

## LAND USE MAP PRODUCTION BY FUSION OF MULTISPECTRAL CLASSIFICATION OF LANDSAT IMAGES AND TEXTURE ANALYSIS OF HIGH RESOLUTION IMAGES

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### ABSTRACT

This paper presents a methodological approach to combine land use information obtained from different processing methods. The first one is a traditional multispectral classification of multitemporal LANDSAT TM images. The second is a textural analysis of high-resolution panchromatic images obtained from aerial orthophotoimages. Both are combined using Decision Theory approach to get the best from each classification. Some test results are presented in order to show the improvement obtained.

### 1 INTRODUCTION

One of the most frequently used methods to obtain a land cover map is the supervised classification of multispectral LANDSAT images, but often the result is not enough accurate for most of the practical remote sensing applications. Even using multitemporal images to capture the phenological evolution of the vegetation along the year, a high level of uncertainty in some classes is often present.

Nevertheless it is very common to have several data sets from a given physical geographic area, either data acquired at different moments or by different sensors, and from each one we may obtain a land use classification using different techniques. Conceptually, each data source is better suited to extract certain characteristics, so it becomes necessary to have a method to combine them getting the best from each one.

A supervised classification provides a likelihood distribution that tells us the assignment probability of a pixel to each one of the legend classes. Using some test areas we can also obtain an individual measure of per cent classification success ratio for each data source. The method we present here to merge two land use maps of the same geographic area relies on the combination of the likelihood (assignment probabilities) and the classification success ratio of each data source. Combining them, we obtain a new assignment probability distribution and, therefore, a new classification.

### 2 PREVIOUS WORK

Since 1982, the ICC has been working on cartographic applications of remote sensing images. One of the first projects was making a 1:250 000 land use map of Catalonia (32 000 Km<sup>2</sup>) using classification techniques applied on existing LANDSAT MSS images. Initially, a 7 classes long legend was defined. Successive projects proceeded to update the information and better resolution images (LANDSAT TM) have been used and a longer legend (20 classes) could be afforded. But achieving a reasonable good map performance (better than 85% good pixel assignment for each class), overloaded the process with an arduous visual inspection using complementary information (aerial photography, field campaigns, etc.) even using different images along the year to take advantage of the phenological vegetation change.

Anyway, complementary geographic information can be obtained and we will use it to improve the classification.

### 3 DATA SETS USED IN THE PROJECT

Two different data sources are used. The first one is a set of multispectral LANDSAT Thematic Mapper images taken at two different year seasons, from which a first classification is obtained. The second data source is a B/W orthophotomap 2.5 meters pixel resolution obtained from panchromatic aerial photography (Fig. 1).



Figure 1. *Orthophoto sample of the test area*

In order to take advantage of its higher spatial resolution compared to the LANDSAT images, a classification is performed on the derived bands obtained by texture analysis. The texture analysis is made using co-occurrence matrix obtained in a square window 12 pixels wide to obtain the same pixel resolution as the first data source.

In order to train the classification and also test the results obtained, some ground truth polygons are extracted from existing aerial photography by visual interpretation.

## 4 METHOD

### 4.1 MULTISPECTRAL SUPERVISED CLASSIFICATION

One of the methods to classify an image containing several information channels is multispectral supervised classification. This is a technique widely used in Remote Sensing, and has proved to be very robust and reliable during the many decades it has been used (Bryan, 1979) (Campbell, 1987) (Chuvieco, 1995).

The classification process provides an array of probabilities to assign each image pixel to each label in the legend. Then we can look for the highest probability in that array and build a new image with the class label assigned to each pixel in order to analyse the spatial distribution of the classification. Anyway, in the method we present, the core process will really manage the probabilities obtained during the classification of each data set combining them to obtain a good merge.

An estimation of the accuracy of our classification can be obtained through a statistical value usually called *kappa index*  $\kappa$ . (Richards, 1993). This statistical value is obtained through the construction of the so called *confusion matrix*. The closer to 1 the more accurate is our classification. We have to note that if we perform a random classification using  $N$  classes, we can obtain percentual indexes of right classification for each class that will be  $100/N$  %. For example, if we have only 2 classes, in a purely random classification we would obtain a 50 % of rightly classified pixels. But if we also calculate the  $\kappa$  index, we would obtain a null value. This value is telling us that our classification is completely inaccurate, and that the results it shows are completely unrelated to the real ground classification.

### 4.2 TEXTURAL ANALYSIS

In a textural analysis (Connors, 1980) (Connors, 1984) (Haralick, 1979) we perform a statistical study of the radiometrical values present inside certain areas of our image. This allows us to study the spatial distribution of grey values and not pixels as isolated entities. To perform this study we build what is called a *co-occurrence matrix*, and from this we obtain some statistical variables that will help us to know the structure of this matrix.

