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CROP CLASSIFICATION FOR THE NILO COELHO SCHEME BY USING LANDSAT TM IMAGES

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Abstract. In this paper were used Landsat TM images and supervised classification in order to distinguish crop areas and obtained the crop classification for the Nilo Coelho scheme. For land-use classification band 4, 5, 3 (Landsat TM) was assigned to Red Green Blue (RGB). A commercial software package (ERDAS Imagine v. 8.5) was available for the processing of the Landsat data. With a supervised classification were used field data to train the classifier. A field survey is made on all classes present in the field. The grapes can be recognized by the bright orange colour (RGB: 4,5,3) and their rectangular shapes. Fully developed banana plantations are easily recognized by the very bright red colour (RGB: 4,5,3). Fruit trees are difficult to classify with satellite images in general due to the variable ground cover and growing stage. Some vegetables can be identified and thus classified on the image but mainly because large vegetable fields are irrigated by a pivot system.

Keywords: remote sensing, image processing, supervised classification.

1. Introduction

The use of satellite images to support land and water management is technically possible since the end of the seventies. Unfortunately, a breakthrough never occurred. The success of remote sensing (RS) applications in land and water management is limited, and, for example, far behind the successes of RS applications in weather and climate studies. Overselling of the technique caused this, among others, and by the low attention universities have given to develop remote sensing algorithms that can be adopted by the commercial sector.

High-resolution images are required to describe land use and to detect changes in crop types and irrigated area. Crop classes have to be known for individual plots (ground truth) to verify the legitimacy of crop cultivation. Landsat multi-spectral data can be used for classifying cropped fields and the type of crop. The overall accuracy is about 85 %. However, large differences in the classification performance of individual crops occur (Bastiaanssen, 1998). The spectral information from irrigated fruit trees cannot be discriminated very well. The spacing between fruit trees and the herbaceous layer between the trees affects the total spectral behavior. Perennial fruit trees also have different ages and sizes, which makes them difficult to differentiate.

Precise estimation of planted areas with agricultural crops of relevant interest to the national economy is of fundamental importance to several aspects such as: estimation of production, commercialization and transport. The use of satellite images to crop classification is possible, but generally is very difficult. When is possible to use together, satellite images and field visits the results are more real.

Medeiros et al. (1996) used Landsat TM images to estimate areas planted with sugarcane, soybean and mayze in the counties of Aramina, Buritizal, Ituverava and Ipuã, located in north of São Paulo state, for the crop year of 1994/1995. In this work, the planted areas with sugarcane, soybean and maize were underestimated by 23% (9930 hectares), 25% (13627 hectares) and 94% (50817 hectares) in relation to the estimate area by the Brazilian Institute of Geography and Statistics (IBGE), so they believed that these results are quite close to reality. With the same purpose, Motta et al. (2001) and Fonseca et al. (2001) used Landsat images to verify the estimation of the crops areas with soybean and cover of mixes (forest, corn, sorghum, sugarcane and water), respectively. Fonseca et al. (2001) concluded that to separate different agricultural targets the digital classification techniques and the sensor spatial and spectral resolution (Landsat TM) are not appropriate. Motta et al. (2001) concluded that the estimation of the area of select crop (soybean) obtained from the unsupervised classification has a good accurate.

The objective of this paper is to verify the use of Landsat TM images to make crop classification on the Nilo Coelho scheme under real conditions. For that were used Landsat TM 5 images (bands 4, 5, 3), software ERDAS Imagine and field visits.

2. Material and methods

2.1. Theory

A digital image is a 2D-array of pixels in which each pixel corresponds to the energy reflected or emitted from the Earth’s surface. The spatial arrangement of the measurements defines the image or image space.

