

# GREENHOUSES DETECTION USING AN ARTIFICIAL NEURAL NETWORK WITH A VERY HIGH RESOLUTION SATELLITE IMAGE

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**KEY WORDS:** Artificial Neural Network, Very High Resolution Satellite Image, Texture Analysis

## ABSTRACT:

Detecting and locating greenhouses in south-east of Spain is very important for politicians and other persons who may take decisions about management of natural resources and who must design agricultural development plans. Agriculture is one of more important economic activities in this zone, and till now, development and disposition of new greenhouses was uncontrolled. In this paper, we present a methodology to detect greenhouses from 1.5 m pixel size QuickBird image, based in Artificial Neural Network algorithm. Thanks to the information introduced as training sites, we “teach” to the mathematical model to classify the image considering its radiometric and wavelet texture properties. This assessment is known as training, and the algorithm to obtain it, back-propagation. Classification accuracy was evaluated using multi-source data, comparing results including and no-including wavelet texture analysis. We conclude that some texture analysis can not improve classification accuracy but if one choose correctly parameters and texture model, it can become better. Actually we are working on automatic detection and actualization of greenhouses distributions.

## 1. INTRODUCTION

Classification is the process by which we develop thematic maps from remote sensors images. Traditionally this process was reached applying visual interpretation and drawing its boundaries manually. Nevertheless with computer apparition, scientists focused in computed aided interpretation.

Information obtained from classified image can help us to designing of development planning or to take decision about natural resources management. In this work, located in Campo de Níjar region, in south-east of Spain, classified image will help to plan agricultural development or to know greenhouses distribution changes due in last years. Greenhouses are structures with the aim of protecting horticultural products of environments agents, mainly the win. Its plastic roofs have a characteristic radiometric behaviour in which classification algorithms base to separate this class of other different classes. Nevertheless, angle vision, plastic chemical composition, age, and photosynthetic activity under plastic can change dramatically it spectral signature. Besides, greenhouse’s owner paint plastic roof with white colour to decrease sun radiation inside in summer time. Due maintenance operations between different crop cycles, plastic roof may temporally disappear in greenhouses. So, all this motives can deteriorate accuracy in greenhouse classification.

There are two traditional approaches in classification of images: supervised and unsupervised. The first one classification of pixel based on characteristics of classes. To characterize a class, operator must to delineate pixel groups corresponding to each interesting class, called training sites. So, a pixel will belong to the class more statistically similar to own properties. In the second one, classification algorithm produces more frequent land cover by the clustering method.

Artificial Neural Network is a supervised classification method, recently applied to land use/cover change detection (Xiou *et al.*,

2002). This is a non-linear mathematical model that imitates the way in which human brain interprets graphical information. This particular parcel of Artificial Intelligence doesn’t require hypothesis a priori about distribution functions or another statistical assumptions. Besides, thanks to the previous learning approach, a neural network is able to classify unknown data.

The aim of this work was to design an appropriate methodology to obtaining classified images from very high resolution satellite. The resultant classification is focused in greenhouses class in south-east of Spain and so, we studied the best texture analysis to improving accuracy. Actually we claim to get automatic change greenhouses cover detection to adapt it to actualization cartographic and thematic information.

## 2. AREA OF STUDY

Campo de Níjar is a region located in province of Almería (Spain) with an approximated surface about 20.000 ha (Figure 1).

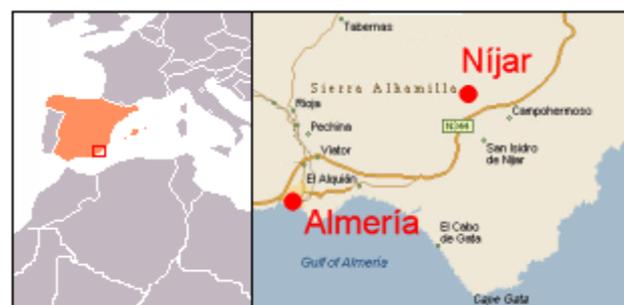


Figure 1. Area of study

Here, there is an intensive agricultural production system based on greenhouses structures. This fact characterizes the landscape, besides coppice natural vegetation, disperse urban cover, a soft

topography, limited by Sierra La Serrata on the south, and by Sierra Alhamilla on the north.

