Great Lisbon Metropolitan Area land use/cover characterization through multi-temporal and multi-resolution VIS components analysis

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ABSTRACT: Urban environments are heterogeneous by nature. Hence, to allow quantitative studies it is necessary to simplify them in combinations of basic land use/cover materials. The Ridd's VIS model (1995) is a conceptual representation that allows simplifying urban environments through the combination of three basic components: vegetation (V), impervious surface (I), and soil (S). More recently, Lu and Weng (Lu & Weng 2004) successfully tested a new combination (vegetation, impervious surface and shadow), more adapted to urban reality.

The majority of urban uses can be interpreted as a combination of those three basic components. The VIS analysis allows to disclose that the mainstream of urban features has its own VIS signature, which is difficult to detect through pixel-by-pixel based classifiers. This work examines the land use/cover characteristics of the Great Lisbon Metropolitan Area (GAML) using sub-pixel classification techniques, mainly linear spectral unmixing (LSU), developing a conceptual model to characterize the occupation standards. The LSU ability to measure the physical composition of urban morphology is also explored and tested.

In this work we use Landsat 5 TM multispectral images (1987 and 1997), Landsat 7 ETM+ panchromatic and multispectral images (2000) and SPOT 5 HRVIR panchromatic (2.5 m supermode pixel size) and multispectral images (2004), evaluating at the same time the land use/cover signatures evolution and the effect of spatial resolution differences on the same signatures measurements.

1 INTRODUCTION

A recurrent subject in diverse remote sensing studies in urban environment is related with the attainment of summary pointers for their components. This type of analysis has been traditionally limited due to spectral heterogeneity of the urban elements relatively to the space definition of the used orbital sensors. That is particularly true in the context of multispectral images with average spatial resolution, as it is the case with the Landsat satellite (30 × 30 m). Due to the spectral heterogeneity it is necessary to deal with a complex mixture of spectral responses. The existence of spectral mixtures in pixels (pixels "not pure" or mixels), in the generally available images in remote sensing, makes difficult the identification of land use cover classes through pixel-by-pixel analytical techniques and constitutes the most significant problem of remote sensing in urban environments. This identification still becomes more difficult when the urban continuum cannot readily be divided in discrete classes, as it is required by these techniques.

In the last ten years, one has taken advantage of the trend to adopt "a flexible" form (in terms of continuous surfaces) to describe the land use cover spatial variation character. In "the flexible" approach, the ratios of the different land use/cover components esteem for each pixel of the image, having represented each type of use as a continuous variation surface. The fuzzy classification and the Spectral Mixture Analysis (SMA) are two used techniques to supply "a flexible" analysis of pixels. The two approaches have their advantages and disadvantages. For example, the boarding fuzzy does not restrict the degree of attributed values belonging to one pixel in different fuzzy images, in form to add a unit; even so it has in consideration the non linear interactions between the different types of uses that are neglected by SMA. In the opposing, the SMA models represent a deterministic approach that transforms the values of the image into physical variables, thus becoming easier to command the analysis and to infer the results than in the case of the fuzzy models, which are based on statistic methods.

The work presented here is based on the SMA approach. In SMA is assumed that the landscape is formed from continuous variations of the idealized types of uses ratios with pure spectrums, called endmembers. The endmembers are recognized in the image as being abstractions of materials with uniform properties that compose land use/cover. In an urban environment, these can include impervious surfaces, green spaces, water bodies and soil. Linear SMA corresponds to the resolution process of the endmembers fractions, assuming that the spectrum measured for each pixel represents a linear combination of spectrums of the endmember that corresponds to the physical mixture of some components of the surface, weighed for the total area. With SMA, (fractions of) the final members areas are quantified to the sub pixel level, allowing the inference of the urban landscape morphologic characteristics in terms of the endmembers composition. The purpose of this work is to explore and to test the applicability of SMA to measure the physical composition of the urban morphology, through multispectral images Landsat 7 ETM+ (2000) and SPOT 5 HRVIR (2004), evaluating at the same time the effect that the differences of spatial resolution can have in the achieved results.

