Resolution Problems in Calculating Landscape Metrics

D. Rocchini

The variation of landscape metrics caused by varying the map input resolution has been investigated. Landscape metrics are spatial indicators used to link spatial patterns with the ecological processes that generate them. An aerial photograph was semi-automatically classified at different resolutions by superimposing a grid with a variable cell dimension (10, 20 and 40 metres) in a GIS environment. The variation of the mostly used landscape metrics was investigated. This approach allows the up-scaling of spatial indices, thanks to the objective ('a priori') definition of the Minimum Mapping Unit. Some metrics showed linear trends over the range of examined scales, and other metrics had non-linear response curves. For the first type of metrics, the translation of information over a wide range of spatial scales seems to be very simple, while for the second this translation appears to be impossible.

D. Rocchini
Department of Environmental Science
University of Siena
via P.A. Mattioli 4
53100 Siena, Italy
rocchini@unisi.it

INTRODUCTION

Remote sensing represents a powerful tool for developing landscape composition and pattern indicators (landscape metrics) as sensitive measures of large-scale environmental change (Kepner *et al*, 2000) and the outcome is improved by geographic information systems (GIS) that have opened many new possibilities in this field of research (Baltsavias, 1996).

Compositional and structural indices applied to landscapes allow their characterisation and the investigation of ecological processes (Herzog and Laush, 2001). A central issue of landscape ecology is the study of spatial patterns over time in order to detect the occurring ecological processes (Turner *et al*, 2001).

Hierarchical structure of the landscape has been accepted by several authors (Forman and Godron, 1986; Turner *et al*, 2001). For this reason, the study of the landscape cannot ignore the scale of observation (Turner *et al*, 1989; O'Neill *et al*, 1991; O'Neill *et al*, 1996; Wu *et al*, 1997; Wu *et al*, 2000). Since the 1980s, the scientific literature (Forman and Godron, 1986; Turner *et al*, 1989) points out that changing grain (resolution) and extent of the study area during landscape analysis could significantly affect final results. More recently, Wu *et al* (2000, 2002) published interesting papers on the use of multiscale analysis in order to predict metric values.

The translation of information from one scale to another is becoming a key issue for landscape ecologists and GIS analysts. This translation is often achieved by means of automatic map resampling, by varying the grain, and therefore the *scale*, of different data to make them comparable. However, all resampling methods (nearest neighbour, bilinear interpolation, cubic convolution) can introduce spatial errors (Turner *et al*, 1989, Gustafson, 1998). Moreover, these methods do not act on the real resolution of data acquisition. For example, a map with a Minimum Mapping Unit (MMU) of 100 metres, resampled at 20 metres, will preserve the pattern recognized at 100 metres, but without increasing the information content.

Another problem is the definition of MMU. As for raster datasets, MMU is associated with pixel size, while for vector datasets it is associated with the data source (topographic map, aerial photograph or satellite image) from which the vector data were derived. However, attention must be paid when migrating from one format to the other. For example, if a map scale is 1:50 000 then the cartographic-printing error could be 0.2 mm. Thus if the map is scanned, transforming 0.2 mm to metres according to the 1:50 000 scale, the minimum pixel size (or the MMU) should be 10 metres. If subsequently the vector lines (contours) are digitized then their planimetric accuracy would be worse than 10 metres. Moreover, concerning land use classification, in most cases maps are derived by digitising polygons around areas of uniform landuse; the MMU is then defined as the area of the smallest polygon: such a definition seems to be completely subjective and approximate. In this paper, grids superimposed on remotely sensed data (e.g. aerial photographs) constrained the operator to classify every single cell having a pre-defined dimension. Therefore, the following analyses were based on an objectively defined MMU.

The aim of this paper is to study the variation of spatial metrics over different scales, using grids at a range of resolutions.

STUDY AREA

The study area is the Natural Reserve of Poggio all'Olmo, on the slope of Mt Amiata (longitude 11°32'26''E, latitude 42°58'36'', datum WGS84), Italy, which occupies an area of almost 440 hectares. The range of elevations varies from 664 to 1016 metres. Total annual precipitation averages 1045 mm and mean annual temperature averages 12.5°C (climate station: Castel del Piano, 639 metres m.s.l.). This area has undergone a dynamic process of forest growth in abandoned pastures and fields. Land use has changed considerably in the area surrounding the reserve, particularly since the Second World War, due to rural depopulation and a cessation/decrease in traditional agricultural practices (e.g. terracing, grazing, maintenance of grazed grasslands by burning, cultivation of chestnut groves, wood-cutting, cultivation of fields, maintenance of hedgerows at field boundaries).