In one pixel, the values in (for example) two bands can be regarded as components of a two-dimensional vector, the feature vector. Plotting all vectors in a two-dimensional graph gives a two-dimensional feature space called a scatter plot. Similarly, this can be done for three bands resulting in a 3-dimensional feature space. Displaying the feature space of an image with 6 bands can be done by creating 2-dimensional scatter plots for all possible band combinations

Classification is the process of grouping similar pixels (more or less the same place in the feature space) into thematic classes. There are two main groups of classification methods:

- non-supervised
- supervised

a. Non-supervised

The non-supervised classification is an entirely mathematical process of grouping individual pixels with similar radiometric properties. In the process only the required number of classes have to be defined. The final classes do not have any thematic meaning. After the classification the analyst has to label each class with a relevant meaning. The process of labelling is therefore highly depended on the skill and intuition of the analyst. A practical approach is to generate more classes than actually needed and group them together after the classification

b. Supervised

With a supervised classification the analyst uses field data to train the classifier. A field survey is made on all classes present in the field. For a classification of mango crop is not sufficient to collect only training fields with mango crop because other land cover classes might have similar spectral properties as the mango crop on that specific time, location, soil type etc.

Sampling rates generally vary between 1% and 3% of which 50% can be set aside for the validation.

One approach is to use the field data as training signatures directly and classify the image afterwards. The other approach is to use the field data only for gaining knowledge on what kind of information can be extracted from the image. Once the analyst has a clear understanding of information content of the image he/she starts selecting training fields on the satellite images.

The first approach is more straightforward but less accurate. Errors in field data have a direct and negative influence on the classification quality. Specific fields with very different spectral signatures compared to other fields of the same class can have a large impact on the classification result.

Once the training set is ready the analyst can use different classification algorithms such as the maximum likelihood, minimum distance or box classifier. The maximum likelihood is the most common used. For each training signature the mean and covariance matrix is calculated. Afterwards for each pixel in the image the statistical distance to each training signature is calculated and assigned to the training signature with the highest probability.

The classification process is an iterative process. Each result should be evaluated and compared with the field data. In case of unsatisfactory results the training set should be adjusted by adding and/or deleting signatures from the areas where the classification does not perform well.

In general the accuracy can be high (80-90%) if multiple images are used, the field size is large, the number of classes limited, the fieldwork extensive and sufficient time available to perform a classification.

2.2. Study area

The study area was the Nilo Coelho scheme with perennial irrigation fruits, on the left bank of the San Francisco River, in the Pernambuco state, Brazil (Petrolina City: latitude 09°09'S, longitude 40°22'W) (**Figure 1**). The perennial fruits are banana, coconut, mango, grapes and some smaller fruits such as guava and acerola. There are two types of entre-preneurial plots: small areas of 20 ha and medium to large areas of 50 ha or more (Brito et al. 2000). Family plots have an average size of 6 ha. The soils have a sand fraction of more than 70%. The climate of Petrolina is semi-arid.

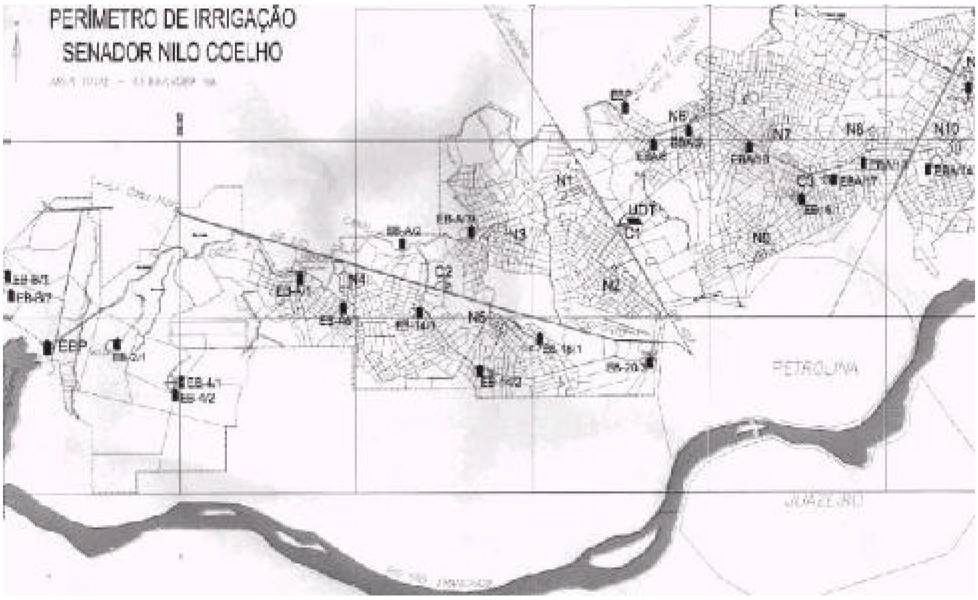


Figure 1. Schematic lay-out of the Nilo Coelho irrigation scheme at the Left Bank San Francisco river near Petrolina in Northeastern Brazil.