2 SPECTRAL MIXTURE ANALYSIS (SMA)

A digital image consists of a composed cells (pixels) bidimensional matrix. Each pixel represents a portion of the terrestrial surface and translates a value of intensity, represented by the radiometric level. This value of intensity results, in general, forms the measurement of the reflected (or emitted) energy for the surface and normally corresponds to the average of all the area covered by a pixel. The spatial resolution of an image is defined by its pixel and conditioned by the Instantaneous Field of View (IFOV) of the sensor optic system. The IFOV corresponds to the measure of a land area recorded by only an element of the detector in one determined instant. The term mixed pixels, or mixels, describes an effect that occurs when different materials of the surface, or types of land cover, are comprised in the register spectrum inside of the satellite IFOV. In this way, it can be indexed more than one land use class in the IFOV, resulting in mixels. So, the number of mixels in an image is a function of the IFOV and the spatial complexity of the analyzed phenomenon.

The analysis of spectral mixture is based on the estimation that the spectrum caught by the satellite corresponds to a combination, linear or not, of each one of the components contained in the IFOV. That is, some materials with different spectral properties are represented by only pixel of the image. The decomposition of a surface area, inside of the IFOV, or one pixel, in a proportional abundance or a finite number of endmembers, assumes that most of the spectral variation of a multispectral image can be described, in a first approach, with the addition of linear spectral mixtures. A model of spectral mixture is a model of physical base, where a mixed spectrum is shaped as a combination of pure spectrums, called endmembers. Linear SMA process the fractions of the endmember, assuming that the spectrum of each pixel in the image represents a linear combination of spectrums of the endmember that corresponds to the physical mixture of some surface components, weight by the total area.

One of the basic concepts to understand SMA is Linear Spectral Purity (LSP). Effectively, if the photons only interact with a component (e.g. sand), then the resultant spectrum is pure inside determined IFOV. The impure spectrum (P_λ) of data pixel is shaped by the sum fractions (f_λ) of the (n) endmembers (and i_λ) contained in the IFOV:

$$P_\lambda = \sum_{i=1}^{n} f_i E_{i\lambda} + \varepsilon_\lambda , \tag{1}$$

where λ represents the spectral band, n the number of endmembers and ε the residual values. For one given collection of endmembers is possible to shape its fractions inside one pixel. The model adjustment can be expressed as the fractions error f (ε_λ in each wavelength) or throughout all the s bands as RMS error.

$$\text{RMS} = \frac{1}{m}\sqrt{\sum_{i=1}^{n} \varepsilon_{i\lambda}} , \tag{2}$$

where m is the number of bands. The LSP process creates the belonging fractions of each pixel in the image for each one of the endmembers, referring them as the endmembers abundance. The potential endmembers identification and selection in a way that the spectral signature of the pixels majority is adequately explained, is the key subject of the spectral pureness. In the case of calibrated images with atmospheric correction, the endmembers can be extracted from libraries of values measured on the surface (with a radiometer). An alternative procedure is to extract the spectrums from the image itself, independently of the image calibration and the atmospheric correction. In some particular cases, as in the hyperspectral analysis, methods as the Spectral Purity Index are prominent in the identification of extreme spectrums inside the feature space, supplying, automatically, the endmembers to the analyst.

The RMS error measures the degree where the spectral variability is explained by the selected endmembers. The pixels with high error help to indicate which spectral components are not well represented in the model. The conceptual model selected to extract the final members of the VIS satellite image was the Ridd VIS model (M.K. Ridd 1995), with the adaptation performed by Lu and Weng (Lu & Weng 2004). This new perspective adds the shadow constriction to the model, who greatly improves its performance in the urban environment.

