The Environmental "Risky" Region: Identifying Land Degradation Processes Through Integration of Socio-Economic and Ecological Indicators in a Multivariate Regionalization Model

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Abstract Although several studies have assessed Land Degradation (LD) states in the Mediterranean basin through the use of composite indices, relatively few have evaluated the impact of specific LD drivers at the local scale. In this work, a computational strategy is introduced to define homogeneous areas at risk and the main factors acting as determinants of LD. The procedure consists of three steps and is applied to a set of ten environmental indicators available at the municipality scale in Latium, central Italy. A principal component analysis extracting latent patterns and simplifying data complexity was carried out on the original data matrix. Subsequently, a *k-means* cluster analysis was applied on a restricted number of meaningful, latent factors extracted by PCA in order to produce a classification of the study area into homogeneous regions. Finally, a stepwise discriminant analysis was performed to determine which indicators contributed the most to the definition of homogeneous regions. Three classes of "risky" regions were identified according to the main drivers of LD acting at the local scale. These include: (i) soil sealing (coupled with landscape fragmentation, fire risk, and related processes), (ii) soil salinization due to agricultural intensification, and (iii) soil erosion due to farmland depopulation and land abandonment in sloping areas. Areas at risk for LD covered 56 and 63% of the investigated areas in 1970 and 2000, respectively.

Keywords Land degradation · "Risky" region · Indicators · Multivariate strategy · Italy

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Introduction

In the methodologies used to evaluate environmental quality there is a tendency toward the application of several thematic indicators (e.g., Basso and others 2000; Niemeijer 2002; Zalidis and others 2002; Bathurst and others 2003; Feoli and others 2003; Incerti and others 2007; Nourry 2008) that are sometimes aggregated into composite indices through various procedures (e.g., Zalidis and others 2004; Yli-Viikari and others 2007; Siche and others 2008). Composite indices provide stakeholders with an exhaustive picture of environmental characteristics at defined geographical scales. Unfortunately, problems can emerge in this assessment including: (i) the criteria to select relevant variables and indicators, (ii) the methods used to normalize the indicators themselves, and (iii) the weighting techniques (Dumanski and others 1998; Lawn 2003; Diodato and Ceccarelli 2004). Moreover, the integration of data collected at various spatial resolutions from various sources remains a crucial aspect needing improvement. A multidimensional approach that can consider both time and space dimensions may adequately explore latent patterns in the variable distribution and describe trends in the main factors affecting environmental vulnerability (D'Angelo and others 2000; Feoli and others 2002; Montanarella 2007; Salvati and Zitti 2008a).

The recognition, quantification, and spatial representation of environmental quality may further benefit from a

division of target landscapes into homogeneous regions (Claval 1987). The several concepts of the 'region' entity primarily depend on the argument of the study, the sensibility of the researcher, and the availability of quantitative information (Nir 1990). Improvements in Geographic Information Systems and data mining procedures that facilitate the use of multivariate analysis for defining regions has increased demand for high-quality data, appropriate spatial tagging, consistency in area definitions, and empirical applications in several environmental fields (Trakhtenbrot and Kadmon 2006; Trouvè and others 2007; van Delden and others 2007; Williams and others 2008).

Among the most important environmental phenomena increasing interest over recent years, Land Degradation (LD) is a reversible process that implies long-term decline in land productivity (Puigdefabregas and Mendizabal 1998). However, coupled with a worsening climate, it may turn into an irreversible phenomenon of desertification (Thornes 2004), with degradation of the ecosystems that interact with the soil layer, such as the groundwater and atmosphere. As a matter of fact, the increase of CO_2 emissions from the soil ecosystem to the atmosphere due to LD is a major factor contributing to the greenhouse effect (e.g., Montanarella 2007). Spatial and inter-temporal comparison of LD risk is a notoriously hard task (Mouat and others 1997; Bathurst and others 2003; Kok and others 2004; Veron and others 2006; Simeonakis and others 2007). In fact, LD should be considered as a multidimensional concept, of which bio-physical variables are only one, albeit important, component. Such variables need to be investigated along with other factors including landscape, human pressure, socio-economic factors, and land management (e.g., Hubacek and van den Bergh 2006).