METHODS

An aerial photograph (grey scale) taken in 1998 (flight height: 6000 metres) was acquired and scanned at high resolution (600 dpi). Due to the rough topography, a rigorous model (orthorectification) was needed in order to geometrically correct the image (Rocchini, 2004; Rocchini and Di Rita, 2005). Orthorectification was based on a digital terrain model (DTM) derived from a 1:10 000 topographic map (pixel size: 10 m) of the study area and on 30 ground control points (GCPs), and was performed using ERDAS IMAGINE 8.4 (www.erdas.com). The final image spatial resolution was approximately 2 m. Positional accuracy was tested by means of 20 additional GCPs and the RMS error never exceeded 4 m. The image was projected onto the National (Italian) Coordinate System (Gauss Boaga Projection, datum Roma 40).

The aerial photograph was subsampled by superimposing a grid with a variable cell dimension (10, 20 and 40 metres). Each cell was semi-automatically classified in order to simulate photointerpretation at different resolutions. The classification process required a manual classification of grids at 10 m spatial resolution. The semi-automatic classification involved strata with 20 m and 40 m spatial resolutions. Where cells of larger cell dimension were completely dominated by a single class at the 10 m level, they were automatically attributed to that class at the 20m and/or 40m level.

The identification of classes was based on Level 3 of the Corine Land Cover system, with some revisions applied to achieve some typical land use types which occur in the area under study (e.g., semi-natural grasslands, thereafter *open formations*). The photo-interpretation was principally based on pixel tone: a gradient from black to white was used in order to recognise *coniferous plantations*, *woodlands*, *shrublands open formations* (grasslands). Additional pattern elements were applied in order to recognise typical land use classes such as *linear formations* (hedges, approximate width 4-6 m), characterised by an elongated shape, *buildings*, characterised by a block shape, and *isolated or grouped trees*, characterised by a black tone and obvious isolation.

The variation of the mostly used landscape metrics (Forman and Godron, 1986; Turner *et al*, 2001) over multiple scales was examined (Table 1) by means of a FRAGSTATS (McGarigal and Marks, 1995) interface within the ARC/INFO (www.esri.com) software. Since the use of grids substantially results in lattice maps, a diagonal algorithm (Moore neighbourhood) for the generation of patches was chosen.

As for *landscape composition*, the calculated metrics were the *number of classes* and *area of each class*. Landscape diversity was calculated by means of the *Shannon diversity index* (Shannon and Weaver, 1962) and the *Pielou evenness index* (Pielou, 1969).

$$H' = -\sum_{c=1}^{M}\left(P_c \ln P_c\right) \tag{1}$$

$$E = \frac{-\sum_{c=1}^{M}\left(P_c \ln P_c\right)}{\ln M} \tag{2}$$

Where: H' = Shannon diversity index
M = number of classes
P_c = proportion of the area occupied by each class
E = Pielou evenness index.

The Shannon diversity index takes into account the abundance of classes and it increases as the number of classes increases or the equitability of distribution of land amongst the various classes increases, ranging from 0 to infinity (Nagendra, 2002). The Pielou evenness index takes into account the maximum possible diversity with the same number of classes, ranging from 0 to 1 (perfect evenness, see also Ricotta and Avena, 2003).

Metric type	Metric name	Metric abbreviation
Landscape composition	Number of classes	-
	Area of each class	-
	Shannon diversity index	H’
	Pielou evenness index	E
Landscape structure	Number of patches	-
	Number of patches per class	-
	Mean Shape Index	MSI
	Area Weighted Mean Shape Index	AWMSI
	Mean Patch Size	MPS
	Patch Size Standard Deviation	PSSD

Table 1. *Landscape metrics studied in this paper. Refer to the text for major explanations and equations.*

As for *landscape structure*, metrics on the *number*, *shape* and *size* of patches were investigated. An overview of these metrics is given by McGarigal and Marks (1995), Baker and Cai (1992) and Turner *et al* (2001).

