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Principal Component Analysis in Monitoring Soybean Fields of Brazil through the MODIS Sensor

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ABSTRACT

The monitoring of the Earth's surface and the dynamics of its vegetation using remote sensing techniques stands out in agricultural activities. The objective of this study was to estimate and map areas cultivated with soybean [*Glycine max* (L.) Merr.] by means of mono and time-series MODIS images in Paraná state through principal component techniques. For this mapping were used vegetation index (EVI and CEI) with the help of as time-series from images of MODIS sensor also was performed by supervised classification algorithms and partially unsupervised with use of principal component analysis. For statistical evaluation parameters were used Kappa and overall accuracy and their respective Z and t-tests. When analyzing the data obtained by the methods used in the estimates of soybean areas it appears that the ratings by the CEI index was highlighted with higher Kappa parameters (κ) and Overall Accuracy (OA), unlike the classifier K-means. For the principal component used five images including vegetation indices, presented to the Kappa 0.48 parameter. The mapping, discrimination and quantification of soybean fields in the state of Paraná was possible with the use of classifiers and MODIS images, which the systematization presented results of Kappa parameters and overall accuracy satisfactory.

Key words: GIScience, agricultural monitoring, remote sensing, orbital sensor

INTRODUCTION

The monitoring of the earth's surface and the dynamics of its vegetation using remote sensing techniques stands out in agricultural activities. Today's, crops have been mainly studied in the context of reviews of the plant by means of biophysical parameters (Bsaibes *et al*., 2009) and estimates of cultivated areas (Pan *et al*., 2012).

In addition to the temporal dynamics of agricultural crops require data to enable monitoring, also it is necessary the use of technologies and methods to analyze the magnitude of such data. Estimation of cultivated areas has been used by satellite images involving concept of probabilistic design, sampling areas of panel and selection probability sample (FAO., 1998). Previous to these estimators, preprocessing and classification methods are worked satellite images for stratification of the areas of interest (Gallego, 2004) which requires working time. For example it is used commonly, vegetation indices, supervised classification (MaxVer) and partially unsupervised (K-means).

For agricultural areas with larger extensions the identification problem is minimized with regard to images and coarse spatial resolution different phenological stages of agricultural crops which can be spectrally differentiated by time-series images (Potgieter *et al*., 2010). Thus, it is essential to know the timing of each agricultural crop according to crop region displayed by an agricultural zoning.

The use of MODIS (MODerate-resolution Imaging Spectroradiometer) aboard the Terra and Aqua satellite appears very useful for mapping large agricultural areas

(Peng and Gitelson, 2012). One of its outstanding features for your choice should be the same present temporal resolution almost daily and production of images with 12-bit quantization in 36 spectral bands. One of the drawbacks relates to the spatial resolution of the images being produced at the nadir of two bands in 250 m (0.620-0.876 μm), five bands in 500 m (0.459-2.155 μm) and 29 bands in 1000 m (0.405-14.385 μm) (Huete *et al*., 1997).

Bernardes *et al*. (2011) evaluated methodology application as time-series with MODIS images according to the spectral behavior of soybeans in Mato Grosso state using principal components. They found that when using all images containing the entire crop cycle, the results showed to be superior when used only a single date.

The objective of this study was to estimate and map areas cultivated with soybean [*Glycine max* (L.) Merr.] by means of mono and time-series MODIS images in Paraná through principal component techniques.

MATERIALS AND METHODS

Characterization of study area: The study area comprised the state of Paraná, in southern Brazil, located in the geographical coordinates Latitude 22°29' to 26°43'S and Longitude 48°20' to 54°38'W (Fig. 1). The altitude varies and 52% of the territory are over 600m and only 3% are less than 300 m. For the climate, are characterized three predominant types, according to Köppen classification are: CFA (subtropical with rainfall well distributed throughout the year and hot summers), Cfb (subtropical with rainfall well distributed throughout the year and mild summers) and Cwa (subtropical with hot summers and dry winters, occurs in the northwest of the state).

