Geoestatistical tools and spectral measurements from AWiFs data for evaluation of N and P contents in cotton leaves

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Abstract. Satellite images and geostatistics are useful tools to assess the nutritional status of plants, and thus, understanding the variability of cotton yield in farmers' fields. The resulting kriged maps provide a unique opportunity to overcome both spatial and temporal scaling challenges and understanding the factors that led to crop yield. To support decisions on improving cotton yield, this study combines the conventional statistic analysis, spatial regression modeling of georreferenced data and AWiFs' vegetations indices assessment. The experiments were carried out in a 47.4 ha commercial field of Goiás state, Brazil. Multispectral satellite images at 56 m spatial resolution were collected in a rainfed cotton field in two dates, on 04/01/2011 and 04/10/2012, from AWiFS sensor during the flowering cotton stage. Measures of leaf nitrogen (N) and phosphorus (P) contents were determined over previously georreferenced central points of 70 plots, each one measuring 80X80 m. Data were analyzed using descriptive statistics and geostatistical analyses by building and setting semivariograms and kriging interpolation. Best correlation was found between IVs and nitrogen contents of cotton leaves. Results indicated that NDVI, MSAVI and SAVI were the best indices to estimate P contents at cotton peak flowering. Identifications of spatial differences were possible using geostatistical methods with remote sensing data obtained from medium resolution satellite images, allowing to identify distinct nutritional needs and growth status of canopy to cotton plants.

Keywords: vegetation indices, spatial variability, kriging, remote sensing, precision agriculture,

1. Introduction

Optimization of crop nutrition is essential for maximizing cotton yield. Reduced nutrition will diminish the crops' yield potential, while too much fertilizer can impact your profitability, increasing costs and risks of groundwater contamination. Macro nutrient elements such as N and P account for plant growth and health and affect cotton yield and fiber quality. Therefore, careful monitoring and management of nutrient levels is important in agriculture to ensure that yield potential will be reached, without inefficient fertilizer application.

However, anything that causes plant stress will affect nutrient uptake. Thus, conventional chemical analyses are usually made to determine nutrient element status of plants using laboratory techniques to achieve the proper cotton fertilization. But, laboratory analyses are expensive, laborious, and time consuming.

Spectral reflectance is being used as a way to solve these problems. Especially in large areas, orbital or suborbital images are very useful in detecting nutritional failures, because provide fast and nondestructive field information's. Remotely sensed data have been widely used to develop vegetation indices as indicators of crop growth, nutrient status assessment and yield prediction (Eitel et al., 2008).

Vegetation indices from spectral reflectance has been the subject of many studies as a method of crop evaluation and management for large areas, since the sensitivity of spectral indices can explain up to 92% of the variability in crop biophysical and biochemical variables (Zhao et al. 2005; Shiratsuchi, et al., 2014).

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Excessive nitrogen delays maturity, can intensify insect infestations and increases the risk of boll rot, reducing lint quality (Robertson and Roberts, 2016). N deficiency will cause pale green leaves, small bolls, drop of fruit and reduced yields.

Differently of N, phosphorus has low mobility in the soil and leaching is not a problem. Instead, mobility to the roots is the prime limitation to uptake. Plants with very low P content exhibit red or purplish color (anthocyanin pigment) in leaves, especially undersides and death of tissue or necrosis may follow (Salisbury and Ross, 1978). Root growth poor and lower stems may be purplish. Thus, insufficient phosphorus results in dwarfed plants, delays fruiting and maturity, and reduces yield. Fortunately, even that the cotton is in flowering stage, there is still time to supplement with extra nitrogen and phosphorus, using plant monitoring. Therefore, N and P visual deficiencies in cotton leaves combined with plant structure and many other physiological changes can be measured through crop reflectance using multi and hyperspectral instruments and have proven to be a strong estimator of cotton leaf N and P status, (Osborne et al., 2002; Zhao et al., 2005; Mahajan et al., 2014).

Additionally, geostatistical estimation makes possible to estimate values at unsampled locations by taking spatial correlation between estimated and sampled points into account. Geostatistics also provides an interpolation technique (kriging) that can predict response variables at unsampled locations (Oliver and Webster, 2014). This interpolation method allows the data visualization into maps and became a useful tool to evaluate the variability of many crop properties (Brandão et al. 2014). Measures readings and spectral data can be converted into maps showing the variability for direct application in precision farming.

