DEFINING AND DETECTING CHANGES IN URBAN AREAS

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Commission VII. WG VII/4

KEYWORDS: Remote Sensing, Human Settlement, Change Detection, Monitoring, Analysis

ABSTRACT:
The general issue developed in this paper is the consistency between the visual description of urban areas and quantitative description obtained through analysis techniques and landscape ecology indexes. Three experiences have been carried out: the first applies landscape ecology indexes to different typologies of urban structures in order to verify whether they can qualify such typologies. The second applies some tools of analysis to different resolution images of the same test area. The third analyses the results and the significance of landscape descriptors, calculated over different urban areas at different scales. Such experiences allow us to gain a better understanding about 1) the efficiency of these descriptors and their limitations in characterizing urban structures, 2) behaviour and significance of descriptors when applied to different resolution, which provides evidence of scale relevance.

1. INTRODUCTION

The description of urban phenomena needs to explicit variables and categories by which we can either differentiate different typologies or subdivide the phenomena into the parts – also differentiated - they are composed of. Description does imply criteria and related differentiations "named" within the various criteria.
Defining such categories depends on the possibility to determine them theoretically in relation to a given discipline, or practically in relation to an analysis technique.
In general indexes and classes provided by analysis techniques have to become useful in order to detect new or already existent categories.

Classes and indexes do have their particular definition in description of datasets in relation to the analysis technique (for example morphologic or statistical analysis) and are certainly useful since they offer the possibility to compare various datasets. Nevertheless it must be emphasised that they are only operational tools such as mathematical operations (as addition or subtraction) and they must be used within contexts that are homogeneous as for their significance. Moreover an analysis process needs a subsequent, very critical step, whereby the results have to be put under interpretation in order to give them meaning with regard to the specific phenomenon under study. An issue that is sometimes neglected - since it is implicit in stating phenomenon itself - is the “scale of reasoning”. Dealing with spatial information, this means the scale of the document by which the analysis is performed. Scale mediates relevance, says Racine (1981). Such statement claims that a change of scale implies a change of the meanings relevant to the description of the phenomenon (Ruas and Bianchin, 2002).
Analysis technique is indifferent to change of scale.
The purpose is to investigate the different meanings that the same index can assume when working at different scales.
While some authors, referring to a matematical concept of scale, claim that scale can be treated as a continuum, we agree with Lacoste (1980) that there are different levels of representation, conceptually differentiated, which in cartography correspond to a change of scale - that is, to a transition from an order of magnitude to another. An order of magnitude is an interval between scales within which a change of meaning does not occur, whereas meanings change from a given interval to the next.

The general question raised here is about the consistency between visual description and quantitative description generated by analysis techniques. The question can be articulated as follows:

1. Can quantitative description qualify settlement typologies according to the qualitative (visual) definition derived from urban discipline?
2. Can quantitative description support qualitative description?
3. Can quantitative description confirm qualitative description?
4. How does quantitative description react to the change of scale?

In order to give an answer, if partial, to these questions, various quantitative analysis techniques have been applied to binary maps of the built space generated from satellite images. The area under scrutiny belongs to the Veneto region and includes concentrated as well as diffuse urbanization. The analysis of such urbanization requires the definition of a set of variables that can qualify different spatial configurations of settlements.
Hence we have worked on:

1. the variables of density and landscape ecology that have been applied;
2. the comparison of the results of their application over different scales and different urban contexts.

In our first work we have applied these techniques to a range of settlement structures belonging to four different typologies and two different time periods. The aim is to verify whether indexes are sufficiently stable but also differentiated, thus allowing to qualify the typologies.
A second work deals with the issue of scale and analyses the density function of the same area at different levels of resolution.

A third work computes the landscape indexes from various analysis techniques over five sub-areas, the same identified in satellite images at different resolution (Landsat, Spot and IKONOS).

2. INPUT IMAGES

The three works are based on maps of the built space obtained through satellite image processing (Pesaresi and Bianchin, 2001). The map from Spot has been slightly corrected with photo interpretation. Images have been co-registered in order to allow comparison.
The following images have been used:

- Landsat 5 TM, 30m, frame 192/28, 08/20/1990
- Landsat 7 ETM+, 30m, frame 192/28, 09/08/2000
- Spot 4 Pan, 10m, frame 062/258, 03/30/2002
- IKONOS Pansharpened, 1m, 07/02/2001.