It was obtained a QuickBird satellite image on December 2004 (Figure 2), with 6% cloud cover, a 8° of nadir angle deviation, 303° azimuth and 90% environment quality. Four bands were available with 2.49 m pixel size, recorded in R, G, B and NIR, and one more panchromatic image, with 0.62 m pixel size.

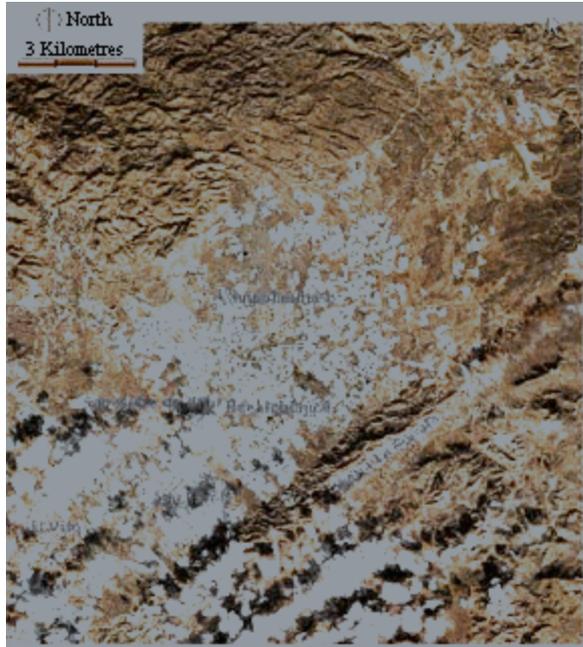


Figure 2. Campo de Nijar. QuickBird satellite image

Table 1 shows box limit coordinates of image.

| Vertex | Latitude | Longitude |
|--------|----------|-----------|
| S-W    | 36.8524  | -2.2233   |
| N-W    | 37.0103  | -2.2219   |
| N-E    | 37.0091  | -2.0305   |
| S-E    | 36.85    | -2.0317   |

Table 1. Box limit coordinates of QuickBird image

These spatial data were analysed by PCI Geomatica V9.1.1 software package, which presents geospatial applications in various fields: remote sensing, GIS, photogrammetry, and cartography.

### 3. ARTIFICIAL NEURAL NETWORK CLASSIFICATION

An artificial neural network is a mathematical model to processing of information. It is an approximate reply of the human brain behaviour across the emulation of the operations and biological neurons connectivity (Tsokalas and Uhring, 1997).

Successful adaptation of artificial neural network to remote sensing is mainly due to:

- Its efficiency is high because it does not need to take assumptions about distribution functions models (Benediktsson *et al.* 1990, 1993; Schalkoff, 1992).

- Time computation use to be shorter than other methods (Bankert 1994; Cote and Tatnall 1995).
- It allows incorporating *a priori* knowledge about class objective and real limits (Brown and Harris 1994; Foody 1995a, b).
- It allows to management of multi-source spatial data, getting synergy classification results (Benediktsson *et al.* 1993; Benediktsson and Sveinsson 1997).

#### 3.1 Neural network architecture

Like human nervous system, an artificial neural network consists of a set of interconnected nodes, called neurons (see Figure 3). Its outlet depends on weighted inlet information from all inlet nodes (Atkinson and Tatnall, 1997).

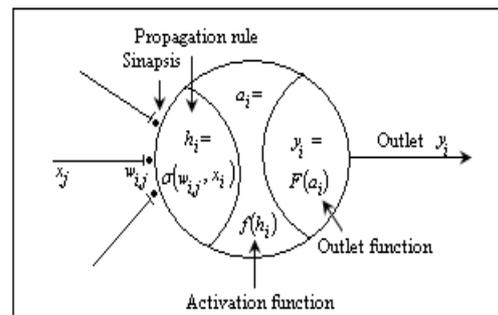


Figure 3. Artificial neuron schema

Neurons use to be clustered in functional units or levels. Figure 4 shows neural network design used in this work. It is composed of tree levels in which inlet level neurons are four channels in multi-spectral satellite image; outlet level neurons are detected classes and hidden level is composed of operational neurons.