3 LAND USE/COVER ANALYSES

To demonstrate the potentialities of the VIS components use in the urban land use/cover, we select several classes. These classes correspond to the used ones in CartusAML project (Tenedório *et al.* 1999), whose final result was a land use/cover map for the Metropolitan Area of Lisbon (equal to the GAML more the Azambuja municipality). This map was obtained through air photograph photo-interpretation, dated 1991 and with a 1:30000 scale. After having identified the classes its components had been extracted and the results were envisaged in a triangular diagram. Figure 1 shows the VIS composition of the classes in a triangular graph, both for a spatial resolution of 30 m (Landsat) and of 10 m (SPOT). Much even so, these classes are not easy to distinguish visually on an image without previous information on the study area. Table 1 shows that each feature element possesses a unique VIS signature. This signature is so characteristic that it is possible to delineate territories based on it and to attribute to these territories the corresponding classes. However, all the previous studies taken under this scope have been restricted to very general classes, in order to prevent the problem of the exceptions (extreme values). Never any has approached to the value of nineteen classes presented here.

Observing the triangular graph (Figure 1 left) referring to the Landsat image we verify that there are 7 classes with higher percentage of impervious surface (4, 8, 13, 14, 15, 16 and 19), 7 with more vegetation (2, 3, 7, 9, 10, 12 and 17) and 5 with more soil (1, 5, 6, 11 and 18). In the first case, the result corresponds almost exclusively to the urban, industrial and commercial classes, appearing as exception the beaches and the quarries, whose spectral reflectances are very similar to the others, normally generating misclassifications. In the green areas the anomalous elements are the water, or flooded, areas, which related directly with the fact that we did not use a mask for the interior water

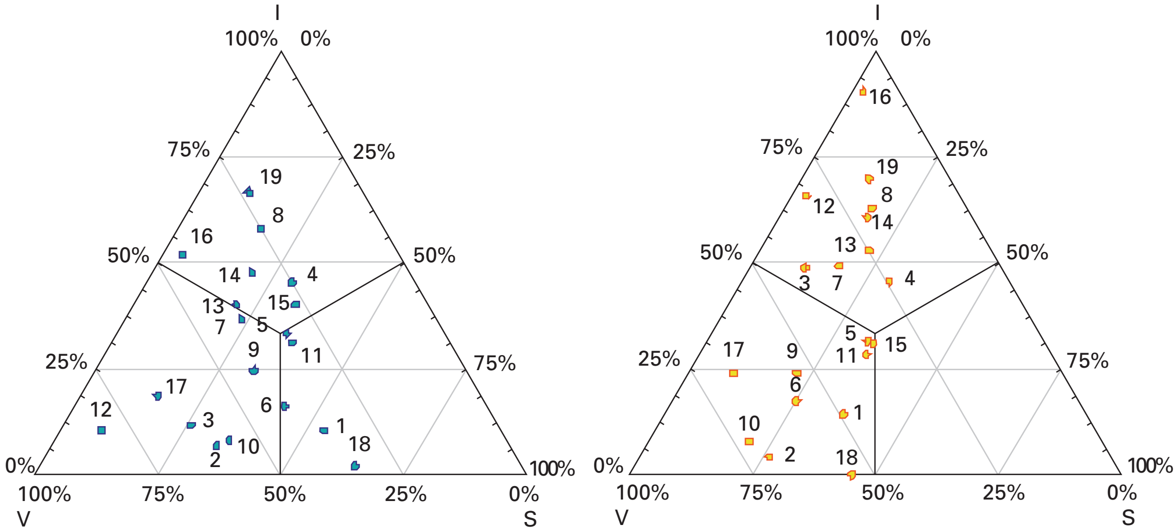

Figure 1. Triangular graphs of Land use/cover classes VIS components: Landsat (left) and SPOT (right).

