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Multi-scale sampling and statistical linear estimators to assess land use status and change

Rocchini, D.[1,2]*; Marignani, M.[2,3]; Bacaro, G.[1,2]; Chiarucci, A.[1,2]; Ferretti, M.[1,2]; De Dominicis, V.[1] & Maccherini, S.[1,2]

[1]*Dipartimento di Scienze Ambientali 'G. Sarfatti', Università di Siena, via P.A. Mattioli 4, IT 53100 Siena, Italy;*
[2]*TerraData srl environmetrics, via P.A. Mattioli 4, IT 53100 Siena, Italy;*
[3]*Dipartimento di Biologia Vegetale, Università di Roma "La Sapienza", Piazzale Aldo Moro 5, IT 00185, Rome, Italy;*
E-mails: michela.marignani@uniroma1.it; bacaro@terradata.it; chiarucci@unisi.it; ferretti@terradata.it; dedominicis@unisi.it; maccherini@unisi.it;
**Corresponding author; Fax +39 057 723 2896; E-mail rocchini@unisi.it*

Abstract

Question: Multi-temporal analysis of remotely sensed imagery has proven to be a powerful tool for assessment and monitoring of landscape diversity. Here the feasibility of assessing land-use diversity and land-use change was tested at multiple scales and over time by means of statistical linear estimators based on a probabilistic sampling design.

Location: The study area (the district of Asciano, Tuscany, Italy) is characterized by erosional forms typical of Pliocene claystone (i.e. calanchi and biancane) that have been subject to the phenomenon of biancane reworking over the past 50 years, mainly owing to the expansion of intensive agriculture.

Methods: Cells at two different scales (50 m×50 m and 10 m×10 m) were classified by two operators according to a multilevel legend, using 1954 and 2000 aerial photographs. Inter-operator agreement and accuracy were tested by Cohen's *K* coefficient. Total land cover estimation for each class was carried out using a multistage estimator, while the variance was estimated by means of the Wolter estimator. Field-based information on plant species composition was recorded in order to test for a relationship between land use and plant community composition by ANOVA and indicator species analysis.

Results: Agreement between photointerpreters and accuracy were significantly higher than those expected by chance, proving that the approach proposed is reproducible, as long as proper quality assurance methods are used. Our data show that, at the two scales considered (50 m×50 m and 10 m×10 m), crops have increased against woodlands and semi-natural areas, the latter showing the highest and significantly different mean species richness. Meanwhile, an increase in the coverage of trees and shrubs was found within the semi-natural areas, probably as a result of secondary succession occurring on typical landscape elements such as biancane.

Conclusions: Inferential statistics made it possible to acquire quantitative information on the abundance of land cover classes, allowing formal multi-temporal and multi-scale analysis. Sampling design-based statistical linear estimators were found to be a powerful tool for assessing landscape trends considering both time expenditure and other costs. They make it possible to maintain the same scale of analysis over time series data and to detect both coarse- and fine-grained changes in spatial patterns.

Keywords: Indicator species analysis; Inferential statistics; Multi-temporal analysis; Remote sensing; Statistical linear estimators.

Nomenclature: Pignatti (1982)

Introduction

Owing to concern about the loss of diversity in landscapes, estimates of land cover status and changes are crucial environmental information for science-oriented resource management, for policy purposes, and for a range of human activities (Cihlar 2000). In this perspective, multi-temporal analysis of remotely sensed imagery has great potential for the assessment and monitoring of landscape diversity (Stoms & Estes 1993; Butaye et al. 1999; Defries & Townshend 1999; Rocchini et al. 2006). However, several problems may arise in interpretation of aerial photographs, involving issues such as scale, observer bias, spatial resolution and costs.

Scale is a key issue in ecological monitoring programs. In practice, thematic classification is structurally, functionally and operationally dependent on the scale at which the interpretation is carried out (Stohlgren et al. 1997; Saura 2002; see also review by Fassnacht et al. 2006). In addition, classification attributes should fit into a given reference framework, such as the CORINE system (i.e. a standardized land use legend used by all the European countries; see, Acosta et al. 2005; Bartholomé & Belward 2005).

Moreover, thematic classification requires great accuracy when defining the boundaries of the elements being studied. This has led to criticism about the definition of the spatial resolution of input data (Burnett & Blaschke 2003) in manual digitization of polygons. "Manual vegetation mapping is not only time/labour intensive, but also subjective" (Müllerová et al. 2005), which limits its reproducibility and introduces a serious source of bias in the resulting cover estimates. Pioneering studies on automated pixel-based classification (Carmel & Kadmon 1998) – now principally used with satellite imagery (see also Townshend et al. 2004) – have not resulted in increased classification accuracy, mainly because of the low spectral resolution of aerial photographs. However, object-based approaches appear promising: in the near future they will likely provide robust algorithms to produce a reproducible classification, also based on robust topological rules (Devereux et al. 2004).

Nevertheless, classification of aerial photographs over vast study areas can be extremely time consuming and costly, particularly considering the need to extract information at high resolutions.