In this context, the objective of this study was to analyze through geostatistical methods, the influence of N and P contents on the spatial identification of some vegetation indices as, Normalized difference vegetation index (NDVI), Soil Adjusted Difference Vegetation Index (SAVI), Modified SAVI (MSAVI), MTVI2 (Second Modified Triangular Vegetation Index), and MCARI2 (Second Modified Chlorophyll Absorption Ratio Index) from AWFIS images, on a cotton commercial field in Goiás state, Brazil.

2. Material and Methods

2.1 Location and field data

This study was conducted for two years in an experimental area of 44.8 ha, located at Pamplona Farm (16º10’16’’ S, 47º37’47’’ W), Cristalina, GO state, Brazil. Soil is Typic Hapludox, with clay, 59.5%; sand, 16.1%; silt, 24.3%; pH in water, 5.67; Ca, 3.11 cmolc dm^3; organic matter, 2.93%; available phosphorus, 3.52 mg dm^3; and potassium, 0.25 $cmol_c\ dm^{-3}$.

A sampling grid was made with 70 points of 80*x*80m. Field data were collected at 110 and 100 DAE (days after emergence) to 2011 and 2012 years, into a 10m radius of the each central point, previously georeferenced. Fertilization was applied in four stages (pre-planting, sowing, emergence and 45 DAE) adding up to a total of 160 kg N ha^{-1} and 204 kg P_2O_5 ha^{-1}

Leaf samples were collected on 30 plants for each point, at peak flowering stage during 2011 and 2012 seasons, considering the date that satellite images were available. Leaf N and P concentrations were determined on duplicate samples of 6 mg of ground leaf material.

2.2 Satellite data

Two images generated by the sensor AWiFS (Advanced Wide Field Sensor) were acquired to identify correlation with cotton yield. The first one on 01/04/2011 (110 DAE), with orbit 327 and point 087, and the second image on 10/04/2012 (100 DAE), (330/089).

The spectral bands of AWiFS sensor used in this work correspond to channel 2(green), 3(red) and 4 (near infrared). After corrections and radiometric calibration of the images, reflectance and vegetation index for two sampling dates were determined. All procedures for image rectification and calibration were performed using software ERDAS IMAGINE® 9.1.

From the reflectance images, spectral indices, NDVI, MSAVI, SAVI, MTVI2 and MCARI were calculated based on the equations provided by many authors and summarized by Shiratsuchi et al. (2014):

NDVI (*Normalized Difference Vegetation Index*)	$NDVI = (\rho_{NIR} - \rho_R)/(\rho_{NIR} + \rho_R)$	Rouse et al. (1973)	(1)
SAVI (*Soil Adjusted Difference Vegetation Index*)	$SAVI = (1+L))(\rho_{NIR} - \rho_R)/(\rho_{NIR} + \rho_R + L)$	Huete (1988)	(2)
MSAVI (*Modified SAVI*)	$MSAVI = \frac{1}{2}\left[2\rho_{NIR} + 1 - \sqrt{(2\rho_{NIR}+1)^2 - 8(\rho_{NIR} - \rho_R)}\right]$	Qi et al., 1994	(3)
MTVI2 (*Second Modified Triangular Vegetation Index*)	$MTVI2 = \frac{1.5[1.2(\rho_{NIR} - \rho_G) - 2.5(\rho_R - \rho_G)]}{\sqrt{(2\rho_{NIR}+1)^2 - 0.5 - 6(\rho_{NIR} - 5\sqrt{\rho_R})}}$	Haboudane et al., 2004	(4)
MCARI2 (*Second Modified Chlorophyll Absorption Ratio Index*)	$MCARI2 = \frac{1.5[2.5(\rho_{NIR} - \rho_R) - 1.3(\rho_{NIR} - \rho_G)]}{\sqrt{(2\rho_{NIR}+1)^2 - 0{,}5 - (6\rho_{NIR} - 5\sqrt{\rho_R})}}$	Haboudane et al., 2004	(5)

where ρ_x, represents the reflectance, and x = AWiFs Green (G), Red(R) and Near Infrared (NIR) bands.

