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Landscape fragmentation as an indicator of coastal landscape quality: an application along the Apulian coast (southern Italy)

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Introduction

This work has been carried out within the framework of the IMCA (Integrated Monitoring of Coastal Areas) Research Project, among the activities aimed at drawing coastal landscape quality maps through the use of indicators derived from satellite RS images. The overall research project, derived from the experience of the European Landscape Convention, tackles the landscape quality issue via a multi temporal and spatial scale approach. The present contribution focuses on fragmentation as this phenomenon, as well as the loss of heterogeneity, initiated by urban settlement processes of dislocation and diffusion, represents the main cause of the landscape ecological efficiency decrease, of the area decay and of the beginning of diseconomy in its management (Forman, 1995).

Methods

In order to quantify fragmentation, at a given spatial scale (defined in terms of both grain and extent), a selected set of landscape pattern indices was computed (FRAGSTATS 3.3, McGarigal & Marks 1995) both at the landscape (ED, LSI, ENN_AM, PLADJ, MESH, SHDI) and the class (CA, NP, ED, LSI, FRAC_AM, MESH) level, for the terrestrial sample plot population (N=78), extracted via an unaligned random sampling procedure from the whole southernmost part of the Apulian peninsula (Southern Italy), corresponding to a single Landsat TM scene. The selection among the whole set of FRAGSTATS, areal, linear and topological, metrics was made to reduce the noise due to between-metrics correlations, whilst being representative of most metric types. For the sample population, interpretation of recent (2004) aerial photographs had already been performed within the framework of the IMCA research project (Miacola *et al.* 2006). The same protocol was applied to categorical maps of the same area, derived, both by past aerial photo-interpretation (1997) and by (unsupervised and supervised) classification, from medium (Landsat TM) resolution satellite image (summer 2004). The supervised classification was intentionally carried out by means of minimum RS data (i.e. one single image), in order to verify the possibility of using relatively inexpensive and time effective cover type maps, which may be useful in other areas where the acquisition of detailed data is either limited or impossible. RS data processing included georectification (RSM error 0.573 pixels) and ground-truth by means photointerpretation of a spatially independent set of polygonal areas than the sample population used for the analysis, randomly and uniformly distributed across the image. Two thirds of such a set where used for training and one third for testing thematic accuracy. The classification was limited to eleven coarse classes (sea, water bodies, wetlands, maquis, pine woods, grasslands, sparse vegetation, cultivated fields, urban areas, clouds, shadows). The choice was made to aggregate both permanent and arable crops within the "cultivated fields" as generally urban growth occurs at the expenses of these classes irrespectively. Statistical analysis was performed by means of normal distribution fitting test (Kolmogorov-Smirnov one-sample test), non parametric correlations (Spearman's) test and PCA (covariance matrix of standard deviation standardised variables), on both data set at both landscape and class levels.

Figure 1 Location map, Landsat TM 7 bands scene, sampling design and examples of photointerpretation and supervised classification on sample areas

Results

The results relevant to the comparison between recent ortophotographs interpretation and supervised classification are presented here. As expected the classified cover map yielded a modicum overall thematic accuracy (p = 0,78; k =0,66) and exhibits a fairly high variability between thematic classes, for the user's accuracy (CVu =0,59). The KS one-sample test for normality (D and Lilliefors not significant or only marginally significant at 0,05 p level) indicates that the normal distribution hypothesis can not be rejected for the indices computed at the landscape level, despite the significance of the χ^2 test for most of the indices, as also confirmed by the general shape of the observed distribution with respect to the hypothesized normal distribution. The relations (Spearman's rank order correlations) within the indices of the photointerpretation data set and those of the supervised classification data set show a similar pattern and point towards ED as a good indicator of fragmentation, in this particular sub-region, given its negative correlation to MESH and its positive correlation to ENN_AM (tables 2a 2b). ED is also positively correlated to SHDI. At the class level the analysis was performed only on the "cultivated fields" and the "urban area" classes, for which the best (among terrestrial covers) thematic accuracy had been obtained and an analogous pattern emerged with ED negatively correlated to MESH and positively correlated to both FRAC_AM and LSI (tables 3a, 3b, 4a, 4b). The pair wise comparison between the indices of the two datasets at both levels indicates significant direct correlations. Principal Component Analysis performed on the indices obtained from the different data sets, both at the landscape and the class level (figure 2) confirms the agreement between the general fragmentation pattern reveale by the indices computed on photointerpretation and supervised classification data, however anticipating the spatial mismatch (figure 3). The ordination of sample plots along a fragmentation gradient (classes of increasing ED, figure 4) was obtained and tested for the construction of fragmentation intensity maps at the subregional scale. Despite the significant correlations between the indices of the two data sets the fragmentation intensity maps obtained from photointerpretation and from supervised classification did not match neither at the landscape nor at the class level (figure 5).

