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# Mapping and discrimination of soya bean and corn crops using spectro-temporal profiles of vegetation indices

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The use of remote-sensing technology has been studied as a way to make the monitoring of agricultural crops more efficient, dynamic, and reliable. The use of data from the Moderate Resolution Imaging Spectroradiometer (MODIS) has proved to be an interesting tool regarding the mapping of large areas, however, some challenges still need to be addressed. One of these is the identification of specific types of crops, especially when they have similar phenologies. The purpose of this study was to perform discrimination and mapping of soya bean and corn crops in the state of Paraná, Brazil, for the 2010/2011 and 2011/2012 crop years. A methodology using spectro-temporal profile information of the crops derived from vegetation indices (VIs), the normalized difference vegetation index (NDVI), enhanced vegetation index (EVI), and the wide dynamic range vegetation index (WDRVI) based on MODIS data was appraised. This method generated a series of maps of the respective crops that were later qualitatively or quantitatively appraised. Some of the maps drawn showed a global accuracy rate above 80% and a kappa coefficient ($\kappa$) of over 0.7. The data areas showed an average difference of 6% for the cultivation of soya beans, and 11% for corn when compared to official data. The WDRVI and EVI were similar and showed better performance when compared to the NDVI in the assessments made. The results demonstrate that the soya bean crop was better mapped compared to corn, particularly in terms of the size of the crop area. The use of spectro-temporal profiles of the VIs assisted in obtaining important information, enabling better identification of crops from regional scale mapping using the MODIS data.

## 1. Introduction

Information about soil cover, its use, and distribution in geographic space, helps to plan activities that involve food production and natural resource management with more reliability. The availability of reliable and up-to-date information about the harvest in a timely manner is important for the agricultural and livestock sectors in order to drive the allocation of resources without compromising the supply of the domestic market. However, the location, scope, distribution, and pattern of change in crops are usually not available based on agricultural statistics, as estimated by official organizations (Lunetta et al. 2010). The use of data from orbital remote sensing offers the potential to obtain spatially distributed information on the use and cover of large areas in a reasonable time frame and at a low cost (Carrão, Gonçalves, and Caetano 2008; Zhang et al. 2008).

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Images of the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor are increasingly used for mapping and crop monitoring on a regional scale, due to its combination of high temporal and spectral resolution with a moderate spatial resolution (250–1000 m) (Brown et al. 2007; Wardlow and Egbert 2008; Galford et al. 2008; Sakamoto et al. 2010). The use of MODIS data for mapping land use/land cover is well established in the literature, be it to evaluate land-cover change (Lunetta et al. 2006, Carrão, Gonçalves, and Caetano 2008; Zhang et al. 2008), crop expansion (Morton et al. 2006; Galford et al. 2008; Arvor et al. 2012), or land crop area estimation (Chang et al. 2007; Wardlow and Egbert 2008; Victoria et al. 2012). Some studies have aimed at agricultural monitoring in large areas using vegetation indices (VIs) based on MODIS data (Wardlow and Egbert 2008, Arvor et al. 2012, Johann et al. 2012; Brown et al. 2013). The majority of studies involving the analysis of VIs have used the indices known as the normalized difference vegetation index (NDVI) (Rouse et al. 1974) and the enhanced vegetation index (EVI) (Huete et al. 1997). However, in the case of areas with dense vegetation, the NVDI becomes saturated, showing a constant response, while the EVI continues to produce a response (Huete et al. 2002). Gitelson (2004) established the VI known as the wide dynamic range vegetation index (WDRVI) with the intention of improving the sensitivity of NVDI under a high-density vegetation cover. This index requires information from the red and near-infrared regions of the electromagnetic spectrum, the same as those contained in the NDVI-MODIS products.

The extraction of sequential VI data supplies information about how variables are changing over time, allowing the creation of time-based profiles. This allows the evaluation of the spectro-temporal pattern through the entire vegetative cycle of the crop, showing the progress of the cycle from the emergence of foliage, through the maturation stage to senescence, thereby demonstrating the performance of the crop (Labus et al. 2002; Jensen et al. 2002). Spectro-temporal profiles of the MODIS VI have spectral, temporal, and radiometric resolutions sufficient for the discrimination of crops (Wardlow, Egbert, and Kastens 2007).

The use of MODIS data in the agricultural monitoring of large areas has the tendency to group crop areas in a single or limited number of thematic classes. Thus, the identification and discrimination of crops sown at the same time and/or which show similar spectro-temporal responses, such as that which occurs with soya bean and corn crops, are yet to be explored (Wardlow and Egbert 2008). This study proposes a methodology with the objective of discriminating and mapping these crops on a regional scale. For this, information on the spectro-temporal profiles of the crops was used, derived from the VIs of the MODIS sensor. The study aimed at mapping the soya bean and corn crops in the state of Paraná, Brazil, for the 2010/2011 and 2011/2012 crop years. Additionally, it also conducted an assessment of the three VIs used, namely the NDVI, EVI, and WDRVI, based on analysis of the information generated.

