A MULTI-APPROACH AND OBJECT-ORIENTED STRATEGY FOR UPDATING LU/LC GEO-DATABASES BASED ON *WORLDVIEW-2* IMAGERY

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ABSTRACT:

Land Use/Land Cover (LU/LC) geo-databases have increasing relevance in many different fields and applications. In this study, we propose the definition of new spectral variables based on the high spectral and spatial resolution of *WorldView-2* imagery. These variables, in addition to texture and structural features extracted from the same images, are applied for object-oriented classification of agricultural, forest and urban areas, and the results are evaluated using available field truth data. Parcel-based approach is employed, where image are segmented according the cartographic boundaries contained in a cadastral geospatial database. Results show that the combination of descriptive features that provide information from different characteristics of the images (spectral, texture, structural) produces a noticeable improvement of the classification results.

1. INTRODUCTION

In the evolution of geoinformation systems, a strategic issue is the application and development of new methods that allow for an efficient generation and update of geographic databases, and by optimally incorporating new remote sensing data and other sources of information. The production and maintenance of Land Use/Land Cover (LULC) geo-databases, at different scales, are fundamental for territory management and for the economic development of regions and countries. Their availability, accuracy and currency provide the basis for decision taking in many subjects, such as natural resources exploitation, environmental protection, urban sprawl monitoring and others. However, the updating procedures are still slow and expensive, due to the tedious photointerpretation tasks and exhaustive field work involved in most of the cases. The technical improvements for the acquisition of spatial data, in terms of spatial, spectral and radiometric resolution, as well as the frequency of their availability, have been important during the last several years. Therefore, this new scenario reveals the need of developing new techniques and algorithms for managing such information, and making it useful to solve specific problems in mapping and geo-database updating.

Satellite image classification has been used for many years for LULC mapping, due to the frequency of the data and, very often, to the lower economic cost compared to the aerial imagery. Traditional digital image classification methods assign a thematic value to each pixel in the image, based on the different digital values of the pixel in multiple spectral bands. This methodology may be appropriate for homogeneous classes or categories, but not for classes characterised by a high spectral mixture or by heterogeneous distribution of the landscape elements. The introduction of texture analysis and features (Haralick et al., 1973; Laws, 1985; Curran, 1988; etc.) improves the results in these heterogeneous areas, but also has the restriction of the border effect (Ferro and Warner, 2002; Ruiz et al., 2004), or misclassification along the limits between classes.

The availability of new high-resolution satellite sensors in the last decade has increased the number and the detail of LULC projects promoted by different administrations and governments, aiming the creation and updating of geo-databases at regional, national, and international levels. However, two main practical and methodological problems arise when high-resolution images are used for LULC classification: First, the higher the detail captured by the images, the higher the internal variability of the areas or plots covered by them (Berberoglu and Curran, 2004). The second aspect is that the spectral information derived from current high-resolution satellite image data is definitely limited by the broad range of the spectral bands and the lack of attention paid to the precise location of these bands along the electromagnetic spectrum, usually restricted to three visible and one infrared bands, in addition to one panchromatic band, that in many cases is only used for resolution merging or image fusion with the spectral bands. This issue has particular relevance when mapping vegetation, and in those projects based on large geographic areas, with many vegetation types and ecological strata.

The internal variability that often exists in the high-detail cartographic units can be faced using object-oriented classification techniques. These methods consider, and even take advantage of the spatial distribution of the elements that compose a particular landscape or an administrative unit, in order to improve the accuracy of LULC classifications. This discipline is attracting the interest of many researchers in the last few years, as reviewed by Blaschke (2010). Using these innovative techniques, each cartographic unit (e.g., a plot or polygon) is analysed as a whole, allowing to spatially relate the pixel values inside the limits, and to generate new descriptive features providing information about the internal variability and the distribution of the elements in the object. The texture features can be computed as a unique value for the object, eliminating the problem of the border effect, and new structural features can be extracted, providing information about the spatial arrangement of the elements inside the objects, such as regular patterns (Ruiz et al., 2007). On the other hand, the problem of the restricted spectral information typical from high-resolution satellite sensors may be handled by using the new images provided by the satellite *WorldView-2*, with 8 spectral bands in the visible and infrared areas of the electromagnetic spectrum, together with the approximately 0.5 m/pixel resolution of the panchromatic band.

The objective of this study is to investigate the use of object-oriented classification methods over high spectral and spatial resolution *WorldView-2* images, and to evaluate its performance on LULC classification for automated geo-database generation and updating. For this purpose, an image covering an area of 100 km^2 has been used, objects have been defined using administrative cartographic limits of the area, and different types of descriptive features have been extracted for every plot (object) from the *WorldView-2* image: spectral, texture, and structural. The area of study is located in the region of Galicia, in the northwest of Spain. The variety of the study area landscape, together with the availability of field samples (ground truth), provide an adequate scenario for testing and evaluation purposes.