Although criticized, the Environmental Sensitive Area Index (ESAI), which is the most used index depicting LD risk of a certain area (e.g., Basso and others 2000), meritoriously refers to the concept of multidimensionality of LD through the analysis of different thematic indicators related to (mainly) bio-physical processes. However, both the ESAI and other similar composite indices are sensitive to the distribution of the original variables, the procedure to calculate the thematic indicators, and the way to aggregate them (Salvati and Zitti 2008b). For example, consider an ESAI based on two thematic indicators describing climate quality and soil characteristics. It is clear that high ESAI scores, which depict worse environmental conditions, reflect a negative contribution of all the input indicators. By contrast, an intermediate ESAI score could result from three different situations: (i) worse climate conditions and high quality soils, (ii) good climate conditions and low-quality soils, or (iii) moderately worse conditions in both climate and soil quality. This example points out that composite indices, such as ESAI, could provide stakeholders with incomplete information on LD risk.

The importance of estimating the contribution of the various thematic indicators entering a composite index was addressed by Casadio-Tarabusi and Palazzi (2004), among others, from a sustainable development perspective. However, this is clearly a general issue that involves different disciplines and arguments. Assessing if the land vulnerability of a certain area depends on specific bio-physical or socio-economic conditions (or both together) seems a simple but meaningful tool to better inform policy strategies contrasting future degradation processes especially in dry, fragile regions. This is particularly important for LD, which is regarded as a process continuously changing over time. Although several studies based on the calculation of composite indices of land vulnerability were recently carried out in the Mediterranean basin, relatively few articles tend to address the impact of specific determinants of LD at the local scale (Tanrivermis 2003; Atis 2006; Hein 2007).

In this article, a statistical procedure that can be envisaged as an alternative to the use of composite indices is presented. The procedure is intentionally simple and develops a three-step multivariate strategy in order to define homogeneous "risky" areas from both bio-physical and socio-economic perspectives (e.g., Patterson and others 2004; Huby and others 2007). We used NUTS-5 municipalities as the elementary spatial unit. This choice allowed us to develop a detailed analysis with outputs that are also understandable to non-technical stakeholders (Nader and others 2008). Finer spatial units usually prevent researchers from using crucial socio-economic data and indicators readily available over time from existing statistical sources.

The multivariate approach we adopted includes a Principal Component Analysis (PCA) carried out on the original data matrix to extract latent patterns and simplify data complexity. Subsequently, a *k-means* cluster analysis was applied on a restricted number of meaningful, latent factors extracted by PCA in order to produce a classification of the study area into homogeneous groups of municipalities. A stepwise discriminant analysis was then performed to determine which indicators provided the higher contribution to defining spatial clusters. Based on these findings and ancillary information, different "risky" regions associated with specific drivers of LD are identified and, consequently, specific mitigation strategies can be delineated at this scale.

Methods

Study Area

The study area includes the NUTS-2 region of Latium, one of 20 Italian regions. In 2000, it was divided into five

provinces (Viterbo, Rieti, Rome, Latina, and Frosinone) and 377 municipalities. It covers an area of approximately 17,065 km^2 and is characterized by a complex topography, with different climatic zones along the elevation gradient. In the last 30 years the region has been subjected to considerable land use changes due to agricultural intensification, urban sprawl, tourism pressure, and industrial concentration. Forest fires and fragmentation of the semi-natural landscape occurred especially around cities. In the same period, climate conditions became drier along the coastal rim (where the average annual precipitation falls to 600 mm from more than 700 mm observed in the 1970s).

Development of Indicator Data Set

LD risk was interpreted by means of different indicators operating in association (Rubio and Bochet 1998; Basso and others, 2000; Salvati and Zitti 2005), which are regarded as *proxies* of the ecological, economic, and social determinants of this environmental phenomenon (Table 1). Some elementary variables and the derived indicators are described in Salvati and Zitti (2007, 2008b).

