USING PASSIVE AND ACTIVE MULTISPECTRAL SENSORS ON THE CORRELATION WITH THE PHENOLOGICAL INDICES OF COTTON

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ABSTRACT: The investment in precision agriculture technologies has been growing as well the investment in vegetation index sensors with different types of data collection. This study aimed to evaluate the NDVI potential use obtained from passive and active multispectral sensors as phenological parameters indicator of cotton growth. The experiment was conducted in cultivated cotton fields during the harvest seasons of 2013/14 and 2014/15. The phenological variables analyzed in the field, were cotton plant height and number of branches per sampled cotton plant. The active sensors Crop Circle and GreenSeeker were mounted on a manual support. The passive sensor Tetracam was installed on a support positioning the sensor at 4 m height from the ground. NDVI readings are positively correlated with plant height and number of branches per cotton plant. Active sensors present exponential correlations between NDVI and phenological readings. Passive sensor, when installed in a support above the cotton canopy level, presents linear correlation between NDVI and phenological readings. NDVI values obtained by the passive sensor are higher than the active sensors. Filtering the raw NDVI values obtained by passive sensor decreases the adjustment of the regression analyses with cotton height and number of branches per plant.

KEYWORDS: vegetation index, variability, multispectral sensors.

INTRODUCTION

Cotton (*Gossypium hirsutum* L.) is a perennial plant that has been adapted to grow as an annual crop. The architecture favorable to the mechanization of cotton crop, the adoption of current technologies and the use of inputs, has made the cultivation of cotton to concentrate in the Cerrado region of Brazil(Leal *et al*., 2009).

Cotton vegetative growth is controlled by the application of a plant growth regulator to balance its growth of vegetative and reproductive structures. In addition, a crop fruit ripener is applied at the end of the crop cycle to stimulate and standardize the opening of the cotton flowers (Echer & Rosolem, 2012). Monitoring growth of phenological plant is important for the determination of the doses recommended for these inputs.Remote sensing techniques can be applied on these phenological evaluations.

Remote sensing techniques, as well the use of vegetation indices (VI) from multispectral optical sensors have an adequate correlation with several attributes of plant growth, such as plant biomass and leaf nitrogen content (Portz *et al*., 2012; Amaral *et al*., 2015). Thus, the field can be divided into regions called application zones, according to the spatial variability of VI, which are considered fundamental in the doses prescription of inputs, especially for cotton crop. This enables their rationalized application, and improves efficiency of the agrochemical inputs, decreases costs and increases crop yield (Salvador & Antuniassi,2011; Amaral *et al.*, 2015).

VI can be estimated applying passive or active multispectral sensors, installed on several platforms, such as satellites, airplanes or onboard of agricultural machines. According to Steinvall et al. (2013), passive sensor, such as multispectral cameras, measures reflected energy fromthe target that was emitted from the sun. Multispectral active sensors have its own source of light and its sensor measures reflected energy from the crop canopy.

The Normalized Difference Vegetative Index (NDVI) isthe best known and most widely usedVI for the characterization and monitoring crops, allowing for the mapping of the crop and asubsequent application of inputs in variable rates (Hill *et al.,* 2010).Raper & Varco (2015) found that the use of VIs containing wavelengths near 700 nm was strongly correlated with the leaf N, total N content and cotton yield fiber. According to Eitel (2008), NDVI is correlated with some biophysical plant variables, such as the leaf area and the mass of green leaves, the water content of leaves and total chlorophyll.

Vegetation phenology such as the crop biomass is difficult to observe from remote sensing sensors. Currently, existing VI are generally applied to estimate seasonal phenological variation in dense crop canopies (Jin & Eklundh, 2014). According to Ma *et al.* (2001), remote sensing techniques, particularly the multispectral reflectance of the visible and the infrared, can provide data to perform correlations between VIobtained above the plant canopy and the existingcrop biomass, making it possible to obtain estimates of yields. Walsh *et al.* (2013) observed this correlation while working with a NDVI sensor for estimating wheat biomass and evaluating the potential production and grain yield in the winter. These authors concluded that the NDVI has a great potential as an estimator of the wheat crop productivity.

There are several multispectral sensors on the market, with different spatial and spectral resolutions, leading to uncertainties regarding the most appropriate use ofVIin precision agriculture technology. This study aimed to evaluate the NDVI potential use obtained from passive and active multispectral sensors as phenological parameters indicator of cotton growth.