2. STUDY AREA AND DATA

The tests have been performed using data from the local administrative area of *A Limia*, located in the region of Galicia (Spain). The landscape is characterized by a broad combination of urban areas, diverse agriculture, forest and shrubland. Figure 1 shows a colour infrared combination of the *WorldView-2* image used.

Figure 1. Overview of the study area in a WorldView-2 colour infrared image composition.

WorldView-2 sensor provides a panchromatic image with approximately 0.5 m/pixel resolution, and 8 visible and near infrared multiespectral bands with 2 m/pixel, having the following spectral ranges: Coastal Blue (400-450 nm), Blue (450-510 nm), Green (510-580 nm), Yellow, (585-625 nm), Red (630-690 nm), Red-Edge (705-745 nm), Near Infrared-1 (770-895 nm), and Near Infrared-2 (860-1040nm).

Cartographic boundaries to define the final objects (plots) were obtained from the Spanish *Land Parcel Information System* (SIGPAC), a national geospatial database oriented to agriculture management. The plots represent a continuous area of land within a parcel for a single agricultural use. Besides, a set of field data samples from the same year was available. These samples have square shape with side sizes of 350 to 500 meters.

3. METHODOLOGY

In this section, a general methodological description of the steps followed in the object-oriented feature extraction and classification approaches is presented, with references to documents containing a more exhaustive explanation. Main classification steps include: Class definition, selection of training samples, descriptive feature extraction, classification method, and evaluation.

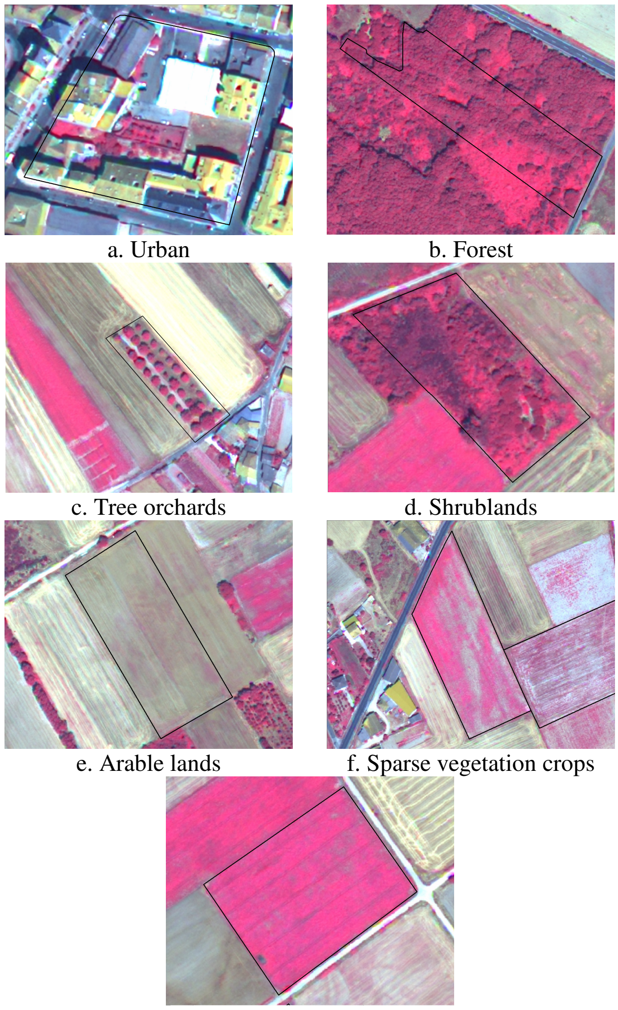


Figure 2. Details of colour infrared image compositions of 7 objects/parcels containing examples of the classes defined.

3.1 Class definition and selection of training samples

A total of seven classes were defined, attending to the requirements of the local and National Mapping Agencies that elaborate the LULC geo-databases in the area (see Figure 2): Urban, Forest, Tree orchards, Shrublands, Arable lands, Sparse vegetation crops, and Irrigated crops. Most of the training samples were selected from the field samples. Besides, additional samples were added by photointerpretation in order to avoid a low representation of some classes. The total number of samples (parcels) was 1172, that would be used for training and evaluation using the cross-validation technique, using independent sets for training the classifier and for evaluation purposes.

As described above, spatial objects were created using the SIGPAC database plot limits. In order to confer coherence to the automatic feature extraction process, which requires a minimum parcel surface, and to preserve the classification accuracy, parcels with a surface lower than 60 m^2 were rejected.

