-13920. 2015.

Dasu. T.. & Johnson. T. (2003). *Exploratory data mining and data cleaning* (Vol. 479). John Wiley & Sons.

FERNANDES, Jeferson Lobato; EBECKEN, Nelson Francisco Favilla; ESQUERDO, Júlio César Dalla Mora. Sugarcane yield prediction in Brazil using NDVI time series and neural networks ensemble. **International Journal of Remote Sensing**, v. 38, n. 16, p. 4631-4644, 2017.

Goel NS. Strebel DE. Thompson RL. Simple beta distribution representation of leaf orientation in vegetation canopies. **Agronomy Journal**. V6. p.800-803. 1984.

GONÇALVES, Renata RV et al. Analysis of NDVI time series using cross-correlation and forecasting methods for monitoring sugarcane fields in Brazil. **International journal of remote sensing**, v. 33, n. 15, p. 4653-4672, 2012.

JENSEN. J. **Sensoriamento Remoto do Ambiente: Uma perspectiva em recursos terrestres** (tradução José Carlos Neves Epiphanio et. al.). São José dos Campos. SP. Parêntese. 2009.

LEMENKOVA, Polina. Python Libraries Matplotlib, Seaborn and Pandas for Visualization Geospatial Datasets Generated by QGIS. **Analele stiintifice ale Universitatii" Alexandru Ioan Cuza" din Iasi-seria Geografie**, v. 64, n. 1, p. 13-32, 2020.

KIMES. D.S.; KIRCHNER. J.A. Diurnal variations of vegetation canopy structure. **International Journal of Remote Sensing**. v. 4. n. 2. p. 257-71. 1983.

KNIPLING. E. B. Physical and physiological basis for the reflectance of visible and near infrared radiation form vegetation. **Remote Sensing of Environment**. New York. V11. P.155-159. 1970

MENESES. P.R. & MADEIRA NETTO. J.S.. orgs. **Sensoriamento remoto: Reflectância dos alvos naturais**. Brasília. UnB/Embrapa Cerrados. 2001. 262p.

MULIANGA. Betty et al. Forecasting regional sugarcane yield based on time integral and spatial aggregation of MODIS NDVI. **Remote Sensing**. v. 5. n. 5. p. 2184-2199. 2013.

PONZONI. F. J.; SHIMABUKURO. Y. E.; KUPLICH. T. M. **Sensoriamento Remoto da Vegetação**. Oficina de Textos. 2012. 176 p.

RANSON. K.J.. L.L. BIEHL AND M.E. BAUER. Variation in Spectral Response of Soybeans with Illumination. View. and Canopy Geometry. **International Journal of Remote Sensing**. Vol. 6. No. 12. pp 1827-1842. 1985.

ROSA. Roberto. **Introdução ao Sensoriamento Remoto**. Uberlândia. EDUFU. 7a ed. 2009.

SWAIN P.H. & DAVIS S.M. 1978. **Remote sensing: the quantitative approach**. New York. McGrawHill. 396 p.

TUCKER, Compton J. Red and photographic infrared linear combinations for monitoring vegetation. **Remote sensing of Environment**, v. 8, n. 2, p. 127-150, 1979.