MATERIAL AND METHODS

The experiment was conducted in cultivated cotton fieldsat Amambaí Farm (18°21'S; 52°37'W - 1st experimental year) and at Campo Bom Farm (18º39'S; 52º40'W - 2nd experimental year), in the municipality of Chapadão do Céu, GO, during the harvest seasons of 2013/14 and 2014/15, respectively.The average annual rainfall in this region is 2,096 mm and the average temperature is 22.5°C. The weather classification, according to Köppen, is tropical climate with a dry season during the winter. The soil classification is dystrophic Red Latosol. The average altitude is 815 m and the land has a slope of 1 to 2%. In both seasons, the cotton variety was FM 975WS and sown at 0.8 m row spacing with an estimated 100,000 plants ha^{-1}.

The soil was fertilized uniformly using 90 kg ha^{-1} of potassium and distributed before the cotton seeding; 82 kg ha^{-1} of phosphorus was applied at sowing in the furrow using NPK 10-00-52 as a source. Calcium nitrate (27% of N) was used for the post-emergence N fertilization at 81 kg

ha^{-1} of N, divided into three applications, at 25, 36 and 47 days after emergence (DAE). The other agricultural inputs (insecticides, fungicides, and herbicides) were applied uniformly during the crop development according to the monitored needs of the crop.

On each experimental year, the field work was performed using a randomized complete block design, represented bymoment of the phenological readings and experimental year. The experimental field was conducted in five randomized blocks and nine replicates for each treatment. Each plot representing VI classes had 10 m in length and width with six rows of plants spaced at 0.80 m. At each sample location, phenological readings of five identified and marked plants around the location were measured to represent the average local variability.

The phenological variables analyzed in the field, were plant height (m) and number of branches per sampled cotton plant. Phenological cotton plant readings were performed to compare the differences between the stadium of the crop and VI. The height of each plant was measured on the main stem between the ground surface until the point of the last fully expanded leaf. The total number of branches was obtained by its counting in the sampled plants around the central sample point, and its result expressed as number per plant. The phenological variables were measured five times during each vegetative cycle, on the first and second experimental period, respectively: 26, 39, 51, 68 and 82 DAE; and 29, 49, 69, 84 and 98 DAE. The variable number of branches per plant

was not measured at the first readings (26 and 29 DAE), once the plant was on the very beginning of the vegetative cycle and there are not available branches.

The NDVI data was collected from the two central rows, discarding the two rows on the border of each side of the plot. The VI readings were acquired by the active sensorsGreenSeeker[TM] RT 200 (Ntech Industries, Ukiah, USA) and Crop Circle[TM]ACS-470 (Holland Scientific, Lincoln, USA), andby the passive sensor through a multispectral camera Tetracam[TM]ADC Lite (Tetracam Industries, Chatsworth, USA). NDVI was calculated based on [eq. (1)].

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

(1)

where,

NIR - reflectance value in the near-infrared wavelength;

RED - reflectance value in the red wavelength.

Active sensors were mounted on a manual support, working at 0.80 m above the crop. GreenSeeker emits active radiation and its readings are at two centered wavelengths in red (660 nm) and near-infrared (770 nm) with a bandwidth of 25 nm. The magnitude of the light reflected by the target is measured by the photodiode detector, which determines the reflectance values for the two bands and calculates the NDVI (Ntech Industries, 2016). The wavelengths filters applied on Crop Circle sensorto calculate NDVI were red (670 nm) and NIR (760 nm). The multispectral camera Tetracam (TCAM) contains the green (520-600 nm), red (630-690 nm) and near infra-red (NIR - 760-900 nm) bands and needsthe sunlight radiation, therefore, being classified as a passive sensor (Tetracam Industries, 2016).

In order to capture the images from the camera, Tetracam was installed on a support positioning the sensor at 4 m height from the ground. This height was enough to capture images from the crop in a 1.8 x 2.5 m samplingarea. Raw and filtered NDVI values obtained fromTetracam images were compared in order to relate the effects of soil exposure on the images reflecting over the VI. The filtering process of each camera image was made eliminating the NDVI values related to the soil, according to a supervised classification of the image using the GIS ArcGis 10.4 (ESRI, 2017). According to this classification, the NDVI values lower than 0.299 were eliminated in each scene. The NDVI values considered in each experimental replication plot were the average of all pixels in each image.