3.2 Per-object feature extraction

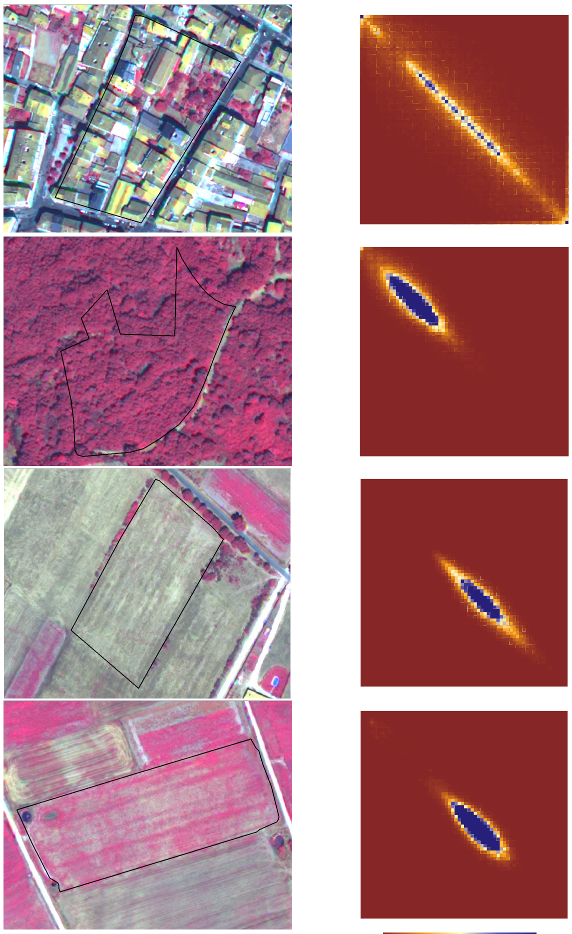
The use of efficient descriptive features is essential for accurate classification. At this point, every plot was independently processed to extract descriptive features that characterize their current land use. The process followed to compute the features used in this study can be considered multi-approach, since three categories of features were extracted: spectral, textural and structural.

Spectral features used provide information about the spectral response of objects on the visible and near infrared regions of the spectrum, which depends on land coverage types, state of vegetation, soil composition, construction materials, etc. These features are particularly useful in the characterization of spectrally homogeneous classes, such as herbaceous crops or fallow fields, *WorldView-2* imagery providing more specific spectral information compared to other sensors available. Mean, standard deviation, minimum and maximum values were computed from the eight spectral bands or *WordlView-2*, and also from the Normalized Difference Vegetation Index (NDVI), calculated by using the red (R) and the first near infrared (NIR1) bands.

Texture features inform about the spatial distribution of the intensity values in the image, being useful to quantify properties such as heterogeneity, contrast or uniformity related to each object (Ruiz et al., 2004). These properties provide additional information about the object, useful to characterize the LULC inside it. Texture features have been computed per-object from the panchromatic band, in order to take advantage of the very high spatial resolution of this band.

For every plot, the features proposed by Haralick et al. (1973) based on the grey level co-occurrence matrix (GLCM) were computed: contrast, uniformity, entropy, variance, covariance or product moment, inverse difference moment, and correlation. Since an object-oriented approach is used, only one GLCM is computed for each object, describing the co-occurrences of the pixel values that are separated at a distance of one pixel inside the plot, and considering the average value of four principal orientations (0º, 45º, 90º and 135º) in order to avoid the influence of the orientation of the elements inside the objects. Figure 3 shows some examples of GLCM computed for plots with different land uses, where the length along the diagonal is related to the contrast, and the width of the value distribution captures the heterogeneity.

This information was completed with the values of kurtosis and skewness of the histogram, representing the shape and assimetry of the histogram of an object. Besides, the mean and the standard deviation of the *edgeness factor* for each plot were computed (Laws, 1985). The *edgeness factor* represents the density of edges present in a neighbourhood, in our case the limits of the object itself.



Legend: *Co-occurrence frequency: min* *max*

Figure 3. Image examples of three different land uses: urban, forest and arable lands (left) and their graphic representation of the GLCM (origin is in the top left corner) computed per-object (right).

Structural features provide information of the spatial arrangement of different elements inside the object, in terms of randomness or regularity of the distribution of the elements. This is the case of alignments or regular patterns that are present in different man-made landscapes, such as the planting patterns of crops and trees in agricultural plots (Ruiz et al., 2007). The structural features have been derived from the semivariogram computed from the panchromatic band. The semivariogram curve quantifies the spatial associations of the values of a variable, and measures the degree of spatial correlation between different pixels in an image. This is a particularly suitable tool in the characterization of regular patterns. For continuous variables the expression that describes the experimental semivariogram is:

$$(h) = \frac{1}{2N}\sum_{i=1}^{N}\left[z(x_i) - z(x_i + h)\right]^2$$

where $z(x_i)$ = value of the variable in position x_i.
N = number of pairs of data considered.
h = separation between elements in a given direction.