As for *patch number*, the number of patches and number of patches per class were investigated. *Patch shape* was studied by means of the *Mean Shape Index* (MSI) and the *Area Weighted Mean Shape Index* (AWMSI).

$$MSI = \frac{\sum_{p=1}^{N} \left(0.25 P_p / \sqrt{A_p}\right)}{N} \qquad (3)$$

$$AWMSI = \sum_{p=1}^{N} \left(0.25 P_p / \sqrt{A_p}\right) \left(\frac{A_p}{\sum_{p=1}^{N} A_p} \right) \qquad (4)$$

Where: *MSI* = Mean Shape Index
N = number of patches
P_p = perimeter of the patch p
A_p = area of the patch p
AWMSI = Area Weighted Mean Shape Index.

MSI is used to estimate the shape complexity, being the minimum value of 1 related to a square (raster format) shape. The AWMSI is an improvement of MSI, because it takes into account the area of each patch.

Patch size was measured by means of *Mean Patch Size* (MPS) and *Patch Size Standard Deviation* (PSSD).

RESULTS

A global generalisation of maps was found from a higher (smaller cell size) to a lower (larger cell size) resolution (Figure 1).

Landscape Composition

Three classes (e.g. linear formations, buildings, and isolated or grouped trees) were lost at a resolution of 40 x 40 metres (Figure 2a). This phenomenon was principally due to structural characteristics of class patches: *size* (classes with smaller patches); *shape* (for linear formations, having a lower horizontal extension); *dispersion* (for buildings and isolated or grouped trees, having patches dispersed in the landscape).

As for the area of each class, besides the value of zero clearly reached by the previously cited classes, the decrease of resolution had no effect on almost all classes, except for shrublands and open formations, with positive and negative distortions, respectively (Figure 2b). This is due to the pattern of open formations, which occurred in strict stripes within shrublands, being joined to the nearest patches of shrublands, by increasing the cell dimension.

Diversity, measured by means of the Shannon diversity index and the Pielou evenness index, showed a slight decrease of the first index and a high increase of the second, as resolution decreased (Figure 2c). Indeed, less abundant classes disappeared (e.g. linear formations, buildings and isolated or grouped trees) by provoking a decrease of Shannon diversity index, and only more abundant classes with more even values persisted, by provoking an increase of Pielou evenness index.

Landscape Structure

The number of patches and number of patches per class showed a linear decrease as the resolution decreased (Figure 3a, 3b). Open formations showed the greatest decrease; this phenomenon demonstrated the presence of several small patches dispersed in the landscape that underwent the previously cited joining phenomenon. On the contrary, coniferous plantations showed no merging, because of their artificial nature, already merged at a resolution of 10 x 10 metres and composed of a few patches with a high dimension.

MSI showed a non-homogeneous trend for all classes (Figure 3c). Moreover, all values approached 1 (except for linear formations at a resolution of 10 x 10 metres): this is explainable by hypothesizing that each class had several small patches with a square shape that caused the distortion of the mean value towards 1. On the contrary, AWMSI showed high values, since it weights the area of the patches, resulting in an underestimate of those smallest patches which led to the distortion of