Table 1. Land use/cover classes VIS components: Landsat and SPOT

ID	Classes	Landsat (30 m)			SPOT (10 m)		
		V	I	S	V	I	S
1	Agriculture	0.36	0.11	0.52	0.50	0.15	0.35
2	Forest	0.60	0.08	0.32	0.69	0.05	0.26
3	Water	0.63	0.12	0.25	0.41	0.48	0.11
4	Consolidated Ancient Nucleus	0.25	0.46	0.29	0.25	0.46	0.29
5	Single Housing Area	0.33	0.34	0.34	0.37	0.32	0.32
6	Bare Soil	0.42	0.17	0.42	0.58	0.18	0.24
7	Public Buildings	0.40	0.38	0.22	0.34	0.49	0.17
8	Multi Housing Area	0.26	0.58	0.16	0.20	0.63	0.17
9	Military Areas	0.44	0.25	0.31	0.54	0.24	0.21
10	Bush	0.57	0.09	0.34	0.72	0.08	0.19
11	Allotted Areas	0.32	0.32	0.36	0.39	0.29	0.33
12	Marsh and Salt Pans	0.82	0.11	0.07	0.32	0.65	0.03
13	Beach	0.40	0.40	0.20	0.26	0.53	0.21
14	Harbour	0.32	0.48	0.20	0.22	0.60	0.17
15	Extractive Areas	0.27	0.40	0.33	0.36	0.31	0.33
16	Big Commercial Areas	0.44	0.52	0.04	0.09	0.90	0.02
17	Urban Green Areas	0.66	0.19	0.15	0.67	0.24	0.09
18	Agriculture/Forest Area	0.34	0.02	0.64	0.55	0.01	0.44
19	Multi-functional Metropolitan Area	0.24	0.67	0.10	0.18	0.69	0.13

and the great majority of these areas are marshes or lagoons (backwaters with much vegetation) with a spectral reply close to the vegetation. In what refers to the equipments and military areas, its appearance in this class illustrates that the equipments are basically natural parks and golf fields, and that the military buildings are spread among the vegetation (camouflage). Finally, in the third case we have all the classes where vegetation punctually exists, including the Single Housing Area where each habitation normally is followed by a small land parcel.

Regarding to the results observed for the same classes (Figure 1 right), but with a space resolution of 10 m (SPOT), we verified that there are 9 classes with higher percentage of impervious surface (3, 4, 7, 8, 12, 13, 14, 16 and 19), 10 with higher vegetation percentage (1, 2, 5, 6, 9, 10, 11, 15, 17 and 18) and none with higher soil percentage.

4 THE GAML LAND USE/COVER STRUCTURE

The land use/cover structure in the metropolitan area of Lisbon discloses a very different distribution, considering the general first level classes (Figure 2): Built areas, Agricultural Areas and Forest Areas (including "natural and half-natural") and an anti-symmetrical distribution between the North and the South edge. The three mentioned above classes were calculated by grouping the set of nineteen subclasses.

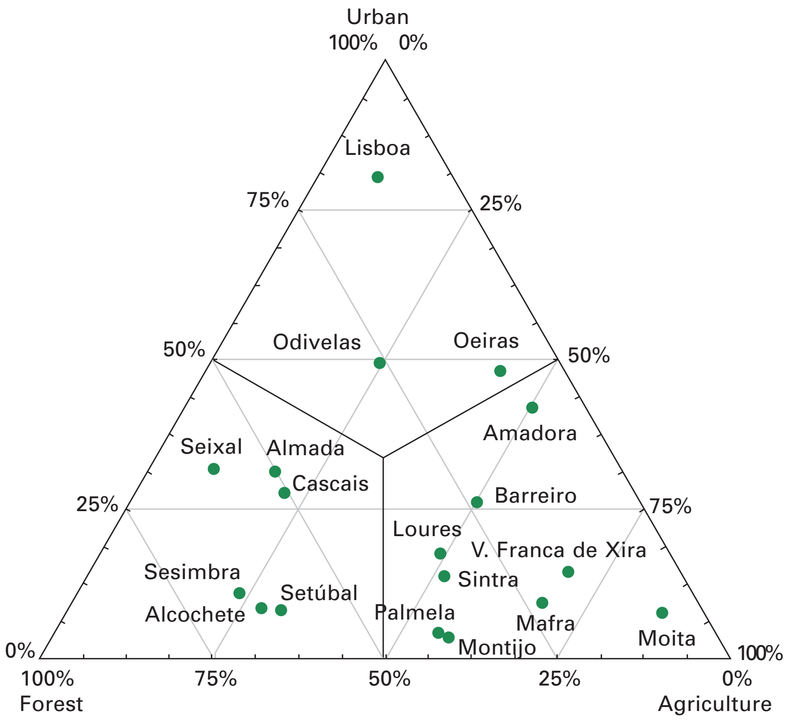

Figure 2. Triangular Diagram of the GAML municipalities according to three land use/cover classes.