2.3 Geostatistc analysis

Data were submitted to statistical analysis for determination of mean, maximum, minimum, kurtosis coefficient, frequency distribution and coefficient of variation (CV). The Kolmogorov-Smirnov test, on which skewness and kurtosis values should be near zero for normal distributions, was used to verify the normality of the data frequency. The coefficients of variation were evaluated based on Warrick and Nielsen criteria (Oliver and Webster, 2014), which classifies as low a CV < 12%, regular CV from 12% to 60% and high to CV > 60%.

Spatial dependence of nutrientes, LAI and IVs obtained from cotton plants were studied by semivariogram analysis (Figures 1, 2). Geostatistical analysis was performed by constructing and adjusting semivariogram and ordinary kriging interpolation using the geostatistical software GEOEST (Vieira et al., 2002).

Semivariograms were estimated by equation (6):

$$\gamma^*(h) = \frac{1}{2\,N(h)} \sum_{i=1}^{N(h)} [Z(x_i) - Z(x_i + h)]^2 \qquad (6)$$

where N(h) is the number of pairs of measured values Z(x_i), Z(x_i + h) separated by a vector h.

It is expected that measurements within some neighborhood are more similar than those separated by large distances (Vieira et al., 2002). If spatial dependence is showed by the semivariogram, unsampled data can be estimated by kriging, with minimum variance and without trend (Oliver and Webster, 2014). Contour maps were made with the estimated data as a function of geographic coordinates. All the results were presented as two-dimensional maps representing the spatial distribution of the values of VIs and leaf contents of N and P.

3. Results and Discussion

Descriptive statistics of cotton nutrients, LAI and IVs were presented in Table 1 for the two sampling date (110 DAE in 2011 and 100 DAE in 2012). All variables showed low CV variation for the two years, whose values were lower than 12%. This indicated that data analysis were homogeneous with significant averages, and so, can be used as representative of the study area. Plant attributes showed skewness and kurtosis coefficients as a normal distribution, agreeing to Motomiya et al. (2011). The nugget effect (C_0) represents non-explained variance, frequently caused by errors in measurement or by properties variations not detected in the sampling scale (Oliver and Webster, 2014). The semivariance model (Sph or Exp), and the parameters, C0, C and range are within each graph of Figures 1 and 2.

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Table 1. Descriptive statistical analysis for leaf cotton contents of nitrogen (N) and phosphorus (P), and also the vegetation indices (NDVI, SAVI, MSAVI, MTVI2, MCAI2 and IAF) obtained from satellite images data at 110 and 100DAE, in 2011 and 2012, respectively.

Year	Variable	Mean	Variance	Std. Dev	CV (%)	Minimum	Maximum	Skewness	Kurtosis
2011	IAF_{11}	1.108	3.42E-03	0.0059	5.275	0.99	1.2	-0.2468	-0.9347
	N_{11} (g kg^{-1})	45.53	5.065	2.251	4.943	41	51.7	0.3934	0.6009
	P_{11} (g kg^{-1})	3.26	4.51E-02	0.2124	6.524	2.8	3.8	0.3529	-0.4055
	$SAVI_{11}$	0.46	4.05E-04	0.002	4.234	0.42	0.53	0.336	0.2783
	$NDVI_{11}$	0.85	7.66E-04	0.0028	3.254	0.8	0.93	1.021	0.6988
	$MSAVI_{11}$	0.49	3.30E-04	0.0012	3.741	0.44	0.55	0.4687	1.409
	$MTVI2_{11}$	0.36	3.94E-04	0.0019	5.566	0.31	0.4	0.4129	-0.2855
	$MCARI2_{11}$	0.36	3.72E-04	0.0019	5.415	0.31	0.4	0.445	-0.0054
2012	IAF_{12}	2.034	3.17E-02	0.1779	8.747	1.42	2.38	-1.143	1.971
	N_{12} (g kg^{-1})	35.53	5.64	2.375	6.684	26.39	41.09	-0.3298	2.445
	P_{12} (g kg^{-1})	2.042	3.96E-02	0.199	9.745	1.68	2.51	0.1731	-0.6035
	$NDV1_{12}$	0.7781	7.72E-04	0.0028	3.57	0.72	0.88	0.8572	2.717
	$SAV1_{12}$	0.6007	1.25E-03	0.0035	5.879	0.51	0.73	1.034	3.269
	$MSAVI_{12}$	0.624	1.14E-03	0.0034	5.405	0.5	0.72	-9.42E-03	3.408
	$MTVI2_{12}$	0.3501	5.12E-04	0.0024	6.46	0.29	0.41	0.268	1.225
	$MCARI2_{12}$	0.343	4.71E-04	0.0022	6.324	0.28	0.4	6.56E-02	1.606