The results of the statistical analyzes were obtained by the use of SigmaPlot 11 software. A data normality test by Shapiro-Wilk was performed. Regression analyses were performed between the cotton phenological readings and measured VIs. Correlation analyses were performed among all variables.

RESULTS AND DISCUSSION

NDVI values were positively correlated with the plant height during the cotton production seasons up to 82 and 98 DAE. Thus, the NDVI readings may be used to estimate the cotton growth. These results are similar to those obtained by Portz *et al*. (2014). Active sensors presented exponential correlations between plant height and NDVI (Figure 1a and 1b). The passive sensor presented linear correlations, using raw NDVI or filtered data (Figure 1c and 1d). Motomiya *et al*. (2009) obtained a linear correlation between these two factors. The higher correlation was obtained by the use of Crop Sensor. Different correlations were obtained with others sensors once their red and NIR wavelengths acquisition characteristics are different.
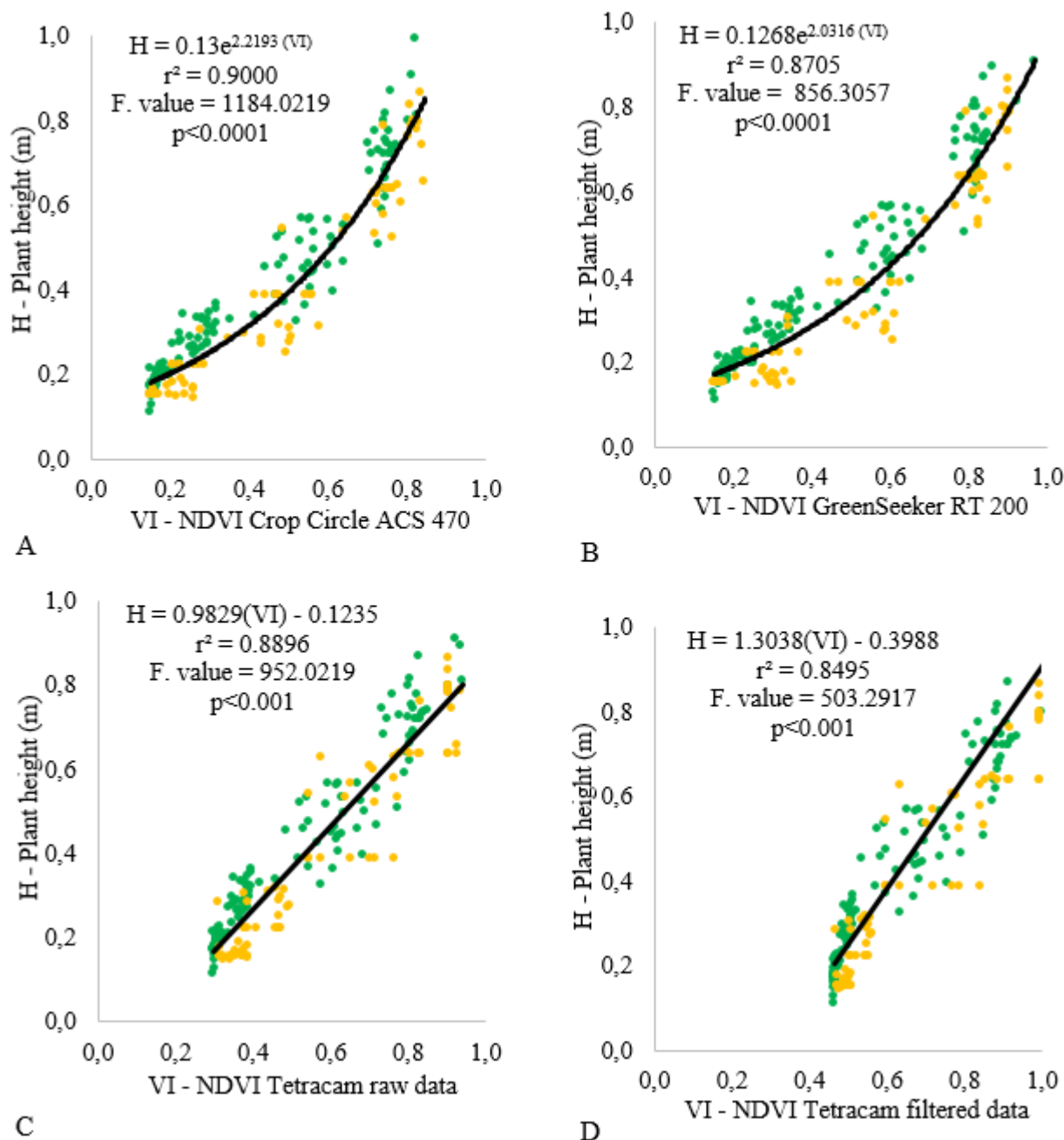
FIGURE 1. Regression analyses between NDVIcalculated from multispectral sensors and from five phenological moments, and height of the cotton plantscultivated on the harvest seasons 2013/14 (yellow dots) and 2014/15 (green dots).