Table 2a - Relations within data set indices (landscape level)

p < 0,001	N	r	p
ed_ph -mesh_ph	78	-0,918	0,00E+00
ed_cl-mesh_cl	78	-0,887	3,36E-27
ed_ph -shdi_ph	78	0,902	2,23E-29
ed_cl-shdi_cl	78	0,919	0,00E+00
ed_ph -enn am_ph	78	0,797	2,64E-18
ed_cl -enn am_cl	78	0,555	1,32E-07

Table 2b - Relations between data set indices (landscape level)

p < 0,001	N	r	p
ed_ph- ed_cl	78	0,583	2,102E-08
mesh_ph-mesh_cl	78	0,629	7,090E-10
shdi_ph-shdi_cl	78	0,743	6,393E-15
lsi_ph-lsi_cl	78	0,583	2,102E-08
pladj_ph-pladj_cl	78	0,586	1,795E-08

Table 3a - Relations within data set indices (class level "urban")

p < 0,001	N	r	p
ed_ph -mesh_ph	24	0,422	ns
ed_cl-mesh_cl	24	0,564	4,09E-03
ed_ph -frac-am_ph	24	0,427	3,75E-02
ed_cl -frac-am_cl	24	0,843	2,27E-07
ed_ph -lsi_ph	24	0,651	5,66E-04
ed_cl -lsi_cl	24	0,822	8,54E-07

Table 3b - Relations between data set indices (class level "urban")

p < 0,001	N	r	p
ca_ph - ca-cl	24	0,835	3,79E-07
np_ph - np_cl	24	0,461	ns
ed_ph - ed _cl	24	0,576	3,21E-03
lsi_ph - lsi _cl	24	0,245	ns
frac_ph - frac_cl	24	0,061	ns
mesh_ph - mesh_cl	24	0,786	5,35E-06

Table 4a - Relations within data set indices (class level "field")

p < 0,001	N	r	p
ed_ph -mesh_ph	75	-0,532	1,76E-06
ed_cl-mesh_cl	75	-0,824	1,14E-19
ed_ph -frac-am_ph	75	0,818	3,22E-19
ed_cl -frac-am_cl	75	0,880	2,83E-25
ed_ph -lsi_ph	75	0,819	2,73E-19
ed_cl -lsi_cl	75	0,958	0,00E+00

Table 4b - Relations between data set indices (class level "field")

p < 0,001	N	r	p
ca_ph - ca-cl	75	0,545	4,33E-07
np_ph - np_cl	75	0,239	ns
ed_ph - ed _cl	75	0,419	1,86E-04
lsi_ph - lsi _cl	75	0,421	1,72E-04
frac_ph - frac_cl	75	0,454	4,28E-05
mesh_ph - mesh_cl	75	0,545	8,80E-07

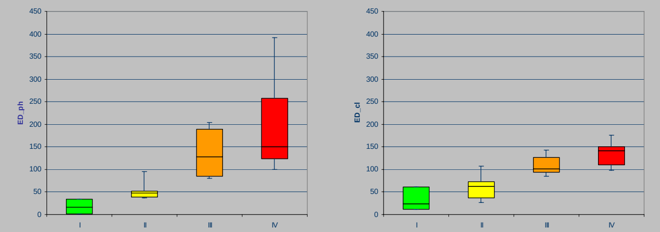

Figure 4 Distribution of samples within classes or increasing ED.

