TEXTURE ANALYSIS TO IMPROVE SUPERVISED CLASSIFICATION IN IKONOS IMAGERY

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ABSTRACT:

The most extensive use of Remote Sensing data is in land cover/land use (LCLU) studies by means of automated image classification. The general objective of this research is to develop an automatic pixel-based classification methodology with the aim to produce a Regional land use map congruent with the CORINE Land Cover legend. Starting point are detailed ground data, already gathered fostering interoperability among several Regional bodies' DBs and high resolution multi-spectral IKONOS imagery.
In the light of land mapping, there are two main features related to IKONOS imagery: lack of spectral information (4 spectral bands) and high spectral variability (high spatial resolution). This results in problems in terms of class information extraction especially using pixel-based image classification methods in which spatial information existing between a pixel and its neighbours is not used. To overcome these deficits, the use of vegetation indexes (NDVI feature and TDVI masks) and texture (GLCM and edge-density features) is investigated with respect to its impact on land cover/land use classification.
The developed spectral/textural classification schema is compared with the classical approach using only spectral information. An accuracy assessment is carried out which shows that image data with 4 IKONOS spectral bands plus NDVI band plus 6 texture bands achieve an accuracy of 80.01% compared to 63.44% of accuracy achieved by using the few spectral bands only. Furthermore it allows the discrimination of 10 CLC classes.
Experimental results show how, starting from available but also binding data (IKONOS imagery and available Regional ground data), a classification schema can be developed with enhanced performance and strong relation to the specific setup.

1. INTRODUCTION

This work is part of a wider project whose general objective is an automatic pixel-based classification methodology aimed at producing a regional CORINE Land Cover (CLC) land use map. Starting points are high resolution multi-spectral IKONOS imagery and ground data already gathered in previous works (Marcheggiani et al., 2008). The images, provided by Marche Region Institution, are mono-temporal (June 2006) and with only 4 spectral bands. The ground data, owned by different bodies of Marche Region public administration at regional level, are large and detailed. Consequently the main goal of this work is the development of a classification schema that can take advantage of all the available data in Region's possession (IKONOS images and Ground data) to investigate the possibility of a land cover mapping trustable enough to be a permanent monitoring service of Marche region territory, congruent with the land use oriented European trend (CLC legend).
In the light of land mapping, there are two main features related to IKONOS imagery: lack of spectral information and high degree of spectral variation due to the high image spatial resolution. This results in problems in terms of class information extraction especially using pixel-based image classification methods in which spatial information existing between a pixel and its neighbours is not used. To overcome these deficits and achieve reliable and accurate results, spectral and texture information (GLCM and edge-density features) are combined together in the proposed classification schema.

A fundamental goal of this research is in fact to explore the image texture information and how to combine it with the spectral signatures to do image analysis. Moreover the use of vegetation indexes (NDVI feature and TDVI masks) is investigated with respect to its impact on land cover/land use (LCLU) classification.
The study case focuses on the north-eastern part of the Marche region, belonging to the Ancona Province. It covers an area of approximately 80 km^2, comprising urban and rural landscape and natural Mediterranean environment, among which the Conero Mountain Natural Park have to be mentioned. Figure 1 gives an overview of the study image and its geographic location.

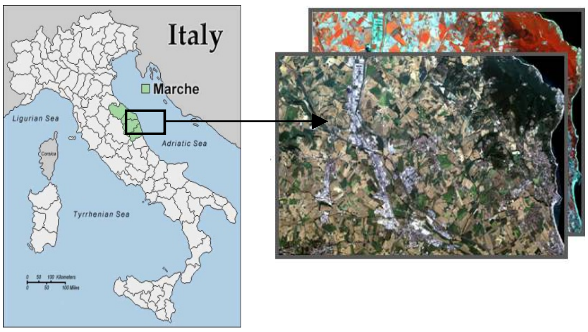

Figure 1. Map of Italy and Marche Region (left), test image in RGB and False Color composition (right).