## 2. Study area

The area comprised by this study included the state of Paraná, located in the South of Brazil, between 22° 29′ S and 26° 43′ S and 48° 02′ W and 54° 38′ W, which occupies an area of 199,880 km$^2$. Paraná is bordered by the Brazilian States of São Paulo, Santa Catarina, and Mato Grosso do Sul, and also has international borders with the neighbouring countries of Argentina and Paraguay to the west, with the Atlantic Ocean bordering the east (Figure 1). The climate of the state has marked differences according to the region, with a predominant subtropical climate to the north, and a temperate climate to the

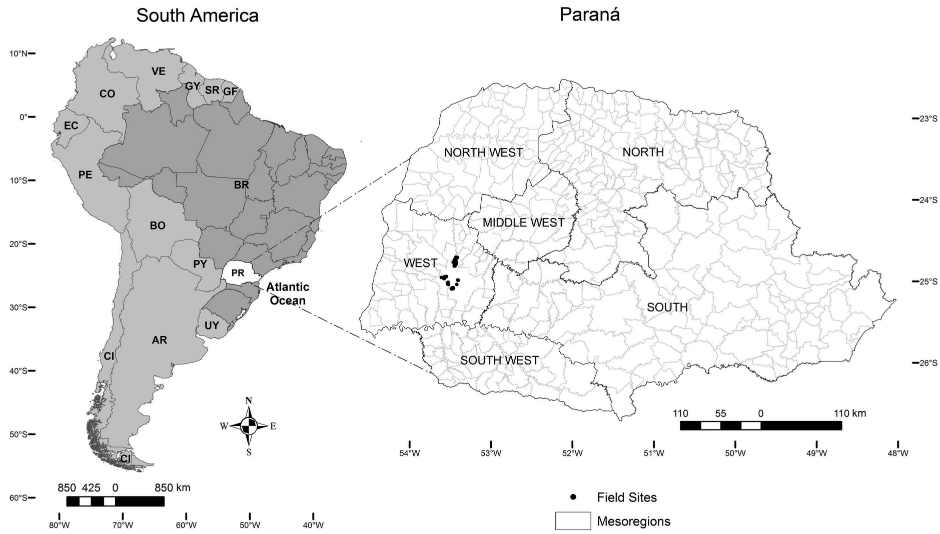


Figure 1. State of Paraná (study area) and location of the field data. The lines dividing the state correspond to the SEAB regional scale adopted in this study.

south, corresponding to the Köppen climate classification groups of Cfa and Cfb, respectively. Approximately 15 million ha are allocated to agricultural production in the state, comprising several different crops, with different types of management. According to data released by the Instituto Paranaense de Desenvolvimento Econômico e Social (IPARDES 2009), 44.6% of the agricultural properties have areas of less than 10 ha, while the other 45.9% have between 10 ha and 100 ha.

Paraná is the second most important producer of grain in Brazil, generating 19.2% of all the country's grain, with the majority originating from soya beans and corn (IBGE 2012). Soya beans are a vital commodity for agribusiness in the state of Paraná that accounts for 20.5% of national production, or 14 million tonnes. The state is also Brazil's most important producer of corn, accounting for 24% of the country's total production, with approximately 13 million tonnes (CONAB 2012). Corn production occurs in two seasons, with the main crop grown between the spring and summer (September to March) and the second smaller crop, or safrinha, being grown between summer and autumn (February to June). In this study, we used data from the first corn crop for our research, as the harvest time is the same as that for soya beans.

## 3. Materials and methods

The methodological procedures used for conducting the present work are summarized in Figure 2.

### *3.1. MODIS data*

The data used were obtained free of charge through the Land Processes Distributed Active Archive Center (LP DAAC), in hierarchical data format (HDF). These data are part of the MOD13Q1.5 product of the MODIS sensor, aboard the Terra satellite. A total of 12 types of products are available, including VI images with a spatial and temporal resolution of

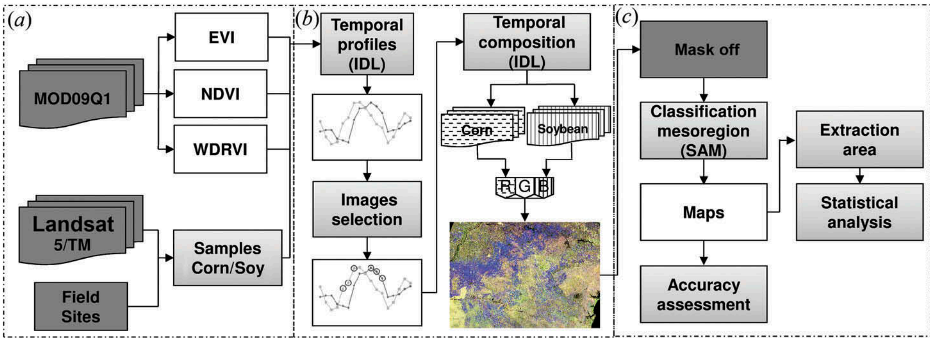


Figure 2. A general overview of the methodology used in the process for discrimination of crops. The dark grey boxes represent input data, while the light grey boxes are processes that were already executed, and the white boxes are the products generated.