The experimental semivariogram representing each object is obtained by computing the mean of the semivariograms calculated in six directions, ranging from 0º to 150º with a step of 30º. Afterwards, each semivariogram curve is filtered using a Gaussian filter with a stencil of 3 positions, in order to smooth its shape and to eliminate experimental fluctuations.

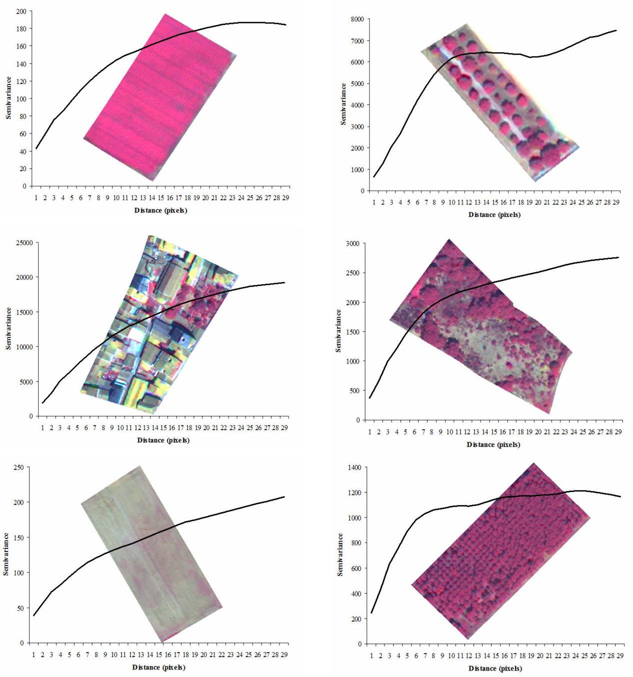
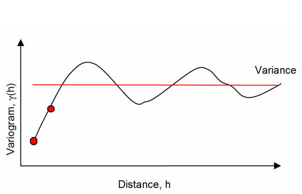
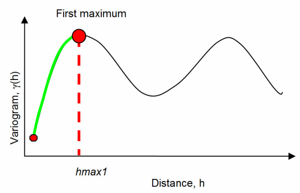


Figure 4. Detail of images and semivariogram graphs for different land uses: irrigated crops, trees orchards, urban, shrublands, arable lands, and forest.

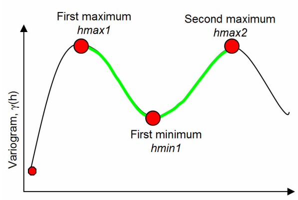
Some semivariogram graphs examples are shown in Figure 4, where this is noticeable that when a periodic spatial behaviour exists, as in the tree orchards plot, the graph presents a cyclic curve, known as *hole effect* semivariogram (Pyrcz and Deutsch, 2003).



a. Near the origin.



b. Up to 1st maximum.



c. Between 1st and 2nd maxima.

Figure 5. Representation of singular points and parameters extracted form semivariogram graphs.

Several structural descriptive features were computed considering the singular points of the semivariogram, such as the first maximum, the first minimum or the second maximum. These parameters characterize the semivariogram behaviour according to the position of the lags used in their definition: near of the origin, up to the first maximum and between first and second maxima.

Ratio between the values of the total variance and the semivariance at first lag:

$$RVF = \frac{Varianza}{\gamma(h_1)}$$

Ratio between semivariance values at second and first lag:

$$RSF = \frac{\gamma(h_2)}{\gamma(h_1)}$$

First derivative near the origin:

$$FDO = \frac{\gamma_2 - \gamma_1}{h}$$

Lag value where the curve γ(h) reaches the first local maximum:

$$FML = h_{\max\_1}$$

Mean of the semivariogram values up to the first maximum:

$$MFM = \frac{1}{\max_1} \sum_{i=1}^{\max 1} \gamma(h_i)$$

Variance of the semivariogram values up to the first maximum:

$$VFM = \frac{1}{\max_1} \sum_{i=1}^{\max 1} \left(\gamma(h_i) - MFM\right)^2$$

Ratio between the semivariance at first local maximum and the mean semivariogram values up to this maximum:

$$RMM = \frac{\gamma(h_{\max\_1})}{MFM}$$

Distance between the first maximum and the first minimum:

$$DMM = h_{\min_1} - h_{\max_1}$$

RVF and RSF features are related to the homogeneity values of the grey levels at long and short distances respectively. FDO feature shows the variability changes of the data at short distances. FML, MFM, VFM and RMM features are related with the overall variability of the grey level values. DMM feature characterizes periodic patterns within an image-object and quantifies the *hole effect*, which is directly related to the variability or contrast of the regularity patterns. These features are fully described in Balaguer et al. (2010).