3. LANDSCAPE ECOLOGY STATISTICS

Spatial statistics of the landscape are quantitative indexes based on geometric features of a homogeneous region called patches. To compute them we used the sw FRAGSTATS of McGarical and al. (2002).

The following landscape indexes have been considered:
1 *patch density* (PD) is the ratio between number of patches and total area. Low values of PD imply the presence of few regions, while increases of PD mean more patches in the area.
2 *edge density* (ED) is the ratio between perimeter of all regions in the area and total area. Low values can be associated with landscapes composed of few, wide regions; high values mean composite landscapes with several regions.
3 *mean patch area* (MA).

4. FIRST WORK

In the area of Veneto region (figure 1), urban studies identify four settlement typologies: concentrated cities, diffuse city, diffuse urbanization, corridors (Indovina et al., 1990).

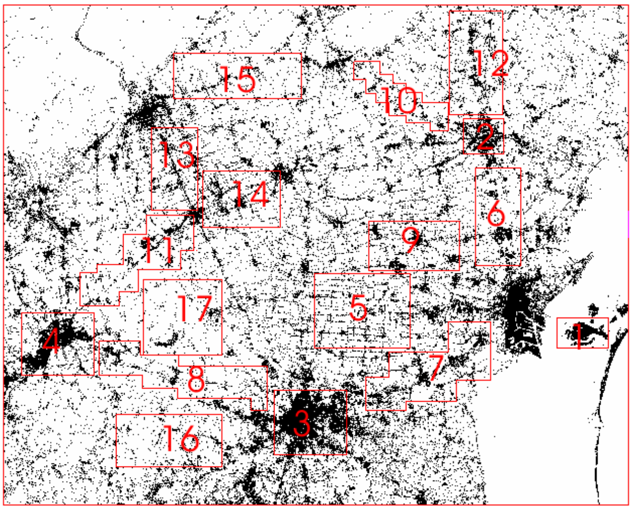

Figure 1. 17 sub-areas belonging to different settlement typologies

17 sub-areas belonging to four typologies have been drawn (Fregolent, 2004).

- For the concentrated city: areas 1_Venice, 2_Treviso, 3_Padova, 4_Vicenza.
- For the diffuse city: areas 5_Roman Centuriation, 6_Terraglio, 7_Riviera del Brenta, 8_Padova-Vicenza axis, 9_Noale-Scorzè, 10_Treviso-Montello axis, 11_Vicenza-Cittadella axis.
- For the corridors: areas 12_Treviso-Ponte della Priula axis, 13_Cittadella-Bassano axis, 14_Cittadella-Castelfranco axis.
- For the diffuse urbanisation: areas 15_Bassano Montello, 16_Bacchiglione, 17_Piazzola del Brenta.

For the above sub-areas, spatial indexes have been computed at two dates, 1990 and 2000, then compared. The comparison shows that:

1. for a given image at date *t* (either for *t*=1990 or *t*=2000) values of indexes for the different typologies are not so different as it could be expected (for example: PD is 14 for area 5, 13 for area 13, ED is 80 for area 2, 83 for area 5 and 88 for area 13, at 2000).
2. it results that the variation of indexes at two dates characterises the four typologies represented in the various sub-areas. The 17 sub-areas develop from 1990 to 2000 according to the typical behaviour of the typology to which they belong independently of their localization. This defines certain territorial uniformity.

In detail:

1. concentrated cities are qualified by a decrease of PD and ED and an increase of MA, which means that they become more compact (figure 2). New built spaces occur in the voids of the core or increase existent patches.

Figure 2. Concentrated cities: variation of indexes in absolute value

2. diffuse city is qualified by a decrease of PD but an increase of ED and MA (figure 3). New built spaces develop contiguously to the existent ones (PD decrease) creating ramifications (ED increase). Such development leads more toward fragmentation than diffusion.

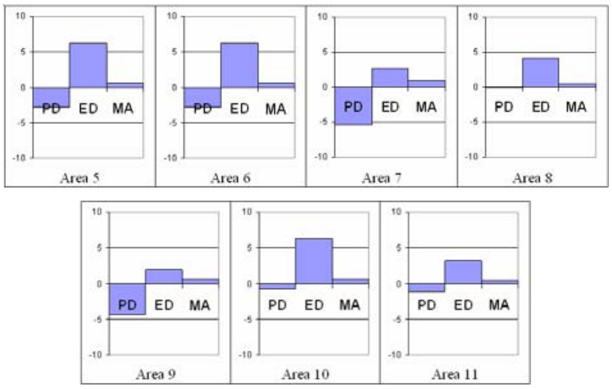

Figure 3. Diffuse cities: variation of indexes in absolute value

3. corridors are qualified by a decrease of PD and ED and an increase of MA (figure 4). Corridors differentiate from concentrated cities through MA absolute value which is always over 2.88 acres for concentrated cities and under 2.32 acres for corridors. Corridors, like concentrated cities, tend to consolidate existent structures.

