Digital images and their application to land use classification

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Abstract

For many Remote Sensing users, classification is the decisive stage of digital image analysis. Digital classification provides cartography and an inventory of the categories that are the object of study. In this paper we analyse a sector of the Natural Park of the Sierra de Mariola (Spain), with the aim of using two digital image classification procedures: supervised and unsupervised classification. We measure the reliability of the classification. The results obtained in the treatment of the image, along with the field data enable us to obtain accurate cartography of the area.

Keywords: computer imaging, supervised classification, unsupervised classification.

1 Introduction

Spatial and aerial remote sensing devices are widely available and constantly improving in terms of their features. This fact, combined with advances in digital imaging techniques, has led to the development of an interest in using remote sensing techniques to study and understand the dynamic evolution of ecosystems. Information obtained using these techniques greatly facilitates the work of those who devise plans for managing, conserving and exploiting the resources of a region.

The Sierra de Mariola is a mountain range located in Spain, in the southwestern part of the Iberian Peninsula. It straddles the provinces of Alicante and Valencia, extends over the counties of Vall d’Albaida, El Comtat and L’Alcoiá
and is flanked by the towns of Agres, Alfas del Pi, Alcoi, Banyeres de Mariola, Bocairent and Cocentaina. Almost rectangular in shape, it lies southwest-northwest and covers a surface area of approximately 16,800 hectares. The mountain features a range of landscapes as a consequence of its location, altitude and size. The climatology is harsh, and snow is not infrequent. It is of great botanical interest, given the mixed woodlands and the wide range of medicinal and aromatic plants to be found there. The wooded areas consist of pine, interspersed with the occasional Valencian oak, maple and ash, located primarily in the area around Pico del Montcabrer (1,390 m over sea-level) and Morro del Comptador. There is also a small but interesting population of yew trees - known locally as the Teixera d’Agres Yew Wood and, until recently, considered the most southerly yew wood in Europe (Pellicer [1]) - located on the northern slopes of Morro del Comptador, very near the Montcabrer mountain refuge. The Sierra de Mariola was recently (2002) designated a Natural Park by the Generalitat Valenciana.

Our aim was to classify this region using a Landsat 5-TM image (May, 2001). The paper is laid out as follows: Section 2 describes the digital definition of the categories (the training phase), which – depending on how the training statistics have been obtained – gives rise to the application of either supervised and unsupervised classification methods by means of which the image pixels are grouped in terms of categories (the allocation phase). Section 3 describes the validation of the resulting map using different precision estimators. The final sections describe our analysis and main conclusions.

2 Classification

In this work, we have used data taken from sensor TM/Landsat 5 (May, 2001), belonging to the bands 3 (0.63-0.69µm), 4 (0.76-0.90µm) and 5 (1.55-1.75µm). The UTM co-ordinates for the image are as follows: NW corner: X=715174 and Y=4297139; NE corner: X=719358 and Y=4297139; SW corner: X =715174 and Y=4294227; SE corner: X=719358 and Y=4294227. Digital classification was based on the digital level (DL) of the pixels in the image, in other words, on the value that numerically translates the radiometric intensity received by the sensor.

The unsupervised method was used to define the spectral classes, which were delimited using Euclidean distance to measure the space between pixels and using the ISODATA classifier as a clustering algorithm (Tou et al [2], Duda et al [3], Bow [4]). The unsupervised method was applied to the three bands of the image, resulting in 11 spectrally homogeneous classes.

The supervised method required certain knowledge of the area of study. Delimitation of the training areas in the image was based on both field work and aerial pictures taken in the same date that the TM image. Once the training areas were selected, the statistics for each category were calculated from the DL for all the pixels in the training areas for this class. This calculation was also made for the three image bands. Supervised classification was carried out using a maximum probability algorithm.
Once the unsupervised and supervised classification methods had been implemented, the categories indicated by both procedures were classified in conjunction for the same image, thereby minimising the drawbacks of each method. The classes were grouped taking into account information categories with spectral significance. It was concluded that land use could possibly correspond to more than one spectral class, and so more than one spectral sub-class for each thematic class was defined. The six categories finally identified for the study were: urban land URB, agricultural land AGR, fallow land FAL, scrubland SCR, wooded mountain WM and unvegetated land UNV.

![Classification results](image)

Figure 1: Classification results.

Once the training phase was complete and the classification categories were decided, the allocation phase commenced. In the allocation phase each pixel in the image was associated with one of the established categories. The maximum probability criterion was used; in other words, each pixel was associated with the class in which it had the highest probability of belonging (Swain et al [5]). Fig. 1 depicts the resulting classification.

3 Classification reliability

The confusion matrix was used to verify the classification results described in Fig. 1. This square matrix had dimensions $m \times m$, where $m$ is the number of categories. The columns indicate the real terrain information, and the rows, the results for our classification. The matrix diagonal expresses the number of verification points for which there is agreement between the reference and classification data, and the remaining values are allocation errors for each of the classes. A series of statistical measures was used to numerically validate the
classification results for the confusion matrix, namely, overall reliability, user reliability, producer reliability, and the kappa statistic (Chuvieco [6], Story et al [7]).