3.3 Classification through decision trees

Objects were classified by using decision trees. A decision tree is a set of organized conditions in a hierarchical structure, in such a way that the class assigned to an object can be determined following the conditions that are fulfilled from the tree roots (the initial data set) to any of its leaves (the assigned class). The algorithm employed in this study is the C5.0, which is the latest version of the algorithms ID3 and C4.5 developed by Quinlan (1993). This algorithm is widely used to deduce decision trees for classifying images (Zhang and Liu, 2005).

The process of building a decision tree begins by dividing the collection of training samples using mutually exclusive conditions. Each of these sample subgroups is iteratively divided until the newly generated subgroups are homogeneous, that is, all the elements in a subgroup belong to the same class. For each possible division of the initial data group, the impurity degree of the new subgroups is computed, and the condition which gives the lower impurity degree is chosen. This is iterated until the division of the original data into homogeneous subgroups is carried out by using the gain ratio as splitting criterion. This criterion employs information theory to estimate the size of the sub-trees for each possible attribute and selects the attribute with the largest expected information gain, that is, the attribute that will result in the smallest expected size of the sub-trees.

A total of ten decision trees were generated for classification, by means of the boosting multi-classifier method, which allows for increasing the accuracy of the classifier. The methodology followed by the boosting to build the multi-classifier is based on the assignment of weights to training samples. The higher the weight of a sample, the higher its influence in the classifier. After each tree construction, the vector of weights is adjusted to show the model performance. In this way, samples which are erroneously classified increase their weights, whereas the weights of correctly classified samples decrease. Thus, the model obtained in the next iteration will give more relevance to the samples erroneously classified in the previous step (Hernandez-Orallo et al., 2004). After the construction of the decision tree set, the class to each object is assigned considering the estimated error made in the construction of each tree.

3.4 Evaluation

Classification assessment was based on the analysis of the confusion matrix (Congalton, 1991), by comparing the class assigned to each evaluation sample with the information contained in the reference database. The overall accuracies of the classifications were computed, as well as the producer and user accuracies for each class (which respectively reveal the errors of omission and commission).

Since the area of study was not very large, and a representative set of testing data was needed to ensure a correct evaluation, the *leave-one-out* cross-validation technique was used. This method is based on using a single observation from the original sample as the validation data, and the remaining observations as the training data. This is repeated such that each observation in the sample is used once as the validation data.

Due to the high number of parameters defined, some features are probably redundant in terms of efficient description of the objects used in our study. The inclusion of these parameters can introduce noise in the classification. Therefore a study of the relationships between the features and their contribution to the classification accuracy has been performed. Statistical linear discriminant analysis has been used to determine the significance of the features for the particular classification problem and for each specific application.

4. RESULTS AND DISCUSSION

Figure 6 shows the evolution of the predicted overall and per-clase accuracies of the classification as new descriptive features are included in the linear discriminant model, considering the different aggregation of features. When spectral, texture and structural features are used, the main accuracy improvement is produced considering the mean of band 5 (Red), the contrast feature of GLCM, and the mean value of band 6 (Red-Edge). Afterwards, the predicted overall accuracy is slowly increasing as new variables as included in the discriminant model. These 25 initial features included –i.e. the most discriminant– combine several spectral attributes representing statistics derived from all the spectral bands of the *WorldView-2* sensor, with a number of texture and structural features computed from the panchromatic band. Graphs show that the combination of descriptive features from different nature allows for a faster increment of the predicted overall classification accuracy.

Analyzing the evolution of the accuracy for each independent class when spectral, texture and structural features are used, the classes *Urban*, *Shrublands* and *Tree orchards* present high accuracy values (around or higher than 80%) with the inclusion of the first variable into the model. *Forest* and *Irrigated crops* classes start with 50% of accuracy, but as following features are added into the model their accuracy values increase. Sparse vegetation crops class is predicted to present a very low accuracy using the two more discriminant features, but when the feature mean of the band 6 (Red Edge) is used, its predicted accuracy value remarkably growths up to 90%. This situation is given for all the descriptive feature aggregation cases. The class *Arable land* is the one that requires the highest number of descriptive features to reach its maximum predicted accuracy.

The overall classification accuracies results as the different combinations of descriptive features are included in the classification are shown in Table 1. In addition, user and producer accuracies for each class considered are presented in graphs in Figure 7. The complete confusion matrices (Table 2, Table 3, and Table 4) of the classification have been appended at the end of this document.

Table 1. Overall classification accuracies as the different combinations of descriptive features are used.