250 m and 16 days, respectively, the images of the spectral bands of the sensor, and the images of the coefficient of quality and reliability of the pixels.

In this study, we used the NDVI, EVI, and the near-infrared (NIR) (band 2) and red (band 1) spectral bands of the images from tile h13v11. To contemplate the whole vegetative cycle of the summer harvest of soya beans and corn, according to the agricultural calendar for the state, the images from 13 August year1 and 25 April year2 were used, totalling 17 images for each crop year (2010/2011 and 2011/2012). The extraction of these images from the HDF was done using the MODIS Reprojection Tool, which was reprojected to the WGS84 projection in GeoTiff format. The VI quality images and pixel reliability were used for the elimination of pixels with noise.

Apart from exploiting the time series for the NVDI and EVI, which are part of the MOD13Q1.5 product, the VI WDRVI (Gitelson 2004; Gitelson et al. 2007; Viña et al. 2011) was also determined using the spectral bands (Equation (1)) (Figure 2(*a*)). This VI considers a weighted coefficient $\alpha$ to reduce the disparity between the contributions of NIR and red. According to Gitelson et al. (2007), the value of $\alpha$ that presents the best linear fit between the VI and biomass for corn and soya bean crops is 0.2, which was the value used in this study.

$$\mathrm{WDRVI} = ((\infty\mathrm{NIR} - \mathrm{red}))/((\infty\mathrm{NIR} + \mathrm{red})). \tag{1}$$

### 3.2. Field data

Field data from 19 different croplands were collected from the western section of the state of Paraná, with an average size of 102 ha (Figure 1) for the crop years studied. These areas were delimited with the aid of a global positioning system (GPS) apparatus for later entry into a geographic information system (GIS). Images obtained from the Landsat 5/TM (thematic mapper) sensor, available during the period of study, were also used. By means of visual interpretation techniques for images, and also by using a false colour composition based on colour R4G5B3, we carried out the identification of plots of soya beans and corn that had the same characteristics as the areas that were defined in the field, with dimensions of at least four MODIS pixels (about 25 ha). With the definition of the boundaries of the plots, only the central pixels of the areas in the MODIS images were considered. In this way, there was a maximum reduction of mixed pixels (pixels composed of different kinds of cover), thereby selecting only pixels that represented, as much as possible, the spectral pattern of each crop under study (Figure 2(*a*)).

### *3.3. Use of spectro-temporal profiles*

With the geographical coordinates of the selected pixels from the croplands, the extraction of data was performed for each VI studied by means of a routine IDL (interactive data language) developed by Esquerdo, Júnior, and Antunes (2011). The extraction of data from images for multiple dates provides information about how variables change over time, which allows the generation of spectro-temporal profiles through the vegetative cycle of the crop. A profile was generated for each selected pixel to later generate average spectro-temporal profiles of the NDVI, EVI, and WDRVI, for each crop and crop year, as shown in Figure 3.

Through the spectro-temporal profiles, it was possible to detect unique spectral responses for each crop representing differences in their developmental cycles. Based on these differences, images with the greatest interval between the spectro-temporal profiles of the crops were identified, which means that the images that best represented each crop separately were selected. Ideal acquisition time frames are those that allow the greatest distinction between crops, not necessarily being in the period of maximum vegetative growth, also known as the vegetative peak (Panigrahy and Sharma 1997). However, each crop can have a different profile, which reflects the regional variations of the state under environmental conditions and/or crop husbandry practices (Wardlow, Egbert, and Kastens 2007). For this reason, we used multiple image dates to perform the same composition for each crop, to account for the variability mainly caused due to different sowing dates in different parts of the state. Thus, through a routine IDL, a composite image was generated that included multiple dates for each crop (soya beans and corn) for each VI and crop year (Figure 2(*b*)), adapted from the procedure described by Johann et al. (2012). The images that were selected in this study are shown in Figure 3.

Based on the composite images, an RGB composition was generated for each VI and crop year. The composite image of the corn crop was positioned on channel 'R', while the composite image for the soya bean crop was positioned on channel 'B'. On channel 'G', the image where both crops were absent was inserted, selected based on the lowest value shown in the spectro-temporal profiles. This means that, in this RGB composition, the areas in blue hues represent soya beans, those in red represent corn, and those in green represent other targets (Figure 2(*b*)).