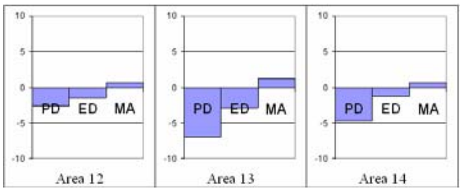

Figure 4 .Corridors: variation of indexes in absolute value

4. diffuse urbanisation is qualified by an increase of PD, ED and MA (figure 5). That means that a tendency toward diffusion is still prevailing.

Figure 5. Diffuse urbanization: variation of indexes in absolute value

	Built surfaces%	N° PATCH	PD 100 hectares	ED m / hectare	MA hectare
CONCENTRATED CITIES					
Area 2, 1990	50,9	268	12,26	103,86	4,16
Area 2, 2000	59,29	165	7,55	79,55	7,86
DIFFUSE CITY					
Area 5, 1990	15,80	1982	19,46	73,54	0,81
Area 5, 2000	26,84	1395	13,69	83,27	1,95
CORRIDORS					
Area 13, 1990	22,53	1296	20,13	90,69	1,11
Area 13, 2000	30,55	845	13,12	87,78	2,32
DIFFUSE URBANIZATION					
Area 16, 1990	9,28	1391	17,27	52,24	0,53
Area 16, 2000	16,14	1578	19,60	74,10	0,82

Table 1. A sample for each settlement typology

5. SECOND WORK

The second work analyses the same area with different urbanizations, identified in various maps of the built space derived from images at different resolution: (Landsat, Spot, IKONOS).
Additionally, two maps, called IKONOS_5 and IKONOS_10, have been made by applying a buffer of 5m and 10m to the IKONOS map, in order to verify whether such operation allows to get the features of Landsat and Spot maps.

5.1 Built surfaces

A first analysis compares built surfaces in the various maps (figure 6).
It results that:

1. Landsat has the higher percentage of built space (51%) while it decreases a little in the Spot (43%) because of the higher resolution.
2. lowest percentage occurs in IKONOS (26%), since built space includes only buildings and roads instead of a continuous urban space like in Landsat and Spot.
3. IKONOS_5 built surface is near to the one of Spot as well as IKONOS_10 to the LANDSAT. Buffers indeed fill voids between objects (roads and buildings) and increase the area of objects.

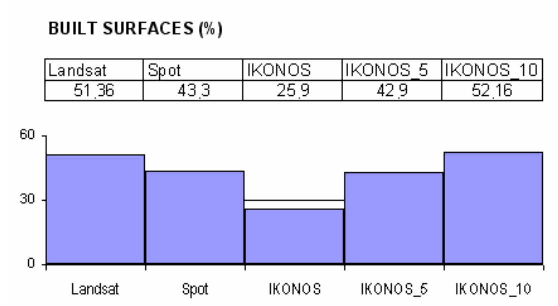

Figure 6. Built surfaces in the various maps

5.2 Mapping built space density

Maps of local density have been produced by processing built space maps with a low pass filter (Pesaresi, 1993), whose kernel corresponds in our case to 1Km^2 of surface (that means 33 x 33 pixels for Landsat, 99x 99 for Spot and 999 x 999 for IKONOS).

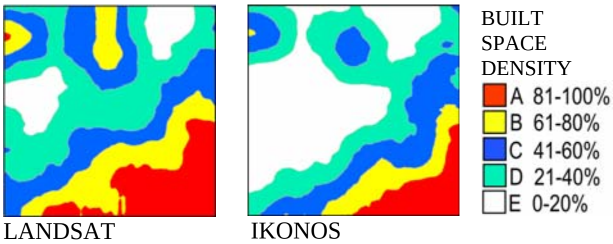

Figure 7.