Results from the geostatistical analysis are presented in Figures 1 and 2, for 2011 and 2012, seasons, respectively.

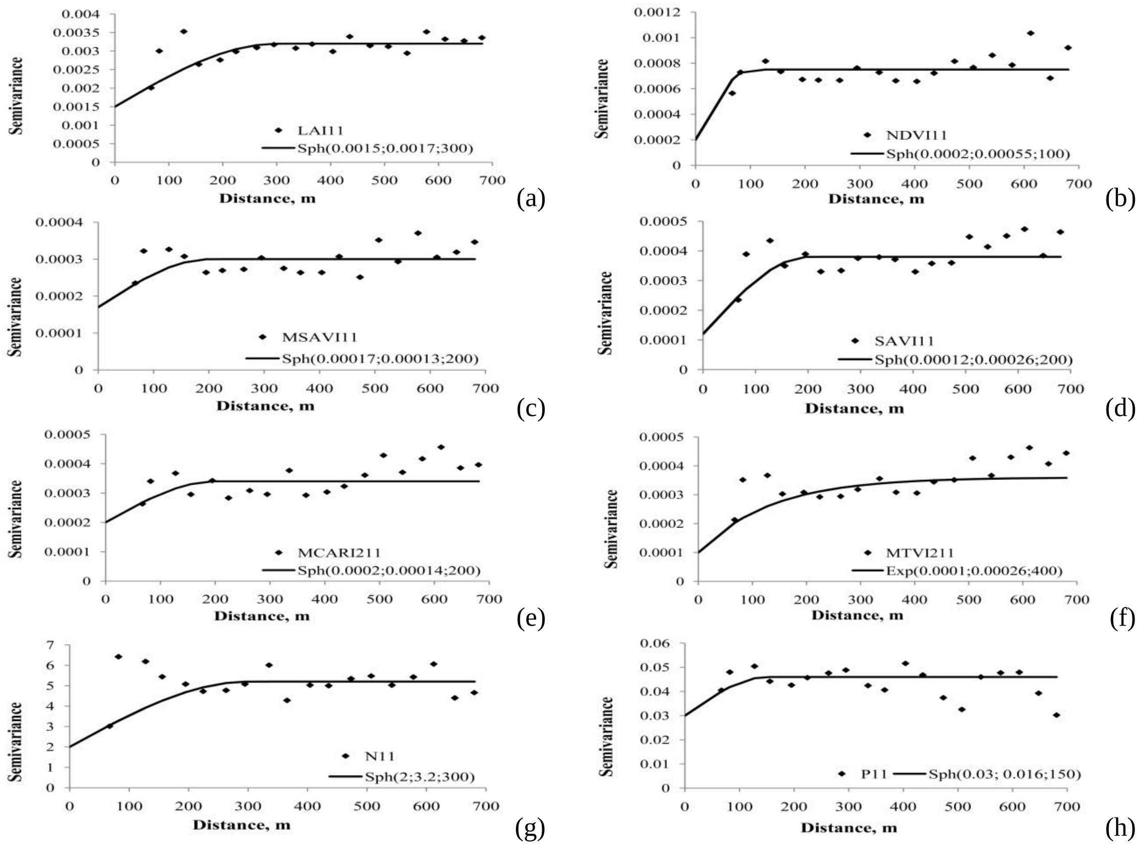

Figure 1. Semivariograms fitted with parameters nugget effect, rang and partial sill of the variable to 2011 data at 110 DAE. (a) LAI_{11}; (b) $NDVI_{11}$; (c) $MSAVI_{11}$; (d) $SAVI_{11}$; (e) $MCARI2_{11}$; (f) $MTVI2_{11}$; (g) Leaf N_{11} content; (h) Leaf P_{11} content.