### *3.4. Classification process*

Before any classifications were made using the RGB compositions of crops, any targets that could complicate their correct designations were removed. To do this, a mask was applied that excluded regions under water, urban development, and forest cover (Figure 2(*c*)). This mask was created based on data from the Institute of Land, Cartography, and Geoscience (ITCG 2012). Owing to the regional variability in environmental conditions and crop management practices, the considered mapping zones should be smaller and more homogeneous for the classification of crops in large areas (Wardlow, Egbert, and Kastens 2007). In this regard, classification by mesoregions was performed, dividing the RBG compositions into six sectors, namely: west, midwest, northwest, north, south, and southeast (Figure 1).

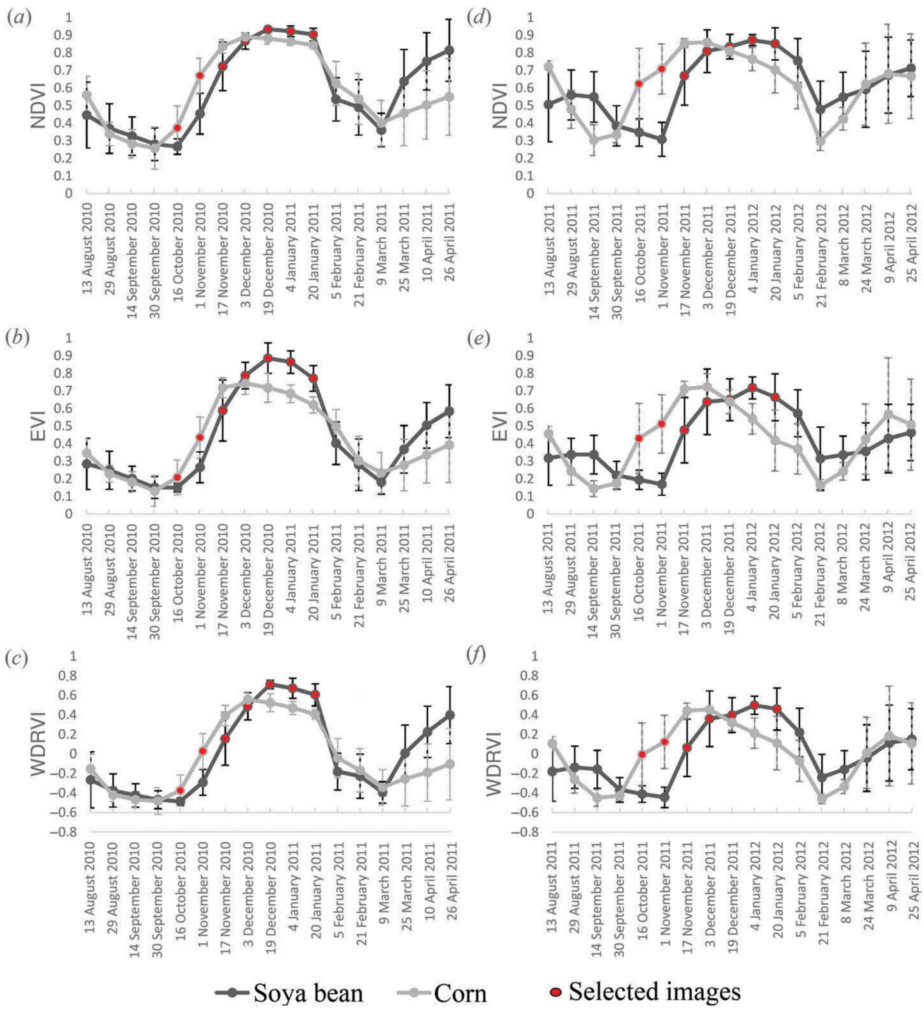


Figure 3. Average and standard deviation of the spectro-temporal profiles for soya bean and corn crops for each of the VIs (EVI, NDVI, and WRDVI), and for the 2010/2011 (*a*), (*b*), (*c*) and 2011/2012 (*d*), (*e*), (*f*) crop years, along with scenes selected for the composition.

To map the different crops, the classification algorithm known as the Spectral Angle Mapper (SAM), which is a method for supervised classification based on a comparison of the spectrum of the image to a reference spectrum, was used (Kruse et al. 1993; Crósta, Sabine, and Taranik 1998; Petropoulos et al. 2010). The classification is executed after defining a maximum acceptable angular value for the angle between the vector defined by the reference spectrums (class samples) and the vector defined by the spectral value of the pixel being classified. The smaller the angular difference between these vectors, the greater certainty that the pixel belongs to the class as mapped. In this study, the maximum angular value was defined after testing larger and smaller angular differences, and establishing the one with the best result in a visual comparison with the Landsat 5/TM images.

