PRODUCING LAND USE/COVER MAPS WITH THE INTEGRATION OF REMOTE SENSING AND ANCILLARY DATA IN A GIS ENVIRONMENT

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The main purpose of the research presented in this paper is the development and validation, through the application to a case study, of an efficient form of satellite image classification that integrates ancillary information (Census data; the Municipal Master Plan; the Road Network) and remote sensing data in a Geographic Information System. The developed procedure follows a layered classification approach, being composed by three main stages: 1) Pre-classification stratification; 2) Application of Bayesian and Maximum-likelihood classifiers; 3) Post-classification sorting. Common approaches incorporate the ancillary data before, during or after classification. In the proposed method, all the steps take the auxiliary information into account. The proposed method achieves, globally, much better classification results than the classical, one layer, Minimum Distance and Maximum- likelihood classifiers. Also, it greatly improves the accuracy of those classes where the classification process uses the ancillary data.

KEYWORDS

Remote Sensing, Census Data, Geographic Information Systems (GIS).

INTRODUCTION

Since the generalization of satellite images, a huge effort has been done to identify, delineate, and measure, in an automatic or semi-automatic form, the different features of the urban space. If for studies over agricultural areas digital image-processing tools have shown their value, when transposed for constructed areas the results seem to be poorer [1][5]. The spatial resolution of the images functioned initially as justification for all the difficulties, and was considered as the main limiting factor in various studies [2][10].

Some authors [1][3][6] have however noticed that, paradoxically, the increase of the spatial resolution may also increase the problems related with the urban area analysis, due to the greater spectral heterogeneities of the urban environment, that leads implicitly to an increase of the variability - as the spatial resolution of an image increases, the details of the image (e.g. roads, houses) start taking form, promoting an erroneous and confused image handling, compromising the extraction of global information, and becoming problematic for a coherent and homogeneous image classification. In fact, urban areas involve spectrally heterogeneous land use classes, making impracticable a correct classification based solely in spectral information, as in traditional classification algorithms.

Geographical Information Systems (GIS) allow an easy integration of multi-source information. This fact can be exploited to produce image classification methods where information other than that collected from remote sensing, and known as ancillary information, is also used. The main purpose of the research presented in this paper is the development and validation, through the application to a case study, of an efficient form of satellite image classification that integrates Census data and Remote Sensing data, in a Geographic Information System.

Till present, only a few works integrated Census data in satellite images classification. One of the most recent and innovative work was held in Portugal, by the National Center for Geographical Information (CNIG) in partnership with the National Statistic Institute (INE). This study [8] aimed to evaluate the growth dynamics of the Great Lisbon Area, using spectral (SPOT images) and ancillary data (Road Network-RN, Digital Terrain Models - DTM and Census). The followed methodology used the DTM for the correction of topographic effects on the images, the RN in a pre-classification stratification (urban/non urban mask) and the Census data in the creation of classification rules for post-classification sorting. In 1998, another important work was presented [12], which used the Census data to produce ‘a priori’ occurrence probabilities of land-use classes and then, using a Bayesian classifier, integrated those probabilities in satellite images (Landsat TM) classification. The methodology presented in this paper can be considered as a step forward on these two works.

Figure 1 depicts the main steps of the hierarchical classification methodology studied in this paper. In the pre-processing stage, this information is made compatible after correction of acquisition errors. Also, using the auxiliary information alone, a binary mask is produced that subdivides the area on study into two clusters - "land" and "water" - and ´a priori´ occurrence probabilities for some urban classes are computed.

