IN SITU REMOTE SENSING AS A STRATEGY TO PREDICT COTTON SEED YIELD

SENSORIAMENTO REMOTO IN SITU *COMO ESTRATÉGIA PARA PREVISÃO DO RENDIMENTO DE SEMENTE DE ALGODÃO*

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ABSTRACT: Crop harvest scheduling and profits and losses predications require strategies that estimate crop yield. This work aimed to investigate the contribution of phenological variables using path analysis and remote sensing techniques on cotton boll yield and to generate a model using decision trees that help predict cotton boll yield. The sampling field was installed in Chapadão do Céu, in an area of 90 ha. The following phenological variables were evaluated at 30 sample points: plant height at 26, 39, 51, 68, 82, 107, 128, and 185 days after emergence (DAE); number of floral buds at 68, 81, 107, 128, and 185 DAE; number of bolls at 185 DAE; Rededge vegetation index at 23, 35, 53, 91, and 168 DAE; and cotton boll yield. The main variables that can be used to predict cotton boll yield are the number of floral buds (at 107 days after emergence) and the Rededge vegetation index (at 53 and 91 days after emergence). To obtain higher cotton boll yields, the Rededge vegetation index must be greater than 39 at 53 days after emergence, and the plant must present at least 14 floral buds at 107 days after emergence.

KEYWORDS: Precision agriculture. Path analysis. Decision trees. *Gossypium hirsutum*.

INTRODUCTION

Upland cotton (*Gossypium hirssutum* L.r. latifolium Hutch.) is one of the most important textile fibers in the world, being one of the major economic important crops in Brazil (CARVALHO et al., 2015). The production cost of cotton crops in the Brazilian cerrado is about three times higher than that of soybean due to the increased number of pesticide applications, more demanding fertilizer of genotypes and more stringent crop treatments (IMEA, 2017; 2018). Therefore, an economically viable production requires techniques to minimize production costs and maximize continuous crop monitoring, such as precision agriculture (PA), which provides the knowledge of the variability of the different factors that directly influence production (SANA et al., 2014).

Monitoring the dynamics of terrestrial vegetation using remote sensing techniques may be relevant for agricultural activities. Currently, crops have been studied mainly by the analysis of their biophysical data for agronomic parameters (SOUZA et al., 2017). Besides remote sensing techniques, the use of vegetation indices (VI) of multispectral optical sensors correlates adequately to various plant growth attributes, such as plant biomass and leaf nitrogen (PORTZ et al., 2012; AMARAL et al., 2015). This fact allows its rationalized application and improves the efficiency of agrochemical inputs, decreases costs, and increases crop yield (SALVADOR; ANTUNIASSI, 2011; AMARAL et al., 2015).

Cruz and Regazzi. (2012) report that path analysis is a multivariate technique that unfolds the correlations between variables in direct and indirect effects on a major dependent variable. This analysis is commonly employed in plant breeding. This work aimed to evaluate the contribution of phenological variables using path analysis and remote sensing techniques on cotton boll yield and to generate a model using decision trees that help predict cotton boll yield.

MATERIAL AND METHODS

The experiment was performed in a cotton crop located in the region of Chapadões, in a 92 ha stand, at Fazenda Amambaí, municipality of Chapadão do Céu-GO (lat. 52°37'17.79 °C; long. 18 °21'21.40"S), in the agricultural year of 2014/15. The soil of the area is classified as Dystrophic Red Latosol (EMBRAPA, 2018). The average annual rainfall is 2,196 mm, and the average temperature is 22.5 °C. The climate of the region is tropical with dry winter, according to the Köppen classification. Its average altitude is 815 m, with predominantly smooth relief with 1 to 2% slope.

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Sowing was carried out on January 10th 2015, without second cultivation, having common beans as the previous crop. The cultivar FM 975WS was used in the experiment, spaced at 0.80 m between rows, totaling a population of 100,000 plants per hectare. Base fertilization followed the soil analysis, according to recommendations for cultivation in cerrado (FREIRE 2015). Fertilization was performed with 15 kg ha^{-1} of Nitrogen, 81 kg ha^{-1} of P_2O_5 in the planting groove, 90 kg ha^{-1} de K_2O applied on the surface, and 22 kg ha^{-1} of Nitrogen applied as topdressing. Phytosanitary treatments and agricultural inputs were applied during the crop development by monitoring the crop, following the standards for pest control and disease in the region (FREIRE 2015).