5 intervals of local density named from A to E have been set. Values refer to the percentage of built pixels over total number: A = 100-81%; B = 80-61%, C = 60-41%; D = 40-21%, E = 20-0%.

	LANDSAT	SPOT	IKONOS	IKONOS_5	IKONOS_10
A	15.35	10.86	7.90	9.82	14.44
B	18.08	17.23	7.91	18.11	18.39
C	26.30	21.48	20.51	22.97	26.35
D	30.15	29.20	27.79	24.81	27.19
E	10.12	21.23	35.89	24.29	13.63

Table 2 . Built space density classes over 5 images

Results reported in the above table show that:
1. Landsat gets the highest percentage of areas ranked in A (A =15%), and IKONOS the lowest (A= 8%).
2. behaviour over intervals of density is similar in Landsat and Spot with a maximum for D (D=30% for Landsat and D=29% for Spot)
3. behaviour over intervals of density in IKONOS is quite different from Landsat and Spot. IKONOS shows higher values for class E (E= 36%).
4. with IKONOS_5 and IKONOS_10 we obtain, for classes A, B and C, percentage values similar to Spot and Landsat respectively.

SPOT	IKONOS A	B	C	D	E	TOT
A	6.75 85.44 62.15	4.11 51.97 37.85	0 0 0	0 0 0	0 0 0	10.86 100
B	1.15 14.56 6.67	1.8 22.75 10.45	11.73 57.19 68.08	2.55 9.17 14.8	0 0 0	17.23 100
C	0 0 0	1.59 20.1 7.4	6.25 30.47 29.09	13.64 49.08 63.51	0 0 0	21.48 100
D	0 0 0	0.41 5.18 1.4	2.53 12.34 8.66	7.16 25.76 24.52	19.1 53.22 65.42	29.2 100
E	0 0 0	0 0 0	0 0 0	4.44 15.99 20.91	16.79 46.78 79.09	21.23 100
TOT	7.9 100	7.91 100	20.51 100	27.79 100	35.89 100	100

In blue : Distribution of each density class of Spot into IKONOS classes. (percentage values)

In pink: Distribution of each density class of IKONOS into Spot classes (percentage values)

Table 3. Cross table

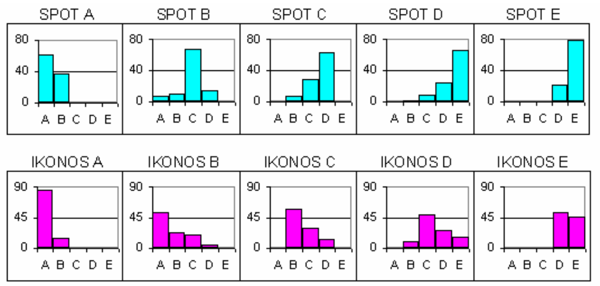

Figure 8. Graphic representation of cross table 3

SPOT	IKONOS_5 A	B	C	D	E	TOT
A	9 91.65 82.87	1.86 10.27 17.13	0 0 0	0 0 0	0 0 0	10.86 100
B	0.82 8.35 4.76	11.34 62.62 65.82	5.07 22.07 34.18	0 0 0	0 0 0	17.23 100
C	0 0 0	0 0 0	10.87 47.32 50.61	3.97 16 18.48	1.73 7.12 8.05	21.48 100
D	0 0 0	0 0 0	6.87 29.91 23.53	12.87 51.87 44.08	9.46 38.95 32.39	29.2 100
E	0 0 0	0 0 0	0.16 0.7 0.75	7.97 32.13 37.54	13.1 53.93 61.71	21.23 100
TOT	9.82 100	18.11 100	22.97 100	24.81 100	24.29 100	100

In blue: Distribution of each density class of Spot into IKONOS_5 classes. (percentage values)

In pink: Distribution of each density class of IKONOS_5 into Spot classes (percentage values)

Table 4. Cross table

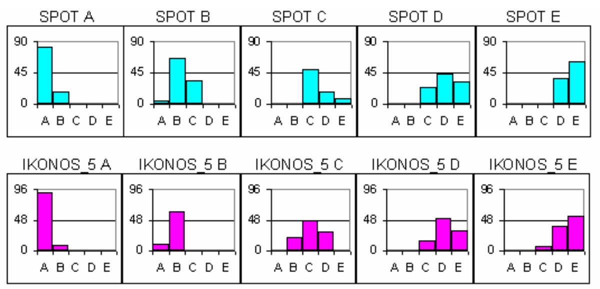

Figure 9. Graphic representation of cross table 4

To provide insight about changes in scale, we analyse - by means of two by two overlays of five maps of density - the distribution of density classes of a given image in the classes of another image at a different resolution. This allows us to answer questions such as: to which density class of IKONOS go pixels of the class A of Spot and so on (tables 3 and 4, figures 8 and 9).