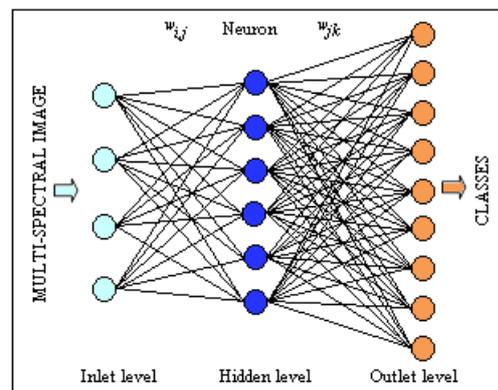


Figure 4. Artificial Neural Network structure

An increment of hidden levels in the design could allow more complex problems resolution, but its generalization ability decreases and training time increments (Foody, 1995b). Lippmann (1987) suggests that if one aggregates a second hidden level, its maximum number of nodes must be limited to triple number of nodes in the first level. In this work, we added one neuron to inlet level, corresponding to texture analysis when it was performed.

Response of each neuron depends on function activation evaluation (Figure 5).

Back-propagation method was used to train our neural network. This is, information travels forward and backward in training process.

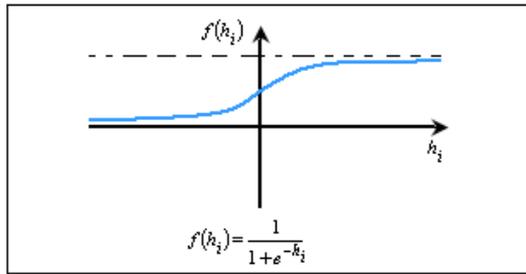


Figure 5. Activation function

### 3.2 Training process: back-propagation

In training process neural network adjusts its free parameters (Yao, 1995). It starts with a set of initial weights associated to relationship between pairs of neurons (or synapses). These values change depending of error committed in classification, following Generalized Delta Rule (Pao, 1989). This process is repeated iteratively until convergence is reached in two phases.

Firstly a set ( $x_p$ ) of inlet data is introduced in neural network. This set is propagated forward network, delivering an outlet ( $y_p$ ), which is compared with desired outlet ( $d_p$ ), obtained from training sites. Error committed in classification at this moment in training process ( $e_p$ ) is calculated according to (1):

$$e_p = \frac{1}{2} \sum_{k=1}^M (d_{pk} - y_{pk})^2 \quad (1)$$

Where  $k$  is neurons outlet index in last level, and  $M$  is total number neurons in this level.

Secondly, classification error is propagated backward, modifying weight factors  $w_p$  using Rumerhart rule (2) (Atkinson and Tatnal, 1997).

$$\Delta w_{ji}(t+1) = \eta \frac{\partial e_p}{\partial w_{ji}} + \alpha \Delta w_{ji}(t) \quad (2)$$

Where  $\eta$  is learning rate and  $\alpha$  is momentum factor. The iterative process finishes when difference between classification error in two iterations  $t$  and  $t+1$  in (2), falls under a threshold value. Parameters affect to velocity which convergence is reached. So, if learning rate is high, mathematical solution will be early encountered but it is possible that in next iteration, classification increases. Using a high momentum factor, these oscillations can be reduced.

## 4. TEXTURE ANALYSIS

It is demonstrated that classification can be better if not only spectral information is considered. Spatial context of a pixel in a image can discriminates two pixels with the same digital level all bands. This fact is specially showed when one classifies a very high resolution image, like satellites QuickBird, IKONOS or airborne spectrometer like AVIRIS or CASI. In these, per-pixel classification analysis loses its validity.

Texture is a very important characteristic used in discrimination of targets in an image. Haralick *et al.*, 1973, proposed a set of 14 texture models based on spatial dependence between neighbours grey levels. Also, statistical texture models was proposed (Jensen, 1996) based on first, second and third order statistics. Relationships between grey levels of pixels in an image are expressed with Grey Level Co-occurrence Matrix computed in a certain direction inside a mobile window image.

Most frequently used texture analysis is Grey Level Co-occurrence Matrix based on second order statistic. Design parameters in this model are: window size, spectral band inlet, derivate textures, depth outlet channel, distance between pixels and arrangement direction.