Used vegetation indices: So, were used MODIS images, which established the EVI values (Enhanced Vegetation Index, Eq. 1) of MOD13Q1 product, tile H13V11, collection 5.0, the

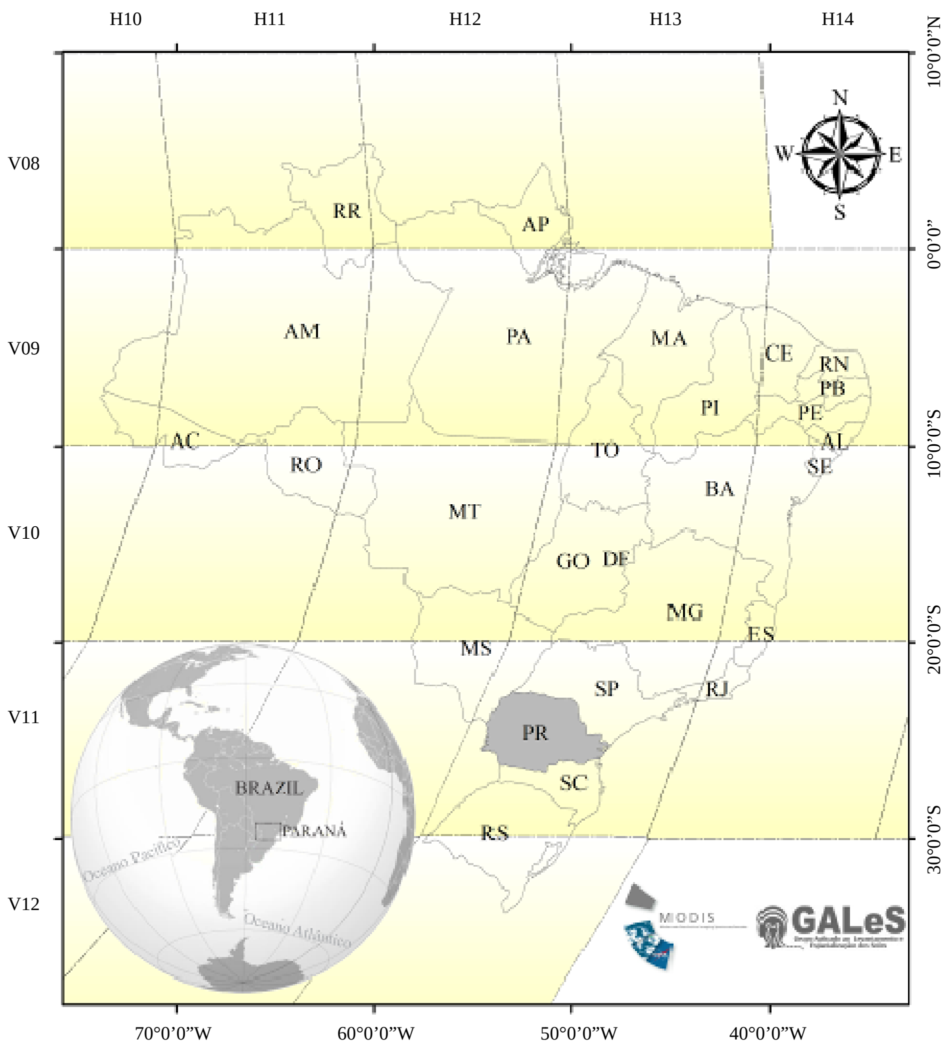

Fig. 1: Location of the study area, ranging in southern Brazil, Parana state and the respective tiles of the MODIS/Terra sensor

composite MODIS images of 16 days (Huete *et al*., 1997) Terra satellite, with spatial resolution of 250 m, downloaded from the USGS LP-DAAC:

$$\text{EVI} = g.\frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + (c_1.\rho_R) - (c_2.\rho_B) + 1} \quad (1)$$

where, $\rho_{NIR}, \rho_R e \rho_B$; reflectance in the spectral range of the near infrared, red and blue, respectively; g: Gain factor (2.5); c_1 and c_2 are the weightings of the atmospheric effects to red (6) and blue (7.5), respectively; l is the correction factor for soil interference.