Spatial dependence of nutrientes, LAI and IVs was observed by experimental semivariograms that were fitted using the best-adjusted model with a smaller root mean square (RMS) and validated by the jack-knifing method (Vieira et al., 2002). With the exception of MTVI2$_{11}$, which was adjusted to exponential model, all data and crop characteristics were fitted to the spherical model.

Satellite images provided good results for predicting N status in first year and N and P status during cotton peak bloom stage to 2012 season. Uptake of nitrogen by cotton peaks at about 2.2 to 3.3 kg per hectare per day during fruiting stage (Rochester et al., 2012; Brandão et al., 2014). To examine if IVs could be used as an alternative for cotton leaf nitrogen content, the Pearson' correlations (*r*) were evaluated. Statistically significant ($p<0.0001$) correlations (***r***) between VIs and N contents were obtained for the first season, with a ***r*** range of 0.67–0.75, while in 2012 correlations were between 0.62 and 0.72. However, by accounting for spatial dependence, regression coefficients may change (Calderón, 2009) and the best way to evaluate the spatial distribution is using kriging maps of estimated data as showed in Figures 3 and 4, for 2011 and 2012, respectively.

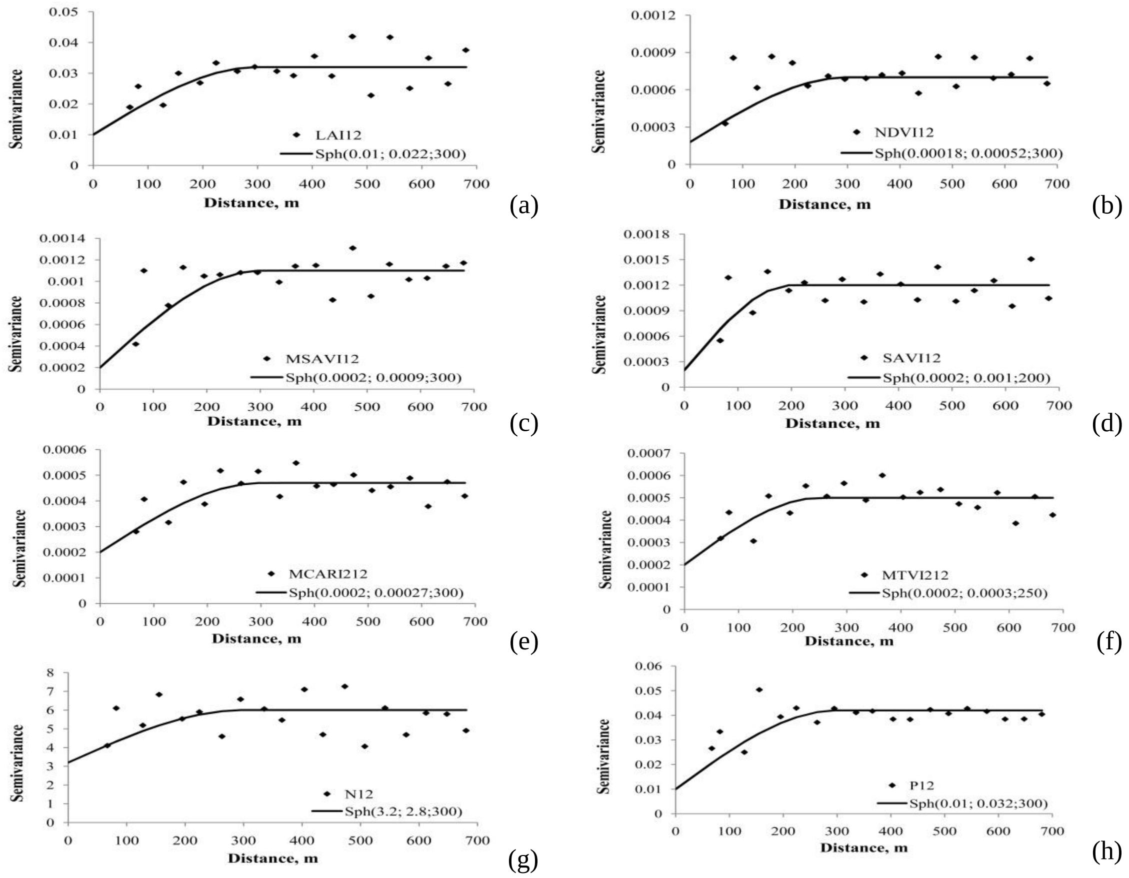

Figure 2. Semivariograms fitted with parameters nugget effect, rang and partial sill of the variable to 2012 data at 100 DAE. (a) LAI$_{12}$; (b) NDVI$_{12}$; (c) MSAVI$_{12}$; (d) SAVI$_{12}$; (e) MCARI2$_{12}$; (f) MTVI2$_{12}$; (g) Leaf N$_{12}$ content; (h) Leaf P$_{12}$ content.