Despite these problems, the classification of airborne imagery has the potential to assess land use status and change, coupling rigorous quality assurance with assessment. In this paper the aim is to: (1) propose a design-based cover estimation from airborne imagery by investigating advantages and disadvantages of this approach for assessing both diversity of land-cover types and their changes over time, by means of statistical linear estimators; and (2) analyse the relationships between the classification of land-cover types and plant species richness and composition. If proven feasible, this approach can be of use to investigate comprehensively land-use status and changes over large areas, at multiple spatial scales.

Methods

Study area

The study area is the district of Asciano (centroid coordinates: longitude 11°31′03″E, latitude 43°15′03″N, datum ED50), a 215 km^2 area situated in the landscape of the Crete Senesi, near Siena, Italy. The typical morphology of the landscape, which is dominated by arable land, derives from the erosion of Pliocene claystone resulting in particular forms of erosion (e.g. calanchi, peculiar eroded claystone hill sides, and biancane, peculiar claystone domes; see Phillips 1998). This particular cultural landscape has been subject to geomorphological simplification over the past 50 years (Guasparri 1993), following the advent of intensive agriculture. The abandonment of traditional activities and the intensification of agriculture are quickly reducing traditional cultural landscapes, leading to a loss of habitats and species diversity in many parts of peninsular Italy (Vos & Stortelder 1992; Phillips 1998).

Sampling design

Sampling units of predefined sizes (50 m×50 m and 10 m×10 m, depending on scale) were selected according to a stratified random sampling over the 215 square kilometres of the area frame (Fig. 1). First, 977 non-overlapping spatial strata, defined as L spatial units (500 m×500 m cells, derived from the UTM (ED50) kilometric grid), were distributed over the study area. Each 500 m×500 m unit l ($l = 1, \ldots, L$) was then divided into N_l 50 m×50 m units, the boundary of the study area being approximated to these units, thus resulting in $1 \leq N_1 \leq 100$ (Fig. 1). One 50 m×50 m unit j was then randomly selected for each l 500 m×500 m unit. Subsequently, each of these 50 m×50 m units j ($j = 1, \ldots, L$) was divided into 25 10 m×10 m units. All the 10 m×10 m units belonging to the selected 50 m×50 m units j were considered for the aerial survey at that scale. A random selection of 98 ($\approx$ 10%) of the 977 50 m×50 m sampling units was selected for the field survey (see section entitled Field sampling and analysis of plant species data). To this end, one 10 m×10 m unit (hereafter referred to as a plot) was randomly selected for each of the 98 50 m×50 m sampling units identified.

Aerial survey and field sampling were combined in order to obtain information on land use and species richness and diversity at several spatial scales. The integrated analysis was performed as follows: aerial photos from different years were photointerpreted at two different scales (50 m×50 m and 10 m×10 m), while field sampling was performed at a scale of 10 m×10 m with four inner subplots (replicates) of 1 m×1 m. The most recent photos were interpreted by two operators to test for agreement between photointerpreters and accuracy with respect to the field survey. Thus, further analysis was

