Landscape and Urban Planning 140 (2015) 42–55

Contents lists available at ScienceDirect

Landscape and Urban Planning

journal homepage: www.elsevier.com/locate/landurbplan

Research paper

Landscape sequences along the urban–rural–natural gradient: A novel geospatial approach for identification and analysis

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HIGHLIGHTS

- Landscapes nested in anthropogenic gradients were spatially identified and classified.
- The patterns and dynamics for each landscape along the gradient were explored.
- A particular focus on urban–rural and rural–natural fringe areas was developed.
- The approach can support a better spatial contextualisation of land use issues.

ARTICLE INFO

Article history:
Received 26 August 2014
Received in revised form 10 March 2015
Accepted 2 April 2015

Keywords:
Landscape gradients
Urban–rural–natural gradient
Fringe areas
Kernel density estimation
Cluster analysis
Landscape metrics

ABSTRACT

Human influence on the environment differs in terms of distribution and intensity, thus producing a gradient of landscape modifications that translates into different landscape structures. Within this variety of landscapes, fringe areas represent complex spaces where dynamic processes and instable conditions can be observed. In this research Kernel Density Estimation, multivariate spatial analysis, landscape pattern analysis, and Principal Component Analysis (PCA) were combined to model and characterise landscape gradients, and to analyse the structural features of fringe areas. This methodology was applied to a rural area of central Italy, using density indicators associated with urbanisation, agriculture, and natural elements considered to be key components for the identification of landscape gradients. The results highlight not only specific "pillar" landscapes, which are dominated by said components, but also transitional landscapes, where the most relevant forms of interaction between land uses were identified. Characterisation of landscape structures along the gradient illustrated different trends in patch density, shape complexity and landscape diversity, demonstrating greater variability in fringe areas than in pillar landscapes. PCA revealed a partial overlap between the main structural characteristics of the agro-forestry matrix and the medium intensity agricultural landscapes, whereas urban fringes and semi-natural fringes were clearly separated. The discovery of the continuous landscape gradients and an understanding of the gamut of landscape types nested along them is crucial in allowing for more effective land-use planning in which also fringe areas become a relevant part of the process.

1. Introduction

European landscapes are intensively changing due to an unprecedented increase in human impacts on ecosystems (Pearson & McAlpine, 2010). Urban sprawl has been recognised as the cause of many relevant impacts that result in the loss of agricultural and natural land and the fragmentation of forests, wetlands and other natural habitats (EEA, 2006; Piorr, Ravetz, & Tosics, 2011). The intensification of agricultural land uses since the second half of the last century has progressively introduced industrial production, with the consequent effects of landscape simplification, degradation of soil and water quality (Vizzari & Modica, 2013), loss of natural habitat (Matson, 1997; Sodhi & Ehrlich, 2010; Tilman et al., 2001) and diversity of wild species (Maron et al., 2012; Gentili, Sigura, & Bonesi, 2014), and the impairment of ecological functions (Flynn et al., 2009). Conversely, the decline of extensively used agricultural areas due to abandonment and their consequent re-naturalisation has been recognised as a process that may lead to conflicts with biodiversity conservation (e.g., threats to farmland birds) (Henle et al., 2008). Thus, human activities are major forces in shaping landscape structure, creating a mosaic of natural and human-managed patches that vary in type, size, shape and

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http://dx.doi.org/10.1016/j.landurbplan.2015.04.001

arrangement. Relationships between the distribution of energy, materials and species are directly influenced by such structures, which appear critical to understanding ecological processes and landscape functions (Botequilha Leitão & Ahern, 2002; Li et al., 2005; Turner, 1990).

Human influences on landscape composition and configuration are so different in distribution and intensity as to make it necessary to consider them as a gradient of landscape modifications (Godron & Forman, 1983). The environmental gradient paradigm, which was originally introduced by Whittaker (1967), states that environmental variation is ordered in space and drives the distribution of the structural and functional components of ecosystems (McDonnell & Pickett, 1990). Thus both simple and complex gradients can be found in landscapes. The former refer to an environmental series due to a single, measured, environmental factor, whereas the latter are based on several factors (man-made or natural), some of which may interact (McDonnell, Pickett, & Pouyat, 1993). Anthropogenic gradients, generated by the increase of human influences on the structure and functions of landscapes, were identified by Forman and Godron (1986) in the specific succession of natural–managed–cultivated–suburban–urban landscapes. Along such a sequence, typical modifications in the structures and functions of ecological systems can be observed (see e.g., Luck & Wu, 2002; McDonnell & Pickett, 1990): introduced man-made patches increase, whereas patches of natural land cover decrease; patch density increases together with patch shape regularity, whereas the mean patch size and landscape connectivity decrease.

In the gradient view, even the urban–rural dichotomy can be thought of as a landscape gradient shaped by a sliding level of human influence from rural to urban landscapes, including ecological processes, flows and movements of goods, energy, people, capital, and information (Modica et al., 2012). This innovative view implies the identification of fringe regions, those particular land use/land cover (LULC) transitional areas, such as peri-urban and agro-forestry areas, characterised by specific and crucial ecological processes. These interfaces represent complex landscapes where more or less markedly unstable conditions arise involving both the internal configuration of the landscape and the relationships with its surroundings. As a result, different evolving environmental and socio-economic equilibriums can be observed (Cavailhès, Peeters, Sekeris, & Thisse, 2004; Valentini, 2006). Urban sprawl, soil sealing, crop system transformations and the abandonment of marginal areas are typical and recognisable processes in these areas (Agnoletti, 2007). In particular, the urban–rural interface represents an intricate space from the economic, environmental and social viewpoint, especially as regards its proximity to and mutual dependence on cities and rural areas (Ives & Kendal, 2013; Vejre, Jensen, & Thorsen, 2010). Land-use conflicts, species and habitat conservation, preservation of cultural heritage, changes in lifestyles, and products and services from multifunctional agriculture are some of the main topics of the discussion on rural–urban linkages (Cavailhès et al., 2009; Marcheggiani, Gulinck, & Galli, 2013; Von der Dunk, Grêt-Regamey, Dalang, & Hersperger, 2011; Zasada, 2011). Conversely, recent decades have seen an increased awareness of the issues emerging from the complex relationship between agricultural, forestry and pastoral activities in agro-forestry interfaces. The dynamics of post-crop cultivation, arising from cultivations being abandoned, determine an uncontrolled evolution in land cover due to their particular environmental conditions. This phenomenon often appears associated with several changes such as a loss of productive land, an increase in the risk of landslides and a loss of biodiversity associated with traditional agricultural management (Agnoletti, 2007; Gellrich & Zimmermann, 2007).

A considerable body of literature has focused on urban–rural fringe areas as multifunctional landscapes, which include a large variety of activities linked to environmental, social and economic functions (Zasada, 2011). The local production of food and bio-fuel for self-sufficiency of urban communities (Erickson, Taylor Lovell, & Méndez, 2013), the values people assign to the features of the agricultural landscape (Ives & Kendal, 2013) and the structure of the landscape patterns (La Greca, La Rosa, Martinico, & Privitera, 2011) represent some of the many landscape issues explored in such contexts. Moreover, urban fringe areas represent a key topic in the academic debate for their potential contribution to a higher quality of life in Europe and to a more globally competitive European community (Watt, 2012). As a consequence, a wide range of approaches and applications have been developed for the spatial detection and characterisation of urban fringe areas along the urban–rural gradient (see e.g., Murgante, Las Casas, & Sansone, 2008; Myers & Beegle, 1947; Pryor, 1968; Wehrwein, 1942; Yang, Zhou, Gong, & Wang, 2012). Many of them have focused on urban sprawl and change detection using remote sensing techniques (Bhatta, Saraswati, & Bandyopadhyay, 2010; Fichera, Modica, & Pollino, 2010; Ji, Ma, Twibell, & Underhill, 2006; Liu & Zhou, 2005; Luo, Yu, & Xin, 2008; Sun, Wu, Lv, Yao, & Wei, 2013; Yu & Ng, 2007). In the majority of such studies, although the urban–rural gradient appears generally identified and investigated, the main focus is on the urban component and its spatio-temporal evolution in light of the ongoing urban growth and sprawl phenomena. The landscape gradient approach has also been adopted to evaluate biodiversity levels in comparison with agricultural intensity (Boscutti et al., 2015; Culman et al., 2010; Gentili et al., 2014) or urbanisation (Dearborn & Kark, 2010; Goddard, Dougill, & Benton, 2010; Kowarik, 2011).