Window must be squared with odd number of pixels. Result obtained in a first position window is assigned to the central pixel in the window and it is transferred to a texture image. Then window is displaced one pixel and a new co-occurrence matrix is calculated.

Figure 6a shows a 10x10 pixels image and a mobile 5x5 pixel window located in the tree first position in texture analysis. And Figure 6b shows pixels with texture value in the resulting image.

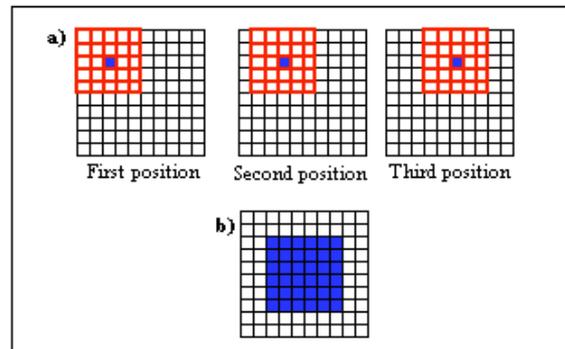


Figure 6. Texture analysis over an example 10x10 image, using a mobile 5x5 window

Window size must be near to target size to discriminate thanks to the texture analysis. Texture models more frequently used in bibliography are:

- Homogeneity: It deliveries high values when co-occurrence matrix shows high values in principal diagonal. This happens when image is locally homogeneous inside mobile window. Homogeneity is calculated with the equation (3):

$$\sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2} \quad (3)$$

Where  $P_{i,j}$  is co-occurrence probability of  $i,j$  levels grey.

- Contrast. This is the opposite to homogeneity, so it is a local variation estimation (equation 4).

$$\sum_{i,j=0}^{N-1} P_{i,j}(i,j)^2 \quad (4)$$

- Entropy. It is high when the elements of co-occurrence have relatively equal values. Low when the elements are close to either 0 or 1 (i.e. when the image is uniform in the window). See equation 5. It is assumed that:  $0 * \ln(0) = 0$

$$\sum_{i,j=0}^{N-1} -P_{i,j} \ln(P_{i,j}) \quad (5)$$

- Angular Second Moment. This is the opposite of entropy. It is high when the co-occurrence matrix has few entries of large magnitude, low when all entries

are almost equal. This is a measure of local homogeneity (equation 6).

$$\sum_{i,j=0}^{n-1} P_{i,j}^2 \quad (6)$$

## 5. WORKFLOW

Previous information about greenhouses distribution in the study zone is scanty. So, a unsupervised classification was applied, using ISODATA algorithm (Tou and Gonzalez, 1974), with the aim of to generate reference information to delineate training sites boundaries. But this wasn't enough because most of the target classes were related with vegetation. Greenhouse's plastic roof is partially transparent; therefore digital level of a pixel belonging to a greenhouse must be influenced by photosynthetic activity.

Chlorophyll pigments are absorbents in red band and reflectives in near-infrared band. So, vegetation indexes can be estimated by the differences between digital levels in these bands presented by each pixel in an image. The vegetation index *VI* model used is presented in equation (7).

$$VI = \frac{(NIR - R)}{NIR} * 100 \quad (7)$$

Where *NIR* and *R* are digital values in near-infrared and red bands. Selection of training sites was done thanks to overlapping unsupervised classification and vegetation index. That way, four greenhouses classes was discriminated and three soil classes depending on its photosynthetic activity level. Besides, water class and asphalted soil class were added to the legend.

Next step was to design a software model, with *MODELER* tools of PCI Geomatica, which allows defining the neural network, training it and achieving classification (Figure 7).

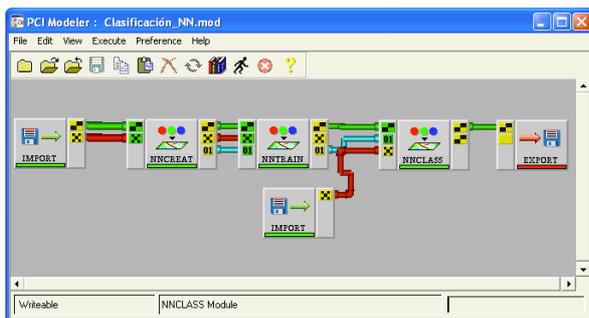


Figure 7. Neural network design, training process and classification models

Once this process was finished, accuracy classification was evaluated. In an attempt to improve these results, three texture analysis were made and incorporated to neural network as an additional inlet neuron.