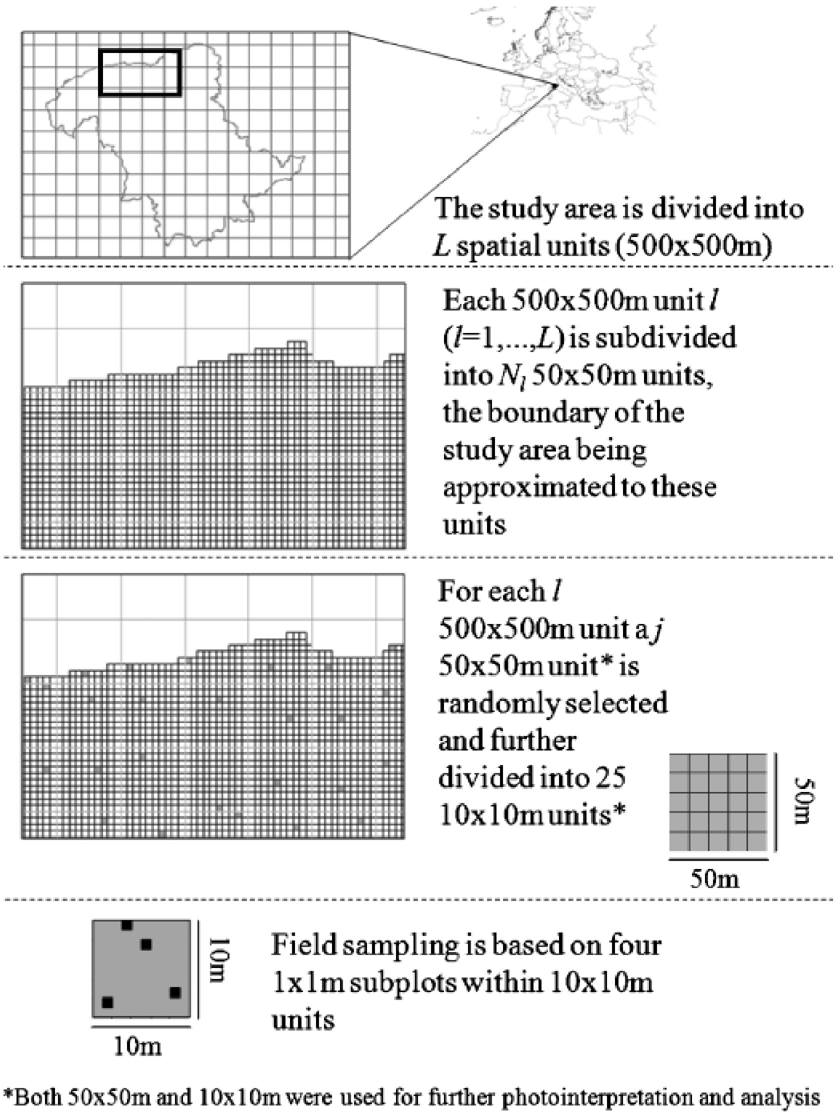

Fig. 1. Stratified random procedure applied for remote and field sampling design. We refer to the main text for major explanations.

performed considering both aerial and field surveys (Fig. 2).

Aerial survey

Photograph interpretation and classification scheme

Aerial panchromatic photographs (grey scale, 8 bit) from 1954 (flight height 6000 m) were acquired and scanned at high resolution (1000 dpi). Orthorectification was performed by using 20 ground control points (GCPs) for each photograph and a Digital Terrain Model (DTM, 10 m pixel dimension). In order to avoid spatial displacement effects (Rocchini 2004; Rocchini & Di Rita 2005) the 50 m×50 m sample (and subsequently the 10 m×10 m sample) was reselected for the 1954 photographs, thus different samples were used to carry out the total (i.e. population) estimate. Photointerpretation of the 977 50 m×50 m units was based on a standardized classification scheme, derived from the INFC legend (National Inventory of Forests & Carbon Sinks, see Table 1 for description of the classes; for further information see De Natale & Gasparini 2003). Heterogeneity within the 977 50 m×50 m units was investigated by photointerpreting the 25 inner 10 m×10 m units (see Fig. 1) using a more detailed classification scheme. The classes used for the

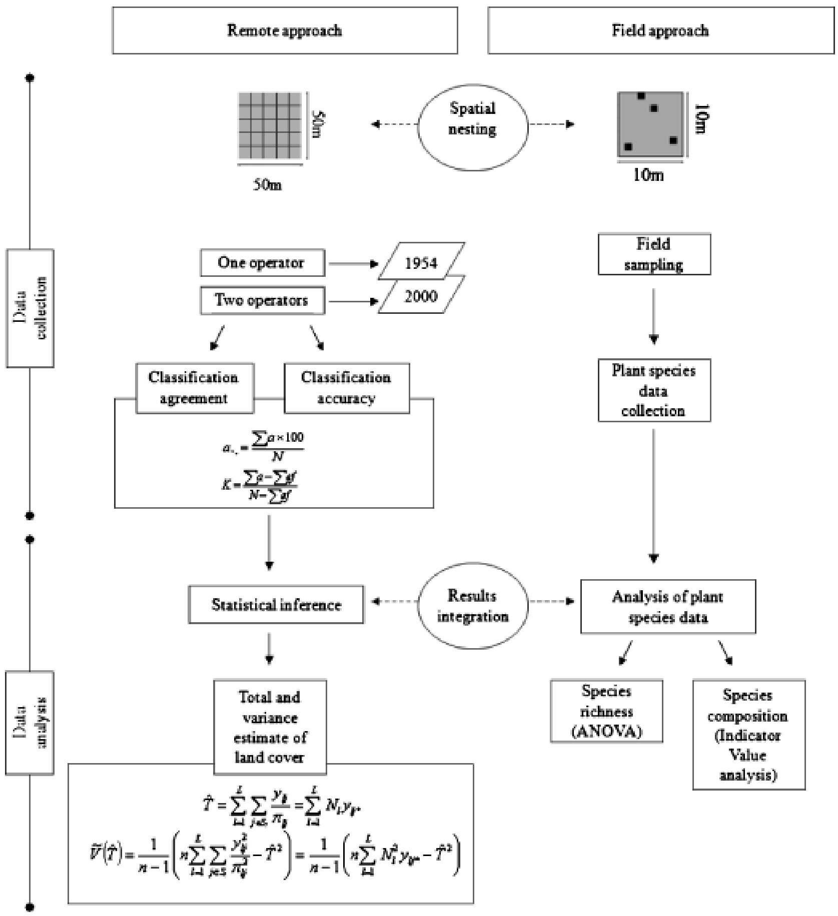

Fig. 2. Collection and analysis of remote and field data. The integration of results is achievable on the strength of the spatial stratification adopted for the sampling design.

Table 1. Classification scheme adopted for the photointerpretation of 50 m×50 m units, derived from the INFC legend (National Inventory of Forests and Forest Carbon Sinks, De Natale & Gasparini (2003) for further information).

