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Processing Pipeline of Sugarcane Spectral Response to Characterize the Fallen Plants Phenomenon

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Abstract. Nowadays, in agronomic systems it is possible to make a variable management of inputs to improve the efficiency of agronomic industry and optimize the logistics of the harvesting process. In this way, it was proposed for sugarcane culture the use of remote sensing tools and computational methods to identify useful areas in the cultivated lands. The objective was to use these areas to make variable management of the crop. When at the moment of harvesting the sugarcane there are fallen stalks, together with them some strange material (vegetal or mineral) is collected. This strange material is not millable and when it enters onto the sugar mill it causes important losses of efficiency in the sugar extraction processes and affects its quality. Considering this issue, the spectral response of sugarcane plants in aerial multispectral images was studied. The spectral response was analyzed in different bands of the electromagnetic spectrum. Then, the aerial images were segmented to obtain homogeneous regions useful for producers to make decisions related to the use of inputs and resources according to the variability of the system (existence of fallen cane and standing cane). The obtained segmentation results were satisfactory. It was possible to identify regions with fallen cane and regions with standing cane with high precision rates.

1. Introduction

The characteristics of the argentinian agricultural production system and the necessity of the producers to achieve greater efficiency, precision and productivity are reflected in the constant demand of tools, data, information and new knowledge related to Precision Agriculture.

Precision Agriculture is a new concept characterized by inputs' management that may vary according to system variability. It is the application of technology and principles to manage the space-time variability associated to the agronomic production. It allow to explore and value the productive and economic benefits of managing the system in a site-specific way.

The implementation of precision agriculture techniques can be achieved in two levels. At strategic level there are several types of sensors which provide data and information about specific applications. At operational level the image acquisition task is increasing its importance and it allow to examine different processes on cultivated lands.

Remote sensing allow to obtain information of the earth surface without making physical contact with it, thus it is the opposite of on site observation [2]. The images of the earth surface can be satellital or aerial and they have different characteristics. The images can be integrated with others layers of spatial information in a Geographic Information System (GIS) using a Global Positioning System (GPS) for



locating positions of interest. The integrated system allow to carry out management actions in the sites of interest.

The commercial emergence of high-resolution images has driven the usefulness of remote sensing for agronomic and precision agriculture purposes. The image acquisition systems which are sensitive to different bands of the electromagnetic spectrum enhance the quality and definition of the information.

Remote sensing can play an important role in monitoring the harvest and planting processes in small-scale fields where updated information is hard to find. Numerous studies [6, 9, 11, 16] show that the spectral information is associated with agronomic variables and can be used to monitor and predict crop yields.

In the present work a workflow to detect and segment homogeneous regions in aerial images of cultivated lands is proposed. The detected regions must have a size and shape of practical use for the producers to manage the farm in a site-specific way.

The crop under study is sugarcane. The cultivation of sugarcane in Argentina is found principally localized in the northwest region of the country (99 %). In Tucumán, Salta and Jujuy it represents, in agreement with [10], one of the most important productive activities. It is also found in scarce extension in the littoral region (1%), in Misiones and Santa Fe.

During the cultivation of sugarcane fields, losses of raw material occur. The losses can be classified in two different ways: *Pre-harvest losses* and *Harvest losses*. The former is related to the canes that are fallen before harvesting, whereas the latter is related to the fact that the harvesting machines are not 100% efficient.

The presence of fallen sugarcane (CC) at the moment of harvesting brings important losses of useful product during the harvesting process and in the sugar mill. It is normal that the canes in a productive area reach an average height but they present variations of their characteristics in different sectors of the field. This might be because of the different conditions of the soil that presents different levels of fertility, humidity, compressing, etc. In addition, each plant is constituted in a different way and manifests in unique form the different external stimulus.

When the plant is young and has developed under the best conditions, it reaches certain height and begins to warp due to its own weight. It breaks if its breakage tension is surpassed, product of the wind or environmental phenomenons as hail. After that, the soil can remain exposed or new green sheets can appear, due to phototropism. These factors expose the great complexity and heterogeneity of the phenomenon under study and make it difficult to analyze and quantify.

When areas with presence of fallen canes are harvested, extraneous material without sucrose can enter the sugar mill. This extraneous material es composed of stalk tops, trash and dust. It represents an important loss of efficiency in the process of manufacture of the sugar, as assure [17]. The quality of the cane affects directly the industrial performance and the quality of the obtained sugar [8].