Overall reliability $F_G$ was calculated as the quotient between the sum of the elements of the diagonal and the total number of sampled points.

$$F_G = \frac{\sum_{i=1}^{m} x_{ii}}{\sum_{i=1}^{m} \sum_{j=1}^{m} x_{ij}}$$  \hspace{1cm} (1)

Producer reliability for class $i$, $F_{pi}$, which indicated the probability that a pixel from class $i$ was correctly classified, was calculated as:

$$F_{pi} = \frac{x_{ii}}{\sum_{j=1}^{m} x_{ji}}$$  \hspace{1cm} (2)

User reliability $F_{ui}$, which indicated the probability that a pixel from class $i$ was correctly classified, was calculated as:

$$F_{ui} = \frac{x_{ii}}{\sum_{j=1}^{m} x_{ij}}$$  \hspace{1cm} (3)

Related to producer and user errors were omission error $E_{oi}$ and commission error $E_{ci}$, each defined, respectively, as:

$$E_{oi} = 1 - F_{pi}$$  \hspace{1cm} (4)

$$E_{ci} = 1 - F_{ui}$$  \hspace{1cm} (5)

The values for $F_{pi}$ and $E_{oi}$ and for $F_{ui}$ and $E_{ci}$ were added as two additional rows and two additional columns, respectively, to the matrix. The verification process required the application of spatial techniques to the selection of a sample that was sufficiently representative of the terrain conditions. The method used here was simple random sampling. Sample size depended on the sample level of confidence and admissible sample error. Taken as the total number of verified pixels was $n=1080$, a number that well covers the minimum threshold of 50 pixels per category (Congalton [8], Hay [9]). Table 1 shows the confusion matrix; rows $F_{pi}$ and $E_{oi}$ were calculated using Equations (2) and (4),
respectively, and columns $F_{ui}$ and $E_{ci}$ were calculated using Equations (3) and (5), respectively. The following abbreviations were used to identify the classification categories: FAL = fallow land; SCR = scrubland; WM = wooded mountain; AGR agricultural land; UNV = unvegetated land; and URB = urban land.

Table 1: Confusion matrix.

<table>
<thead>
<tr>
<th></th>
<th>FAL</th>
<th>SCR</th>
<th>WM</th>
<th>AGR</th>
<th>UNV</th>
<th>URB</th>
<th>Total</th>
<th>$F_{ui}$</th>
<th>$E_{ci}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>FAL</td>
<td>133</td>
<td>1</td>
<td>1</td>
<td>4</td>
<td>9</td>
<td>0</td>
<td>148</td>
<td>0.90</td>
<td>0.10</td>
</tr>
<tr>
<td>SCR</td>
<td>1</td>
<td>145</td>
<td>3</td>
<td>6</td>
<td>6</td>
<td>0</td>
<td>161</td>
<td>0.90</td>
<td>0.10</td>
</tr>
<tr>
<td>WM</td>
<td>1</td>
<td>5</td>
<td>290</td>
<td>11</td>
<td>0</td>
<td>1</td>
<td>308</td>
<td>0.94</td>
<td>0.06</td>
</tr>
<tr>
<td>AGR</td>
<td>10</td>
<td>12</td>
<td>12</td>
<td>234</td>
<td>3</td>
<td>3</td>
<td>274</td>
<td>0.85</td>
<td>0.15</td>
</tr>
<tr>
<td>UNV</td>
<td>13</td>
<td>2</td>
<td>3</td>
<td>7</td>
<td>109</td>
<td>1</td>
<td>135</td>
<td>0.81</td>
<td>0.19</td>
</tr>
<tr>
<td>URB</td>
<td>2</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>46</td>
<td>0</td>
<td>54</td>
<td>0.85</td>
<td>0.15</td>
</tr>
<tr>
<td>Total</td>
<td>160</td>
<td>165</td>
<td>311</td>
<td>262</td>
<td>131</td>
<td>51</td>
<td>1080</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$F_{pi}$</td>
<td>0.83</td>
<td>0.88</td>
<td>0.93</td>
<td>0.89</td>
<td>0.83</td>
<td>0.90</td>
<td></td>
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<tr>
<td>$E_{pi}$</td>
<td>0.17</td>
<td>0.12</td>
<td>0.07</td>
<td>0.11</td>
<td>0.17</td>
<td>0.10</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

4 Analysis of results

The overall reliability of the map was calculated, using Equation (1) and the values of the confusion matrix diagonal, as $F_G = 0.886$. This value was used to calculate the confidence interval for the real level of reliability achieved by the classification. The sampling error was 0.967; the significance level of $\alpha = 0.05$ indicates that there is a 95% probability that the real reliability value is located between 86.705% and 90.495%.

Nonetheless, given that an overall value may hide differences between categories in terms of precision, the confusion matrix $F_{ui}$, $E_{ci}$, $F_{pi}$ and $E_{pi}$ columns/rows were analysed individually. This analysis revealed that wooded mountain WD was correctly classified (93%) with the greatest frequency and hence had the lowest omission error (7%). The fallow land FAL and unvegetated land UNV classes, on the other hand, were correctly classified (83%) on the least number of occasions. The inclusion of 13 verification points from the unvegetated land UNV category in the fallow land FAL category and of 9 verification points from the fallow land FAL category in the unvegetated land UNV category was due to the similarity between the spectral patterns for these categories. For the wooded mountain WM class, $F_{ui} = 94\%$, which means that 94% of the pixels classified as such genuinely corresponded to this category. Consequently, the commission error for wooded mountain WM was a minimal 6%. The highest commission error (19%) occurred with the unvegetated land UNV category; in other words, this category represents the area of the map that least mirrors reality.
5 Conclusions

Our combined use of supervised and unsupervised classification methods has produced a land use map for the area of the Sierra de Mariola Natural Park that is 86.705% to 90.495% reliable.

The wooded mountain category, with a producer reliability ($F_{pi}$) of 93% and a user reliability ($F_{ui}$) of 94%, was the class that was on most occasions correctly classified and which, therefore, most closely reflects reality. The unvegetated land category showed the lowest levels of reliability for both $F_{pi}$ and $F_{ui}$; nonetheless, the corresponding values can still be considered acceptable.

The technique described can therefore be considered an efficient method for describing and mapping the variety in land use in the Sierra de Mariola area of the Valencian Autonomous Community.

Acknowledgement

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References