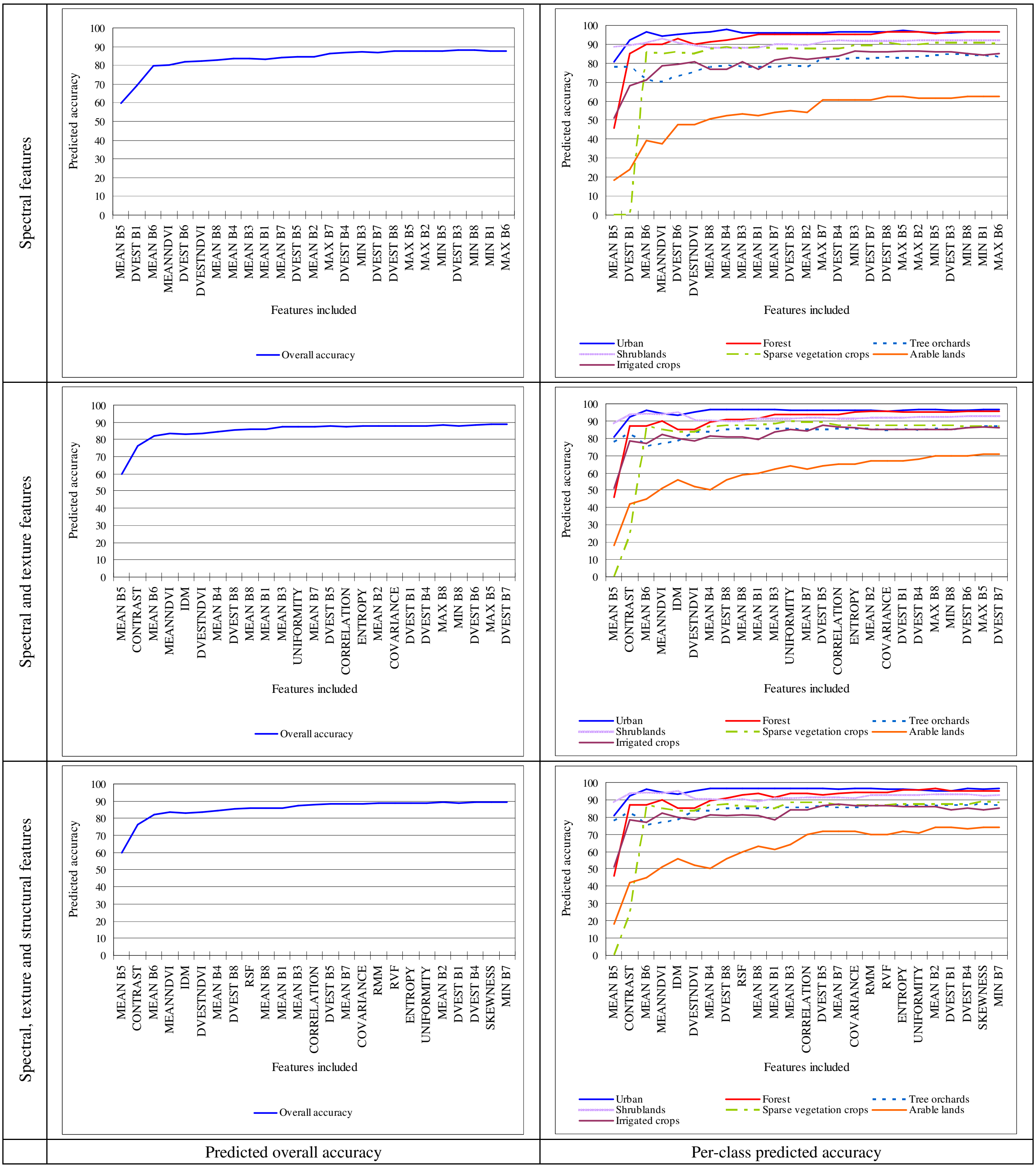
Features	Overall accuracy
Spectral features	84.0
Spectral and texture features	87.2
Spectral, texture and structural features	89.0

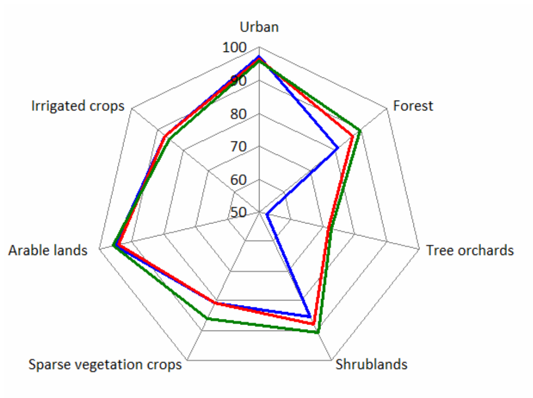
When only spectral features are employed an overall accuracy of 84% is obtained, but a significantly low producer accuracy value is obtained for *Tree orchards* class. This class presents a high confusion degree with *Forest*, *Shrublands* and *Sparse vegetation crops* classes. This is produced due to *Tree orchards* plots often present small dimensions and mixed land uses. *Forest* and *Shrublands* classes are frequently confused in the classification due to their spectral similarities. In the same sense, *Sparse vegetation crops* and *Irrigated crops* also present a notable degree of confusion in their class assignation. (see Table 2).