### 3.5. Area comparison analysis

Data regarding the area of each crop were obtained from the maps generated for each crop year and VI. These data were then compared with the official area data, as made available by the Secretary of Agriculture and Supplies of Paraná (SEAB 2013) at the municipal level. The analysis was done through a model of simple linear regression and its coefficient of determination ($R^2$). The mean error (ME) (Equation (2)), root mean square error (RMSE) (Equation (3)), and the enhanced Willmott concordance coefficient as proposed by Willmott, Robeson, and Matsuura (2012) (dr) (Equation (4)) were the statistical indicators used. The dr coefficient establishes the accuracy of the method, and the degree of detachment of the estimated values in relation to the values observed (official data). This index varies between –1 and 1, with positive values close to one indicating better agreement.

$$\mathrm{ME} = \frac{1}{n}\sum_{i=1}^{n}(O - E), \tag{2}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(O - E)^2}, \tag{3}$$

$$\mathrm{dr} = 1 - \frac{\sum_{i=1}^{n}|E - O|}{2\sum_{i=1}^{n}\left(\left|O - \overline{O}\right|\right)}, \tag{4}$$

where $n$ = the number of municipalities; $O$ = the area of the crop (soya bean or corn), officially stated by SEAB; $E$ = the crop area as obtained through mapping; $\overline{O}$ = the mean crop area (corn or soya beans) as officially obtained by SEAB.

### 3.6. Map accuracy analysis

In land-cover area estimation using satellite images, it is important to emphasize that there are two main sources of error when counting the number of pixels classified and multiplied by the area represented by each pixel: the presence of mixed pixels and the misclassification of pure pixels (Gallego 2004). Thus, to carry out an appraisal of the accuracy and misclassification of the maps created, assuming the impact of mixed pixels, the error matrix technique was used to calculate the overall accuracy, kappa coefficient ($\kappa$), and the omission and commission errors (Congalton 1991; Foody 2002). In order to create the error matrices, a stratified random distribution per class of 150 sample points in each map was performed. To achieve this, images from Landsat 5/TM scenes 223/77 and 224/77, with false colour composition (R4G5B3), were used to audit the samples. The decision to classify samples was then done through visual inspection of each point. After this process, the error matrices were obtained for each map generated.

## 4. Results and discussion

### 4.1. Crop maps

The maps obtained based on the VIs derived from the MODIS sensor are shown in Figure 4. The spatial distribution of crops in the maps is consistent with the general patterns of land use in the state of Paraná, when visually compared to the maps showing the land cover in previous studies (Johann et al. 2012) and that supplied by the Institute of Land, Cartography, and Geoscience (ITCG 2012). The main croplands of soya beans and corn are distributed principally from the west to the north regions of the state, with the presence of more scattered areas in the south. This distribution also reflects the differences in the type of soil, water availability, and climate throughout the state, all of which are part of the pedoclimactic requirements for the cultivation of these two crops.

In a visual comparison of the maps, subtle differences between the VIs within the same crop year studied are evident (Figure 4). These variations stem from different sensitivities of the VIs to variability in vegetation, resulting in different responses to the monitoring of vegetation dynamics, as can be seen in the spectro-temporal profiles of the different crops (Figure 3).

### 4.2. Statistics for comparison of area data

The total differences between the areas obtained in the maps for each VI and the official areas as informed by SEAB are shown in Figure 5. In general, the areas obtained through mapping have been underestimated in relation to those from the SEAB, varying for each VI and crop as studied. The data obtained in mapping for soya beans have been underestimated by 6% on average. In the case of corn, the difference was even larger, with an average of approximately 11%. The closest results were obtained by using the VI WDRVI, with a difference of 2.1% in the 2011/2012 crop year for soya beans, and 4% in the 2010/2011 crop year for corn (Figure 5). Our results corroborate those presented by Chang et al. (2007) and Wardlow and Egbert (2008), who, on mapping