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2. METHODOLOGY

The proposed classification schema is pointed out below in Figure 2.

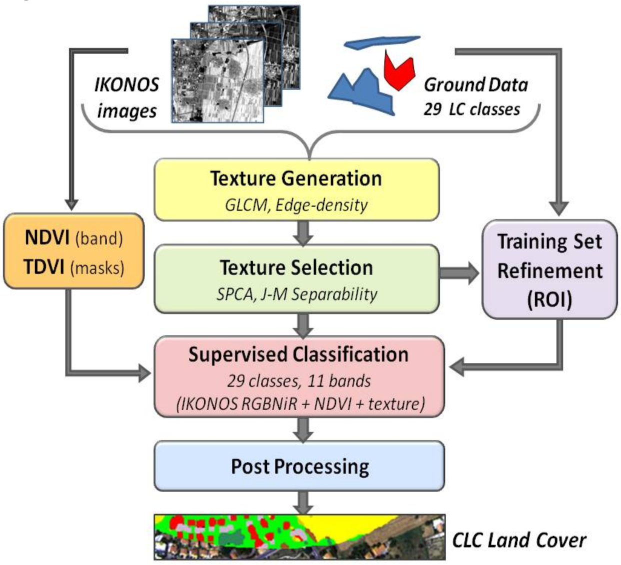


Figure 2. Workflow diagram describing the developed classification schema

The input data are multi-spectral IKONOS images and available ground samples gathered from different Information Systems owned by Marche Region and organized in independent learn and control samples. They are organized in 29 LC classes according to their cover type and they mostly differ from the CLC land use oriented nomenclatures. This means that, to match the CLC legend, they must be grouped together according to their use (agriculture, settlement etc.) that often doesn't fit their spectral response, making the supervised training process difficult. In this context another objective of this research is to investigate the best way to combine the 29 LC classes into CLC nomenclatures.

Vegetation indexes are investigated with different purpose: NDVI to generate an additional band and TDVI to build binary masks trough which three supervised classifications are carried out independently.

Texture features can be generated after having chosen the spectral bands to process and set the window size parameter (semivariogram/correlogram-guided texture feature generation). In particular 28 different texture features are generated according to two different texture approaches (GLCM and edge-density features). By means of Standardized PCA these 28 texture features are reduced or selected according to their loading factor, augmented by the four spectral bands and the NDVI feature and grouped into three different feature sets that differ only in the texture subset selection (IKONOS RGBNiR + NDVI + texture). According to the Jeffries-Matusita (J-M) average separability distance the best suited feature set can be chosen. It is used to refine the training data and to run the three TDVI masked supervised classification. A post processing step is needed to match the CLC legend and improve the spatial consistency of the pixel-based classification.

Hereafter the different steps shown in Figure 2 are explained in more details.

2.1 Semivariogram/correlogram-guided texture feature generation

Texture features could be theoretically calculated for each spectral band and for many window sizes but with the disadvantage of increasing the feature space dimensionality and redundancy. Some choices must be made.

2.1.1 Spectral band analysis

- AIM: to minimize feature space dimensionality by selecting optimal channels for texture measures.
- RESULT: Red and NiR bands are selected. They show highest variances for the different land covers and low correlation.

The following strategy to select the best band combination is chosen. The 29 LC classes samples are downgraded in 5 main cover classes and used as masks to compute covariance matrices. According to the different 5 LC main classes, the Red and the NiR band always correspond to the highest variances which indicate strongest texture features. Moreover they show low correlation.

2.1.2 Geostatistical correlogram/semivariogram analysis

- AIM: to investigate the optimum window size to use to generate texture features
- RESULT: 3x3,5x5 and 7x7 window sizes for the Red band, 3x3 and 5x5 for the NiR band

Semivariograms and Moran's *I* correlograms of all the 29 LC land cover classes are sequentially computed for lag distances increasing to 20 pixels. The radiometric spatial autocorrelation of the each particular LC class can be quantified in terms of the lag (*range*) that results in the maximum variability (*sill)* for the semivariogram and at the same time in a very close to zero Moran's *I* value. An example is displayed in Figure 3 and is related to one of the 29 LC classes (class 40305, Sparsely vegetated areas).