The sampling points were randomly distributed on the cotton stand at 23 DAE (days after emergence), corresponding to the phenological stage V5 (fifth true leaf), according to the classification proposed by Marur and Ruano (2001). Thirty points were determined in the field, based on the methodology described by Salvador and Antuniassi (2011). The points were distributed randomly at different sampling distances (Figure 1). At each sampling point, the phenological indices of five plants were measured to represent the local variability by their mean. These plants were marked to identify them for the following samplings. A GNSS Trimble Nomad (Sunnyvale, USA) was used to navigate to the sample points, in the Farm Works Mobile field sampling software of the same company.

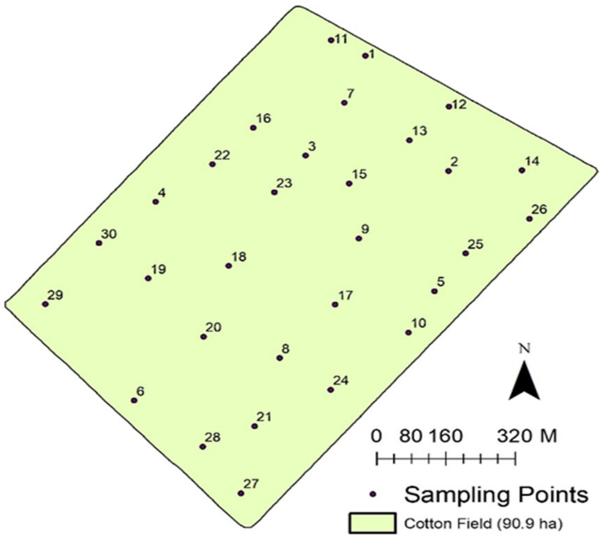

Figure 1. Statement of the evaluated points.

The following phenological variables were evaluated at 30 sample points: plant height (PH) at 26, 39, 51, 68, 82, 107, 128, and 185 days after emergence (DAE); number of floral buds at 68, 81, 107, 128, and 185 DAE; number of bolls at 185 DAE; Rededge vegetation index at 23, 35, 53, 91, and 168 DAE; and cotton boll yield. PH of each point was measured on the main stem from the soil surface to the insertion of the last fully expanded leaf.

VI data was collected using the active multispectral sensor N-Sensor ALS (Yara International ASA, Duelmen, Alemanha). This device is an active optical canopy sensor that emits its own light source and has spectral readings at the red and near-infrared edge wavelengths of 730 nm and 760 nm, respectively. The quartiles method of the values of the vegetation indices enabled the classification of the interpolated cells into three classes. The main function of this sensor is to detect the difference of reflectance, allowing the inference on the photosynthetic rate by a VI, according to Equation 1 (PORTZ et al., 2012).

$$VI\ Rededge = (\mathrm{nl}\,\rho 760 - \mathrm{nl}\,\rho 730) * 100 \qquad (1)$$

Where: VI = vegetation index; nl = natural logarithm; ρ = reflectance at the respective wavelength.

The N-Sensor was attached on the top of the cab of a self-propelled John Deere sprayer Model 4730 (Catalão, Brazil), at 3.10 m from the ground. The range scanned by the sensor has an average width of 3 m along the machine's travel path. The travel path was 30 m wide. To obtain the VI, plot scanning was carried out at 23, 35, 53, 91, and 168 DAE, at different phenological stages of the cotton crop.

The crop was harvested using a John Deere 7760 (DesMoines, EUA) cotton harvester, and the yield variability in the area was determined by a GreenStar Harvest Doc harvest monitoring system of the same company. At the end of the cycle, cotton yield data were evaluated, which had been obtained in the harvester containing yield sensors with georeferenced data. Thirty points were located over the map, using ArcGIS 10.5 software. After interpolation by the ordinary kriging methodology, the point yield information correlated to the other components was calculated by the mean of the points obtained within a 10 m radius of the control sampling point.