Climate and soil characteristics represent the most important factors affecting LD risk in the Mediterranean basin (Sharma 1998; Kosmas and others 2000a; Sivakumar 2007). An empirical analysis, with the aim of detecting the role of several indicators of LD, suggests that Aridity Index (ARIDITY) and Available Water Capacity of the soil (SOILAWC) are the most important indicators explaining spatial patterns of LD risk in Italy. Additional variables describing climate (e.g., rainfall rate, precipitation intensity, number of rainy days, rainfall seasonality index, soil moisture rate, and drought index) and soil quality (e.g., soil depth, texture, and organic carbon) were correlated to ARIDITY and SOILAWC, respectively. One reason why ARIDITY clearly describes the relation between climate change and LD is that it takes into account both the reduction in rainfall amount and the increase in temperature. These variables represent the

most evident changes in climate patterns. In the present study, ARIDITY was obtained as the ratio between annual average rainfall and reference evapotranspiration. It was derived for two long-term periods (i.e., 1951–1970 and 1981–2000) from about 200 monitoring stations evenly distributed within the study area (see Salvati and Zitti 2008b and references therein). Concerning SOILAWC, data were derived from an Italian database of soil characteristics, built with more than 18,000 samples, with ancillary information taken from thematic cartography (ecopedological and geological maps of Italy) and additional sources (Digital Elevation Models and land use maps) (Salvati and Zitti 2008a). Finally, the importance of soil erosion has also been widely recognized over the Mediterranean area since it is the end result of climate, soil, and vegetation processes (e.g., Kosmas and others 2000a). In this study, the erosion rate (SOILERO) was estimated from the Italian map of soil erosion risk, which applies the USLE methodology. This map was produced by JRC on the behalf of the Italian Ministry for the Environment.

The impact of land use changes on LD risk (Le Houerou 1993; Kosmas and others 2000b; Hein 2007) was assessed as a result of practices such as the intensification of agriculture, land abandonment, and the unsustainable management of woodlands. Crop intensity (CROPINT), which is an estimation of the long-term sustainability of this human activity, was measured through the indicator described in Salvati and others (2007). Data were obtained in 1970 and 2000 from the Italian National Census of Agriculture (ISTAT 2006). The abandonment of marginal agricultural lands (AGRLOSS) was estimated according to the variation in the agricultural utilized area in 1961–1970 and 1990–2000. This may reflect unbalanced population dynamics between internal and coastal areas triggering soil erosion in uplands and mountain zones (Le Houerou 1993; Tanrivermis 2003). Finally, landscape quality was estimated, over time, through an indicator of woodland cover (WOODCOV) developed from census data. Changes in woodland cover may indicate processes of deforestation at the local scale. These processes

Table 1 Indicators used in the assessment of LD risk, related research dimensions, unit of measurement, and statistical sources

Research dimension	Indicator (abbreviation)	Unit of measure and relation with LD	Source
Socio-economic	Population density (POPDENS)	People km^{-2} (+)	Census of Population
	Population growth (POPGROW)	% (+)	Census of Population
	Tourism concentration (TURCONC)	Workers km^{-2} (+)	Census of Industry
	Industrial concentration (INDCONC)	Equivalents km^{-2} (+)	Census of Industry
	Crop intensity (CROPINT)	% (+)	Census of Agriculture
Bio-physical	Loss in cultivated surface (LOSSAGR)	% (−)	Census of Agriculture
	Woodland cover (WOODCOV)	% (−)	Census of Agriculture
	Aridity index (ARIDITY)	mm/mm (−)	Meteorological Statistics
	Available Water Capacity (SOILAWC)	mm (−)	Ministry of Agriculture
	Estimated soil erosion rate (SOILERO)	T ha^{-1} y^{-1} (+)	Ministry of Environment

lead to increased overland flow, at least in the first years after the removal of vegetation, and likely affect runoff more than any other single factor (Kosmas and others 2000b).