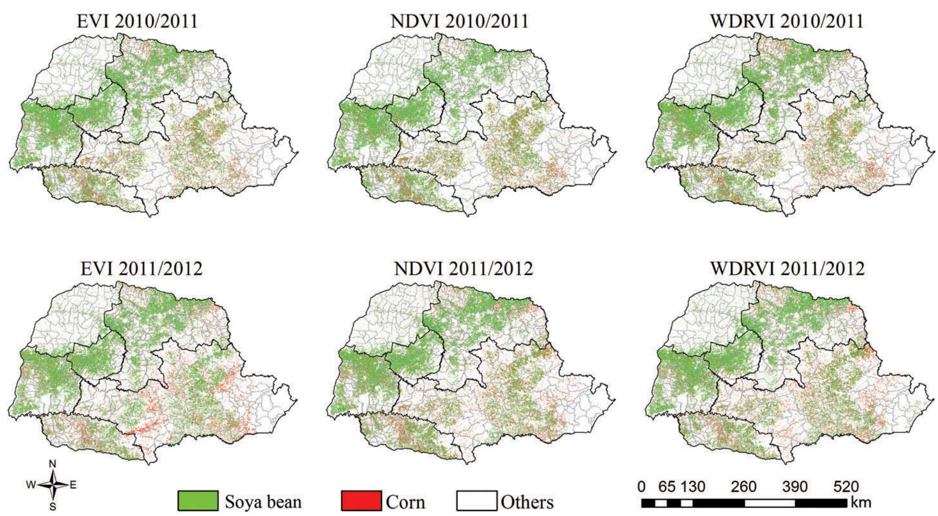


Figure 4. Crop maps of soya beans and corn for the 2010/2011 and 2011/2012 crop years obtained from the VIs (EVI, NDVI, and WRDVI).

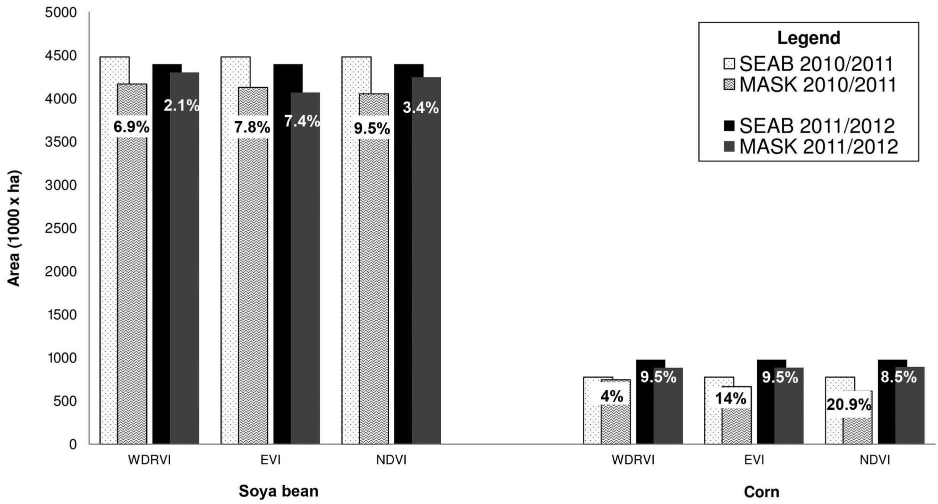


Figure 5. Total differences between the areas obtained through mapping, for each vegetation index (VI), compared with the official areas as informed by the SEAB.

large expanses of land areas with soya beans and corn, came to the conclusion that when using the MODIS sensor, the mapped area tends to underestimate the official data.

For a more detailed analysis between the mappings and the official data, statistical variables were calculated, as shown in Table 1. Using the ME, the crop area for soya beans was underestimated, on average, by 775 ha. In the case of corn, the average underestimate was 268 ha at the municipal level.

In order to verify the discrepancies between official areas (SEAB) and estimated areas (mapping), the RMSE was determined, with the lowest discrepancies obtained for soya beans, confirmed by the concordance index (dr = 0.84, on average) and the coefficient of determination ($R^2$ = 0.89, on average), both of which are evidently greater than in the case of corn (dr = 0.67 and $R^2$ = 0.49, on average). In general, the VIs WDRVI, and EVI showed results for the mapped area closer to the official data.

The greatest discrepancies occurred in municipalities where the total areas disclosed by the SEAB were small (less than 100 ha), i.e. the size of the croplands had a significant effect on the quality of the classification. Lobell and Asner (2004) appraised the impact of heterogeneity on the mixture of subpixels in MODIS data with regard to the classification of crops, and observed that the RSME declined as the size of the area analysed increased, detecting RMSE values below 5% in mapping croplands of about 300 ha.

### 4.3. *Map accuracy analysis*

The accuracy of the mapping analysis was done through the overall accuracy and $\kappa$ with $Z$-test values (Congalton 1991) at a 5% significance level, obtained by using an error matrix (Table 2). From the VIs used, the WDRVI and EVI showed that the classification of the crops obtained has a consistent spatial distribution, based on the references provided by the images Landsat 5/TM, with an overall accuracy over 80% and a $\kappa$ over 0.7.