NDVI readings values in both crop seasons using the passive sensor were higher, with average NDVI value for each image starting above 0.2, even from the first phenological crop readings. The data collected above the cotton canopy by the passive sensor may have presented a minimization of interference caused by the soil due to higher height of the acquiring images above the crop row, capturing a higher proportion of the plant mass than soil, generating higher NDVI values.

The measured variability of plant height and VI can be related to several factors of soil, weather and seeding at the crop establishment, which are difficult to be related what was the more dominant. Iqbal *et al.* (2013) concluded that differences in the soil physical properties influence crop growth and the NDVI values, causing spatial variability in the cotton growth and yield.

Applying the filtering process over each multispectral image (Figure 2c) increases its processing time and didn't allow a better adjustment on the equation (Figure 1d - lower r^2).The

images obtained by the Tetracam camera at the support level (Figure 2) resulted in a high spatial resolution (0.002 m). This spatial resolution reflected over the higher number of sampling data for each calculation of the average NDVI in the scene, from 24,000 sampling records per plot and differing from 50 sampling records per plot obtained by active sensors.
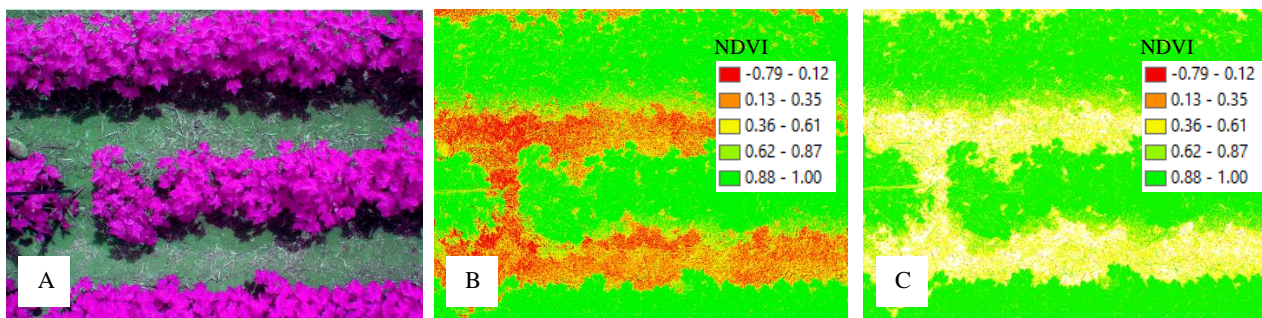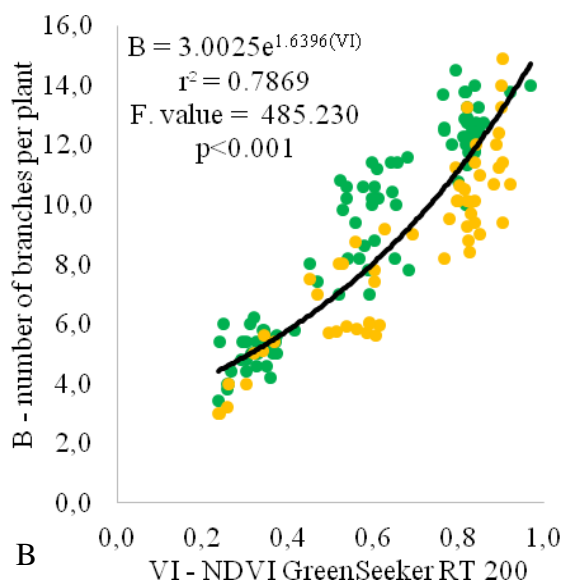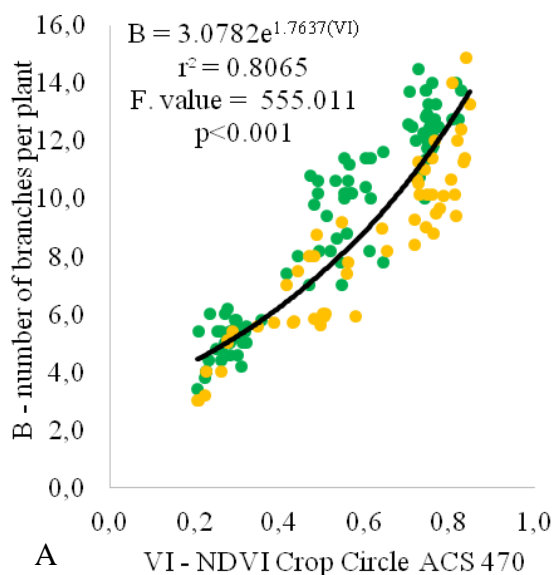