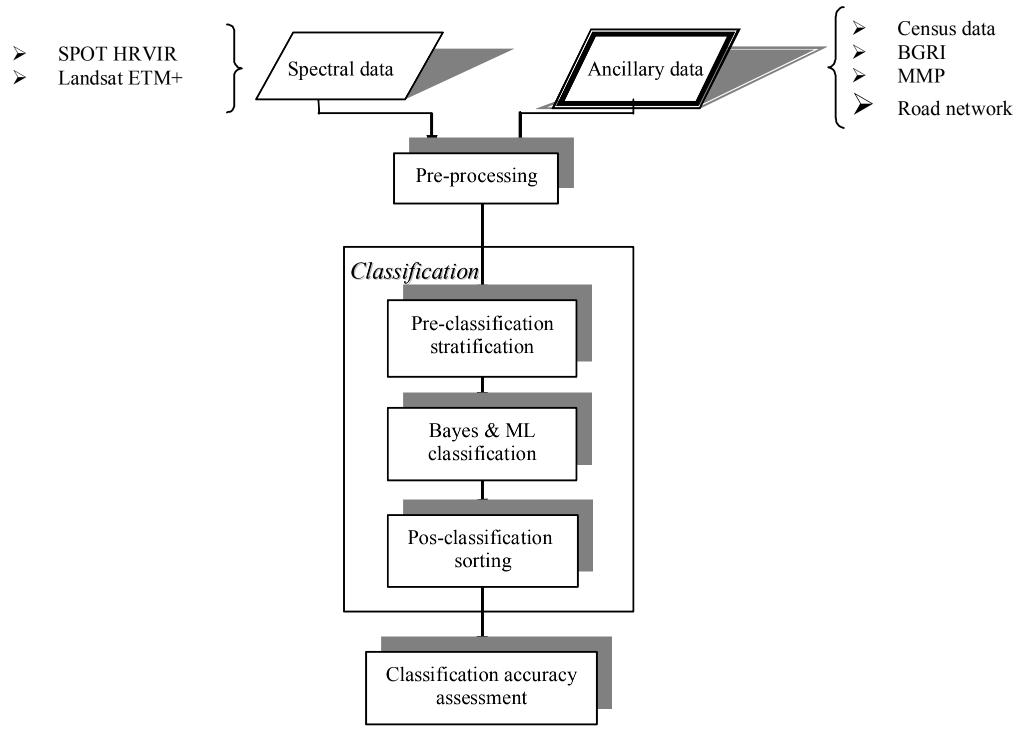


Figure 1: Schematic flow-chart of the overall procedure.

The developed procedure follows a layered classification approach, being composed by three main stages: 1) Pre-classification stratification; 2) Application of a Bayesian classifier; 3) Pos-classification sorting. Common approaches incorporate the ancillary data before, during or after classification, through the aforementioned steps. In the proposed method, all the three steps take the auxiliary information into account. In the first stage and using the vector statistical base alone, a binary mask is produced that allows subdividing the area on study into two clusters: "land" and "water". The second stage comprises four steps:

i) Using a simple Isodata classifier (which uses both the satellite and contextual bands), the cluster "land" is further subdivided in two more areas: "urban" and "no urban".

ii) The "urban" area obtained in i) is intersected with the statistical vector base (dasymetric technique), producing a new layer that links the statistical information to the built up areas.

iii) Using the census data, “a priori” occurrence probabilities for the different land use/cover are computed, which will be used with the Bayesian classifier.

iv) Application of a Bayesian classifier.

In the third and last stage and in order to improve the results of the Bayesian classifier, the working area (in our study, Oeiras) Master Plan is used to correct misclassifications in the residential areas.

Experimental classification results are presented, together with common classification error measures. Also, a comparison with classic, one layer, classification strategies (Minimum Distance and Maximum- likelihood) is provided.

DATA SET

The multi-source information used in this paper can be divided in two main groups: spectral data (raster format) and ancillary data (vector and ASCII formats). The former corresponds to SPOT HRVIR - P and XS (2004), and Landsat ETM+ (2001) satellite images; the later corresponds to the results of the Portuguese Population General Census statistics (2001), referenced to the subsection vector basis (equivalent to the UK enumeration district, known as BGRI), the Municipal Master Plan (1994) of the area under study and the Roads Network (1998). The Portuguese Population General Census statistics comprises a large set of data, divided into four subgroups: “Families”, “Dwellings”, “Individuals” and “Buildings”. Taking into account previous works experience [4] [13], a first selection of census data (table 1) was made.

FIELDS	**MEANING**
Number of familiar dwellings	All that have, at least, one family
Number of classical dwellings	All that belong to classical buildings
Number of collective dwellings	Hotels, hospitals, prisons
Number of present individuals	All the individuals that live in the subsection (whether they where present or not at the time of the inquire)
Number of classical buildings	Buildings built up with resistant material (for which a lifetime of at least 10 years is expected)
Buildings by construction date	Buildings by construction date
Buildings by number of floors	Buildings by number of floors
Exclusively residential buildings	Exclusively destined for residential purposes
Mainly residential buildings	Mainly destined for residential purposes
Mainly non residential buildings	Mainly destined for non residential purposes

Table 1 - First selection of statistical information.

The Road Network was selected because it already exists in vector format and so could be inserted in the final classification with a 100% precision. Moreover, the inclusion of the Road Network allows removing from the classification a class – “roads” – that has great similarities (identical digital values) with the multi-family housing area, allowing calculating with better precision this last one. In what concerns the Municipal Master Plan (MMP), although the represented classes are predominantly an indication of what is or not, allowed to construct in the future, some classes represent the existing land uses at the plan elaboration date. These were used in post-classification sorting rules, with the objective to improve the classification results.

Considering the spectral data, it was decided to use all the SPOT HRVIR bands (1 panchromatic and 4 multispectral) and Landsat ETM+ (with exception of band 6 that was excluded due to its weak spatial resolution). This option allows to simultaneously exploiting the better spatial resolution of SPOT images, and the higher spectral resolution of Landsat images. The methodology proposed in this paper was tested over a geographical area with 2.3 km height by 4 km width (see figure 2), belonging to the Lisbon Metropolitan Area (LMA).