Leaf nitrogen content is a good indicator of healthy plants. Plant vigor was represented as dark gray color on Figure 3b for high N values, which varied from 41 to 45.5 g kg^{-1} in 2011. The great N content, stimulate crop growth and produce a greater amount of biomass, which further influenced the optical properties of the crop canopy. In 2011, these values were above sufficiency range for nitrogen in this cotton peak flowering stage, (35-43 g kg^{-1}).

For the second year (Figure 4b), N leaf contents do not reached the expected values, and ranged from 26 to 41 g kg^{-1}. Thus, in 2012 nitrogen content to many experimental plots were bellow the expected, indicating that cotton plants were still in high consuming of the nutrient. This fact may be explained by the high rainfall occurred during the three first months of 2012,

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which caused leaching and also displacement of soil surface along the crop area, bringing delay in plant development (Rochester et al., 2012).

Satellite images at 110 and 100 DAE (Figure 3b and 4b) presented good correlations with the strong leaf greenness. All indices showed great similarity in spatial distribution maps for the two seasons, confirming the good correlation observed, indicating that the IVs obtained by AWIFS images can be useful in estimating the leaf nitrogen content for this culture.

LAI presented a CV lower than 12%, indicating homogeneous data set during 2011 and 2012 seasons, (Figures 3 and 4). The results indicating that plants cover almost all the space between the sowing lines with mean values of 1.11 and 2.03, for 2011 and 2012. Apparently, this difference between LAI values was probably because in the first year, phosphorus foliar contents were higher than in second season, allowing plants to grow taller. In addition, excessive rainfall in 2012 interfered with growth regulator application.