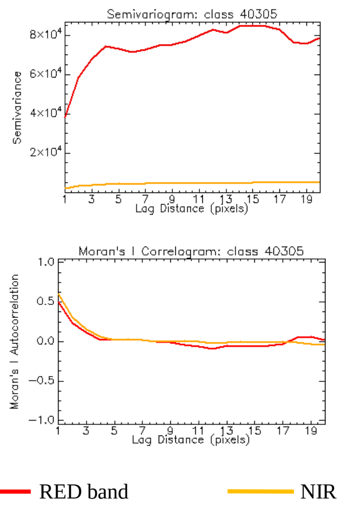


Figure 3. Red and NIR Semivariogram/Correlogram plots

Having a look to all the 29 pairs of LC class variograms and correlograms, they indicate that semivariances for Red band mostly start to saturate at a lag of 5 while some classes require 3 and 7 pixels of kernel size. Instead in the NiR band each land cover class reveal spatial correlation for lag distance of less than 5 pixels. Consequently 3x3, 5x5 and 7x7 are used as window sizes for the GLCM computation from the Red band, and two window sizes (3x3 and 5x5) are used to create NiR co-occurence features. The same window sizes are taken into account for the edge density image generation.

2.1.3 Texture feature generation

- AIM: generation of optimal texture features to add to the originals multispectral bands, before running the classification.
- RESULT: 20 GLCM features + 8 edge-density features = 28 texture features generated.

Two different kinds of texture are generated: Grey Level Co-occurrence (GLCM) and edge-density features.

***GLCM texture generation*:** As suggested by Hall-Beyer (2000) a combination of only four GLCM measures (Haralick, 1973) are selected to avoid that texture features are correlated with each other. In particular mean (MEAN), Variance (VAR), Entropy (ENT) and Homogeneity (HOM) are computed for the Red and NiR bands and five window size (respectively 3x3, 5x5 and 7x7 for the Red band and 3x3 and 5x5 for the NiR band) leading up to the generation of 4 x 5= 20 GLCM features. For reducing the degrees of freedom of the GLCM texture generation, the distance between pixels for the co-occurrence matrix computations is maintained constant at one and the average of the four main inter-pixel angles (0°, 45°, 90° and 135°) is used, based on the assumption that no land cover exhibits a preferential directionality. The gray scale quantization levels is set to 64: it allows to have a better computational and statistical performance and reduce processing time limiting the size of the co-occurence matrix to 64 x 64 (instead of 2048 x 2048 because of the radiometric resolution of 11 bit).

Edge-density texture generation: As done before, edge density maps are produced processing the Red and NiR bands. Firstly, each band is filtered using a Laplacian high pass filter; secondly, edges are found by thresholding the filtered image based on histogram interpretation. Finally, an average filter is used to produce the edge density map, counting the edge points in each position of the moving kernel and dividing the number of edge points by the window size. Two different thresholds for the Laplacian filter are selected interactively for each band (T_{R1} and$T_{R2,}$ T_{NiR1} and T_{NiR2}) and 9x9 and 15x15 are used as average filter's window sizes. 4 x 2 = 8 edge-density images are generated from the Red and NiR bands.

2.2 Texture selection

Before adding the collected 28 texture features as additional bands to the IKONOS imagery, they are investigated and sorted according to the standardized Principal Component Analysis (SPCA) with the aim to extract optimum linear combinations (Principal Components) of the original texture features that contain as much as possible variability of the original data.