FIGURE 2. Multispectral false color image (A - RGNIR) from Tetracam sensor, raw NDVI image (B - soil and shadows interferences), and filtered NDVI image (C - reduced soil interference).

NDVI values were positively correlated with the number of branches per plant during the cotton production seasons up to 82 and 98 DAE (Figure 3). Active sensors also presented exponential correlations between number of branches per plant and NDVI (Figure 3a and 3b). The passive sensor also presented linear correlations using raw NDVI or filtered data (Figure 3c and 3d). Thus, the NDVI readings may be used not only to estimate the cotton height, but also to estimate the distance in between cotton branches allowing recommendingdoses of plant growth regulator on cotton crops. Cotton growth regulator is applied to balance growth of vegetative and reproductive structures.Montomiya et al. (2014) used different doses of a growth regulator containing 0, 30 and 60 g ha^{-1} of the active ingredient chlormequat chloride, applied over a cotton field and obtained a variation of the NDVI related to these doses.

$$B = 3.0782e^{1.7637(VI)}$$
$$r^2 = 0.8065$$
F. value = 555.011
$$p<0.001$$

$$B = 3.0025e^{1.6396(VI)}$$
$$r^2 = 0.7869$$
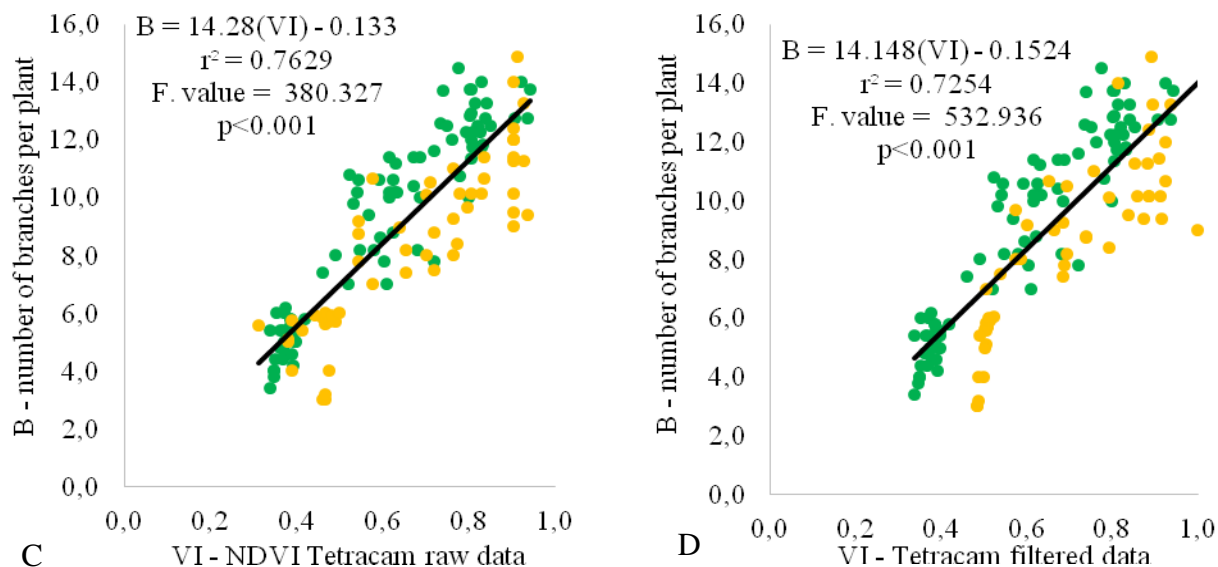F. value = 485.230
$$p<0.001$$