The impact of socio-economic factors on LD risk is assessed as a result of processes such as relocation of people along the coastal areas, increasing population density around the major cities, and concentration of economic activities (e.g. industry, tourism) with its consequent impact on soil and water (Tanrivermis 2003; Salvati and Zitti 2005, but see also Loumou and others 2000). As an example, population increase has a direct impact on soil sealing due to human expansion over productive lands. At its simplest level, human factors can be expressed in terms of population density (POPDENS) measured at the municipality level, in 1971 and 2001, by the National Census of Household. A demographic variation index (POPGROW) calculated for a ten-year horizon was further defined at the same geographical scale. Moreover, a *proxy* for industrial concentration (INDCONC) was developed for each municipality by measuring the impact of industries on soil and water pollution. This indicator takes into account different economic activities, placing a weight on each based on their respective impacts in terms of organic wastes (e.g., Salvati and Zitti 2005). Data were collected through the National Census of Industry and Services in 1971 and 2001. Finally, tourism concentration (TURCONC) was calculated as the density of employees (*per* municipality surface) in the same year and from the same source. Tourism growth affects the level of LD if coupled with other socio-economic factors. In southern Europe it induces urban sprawl and thus land fragmentation in low-density, ecologically-relevant coastal areas and enhances the construction of infrastructure and increases water demand during summer months.

Following Salvati and Zitti (2007), an ESA-like, composite index of LD (ISD) was used as a control in the following analyses. The ISD was calculated (at the same time and space) as the arithmetic mean of the ten indicators transformed according to their relation with LD (Salvati and Zitti 2008b). The ISD ranges between 0 (the lowest LD risk) and 1 (the highest LD risk). Average values of the selected indicators and the ISD by year and elevation are provided in Table 2.

Statistical Analysis

A Principal Component Analysis (PCA) was performed separately for the two time points (i.e. 1970 and 2000) and applied to the matrix composed of the ten (standardized) indicators in order to (i) extract the most important latent, uncorrelated factors and to (ii) synthetically describe the relationships among bio-physical and socio-economic indicators. To assess the quality of PCA outputs, the Kaiser-Meyer-Olkin measure of sampling adequacy, which tests whether the partial correlations among variables are small, and Bartlett's test of sphericity, which tests whether the correlation matrix is an identity matrix, were used to indicate if the factor model was appropriate to analyze original data (e.g. Salvati and Zitti 2005). Because the analysis was based on the correlation matrix, the number of significant axes (m) was chosen by inspecting the scree-plot and retaining components with eigenvalues higher than 1. According to the results of PCA, an intermediate matrix was built separately for the two time points, and the m PCA factor scores estimated for each municipality were placed in columns (Harman 1976).

A non hierarchical cluster analysis (using standard *k-means* computation strategy) was carried out on the intermediate matrix (377 municipalities × m factor scores) in order to achieve a classification of the municipalities into homogeneous partitions. Following the parsimony criterion, the procedure was conducted for a set of possible solutions

Table 2 Indicator's average value (± standard error) by elevation and year in Latium

Variable	Unit of measure	1970			2000			Rank test[a]
		Lowlands	Uplands	Mountain	Lowlands	Uplands	Mountain	
POPDENS	People km^{-2}	482(170)	152(11)	62(5)	583(183)	200(15)	63(6)	−8.8**
POPGROW	%	0.41(0.1)	−0.03(0.0)	−0.18(0.0)	0.07(0.0)	0.05(0.0)	−0.02(0.0)	−10.9**
TURCONC	Workers km^{-2}	1,687(1,543)	34(4)	14(3)	2,779(2,301)	53(6)	20(6)	−9.9**
INDCONC	Equival. km^{-2}	759(190)	206(54)	58(15)	869(267)	182(31)	61(18)	−0.6
CROPINT	%	0.84(0.0)	0.75(0.0)	0.42(0.0)	0.89(0.0)	0.74(0.0)	0.33(0.0)	−2.8**
LOSSAGR	%	−0.18(0.1)	−0.11(0.0)	−0.15(0.0)	−0.98(0.4)	−0.33(0.0)	−0.38(0.1)	−6.4**
WOODCOV	%	0.15(0.0)	0.30(0.0)	1.24(0.4)	0.15(0.0)	0.32(0.0)	0.99(0.1)	−2.0*
ARIDITY	mm/mm	1.28(0.0)	1.46(0.0)	1.68(0.0)	0.97(0.0)	1.05(0.0)	1.13(0.0)	−16.8**
SOILAWC	mm	151(5)	155(1)	163(2)	151(5)	155(1)	163(2)	–
SOILERO	T ha^{-1} y^{-1}	2(0.6)	6(0.4)	5(0.3)	2(0.6)	6(0.4)	5(0.3)	–