The combination of spectral and texture features produces a increase of the overall classification accuracy up to 87.2%, mainly caused for the noticeable improvement in the classification of *Tree orchards* class. As a result of this improvement, *Forest* and *Shrublands* user and producer accuracies present slightly increments (see Table 3).

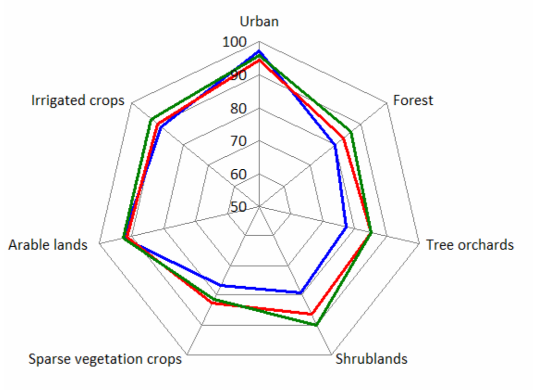
When structural features are also included in the classification process, the producer and user accuracies show modest improvements for all classes (see Table 4). As a result, the overall classification accuracy reaches up to 89%.

Figure 8 graphically shows some examples of the result of the object-based classification using spectral, texture and structural descriptive features derived from *WorldView-2* for the study area.





a. Producer accuracy



b. User accuracy

Legend:

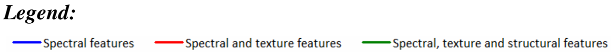


Figure 7. Producer and user accuracies for defined classes as different combinations of descriptive features are used in classification.

5. CONCLUSIONS

The use of *WorldView-2* band 6, the Red Edge band, clearly improves the classification of agricultural vegetation classes, being one of the most efficient features to differentiate between these land cover classes, as shown by the forward stepwise discriminant analysis results. Considering that the area of study presented a combination of vegetation and non vegetation classes, the complete set of spectral bands provide a variety of spectral information, increasing the overall accuracy of the classification for the seven-class problem proposed.

The texture and structural features extracted from the panchromatic band in a per-parcel basis provide a very interesting synergy with the spectral information to classify the cartographic units. The kind of information they add is complementary to the spectral response, transforming the problem of internal variability in an advantage to better characterize parcels. This is not only due to the very high spatial resolution of the panchromatic image, but also to the 11 bits radiometric resolution, that increases the sensitivity of the variables computed and the contrast of the information captured.

The case studied is representative of many current projects of LULC database creation and updating, that is why the good results obtained, close to 90% of overall accuracy, allow us to be optimistic for the use of these new available images in updating existing thematic databases and creating new ones. The combination of the high spectral, spatial and radiometric resolutions of the data, and the exhaustive extraction of information using object-oriented techniques and a multi-approach based on spectral, texture and structural features, provide a very promising scenario for their practical application in LULC mapping, and to progressively introduce automated processing methods at production levels in this very current remote sensing field of applications.