From this analysis it emerges that:

1. most (percentage more than 50%) of the pixels of a given class of IKONOS pass to the higher density class in Landsat and Spot.
2. Landsat and Spot density classes distributions are similar even spatially.
3. IKONOS_5 and Spot density classes distributions are similar: nearly all pixels belong to the same classes of density, and this mainly for classes A (92%) and B (63%).

The same remarks are valid for IKONOS_10 with regard to Landsat.

6. THIRD WORK

In the study area analysed above, according to urban studies, five different sub-areas displayed and drawn in the fig. 14 can be identified: 1_compact core; 2_suburban area; 3_ connection area; 4_scattered settlements; 5_ industrial area.
The issue under consideration is to what extent landscape indexes can be used to characterize and identify different urban structures. Such analysis is set forth on the five images mentioned above, on which the same five sub-areas have been drawn.

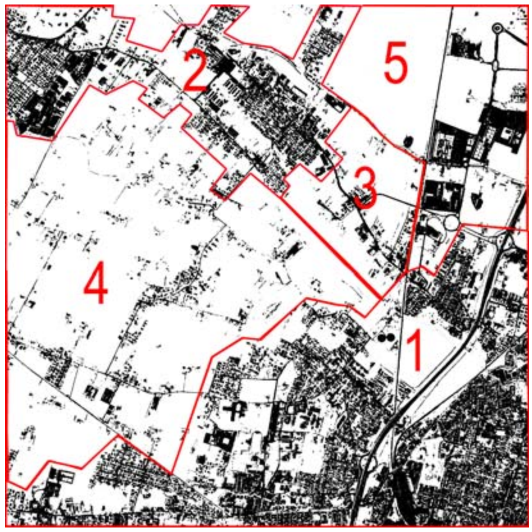

Figure 10. Study area and 5 sub-areas drawn on map from IKONOS

6.1 Statistics of landscape

Results from spatial statistics mentioned in paragraph 3, bring out some interesting points:

1. **Areas 1 and 2** show low values of PD (5 and 8) and ED (45 and 106) in Spot and Landsat, while they are high (PD=447; ED=747) in IKONOS (table 5, figures 11 and 12). MA is high in Spot and Landsat, very low in IKONOS.

Statistics clearly demonstrate two different ways to represent concentrated urban areas: uniform and compact in Landsat and Spot; a dense set of single elements in IKONOS.
For these areas IKONOS_5 and IKONOS_10 provide a representation quite similar to Landsat and Spot.

AREA 1	BUILT %	N°PATCH	PD	ED	MA
land	79.86	24	4.5	44.97	17.73
spot	72.91	43	8.08	105.8	9.03
ikonos	45.28	2380	447.37	746.97	0.10
Ikonos 5	75.35	39	7.32	119	10.20
Ikonos 10	82.31	27	6.16	89.87	16.22
AREA 2					
land	68.07	30	12.57	64	5.41
spot	57.04	44	18.44	124.15	3.09
ikonos	35.11	1298	543.92	658.37	0.06
Ikonos 5	61.06	45	18.85	78.78	3.23
Ikonos 10	73.56	34	14.24	67.37	5.16

Table 5. Indexes for areas 1 and 2 in absolute values

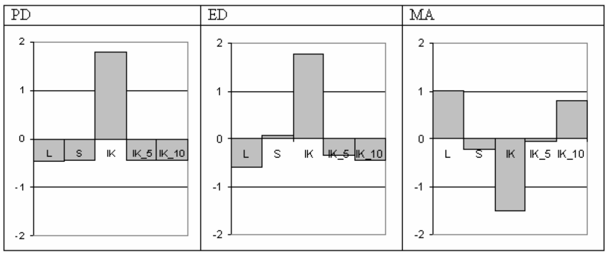

Figure 11. Area1: normalized graphs of indexes

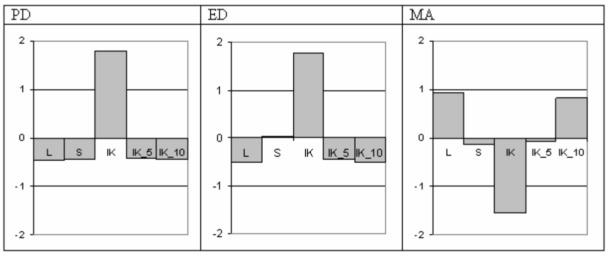

Figure 12. Area 2: normalized graphs of indexes

2. **Areas 3 and 4** show in Spot and Landsat PD and ED values higher than those of areas 1 and 2, while MA is lower (table 6, figures 13 and 14).