A co-occurrence matrix  $S(\delta, T) = [s(i, j, \delta, T)]$  is a matrix where each element is the estimated probability to have the radiometric values  $i$  and  $j$  given the displacement vector  $\delta = (\Delta x, \Delta y)$  and window  $T$  (size and profile of region used to estimate these probabilities).

From this matrix we can calculate the following six new variables:

$$1. \text{Inertia } I(\delta, T) = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} (i - j)^2 s(i, j, \delta, T)$$

$$2. \text{Cluster Shade } A(\delta, T) = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} (i + j - \mu_i - \mu_j)^3 s(i, j, \delta, T)$$

$$3. \text{Cluster Prominence } B(\delta, T) = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} (i + j - \mu_i - \mu_j)^4 s(i, j, \delta, T)$$

$$4. \text{Local Homogeneity } L(\delta, T) = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} \frac{1}{1 + (i - j)^2} s(i, j, \delta, T)$$

$$5. \text{Energy } E(\delta, T) = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} [s(i, j, \delta, T)]^2$$

$$6. \text{Entropy } H(\delta, T) = - \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} s(i, j, \delta, T) \log(s(i, j, \delta, T))$$

$$\text{where } \mu_i = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} i s(i, j, \delta, T) \quad \mu_j = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} j s(i, j, \delta, T)$$

and  $L$  is the number of radiometric values in the processed image.

This way we obtain several new images that we can interpret as information channels and construct a new multispectral image grouping those statistical variables (Fig. 2).



Figure 2: False colour image (cluster prominence, inertia and local homogeneity)

### 4.3 EVIDENCE THEORY

Mathematical Evidence Theory (Shafer, 1976) (Lee, 1987) (Moon, 1990) is a topic where the data sources are treated independently, and their contributions are combined to obtain a new common rule for the pixel labelling procedure.

The technique essence is related to the assignment to different labels of what is called *evidence mass*, combining the probability to assign a pixel to each class and the uncertainty in our assignment process. The total evidence mass available for assignment to the candidate label is 1.

To combine these two classifications we need an estimation of their uncertainty. We can achieve this from the  $\kappa$  index. We obtain the classification uncertainty  $\theta$  simply by:

$$\theta = 1 - \kappa$$

The Evidence Theory allows us to join two mass distributions to combine evidences to assign a pixel to each class and obtain a label which is jointly preferred and for which the overall uncertainty should be reduced. This is done through the mechanism of the Dempster orthogonal sum (Richards, 1993).

## 5 RESULTS AND DISCUSSION

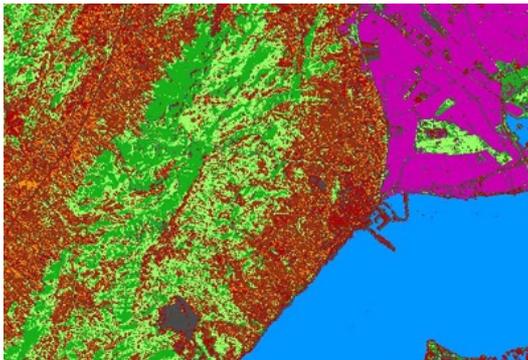
### STUDY SITE

An area in the South of Catalonia has been selected as a test site, covering part of the Ebro river delta. It is specially interesting because presents many textural variations and we believe that it should show a clean contribution of textural variables to the classification process.

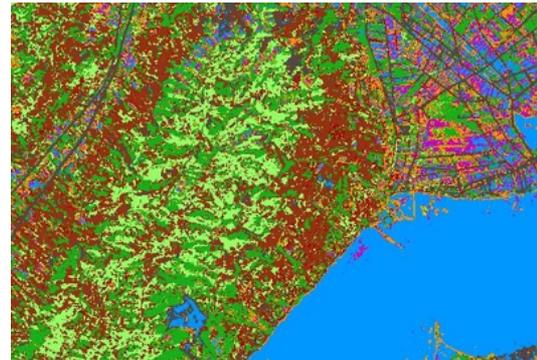
The land cover classes defined are:

- Forest, including different species (pine, ilex, oak, etc.)
- Shrub, including abandoned crops
- Water, basically seawater
- Urban zones, dense and spread, no communication tracks included
- Bare soil, soils without vegetation (rocks, quarries, roads, highways, etc.)
- Irrigated crops (rice, lettuce, beans, etc.)
- Non-irrigated crops (grain, wheat, barley, etc.)
- Fruit trees (hazel wood, almond, olive, vineyard, etc.)

Using the LANDSAT and the texture derived images two preliminary classifications (figures 3 and 4) are obtained.