First, the Pearson's correlations between the phenological variables and yield were estimated. Due to the great number of variables in each class, the correlation network was used to graphically express the results, in which the proximity between the nodes (traces) is proportional to the absolute value of the correlation between them. The thickness of the borders was controlled by correlations estimations, where positive correlations were highlighted in green, while negative correlations were represented in red. This analysis was performed in the free software RBio (BHERING, 2017).

Subsequently, the multicollinearity analysis of the X'X correlation matrix was performed based on the Montgomery & Peck (2001) classification. Afterward, path analysis was carried out considering yield (Y) as the main dependent variable and the others as explanatory variables. The phenological variables that present high direct effect (in module) and in the same direction of their correlations to Y were identified. Finally, variables were used to generate a decision tree algorithm, considering Y as dependent. In this process, 80% of the data were used for algorithm training, and 20% for validation. The accuracy of the model was evaluated by the correlation between the estimated and observed values in each step. These analyses were performed using the Genes software (CRUZ, 2013).

RESULTS AND DISCUSSION

Correlation between phenological variables and yield

The linear correlations between cotton phenological variables and Y are shown in Figure 2. The highest correlation was observed between Rededge VI 23 DAE and Rededge VI 35 DAE (r = 0.8405). The phonological variable floral buds at 107 DAE presented the highest correlation to yield. In general, the vegetation index measured at different phenological stages of cotton plants was inter-correlated to the plant height at the initial stages. This fact happens because the vegetative growth of this crop produces a lot of plant matter originating from the increase of branches and leaves, covering the soil and increasing VI values. Souza et al. (2017) evaluated the correlation of VI to phenological indices in cotton and reported values of over 80% of similarity for plant height and over 70% for number of branches per plant. Motomiya et al. (2014) observed the behavior of the interaction of growth regulator doses, nitrogen topdressing, and VI, where they presented increasing VI values at the initial stages of the cotton crop until 67 DAE. After this evaluation, the VI values observed were stable due to VI saturation and the change to the crops' reproductive cycle.

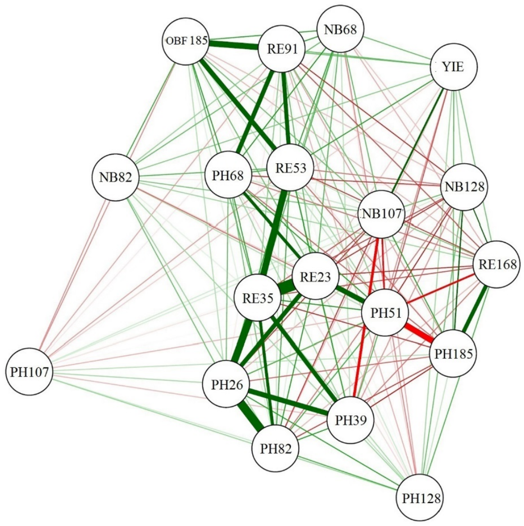

Figure 2. Pearson's correlation network between phenological variables and yield (Y).
** Y: yield; PH_AAA: plant height at AAA DAE; FB_BBB: number of floral buds at BBB DAE; BOL185: number of bolls at 185 DAE; RE_DDD: vegetation index at DDD DAE.

Linear correlations can be easily interpreted using the graphical network correlation technique. Usually, these results are expressed in an n × n dimension table, where n represents the number of variables evaluated. In this case, the large number of variables evaluated could compromise the overall interpretation of the results. The efficiency of this innovative technique has already been proven in other studies that evaluated a large number of variables (URSEM et al., 2008; DILEO et al., 2011; SILVA et al., 2016).

Thus, although important, the Pearson's correlation coefficient may lead to misunderstandings about the relationship between two variables, and may not be an actual measure of cause and effect. A high or low correlation coefficient between two variables s can be the result of the effect that a third variable or a group of variables have on that couple or variables, not giving the exact relative importance of the direct and indirect effects of these factors (CRUZ & REGAZZI, 2012). Therefore, path analysis was performed, which investigates the cause and effect relationship. Based on Teodoro et al. (2014), path analysis provides detailed knowledge of the influences of the variables and justifies the existence of positive and negative correlations, of high and low magnitude, between the studied variables.