The EVI is an vegetation index that is designed to mitigate the effects of soil (adjusted by SAVI) and atmosphere (adjusted by ARVI) in the mapping of vegetation. In addition to the EVI, were used for further analyzes the images of the product MOD13Q1: blue, red and near infrared.

All images were obtained originally in HDF format (hierarchical data format) and sinusoidal projection, were processed according to the development of batch automation routines (Silva, Jr., 2014). Thus, the data have been redesigned for geographic coordinates (Latitude and Longitude), DATUM WGS-84 (World Geodetic System 1984) and automatically converted into GeoTIFF format. The dates corresponding to the time-series used are shown in Table 1.

Procedures classifier supervised and partially unsupervised: The methodological procedures consisted in the application of different digital image processing routines, which can be summarized in three main stages: (a) Pre-processing, (b) Highlight: A contrast was assigned linear for better discrimination of targets and (c) Rating.

After the appropriate treatment applied to the MODIS was applied supervised classification pixel by pixel, based on the maximum likelihood algorithm (MaxVer-ICM-Conditional Modes interated) as described by Moreira (2011) (Eq. 2), for processing by Principal Component (PC).

$$P_C = [-0.5 \log_e(\text{Det}(V_c)] - [0.59X - M_c)^T (V_c)^{-1}(x - M_c)] \quad (2)$$

Table 1: Dates to time-series composition used comprising from soil preparation to the final stage of soybean

Julian day	Date	Year
161	6/10	2010
177	6/26	2010
193	7/12	2010
209	7/28	2010
225	8/13	2010
321	11/17	2010
337	12/3	2010
353	12/19	2010
001	1/1	2011
017	1/17	2011
033	2/2	2011
049	2/18	2011

where, X = Measurement vector of unknown pixels; P_c = Probability of the vector X is marked in the class c; V_c = Covariance matrix of class c contemplating all the bands (K, ..., L); Det (V_c) = Determinant of the covariance matrix V_c; M_c = Mean vector for each class c and T = Transposed matrix.

Furthermore, it was applied to partially unsupervised classification supported by the K-means algorithm. The platform used in this step was the Environment for Visualizing Images (ENVI version 5.0) (ENVI., 2004).

For better separation of the classes and assistance in consideration of each sample for classes soy and non-soy, CEI was used vegetation index, wherein the threshold are considered $\geq$0.28 soybean pixels (Rizzi *et al*., 2009).

In the supervised and unsupervised classifications, the transformation was performed by Principal Component (PC) for reducing the size of data obtained from the images of the MOD13Q1 product, spectral bands blue, red, near infrared, in addition to the vegetation indexes EVI and CEI.

For the classification selected the CP's more variance. The first two components (PC1 and PC2) contained more than 99% of variability of the spectral information in the area. This technique has principles for the statistical analysis of a large number of variables. The advantage of this application is the removal of the correlation set of selected bands with simultaneous compression of most information. The operation of forming a main component is made to calculate the new value of each pixel in the formation of a new image. The same operation is repeated with the other components, which is calculated by Eq. 3 for the first and other key components (Meneses and Almeida, 2012).

$$\begin{aligned} PC_1 &= 0.05x_{ij1}(B) + 0.12x_{ij2}(R) + 0.41x_{ij3}(NIR) \\ &+0.39x_{ij4}(EVI) + 0.30x_{ij5}(CEI) \end{aligned} \quad (3)$$

where, CP_{1ij} is the value of the pixel in line i and j column of the first principal component; $x_{ij1...5}$ is the value of the pixel in line i and column j of each of the original bands 1 to 5.

The new principal components are related to the brightness values of all the original images. According to Meneses and Almeida (2012) in a hypothetical representation in the distribution is considered two-dimensional space of the brightness values of the pixels in two bands, the pixels present in the first component (PC1), or first major axis, the larger the variance, while in the second component (PC2) the variance is smaller (Fig. 2).

Possession of processed and applied techniques images, thematic maps of soybean fields were generated by principal components with Maxver-ICM algorithm and K-means (EVI Julian Day 017 because it is the day on which the greatest force occurs soybean vegetative). These procedures were carried out to compare the methodology commonly used in the proposed methodologies. The applied synthetic methodology is shown in Fig. 3 flowchart.