2.2.1 Standardized Principal Component Analysis (SPCA)

- AIM: to reduce the generated texture features to the maximum number of uncorrelated data
- RESULT: 3 different feature sets are constructed:
  – 1st *Feature set* : 4 GLCM PCs + 4 spectral bands + 1 NDVI
  – 2nd *Feature set*: 6 GLCM&edge PCs + 4 spectral bands + 1 NDVI
  – 3rd *Feature set*: 12 high "loading" features + 4 spectral bands + 1 NDVI

Assuming that the original texture features are more or less equally important, the problem to tackle is that the 28 texture variables have very different means and/or standard deviations. In this case a normalization is needed to avoid the importance of a variable being determined its variance that could dominate the whole covariance matrix and hence all the eigenvalues and eigenvectors. This standardization is done by running the Standardized PCA (SPCA) that equalizes dissimilar variations in the data set by using a correlation matrix instead of a covariance matrix (PCA). In particular the SPCA is performed two times (to the 20 GLCM features first and then to the 28 GLCM&edge features) to construct three different feature sets that later on must be investigated and selected before going on with the maximum likelihood classification process. Compromising three different selection guidelines (cumulative percentage, Scree plot and Kaiser's rule), the first four GLCM PC bands and six GLCM&edge PC bands are selected along with the original four spectral bands and the NDVI band to build the 1st and the 2nd feature set (to the amount of 9 and 11bands).Then, based on computed component loadings, the band combination (12 GLCM&edge bands) that have higher variance explained on various PCs is selected and added to the other 5 features (spectral bands and NDVI) to build the 3rd feature set (to the amount of 17 bands).

In order to guarantee that each source (spectrum, texture and NDVI) makes the same contribution to the feature space and avoid scale effects in the Maximum Likelihood statistic computation, each source of data is stretched from 0 to 1before running the classification schema.

2.2.2 Separability analysis

- AIM: to select the best suited feature set assessing class separability and expected classification errors for different feature combinations.
- RESULT: the second feature set (GLCM&edge) is selected because it corresponds to higher average separability of LC classes.

Average separability measures between each LC class are calculated using the three different built feature sets that include the 4 original image channels, the NDVI and different texture subsets (GLCM, GLCM&edge-density and "Loading"features). So, first, the pairwise J-M distances between each pair of classes is determined for all combinations of two, then the average J-M distance is computed for each class.

Figure 4 represents the average separabilities of the 29 LC classes as function of the average J-M distance.

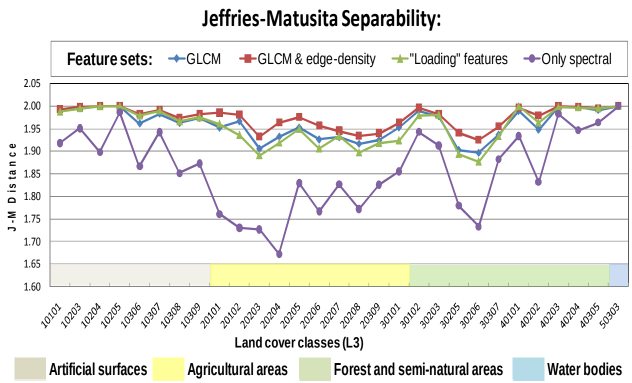


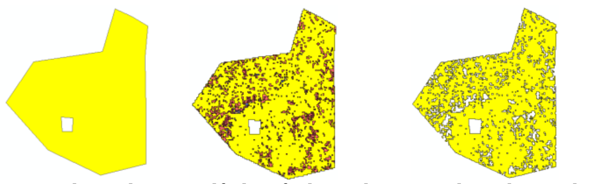
Figure 4. J-M Average separability for L3 cover classes

As shown in Figure 4, the second feature set (PCs from GLCM & edge-density features) is the best feature combination in order to separate the given LC classes because it shows mostly higher values for the average J-M distances. The separability of clusters generated using multispectral bands in combination with the selected texture images, has improved especially for agricultural areas and some forest and semi-natural classes. Without texture the average J-M distance is often below 1.9 that is the threshold below which the separability is indicated to be poor.