FIGURE3. Regression analyses between NDVI calculated from multispectral sensors and from four phenological moments, and number of branched per cotton plants cultivated on the harvest seasons 2013/14 (yellow dots) and 2014/15 (green dots).

NDVI sensor values were correlated with the phenological indices of cotton by the Pearson correlation coefficient (Table 1), which has dimensionless values and ranging from -1 to 1. The sign indicates positive or negative direction of the relationship and the value suggests the strength the relation between the variables. The positive values of this correlation considered to be weak range from 0.100 to 0.200, moderate range from 0.300 to 0.490, and strong range from 0.500 to 1.000. The strongest correlation obtained between NDVI sensors was 0.989, coming from the raw datagained by Tetracam and Crop Circle. The strongest correlation obtained between NDVI sensors and phenological readings was 0.960 coming from the raw data gained by Tetracam and cotton height. The lowest correlation but still considered strong was 0.832, obtained by the analyses between the plant height and number of branches per plant. In general, plant height has higher correlations with NDVI sensors than number of branches per plant. Almeida *et al.* (2012), studying spatial variability of biomass production and grain yield, obtained higher correlationvalue by using the same active GreenSeeker sensor, corroborating to the results obtained by Vian *et al.* (2014), which had a correlation of 0.710.

TABLE1. Pearson correlations between the NDVI of different sensors andphenological measurements of the cotton crop: height and number of branches.

	Crop Circle ACS 470	GreenSeeker RT 200	Tetracam ADC raw data	Tetracam ADC filtered data	Plant height
GreenSeeker RT 200	0.988*				
Tetracam ADC raw data	0.989*	0.986*			
Tetracam ADC filtered data	0.977*	0.971*	0.970*		
Plant height	0.955*	0.948*	0.960*	0.943*	
N. of branches	0.892*	0.880*	0.853*	0.889*	0.832*

*:P values significant for the 1% level by Pearson's correlation.

The correlations between NDVI values obtained by active sensorsand cotton crop phenology remained close to NDVI values obtained by the image with the passive Tetracam sensor installed on the support,regarding their raw values or filtered values.For Koundauri *et al.* (2006), an image with

higher quality and higher resolution are basic requirements for applications in precision agriculture in order to obtain reliable results. Vian *et al*. (2014), studying digital images in corn cropfor the purposes of soil, straw, and corn plant coverage classificationobtained a high correlation value between the percentage of this plant's coverage in relation to the soil and itsyield. According to the authors, high percentages of plant coverage resulted in less soil and straw interference in the final image result.Samseemoung *et al.* (2012), studying remote sensing at low altitude and capturingimages by different platforms in soybeancrop observed that the crane is more stable as a support in the acquisition of the scenes, leading to a higher quality of the final result when compared to the use ofthe unmanned air vehicle.

Several authors used NDVI in studies correlating VI with some phenological indices in different agricultural crops such asEitel (2008), Salvador & Antuniassi (2011), Almeida *et al*. (2012), Walsh *et al.* (2013) and Gehrke & Greiwe (2013); however, VI often suffers variations caused by local conditions, by the mode of application or by characteristics that are intrinsic to the sensors, such as spatial and spectral resolution. Therefore, studies involving NDVI should be properly characterized related to its condition of use, and comparative results between experiments must be analyzed carefully.

CONCLUSIONS

NDVI readings are positively correlated with plant height and number of branches per cotton plant. Active sensors present exponential correlations between NDVI and phenological readings. Passive sensor, when installed in a support above the cotton canopy level, presents linear correlation between NDVI and phenological readings.

NDVI values obtained by the passive sensor are higher than the active sensors.

Filtering the raw NDVI values obtained by passive sensor decreases the adjustment of the regression analyses with cotton height and number of branches per plant.

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