The quality of the raw material (cane) can be affected by changing aspects of the sugarcane agriculture. Some of these aspects are the introduction of new cultivars, climatic variations, the use of ripening chemists, changes in the cultural practices and in the systems of harvest or the appearance of illnesses or infections in the plants.

It is observed that the content of extraneous material picked up together with the cane harvested in mechanized way is appreciably lower than in the semi-mechanized way, being in the range 2 to 5,7%. At the same time, the values of fiber (plant residues) rise from 14 to about 18% due to the presence of increased amount of plant parts after a less efficient harvesting [15]. As a result, the producers are paid for a significant part of the weight of the extraneous material of the collected raw material at the same price of the cane, because the way of sampling and analysis of this parameter is generally inadequate.

Washing tables, to wash the cane, have been installed in several mills. This was done to reduce to the minimum possible the percentage of extraneous material delivered with the sugarcane. There, it is removed the present dust with big quantities of water (about 3 m³ of water by ton of cane). This supposes a saving of money but adds problems like bigger costs for the required electric power, the water and the additional manual labor. Some studies also confirm that during cane washing some percentage of sucrose

is lost [5]. Moreover, this technique requires availability of a piece of land to install settling tanks of sand and mud to reuse the water.

A promising strategy to achieve the reduction of the impact of the fallen cane and the extraneous material takes root in achieving a better operative efficiency in harvesting the cane, fundamentally in sectors with fallen cane, previous to the entrance of the raw material to the factories.

At present, the quantization of the amount of fallen cane in productive squares is an expensive and inefficient process. It requires sending evaluators to the fields. They must explore big surfaces of land to obtain a representative sampling that permits an estimation of fallen cane incidence. The movement around the field produces damage, requires many man hours of work and generates estimations with a high degree of uncertainty.

Other strategy consists in carrying out flights over the cultivated lands with specialists who estimate the percentage of fallen cane according to what is observed from the air and their experience. This strategy is subjective and depends on the available specialists in each area of interest.

Up to now, a report of some methodology with measurable precision to determine the affected area with fallen cane has not been observed. Such methodology would allow to plan a better way of harvesting the affected area and calculate its associate costs.

With this goal in mind and in conjunction with the National Institute of Agricultural Technology of Argentina (INTA), the group has worked on the application of computational methods on high-resolution aerial images of the cultivated lands. Those methods were implemented for the purpose of adjusting image characteristics and extracting useful information to identify areas with fallen cane and areas with standing cane. Because of the characteristics of the task and the available data, it was proposed to address the problem with image processing techniques and machine learning methods.

2. Objective

The objective of the work is to develop specific techniques in order to identify areas with homogeneous characteristics in multispectral aerial images. The main interest is to identify areas with fallen cane and areas with standing cane to make harvesting plans of sugarcane productive lands.

3. Materials

A set of images was obtained from a Sky Arrow 650TCNS ERA airplane. The airplane was equipped with a Global Positioning System (GPS), a Geospatial MS4100 multispectral camera and a system of control and storage of data. The camera took images in three bands of the electromagnetic spectrum: green (530-580 nm), red (650-685 nm) and near infrared (770-830 nm) with a resolution of 1920 x 1075 pixels. The GPS provided the position, altitude and height in synchronism with the acquisition of each image.

A flight was carried out on 5th May 2008, moment of the sugarcane growing cycle where the presence of fallen cane is clearly evident. The flight was carried out in the solar midday to have homogeneous illumination in the surface. The flight plan was designed for an altitude of 1200 m, resulting a pixel size of 0.7 meters by side.

The Red and Near Infrared channels were used to calculate the Normalized Difference Vegetation Index (NDVI) [12] of each image. The NDVI is defined as follows: $NDVI = (NIR - Red) / (NIR + Red)$, where *NIR* and *Red* are the fractions of Near Infrared and Red (respectively) radiation reflected by the earth's surface and detected by the camera.

With the supervision of an agricultural engineer the images were labelled in the classes of interest, using the application Label Me [13]. The labelling classes were: standing cane (CP), fallen cane in the form of patches (CCP), fallen cane in big areas (CCA), fallen cane with phototropism (CCF) and areas of exposed ground (C). All the fallen cane types were grouped together in a fallen cane class (CC) because

the main interest of the research is to distinguish between areas with fallen cane and areas with standing cane.