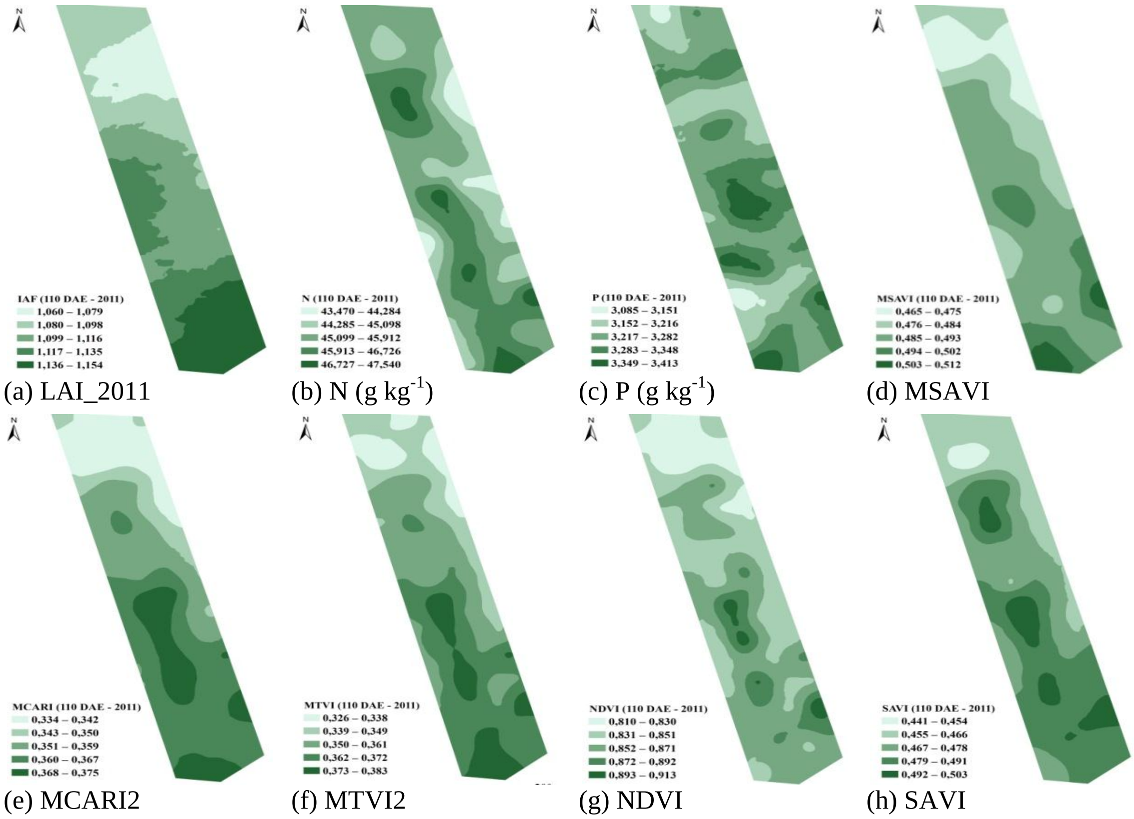

Figure 3. Maps for satellite image and field data during 2011 season, showing spatial distribution of: (a) LAI_{11}; (b) Leaf N_{11} (g kg^{-1}); (c) Leaf P_{11} (g kg^{-1}); (d) $MSAVI_{11}$; (e) $MCARI2_{11}$; (f) $MTVI2_{11}$; (g) $NDVI_{11}$; (h) $SAVI_{11}$.

Despite the height of the plants, the results showed a lower reflectance in 2012 than observed in 2011. Probably this is due to the P deficit, which left some leaves purplish at the points with a lower P_{12} content. Similar results were found to corn by Osborne et al. (2002), that observed purpling at the leave margins in the P stressed plots. Salisbury and Ross (1978) stated that anthocyanin strongly absorbs in the green region while reflecting in the blue or red region of the spectrum.

In 2012, the leaf mean content of P_{12} was below the sufficiency range in all analysis, which ranged from 1.68 to 3.38 g kg^{-1}, indicating that, during the cotton flowering stage, there is still high demand for P. Similar results were obtained by Motomiya et al. (2011), which found average values below the level of sufficiency for cotton in the same stage. According to Rochester et al (2012), nutrients are taken up throughout the growing season, agreeing with

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the demand for nutrients stated by developing crop biomass and boll load. Phosphorus uptake is completed by the time the crop reaches the 50% open boll stage . P uptake by cotton varies in a range of 0.2-0.74 kg ha^{-1} per day during flowering stage (Mullins and Burmester, 2010).