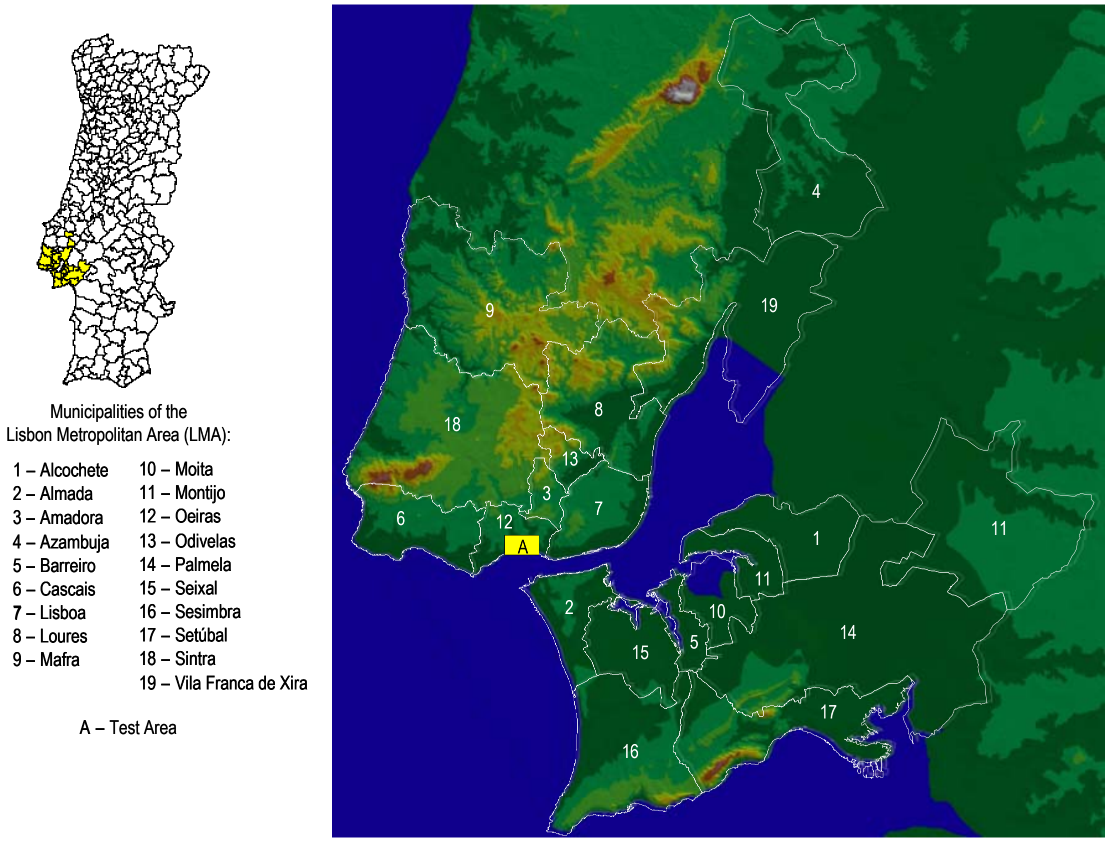
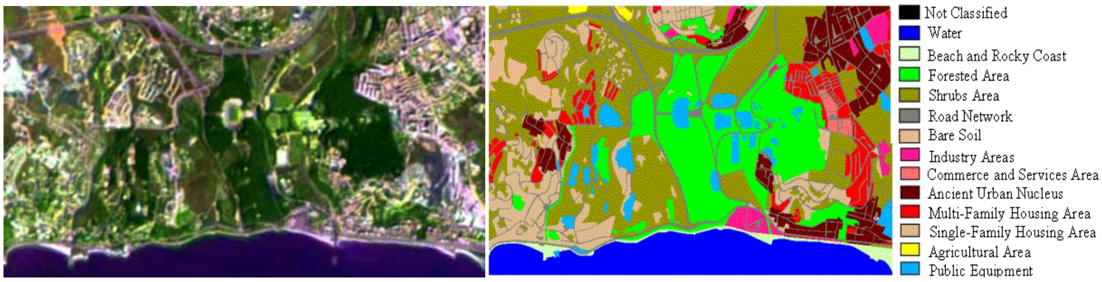


Figure 2 – Location of the test area in the LMA

The land use/cover classes considered (see figure 3 a) are those desired for the LMA land-use cover map.



a) b)

Figure 3 - Area on study: a) Color composite of SPOT and Landsat bands; b) Photo-interpretation map (2004).