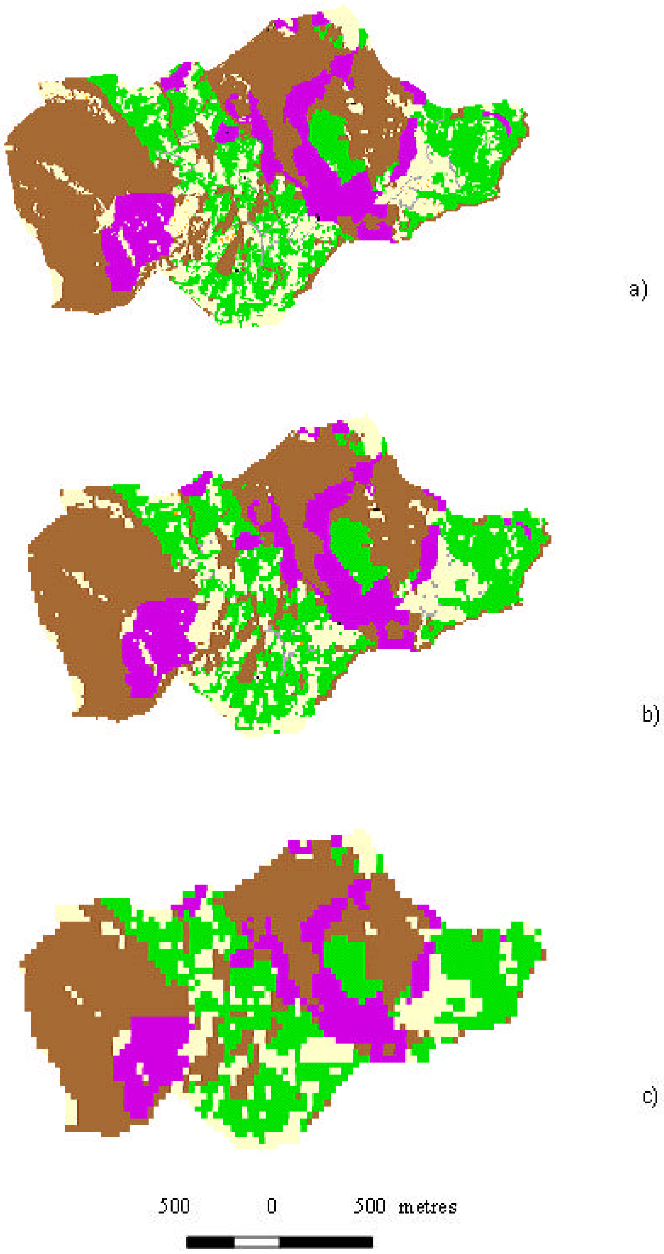

Figure 1. *Maps with different spatial resolution derived from the classification of aerial photographs: a) 10 x 10 metres; b) 20 x 20 metres; c) 40 x 40 metres. Brown: woodlands; green: shrublands; yellow: open formations; black: buildings; orange: isolated or grouped trees; grey: linear formations; violet: coniferous plantations.*

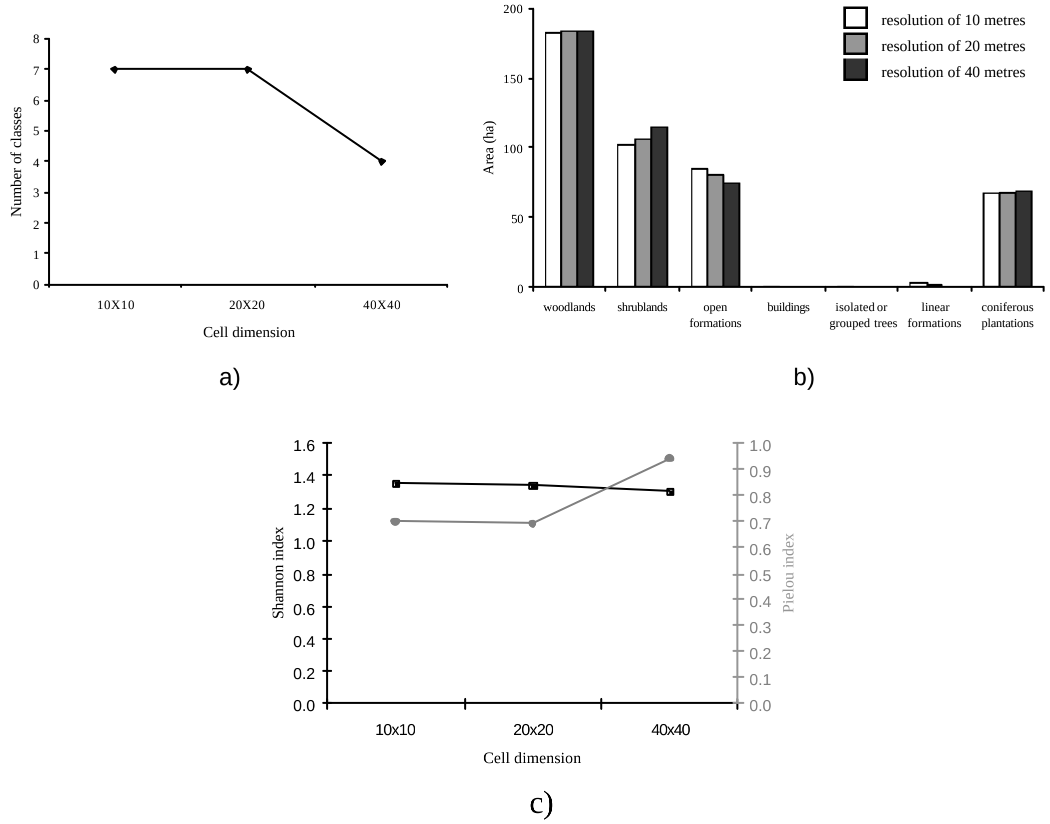

Figure 2. *Landscape composition metrics: a) number of classes, b) area of each class; c) Shannon and Pielou indices (black and grey line, respectively). Cell dimensions are shown in metres. As for the area of each class, the plot is biased towards the high values of woodland, shrubands, open formations and coniferous plantations, thus resulting in a flattening effect in the values of buildings, isolated or grouped trees, and linear formations. These classes were lost only at a scale of 40x40 metres.*