In the significance test of accuracy indices, at a 5% significance level, all the $\kappa$ calculated were significant ($Z \geq 1.96$), therefore rejecting the null hypothesis. We also

Table 1. Statistics for comparison of map areas generated, in relation to the official data (SEAB), for the crop years 2010/2011 and 2011/2012, at the municipal level.

| | Crop season 2010/2011 | | | | | | Crop season 2011/2012 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Soya beans | | | Corn | | | Soya beans | | | Corn | | |
| Statistics | WDRVI | EVI | NDVI | WDRVI | EVI | NDVI | WDRVI | EVI | NDVI | WDRVI | EVI | NDVI |
| *N* | 365 | 365 | 365 | 382 | 382 | 382 | 361 | 361 | 361 | 382 | 382 | 382 |
| ME | 859 | 966 | 1171 | 102 | 305 | 446 | 286 | 929 | 440 | 263 | 254 | 239 |
| RMSE | 4488 | 4223 | 4460 | 2609 | 2540 | 2566 | 4941 | 4339 | 4974 | 2640 | 2626 | 2675 |
| dr | 0.85 | 0.86 | 0.84 | 0.64 | 0.66 | 0.67 | 0.83 | 0.84 | 0.83 | 0.71 | 0.69 | 0.69 |
| $R^2$ | 0.89 | 0.91 | 0.90 | 0.43 | 0.43 | 0.45 | 0.87 | 0.90 | 0.87 | 0.53 | 0.58 | 0.52 |

Note: *n*, number of samples; ME, mean error (ha); RMSE, root mean square error (ha); dr, Willmott's index; $R^2$, coefficient of determination.

Table 2. Results of the accuracy analysis for the mapping of soya bean and corn crops, in the 2010/2011 and 2011/2012 crop years.

| Vegetation indices | OA (%) | Kappa coefficient ($\kappa$) | *Z*-score* | ** |
|---|---|---|---|---|
| | | Crop season 2010/2011 | | |
| WDRVI | 86.00 | 0.78 | 18.02 | a |
| EVI | 83.33 | 0.74 | 16.28 | a b |
| NDVI | 78.00 | 0.66 | 12.97 | b |
| | | Crop season 2011/2012 | | |
| WDRVI | 85.33 | 0.77 | 18.24 | a |
| EVI | 80.00 | 0.69 | 14.70 | a |
| NDVI | 72.00 | 0.56 | 10.42 | b |

Notes: (*) At the 95% confidence level. (**) Same letter: do not differ significantly ($p \geq 0.05$).

verified that the $\kappa$ for the VIs of WDRVI and EVI were not significantly different, being greater than the VI NDVI at a 5% significance level, as calculated by significance tests of differences between the accuracy indices. This means that the differences in sensitivity to the variability of vegetation from the VIs influenced the quality of the classification. Viña et al. (2011) evaluated the sensitivity of different VIs to detect changes to the leaf area index (LAI) and showed that the VIs, WDRVI, and EVI were more significant than the NDVI, in cases where LAI > 2 $m^2$ $m^{-2}$. However, the WDRVI showed slightly higher sensitivity than that of the EVI.

Based on the error matrix, it was possible to establish the accuracy of each class, together with the errors of commission (inclusion errors) and errors of omission (exclusion errors) present in each classification. Through the intraclass errors obtained for each map, the 'corn' class had the largest errors (40.3% on average) (Figure 6). As these are commission errors, this means that the process of classification erroneously included targets which belonged to other classes in the 'corn' category. Some of these errors come from soya bean areas with early planting, which were present in the detection window of corn. As the crops have similar spectral responses (Figure 3), some of these areas were mistakenly mapped within the 'corn' category. One possible solution to improve the mapping of corn crops using the proposed methodology would be through the use of composite images with smaller compositional periods. This would allow a larger detection window, and better identification of spectral differences, assisting in the discrimination of crops with a similar phenology, such as soya beans and corn. For example, Guindin-Garcia et al. (2012) concluded that the eight-day MOD09Q1 (250 m) product may be a better way to monitor agricultural crops due to its greater temporal resolution, when compared to MOD13Q1, which has a temporal resolution of 16 days.

In the 'soya beans' and 'others' classes, the omission errors prevailed, with averages of 20.33% and 27.31% respectively. This means that elements belonging to these classes were not incorporated into them. The spatial resolution of the MODIS sensor (250 m) often causes pixels on the edge and within small croplands to have a higher spectral mixing with other elements that are present in the vicinity, which normally prevents their correct classification, thereby adding to the omission errors. Another factor that contributed to the increase of soya bean class omission errors arose from the pixels misclassified as corns. Taking into account the corn commission errors with the soy omission errors in Figure 6, one can observe in the different classifications that when the corn commission errors increase, the soya bean class omission errors increase as well.