DATA PRE-PROCESSING

Spectral data correction

Before starting with the classification process, it was necessary to make the different sets of information compatible. The main problem here is the traditional dichotomy raster-vector. In this case, considering the satellite images as the main source of information, it was decided to work, whenever possible, in raster format. The satellite images were further georeferenced using an ortophotomap (with 1:10 000 scale) of the region under study. The resample process assures a common spatial resolution in all satellite bands – 2.5 x 2.5m per pixel – that corresponds to the maximum available spatial resolution (SPOT HRVIR P in supermode).

Ancillary data processing

Once the BGRE corrected, it was possible to fulfill all the operations related with the ancillary data handling (figure 4), namely: creation of a water/land binary mask; production of a first binary map representing the urban and non-urban uses; calculation of the ´a priori´ occurrence probabilities for the urban classes; creation of a contextual urban band - all to be used in the satellite image classification process.

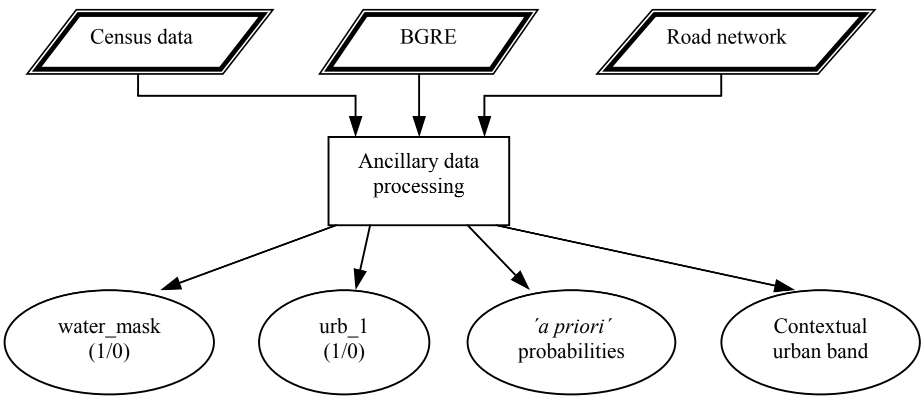


Figure 4 - Input and output data of the ancillary data processing block.

In order to obtain the water/land mask, the region corresponding to Tagus River was detected on the area on study. This was accomplished using the corrected BGRE, that presents the coast limits perfectly (statistical subsections do not exist inside the water), and transforming the result in a binary image (´1´- water; ´0´- land). Note that even many of the traditional classifiers obtain almost always 100% accuracy when classifying the pixels representing the “water” class, they usually fail in areas presenting a mixture of uses (mainly near the coast), often referred as mixels. In these situations, it is common that elements of the shoreline be classified as water and vice-versa.

The statistical data (Census data and BGRI) also allowed to identify the subsections without buildings and considered as non-urban areas. These sections were unified with the Road Network, giving origin to the first urban/non-urban binary mask (´urb_1´).

Concerning the ´a priori´ occurrence probabilities for the urban classes, from the first selection of data, presented in table 1, one second choice was made, pointing only to the information related with the sub-group ´buildings´ (last six rows of table 1). Several reasons supported this option: i) buildings data contains information that can be efficiently correlated with reflectance (in contrast to what happens to the dwellings, that are "invisible" from satellite images); ii) buildings data provides the sufficient information for the ´a priori´ probabilities computation, for some of the urban classes seek for the LMA land use/cover map (see figure 3), namely: ´Commerce and Services´, ´Ancient Urban Nucleus´, ´Multi-family Houses´, ´Single-family Houses´ .

Once selected the Census indexes, it was necessary to establish formulas to calculate the occurrence probabilities of the four above-mentioned urban classes. The buildings exclusively or mainly destined for residential purposes, with more than two floors, have been considered as Multi-family Housing. The buildings exclusively or mainly destined for residential purposes, with one or two floors, have been considered as Single-family Housing. The Ancient Urban Nucleus was established as the set of buildings constructed up to 1945, inclusively. In fact, in the 40´s occurred an alteration in the type of materials used in construction, fact that is also perceivable on the satellite images, which allows a significant correlation between the two types of data (spectral and statistical). The Commerce and Service buildings have been considered those buildings mainly destined for non-residential purposes (last row of table 1), independently of the construction date or number of floors.

The ´a priori´ occurrence probabilities will be given by:

$$\mathrm{p}(\text{´Multi-family Houses´}) \equiv \mathrm{p}(\mathrm{MFB}) = \frac{MFB}{TB} \tag{1}$$

$$\mathrm{p}(\text{´Single-family Houses´}) \equiv \mathrm{p}(\mathrm{SFB}) = \frac{SFB}{TB} \tag{2}$$

$$\mathrm{p}(\text{´Ancient Urban Nucleus´}) \equiv \mathrm{p}(\mathrm{AUN}) = \frac{AUN}{TB} \tag{3}$$

$$\mathrm{p}(\text{´Commerce and Services´}) \equiv \mathrm{p}(\mathrm{CS}) = \frac{CS}{TB} \tag{4}$$

Where:

MFB_t = number of multi-family buildings;

SFB_t = number of single-family buildings;

CS = number of buildings mainly destined for non residential purposes;

TB = total number of buildings;

MFB = number of multi-family buildings, constructed after 1945;

SFB = number of single-family buildings, constructed after 1945;

AUN = number of (exclusively or mainly) residential buildings, constructed before 1945.