**Figure 3:** *LANDSAT multispectral classification*



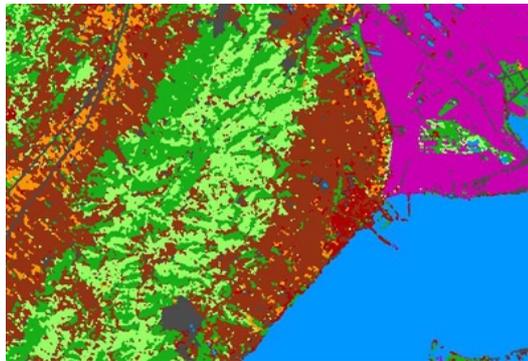
**Figure 4:** *Classification from textural analysis*

In the LANDSAT classification we can observe that there is a good classification of water, bare soil, forest and irrigated land. There is some confusion among non-irrigated land and fruit trees. In the textural analysis there is a great confusion in the irrigated land zone, but a good agreement and discrimination between the non-irrigated land and the fruit trees. Some confusion among water and bare soils also exists.

The  $\kappa$  indexes for these two classifications are:

$$\begin{aligned}\kappa (\text{LANDSAT}) &= 0.71 \\ \kappa (\text{Texture}) &= 0.67\end{aligned}$$

Using the Evidence Theory to combine the classification probability distributions for each pixel from each data source, we obtain a final classification (Figure 5).



**Figure 5:** Final classification obtained using the evidence theory

If we calculate the  $\kappa$  index for this final image we obtain  $\kappa$  (Evidence theory) = 0.83 which is clearly better than the preceding two values obtained from the independent classifications. We can resume these values in Table 1.

	LANDSAT	TEXTURAL	EVIDENCE
$\kappa$	0.71	0.67	0.83

**Table 1:** Global accuracy  $\kappa$  index for each classification method.

The  $\kappa$  index is calculated from the final confusion matrix (Table 2).

	Bare Soil	Shrub	Forest	Urban	Water	Irrigated	Non irrig.	Tree crops
Bare Soil	2720	14	27	175	0	11	32	54
Shrub	12	2454	359	27	0	0	34	94
Forest	198	373	2817	108	7	0	82	68
Urban	16	0	0	961	0	0	70	11
Water	36	0	0	108	30211	0	17	0
Irrigated	95	0	0	4	1	2494	0	0
Non irrig.	49	0	0	17	0	0	1569	33
Tree crops	297	419	151	750	0	0	626	4712

Table 2. The final confusion matrix obtained, comparing ground truth test data and the final classification

The main objective has been to reduce the relative confusion between the arboreal fruit crop, non-irrigated land and shrub cover of the LANDSAT image. These are problematic land covers that always present a great challenge to the usual LANDSAT thematic land cover classification methods. The use of texture was aimed to solve this problem. Also the urban cover classification was improved respect to previous classifications.

## 6 CONCLUSIONS

The combination of familiar multispectral LANDSAT classification methods and the texture analysis using the evidence theory and the Dempster orthogonal sum, allows us to isolate the best characteristics from each classification method and data source to finally obtain an improved classification.

Further research will explore new data sets in order to improve the classification. The most promising is Digital Elevation Model derived information (terrain orientation, altitude, slope) and climatic (temperature, rain) information but an adapted tool analysis will be necessary to include them in the final decision merge.

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**REFERENCES**

- Bryan, J. (1979). On the clustering of multidimensional pictorial data. *Pattern Recognition*, 11: 115-125.
- Campbell, J.B. (1987). *Introduction to Remote Sensing*. Ed. Guilford Press. New York.
- Chuvieco, E. (1995). *Fundamentos de teledetección espacial*. Ed. Rialp. 2ªed. Madrid.
- Connors R.W. and Harlow, C.A. (1980). A theoretical comparison of texture algorithms. *Transactions on Pattern Analysis and Machine Intelligence*. Vol PAM1-2, no. 3: 204-222.
- Connors, R.W., Trivedi, M.M. and Harlow, C.A. (1984). Segmentation of a high-resolution urban scene using texture operators. *Computer Vision, Graphics and Image Processing*. **25**: 273-310.
- Haralick, R.M. (1979). Statistical and structural approaches to texture. *Proceedings of the IEEE*. 67: 786-804.
- Lee, T., Richards, J.A. and Swain P.H. (1987). Probabilistic and evidential approaches for multisource data analysis. *IEEE Transactions in Geoscience and Remote Sensing*. GE-25: 283-293.
- Moon, W.L. (1990). Integration of geophysical and geological data using evidential belief function. *IEEE Transactions in Geoscience and remote sensing*. 28: 711-720.
- Richards, J.A. (1993). *Remote Sensing Digital Image Analysis, An Introduction*. Ed. Springer-Verlag. 2ª ed.
- Shafer, G. (1976). *A mathematical theory of evidence*. Ed. Princeton UP. New Jersey.