Adapting the VIS components to the municipality level (average value for each territorial unit) we also achieved interesting results. The analysis based on the Landsat images leads (Figure 3 left) to the discrimination of four groups. The first one corresponds to areas strongly impervious, essentially Lisbon and Amadora. The second, where soil predominates, is constituted by the agricultural municipalities of the GAML: Moita, Palmela, Montijo and Alcochete. Finally, the cluster where the vegetation prevails can be subdivided in two sub-groups; one that already presents one strong component of impervious and that is constituted by Oeiras, Odivelas, Barreiro, Seixal, Almada and Cascais and another one, where the impervious still does not become to feel so strong and that embraces Loures, Sintra, Sesimbra, Setúbal, Mafra and Vila Franca de Xira. When passing to SPOT images (Figure 3 right) we verified that Oeiras starts to integrate the group of the most impervious and that the separation between the two vegetation sub-groups becomes narrower. Moreover, the established phenomenon when analyzing the land use/cover classes – the relative importance of soil loss – also gives the impression of a strong influence, implying that, with exception of Palmela, all the municipalities that can be found in the group of soil predominance, are being enclosed in the vegetation predominance one.

5 URBAN EVOLUTION ANALYSES

The selection of the land use/cover classification variables is especially crucial in this type of analysis because it would be ideal that the images allowed evaluating the degree of urbanity

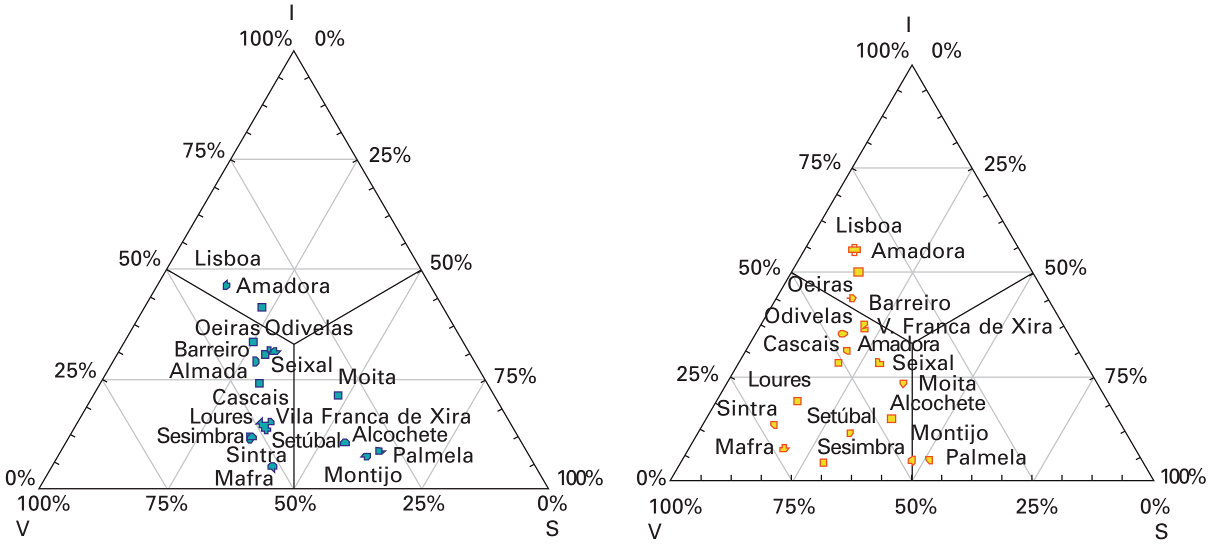

Figure 3. VIS composition of the GAML municipalities. Landsat (left) and SPOT (right).