the mean value (Figure 3d). The negative trend found in all classes was due to the decrease of edge density, and therefore the shape complexity, of the patches. Coniferous plantations did not undergo this effect, as highlighted by the number of patches for this class. Their patches were therefore dense, with a large dimension and with a simple shape (artificial formations).

MPS showed a positive trend for all classes; however, PSSD exceeded the average in all cases (Figure 3e), indicating that size values deviated significantly from the mean value. In fact, the analysis of the distribution of patches with respect to their size (Figure 4, shrublands patches distribution as an example) showed several small-size and few large-size patches, namely a distribution far from a typical Gaussian form.

DISCUSSION

In this paper it has been demonstrated that a restricted set of indices can generate a large quantity of information on landscape patterns. Identifying a set of non-redundant indices is a primary issue for landscape analysis. O'Neill *et al* (1988), in a pioneer study on landscape indices, underlined that a restricted set of indices could identify significant aspects of spatial patterns; on the other hand, Steinhardt*et al* (1999) pointed out that no single index provides a complete interpretation of the landscape processes. Results obtained in this paper agree with these concepts, indicating that a *landscape metrics net* is required to relate landscape metrics in order to explain landscape patterns. For example, the fact that MSI showed values approaching 1 and AWMSI showed very different results is explainable only by hypothesizing that for each class (except for linear formations), the distribution of the patches was that in Figure 4: many small-size and few large-size patches. This hypothesis was demonstrated by the values of PSSD, higher than the mean (MPS), which indicated a non-Gaussian distribution of the patch size.

Also, the knowledge of the variations of the indices over multiple scales is very important for the identification of the *scale of heterogeneity* (patchiness) of the landscape, in order to carry out analyses at an appropriate scale (Gustafson, 1998). Indeed, results of the analyses for the same area can vary because of the spatial resolution (Johnson and Howarth, 1987), and some patterns or processes can be recognized only at specific resolutions (Jelinski and Wu, 1996). A phenomenon could remain undetected because of an improper matching with the scale of analysis (Stohlgren *et al*, 1997).

For example, in investigating the fragmentation of open formations in the last 50 years in the Reserve of Poggio all'Olmo, a resolution of 40 x 40 metres may hide some fundamental ecological phenomena, e.g. changes in fine grained patterns such as linear formations, grouped trees, etc… (Rocchini *et al*, 2005). As a pragmatic example, the bundling of open formations as shrubs, viewed in Figure 2b, may provoke an underestimate of smaller patches of the open formation. On the contrary, the resolution of 10 x 10 metres is more suitable for the investigation of this phenomenon, particularly with respect to the limited extent of the study area. Otherwise, in investigating the spread of coniferous plantations, a suitable resolution should be the 40 x 40 metres because of the invariance of this class with respect to all the investigated metrics. A choice of a resolution of 10 x 10 metres could be only time and cost expensive.

On the other hand, the application of multiple scales (resolutions) can provide for information otherwise ignored. For example, the artificial nature of coniferous plantations has been highlighted by means of the cited invariance.

Another issue is concerned with the comparability among maps that have different origins and resolutions. Turner *et al* (1989) point out that measures made at different resolutions could not be compared, while Wu *et al* (2000; 2002), following this research approach, demonstrate that predictable metrics allow the translation of information from one scale to another. Some of these metrics were investigated in this paper and showed consistent patterns over a wide range of scales (e.g. number of patches, AWMSI, MPS, PSSD) and are therefore considered predictable metrics. On the contrary, other metrics (e.g. MSI), showed non-linear patterns, as highlighted by the non-homogeneous trend of this index for all classes.

Wu *et al* (2000; 2002) considered several indices of this last type (e.g. contagion, fractal dimension) by submitting a challenge to the scientific community: how to develop systematic procedures for the translation of information from one scale to another when simple scale laws do not occur?