Of course, the four probabilities summation must equal one. Note however that some of the required indexes (namely MFB, SFB and AUN) are not directly available from table 1. For instance, this table tell us the number of multi-family houses and the number of buildings constructed after 1945, but not the ´number of multi-family buildings, constructed after 1945´, as required. Taking these facts into account, the following strategy for the ´a priori´ probabilities computation was adopted:

1. Compute p(CS)=CS/TB

2. If p(CS)>0.8 then

    p(CS)=1, p(MFB)=p(SFB)=p(AUN)=0

else

    p(CS)=0

3. If p(CS)=0 then

    p(AUN)=AUN/TE

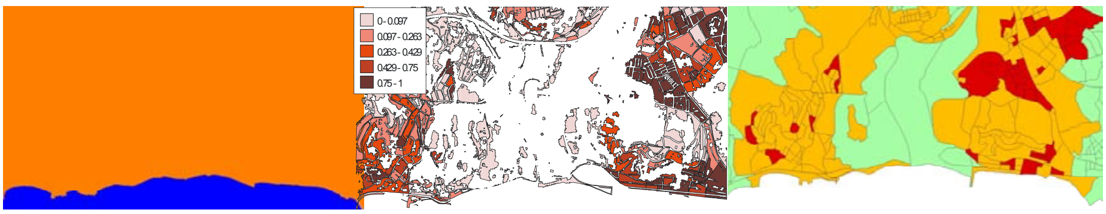
    p(MFB)=(MFB_t – α AUN)/TE

    p(SFB)=(SHB_t – β AUN)/TE

The parameters α and β ($\alpha+\beta=1$) accounts for the fraction of ancient buildings that are multi-family and single-family, respectively. In the experimental results we used $\alpha=\beta=0.5$.

The final step of the ancillary data processing block is the creation of a contextual urban band, establishing three great groups of subsections - subsections strongly urbanized, subsections low urbanized and subsections with little probability of having buildings. This was accomplished with a simple clustering technique using, as parameters, the buildings density (number of buildings/km2) and the population density (number of individuals/km^2), in each subsection.

Figure 5 presents some of the outputs produced by the ancillary data processing block (the urban/non-urban mask is represented in figure 5-a)).



a) b) c)

Figure 5 - Ancillary data processing outputs: a) water/land binary mask (´water_mask´); b) ´ a priori´ probabilities image correspondent to the ´multi-family buildings´ class (probability values were quantified in five levels for representation); c) contextual urban band.

CLASSIFICATION METHODOLOGY

The developed classification procedure, as mentioned before, follows a layered classification approach, being composed by three main stages: 1- Pre-classification stratification; 2 - Application of Bayesian and Maximum-likelihood classifiers; 3- Pos-classification sorting. Common approaches incorporate the ancillary data before, during or after classification, through the aforementioned steps. In the proposed method, all the three steps take the auxiliary data (or data extracted from it) into account.

Pre-classification stratification

The objective of this stage (figure 6) is to have, at the classifier input, three main stratums – "water", "urban areas", "non-urban areas" – that will be processed individually. The pre-processing stage already produced a "water/land" binary mask, that allows isolating in all the bands (satellite images and the contextual urban band) the use "water", and a first approximation of the "urban/non-urban" binary mask (urb_1). In this stage, a more accurate version of the "urban/non-urban "binary mask (urb_fin) is produced.

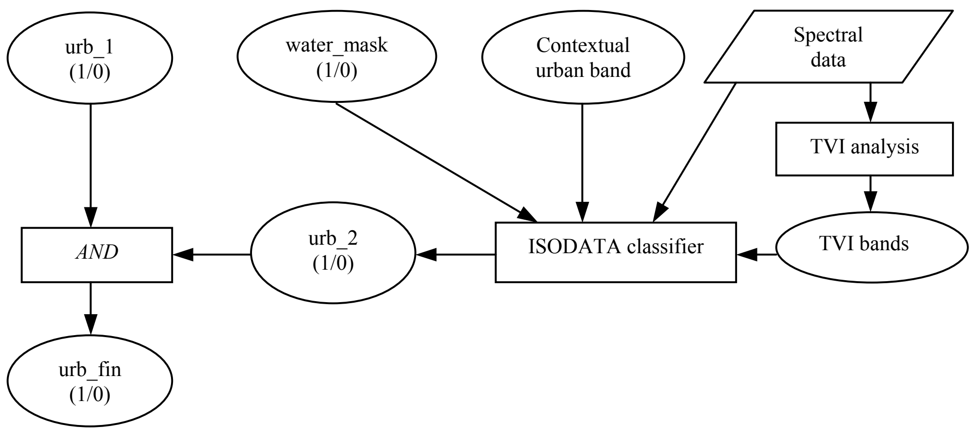


Figure 6 - Schematic flow-chart of the pre-classification procedure.