[a] Results of a Wilcoxon Signed Ranks test carried out on data measured in 1970 and 2000 over all municipalities of Latium; * $0.01 < P < 0.05$; ** $P < 0.01$

(i.e. cluster numbers) ranging from 3 to 13 clusters. Based on the available data, a higher number of clusters was considered inappropriate for depicting the characteristics of the different regions in the study area. The most efficient partition (i.e., the number of clusters chosen in order to gain the most effective segregation of municipalities) was identified by using standard diagnostics, including the pseudo F statistic and the Cubic Clustering Criterion (Duran and Odell 1974).

Based on cluster membership, average values of the standardized indicators were then calculated for each cluster of municipalities in both 1970 and 2000. These values are standard (z) scores indicating (positive or negative) deviations from each indicator average. According to the relationship with LD risk (see Table 1), scores higher than 0.5 were used to identify the indicators possibly involved in LD for each cluster. At least three indicators, with a score higher than 0.5, were considered necessary to classify a cluster as potentially "risky". Alternatively, two indicators having higher scores than the threshold with one of them having a higher score than 1 were considered sufficient to design a cluster as potentially "risky". Although based on a quantitative, standard assessment, we agree that the procedure developed here to identify potentially "risky" clusters depends on a subjective choice. However, such a technique, which provides meaningful outputs as far as land vulnerability is concerned (see the 'results' paragraph), may stimulate the development of more sophisticated procedures aimed at identifying "risky" clusters.

Finally, a Discriminant Function Analysis (DFA) was carried out to identify the indicators that contribute the most to the discrimination among the selected clusters. Models were estimated separately for the two time points by using a linear DFA. Weighted DFA was applied in order to take into account the different surface areas of each municipality. Indicators entered each model according to the results of the F test with a probability level fixed to 0.01.

Results

Principal Component Analysis

Preliminary analysis suggested that PCA can be applied to the original data matrices. Both the Kaiser-Meyer-Olkin measure of sampling adequacy (0.60 and 0.64 in 1970 and 2000, respectively), and Bartlett's test of sphericity ($\chi^2 = 482$, $P < 0.001$ and $\chi^2 = 421$, $P < 0.001$ in 1970 and 2000, respectively) indicate that the factor model is appropriate to analyze these data. PCA identified four significant latent factors explaining 59.6 and 58.4% of the total variance in 1970 and 2000, respectively (Table 3). These factors were then used in cluster analysis. The plot of factor loadings on the first two axes (Fig. 1) indicated that clear

Table 3 Results of Principal Component Analysis

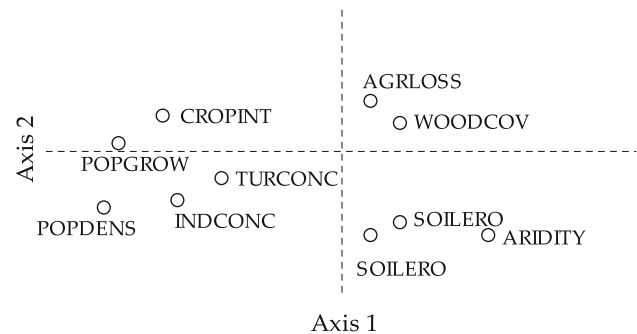| Factor	1970		2000	
	Explained variance (%)	Cumulated variance (%)	Explained variance (%)	Cumulated variance (%)
1	22.86	22.86	23.17	23.17
2	14.12	36.98	13.07	36.24
3	11.83	48.81	11.67	47.91
4	10.81	59.63	10.48	58.38