50×50 classes	Description
Artificial use	Urban settlements and isolated housing, commercial and industrial buildings, roads
Crops	Arable land, vineyards, olive groves, artificial wood plantations
Woodlands and semi-natural areas	Natural and semi-natural woodland areas, areas with herbaceous vegetation and shrublands, pastures, grasslands, bare soil areas such as calanchi and biancane
Water	Lakes, natural or artificial basins, streams, pipes

10 m×10 m classification, defined on the basis of surface predominance, were: artificial use, crops, trees and shrubs, pastures, bare soil or sparse vegetation, natural and artificial lakes.

Quality assurance: classification agreement and accuracy

The 1954 photographs were photointerpreted by a single operator while the 2000 photographs were photointerpreted by two different operators, in order to ensure the quality of the approach used by testing the classification agreement between operators (Fig. 2). Two operators were used only for the most recent photographs (2000) since the aim was to check for both classification agreement and accuracy using the same photograph classified by different photointerpreters. Similar comparisons for the 1954 photographs would not add significant information regarding the extent to which the proposed approach is replicable.

Classification agreement (i.e. the agreement between operators when classifying the same 50 m×50 m or 10 m×10 m unit) was measured by the two most commonly used tests: overall agreement (Equation (1)) and Cohen's K coefficient, which also takes into account the probability of agreement occurring by chance (Equation (2)) (for further details see Cohen 1960; for a comprehensive review see Congalton 1991).

$$a_{\%} = \frac{\sum a \times 100}{N} \tag{1}$$

where a = raw agreement; N = total number of cases.

$$K = \frac{\sum a - \sum ef}{N - \sum ef} \tag{2}$$

where K = Cohen's coefficient and ef = expected frequency of agreement by chance.

The agreement between the classification based on the aerial survey and the classification based on the field survey (i.e. classification accuracy; see section entitled Field sampling and analysis of plant species data) was also based on the overall agreement, hereafter named "overall accuracy", and the Cohen's K coefficient.

Statistical inference via linear estimators

Total land cover estimation for each class was carried out using a multistage estimator, while the variance was estimated by means of the Wolter estimator (Wolter 1985; Equations (3) and (4), for estimates at the 50 m×50 m scale).

$$\hat{T} = \sum_{l=1}^{L} \sum_{j \in S_l} \frac{y_{lj}}{\pi_{lj}} = \sum_{l=1}^{L} N_l y_{lj^*} \tag{3}$$

$$\begin{aligned} \tilde{V}(\hat{T}) &= \frac{1}{n-1}\left(n \sum_{l=1}^{L} \sum_{j \in S_l} \frac{y_{lj}^2}{\pi_{lj}^2} - \hat{T}^2\right) \\ &= \frac{1}{n-1}\left(n \sum_{l=1}^{L} N_l^2 y_{lj^*} - \hat{T}^2\right) \end{aligned} \tag{4}$$

where N_1 = number of 50 m×50 m units within the 500 m×500 m unit l; $\pi_{lj} = \frac{1}{N_l}$ = inclusion probability of 50 m×50 m units j within the 500 m×500 m unit l; j^* = index identifying the 50 m×50 m unit selected within the 500 m×500 m unit;
$y_{lj} = \begin{cases} 1 & if \quad j \in c \\ 0 & if \quad j \notin c \end{cases}$ for a class c; $n = \#(S) = 977$
where S denotes the set of indices that identify the 50 m×50 m units selected within the area.

Based on the calculation of variance, the 95% confidence interval was calculated as:

$$CI_{95\%} = \hat{T} \pm 1.96\sqrt{\tilde{V}(\hat{T})} \tag{5}$$

where $\mathrm{CI}_{95\%}$ = 95% confidence interval; $\hat{T}$ = total estimate (as in Equation (3)); $\tilde{V}(\hat{T})$ = variance (as in Equation (4)).

Total and variance estimates were carried out at both spatial scales (50 m×50 m and 10 m×10 m) considering both survey years (1954 and 2000).

Field sampling and analysis of plant species data

Vascular plant species composition (presence/absence) was recorded within each of the 98 selected 10 m×10 m plots by using four randomly selected 1 m×1 m subplots per 10 m×10 m plot (total 392 subplots; Figs. 1 and 2), located following a restricted random procedure. For a complete discussion of the statistical properties of this sort of nested sampling procedure, which represents one of the most cost effective approaches for gathering plant species-composition data, and is based on an objective sampling design, see Kumar et al. (2006) and Baffetta et al. (2007).

The data on species richness per subplot were normalized by an iterative Box-Cox transformation. A maximum likelihood approach gave the best value of $\gamma = 0.066$ where γ is the Box-Cox power (Legendre & Legendre 1998).