The pre-classification procedure consists in an ISODATA algorithm having, as inputs: the spectral bands, the contextual urban band, and two TVI (Transformed Vegetation Index) bands obtained from each group (SPOT and Landsat) of satellite images (the purpose of the water mask is merely to exclude, from all these inputs, the water region). These indexes represent the surface biomass content, constituting a valid aid in the urban/non-urban differentiation. The reason for choosing a ISODATA algorithm is related with two factors: i) the intention to not define land use/cover classes at this time; ii) the knowledge of previous works9, stating that the conjugation of a ISODATA classifier with a contextual band (similar to the one used in this work), may improve the classification results in 10%. The TVI was applied due to its strong correlation with the construction density [11] and its capability to improve the discrimination of urban areas [7].

$$TVI(Landsat) = \sqrt{\frac{TM4 - TM3}{TM4 + TM3} + 0.5}$$

(5)

$$TVI(SPOT) = \sqrt{\frac{XS3 - XS2}{XS3 + XS2} + 0.5}$$

The best result (in terms of maximizing the discrimination between constructed and non-constructed areas) was achieved with six classes on the ISODATA algorithm. Reclassifying the resulting image, allowed to create a new urban/non-urban mask (urb_2), which was intersected with the previous one (urb_1) to obtain the final mask (urb_fin). The three urban masks are presented in figure 7. These masks allow a progressive improvement in the urban-rural differentiation, as shown by the increase of the resulting overall accuracies: 48% for urb_1, 80% for urb_2 and 93% for urb_fin.

a) b) c)

Figure 7 - Urban/non-urban binary masks: a) urb_1; b) urb_2; c) urb_fin.

Application of Bayesian and ML classifiers

The second stage of the classification procedure is schematically represented in figure 8. The urban (urb_fin) and water (water_mask) binary masks, obtained in previous steps, are crossed with all spectral bands, producing two new images for each original image: one with the non-urban uses (´Forest´, ´Shrubs´, ´Bare Soil´, ´Agricultural´, ´Roads´, ´Beach´, ´Public Equipment´) and another with the urban uses (´Commerce and Services´, ´Ancient Urban Nucleus´, ´Multi-family Houses´, ´Single-family Houses´, ´Industry´, ´Public Equipment´).

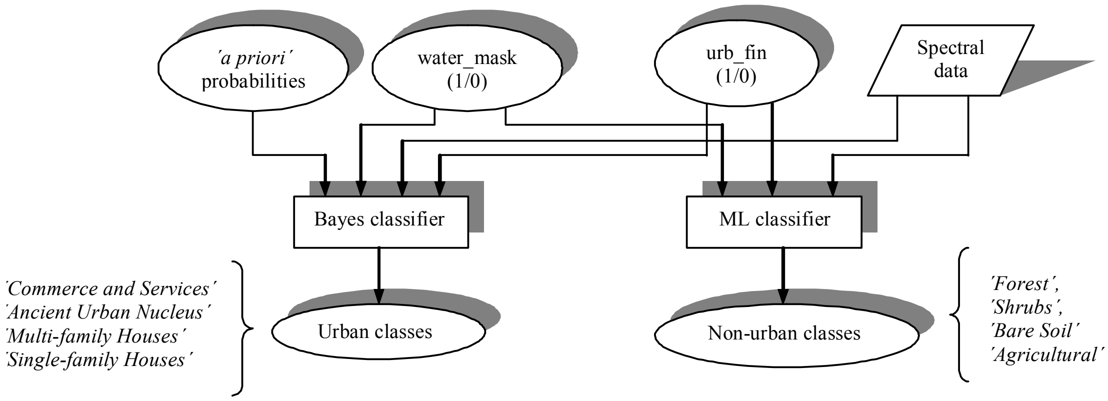


Figure 8 - Schematic flow-chart of the Bayesian and ML classification procedures.