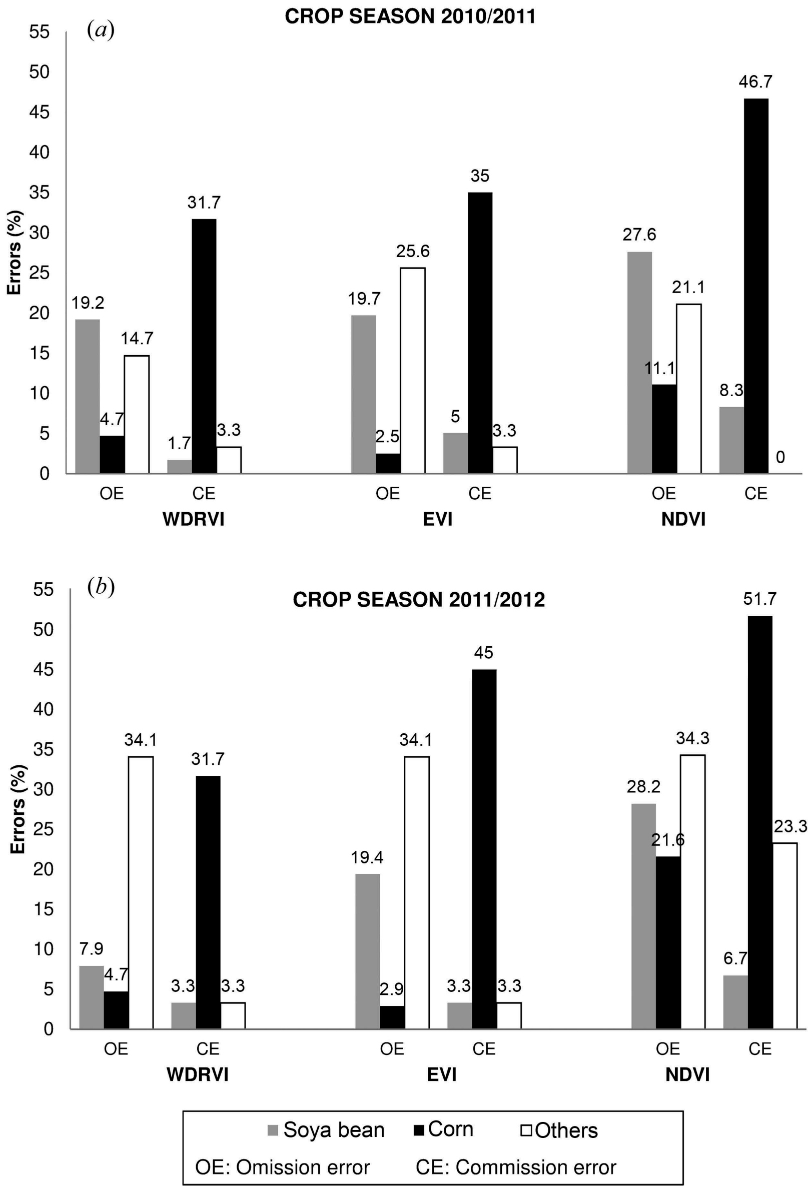


Figure 6. Omission errors (OEs) and commission errors (CEs) for the classes: soya bean; corn; others. For the 2010/2011 (*a*) and 2011/2012 (*b*) crop seasons.

Our results show that the soya bean crop was better mapped in relation to the corn crop. This is also due to the large croplands used for this crop in the state, which makes its mapping with MODIS data easier. This is different than in the case of corn, which is normally cultivated in smaller and more scattered areas, thereby increasing the number of mixed pixels. As mentioned before, the size of the croplands has an effect on the quality of classification using this sensor.

The use of the SAM classification algorithm may have also influenced the final quality of the maps generated, since the choice of the threshold angle has an important effect on the overall efficiency of the classification. In addition, this supervised classification method requires samples that represent pixels for each class of interest, and the insertion of pixels that cause spectral confusion could lead to errors in the classification. This problem generally increases in sensors with low spatial resolution and for heterogeneous surfaces (Petropoulos et al. 2010). The use of non-parametric classifiers could reduce this problem, because they are not based on inferential statistics, but rather on 'machine learning' techniques, which construct a distribution model using evidence collected based on the orientation of the data itself (Gahegan 2003).

## 5. Conclusions

The methodology used in this study for the mapping and discrimination of agricultural crops using spectro-temporal profiles of VI based on MODIS data has shown itself to be applicable in the detection of patterns and spectral differences between soya bean and corn crops, enabling their classification on a regional scale.

The mappings present coherent general patterns for the spatial distribution of crops, in accordance with those reported for the state and with good accuracy by means of Landsat 5/TM data. The area data obtained had lower degrees of discrepancy and high concordance levels for soya bean crops compared to corn, when compared with the official data.

The different VIs studied show differences in sensitivity to vegetation variability, thereby influencing the quality of classification. The VIs WDRVI and EVI were similar and generated spectral information that offered a better distinction for mapping the crops under study.

This study provides a methodology for quick identification of the spatial distribution of crops on a regional scale, providing spatially distributed data area, with the possibility of conducting an error analysis. This is valuable information in aiding commercial and political decision planning in agribusinesses, and can also be regarded as an important tool for complementation of surveys conducted by official institutions, subject to the limitations established for the use of images from the MODIS sensor.

## Disclosure statement

No potential conflict of interest was reported by the authors.

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