Path analysis on yield

To obtain the direct and indirect effects of path analysis, the matrix X'X must be well-conditioned. In the presence of multicollinearity, the variances associated with the path coefficient estimators can reach exceedingly high values, becoming unreliable. In addition, the parameter estimates may assume absurd values or these values may not be coherent with the studied biological phenomenon (CRUZ & REGAZZI, 2012). According to the Montgomery & Peck (2001) criterion, the Pearson's correlation coefficient matrix showed weak multicollinearity since the condition number was lower than 100. Since multicollinearity was not detected, all the variables evaluated in the path analysis were used (Table 1).

Table 1. Path analysis of plant height (PH), number of floral buds (FB), number of bolls (BOL), and vegetation indices evaluated at different days after emergence on cotton boll yield.

Effect	PH 26	PH 39	PH 51	PH 68	PH 82	PH 107	PH 128	PH 185	FB 68	FB 82	FB 107	FB 128	BOL 185	RE 23	RE 35	RE 53	RE 91	RE 168
direct via Y	0.68	-0.26	-0.03	-0.31	-0.39	-0.25	0.34	0.09	0.26	-0.52	0.31	-0.27	-0.13	0.06	-0.57	0.92	0.17	0.37
indirect via PH26	---	0.43	0.24	0.20	0.50	0.12	0.29	-0.21	0.18	0.20	-0.28	-0.10	0.10	0.41	0.47	0.30	-0.02	-0.09
indirect via PH39	-0.16	---	-0.09	-0.05	-0.12	0.03	-0.03	0.12	-0.04	0.00	0.14	0.05	0.00	-0.11	-0.15	-0.09	0.00	0.07
indirect via PH51	-0.01	-0.01	---	-0.01	-0.01	0.00	0.00	0.02	0.00	0.01	0.02	0.01	0.00	-0.02	-0.02	-0.01	-0.01	0.02
indirect via PH68	-0.09	-0.06	-0.14	---	-0.09	0.00	0.02	0.10	-0.14	-0.01	-0.04	0.13	-0.14	-0.18	-0.14	-0.12	-0.19	0.09
indirect via PH82	-0.28	-0.17	-0.15	-0.11	---	-0.04	-0.15	0.15	-0.02	-0.07	0.16	0.10	-0.02	-0.18	-0.22	-0.15	-0.04	0.05
indirect via PH107	-0.04	0.03	0.03	0.00	-0.02	---	-0.05	-0.03	0.01	0.05	-0.02	-0.02	0.05	0.00	0.01	0.04	0.04	0.00
indirect via PH128	0.14	0.04	-0.03	-0.02	0.13	0.06	---	0.04	-0.08	0.06	-0.05	0.10	-0.01	0.03	0.05	0.00	-0.05	0.12
indirect via PH185	-0.03	-0.04	-0.06	-0.03	-0.03	0.01	0.01	---	0.00	0.01	0.04	0.04	0.00	-0.04	-0.04	-0.02	-0.02	0.05