Despite all of these applications, studies aiming to understand the types of landscape structures along the entire gradient of LULC changes due to the different intensities of anthropogenic landscapes are still missing. Discovering the continuous landscape gradients and understanding the gamut of landscape types nested along them is crucial to allowing effective land-use planning. In fact, if new spatial planning concepts are needed for the rural–urban fringe to integrate gradual densification of built-up areas with preservation of green areas and agriculturally managed open space (Piorr et al., 2011), further attention to rural–natural fringes is required to maintain their relevant functions and related ecosystem services. To this end, the landscape gradient approach proposed by McGarigal and Cushman (2005) in the area of spatial ecology seems promising. This landscape gradient model is based on variable intensities and evaluates a continuous rather than a discrete spatial heterogeneity. Several advantages are recognised in modelling environmental variation as continuous gradients, such as overcoming the subjectivity of defining cut points for variability categorisation and a better description of ecological processes that occur with different intensities in the environment (e.g., organism perception, distribution of resources) (Bridges, Crompton, & Schaffer, 2007).

Among the several analysis tools useful for studying the continuous variation of spatial heterogeneity, density analysis provides a direct assessment and visualisation of phenomena intensity. Density analysis has been widely applied in quantitative geography for many different purposes, for example, urban population analysis (Griffith, 1981), crop yield estimation (Myers & Foale, 1981), forest assessment (Franklin, Michaelsen, & Strahler, 1985), and landscape ecology studies (Farina, 2006). Density analysis tools, available within the GIS environment, allow researchers to transform values measured at specific locations on continuous surfaces to obtain the general trend of the spatial distribution for the considered variable (Bailey & Gatrell, 1995). Kernel Density Estimation (KDE) has already been used to represent and analyse spatial trends generated by landscape features as well as their potential ecological interactions or influences on the surrounding landscape (Cai, Wu, & Cheng, 2013; Modica et al., 2012; Vizzari, 2011a) and for

Table 1
Main metadata of data sets used for the analysis (*CAP = Common Agricultural Policy*).

Layer	Data owner	Format	Reference scale	Time period content
Land use	Regional Land Planning Department	Vector–Polygons	1:10.000	Year 2000
CAP data	Regional Department of Agriculture	Tabular	–	Year 2000
Cadastral parcel centroids	Regional Land Planning Department	Vector–Points	1:2.000	Year 2002
Olive groves	National olive trees inventory	Vector–Points	1:1000	Year 2001
Population data	ISTAT–Italian Statistics National Institute	Tabular	–	Year 2000
Census zones	ISTAT–Italian Statistics National Institute	Vector–Polygons	1:2000	Year 2000

the spatial modelling of landscape quality (Vizzari, 2011b). Unlike other gridding techniques, KDE results are very useful for uncovering structural features in the data, which a parametric approach might not reveal (Wand & Jones, 1995). KDE produces smoothed surfaces by applying a moving window superimposed over a grid where the density of studied variables is estimated at each location according to a kernel function (Bailey & Gatrell, 1995). Like other generalisation methods, KDE attenuates the effects of both uncertainty and errors existing in the source data, depending on the kernel function and bandwidth used in the analysis (Simonoff, 1996). The degree of smoothing is controlled by the kernel bandwidth (Gatrell, Bailey, Diggle, & Rowlingson, 1996); generally, its definition is a sensitive step because a wider radius shows a more general trend, smoothing the spatial variation of the variable, while a narrower radius highlights more localised effects in the distribution (Borruso, 2008; Jones, Marron, & Sheather, 1996). Two main approaches to determine bandwidth can be found in the literature: the first, more frequently employed, uses a fixed bandwidth to analyse the entire distribution, while the second implements a local adaptive bandwidth (Danese, Lazzari, & Murgante, 2008). However, the examination of resultant surfaces for different values of bandwidth remains a common method supporting the definition of this parameter (Bailey & Gatrell, 1995; Lloyd, 2007).

Clustering procedures are commonly used to describe multivariate data in terms of groups (clusters) that are characterised by strong internal similarities (Everitt et al., 2011; Jain, Murty, & Flynn, 1999). These procedures are often used for LULC classification based on multiband raster data (remote sensed images or scanned photographs) and can be either supervised or unsupervised (Campbell, 2002; Lillesand & Kiefer, 2008; Richards, 1999). Unsupervised classification methods are very powerful because they may identify a number and composition of classes that do not correspond to predetermined notions about the landscape structure (Irvin, Ventura, & Slater, 1997). The *k*-means procedure is among the most widely used unsupervised clustering algorithms (MacQueen, 1967). A very popular variant of this technique is ISODATA (Iterative Self-Organising Data Analysis Technique) (Ball & Hall, 1965), which is commonly used for unsupervised classification of digital images (see e.g., Ali et al., 2013; Lioubimtseva & Defourny, 1999; Richards, 1999; Usha & Singh, 2013; van der Kwast et al., 2009). Like *k*-means, this technique organises data iteratively into a number of groups, where objects of the same group are more similar than those belonging to different groups, computing the minimum square average distance of each point from its nearest centre. The main difference from the *k*-means algorithm is that the user is required to indicate a rough estimate of the number of clusters. The ISODATA algorithm uses different heuristic methods to optimise this number by removing small clusters, merging neighbouring clusters or splitting larger and more widespread clusters.

Landscape pattern analysis is widely used to explore landscape structural characteristics by means of a large number of spatial metrics (Botequilha Leitão & Ahern, 2002; Forman & Godron, 1986; Godron & Forman, 1983; Li et al., 2005; McGarigal & Marks, 1995; Palmer, 2008; Turner, 1990; Uuemaa, Antrop, Roosaare, Marja, & Mander, 2009; Wu, 2000) both in urban growth studies and land use change modelling (Herold, Couclelis, & Clarke, 2005; Liu & Zhou, 2005). Within this framework, the transect method has been widely used for the analysis of urban to rural gradients (Hahs & McDonnell, 2006; Wang, Li, Wu, & Song, 2006; Yang, Zhou, Gong, & Wang, 2010) and in spatio-temporal pattern detection (Fichera et al., 2010; Luck & Wu, 2002; Weng, 2007). However, the comparison of metrics referring to the same extents, even if it allows a simpler and more intuitive interpretation of changes within specific areas, may result in an incomplete understanding of the evolution of the landscape gradient configuration and the spatial structure of transitional landscapes (Vizzari, 2011a).

In the framework depicted above, we propose the integration of both continuous and categorical approaches to identify and characterise landscape gradients. This approach will better capture and analyse the gradual changes of LULC composition and configuration across the landscape. Our hypothesis is that density analysis provides the measure of LULC intensity variation, expressing the general trend of the spatial distribution for a given variable. The subsequent identification and structural analysis of homogenous landscapes allows us to objectively represent the complex organisation of these intensities using well-known tools (categorical maps) effective for planning processes. So we expect that measuring the intensity of key land uses will allow us to obtain the spatial models of several landscape gradients along which the well-known urban–rural fringes co-exist with other types of transitional landscapes. Starting from this hypothesis, an explicit spatial landscape analysis was conducted in a rural area of central Italy. The study aimed to answer the following research questions: (i) Are the spatial intensities of urbanisation, agriculture, and natural habitat key components for the identification of anthropogenic landscape gradients? (ii) How are transitional landscapes distributed along the gradient and to what degree are their structural patterns different? To this aim, KDE, multivariate spatial analysis, landscape pattern analysis, and Principal Component Analysis were combined to model and characterise landscape gradients and to analyse the structural features of fringe areas.

This paper describes the proposed approach through Section 2 in which the study area is introduced and the methodological steps followed in this application are explained in detail. In Section 3, we present the characteristics of landscape sequences found along the gradient in terms of their main features and characteristics of landscape-level structural patterns. We then move on to examine the complexity of LULC spatial patterns within the fringe areas detected along the gradient. Section 4 is aimed at an overall analysis and interpretation of the research findings in light of the most recent landscape issues and relevant bibliography. In the final part of this section and in Section 5, we highlight key aspects related to the application of the proposed methodology as well as its potential role within the landscape analysis and planning processes.

2. Materials and methods

2.1. Study area

The 493 km^2 study area comprises the Italian municipalities of Assisi, Bastia, Bettona, and Cannara (Fig. 1). This area of central

Fig. 1. Geographic location of the area under investigation.