What resulted from this labelling was a set of labelled subimages, corresponding to the CP class or the CC class.

4. Methods

4.1. Spectral signature analysis

In remote sensing it is assumed that specific objects interact in a unique and characteristic way with the electromagnetic radiation given off by the sun and that reach the earth. This interaction describes the spectral response of the objects, which is also called spectral signature. In this work, the spectral response of vegetation is of interest.

The spectral response of an object located on earth surface depends on five factors: reflectivity, absorptivity, emissivity, transmissivity and dispersion. These concepts explain the interaction between the objects and the electromagnetic radiation.

The spectral response curve or spectral signature of vegetation shows low values at wavelengths corresponding to Red and Blue (visible light). On the other hand, it presents a lower peak at Green wavelengths. These peaks and valleys are produced by Red and Blue light absorbed by chlorophyll and other pigments.

The spectral response of sugarcane plants varies according to their state (see Figure 1). At visible wavelengths of the electromagnetic spectrum, corresponding to Green and Red light, the reflectance of the canopy is lower than the bare soil; at Near Infrared wavelengths the vegetation and the bare soil have different reflectances but are similar at Middle Infrared wavelengths. The Middle Infrared wavelength band is important for separating trash from others states of the crop.

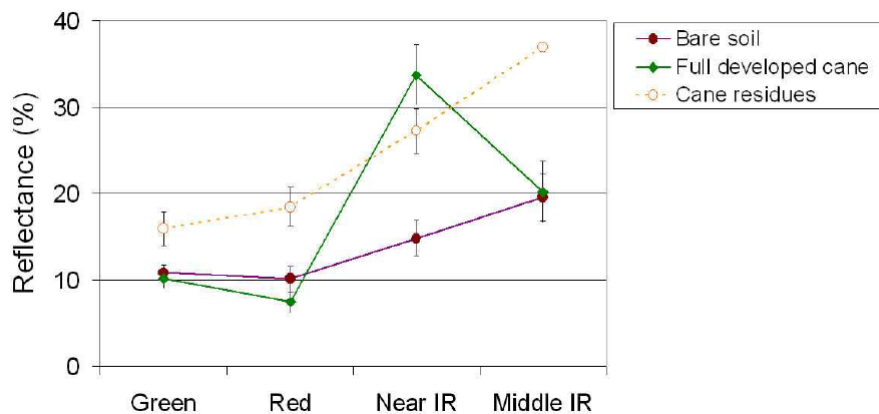


Figure 1: Mean and standard deviation of spectral response of sugarcane in different states and bare soil. [9]

From the photometric point of view, the Normalized Difference Vegetation Index (NDVI) shows healthy vegetation if it takes high values and values near zero shows bare soil and dry vegetation.

4.2. Preprocessing

In order to obtain standardized images with similar illumination level, the set of images was processed with an algorithm called Texture+Cartoon [4]. It decomposes a given image f in two components:

$$f = u + v \quad (1)$$

where u represents the geometric component, called Cartoon, and the component v represents the textural part with oscillating patterns.

For each pixel in the images it needs to be decided whether it belongs to the cartoon part or to the textural part. This decision is made by computing the Local Total Variation (LTV) of the image around the pixel and comparing it to the LTV of the same image around the pixel after applying a low pass filter.

The texture components of the images are considered a version with normalized brightness. They conserve the patterns given by the fallen and standing cane.

4.3. Feature extraction

Considering that the sugarcane cultivation has pronounced alterations in the spatial distribution, it was suggested to address the problem using texture characteristics. In [10] it was reported the use of the entropy, which is a common texture feature used in precision agriculture. Nevertheless, it provides insufficient information to distinguish the different states of the cane. For that reason, the present work proposes to incorporate and test other statistical descriptors divided in three groups: mean, standard deviation and entropy (Group 1); variance, smoothness, uniformity and entropy (Group 2); contrast, energy and homogeneity extracted from the co-occurrence matrix (Group 3). These descriptors are described in [2] and [7].

Using square windows of 11x11 pixels (the window size corresponds to an area of 7.7 meters per side in the sugarcane field), which were moved over the preprocessed images, the texture descriptors were calculated in the three channels of the images (Infrared, Red, Green) and in the NDVI. For each window, the different groups of statistical descriptors were calculated. Doing this in all the labelled images resulted in three data sets with vectors \mathbf{x} corresponding to the different groups of texture characteristics and a label y corresponding to the state of cane associated with \mathbf{x} (CC or CP).