2.3 Training set refinement (ROI)

- AIM: to improve ROI's representativeness.
- RESULT: class signatures are "cleaned" using the selected 2nd feature set and redefined as final ROIs.

Outlying pixels (in feature space) are deleted before computing the final class signatures. This can be done by self-classifying the training pixels according to the 2nd feature set. Misclassified pixels are excluded from the training set recalculating the final ROI (Region Of Interest) signatures only according to the well classified training pixels. In the Figure 5 is shown an example (class 40202) to summarize the "cleaning" workflow.



Original sample Self-classified sample "Cleaned" sample (ROI)

Figure 5. Class 40202 cleaning and ROI generation

Which kind of texture should be taken into account to improve the accuracyThe improvement in the training data can also be checked again in terms of statistical J-M separability: before the "cleaning" a lot of critical J-M distances (lower than 1.9) indicate classes non well separated with some overlaps in their density functions. Improvements are instead shown after the refinement: the number of critical class pairs decreases from 40 to 22 (highlighted in pink in Figure 6). Looking more closely at this J-M matrix (Figure 6), it is possible to investigate which LC classes are still not sufficiently separated in the given feature space and how to manage them. When the non separable LC class pairs belong to the same CLC class (level 1 or 2), it is not really a problem: according to the final CLC nomenclature, they be merged after the classification into more generalized CLC classes. Problems remain when it is not possible because the "critical" classes differ in the CLC level 1 itself. It is for example the case of the class 40305 (sparsely vegetated areas) not separable from the class 10308 (mix coverage buildings) even if belonging to different CLC level 1 class: Forest and semi-natural areas the former, Artificial surfaces the latter.
An expedient to overcome this problem is the use of vegetation indices.

2.4 Vegetation Indices

- AIM: to improve the classification accuracy and minimize the error matrix off-diagonal elements.
- RESULT: two vegetation indexes are generated:
  - NDVI to use as additional band in the selected feature set
  - TDVI to build three masks trough which run three supervised classifications.

TDVI (Bannari et al. 2002) is employed to develop thresholds useful to build binary masks (Figure 8) trough which three supervised classification processes are carried out independently.
Studying the TDVI histograms associated with the more critical classes, two thresholds (T_1=-1.2 and T_2=-0.6) are developed with the aim to identify pixels likely to belong to particular classes. For example in Figure 8 it is shown how T_2 can help to distinguish the mix coverage building class with value mostly below T_2 from the sparsely vegetated areas class with value mostly above T_2.

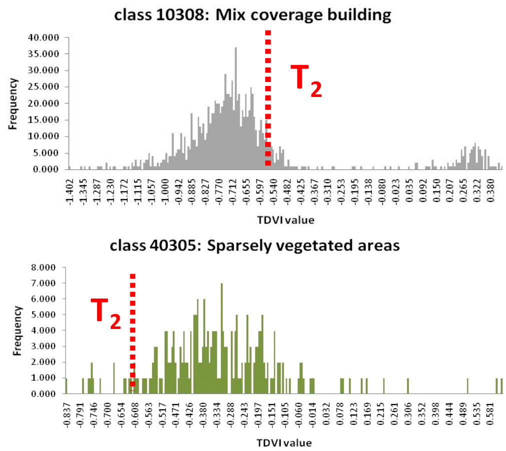


Figure 7. TDVI Histogram thresholding

29 L3 : Jeffries-Matusita separability class pairs considering the whole set of 11 bands (4 spectral + 6 PCs texture bands+ 1 NDVI) 29