Italy is characterised by a rural landscape consisting of 54% agricultural land, 34% forests and semi-natural areas, 9% built-up areas and 3% wetlands and water bodies (Corine Land Cover 2006, a personal elaboration). The area is morphologically characterised by a wide, central plain in which intensive agricultural farms, urban and productive settlements are located. The plain continues on the NE and SW sides with low hillsides dominated by an olive-growing agricultural area. The higher, innermost hills are mainly occupied by agro-forestry areas, woodlands and grasslands of varying sizes. In the middle of the area rises Mount Subasio (1290 m), which, together with the city of Assisi, is the most prominent element of cultural identity for the entire landscape. Despite its limited extent, due to its particular landscape composition and configuration, featuring a variegated mosaic of urban, agricultural, and natural patches, this area was found to be very suitable for the application and validation of the proposed methodology.

2.2. The methodological approach

Three main steps were taken: (a) spatial modelling of gradients generated by key landscape components; (b) spatial multivariate analysis and landscape classification; and (c) analysis of the landscape structure. The main characteristics of each data set used in the application are reported in Table 1, while a comprehensive diagram of the methodological steps is shown in Fig. 2. All of the spatial data processing and analysis steps described hereinafter were performed inside Esri ArcGIS^{TM} and its Spatial Analyst^{TM} extension, even though they are implementable using modern open-source software.

2.2.1. Spatial modelling of landscape gradients generated by key landscape components

Urban settlements (population), agriculture, and natural habitat were assumed to be key land uses generating the landscape gradients and, in the first stage, were analysed to obtain independent gradients of LULC intensity. These land uses were measured using four spatial indices: Urban Density Index (UDI – the number of inhabitants per square kilometre); Arable crop Density Index (ADI – the percentage of landscape area occupied by arable crops); Olive grove Density Index (ODI – the number of olive trees per hectare of surface); and Natural elements Density Index (NDI – the percentage of landscape area occupied by natural areas).

The source for population density was the official census data available for the year 2000 (ISTAT, 2001) linked to a census zones layer. To improve the spatial accuracy of census data, urban cells were extracted from a LULC dataset, available for year 2000 in raster format (cell size, 50 m), and converted to a point layer. A spatial matching process allowed us to associate to every point the total population of a census zone averaged with the total number of points falling in the same zone. The gradient of agricultural land uses was studied by separating the two dominant crops in the area: arable crops and olive groves. The spatial distribution of arable crops was obtained from the Common Agricultural Policy (CAP) regional database (year 2000) linked with the geo-referenced centroids of the cadastral parcels. The data source for the spatial distribution of olive groves was the national olive tree inventory. For each olive grove parcel, the centroid, linked to the total number of trees, was calculated using a “feature to point” GIS tool. Finally, natural areas were identified as forests and grassland whose cells were extracted from the above-mentioned LULC dataset.

The objective of the subsequent KDE application was to transform the values measured at specific locations on continuous surfaces to measure the general spatial distribution trend for the considered variable. The quartic function, a simplification of the Gaussian model (Gatrell et al., 1996; Levine, 2006), was adopted and four different bandwidths (250, 500, 750, and 1000 m) were tested (Lloyd, 2007; Vizzari, 2011a). The value of 500 m was finally chosen and the KDE analysis was performed on the urban, arable crop, olive grove, and natural features layers to obtain the four spatial indices defined above: UDI, ADI, ODI, and NDI. Cell size for KDE layers was set at 50 m, consistent with the scale of analysis (Hengl, 2006).

2.2.2. Spatial multivariate analysis and landscape classification

Landscape subdivision was obtained by exploring spatial relationships between the components’ gradients by means of a cluster analysis. In this study, ISODATA cluster analysis was carried out using a sample size of 5 cells, 10 initial classes and 200 iterations. Within ArcGIS, cluster signatures produced by ISODATA were used in a maximum likelihood classification procedure in order to obtain a pre-final landscape subdivision. To produce a more effective subdivision of the study area, smaller areas (less than 10 ha) were merged with wider adjacent zones. This phase was performed using the following three-step procedure: (a) create individual zones with the “Region group” tool using the four neighbouring cells; (b) reclassify (with the “Reclass” tool) cells falling within areas less than 10 ha wide to “NoData” to produce a mask layer; (c) dissolve such areas into surrounding wider areas using the “nibble” tool, with the said mask layer and the classified grid as input layers.

To investigate some of the different types of linear urban–rural–natural gradients within the study area, a cross-section analysis was developed along three significant directions of the resulting classification. The starting point of all three sections was placed within an urban landscape located in the central plain area. A regular point sampling procedure, using a “Densify” tool (distance 100 m), and a subsequent iterative “Extract Values to Points” process allowed us to collect the related landscape type sequences (cluster IDs), and the local trends of the four spatial index values (UDI, ADI, ODI, NDI) for each point along the three sections. These values were then graphically plotted to represent and analyse effective cross sections of the entire gradient identified within the study area.

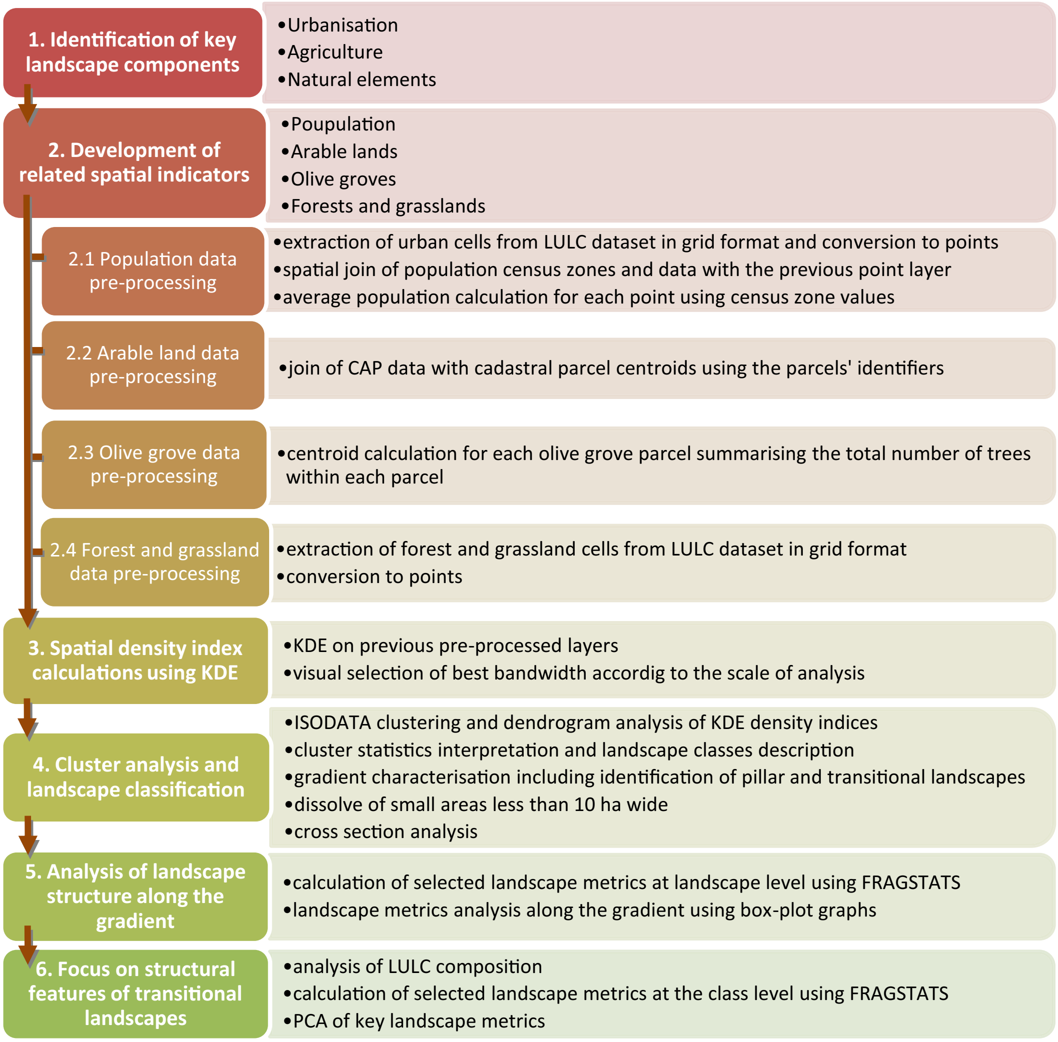

Fig. 2. Flowchart of the methodology.