To investigate the relationship between plant species richness and remotely sensed classes, the transformed data on plant species richness per subplot were analysed using a mixed-model nested ANOVA. By this model we tested for the effect of fixed factors such as land cover classes (level 1 classification) and random factors such as plots within classes on species richness. Summarizing, the model incorporated the following factors: (1) land cover class (fixed factor with three levels: artificial, crops, woodlands and semi-natural areas. No subplots fell within the "water" class); and (2) 10 m×10 m plots (random factors nested within classes). Whenever ANOVA detected significant differences for the factors, independent comparisons were performed (Underwood 1997) using Tukey's test.

The contribution of particular species as indicators of the dominating physiognomy characterizing the different land cover classes was also assessed by performing an indicator species analysis (Dufrene & Legendre 1997; McCune & Mefford 1999). The method combines information on the concentration of species, defined as species frequency in the subplots, in two or more groups defined a priori, considering the constancy of occurrence of a species in a particular group. This comparison produces an indicator value (IV) for each species in each group, ranging from zero (no indication) to 100 (perfect indication). The results were tested for statistical significance using a Monte

Carlo technique: the null hypothesis is that the indicator value observed is no higher than that expected by chance (i.e. that the species has no indicator value, since its presence is the same as that expected by chance).

Results

Aerial survey

Quality Assurance: classification agreement and accuracy

Agreement between photointerpreters, based on the most recent photographs (2000, see the corresponding Methods section entitled Quality assurance: classification agreement and accuracy) was 91.09% and 91.12% at 50 m×50 m and 10 m×10 m, respectively. Cohen's K coefficients were 0.81 and 0.84 at 50 m×50 m and 10 m×10 m, respectively, and they were significantly different from zero ($P<0.01$), indicating that agreement was significantly higher than expected by chance. Accuracy (i.e. the agreement between aerial classification and field-based classification) at the 10 m×10 m scale was 74% and 77%, for operators 1 and 2, respectively, and therefore lower than the agreement between photointerpreters. However, Cohen's K coefficient was significantly different from zero in both cases (0.52 and 0.60, for operators 1 and 2, respectively, with $P<0.01$ in both cases).

Land-cover estimates: status and change

Since agreement between observers was high, the results presented here were based on the classification of only one of them. The 2000 data were in line with the CORINE Land Cover level 2 data (standardized to the classification scheme used) for the same study area (Table 2).

Multi-temporal analysis at the 50 m×50 m scale showed a substantial increase in crops compared

Table 2. Comparison between photointerpreted data (scale 50 m×50 m, 2000) and CORINE land-cover data (standardized to the classification scheme used).

Class	% CORINE land cover	% 50 m×50 m units
Artificial use	0.9	1.3 ± 0.7
Crops	66.5	66.1 ± 3.3
Woodlands and semi-natural areas	32.5	32.3 ± 3.1
Water	0	0.3 ± 0.4

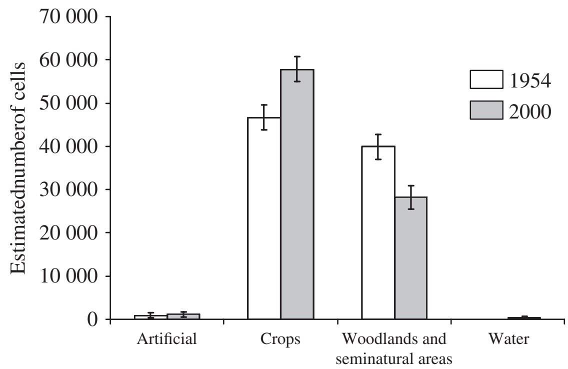

Fig. 3. Temporal variation between 1954 and 2000 in the frequencies of the land cover classes recorded in the 50 m×50 m cells. Error bars represent the 95% confidence interval.

with woodlands and semi-natural areas (Fig. 3). Artificial areas remained almost unchanged. No water bodies were detected on the basis of the 1954 photos, while 300 50 m×50 m units were assigned to this class in the year 2000.

The proportions of 10 m×10 m units assigned to different categories within each 50 m×50 m classified unit are reported in Fig. 4. Within the artificial use class (estimated total: 1.1×10^3 cells; 1.3% of the total), 67% was constituted by urban settlements, isolated houses, industrial buildings and roads (Fig. 4), which were interspersed with crops, trees and shrubs and pastures. This composition remained almost unchanged over the period 1954-2000 and fitted the characteristics of a poorly industrialized or built-up landscape matrix.

Crops were by far the most frequent land-use category, amounting to 57.8×10^3 cells (66.1% of the total), with an increase between 1954 and 2000 (Fig. 3). Intra-class heterogeneity (Fig. 4) was unchanged between 1954 and 2000: crops maintained a high level of homogeneity, with trees and shrubs and pastures occupying less than 10% of the class on both survey dates. This pattern reveals a homogeneous landscape matrix dominated by intensive agriculture and characterized by a scarcity of ecological corridors such as remnant hedges and woods.

Woodlands and semi-natural areas were the second most frequent land use category (Fig. 3), covering 28.2×10^3 cells, amounting to 32.3% of the total. A higher intra-class fragmentation was evident in 1954 (Fig. 4), when trees and shrubs were limited to 49.7% of "woodlands and semi-natural vegetation" class, the remaining land being divided into pastures, bare soil (42.3%) and crops (6.2%).