Statistical analysis: Assessing the quality of thematic maps of vegetation index (CEI), principal components (MaxVer-ICM) and K-means, was performed using a set of samples and independent of those used for the construction of models. This approach was adopted because it allowed the evaluation of all the processes ratings.

To generate the independent set of samples, traveled to different regions of the state identifying areas that showed the soybean crop during the period chosen for assessment of MODIS images.

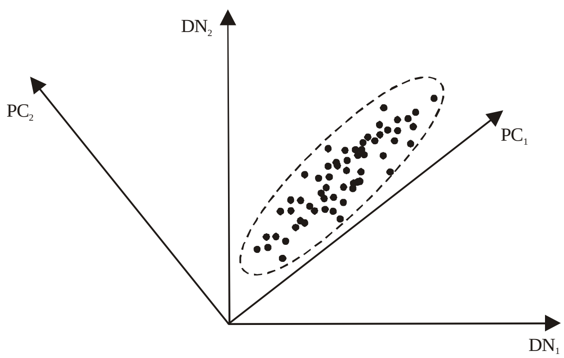

Fig. 2: Spectral rotation of the original axes with high correlation to axes PC uncorrelate

We marked a total of 172 reference points of culture. For this we used a Trimble GPS receiver brand, model GeoExplorer 2008 Series with L1 carrier and accuracy better than 5 m after correction of the data.

For non-soy points were collected by trained specialist through visual interpretation of a temporal series of MODIS images (Freitas *et al*., 2011). These 346 points were distributed throughout the area and were generated randomly and independently. For all samples proceeded category established for the analysis (Congalton and Green, 2009), the whole being considered satisfactory for analysis.

The quality rating was quantitatively evaluated by the Global Accuracy coefficients (EG) and Kappa (κ), both derived from the confusion matrix (Congalton and Green, 2009). In addition, the errors and the accuracy were extracted under the producer and user views (Antunes *et al*., 2012). These metrics allow better assess the final classification of soybean areas.

Having the values and under the hypothesis of equality between two accuracy coefficients coming from different classifications ($\kappa 1 = \kappa 2$). It was established as null hypothesis (H0) equality of classifications and the reverse for their differences (H1) at a level of 0.05 significance ($p<0.05$).