Table 2 shows parameters of texture analyses selected in this work.

|            | Inlet band | Window size (pixel) | Spatial relation | Texture model |
|------------|------------|---------------------|------------------|---------------|
| Analysis 1 | Blue       | 35 x 35             | 1,1              | Homogeneity   |
| Analysis 2 | NIR        | 43 x 43             | 1,1              | Homogeneity   |
| Analysis 3 | NIR        | 17 x 17             | 1,1              | Homogeneity   |

Table 2. Parameters of texture analysis

## 6. RESULTS

Figure 8 shows unsupervised classification result, where legend is composed of thirteen clusters with higher frequency.

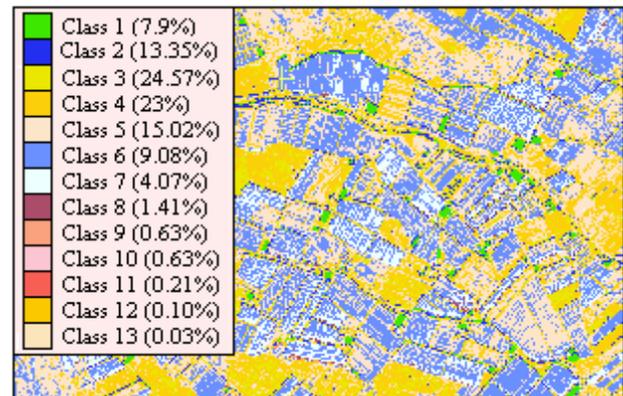


Figure 8. Unsupervised classification. Percentages represent number of pixels in each of thirteen more representative classes in relation to total image

Vegetation index can be seen in Figure 9. Training sites were delimited on dispersed location belonging to nine classes selected. It is necessary to mention that target class in this work is greenhouses. Design criteria of legend were to dismiss confusions between greenhouses and no-greenhouses class. Even more, after various attempts of training process, we conclude that there not was one only kind of greenhouse. Differences between greenhouses were depending on crop development and of plastic roof.

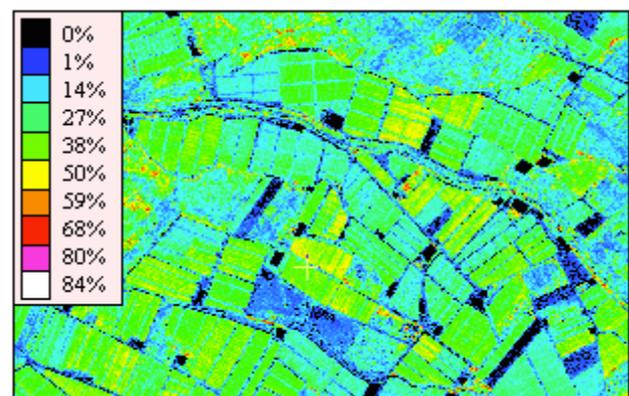


Figure 9. Vegetation Index

Classification result without texture analysis is showed in Figure 10. For evaluation of the accuracy, a stratified random sampling was made, with 450 sample points, to calculate the general accuracy (83%).