indirect via FB68	0.07	0.04	-0.01	0.12	0.02	-0.01	-0.06	0.00	---	0.08	0.08	-0.03	0.11	0.09	0.09	0.11	0.11	-0.04
indirect via FB82	-0.15	0.00	0.15	-0.01	-0.10	0.11	-0.09	-0.08	-0.16	---	-0.14	0.02	-0.21	0.04	-0.03	-0.18	-0.11	-0.10
indirect via FB107	-0.13	-0.17	-0.16	0.04	-0.13	0.03	-0.05	0.14	0.10	0.08	---	0.09	0.09	-0.11	-0.11	0.04	0.09	0.08
indirect via FB128	0.04	0.06	0.12	0.11	0.07	-0.02	-0.08	-0.14	0.03	0.01	-0.08	---	0.03	0.11	0.10	0.07	0.11	-0.13
indirect via BOL185	-0.02	0.00	-0.02	-0.06	-0.01	0.03	0.00	0.01	-0.06	-0.05	-0.04	0.02	---	-0.04	-0.05	-0.08	-0.09	0.02
indirect via RE23	0.04	0.03	0.04	0.04	0.03	0.00	0.01	-0.03	0.02	-0.01	-0.02	-0.03	0.02	---	0.05	0.03	0.02	-0.03
indirect via RE35	-0.39	-0.34	-0.26	-0.25	-0.32	0.03	-0.09	0.24	-0.20	-0.03	0.19	0.20	-0.20	-0.48	---	-0.38	-0.13	0.20
indirect via RE53	0.40	0.32	0.17	0.35	0.37	-0.16	0.01	-0.26	0.39	0.32	0.11	-0.25	0.57	0.41	0.61	---	0.55	-0.35
indirect via RE91	-0.01	0.00	0.04	0.10	0.02	-0.03	-0.02	-0.03	0.07	0.03	0.05	-0.07	0.11	0.05	0.04	0.10	---	-0.06
indirect via RE168	-0.05	-0.10	-0.19	-0.10	-0.05	0.00	0.13	0.22	-0.06	0.07	0.10	0.18	-0.05	-0.16	-0.13	-0.14	-0.13	---
Total	0.01	-0.21	-0.34	0.00	-0.12	-0.09	0.19	0.33	0.30	0.23	0.53	0.19	0.31	-0.10	0.00	0.43	0.31	0.27

The estimate of the coefficient of determination was of high magnitude ($R^2 = 0.81$) and indicates that more than 80% of the variation of cotton boll yield is explained by the phenological variables. The use of path analysis in cotton plants has been only used for breeding purposes (TYAGI et al., 1998; IQBAL et al., 2003; HOOGERHEIDE et al., 2007; FARIAS et al., 2016).

The identification of the variables that have a cause and effect relationship with the main dependent variable (Y, in this study) requires the investigation of the direct effects obtained by the path analysis and the Person's correlations. Variables with a high direct effect on Y, but with correlations in inverse magnitude to this effect should not be used as predictors. For instance, PH26 has a high direct effect on Y; however, it has a low linear correlation. This result indicates that other variables interfere with this association by an indirect effect, as verified for PH82 and RE35.

Therefore, the main variable that could be used to predict Y was RE53 since it has a high direct effect (0.92) and in the same direction of their correlation with the main dependent variable. The representativity of the vegetation indices can be explained by the relation between the maximum production of leaves and branches, the high photosynthetic activity for the production of fruits in RE53. It is possible to verify in Figure 3 that the variability of these variables has high similarity.

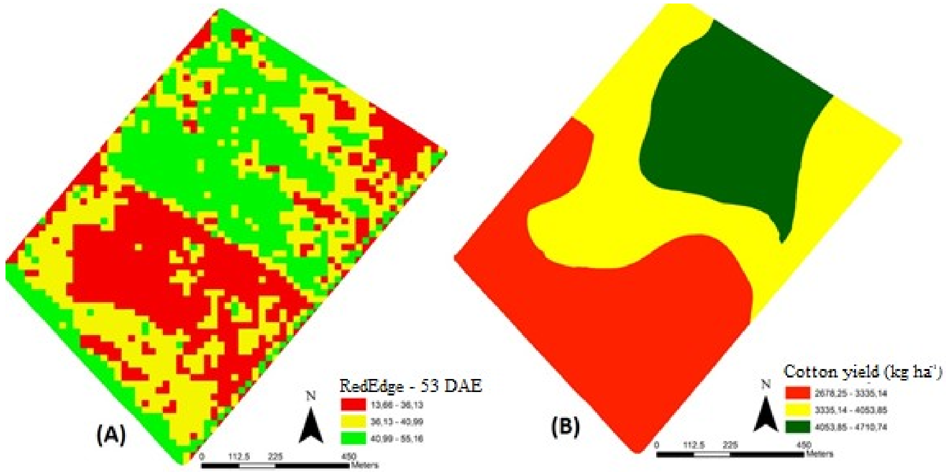

Figure 3. Red edge at 53 DAE (A) and cotton yield (D) maps of variability observed in sample points.