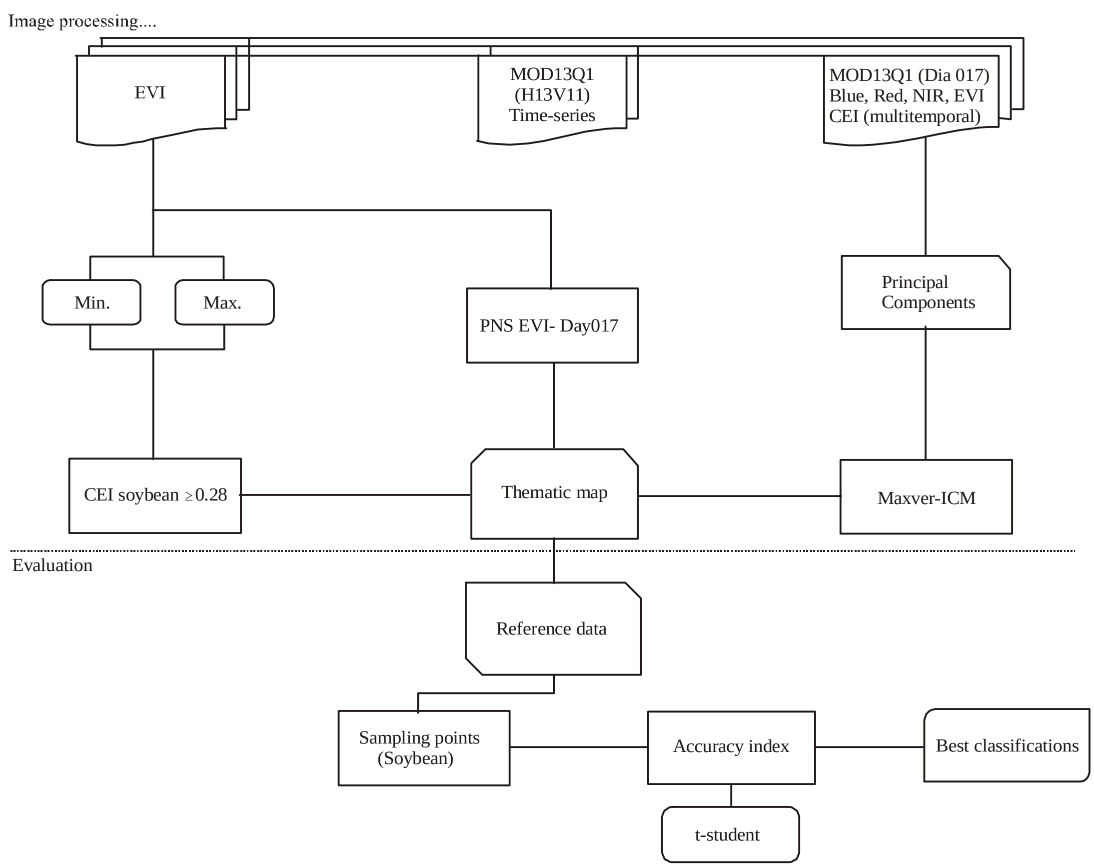

Fig. 3: Representative flowchart of the classification process by MODIS images

RESULTS AND DISCUSSION

Figure 4 shows the principal components of the processing system of orthogonal axes rotated or components. The area of the first component rotated axes has no correlation with the second component, which perfectly information shows the concentration of the first component.

According to Meneses and Almeida (2012), the variance is a measure of the information content of the image, the first component or first axis aggregates larger amount of spectral information to produce an image with the largest pixel information present in the first component (PC1), or first major axis greater variance while in the second component (PC2) the variance is smaller.

Therefore, the principal component could define the number of dimensions that are present in the data set and fixed coefficients which specify the positions of the axes pointing in the direction of higher variability of the data. Therefore, any correlations between the images were deleted, can be noticed in symmetry of the data (Fig. 4).

Table 2 shows the matrix of correlation coefficients calculated for the five images in the two crops studied. All coefficients ranged from -1 to 1. The high values indicate that the positive correlation between bands is positive and decreases when the correlation coefficient approaches zero. Table 3 shows the covariance matrix in relation to the bands that vary together for both crop years.

Diagonal matrix can be checked measuring the variance of each band. For both crops band near-infrared and EVI having the highest variance, i.e., contains more information and greater contrast in the main spectral components.

The eigen values of the principal component are shown in Fig. 5. There is variance in all the original images, but after completion of the largest principal component variance is the first component, with successively lower values, reducing the dimensionality of the data. The first three components account for more than 99.5% for both crops, virtually the total variance of all the five original images.

Thus, the first three components were formed RGB composition to assist in the interpretation of the classification of the first component and the remainder was discarded to representing less than 0.5% of the information. Commonly from the fourth component images show noise, so were discarded.

When analyzing the data obtained by the methods used in the estimates of soybean areas have found that rankings through MaxVer-ICM ally the main components was highlighted with higher Kappa parameters (κ) and Overall Accuracy (OA), unlike classifier K-mean and CEI index (Table 4).

The classification with the CEI index obtained OA parameters and κ of 0.40. The κ value shows the conformity of

Table 2: Correlation coefficient matrix for MODIS images in crop year 2010/2011

Correlation	Blue (017)	Red (017)	NIR (017)	EVI (017)	CEI
Blue (017)	1.00				
Red (017)	0.79	1.00			
NIR (017)	0.48	0.64	1.00		
EVI (017)	0.42	0.53	0.98	1.00	
CEI	0.40	0.54	0.92	0.92	1.00