The three groups of statistical descriptors were tested and it was evaluated their provision of information at the moment of distinguishing between the CC class and CP class. Eventually, one of the groups was selected to segment the aerial images.

4.4. Segmentation

To select the classification model, it was carried out a search in the specialized literature. The machine learning methods most commonly used to perform the classification task of multispectral images are: Random Forests, Bagging, Boosting, Decision Trees, Artificial Neural Networks, Support Vector Machines and K Nearest Neighbors. However, when comparing the different methods it was found in several studies, described in [1], that the methods based on trees, in particular the Random Forests, have superior performance in classification tasks of multispectral images.

Using the labelled data set it was possible to train supervised learning methods based on trees. Primarily, it was used as classifier a simple model like a Decision Tree [14]. However, its high rate of misclassification motivated the use of a more complex model like Random Forest [3].

A Random Forest is a classifier consisting of a collection of tree-structured classifiers $\{h(\mathbf{x}, \Theta_k), k = 1, \dots\}$ where Θ_k are independent identically distributed random vectors and each tree casts a unit vote for the most popular class at input \mathbf{x} .

Each new training set is drawn, with replacement, from the original training set. Then a tree is grown on the new training set using random feature selection. The trees grown are not pruned.

Bagging can be used to give ongoing estimates of the generalization error (PE^*) of the combined ensemble of trees. Given a specific training set T , form bootstrap training sets T_k , construct classifiers $h(\mathbf{x}, T_k)$ and let these vote to form the bagged predictor. In each bootstrap training set, about one third of the instances are left out. For each $\{y, \mathbf{x}\}$ in the training set, aggregate the votes only over those classifiers for which T_k does not contain $\{y, \mathbf{x}\}$. This is the out-of-bag classifier. Then the out-of-bag estimate for the generalization error is the error rate of the out-of-bag classifier on the training set.

Summing up, with the three data sets constructed with the different groups of texture characteristics (\mathbf{x}) and the labels y , three Random Forests with N trees each one were trained. The three models were compared and it was selected the one with better performance in the classification task. Afterwards, the selected model was used to segment the aerial images of sugarcane fields. For this, the texture characteristics were also calculated over windows of 11×11 pixels and the obtained vectors were put down the whole forest to get as a result if they belong to the class CC or CP. Doing this with all the pixels of the images resulted in a set of segmented images. Such images clearly showed regions with standing cane and regions with fallen cane in accordance with the precision of the model.

To measure their performance, the three trained models were cross-validated using 10-folds from the corresponding training set. An evaluation error was calculated with a set of reserved vectors which were not used for training. Finally, it was calculated the out-of-bag error during the training of each Random Forest model.

4.5. Post-processing

At this point, it would be useful to recall that the main objective of this work is to obtain information from the multispectral aerial images. That information may help to make decisions at the moment of harvesting the sugarcane fields. With the segmented images the agricultural engineers or producers should be able to make a harvesting plan. The goal of that plan is to harvest optimally the sugarcane, taking in mind the preharvest state of the plants.

The agricultural engineers could differentiate the harvesting of the standing sugarcane from the harvesting of the fallen cane if they consider that the size of the affected areas is considerable and worth it. They should also take into account other factors like how the harvesting machine works, the characteristics of the fields, operative costs, between others.

A post-processing stage was applied to the segmented images to improve the extraction of useful information. The resulting areas were made closed patches with all the bounded pixels of the same class. Small sparse areas were eliminated. For that purpose, it was used an implementation of the Region Growing algorithm.

The algorithm receives as inputs an image that contains the region of interest, a point (x, y) inside the region and a threshold t . The region is iteratively grown by comparing all unallocated neighbouring pixels to the region, starting from the initial input point. The difference between a pixel's intensity value and the region's mean, is used as a measure of similarity. The pixel with the smallest difference measured this way is allocated to the respective region. This process stops when the intensity difference between region mean and new pixel becomes larger than t .

To get the desired results, it was proposed to apply this algorithm iteratively with different seed points. For seed points it was proposed to create a grid over the image with points equidistant both in the x coordinate and in the y coordinate. Then, for each point (x, y) , it was carried out the region growing algorithm. When detecting that a point (x, y) belonged already to a region identified in a previous iteration it was not reapplied the method.