Regression tree using the variables selected by path analysis

After selecting the variables that have a cause and effect relationship (FB107, RE53, and RE91) on Y, a regression tree was constructed considering Y as the main dependent variable (Figure 4). This technique allows recognizing complex patterns to estimate a main dependent variable with continuous distribution (Y, in this study). The use of this technique to predict cotton boll yield up to now is still unprecedented.

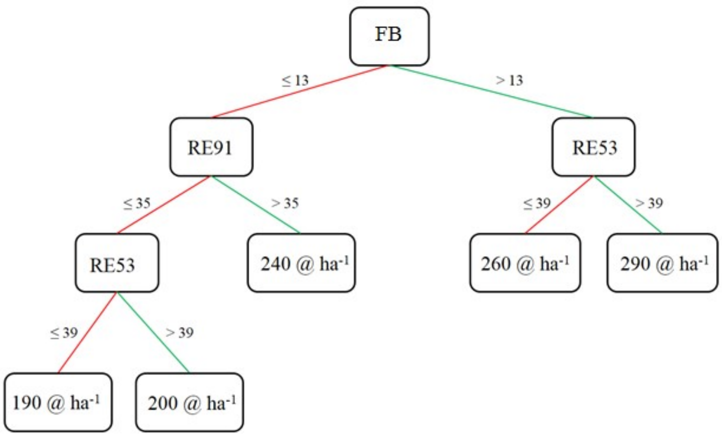

Figure 4. Decision tree generated with the variables FB, RE53, and RE91, selected by path analysis.

This study used four nodes and provided a correlation between the estimated and observed values for Y of 0.72 at the training stage (80% of the data) and 0.73 at the validation stage (20 % of data). Results revealed credibility for Y prediction from the variables selected by the path analysis.

Thus, to obtain the highest yields, the number of floral buds (FB) at 107 DAE must be higher than 13, and the vegetation index RE at 53 DAE must be greater than 39 (Figure 2). If the estimate of this index is lesser than 39, the farmer needs to ensure a high number of floral buds to reach 260 @/ha. Therefore, the vegetation index RE53 is as a threshold for guiding crop yield estimates.

CONCLUSIONS

The number of floral buds at 107 days after emergence and the Rededge vegetation index measured at 53 and 91 days after emergence are the main variables to predict cotton boll yield.

To obtain the highest cotton boll yield, the Rededge vegetation index must be greater than 39 at 53 days after emergence and the plant must present at least 14 floral buds at 107 days after emergence.

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RESUMO: O escalonamento de colheitas e a previsão de ganhos e perdas requerem estratégias que estimam a produtividade das culturas. Este trabalho teve como objetivo investigar a contribuição de variáveis fenológicas utilizando técnicas de análise de trilha e sensoriamento remoto sobre a produtividade de algodão em caroço e gerar um modelo utilizando árvores de decisão que ajudam a prever esta variável. O campo de amostragem foi instalado em Chapadão do Céu, em uma área de 90 ha. As seguintes variáveis fenológicas foram avaliadas em 30 pontos amostrais: altura das plantas aos 26, 39, 51, 68, 82, 107, 128 e 185 dias após a emergência (DAE); número de gemas florais aos 68, 81, 107, 128 e 185 DAE; número de cápsulas a 185 DAE; Índice de vegetação Rededge em 23, 35, 53, 91 e 168 DAE; e produção de algodão em caroço. As principais variáveis que podem ser utilizadas para prever a produção de caroço de algodão são o número de gemas florais (aos 107 dias após a emergência) e o índice de vegetação de Rededge (aos 53 e 91 dias após a emergência). Para obter maiores produtividades de algodão, o índice de vegetação de Rededge deve ser superior a 39 aos 53 dias após a emergência e a planta deve apresentar pelo menos 14 gemas florais aos 107 dias após a emergência.

PALAVRAS-CHAVE: Agricultura de precisão. Análise de trilha. Árvores de decisão. *Gossypium hirsutum***.**

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