without being necessary to appeal to another type of information. The Ridd model suggests that the ratio of impervious surface must be the most important pointer of an urban place. The perspective is clearly to underline the constructed environment. On the other hand, the bare soil is related with the development because, usually, it is prepared for urbanization (M.K. Ridd 1995). Thus, the soil percentage in combination with the impervious surface percentage must constitute a reasonable index of the constructed environment. Some indications still state (Lu & Weng 2004) that the shade fraction in combination with the impervious surface offers an additional measure of urbanity. In this way, we opted to use the gradient developed by Weeks (J.R. Weeks 2003):

$$\text{Urban Gradient } [\text{Im pervious} + (2\sqrt{\text{Soil}}) + (2\sqrt{\text{Shadow}})] \times 100 \quad (3)$$

Using a quantitative measure that allows the comparison between different places and dates, makes it possible to compare regions with base in an index that varies between the absolute zero (green) and a flexible superior limit (allowing the possibility of the urban places evolution). Figure 4 shows the results of the urban gradient calculations for the years of 1985 and 1997, being particularly evident the strong decrease that occurred in these 12 years, of the green zones in detriment of the impervious surface and the soil. In this particular case the ratio of pixels with a gradient value situated between 75 and 99 (strongly urbanized areas) evolutes from 0.03 in 1985 (maximum of 1) to 0.38 in 1997, indicating an important urban pressure on the natural resources and strengthening the idea of their urgent preservation need. Between 1997 and 2000 (Figure 4) the situation remained stable, indicating that the urban growth occurred in areas turn impervious up to 1997. Although this

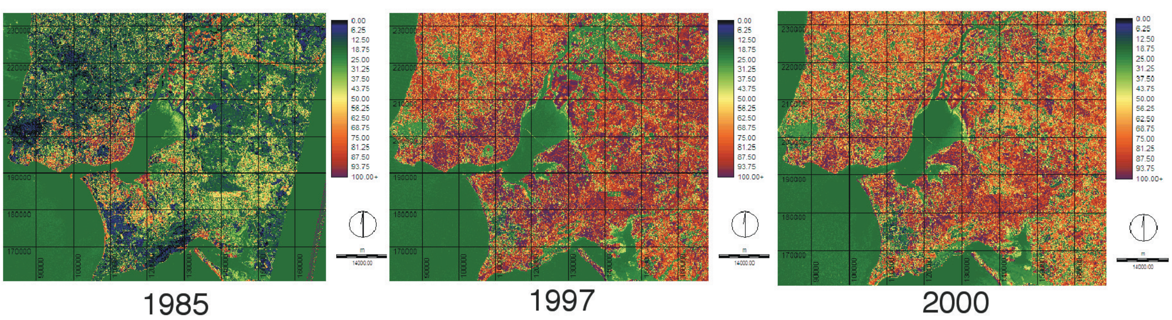

Figure 4. Multi-temporal Landsat based urban gradient.

situation can indicate a hold back of the urban growth, it still inspires some concerning, claiming for measures that aim the green spaces protection.

6 REMARKS

In this study it was verified that through LSU it is possible to univocally identify the land use cover classes and that this approach is also valid to characterize the land use cover structure at a municipality level. It was also proven that the space resolution is important, but not basic; in fact the obtained results for the Landsat images (30 m) seemed, face to the cognitive knowledge of the study area, sufficiently easier to interpret and/or to justify, than the gotten ones through the analysis of SPOT images (10 m).

The VIS model proved to be a valid support for LSU. The resultant images supply sub-pixel level information of the urban areas VIS components, allowing the simplified representation of heterogeneous areas as combinations of basic ground components. In this way, the urban studies can be led not just in a qualitative perspective, but also quantitatively. The resultant image contains a considerable amount of information that normally is not pull-out of the satellite images through the standard pixel-by-pixel classifiers. This panel can be sufficiently useful in diverse related urban studies as the population alterations, urban growth and land use cover changes.

The creation of an urban gradient based in orbital data presents the advantage to provide a relatively accessible form of understanding the alterations in the urban rural fringe. The question of the scale can be placed in this context since agricultural and urban areas do not share an equitable total area. However, a discriminate analysis, applied only on determined cities (Lisbon and Setúbal), did not produce results significantly different of those produced for the all region.

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