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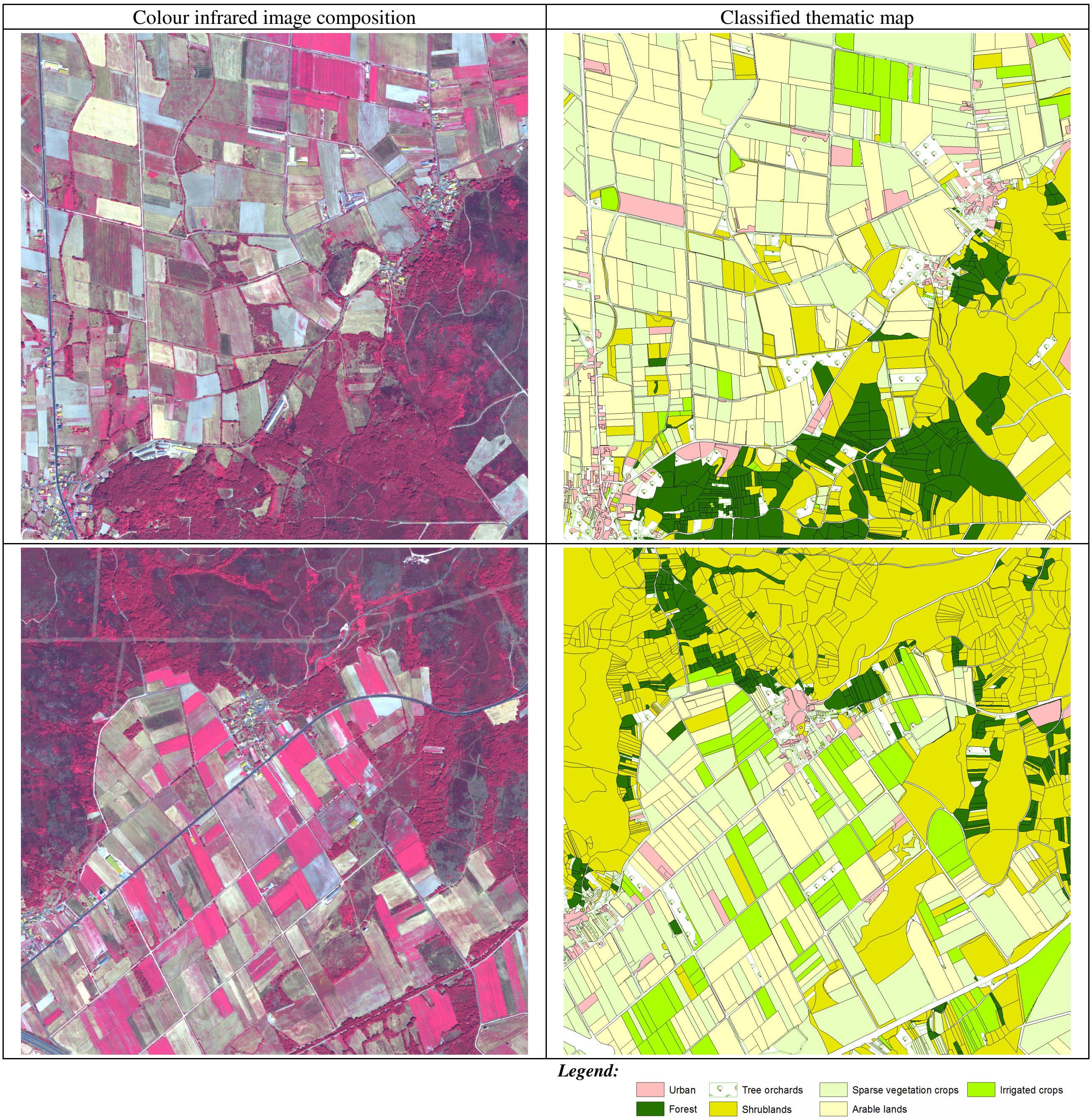

Figure 5. Graphical example of classification result.

Table 2. Confusion matrix of classification when spectral features are used in the classification.

Reference

Classified as

	Urban	Forest	Tree orchards	Shrublands	Sparse vegetation crops	Arable lands	Irrigated crops	Total	User accuracy
Urban	136		2		1	1		140	97.1
Forest		175	10	34			1	220	79.5
Tree orchards	1	1	57	5	6	3	1	74	77.0
Shrublands		40	20	229	1			290	79.0
Sparse vegetation crops	1		13		109	5	14	142	76.8
Arable lands	2		5		7	172		186	92.5
Irrigated crops		1	2		11		106	120	88.3
Total	140	217	109	268	135	181	122	1172	
Producer accuracy	97.1	80.6	52.3	85.4	80.7	95.0	86.9		**84.0**

Table 3. Confusion matrix of classification when spectral and texture features are used in the classification.

Reference

Classified as

	Urban	Forest	Tree orchards	Shrublands	Sparse vegetation crops	Arable lands	Irrigated crops	Total	User accuracy
Urban	135		4		1	3		143	94.4
Forest		188	13	26				227	82.8
Tree orchards	2	3	78	5	2	2		92	84.8
Shrublands		25	12	236	1			274	86.1
Sparse vegetation crops				1	109	6	16	132	82.6
Arable lands	3		2		11	170		186	91.4
Irrigated crops		1			11		106	118	89.8
Total	140	217	109	268	135	181	122	1172	
Producer accuracy	96.4	86.6	71.6	88.1	80.7	93.9	86.9		**87.2**

Table 4. Confusion matrix of classification when spectral, texture and structural features are used in the classification.

Reference

Classified as

	Urban	Forest	Tree orchards	Shrublands	Sparse vegetation crops	Arable lands	Irrigated crops	Total	User accuracy
Urban	134		6					140	95.7
Forest		194	12	20				226	85.8
Tree orchards	3	5	79	3	1	1	1	93	84.9
Shrublands		18	8	243			1	270	90.0
Sparse vegetation crops			2	2	116	7	16	143	81.1
Arable lands	3		2		9	173		187	92.5
Irrigated crops					9		104	113	92.0
Total	140	217	109	268	135	181	122	1172	
Producer accuracy	95.7	89.4	72.5	90.7	85.9	95.6	85.2		**89.0**