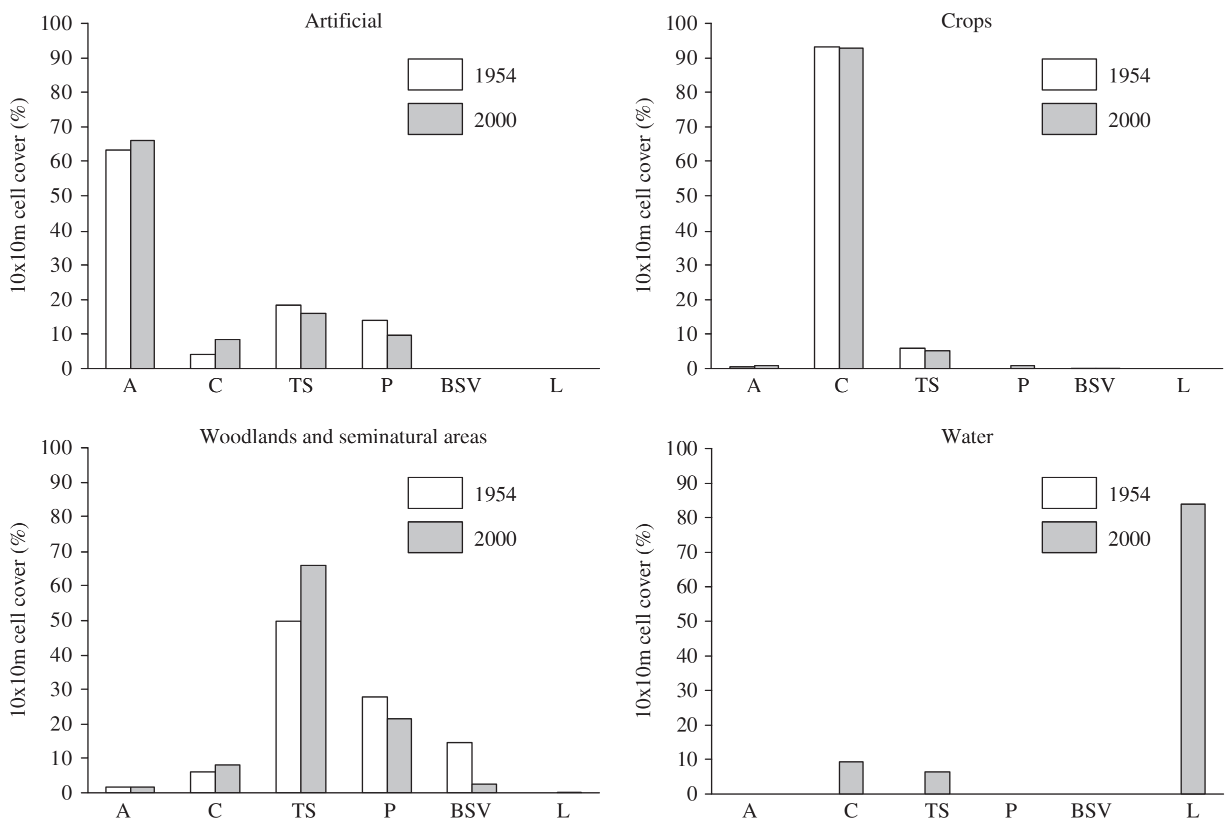

Fig. 4. Temporal variation between 1954 and 2000 in the frequencies of the land cover classes recorded in the 10 m×10 m cells, as percentages within the 50×50 m cells. Classes used for the 10 m×10 m classification (*x* axis) were based on inner dominance: A, artificial; C, crops; TS, trees and shrubs; P, pastures; BSV, bare soil or sparse vegetation; L, natural or artificial lakes.

Artificial areas occupied a small area in both survey years. A general increase in trees and shrubs was found, indicating encroachment on open areas such as pastures and bare soil (i.e. typical badlands formations such as calanchi and biancane; see Fig. 4).

Water bodies (Fig. 4), detected only in 2000, were represented by artificial lakes for irrigation (84% of the water class). Fragments of crops and trees occasionally occurred within the class.

Species richness and indicator species analysis

A total of 244 species was recorded in the 392 (i.e. 98×4) subplots. Species richness per subplot ranged from 0 to 25 (mean 6.1). Mean species richness differed among the classes (Table 3): woodlands and semi-natural areas showed the highest species richness, while the species richness of artificial use and crops classes was similar ($P>0.05$, Tukey's test, Table 4).

Table 3. Nested analysis of variance on the number of species per subplot. Summary of the results of a mixed model nested ANOVA for species richness. $^{***}P<0.001$.