2.3. The Landsat image

High-resolution images are required to describe land use and to detect changes in crop types and irrigated area. Crop classes had to be known for individual plots (ground truth) to verify the legitimacy of crop cultivation. For this purpose, a Landsat Thematic Mapper 30 m resolution satellite images were used. The Landsat 5 image used was obtained in 9 August 1998 (path 217 and row 67). For the crop classification was used three bands: near infra-red (band 4), middle infra-red (band 5) and red (band 3). When three bands are displayed at the same time, each band is assigned a colour band to form a colour composite (**Figure 2**). For land-use classification band 4, 5, 3 (Landsat TM) assigned to Red Green Blue (RGB) is a common used one. A commercial software package (ERDAS Imagine v. 8.5) was available for the processing of the Landsat data (to calculate the NDVI and a supervised classification).

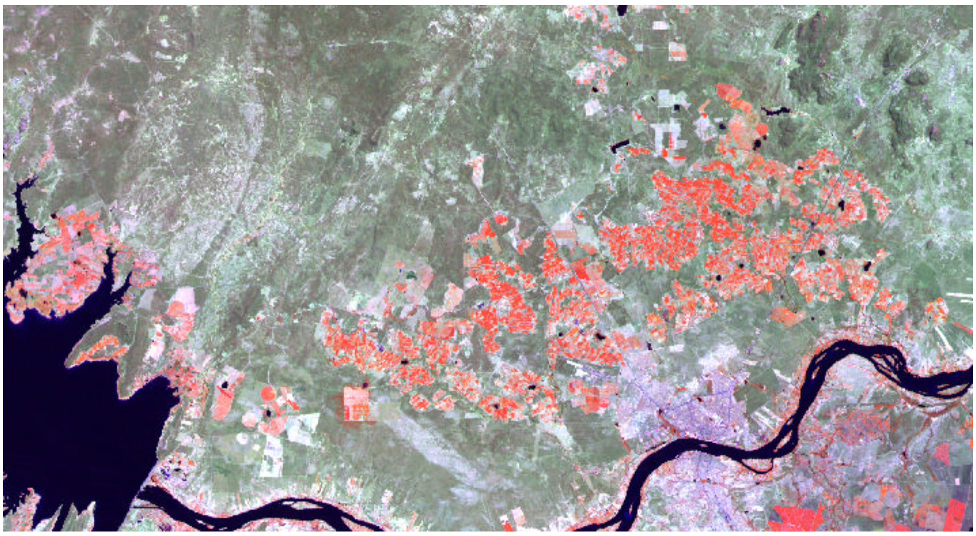


Figure 2. Landsat TM image 9 August 1998. Composition of bands 4, 5 and 3 assigned to RGB.

With a supervised classification were used field data to train the classifier. A field survey was made on all classes present in the field, for example mangos orchards, bananas orchards, guavas orchards, coconuts orchards, grapes, vegetables and native vegetation.

Large differences in the classification performance of individual crops might occur (Bastiaanssen, 1998). The spectral information from irrigated fruit trees can not be discriminated very well. The spacing between fruit trees and the herbaceous layer between the trees affects the total spectral behavior. Perennial fruit trees also have different ages and sizes, which makes them difficult to differentiate.