The distance between the grid points in both coordinates (Δx and Δy) defined in some way the minimum size of the regions that could be identified. These distances depend on each case of study and this is the part of the process that requires assistance from the user. They were made some tests with different values of Δx and Δy .

	<i>Out-of-Bag Error</i>	<i>Cross-validation Error</i>	<i>Evaluation Error</i>
Model 1	7,8%	7,3%	7,6%
Model 2	9,7%	9,4%	12,2%
Model 3	13,2%	12,8%	16,1%

Table 1: Error values of the Random Forests trained with the different groups of texture descriptors.

5. Results

The amount of trees used in each Random Forest was fixed to 50. For each group of texture descriptors, a set of 385 feature vectors was constructed. Each feature vector corresponded to one of the windows of 11x11 pixels obtained from the labelled images. Before training, from each set of vectors, a group of 77 (20%) vectors (y, \mathbf{x}) was reserved and not used for training. The remaining 308 vectors were used for training.

The resulting classification errors obtained with the trained models are listed in Table 1. Model 1 was trained with the descriptors: Mean, Standard Deviation and Entropy (Group 1); Model 2 was trained with the descriptors: Variance, Smoothness, Uniformity and Entropy (Group 2); and Model 3 was trained with the descriptors: Contrast, Energy and Homogeneity extracted from the co-occurrence matrix (Group 3).

As it can be seen in the error table, the model with better classification performance is the model trained with the descriptors Mean, Standard Deviation and Entropy (Model 1). For this model it was also calculated the Sensibility, resulting of 92%, and the Specificity, resulting of 94%.

Model 1 was selected and used to segment the aerial multispectral images in order to obtain information about the affected areas with fallen cane.

As an example, in figure 2a there is an multispectral aerial image taken from the available set of images. Figure 2b shows the segmented image and figures 2c, 2d, 2e and 2f show the resulted images after post-processing with different values for Δx and Δy . The dark pixels correspond to the background of the picture. The blue pixels are fallen cane (CC class) and the green pixels are standing cane (CP class). It was also possible to calculate the real size of each detected area.

In Figures 3 is shown another example.

After applying the post-processing to different segmented images, about 10 to 16% of the pixels of each image changed of class with respect to the class assigned during the segmentation. This is the price that must be paid in order to obtain more valuable information from the segmentation.

6. Conclusions

In this paper, a pipeline to process multispectral aerial images of sugarcane productive squares and obtain data sets in order to estimate the state of the sugarcane (standing cane or fallen cane) was presented.

This pipeline includes 5 steps: image labelling, image filtering, feature extraction, image segmentation and postprocessing. The labelled datasets were built by means of a web tool to support the interaction with the experts of INTA. A Cartoon-Texture filter was used for the image filtering step. The filter was used to standardize the images respect to the brightness levels. The features extracted were groups of texture statistics from the original images and NDVI index, both used extensively for the agricultural engineer to characterize different cultures. Image segmentation process involved the use of machine learning methods with different complexity level. The Random Forest algorithm allowed to obtain a good performance for this application. The model trained with the characteristics Mean, Standard Deviation and Entropy had a cross-validation error of 7,3% and an evaluation error of 7,6%. The resulting segmented images presented several complex zones and small sparse areas in which the combine harvester can not work. For this problem, a post-processing by Region Growing was used.

Taking everything into account, the proposed approach has demonstrated to provide valuable information for estimating the state of the sugarcane, apply different policy actions in relation to harvest

methods, estimate associate costs, etc. In addition, its modular aspect guarantees the reusability of some processing steps to other images and cultures. As a result, the production of sugarcane and the manufacture of sugar could be more efficient and profitable.