2.2.3. *Analysis of the landscape structure*

A set of landscape metrics was used to examine both landscape–level properties along the gradient and spatial patterns of LULC classes within fringe areas (Table 2). The dynamics of patch size (MPS), patch density (PD), patch shape (MPS) and landscape diversity (SIEI) were analysed at the landscape level (study level "l", Table 2) to test the hypotheses of landscape structural responses along a human transformation gradient postulated by Forman and Godron (1986). For this purpose, box–plot graphs showing the entire gamut of landscapes along the gradient were used. At the class level, the analysis aimed to analyse LULC dynamics in the transitional landscape. A principal components analysis (PCA) was then used to determine whether a reduced set of factors could be used to explain the structural variation observed in the fringe landscapes and to discover existing relationships between the key LULC patterns (woodland, built-up area, arable land). Patterns of composition (PLAND), fragmentation (PD, MPS, MNN), and shape complexity (MSI) were computed (study level "c", Table 2) for each of the three classes. Thus, a set of 15 variables previously tested for normality (Lilliefors test $p < 0.05$) and linearly normalised between the values of 0 and 1 were processed by PCA. The "vegan" package (Oksanen et al., 2011) in the R statistical software package (R Core Team, 2008) was used and ellipses grouping observations associated with the types of fringes (95% confidence) were also calculated and plotted.

3. Results

3.1. *Spatial analysis of landscape gradients*

The ISODATA multivariate analysis allowed the identification of eight landscape types (Fig. 3), which were denominated according to their specific characteristics (Table 3). The dendrogram produced by the cluster analysis shows the similarity aggregation of the eight typologies of landscape (Fig. 4a). Considering the third level of aggregation (distance approximately equal to 4.13), five main groupings can be distinguished: urban and urban–agricultural landscapes (U, UAT), olive grove-dominated landscapes (AOG), arable crop-dominated landscapes (AMI, AHI), agri-forestry landscapes (AFM, ANT), and nature-dominated landscapes (N). In light of the similarities highlighted by the aforementioned dendrogram, the eight clusters can be ordered according to a typical urban–rural–natural landscape gradient, which is useful for studying the variation trends of the four spatial indices used in the analysis (Fig. 4b). As expected, UDI assumes a decreasing trend when moving from the most urbanised (U) to agricultural landscapes. ADI (not considering AOG landscapes) shows an increasing trend from the most urbanised to the most agricultural landscapes, and a decreasing trend towards the most natural landscapes. ODI assumes the highest values in AOG landscapes, but it also shows a modest incidence in agri-forestry landscapes (AFM, ANT) due to the

Table 2
Landscape pattern metrics, calculated by FRAGSTATS (McGarigal & Marks, 1995), used to characterise landscape structures along the gradient and LULC dynamics in transitional landscapes (c = class level, l = landscape level).

Landscape metrics	Abbreviation	Study level	Description
Patch density	PD	c, l	Number of patches per 100 ha
Largest patch index	LPI	l	Percentage of the total landscape comprising the largest patch (%)
Landscape shape index	LSI	l	Total length of patch edges within the landscape divided by the total area adjusted by a constant for a standard square (raster format)
Simpson's Evenness Index	SIEI	l	Measures the probability that any two cells selected at random would be different patch types
Percentage of landscape	PL	c	Proportion of the landscape occupied by patch types (%)
Mean patch size	MPS	c	Average area of patches in the landscape (ha)
Mean Shape Index	MSI	c	Patch perimeter divided by the minimum perimeter possible of a maximally compact patch (in a square raster format) with a corresponding patch area
Mean Nearest Neighbour Distance	MNN	c	The mean of the shortest distance between similar. patches (edge to edge)

presence of olive groves in these LULC mosaics. NDI (not considering AOG landscapes) also shows a characteristic, increasing trend when moving from more agricultural towards more natural landscapes. Four so-called "pillar" landscapes were recognised at the maximum values of the gradient indicators (U, AOG, AHI, N), while the other areas were considered transitional landscapes (UAT, AMI, AFM, ANT) due to their particular composition and position along the gradient.

The three cross sections allowed us to represent some different types of linear urban–rural–natural gradients within the study area (Figs. 3 and 5). Each cross section (S) highlights a particular trend of the four spatial indices and a related, specific sequence of landscapes produced by the ISODATA classification. Because of their location in the study area, all of these gradients are characterised by a former urban–agricultural–urban sub-gradient bounded by two U landscapes (S1 and S2: 0–4.2 km, S3: 0–6.7 km) and by a subsequent urban–agricultural–natural sub-gradient bounded by U and N landscapes (S1: 4.2–9 km; S2: 4.2–7.5 km; S3: 6.7–11.6 km). In the final portion of the gradient, the second section also shows a particular natural–agricultural–natural sub-gradient (S2: 7.5–12.8 km).

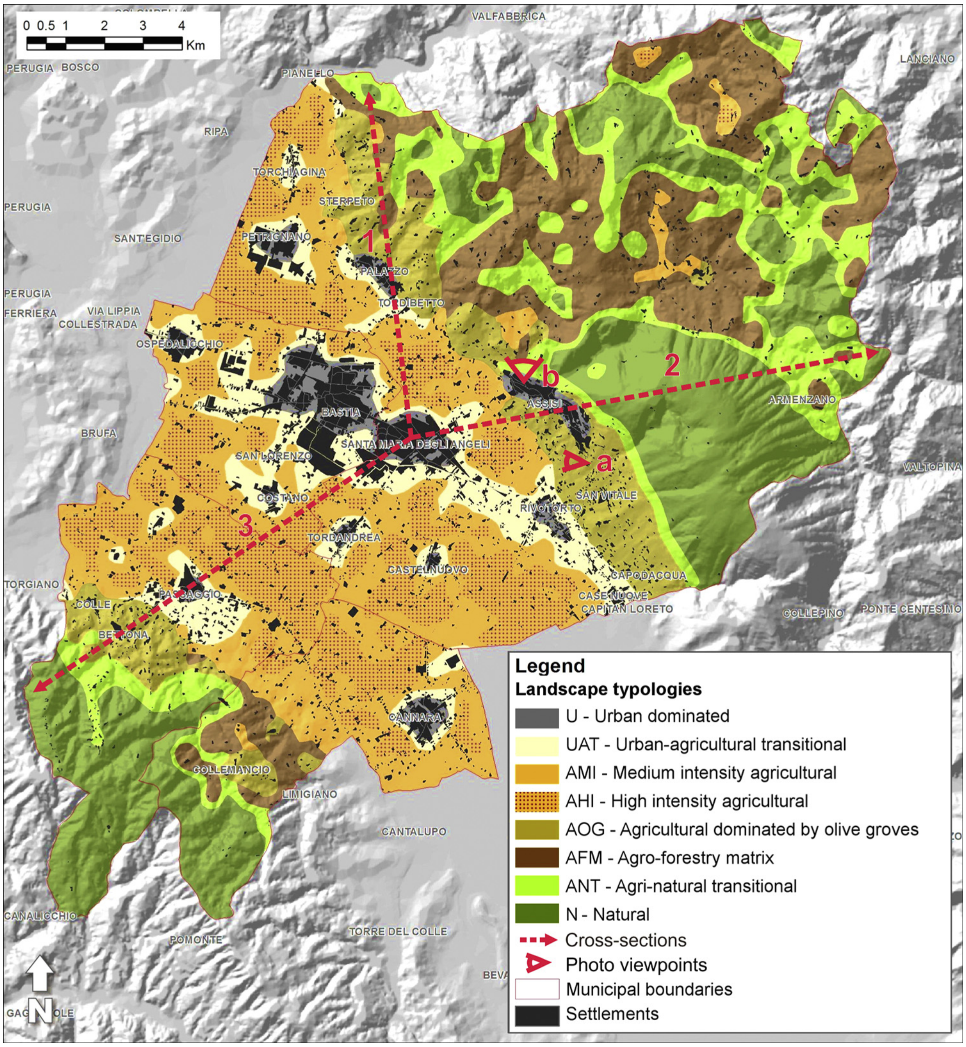

Fig. 3. Landscape types produced by cluster analysis. Locations of the sample cross-sections (Fig. 5) and of the photo viewpoints (Fig. 6) are also plotted.