The ´Forest´, ´Shrubs´, ´Bare Soil´ and ´Agricultural´ uses, belonging to the non-urban images, were extracted using a Maximum-likelihood classifier. In this classifier the probability of a given pixel (X) fit in a category is defined from the density likelihood function for a normal distribution, which is represented by the mean vector of Mk class and by the co-variance matrix Ck.. Numerically this classifier is expressed as:

$$F_k(X_i) = (2)^{-n/2} |C_k|^{-0.5} \exp\left[-0.5(X_i - M_k)' C_k^{-1} (X_i - M_k)\right] \quad (6)$$

Where Fk (Xi) is the probability of a pixel (Xi) vector (with each pixel i = 1, 2, ..., N) belong to a spectral (training) class K. Note that, as mentioned before, the ´roads´ use was already available through the Road Network ancillary data. The ´Beach´ and non-urban ´Public Equipment´ are obtained in the next classification step, using post-classification rules, together with the Municipal Master Plan (MMP).

The urban images and the four ´a priori´ probabilities images constitute the base for the Bayesian classifier application. These probabilities allow discriminating four urban classes (´Commerce and Services´, ´Ancient Urban Nucleus´, ´Multi-family Houses´, ´Single-family Houses´) that, due to their similar spectral responses, would be misclassified if a ML classifier were applied. The Bayesian classifier is expressed as:

$$G_K(X_i) = \frac{F_K(X_i)P(K)}{\sum_K F_K(X_i)P(K)} \quad \text{where K=1, 2, ..., K.} \quad (7)$$

Where GK (Xi) is the ‘a posteriori’ probability of class K, given the spectral – Fk (Xi) - and the contextual - P (K) (also known as conditional) – probabilities.

The ´Industry´ and urban ´Public equipment´ uses are extracted in the next classification step, using both post-classification rules and the MMP.

The training areas (necessary in the first step of both Bayesian and ML classifier) were delimited over a color composition offering an adequate visual discrimination of the different uses. This composition was obtained through the following steps: 1 – production of a first composition using the 7, 4 and 1 TM bands assigned, respectively, to the R, G and B channels; 2 – transformation of the color space from RGB to IHS; 3 – substitution of channel I by the SPOT-pan band; 4 – transformation of the color space from IHS to RGB.

Post-classification sorting

The last stage of the classification procedure re-classifies pixels attributed to the wrong classes in the previous steps, through the application of contextual rules and the use of information directly available from the ancillary data (Road Network and MMP).

For the area on study, four different classes of use are considered in this step: ´Roads´, ´Beach´, ´Industry´ and ´Sports Equipment´ (a sub-class of the ´public equipment´), like football fields and tennis courts. The ´roads´ class is directly available from the Road Network. The remaining classes results from the information available in the MMP or, for the missing cases, from the following contextual rules:

• ´Beach´- pixels that, although belonging to the urban areas (value ´1´ in the urb_2 mask), were not classified in any of the urban classes, and at a geographical position not far from 200 m of the line coast;

• ´Industry´ - pixels classified in urban classes (value ´1´ in the urb_fin mask), but signalised as ´industry´ in the MMP;

•´Sports Equipment´- pixels classified as ´Shrubs´ or ´Bare soil´, comprising a region with an area and perimeter typical of football fields (smaller size minus half a pixel and higher size plus half a pixel) or tennis courts (lower and higher bounds achieved by size minus and plus half pixel), with the right compactness ratio, belonging to just one subsection, near a road and, just for the football fields, with an North-South orientation.

All the extracted classes are then integrated in the final classification map, according to the following algorithm:

•The replenishment of the final map is performed from the highest to the lowest confidence classes, namely:

1. ´Roads´ (extracted from the Roads Network)
2. ´Commerce and Services´; ´Ancient Urban Nucleus´ (obtained from the Bayes classifier)
3. Other urban classes (obtained from the Bayes classifier)
4. Sports Equipments´; ´Beach´ (resulting from the MMP and/or contextual rules) and ´Industry´ (resulting from the urb_fin mask and MMP)
5. Non-urban classes (resulting from the ML classifier)

•Once a label (class) has been attributed to a pixel, it cannot be overwritten by another label.

EXPERIMENTAL RESULTS AND CONCLUSIONS

For the case study, the Kappa index of the final map was 0.30 higher than the value achieved with both the classical maximum likelihood and minimum distance classifiers. Also, it allows the identification of land use/cover classes (e.g., commercial areas), "invisible" to the satellites. As an example of this line of work please regard the three following land use/cover maps: minimum distance (figure 9 a) and proposed method (figure 9 b).