Fig. 1 PCA factor loadings (1970)

relationships existed among environmental indicators in 1970. The selected indicators clustered into four groups: (i) climate/soil indicators (ARIDITY, SOILAWC, SOILERO), (ii) population and economic indicators (POPDENS, INDCONC, TURCONC), (iii) variables indicating additional anthropogenic pressures on land (POPGROW, CROPINT), and (iv) landscape indicators (WOODCOV, AGRLOSS). A similar pattern was observed in 2000 (not shown). Additionally, factor 1 discriminated among two different types of indicators: socio-economic indicators (POPDENS, POPGROW, INDCONC, TURCONC, and CROPINT) were associated to negative axis values, while the biophysical indicators (ARIDITY, SOILAWC, SOILERO, WOODCOV, AGRLOSS) were linked to positive axis values. Factor 2 may be interpreted as a land quality gradient, with landscape indicators positively associated to this axis, and climate/soil, as well as demographic indicators, negatively correlated to the same factor. This axis reflects elevation and urban–rural gradients to which LD risk is associated in the study area.

Clusters and Discriminant Function Analysis

According to the values of the pseudo F statistics and Cubic Clustering Criterion, the partition that best discriminates among municipalities, in terms of LD risk, was formed by nine clusters in both 1970 and 2000 (Tables 4 and 5). In 1970, clusters 1–3 included urban and peri-urban municipalities featuring low environmental quality and high

Table 4 Clusters of municipalities in 1970 by average score of standardized indicators

	1	2	3	4	5	6	7	8	9
ISD	0.424	0.448	0.351	0.332	0.357	0.290	0.317	0.329	0.285
POPDENS	**7.47**	**4.63**	**1.51**	−0.26	0.11	−0.10	−0.36	−0.19	−0.57
POPGROW	**1.49**	**3.52**	**1.82**	0.16	−0.02	−0.08	−0.62	−0.33	0.00
TURCONC	**19.37**	−0.03	0.04	−0.05	−0.05	−0.06	−0.07	−0.06	−0.06
INDCONC	**1.55**	**6.22**	**0.68**	−0.17	−0.06	−0.10	−0.21	−0.10	−0.26
CROPINT	**0.60**	**0.73**	**0.82**	**0.51**	0.38	0.38	−1.25	−0.29	−1.85
LOSSAGR	0.11	−0.43	−0.07	0.40	**−2.61**	0.06	0.10	0.00	0.36
WOODCOV	−0.18	−0.17	−0.18	−0.12	−0.12	−0.07	−0.01	0.32	18.48
ARIDITY	**−1.18**	−0.33	**−0.76**	**−1.36**	0.03	0.20	0.80	0.65	0.72
SOILAWC	−0.06	−0.38	−0.09	**−0.67**	−0.14	0.42	0.52	−1.91	−3.72
SOILERO	−0.51	0.07	−0.09	−0.50	**2.61**	−0.12	0.19	−0.12	−0.51
N	1	5	25	71	16	144	89	26	1

Bold values indicate variables potentially affecting LD risk; see methods for details

pressure due to population density and economic activities (Table 4). The municipality of Rome belongs to cluster 1. The three clusters differ in their distances from Rome (higher in cluster 3) and population density (lower in cluster 3). Cluster 4 included rural municipalities with dry climate conditions, low quality soils, and strong crop intensity coupled with moderate human pressure. Rural, inland municipalities with considerable depopulation rates and land abandonment, associated with important soil erosion phenomena, clustered into the fifth group. Cluster 6 was composed of rural municipalities with discrete ecological conditions and moderate human pressure. Finally, clusters 7–9 included inland municipalities featuring good environmental conditions and low human pressure in a disadvantaged socio-economic context. Differences within the three clusters mainly depended on elevation, thus indicating increasing economic marginalization. Cluster 7 included

uplands municipalities, cluster 8 had mountain municipalities, and cluster 9 only one marginal, mountain municipality placed into the boundaries of a national park, with good ecological conditions and negligible human pressure.