Table 3
Characterisation of clusters obtained from ISODATA classification.

CODE	Landscape typology	Description
U	Urban dominated landscapes	Continuous urban fabric including, near the boundaries, portions of mixed and fragmented agricultural spaces incorporated into the settlements
UAT	Urban–agricultural landscapes	Areas including discontinuous urban fabric immersed in an agricultural matrix consisting predominantly of arable crops and, only marginally, of woods
AOG	Agricultural landscapes dominated by olive groves	Areas predominantly occupied by olive groves, interspersed with arable crops and settlements, extended in the downhill slopes of the study area
AMI	Medium intensity agricultural landscapes	Areas featuring rare settlements spread over a matrix of agricultural land uses characterised by a medium density arable lands
AHI	High intensity agricultural landscapes	Areas characterised by a continuous high density cultivated matrix characterised by arable lands and very sparse settlements
AFM	Agro-forestry matrix landscapes	Areas characterised by arable lands and very sparse settlements, inserted into a mosaic of woodlands, extended in the hilly portion of the study area
ANT	Agro-natural landscapes	Areas predominantly occupied by natural habitats, sometimes interrupted by crops, extended in proximity or around the natural landscapes
N	Natural landscapes	Areas occupied almost exclusively by natural habitats, especially forests, extended mainly in the mountain portion of the study area

As expected, U and AOG landscapes show only a relative dominance of their feature land use in some cases. Specific landscape sequences are also identified in some significant photos taken in the area (Figs. 3 and 6). It is interesting to note that the types of landscapes along the gradient capture the gradual change of land use intensity.

3.2. *Characterisation of landscape structures along the gradient*

The box–plot graphs show different trends for the metrics calculated for each landscape type along the typical urban–rural–natural gradient defined above (Fig. 7). Patch density increases from urbanised areas to agricultural landscapes, with the exception of intensive agricultural landscapes (AHI), where the value falls dramatically. The same metric decreases progressively when moving from agro-forestry matrix areas to the most natural areas. In general, not only landscapes dominated by traditional agriculture (AOG, AFM) and natural land covers (ANT, N) but also intensive agricultural landscapes (AHI) are characterised by a lower variability in PD. As regards the dominance of the landscape by a few land uses, LPI shows a high variability for all of the landscapes along the gradient, with higher values within "pillar" landscapes

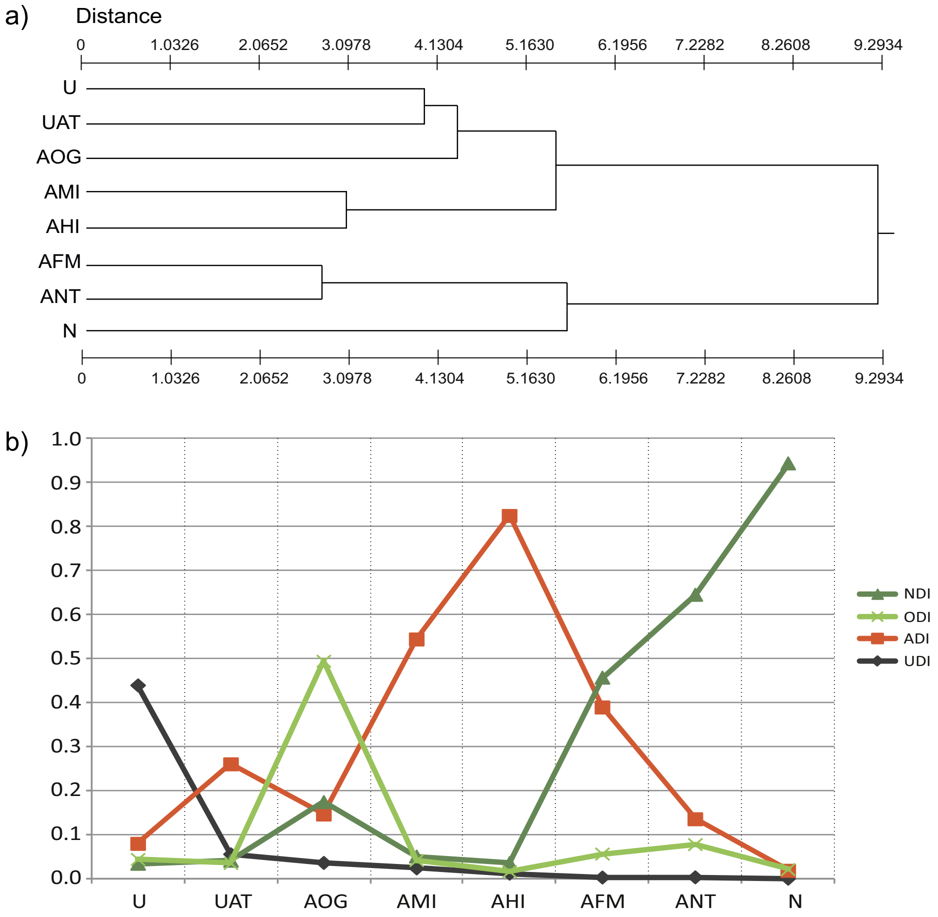

Fig. 4. Dendrogram showing the similarity between landscape typologies identified by the cluster analysis (a) and average values of the four spatial indicators within the landscape typologies along a typical urban–rural–natural gradient (b).

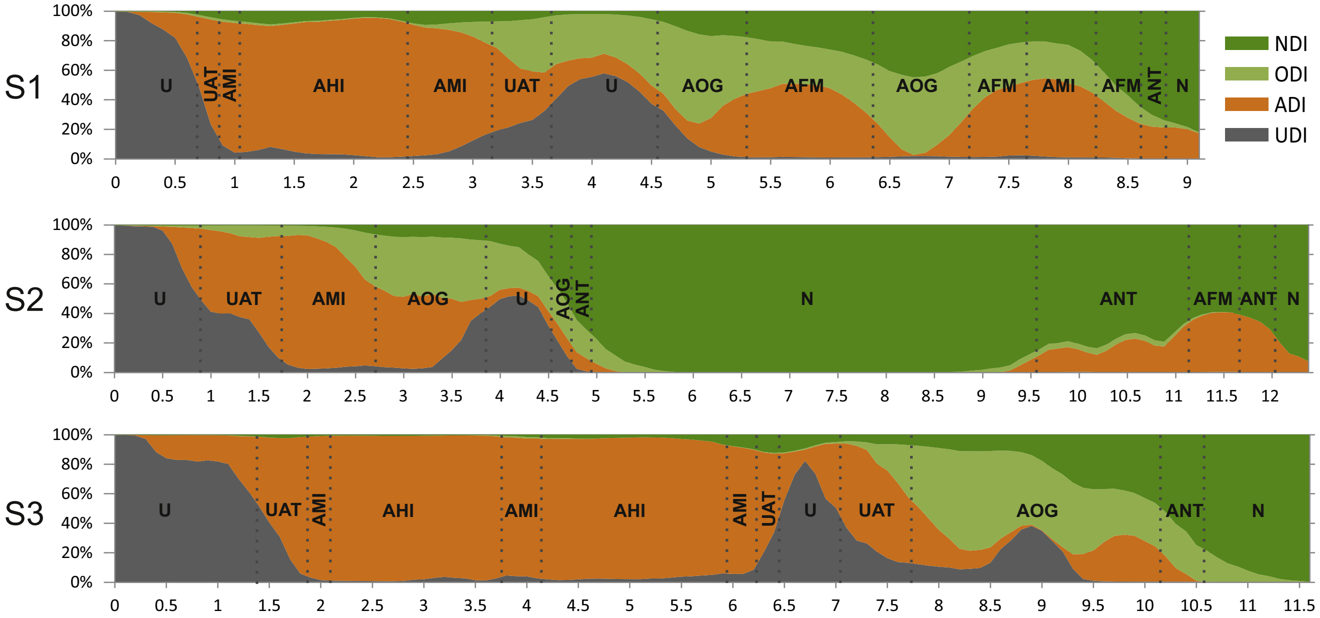

Fig. 5. Sample cross sections along significant directions of the resulting landscape classification. UDI = Urban Density Index, ADI = Arable crop Density Index, OLI = Olive grove Density Index, NDI = Natural elements Density Index. The density indices are plotted as a percentage of their total sum. On the x-axis is the distance from the section origin, expressed in kilometres. The codes associated with the landscape typologies are reported in Table 3.