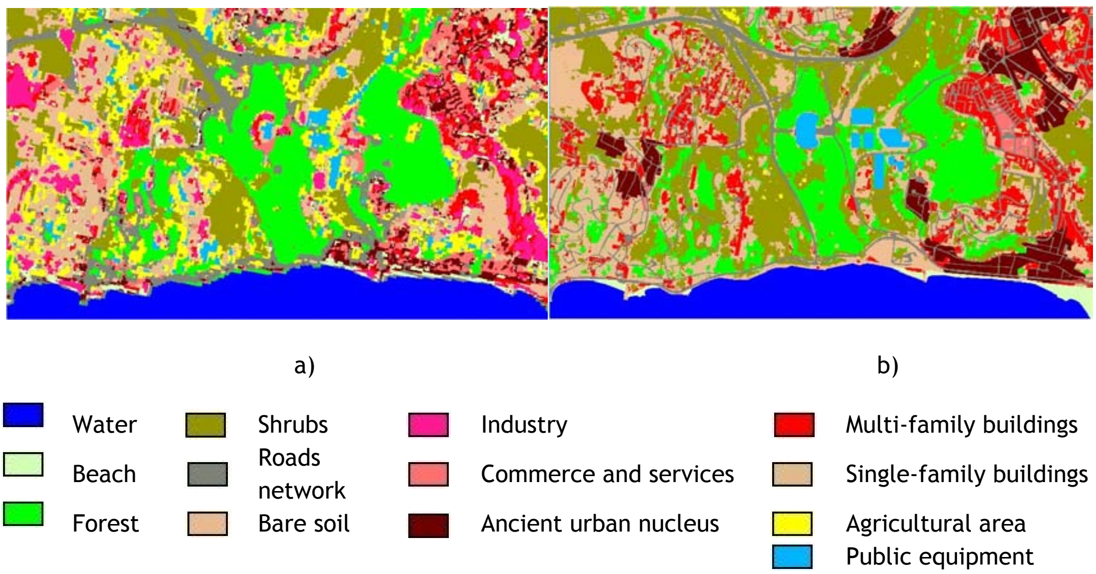


Figure 9 - Land use/cover maps: a) Minimum distance and b) Proposed method

To verify the accuracy of the proposed method (and compare it with other classifiers) three tables were produced, where it is possible to see Overall Accuracy and Kappa Index (table 2), and the

Omission Errors (OE), Commission Errors (CE), Producers Accuracy (PA) and Consumers Accuracy (CA) for each class (table 3).

Classifier	Kappa index (0 – 1)	Overall Accuracy (%)
Maximum Likelihood	0.35	36.5
Minimum Distance	0.36	37.8
Proposed Method	0.67	70.5

Table 2 - Overall Accuracy and Kappa for three Classifiers

Classes	**Minimum Distance**				**Proposed Method**			
	OE (0-1)	**CE (0-1)**	**PA (%)**	**CA (%)**	**OE (0-1)**	**CE (0-1)**	**PA (%)**	**CA (%)**
1. Water	0.05	0.01	94.9	98.6	0.00	0.00	99.9	99.9
2. Beach and Rocky Coast	0.78	0.87	21.6	12.8	0.01	0.01	98.9	99.0
3. Forested Area	0.29	0.29	70.3	70.0	0.29	0.24	70.2	75.0
4. Shrubs Area	0.61	0.15	38.6	84.6	0.34	0.24	65.1	75.9
5. Road Network	0.76	0.73	23.6	26.8	0.00	0.00	100.0	100.0
6. Bare Soil	0.74	0.85	25.1	14.8	0.45	0.78	54.3	21.7
7. Industry Areas	0.88	0.96	11.9	3.6	1.00	0.00	0.0	100.0
8. Commerce and Services Area	0.78	0.97	21.5	2.0	0.00	0.01	99.1	98.5
9. Ancient Urban Nucleus	0.82	0.74	17.0	25.7	0.01	0.01	98.7	98.9
10. Multi-Family Housing Area	0.81	0.76	18.0	23.0	0.42	0.60	57.6	39.3
11. Single-Family Housing Area	0.66	0.64	33.1	35.4	0.46	0.45	53.1	54.8

12. Agricultural Area	0.77	0.99	22.3	0.5	0.73	0.65	26.9	34.3
13. Public Equipment	0.85	0.75	14.6	24.6	0.68	0.02	31.8	97.3

Table 3 - Omission Errors (OE), Commission Errors (CE), Producers Accuracy (PA) and Consumers Accuracy (CA) for each class

From figures and tables some preliminary conclusions can be drawn:

1.The proposed method achieved, in a global perspective, better results than the traditional ones as we can see through the table 1.

2.In a more detailed analysis, it is possible to see that the proposed method gets a better accuracy for all classes except shrubs (4).

3.The proposed method has improved the overall accuracy (higher than 97 %) of the classes where was a direct use of statistical information, mainly classes 1, 2, 5, 8, 9 and 13. Note that class 5 (Road Network) already exists in digital format; witch justifies the 100% accuracy.

4.Urban classifier failed in part the analysis of industrial areas because in this particularly case it was totally dependent of a classification rule, and, due to the poor quality of the MMP, it just identifies the near water ones.

5.The proposed method allows the identification of classes (e.g., ´Commerce and Services´), "invisible" on the satellite images.

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