CLASS	10101	10203	10204	10205	10306	10307	10308	10309	20101	20102	20203	20204	20205	20206	20207	20208	20309	30101	30102	30203	30205	30206	30307	40101	40202	40203	40204	40305	50303	CLASS
10101																														10101
10203	2.00																													10203
10204	2.00	2.00																												10204
10205	2.00	2.00	2.00																											10205
10306	1.99	2.00	2.00	2.00																										10306
10307	1.99	2.00	2.00	2.00	1.76																									10307
10308	1.98	2.00	2.00	2.00	1.87	1.98																								10308
10309	2.00	2.00	2.00	2.00	1.89	2.00	1.66																							10309
20101	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00																						20101
20102	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	1.85																					20102
20203	1.99	2.00	2.00	2.00	2.00	2.00	2.00	2.00	1.92	1.89																				20203
20204	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	1.92	1.92	2.00																			20204
20205	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	1.94	1.97	1.90	2.00																		20205
20206	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	1.98	1.98	1.99	1.89	1.97																	20206
20207	1.99	2.00	2.00	2.00	2.00	2.00	2.00	2.00	1.93	2.00	1.80	2.00	1.99	2.00																20207
20208	2.00	2.00	2.00	2.00	2.00	2.00	1.99	2.00	1.99	2.00	1.90	2.00	1.95	1.99	1.94															20208
20309	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	1.95	2.00	1.99	2.00	1.79	1.80														20309
30101	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	1.98	2.00	2.00	2.00													30101
30102	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	1.99	2.00	1.99	2.00	2.00	2.00	2.00												30102
30203	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00											30203
30205	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	1.99	2.00	1.99	2.00	1.95	2.00	2.00	2.00	1.81	2.00	1.94										30205
30206	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	1.98	2.00	1.96	1.99	1.80	2.00	2.00	2.00	1.99	1.93	1.68	1.69									30206
30307	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	1.98	2.00	1.96	2.00	2.00	2.00	1.79	2.00	2.00	1.69	1.98								30307
40101	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	1.99	2.00	1.94	2.00	2.00	2.00	1.99	2.00	2.00	1.99	1.98	1.98							40101
40202	1.97	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	1.91	2.00	2.00	2.00	1.88	1.83	1.57	2.00	2.00	2.00	2.00	2.00	2.00	2.00						40202
40203	2.00	1.98	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00					40203
40204	2.00	1.97	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	1.98				40204
40305	2.00	2.00	2.00	2.00	2.00	2.00	1.87	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00			40305
50303	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00		50303
CLASS	10101	10203	10204	10205	10306	10307	10308	10309	20101	20102	20203	20204	20205	20206	20207	20208	20309	30101	30102	30203	30205	30206	30307	40101	40202	40203	40204	40305	50303	CLASS

Artificial surfaces
Agricultural areas
Forest and semi-natural areas
Water bodies

J-M values < 1.9, same CLC level 2 class
J-M values < 1.9, different CLC level 2 class
J-M values < 1.9, different CLC level 1 class

Figure 6. J-M separability class pairs distances after ROI "cleaning"

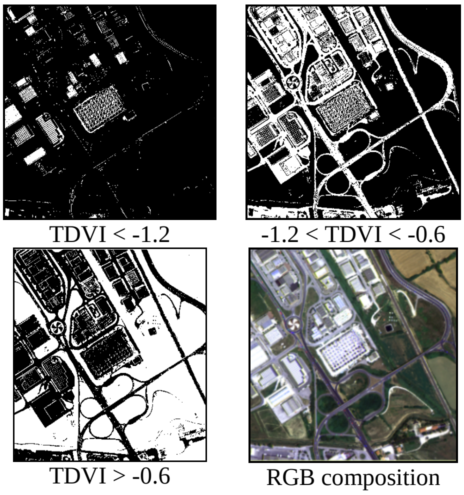


Figure 8. TDVI masks and RGB composition

After having defined the two thresholds, it is possible to study all the 29 TDVI class histograms to decide which sample use as ROI in each specific classification process. With these three ROI subsets three complementary Maximum Likelihood (ML) classification can be carried out independently.

2.5 Supervised classification

- AIM: to classify each pixel into one of the 29 LC classes.
- RESULT: merging of three complementary classification maps.