(urban, intensively cultivated, and natural). As expected, the highest median values were found for urbanised areas (U), intensive agricultural landscapes (AHI), and natural landscapes (N), which is an effect of a landscape matrix dominated by settlements, croplands and forest habitats, respectively.

LSI shows a parabolic-shaped trend moving from the most urbanised (U) to intensive agricultural landscapes (AHI). Higher shape complexity (median value) is associated with traditional agricultural landscapes (AOG) dominated by olive groves. Moving towards the most natural landscapes (N), LSI assumes lower values on average, but with a higher variability within agro-forestry transitional landscapes (AFM, ANT). Landscape diversity, quantified by the SIEI index, shows a parabolic tendency moving from urban towards the most intensive agricultural landscapes, with a higher median value associated with olive grove-dominated areas (AOG). Landscape simplification associated with intensive cultivation is also confirmed by the lowest SIEI values, whereas an even distribution among patch types results mostly in transitional landscapes from urban to agricultural areas (UAT, AMI) and in less intensive agricultural landscapes (AFM, ANT).

3.3. *Characterisation of LULC processes in the transitional landscapes*

The analysis of landscape composition in terms of LULC (PLAND) was developed specifically for peri-urban and agro-forestry transitional landscapes (UAT, AMI, AFM, ANT). The results show a diffuse presence of settlements, but their incidence indicates a characterising effect only in transitional urban–agricultural landscapes (UAT) (Table 4). The occurrence of arable land within the four landscape typologies is also generally higher in the most natural landscapes. Semi-natural habitats occupy significant portions of landscape area within the rural-forestry fringes, whereas natural habitats in urban–rural areas are represented by woodlands. Furthermore, tree crops (olive groves, orchards, and vineyards) are less important in the characterisation of the four transitional landscapes.

Table 5 shows the proportion and the cumulative proportion of the factorial components resulting from PCA. The first four axes, accounting for 68% of the variability, were selected for subsequent analysis (cut-off based on the scree plot). In light of its substantial

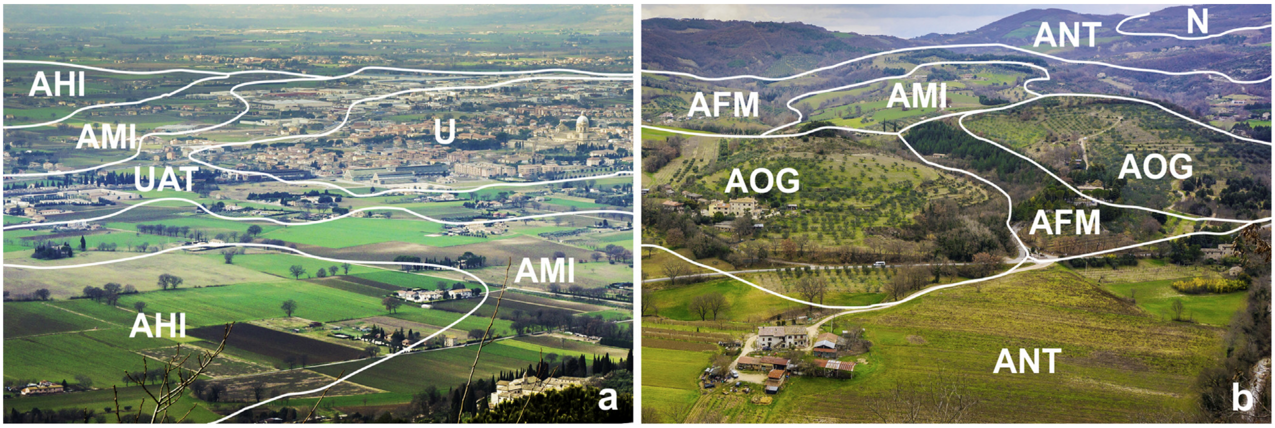

Fig. 6. Landscape sequences observed from two significant observation points. The locations of photo viewpoints (a, b) are showed in Fig. 3.

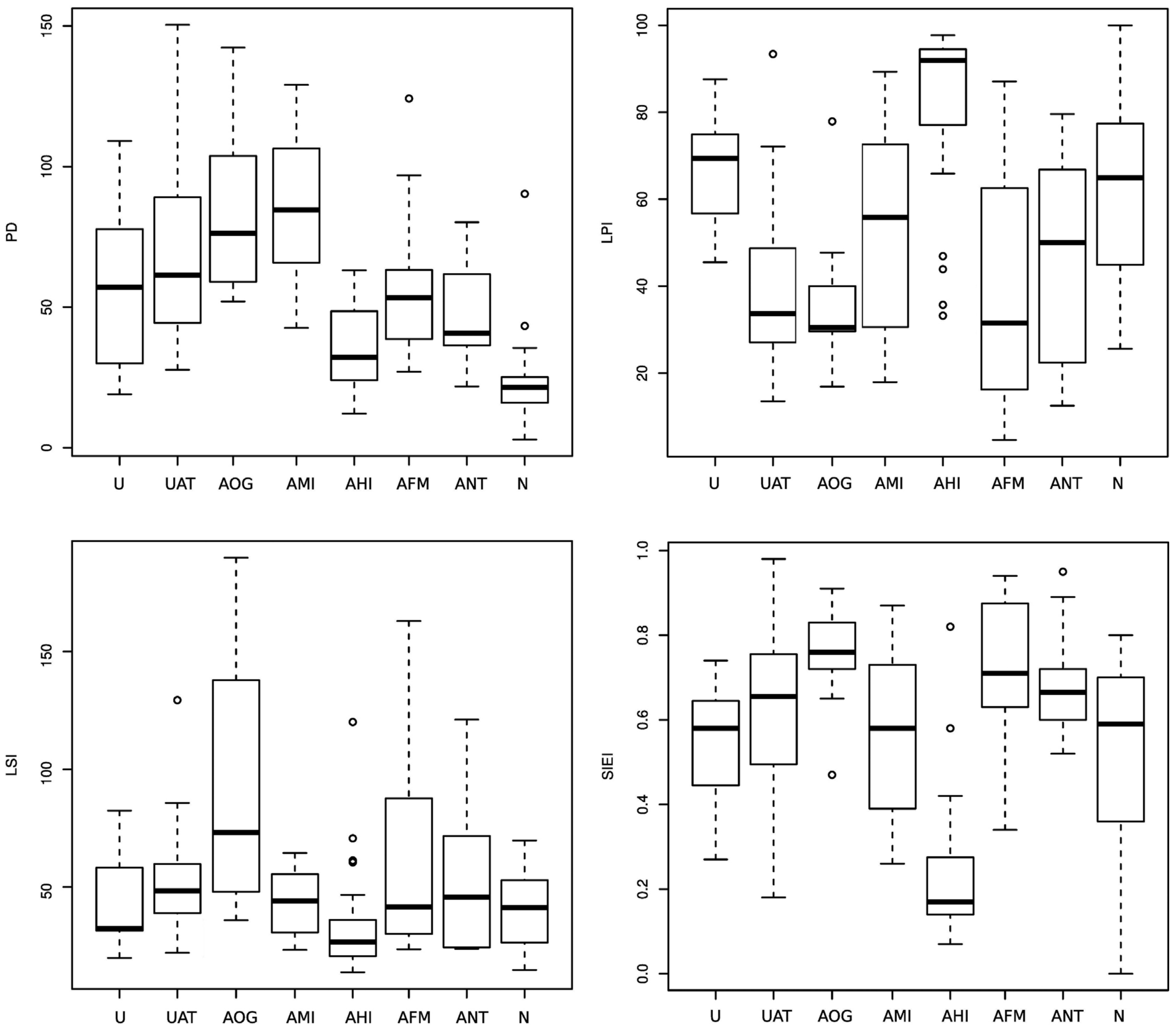

Fig. 7. Values of Patch Density (PD), Landscape Shape Index (LSI), Largest Patch Index (LPI) and Simpson's Evenness Index (SIEI) calculated for the eight landscape types. Median (line in grey box), upper and lower quartiles (box), maximum-minimum range (whiskers), and outliers are shown.