Fragmented areas are represented by numerous patches spread over the territory whose minimum size is defined by pixel size, that means of 100m^2 for Spot (10m) and 900 m^2 for Landsat (30m). In IKONOS the same areas are composed of patches whose mean size is of 200 or 300m^2. PD, ED and MA values are lower .

For these areas IKONOS_5 and IKONOS_10 do not give a representation similar to Landsat and Spot. Indexes values of first ones compared to the latter are: PD higher and SD values lower. For example : in area 3, PD is 82 and MA 0.17 for IKONOS_5 to 41 and 0.48, respectively for Spot; in area 4, PD is 74 and MA 0.16 for IKONOS_5 to 40 and 0.55, respectively for Spot. Buffers entail only augmentation of surface of IKONOS patches.

AREA 3	BUILT %	N°PATCH	PD	ED	MA
land	29.27	18	24.03	78.18	1.21
spot	23.00	31	41.38	169.28	0.55
ikonos	14.17	299	399.19	526.5	0.03
Ikonos 5	20.22	91	82.30	165.33	0.16
Ikonos 10	27.60	71	94.79	119.67	1.05
AREA 4					
land	28.49	130	25.14	77.87	1.13
spot	19.95	211	40.8	142.66	0.48
ikonos	7.10	1992	385.27	317.35	0.02
Ikonos 5	12.95	383	74.07	141.78	0.17
Ikonos 10	19.10	181	35.01	102.45	0.55

Table 6. Indexes for areas 3 and 4 in absolute values

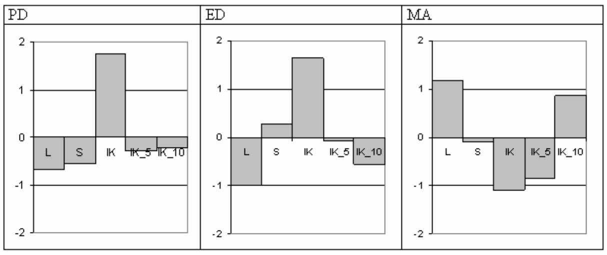

Figure 13. Area3: normalized graphs of indexes

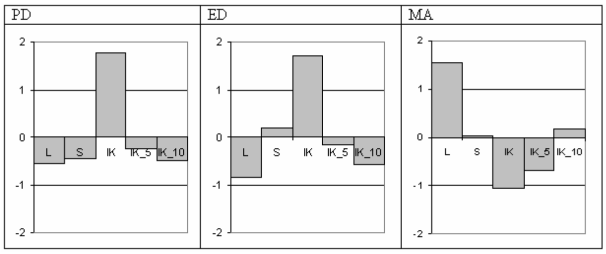

Figure 14. Area 4: normalized graphs of indexes

3. **Area 5** displays PD and AS values in Landsat and Spot ranged between values of fragmented areas and concentrated ones (table 7, figure 15). In IKONOS MA value is higher than the one shown by concentrated areas, while PD and ED are low. Statistics suggest a representation of industrial area similar over scales, shaped into a set of patches medium-wide sized .

IKONOS_5 and IKONOS_10 give a representation similar to Landsat and Spot.

AREA 5	BUILT %	N°PATCH	PD	ED	MA
land	30.78	39	19.04	49.58	1.62
spot	24.17	53	25.87	111.41	0.93
ikonos	19.63	262	127.88	217.35	0.15
Ikonos 5	25.93	58	28.31	123.8	0.92
Ikonos 10	35.58	45	21.97	91.34	1.62