Source of variation	*df*	SS	MS	*F*
Intercept	1	312.0927	312.0927	279.0213***
Class	2	25.4806	12.7403	13.3113***
Plot (Class)	95	106.26	1.1185	12.1005***
Residual	294	23.1666	0.0788	

Species classified as indicator species for the photointerpreted land cover classes (Table 5) showed a high and statistically significant Indicator Value ($P<0.001$). Five indicator species were indicated for the artificial use class (*Papaver rhoeas*, *Brachypodium rupestre*, *Quercus ilex*, *Plantago lanceolata* and *Bromus erectus*) but, because of the small sample size (four subplots, compared to 268 for crops and 120 for woodlands and semi-natural areas), this class was excluded from further indicator species analysis (Table 5).

Table 4. Mean number of species in the different classes. Different letters indicate significant differences with $P<0.01$. Artificial use and crops were not statistically different from each other but they were both statistically different from woodlands and semi-natural areas.

Class	Number of species (mean ± SE)
Artificial use	3.7 ± 0.2a
Crops	5.0 ± 0.2a
Woodlands and semi-natural areas	8.7 ± 0.4b

Table 5. Indicator species with respect to the photointerpreted classes. Note that Artificial and Water classes were excluded from the analysis because of the unbalanced sampling size for each class (Artificial, four plots; Crops, 268 plots; Woodlands and semi-natural areas, 120 plots; Water, 0 plots), which derives from the random selection of the field sample.

Species	Class	Observed indicator value (IV)	Indicator value (IV) derived from randomized groups (mean ± SD)	*P*
Triticum aestivum	Crops	63.4	27.6 ± 2.07	<0.001
Avena fatua	Crops	37.4	21.4 ± 1.98	<0.001
Lolium perenne	Crops	32.5	18.1 ± 1.98	<0.001
Rubus ulmifolius	Woodlands and semi-natural areas	31.8	9.4 ± 1.46	<0.001
Ligustrum vulgare	Woodlands and semi-natural areas	26.8	7.7 ± 1.32	<0.001

Discussion

Advantages and disadvantages of design-based cover estimation from airborne imagery

Inferential statistics permitted the acquisition of quantitative information on the abundance of land-cover classes, allowing multi-temporal and multi-scale analyses on a formal basis. This is of help in detecting processes that are typical of particular spatial scales (e.g. fine-scale shrub and wood encroachment). Moreover, as noted by Cihlar et al. (2000), who implemented an image subsampling approach for land cover classification, when dealing with the extraction of quantitative landscape information, measures of statistical confidence need to be obtained. This can be done only if the probability of each sample is known, as shown in this paper. Such a procedure is much more cost-effective than traditional land-cover estimates derived from digitized maps, which do not guarantee an a priori definition of the MMU (Minimum Mapping Unit – see Müllerová et al. 2005).

Unlike a map-based approach, the proposed sampling approach makes it possible to acquire information on landscape composition rather than landscape structure. Thus, no information about landscape structure, as obtained by commonly used patch-based metrics (e.g. shape metrics, isolation metrics; for a comprehensive review see Wu et al. 2002) can be calculated. Meanwhile, a semi-variogram-based theory, considering not only pixel composition but also the pixel structuring (Cressie 1993), could help to solve this issue in a straightforward manner. It is worth noting that, generally speaking, a map would be highly beneficial to illustrate the spatial extent of changes. The lack of a map would probably represent a defect in most spatial approaches to landscape change (Rocchini & Ricotta 2007). However, the improper use of coloured maps without considering MMU problems would lead to quantitatively incorrect results (Rocchini et al. 2006). Moreover, while automatic boundary delineation techniques such as segmentation (Burnett & Blaschke 2003) could be used to address the problem of MMU definition, it should be stressed that panchromatic imagery would require manual post-classification due to the poor spectral resolution of the 8-bit single band (panchromatic) support (Marignani et al. 2008). This would imply an increase in time and effort, thus limiting the powerfulness of segmentation for large study areas such as that analysed here. Even if the proposed method does not allow us to build "maps", it represents a robust and above all reproducible approach. It is worth remembering that this paper focuses on the quantitative problems that arise when approaching landscape status and changes at a specific spatial scale, even if the method is restricted to coverage or abundance of classes and changes between them, mainly based on pixel counting.

Nevertheless, pixel counting (like that used in this paper) could be misleading because it does not take into account the probability of obtaining mixed pixels (i.e. pixels with a high inner heterogeneity; see also Congalton 1991; Fisher 1997; Cracknell 1998; Foody 2000). Conversely, because of the dependence of information contained in landscape metrics (in this case, area covered by classes) on the spatial resolution associated with their calculation (the well known MMU Problem: see, for example, Openshaw

1984; Jelinski & Wu 1996), cells with a predefined dimension at different resolutions guarantee a robust definition of the MMU during classification procedures. This permits (1) the association of the landscape pattern to the ecological processes that generate them (acting at a given scale) in a quantitative way, and (2) the translation of information from one scale to another (Wu & Qi 2000; Wu et al. 2002). It is worth recalling that results of analyses for the same area can vary because of the spatial resolution (Johnson & Howarth 1987) and that some patterns or processes can only be recognized at specific resolutions (Jelinski & Wu 1996). A phenomenon could remain undetected because of improper matching with the scale of analysis (Stohlgren et al. 1997).