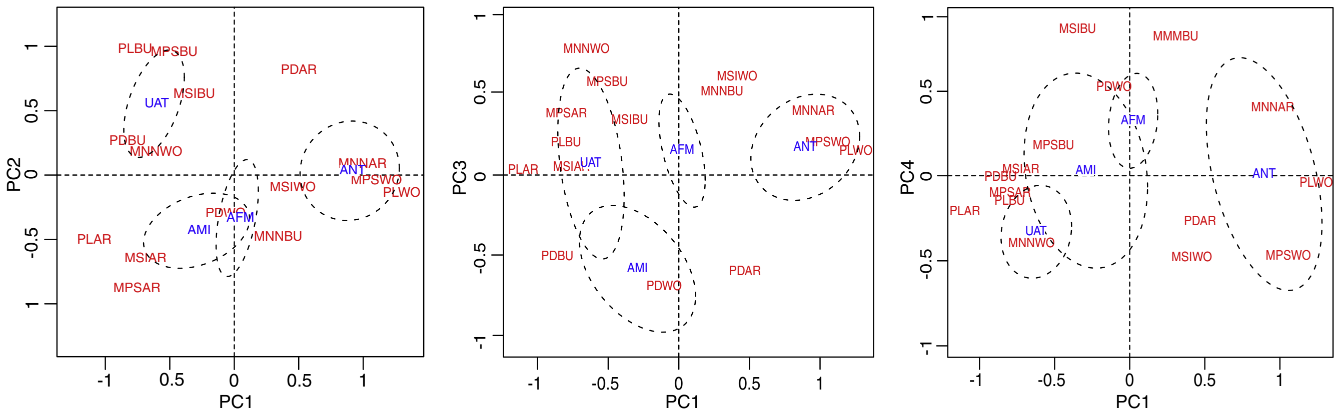

Fig. 8. Ordination biplot depicting the first four axes of PCA. The centroids of areas belonging to the gradient landscape classes and the standard error of their average scores are shown (blue labels and dashed elliptic lines with 95% confidence limit). The selected constrained variables are plotted in red: WO = woodland, BU = build up, AR = arable land, PL = percentage landscape, PD = Patch Density, MPS = mean patch size, and MNN = nearest neighbour distance. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 4
Percentage of landscape occupied by the different land uses in fringe areas.

	UAT	AMI	AFM	ANT
Woodlands	3	4	31	58
Orchards	0	0	0	0
Olive groves	1	2	5	6
Vineyards	3	3	0	0
Built-up	26	9	4	2
Grasslands	0	0	8	13
Arable lands with trees	4	2	3	1
Arable lands	63	80	49	20

Table 5
PCA computed from indices of composition (PLAND), fragmentation (PD, MPS, MNN), and shape complexity (MSI) calculated for the three key LULC classes (woodlands, built-up, arable lands). Eigenvalues and explained variance (individual and cumulative) of the most significant components are reported.

	PC1	PC2	PC3	PC4	PC5	PC6
Eigenvalue	4.588	2.550	1.696	1.401	1.292	0.997
Proportion explained	0.306	0.170	0.113	0.093	0.086	0.066
Cumulative proportion	0.306	0.476	0.589	0.682	0.768	0.834

contribution to the variability, the first component (PC1, accounting for 30% of variation) can be interpreted as a gradient of land use intensity because it is directly related to a higher presence of woodland, a decrease and shape simplification of arable lands and a decline of urban areas. The second axis (PC2, accounting for 17% of the variation) better explains the urbanisation gradient, as the increase in urban areas' presence and shape complexities matches with fragmentation and shape simplification of arable lands. By observing the position of the considered variables along such structural gradients, is possible to highlight which of them is more important for the characterisation of fringe areas (Fig. 8). As expected, UAT landscapes are marked by wider (PLBU, MPSBU), more complex (MSIBU) and dense (PDBU) built-up patches as well as more dispersed woodland patches (MNNWO). AMI and AFM landscapes show a partial overlap due to their similar medium patch density of woodlands. Based on the ellipse orientation, AMI landscapes appear to be differentiated by a higher incidence of arable lands (PLAR), with wider patches (MPSAR) and more complex shapes (MSIAR), while AFM landscapes are distinguished by more sparse settlements (MNNBU). ANT landscapes, as expected, are characterised by a higher presence of woodland (PLWO) with larger (MPSWO) and more complex patches (MSIWO).

Regarding the other two axes, the third (PC3, accounting for 11% of the variation) is mainly associated with isolation and complexity of woodlands, while the fourth (PC4, accounting for 10% of the variation) is related to the complexity and isolation of built-up patches. PC3 allows for better differentiation of urban–rural fringes, indicating a higher fragmentation of woodland (PDWO) in AMI landscapes compared to AFM and a high variability of the same features within UAT landscapes. PC4 highlights more complex (MSIBU) and isolated (MNNBU) built-up patches within AFM than UAT landscapes, as well as higher variability of the same metrics within AMI and ANT landscapes.

4. Discussions

Results confirm that anthropogenic landscapes feature gradients of LULC characterised by different structures, and may be classified according to the succession postulated by Forman and Godron (1986). As suggested by Prados (2009), the lack of a single, effective polarisation between city and countryside and the existence of interdependence among demographic processes, socio-economic and residential development in urban and rural areas provide complex landscape gradients. This interdependence influences drivers of landscape change (e.g., agriculture, demand for natural resources, urbanisation) that, as a consequence, occur in different forms and with different dominant factors from area to area. For example, the role of agriculture goes beyond its main function of food production and passes from supporting the production of public goods (healthy food, countryside of great aesthetical and recreational value) in the more urbanised areas (Piorr et al., 2011) or in typical landscapes (Torquati, Vizzari, & Sportolaro, 2011) to agricultural industrial production in intensively cultivated areas and to the conservation of typical landscape features, forest production and habitat diversity in agri-forestry and natural landscapes. These changing functions, recognisable along the gradient, are clearly linked with the different landscape structures and spatio-functional interactions of the different LULC classes (Laterra, Orúea, & Boomana, 2012), producing the complex and variegated framework called landscape multi-functionality (Fig. 9).

The eight landscapes' patterns showed specific trends of metrics along the gradient, with a substantial confirmation of the predictions postulated by Forman and Godron (1986). Two opposite trends were found for patch density (PD) values. First, the landscape metric increased from urban areas to those characterised by medium intensity agriculture. Second, it decreased from agro-forestry landscapes to natural areas, with a predictable, related reduction in intensively cultivated and natural areas, where large and regular patches were covered by dominating LULCs, such as arable crops and woodlands, respectively. These results are comparable with what Zhang, Wu, Zhen, and Shu (2004) found for urban–rural gradients in the Shanghai metropolitan area, where increases in PD, edge density and landscape shape complexity (LSI) were detected. Moreover, as highlighted by Weng (2007), a positive relationship between degree of urbanisation, landscape fragmentation, loss of natural habitat and agricultural land uses was identified, especially in urban–rural fringe areas (UAT, AMI). These key dynamics have led to a vigorous debate about two opposing issues associated with these areas: an environmental sensitivity towards the deep and rapid transformations generated by urbanisation on one hand, and the pressure for employment, recreational activities, and reduction of food insecurity for the urban population on the other (Lovell, 2010; Thapa & Murayama, 2007). In a study concerning political and planning approaches to support multifunctional agriculture in peri-urban areas, Zasada (2011) noted how agriculture in these areas can supply key services derived from its environmental, social and economic functions in response to the consumption-oriented requirements of urban society. Bio-energy, community food demand, fresh water production, social/hobby farms and rural tourism are examples of drivers within the changing nature of rural–urban relationships that may be development opportunities for fringe spaces (Piorr et al., 2011; Scott et al., 2013). However, species and habitat conservation, negative visual impacts of multi-storey architecture, preservation of cultural heritage and changes in the lifestyles of rural populations were some of the main conflicts highlighted for these transition areas (Von der Dunk et al., 2011). The said landscape fragmentation trend is reversed when we consider the gradient from agri-forestry fringes to natural landscapes (AFM, ANT, N) as a progressive and direct effect of dominant, well-connected natural habitats. These transitional landscapes, where cultivation is being progressively abandoned as a consequence of local, environmental and socio-economic conditions, are very common in mountainous and hilly parts of the study area. These spaces are very rich in semi-natural habitats, which coexist and interact with extensively managed agricultural areas. As reported by Ostermann (2008), some of these transitional spaces are among the richest in habitats that are fundamental to supporting biodiversity and endangered species. These landscapes have proved to be strongly dependent on farming activities to maintain habitat diversity and counter the re-naturalisation process,