CONCLUSION

In this paper, the issue of scale dependence of landscape metrics was addressed and the effect of scale was discussed. To summarise, when aiming to quantitatively relate landscape pattern to ecological processes that generate them, great attention must be paid to the input spatial resolution (MMU). In fact, no inference regarding the translation of information from one scale to another (whose solving is to date *in itinere*, as stated in the final part of the *Discussion*) could be made until the input scale (e.g. resolution) is correctly defined.

In this paper, grids were superimposed on an aerial photograph in order to simulate photointerpetation at different resolutions and to guarantee a robust definition of the MMU during classification procedures, however this approach is very labour intensive. On the other hand, common photointerpretation (polygon digitisation) appears to be subjective and not repeatable. In fact, although this method could be applied at a given scale of visualisation, the resulting objects (patches or polygons) could vary from one interpreter to another, thereby not assuring the same final MMU.

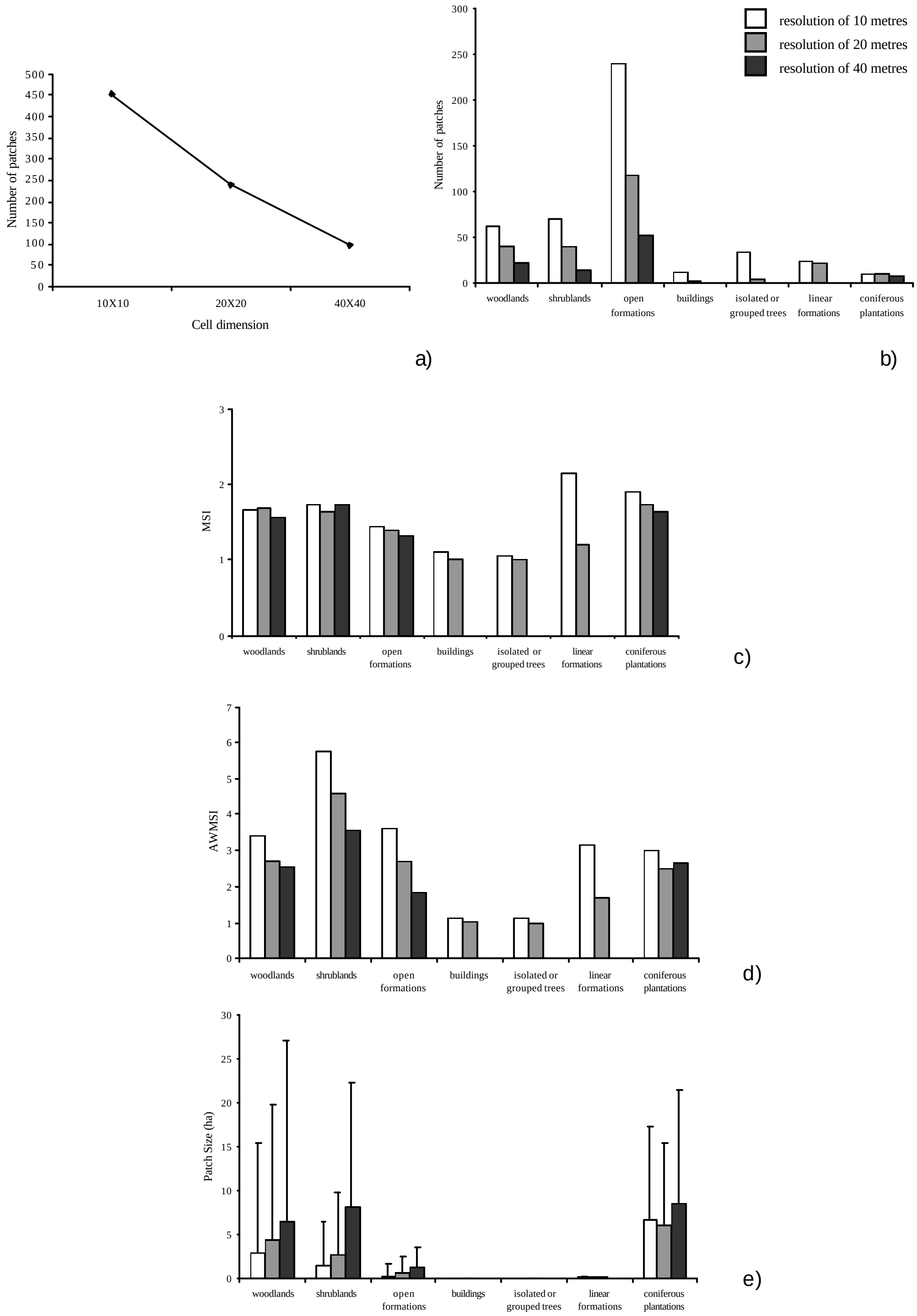

Figure 3. *Landscape structure metrics: a) number of patches; b) number of patches per class; c) Mean Shape Index (MSI); d) Area Weighted Mean Shape Index (AWMSI); e) Patch size: Mean Patch Size (MPS), columns, and Patch Size Standard Deviation (PSSD), bars.*

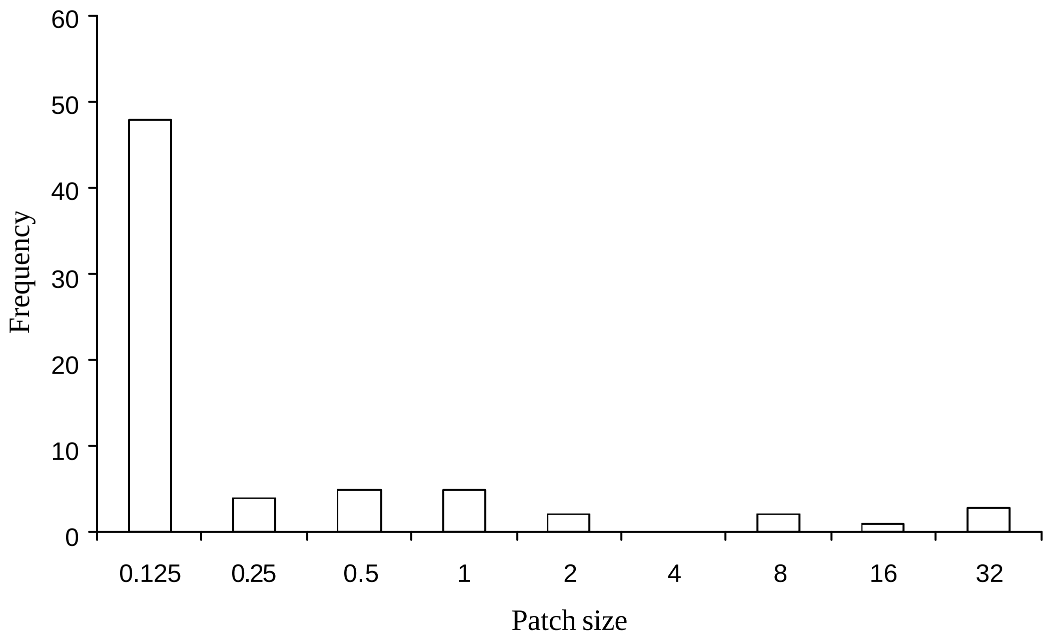

Figure 4. *'Shrublands' patches distribution with respect to size (in hectares), resolution of 10x10 metres.*

That is why using the pixel dimension of rasterised maps derived from manually digitised polygons, is not a valid approach for defining the MMU.

Moreover, since the *demand for rapid mapping operations such as database generation and updating is continuously increasing* (Armenakis *et al*, 2003), automated classification techniques should be encouraged. However, due to the generally low spectral resolution of aerial photographs, pioneering studies on automated *pixel-based* classification (Carmel and Kadmon, 1998) – nowadays principally used with satellite imagery (see also Townshend *et al*, 2004) – did not result in any positive outcomes. The only approach that shows promise appears to be *object-oriented* classification (segmentation) techniques based on agglomerative algorithms that utilise a user defined threshold resulting in identification of objects (e.g. vector polygons in GIScience or patches in Landscape Ecology), generated at a given specified scale. Moreover, this type of approach could seriously reduce problems in automated multi-scale classification (and contribute to the translation of information over multiple scales), since it is based on topological rules among hierarchical objects/patches (Burnett and Blaschke, 2003; Devereux *et al*., 2004; Schiewe, 2005).

This paper demonstrates the dependency of the quality of information contained in landscape metrics on the spatial resolution associated with their calculation. Advances into the application of landscape metrics to assist with the description of spatial patterns and associated ecological processes will also assist with the development of innovative classification techniques for interpretation of remotely sensed images.

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