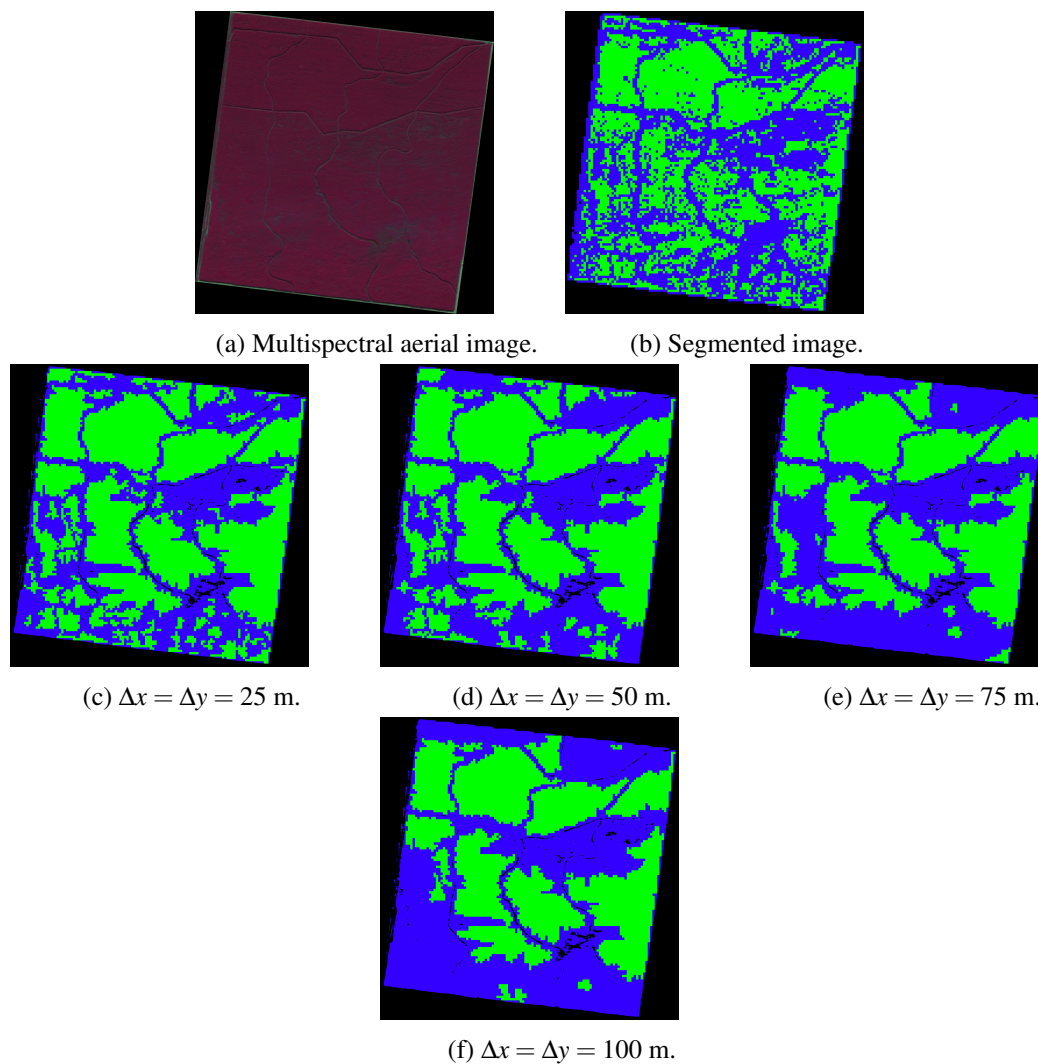
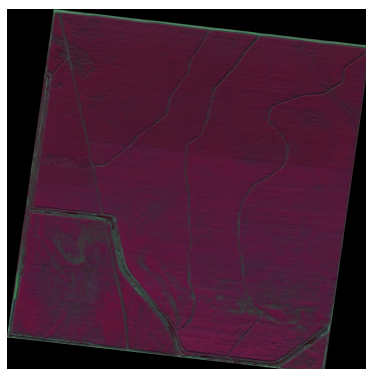
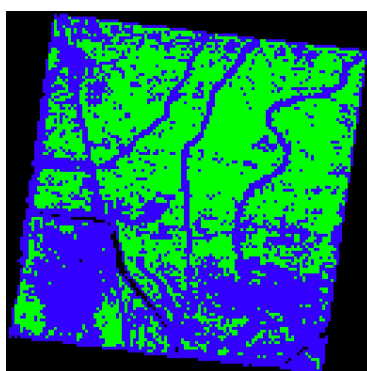


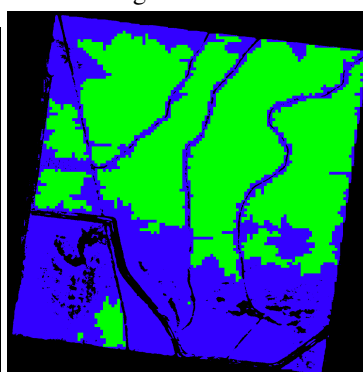
Figure 2: Example images



(a) Multispectral aerial image.