The three ML classifications are initially performed by default assuming that all the cover classes are equally likely. Then they are adjusted using a-priori information gathered by means of a ROC (Receiver operating characteristic) analysis linked to the LC ground data. By means of ROC curves is possible to visualize the performance of the classification method, in order to select proper decision thresholds providing the best classification with the minimum error rate. This ROC analysis is performed for each classification (3 times) and for all the ROI involved with the wise to take into account only the ground information allowed by the specific mask used. This a-prior information can give a crucial effect to classification results. In this way the ground data give again a powerful hint to drive the classification schema development.
After having performed the three ML classifications, the three outputs are merged into a single classified map by means of raster calculations.

2.6 Post- classification data manipulation

- AIM: to match the CLC legend and improve the spatial consistency of the pixel-based classification.
- RESULT: final CLC land cover map

The merged classified image is post-processed combining the 29 LC classes into10 generalized classes, according to the CORINE Land Cover nomenclature.
Finally post-classification techniques (majority analysis, sieving and clumpling) are applied to the CLC classified output in order to eliminate the 'salt and pepper' noise, removing gaps within areas covered by a predominant class.

3. RESULTS

In Figure 9 the performance of the developed spectral/textural classification schema is assessed drawing a comparison between the results obtained using only the spectral band and the improved results achieved integrating texture features (without and with the use of the TDVI mask).

Corine Land Cover Legend		SPECTRAL	SPECTRAL + TEXTURE	
			without TDVI masks	with TDVI masks
Code	DESCRIPTION	Prod. Acc. (Percent)	Prod. Acc. (Percent)	Prod. Acc. (Percent)
1.1	Urban Fabric	98.61	97.19	96.02
1.2	Industrial, commercial and transport units	39.45	60.21	73.95
2.1.1	Non-irrigated arable land	47.33	81.32	77.3
2.2	Permanent crops	30.29	64.25	68.25
2.3	Pastures	94.29	74.77	74.71
3.1	Forest	93.06	97.11	96.02
3.2	Scrub and/or herbaceous vegetation assoociations	62.06	91.21	88.19
3.3	Open spaces with little or no vegetation (beaches,dunes,bare rocks)	39.22	48.64	64.99
3.3.3	Sparsely vegetated areas	91.95	94.85	88.63
5.2	Marine waters	100	97.17	99.01
Code	Overall Accuracy (Percent)	63.44	74.38	80.07

Figure 9. Accuracy comparison (spectral versus. spectral+texture features)

Comparing the spectral and spectral/texture classifications in Figure 9, it is clear that spectral classification is better suited for those land use classes with a specific spectral response and well differentiated from the rest of the units, such as pastures (class 2.3) and marine waters (class 5.2). The distribution of grey levels in these two classes is very homogeneous, so they are more difficult to discriminate by texture methods. Rather, adding texture, their accuracy get worse. On the other hand, texture techniques are very efficient in classifying landscape units that contain a high spectral heterogeneity, such as permanent crops, scrub and/or herbaceous vegetation associations and non-irrigated arable land (class 2.1). These classes are not very accurate when classified using the spectral band only. For example, taking texture measures into account (without TDVI masks) the accuracy of the permanent crop is really improved (from 30.29% to 64.25%).
Similar explanation can be given for the industrial, commercial and transport units: the high edge density encountered in industrial area (class 1.2) allow to separate them from the other classes and especially from the open spaces with little or no vegetation (class 3.3) that were shown to be very spectrally similar. Regarding these two class an additional improvement is given by the mask use: class 1.2 can even reach an accuracy of 73.95%. while class 3.3 , although improving, still does not reach a satisfactory accuracy. This verifies the use of TDVI masks in the classification schema. However for this last class (class 3.3) problems can be caused above all by a bad training. In fact, having a close look at the particular samples generating the signature, for this class it is clear that they are mostly made up of beaches (very few samples for the other LC classes grouped into this class 3.3) and especially spectrally "mixed" beaches, as they can be in June in Italy because of beach umbrella and so on.
Another interesting aspect is that the integration of spectral and texture bands for classification has a synergic effect on the results, in some cases even improving the accuracy of both groups of classes (homogeneous and not). However, it is important to note that , according to the truth data available, the reported results refer to the inner truth areas of the texture units

and not to the borders between textures. Further work should be done to reduce the border effect.
A visual inspection of the final CLC map (Figure 10) confirms that the results of this developed classification schema are reasonably good. However an object-based post classification method is advisable.