As stressed by Cihlar (2000), reproducibility is a crucial criterion in land cover classification (i.e. the same result should be obtained by various analysts given the same input data). In this paper we focused on the scale properties of land cover classification (i.e. maintenance of the same MMU) rather than on issues of thematic attribution. However, it should be noted that classification is in its very nature a human construct (Palmer et al. 2002), with the analyst playing a key role in the entire classification process. At present, even considering thematic attribution, the proposed methodology represents a reproducible approach on the strength of the high classification agreement achieved between different photointerpreters.

Contribution of land use and species information to explaining ongoing ecological dynamics

Remote sensing has long been used to relate field data directly to the spectral properties of mapped habitats and vegetation communities (Nagendra 2001; Palmer et al. 2002; Acosta et al. 2005; Thessler et al. 2005; Fassnacht et al. 2006; Marignani et al. 2007; Rocchini et al. 2007). In our study the remote approach, performed at multiple scales of analysis, allowed us to separate vegetation physiognomy. Moreover, the results obtained from remotely sensed data were closely related to the information gathered for plant species richness and composition. In the crops class, the homogeneous landscape matrix dominated by intensive agriculture was confirmed by the low values of species richness (comparable to the species richness of the artificial areas), reinforced by the high values of the indicator species *Avena fatua* and *Lolium perenne* (see Table 5), which are typical cereal weeds; this means that a few very abundant species characterize these environments. Species indications confirm that the crops class is principally occupied by agriculture and lacks areas of natural vegetation, with a scarcity of natural elements, such as hedgerows and remnant woodlands.

In contrast, the woodlands and semi-natural areas class was characterized by a higher species richness and by indicator species that suggested the presence of transitional woodland shrubs rather than real forests. *Rubus ulmifolius* and *Ligustrum vulgare* are typical shrubland species that characterize secondary succession as well as marginal vegetation found in impluvia and edges (De Dominicis 1980; Chiarucci et al. 1995; Maccherini et al. 1998, 2000).

The trend observed from remote sensing and confirmed by field data is coherent with the European situation in which the recent abandonment of traditional management techniques in favour of the intensification of agriculture has drastically reduced natural and semi-natural areas, producing a general homogenization of the landscape (Vos & Stortelder 1992; Bakker & Berendse 1999; Stoate et al. 2001; van Eetvelde & Antrop 2004).

This tendency, together with the loss of the traditional state of dynamic equilibrium between anthropogenic management and natural dynamics, is allowing woody species to progressively encroach on open habitats and directly influences biodiversity at species, community and landscape scales (Mazzoleni et al. 2004; Tatoni et al. 2004; Rocchini et al. 2006). An increase in surfaces used for crop cultivation in relation to those covered by woodlands and semi-natural areas in the study area was clearly visible from 1954 to 2000. Meanwhile, an increase in the coverage of trees and shrubs was noticeable within the woodlands and semi-natural areas, probably as a result of secondary succession occurring on typical landscape elements such as biancane. A decrease in pastures and bare soil or sparse vegetation was observed in the "woodlands and semi-natural vegetation" class, accompanied by an increase in trees and shrubs. This suggests a secondary succession pattern in these areas, as also demonstrated by the presence of *R. ulmifolius* and *L. vulgare* as indicator species of woodlands and semi-natural areas.

The general trend from 1954 to 2000 showed an ecological dynamic that is leading to a more coarsely grained pattern even at a detailed scale, by losing the remnants of ecological corridors (i.e. hedges and marginal woods) and typical geomorphological landforms (such as calanchi and biancane) of 1954, with a homogenization of the landscape matrix towards an extensive agriculture framework. Furthermore, the abandonment of pastures and reduced grazing pressure on biancane fields are the main factors behind the priorities on conservation of these geomorphological landforms. In fact, when disturbance induced by humans decreases and eventually stops, shrubs promptly encroach on abandoned lands, leading to an overall homogenization of the landscape (Noy-Meir et al. 1989).

Thus, both the increase in the crop area and the encroachment on semi-natural formations, such as grasslands, by dense shrubs and woods are expected to convert a complex landscape matrix into a highly homogeneous system, adversely affecting the overall diversity of the areas examined (Baessler & Klotz 2006).

Conclusions

The feasibility of land-use diversity assessment at multiple scales by means of statistical linear estimators was tested in this paper. In particular, we presented an integrative approach combining remotely sensed and field-based data. The proposed sampling design was useful for studying ecological dynamics at several spatial scales, in that it allowed analyses starting from the community level (e.g. ANOVA and indicator species analysis) up to the landscape level. Moreover, the comparison between observers proved that the proposed approach is reproducible, as long as proper quality assurance methods are used.

Multiscale sampling and statistical linear estimators seem to be essential in different respects: first, they make it possible to extract quantitative data for the attribute of interest; second, they improve cost efficiency; third, they allow one to maintain the same scale of analysis over time series data; and fourth, they permit the detection of both coarse- and fine-grained spatial pattern changes. The proposed approach therefore seems to be both feasible and reliable for land-cover estimation over large areas.

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