(b) Segmented image.



(c) Post-processed image ($\Delta x = \Delta y = 100$ m).

Figure 3: Example images

References

- [1] Ozlem Akar and Ogur Gungor. Classification of multispectral images using random forest algorithm. *Journal of Geodesy and Geoinformation*, (2):105–112, 2012.
- [2] Ángel Ruiz Alonso. Comportamiento y análisis de descriptores de texturas en imágenes MODIS, 2011.
- [3] Leo Breiman. Random forests. *Machine Learning*, 45:5–32, 2001.
- [4] Antoni Buades, Triet M. Le, Jean Michel Morel, and Luminita A. Vese. Fast cartoon + texture image filters. *IEEE Transactions on Image Processing*, 19(8), 2010.
- [5] S J Clarke. Losses associated with cane yard operations and cane washing. *Proceedings of The South African Sugar Technologists' Association*, pages 139–144, 1991.
- [6] Lênio Soares Galvao, Antônio Roberto Formaggio, and Daniela Arnold Tisot. Discrimination of Sugarcane Varieties in Southeastern Brazil with EO-1 Hyperion Data. *Remote Sensing of Environment*, (94):523–534, 2005.
- [7] Rafael C. Gonzalez, Richard E. Woods, and Steven L. Eddins. *Digital Image Processing Using MATLAB*. Gatesmark Publishing, 2 edition, 2009.
- [8] J E Larrahondo. Calidad en la caña de azúcar: el cultivo de la caña en la zona azucarera de Colombia, cali. Technical report, Centro de Investigación de la Caña de Azúcar de Colombia (CENICAÑA), 1995.
- [9] Valentine Lebourgeois, Agnes Begue, Pascal Degenne, and Eric Bappel. Improving harvest and planting monitoring for smallholders with geospatial technology: the reunion island experience. *International Sugar Journal*, 109(1298):109–119, 2010.
- [10] D Perez, C Fandos, L Mazzone, F Soria, P Scandalaris, and J Scandalaris. Caña de azúcar en tucumán y argentina: evolución de algunos aspectos económicos y productivos de la campaña 2004. Reporte agroindustrial. Estadísticas y márgenes de cultivos tucumanos. Vol. 2, Boletín Num. 6, Instituto Nacional de Tecnología Agropecuaria, Estación Experimental Agroindustrial Obispo Colombres, Tucumán (Argentina), 2005.
- [11] Noé Aguilar Rivera, Guadalupe Galindo Mendoza, and Javier Fortanelli Martnez. Evaluación agroindustrial del cultivo de caa de azcar (saccharum officinarum l.) mediante imgenes spot 5 hrv en la huasteca mxico. *Revista de la Facultad de Agronoma*, 111(2), 2012.
- [12] J W Rouse, R H Haas, J A Schell, and D W Deering. Monitoring vegetation systems in the great plains with erts. In *Third ERTS Symposium*, volume 1, pages 309–317. NASA, Washington D.C. (USA), 1973.
- [13] B C Russel, A Torralba, K P Murphy, and W T Freeman. Labelme: a database and webbased tool for image annotation. *International Journal of Computer Vision*, 77(1–3):157–173, 2008.
- [14] Agustín Solano, Gerardo Scheneider, Alejandra Kemerer, and Alejandro Hadad. Characterization of multispectral aerial images of sugarcane. *Journal of Physics: Conference Series*, 477, 2013.
- [15] Gabriel Sustaita. *Modelo estratégico para la industria azucarera regional*. MBA, Universidad Católica del Norte Santo Tomás de Aquino, Fundación del Tucumán, Pontificia Universidad Católica de Valparaíso, 2005.
- [16] Prasad S. Thenkabail, Ronald B. Smith, and Eddy De Pauw. Hyperspectral vegetation indices and their relationships with agricultural crop characteristics. *Remote Sensing of Environment*, 71(2):158–182, 2000.
- [17] J Tonatto, E R Romero, M F Leggio Neme, J Scandalaris, J Alonso, P Digonzelli, L Alonso, and S Casen. Importancia de la calidad de la materia prima en la productividad de la agroindustria azucarera. Gacetilla Agroindustrial de la EEAOC, num. 67, Instituto Nacional de Tecnología Agropecuaria, Estación Experimental Agroindustrial Obispo Colombres, Tucumán (Argentina), 2005.