Table 3: Covariance matrix for MODIS sensor images in the year-crops 2010/2011

Covariance	Blue (017)	Red (017)	NIR (017)	EVI (017)	CEI
Blue (017)	0.000436				
Red (017)	0.000455	0.000755			
NIR (017)	0.001933	0.003379	0.037373		
EVI (017)	0.002603	0.004310	0.055934	0.086699	
CEI	0.000600	0.001061	0.012685	0.019326	0.005106

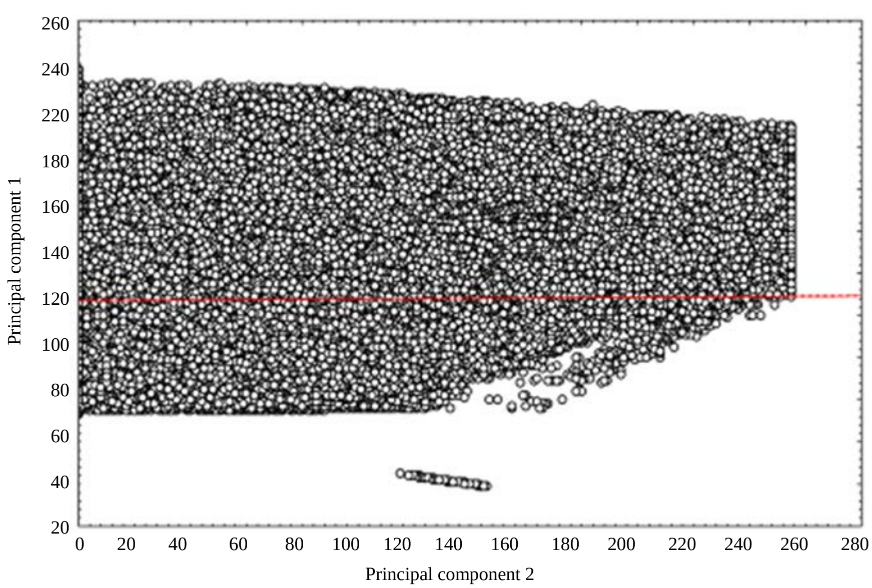

Fig. 4: Decorrelation first and second main component of spectral data by rotating the original axes of the crop year 2010/2011

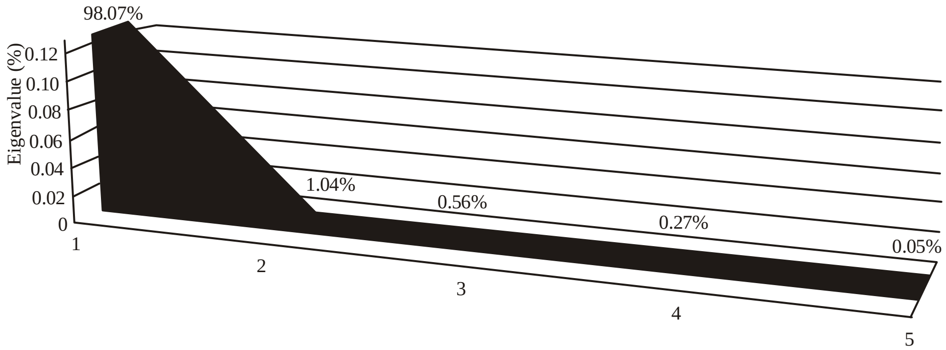

Fig. 5: Eigenvalue for the components made of the analyzed images to the crop year 2010/2011

Table 4: Confusion matrix of function in different ratings soybean area estimation methods and their values of κ indices and OA for the crop year 2010/2011

	Reference			
Classification	Soybean	Non-soybean	Σ	
CEI				
Soybean	75	07	82	κ = 0.40
Non-soybean	97	167	264	OA = 0.70
Σ	172	174	346	
K-means				
Soybean	113	58	171	κ = 0.32
Non-soybean	59	116	175	OA = 0.66
Σ	172	174	346	
Principal component				
Soybean	97	14	111	κ = 0.48
Non-soybean	75	160	235	OA = 0.74
Σ	172	174	346	

Table 5: Error and accuracy of the producer's point of view and the consumer to the error matrix for soybeans class built from the images

	Producer		User	
Method of analysis	Error	Accuracy	Error	Accuracy
CEI	0.56	0.44	0.08	0.91
K-means	0.34	0.66	0.34	0.66
Principal component	0.44	0.56	0.13	0.87

marks obtained. The Kappa index has advantages over the overall accuracy because it incorporates all elements of the error matrix, objects classified correctly or not. Furthermore, the κ evaluates accuracy because the subject is more sensitive to changes in consumer and producer errors and evaluates the spatial coincidence between two situations (Moreira, 2011).