In 2000, the characteristics of the nine selected clusters were similar to those extracted in 1970 (Table 5). The first three clusters included urban and peri-urban municipalities (again, the Rome municipality clustered alone in group 1), the fourth group represented municipalities with low-quality climate conditions in high-intensification agricultural areas. Rural municipalities, featuring depopulation and loss in cultivated surface linked to soil erosion risk, clustered into the fifth group. Inland, rural areas with good ecological conditions and moderate human pressure clustered into the sixth group, while the last three clusters included economically disadvantaged mountain municipalities with good ecological conditions.

Table 5 Clusters of municipalities in 2000 by average score of standardized indicators

	1	2	3	4	5	6	8	7	9
ISD	0.483	0.463	0.417	0.395	0.366	0.370	0.285	0.332	0.250
POPDENS	**6.37**	**2.67**	0.26	−0.23	−0.10	−0.06	−0.35	−0.08	−0.48
POPGROW	−0.91	0.20	**1.78**	−0.01	−0.33	0.05	−0.06	−0.32	−0.89
TURCONC	**19.33**	0.11	−0.03	−0.05	−0.06	−0.06	−0.07	−0.06	−0.07
INDCONC	**1.77**	**2.71**	−0.12	−0.17	−0.15	−0.16	−0.28	0.25	−0.32
CROPINT	**0.83**	**0.95**	**0.59**	**0.68**	0.06	0.60	−0.57	−0.17	−1.42
LOSSAGR	−0.26	0.01	0.09	0.30	**−0.96**	−0.10	0.30	0.17	−0.01
WOODCOV	−0.36	**−0.56**	−0.47	−0.18	−0.38	−0.45	1.06	−0.15	0.58
ARIDITY	**−1.58**	**−0.81**	**−1.11**	**−0.90**	0.57	−0.16	0.11	1.20	0.80
SOILAWC	−0.06	−0.11	0.23	**−0.90**	0.19	0.50	0.84	−1.55	0.15
SOILERO	−0.51	0.06	−0.39	−0.55	**2.11**	−0.01	−0.32	−0.13	−0.09
N	1	20	43	50	34	75	53	39	63

Bold values indicate variables potentially affecting LD risk; see methods for details

Table 6 Results of Discriminant Function Analysis by year

	1970			2000		
	Wilks Λ	Partial Λ	F	Wilks Λ	Partial Λ	F
POPDENS	0.009	0.58	44.11	0.009	0.64	28.99
POPGROW	0.007	0.78	16.68	0.010	0.58	37.91
TURCONC	0.007	0.79	16.15	0.007	0.90	5.78
INDCONC	0.012	0.42	82.52	0.008	0.73	19.34
CROPINT	0.009	0.56	48.07	0.011	0.53	45.73
LOSSAGR	0.008	0.63	34.49	0.008	0.80	12.89
WOODCOV	0.006	0.84	11.12	0.008	0.780	14.60
ARIDITY	0.010	0.51	58.43	0.011	0.57	39.29
SOILAWC	0.010	0.50	59.92	0.013	0.47	58.91
SOILERO	0.008	0.65	31.68	0.012	0.49	53.53

DFA results are reported in Table 6 separately for the two years of study. Different indicators contributed to cluster discrimination in 1970 and 2000. In 1970, IND-CONC appeared as the most significant factor followed by climate/soil factors (ARIDITY and SOILAWC) and human pressure indicators (CROPINT and POPDENS). In 2000, ecological (especially soil) factors were the most important indicators followed by CROPINT and POPGROW. In both years, TURCONC and WOODCOV accounted for a limited contribution to region discrimination. Differences observed in the two investigated periods may depend on changes in the economic structure and socio-demographic assets of Latium. As an example, industrial concentration grew rapidly from the 1950s to 1980s, and DFA reflects its varying role in the two study periods.