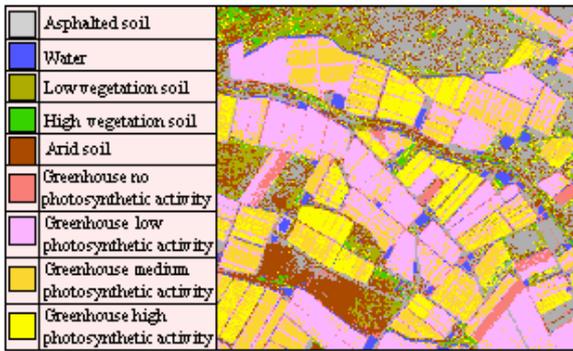


Figure 10. Classified image using neural network, without texture analysis

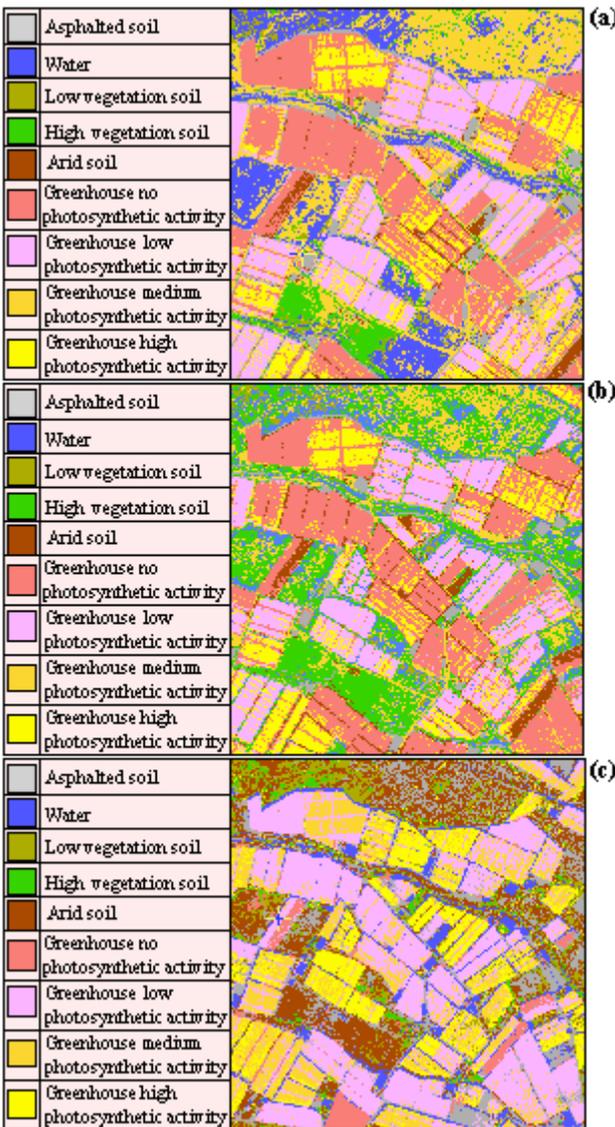


Figure 11. Classified image using neural network, adding the three texture analyses showed in Table 2 (in the same order)

In Figure 11, classification results including three texture analyses, in the same order showed in Table 2, can be observed. Table 3 resumes all accuracy index obtained. Obviously, accuracy in c) classified image deliveries the best result. But not only because general accuracy is higher. In cases a) and b), pixels belonging to arid soil in top of some greenhouse's roofs

can be seen. Besides, greenhouses acquire a more homogeneous aspect according to its photosynthetic activity.

| Texture Analysis | Inlet band | Window size (pixel) | No. sample points | General accuracy |
|------------------|------------|---------------------|-------------------|------------------|
| No texture       | -          | -                   | 450               | 83%              |
| a) Homogeneity   | Blue       | 35 x 35             | 450               | 83%              |
| b) Homogeneity   | NIR        | 43 x 43             | 450               | 85%              |
| c) Homogeneity   | NIR        | 17 x 17             | 450               | 85.7%            |

Table 3. Accuracy evaluation results on four classified images obtained

This maybe occurs because window size chosen in c) case. Average size of greenhouses is closer to 17 pixels (42 meters) than others window sizes.

### 7. CONCLUSIONS

Artificial neural network is an adapted method to greenhouses discrimination from a very high resolution satellite image.

Accuracy classification improves when a textural analysis is added as on more inlet neuron. But it is critical to choose right texture model and its parameters. The more important of these is window size which must be closer to target size to discriminate in the image. Actually, we are developing a study about relationships between target size and window size in texture analysis to dismiss error discrimination this targets. This study includes various windows sizes, texture models and target objects, always using very high resolution satellite images.

In that sense, lacunarity is a texture analysis particularly interesting as technique for the analysis of spatial patterns (Plotnick *et al.*, 1996; Myint and Lam, 2005). We hope to improve accuracy classification even more.

It can be considered these studies like previous to automatic detection of greenhouses cover changes. If an artificial neural network can discriminate adequately greenhouses class, maybe it can be possible to detect its changes using multi-temporal data. It will require a generalization of our actual artificial neural network and a different strategy to its training.

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