Still on the Overall Accuracy parameter, all hits were up 74% (Table 4), below the recommended by Foody (2002), who points out that to be desirable, a classification must achieve higher index hits 85%.

The κ, which evaluates the agreement or disagreement between the classifications made ranged from 0.32 (K-means) and 0.48 (Principal Component) which, according to the classification proposed by Landis and Koch (1977), is reasonably good quality (κ>0.21 and 0.81), respectively.

Thus, it can be said that the thematic maps generated for the soybean crop especially when used the main component, approached the official data. The values are also significant when compared with studies using the same sensor, but with another methodology, as Lamparelli *et al*. (2008) that, in

Table 6: Error and accuracy of the producer's point of view and the consumer to the error matrix for non-soy class built from the images

	Producer		User	
Method of analysis	Error	Accuracy	Accuracy	Error
CEI	0.04	0.96	0.37	0.63
K-means	0.33	0.67	0.34	0.66
Principal component	0.08	0.92	0.32	0.68

estimating soybean with MODIS data, obtained Kappa parameter between 0.60-0.80.

The lowest value of the parameter Kappa and global accuracy were found for the partially unsupervised algorithm (K-means), may be associated with greater confusion in natural vegetation and consequent overestimation of soybean areas.

Therefore, the evaluation shows that the binders those based on pixel-by-pixel structure such as, for example, the main component used in MaxVer rely on the user's acquisition of samples have finer accuracy and good results. Furthermore, the combination of MaxVer with the ICM presents the results tend to improve as it considers the spatial dependence on the classification, i.e., the assigned class depends on both the value observed in this pixel as the class assigned to its neighbors (Moreira, 2011).

The results here are similar to those obtained by Rudorff *et al*. (2007), in Rio Grande do Sul state to estimate the soybean crop with MODIS, where they obtained overall accuracy parameters of 76.17% and Kappa 0.50, considered by Pax-Lenney and Woodcock (1997) as good performance.

To measure the accuracy of each category (soy and non-soy), we used a mistake by the producer's point of view and from the consumer to the crop years studied (Table 5, 6) for analyzing the inclusion of mistakes and omission errors present in the ratings (Antunes *et al*., 2012).

When analyzing the data from the producer and consumer errors (inclusion and omission, respectively), it is noteworthy that the lowest value for the inclusion error for soybeans class was obtained with the classification through the main component, with errors 0.44 and 0.13. Thus, the producer of error occurs when an object is included in the class to which it does not belong and consumer error when an object is deleted from the class to which it belongs (Johann *et al*., 2012).