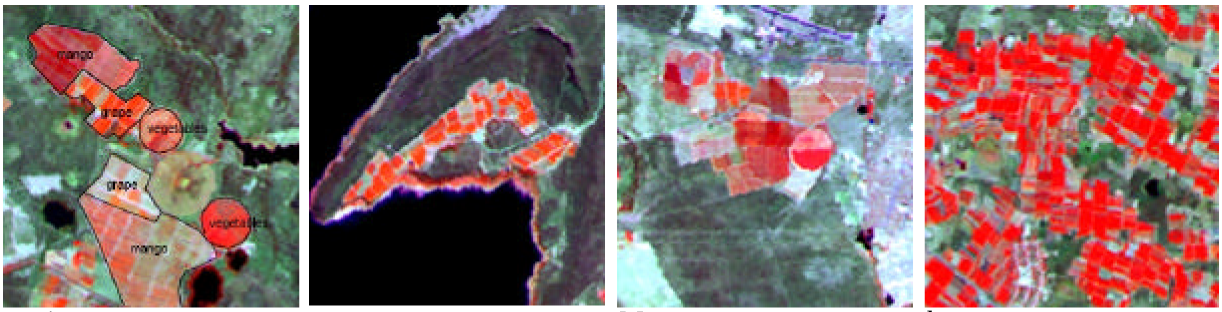
3. Results

The grapes can be recognized by the bright orange colour (RGB: 4,5,3) and their rectangular shapes. Just after the pruning the LAI is very low resulting in different spectral behaviour. In that case the spectral signature is for a large part determined by the soil type and therefore difficult to classify in an automatic way (**Figures 3 and 4**).

Fully developed banana plantations are easily recognized by the very bright red colour (RGB: 4,5,3). Young banana plantations are difficult to distinguish because the spectral signature is largely determined by the ground cover between the banana trees (**Figure 3 and 4**).

Fruit trees are difficult to classify with satellite images in general due to the variable ground cover and growing stage. In most cases the spectral signature of fruit trees is for a large part determined by the ground cover between the trees. This can be bare soil, grass and in case of intercropping; different crops (**Figures 3 and 4**). The potential for discriminating fruit trees is therefore highly depended on the size and spacing of the trees. Fully developed mango trees can be recognized on the image as dark red. Young mango trees have similar spectral signatures as guava and coconut trees.

Some vegetables can be identified and thus classified on the image but mainly because large vegetable fields are irrigated by a pivot system (**Figures 3 and 4**).



various crops *grape* *Mango* *banana*

Figure 3. Examples of crop classification from the Landsat image of 9 August 1998.

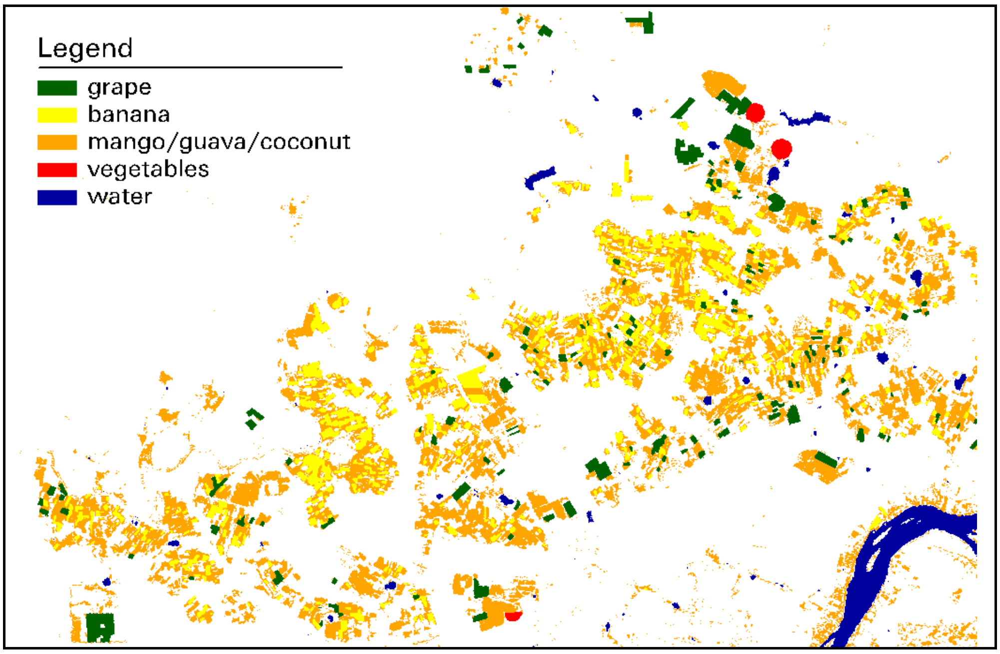


Figure 4. Classification result of the Landsat-TM5 image of 9 August 1998

4. Conclusions

It was very hard to make the crop classification for The Nilo Coelho scheme because of several aspects. The spacing between fruit trees and the herbaceous layer between the trees affects the total spectral behavior. Perennial fruit trees also have different ages and sizes, which makes them difficult to differentiate.

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