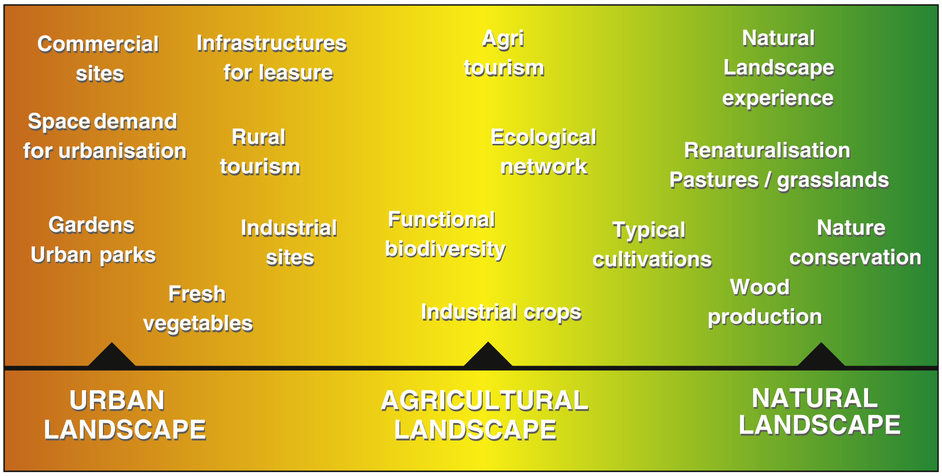

Fig. 9. Dominant factors along the urban–rural–natural gradient linked with drivers of landscape change.

hydro-geological deterioration (Agnoletti, 2014) and consequent loss of landscape diversity (Kleijn, Berendse, Smit, & Gilissen, 2001).

SIEI showed a fluctuating trend of landscape diversity along the gradient. It increases from urbanised areas to olive grove-dominated landscapes, and then decreases dramatically towards intensive agricultural landscapes (AHI) as a direct consequence of land use simplification, which has been highlighted in previous studies (see e.g., Duelli & Obrist, 2003; Henle et al., 2008; Leinwand, Theobald, Mitchell, & Knight, 2010). In such areas where agriculture has moved from extensive to intensive forms, the relevant land-use changes are often generated by the introduction of monoculture and by land-consolidation projects aiming to improve conditions for production by means of irrigation infrastructure, the elimination of semi-natural areas (e.g., ditches, hedges) and the formation of wide, regularly shaped fields (Bonfanti, Fregonese, & Sigura, 1997). On the contrary, urban–rural transitional landscapes (UAT, AMI) are characterised by the highest variability of patch diversity, due to their intrinsic characteristics of the LULC mosaic. Olive growing landscapes (AOG) appear quite distinctive along the gradient of the study area, due to their particular composition dominated by olive groves yet also characterised by arable lands, natural elements, and diffused settlements that result in a very high diversity and quality of the landscape (Figs. 5 and 7). Indeed, they represent one of the most ancient, varied landscapes in the Mediterranean area, substantially unchanged in structural terms (e.g., growing systems) and distribution in Italy (Agnoletti, 2014). A different trend in landscape diversity characterises the other part of the gradient, including transitional agri-forestry landscapes (AFM, ANT), where low urbanisation, tree cultivation (mainly olive groves) interspersed with arable land and natural habitats make landscape patterns generally very heterogeneous. These rural–natural fringes are usually characterised by a mosaic of low-intensity agriculture, where cultivated plots associate closely with semi-natural habitat (e.g., woods, bushes, ponds, unfarmed patches, ditches, small rivers, hedges) (Fig. 6b). Within such contexts, high nature value farmlands (HNVF) can be identified (Andersen et al., 2003) as areas in which bio-diversity establishes a good level of ecological stability and agricultural practices have maintained less intensive productions (Biala, Terres, Pointereau, & Paracchini, 2008). It has been estimated that 50% of all species in Europe, including endemic and rare species, depend on agro-forestry ecosystems linked with HNVF (Paracchini et al., 2008; Kristensen, 2003).

The hypothesis of the coexistence of urban–rural fringes with other types of transitional landscapes was confirmed. Analysis of LULC structures in the four transitional landscapes substantially confirmed the gradient measured by density analysis on the basis of patch metrics. Assessments of grouping observations according to the type of fringes along the most important components (Fig. 8) highlighted a partial overlap between agricultural transition areas (AFM, AMI), whereas urban and semi-natural fringes (UAT, ANT) were clearly separated. The last dichotomy can be explained by considering the strong impressions given by corresponding adjacent pillar landscapes (urban and nature dominated landscapes), while the similarity between the rural fringe areas was rather unexpected. Urban–rural and rural–natural fringe areas originate from different processes and are recognisable mainly in urban sprawl and the progressive advance of woodlands to replace agro-pastoral activities. Both processes operate progressively on the original cultivated land, producing a recognisable footprint in the landscape structure, while the persistence of agriculture practices in the rural fringes maintained more homogeneous landscapes.

Unlike previous studies aimed at urban–rural gradient detection and analysis of peri-urban areas, this study has focused on the classification and analysis of the entire urban–rural–natural gradient generated by the variable intensity of land uses that characterise anthropogenic landscapes. Though the methodology is apparently quite complex from a technical viewpoint, it appears effective and easily adaptable, including through a diachronic approach, to different types of landscapes and land use gradients. The KDE technique and multivariate analysis for modelling and classifying landscape gradients, in particular, demonstrated that these techniques are applicable even when beginning from extremely different data sources regarding urban, agricultural and natural features. Representations produced by cross-section analysis are very useful for investigating the local trends of spatial density indices and the role of land uses in generating different typologies of landscape sequences within what can be considered a continuous, multi-dimensional urban–rural–natural gradient. The subsequent characterisation of landscape patterns using spatial metrics allows a deeper comprehension of the landscape structures and organisation occurring along the entire gradient. The combination of such techniques allows the identification of different landscape typologies along the anthropogenic gradients, supporting the interpretation of the spatio-functional interactions that exist in the landscape. In future applications, as already proposed in other studies (McGarigal, Tagil, & Cushman, 2009), the exploration of spatial heterogeneity could be performed by means of continuous indices rather than traditional landscape metrics that start from discrete, categorical maps. However, the adoption of such an approach still appears limited, mainly by the requirement that proper, native, continuous data be analysed and for specific, often expensive, software for surface metrics calculation as well as by the tricky interpretability of the metrics themselves.

5. Conclusions

The entire gamut of landscapes nested along anthropogenic gradients generated by land-use diversity and intensity have rarely been considered in the literature, although LULC reciprocal interactions along such gradients play a crucial role for the goods and services that the environment provides for humans. Fringe areas, because of their peculiar features, are central issues in the scientific debate on sustainable planning and development strategies. Traditionally, the focus has been mainly on urban–rural fringes, which have been viewed from an urban-centric perspective to fulfil the needs of an increasingly urbanised society, whereas explicit policy interventions would be required to manage those areas as places in their own right. Beyond these broadly investigated contexts, it appears extremely relevant to identify and characterise the agro-forestry fringes in view of their particular values and dynamics. In this framework, our study proposes a spatially explicit methodology useful for the detection and characterisation of different landscapes expressed by land use gradients. The spatial intensity of urbanisation, agriculture, and natural resources can be assumed to be a key component in the identification of anthropogenic landscape gradients, to obtain integrated information that can be used to support decisions regarding the spatial arrangement, intensity and functionality of land uses. Is it essential to integrate consideration of the entire landscape gradient into planning process topics such as landscape multi-functionality and ecosystem services provided for human well-being.

Acknowledgements

This research, initially undertaken as a project named “Agricultural peri-urban landscapes of Umbria: identification, planning, and management” and funded by the Bank of Perugia Foundation (project code 2009.010.0417), was further developed within the framework of the project TRUSTEE (Towards RUral Synergies and Trade-offs between Economic development and Ecosystem services) funded by the funding bodies partners of RURAGRI ERANET (contract FP7 235175) – Italian partner of TRUSTEE is supported by Ministry of Agricultural, Food, and Forestry Policies. The authors would like to thank anonymous reviewers for their constructive comments and suggestions on the earlier version of this paper.

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