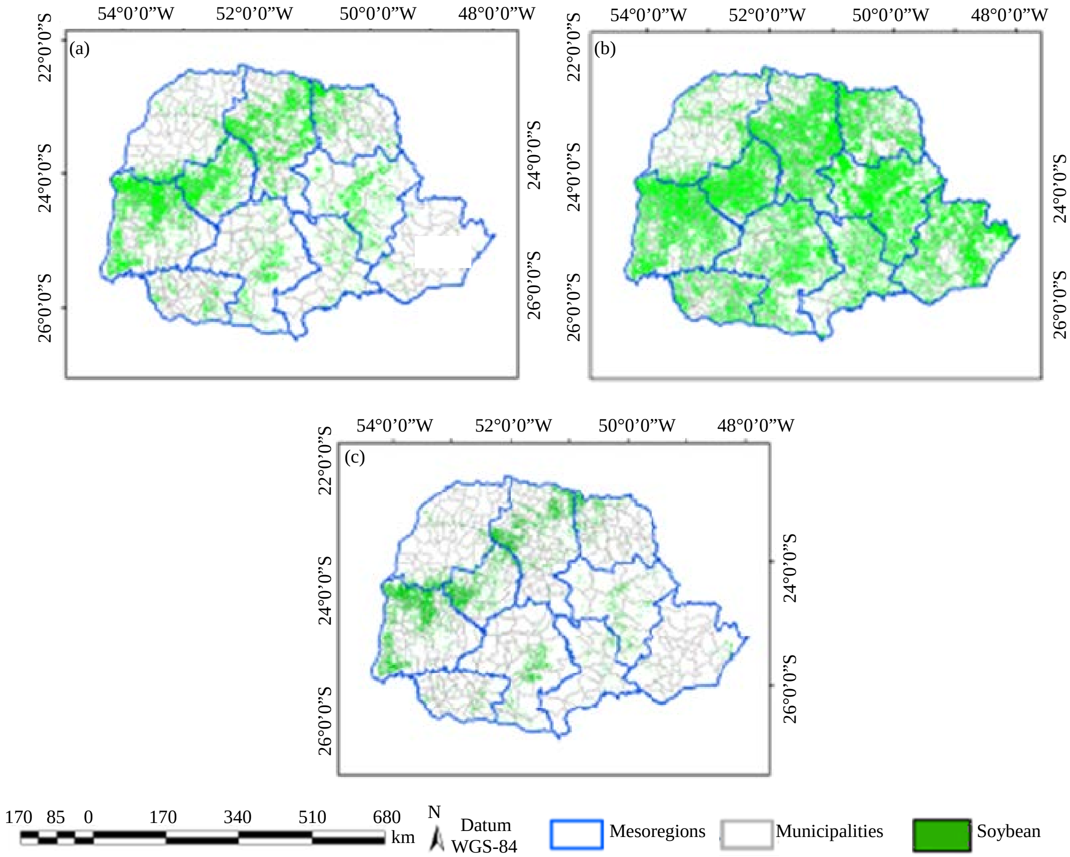

Fig. 6: Spatial distribution of areas cultivated with soybeans in the crop year 2010/2011 according to their respective classification techniques (a) Principal components, (b) K-mean and (c) CEI

Table 7: Hypothesis test to compare the results of accuracy between the vegetation indices for the crop year 2010/2011

$Kappa_1$ versus $Kappa_2$	Z	p-value
K-means ×principal component	-2.39	0.0084*
K-means×CEI	-1.11	0.1335^{ns}
Principal component×CEI	1.43	0.0757^{ns}

^{ns}Not significant, *Significant at 0.05 level of probability

On the other hand, as regards the non-soy class (Table 6), we can highlight the value obtained in the present method of producing error in the CEI. As for the consumer can't observe the same, since the errors obtained were 0.04, 0.33 and 0.08 with, as a consequence, higher estimated grade soy and non-soy reduction class.

In general, better results were obtained for soybean class with CEI technical and principal components, possibly due to the fact that, unlike the K-means, these techniques take into consideration various images and time-series.

Hypothesis tests, depending on the results of the products are shown in Table 7.

Using the Z test was verified that the classification of principal components showed higher κ value when compared to the K-means and the CEI Table 7.

For the parameter κ, most of the tests resulted in no significant differences, except for the aforementioned comparison. It is noteworthy that, the closer to zero the p-value, the greater the evidence against the hypothesis of equality, just fact not observed when comparing the parameters of some classifications.

Figure 6 shows the spatial distribution of the soybean crop in Paraná obtained by different classifier systems. By observing the distribution of soybean class similarity can be seen between the areas in the CEI and principal components. The only exception is displayed by the classifier K-means, due to its generality and overestimate the mapped areas.

The overestimation had a similar partially unsupervised classification (K-means), which was expected by the lack of training for generation of classification.

CONCLUSION

- The mapping, discrimination and quantification of soybean fields in the state of Paraná was possible with the use of classifiers and MODIS images, which the ystematization presented results of Kappa parameters and overall accuracy satisfactory

- The use of MaxVer-ICM algorithm combined with multivariate technique of principal component analysis was superior when compared to the CEI index and the classifier partially unsupervised (K-means)

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