Table 7. Indexes for area 5 in absolute values

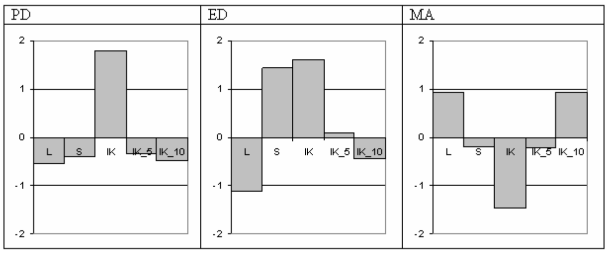

Figure 15. Area5: normalized graphs of indexes

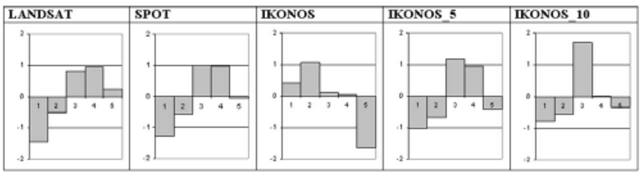

Figure 16. Normalized graphs of patch density

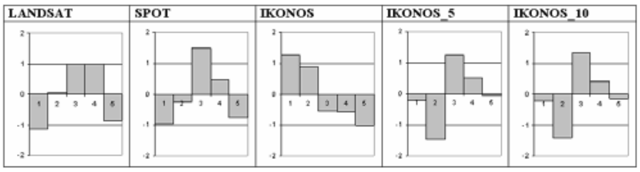

Figure 17. Normalized graphs of edge density

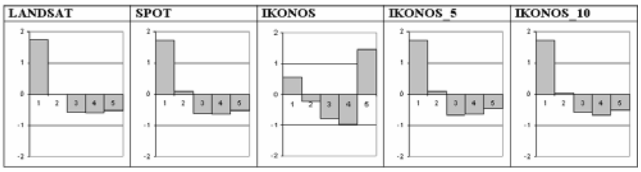

Figure 18. Normalized graphs of mean patch area

7. CONCLUSIONS

With regard to the questions formulated in introduction, the experiences that we have carried out allow us to draw the following conclusions:

1. Landscape indexes analysed display values that are not enough different to be assumed as variables characteristic of various urban typologies. A reason for that could be an inadequate or incomplete correspondence between conceptual and cartographic definition of sub-areas. What are the limits of concentrated and diffuse city? Conversely, the analysis of the evolution of every sub-area, made using the same spatial definitions, enables to identify a trend of development both stable and characteristic of the various typologies.

2 Although calculated indexes were not characteristic, regarded as a whole (i.e. rejecting anomalous values) they offer a comparative description among various sub-areas. Spatial configurations can be analysed in detail with reference to the specific meaning of indexes: for example edge density together with mean size of patches gives information about fragmentation, etc...

3. As supposed and foreseen, working at different scales (IKONOS *vs* Spot and Landsat) entails working on different phenomena. To sum up the results drawn from the second work:

- Density function shows great diversity with regard to the attribution of pixels to a given class of density.
  In IKONOS: low density surface is 36% as against 10% of Landsat, while high density surface is 15% in Landsat as against 8% in IKONOS. Such diversity is overcame through a buffer applied to IKONOS, this mainly for high density classes.
- Through the overlay of density classes maps a systematic migration from a given density class of IKONOS into the next class at higher density of Spot can be observed. Such migration is recovered in IKONOS_5, whose density classes distribution is near to Spot.

What happens is that in IKONOS the single building is detected individually, while in Landsat and Spot either it is missing or it is aggregated to the adjoining buildings. This explains the maximum of built area in Landsat, the increase of low density surface in IKONOS and the migration of density classes of IKONOS towards higher density classes of LANDSAT. Buffers allow to recover Spot and Landsat values with regard to :
- total built surface
- high density classes (A and B) since buffer fills the voids between adjoining buildings.

Conversely, in low density values (C, D, E) the Spot and LANDSAT values cannot be recovered because of the dispersion of buildings and the variability of configurations.

In the third work, tables and their graphical representations clearly show how indexes calculated over the 5 input images display normalized values always opposite to IKONOS ones in comparison with other images.
This because meaning of landscape indexes is completely different when applied at different resolutions.
It is worth noting that ED is an index of dispersion and fragmentation only at Spot and Landsat (Herold, 2001) and not at IKONOS resolution. In IKONOS, ED is higher in concentrated areas compared to scattered settlements, since a higher number of buildings - and consequently a bigger perimeter value – is associated to the same surface.
In this last instance, too, buffers applied to IKONOS allow us to recover the behaviour of indexes at lower resolution for concentrated urban areas.

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