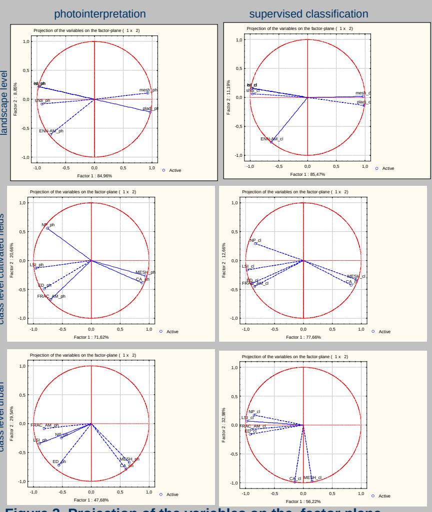

Figure 2 Projection of the variables on the factor plane.

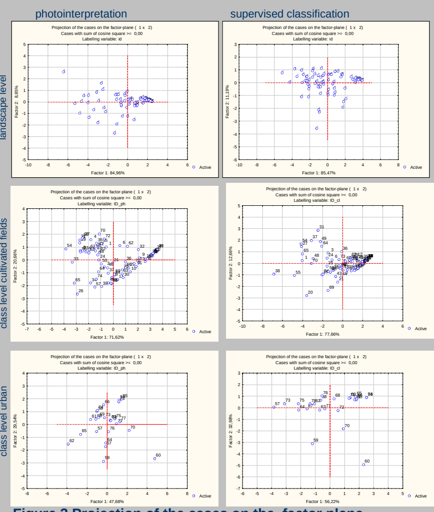

Figure 3 Projection of the cases on the factor plane.

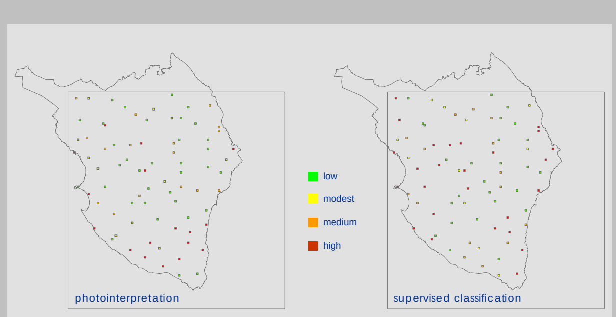

Figure 5 Fragmentation intesity maps for the landscape level.

Discussion

Preliminary results are encouraging in many respects. The distribution analysis performed on the indices computed on the different data sets shows, for this particular landscape at the given scale, a trend towards a normal distribution model, thus contributing to the ongoing debate (Remmel and Csillag 2003) on the uncertainties about the possibility of statistically comparing indices computed at different times and places, derived from a lack of knowledge about their distribution. The correlation analysis within the same dataset allows for the identification of a landscape/scale specific fragmentation indicator (ED) among the selected LPIs. The PCA is useful for the definition of a fragmentation gradient between samples. The results indicate that the procedure adopted is useful for the recognition of the fragmentation pattern and that even medium thematic accuracy supervised classification can be reliably be used for such a purpose, thus confirming the potential for using cost and time effective categorical maps for the description and monitoring of landscapes fragmentation, as well as for testing hypotheses concerning fragmentation scaling relations in both space and time (Wu, 2004; Jelinski and Wu 1996). The spatial results instead, show that a higher degree of overall thematic accuracy, as well as a lower variability degree among class thematic accuracy are probably required to draw fragmentation intensity maps at the subregional scale, as well as to interpreting the change processes and obtain intelligent maps based upon the integration of field (aerial-photo interpretation) and RS data, in order to achieving the twofold purpose of performing a phenomenological study aimed both at modelling coastal landscape transformations and identifying new survey categories that may have the temporal dimension as the main parameter (e.g. speed of change).

References

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