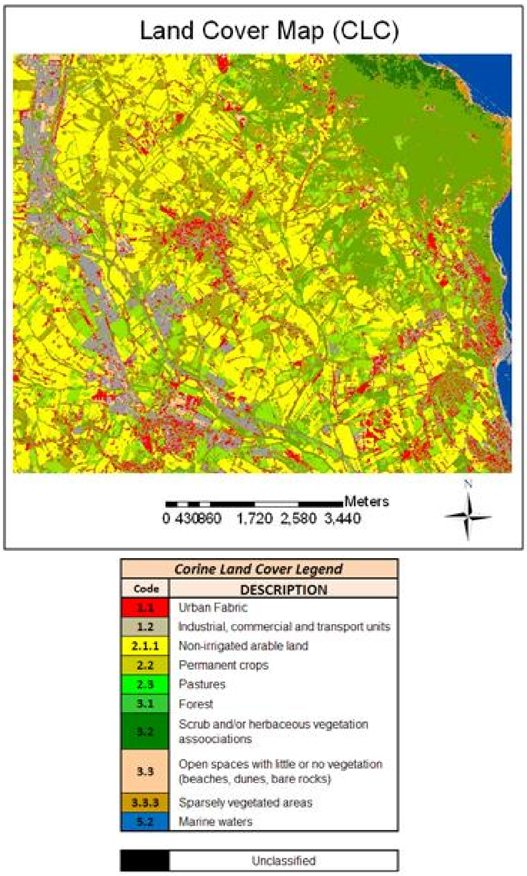


Figure 10. Final Corine Land Cover map with legend

4. CONCLUSION

The research shows how is possible to recycle and get benefit from large and detailed available ground information taking advantage from the IKONOS imagery and the potentiality offered today by remote sensing techniques.
To get satisfactory results it is necessary to develop a supervised classification schema integrating texture features.
The study confirms the utility of textural analysis to enhance the per-pixel classification accuracy. In particular it shows how is possible to extract texture features using second order GLCM statistics and edge-density images and how, after a targeted feature selection by means of the PCA, is possible to use them as additional bands in the classification schema. These new textures turn out to be useful auxiliary data especially for high resolution data sets suffering from high spectral heterogeneity. By incorporating these texture features in the classification schema, it is possible to achieve a higher classification accuracy compared to the classification of the original IKONOS image.
Particular improvements are shown especially in discriminating between agricultural species and semi-natural areas (e.g. open space with little or no vegetation). In particular permanent crops are impossible to discriminate without texture from the other classes
The overall accuracy increases to 80.0 % with a Kappa Coefficient of 0.7337 and the Producer's accuracies for the different classes increase as well.
Important to underline is that the use of texture features makes it possible to well-identify more CLC classes (10 CLC classes in the study case): thus it is fair to think that, increasing the amount of information extracted from the image, it is possible to reduce the support given by the photointerpreter in CLC map generation.
This work demonstrates the need of a spectral/textural image analysis for a more accurate land cover type discrimination when thematic classes are very heterogeneous (high within-class spectral variance) and spectral information is no longer a sufficient indicator for the classification.
Anyway no general rules can be recommended by this study for the texture measure selection: the most appropriate combination of texture features depends strongly on the surface properties of the land cover types of interest. What is found by this research is to optimize the window size according to the available ground data and also to choose the best feature set in terms of separability analysis (linked again to the collected ground data).

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