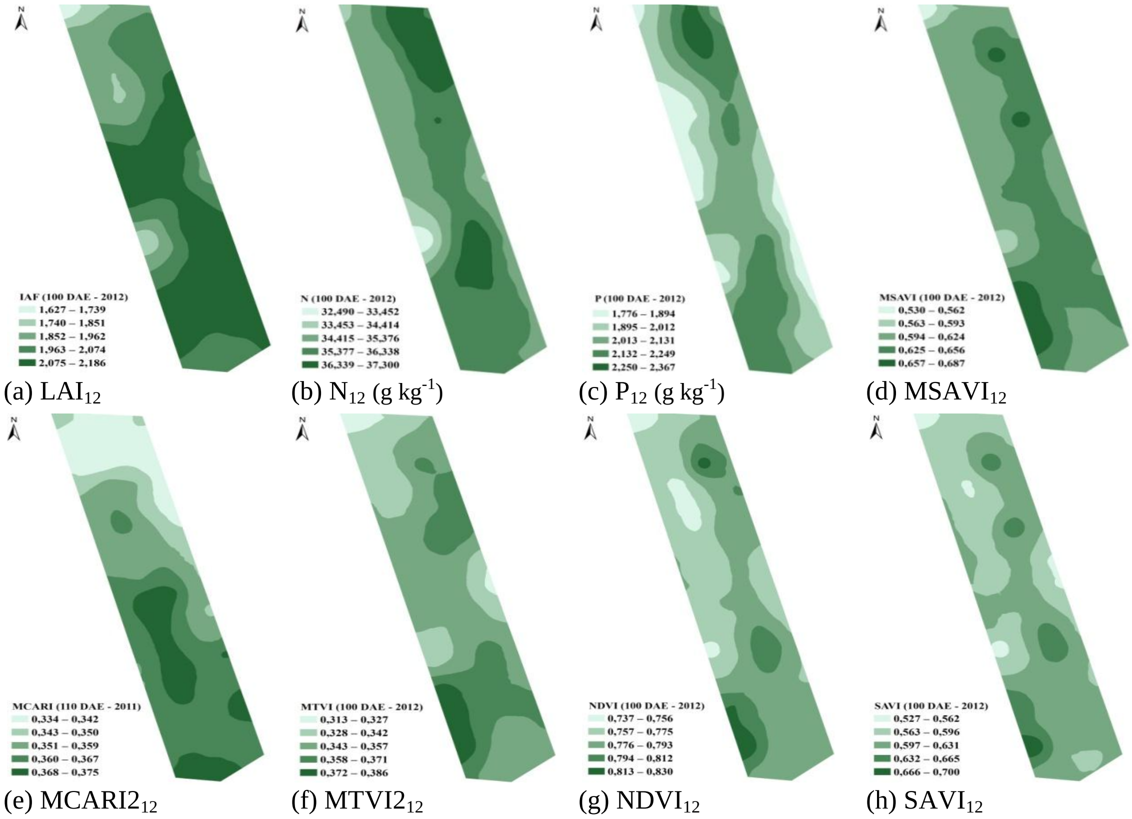

Figure 4. Maps for satellite image and field data during 2012 season, showing spatial distribution of: (a) LAI_{12}; (b) Leaf N_{12} (g kg^{-1}); (c) Leaf P_{12} (g kg^{-1}); (d) $MSAVI_{12}$; (e) $MCARI2_{12}$; (f) $MTVI2_{12}$; (g) $NDVI_{12}$; (h) $SAVI_{12}$.

Best similarities with phosphorus spatial distribution were observed in 2012 for $NDVI_{12}$, $SAVI_{12}$ and $MSAVI_{12}$ (Figure 4), that presented statistically significant correlations of 0.52, 0.42 and 0.41 with P_{12} contents. Perhaps, the reflectance data were influenced by light purple color in some experimental spots where P content were very low. Özyiğit and Bilgen (2013), studying reflectance bands to represent cotton P contents, founded best agreement of the spatial distribution in the experimental area to red bands (675 and 680 nm).

On the other hand, even with very green plants and sufficient P_{11} contents (2.8-3.8 g kg^{-1}) as presented in 2011, $MSAVI_{11}$ and $NDVI_{11}$ kept significant ($p<0.001$) correlations with P_{11} contents (***r*** = 0.39 and 0.36), and both IVs kriging maps showed similarities on distribution, where the highest and lowest values practically occur in the same position of the study area.

4. Conclusions

There was spatial dependence for all data analyzed, but the spatial dependency to nitrogen was higher than phosphorus.

Similarities observed to both years in the spatial distribution of vegetation indices (IVs) obtained by AWiFs data and foliar content of nitrogen and phosphorus, indicated that satellite data can estimate nutritional requirements of N and P at peak flowering stage of cotton.

Normalized difference vegetation index (NDVI), Soil Adjusted Difference Vegetation Index (SAVI) and Modified SAVI (MSAVI) were good correlated with nitrogen and phosphorus contents of cotton leaves, even with cotton in low rate nutrition.

Identifications of spatial differences were possible using geostatistical methods with remote sensing data obtained from medium resolution satellite images, allowing to identify distinct nutritional needs and growth status of canopy to cotton plants.

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