Identifying "Risky" Regions

Clusters were then aggregated into four regions according to the average values of the selected indicators, elevation, and distance to Rome. Clusters were pooled together and thus classified into the same region if they share at least 60% of variables with higher scores than the threshold. Additional information was used at this stage (see the reference list reported in Table 7) to identify the major functional drivers of LD according to the local environmental and socio-economic configuration observed in each region. Regions 1, 2, and 3 (including municipalities belonging to clusters 1–5) were classified as potentially at risk. Areas with good environmental conditions and moderate human impact belonging to clusters 6–9 were regarded as not vulnerable to LD and grouped into a residual region.

LD drivers differ in the three "risky" regions (Table 7). Soil sealing, fragmentation of traditional agricultural land, and fire risk were considered the main causes of LD risk in region 1 (whose surface encompasses the provinces of Rome and Latina). In region 2, which includes the 'Tuscia' rural district belonging to Viterbo province, the causes of LD risk were mainly attributed to agricultural intensification. Here soil salinization and compaction due to heavy mechanization, water shortage, and unsustainable irrigation practices were the major threats to rural land when reductions in rainfall and summer droughts occur. Region 3 could be regarded as a 'depopulation and soil erosion' area. A downward environmental 'spiral' is likely active here due to a process involving depopulation, land abandonment, loss in cultivated surface, soil erosion, and enhanced economic marginalization.

Table 7 "Risky" regions to LD: a synthesis of the results obtained in this study

Region number and brief description	1970 (#) cluster	2000 (#) cluster	Elevation zone	Major environmental problems	1970 (%) Surface	2000 (%) Surface	Source
1. Urban and peri-urban areas with dry climate, high population density and economic pressure[a]	1–3	1–3	Coastal and lowland areas including Rome and the 'Agro Romano' rural district	Soil sealing due to urban sprawl, fire risk, deforestation, and landscape fragmentation	40.9	47.1	1,2,3,5
2. Rural municipalities with dry climate, low/medium soil quality and agricultural intensification[a]	4	4	Coastal and inland lowlands especially in Viterbo province	Soil salinisation and compaction due to heavy mechanisation, unsustainable irrigation, landscape fragmentation	11.3	8.4	1,2,4
3. Rural municipalities featuring strong depopulation and land abandonment coupled with high soil erosion risk[a]	5	5	Hilly/mountain areas in Rieti and Latina provinces	Soil erosion	4.1	7.6	3,4,5
4. Rural areas with discrete/good environmental conditions and moderate/low human pressure	6–9	6–9	Hilly areas, especially in Sabina rural district, and marginal areas of Apennines	–	43.7	36.9	3,5

[a] Indicates "risky" regions. Sources include Salvati and Zitti (2005), Salvati and others (2007), Salvati and Zitti (2007), Salvati and Zitti (2008a), Salvati and Zitti (2008b)

The remaining territory (Region 4), classified as not vulnerable to LD, included contiguous, hilly municipalities from traditionally rural areas of Rieti and Frosinone provinces (the agricultural districts of 'Sabina' and 'Ciociaria', respectively), featuring discrete environmental conditions and moderate human pressure. However, climate conditions resulting in dryness, agricultural intensification, deforestation, and a generalized increase in population density and urban sprawl could increase vulnerability of these lands in the medium/long term. Region 4 also included marginal, contiguous municipalities of the Apennines, which share good ecological conditions and generally low human pressure. In these lands, increasing vulnerability might be associated (over the long term) with worsening climate conditions due to intense rainfall and increasing depopulation, causing land abandonment and thus soil erosion.

Figure 2 maps the "risky" regions in both 1970 and 2000. Some changes in the surface of each region were
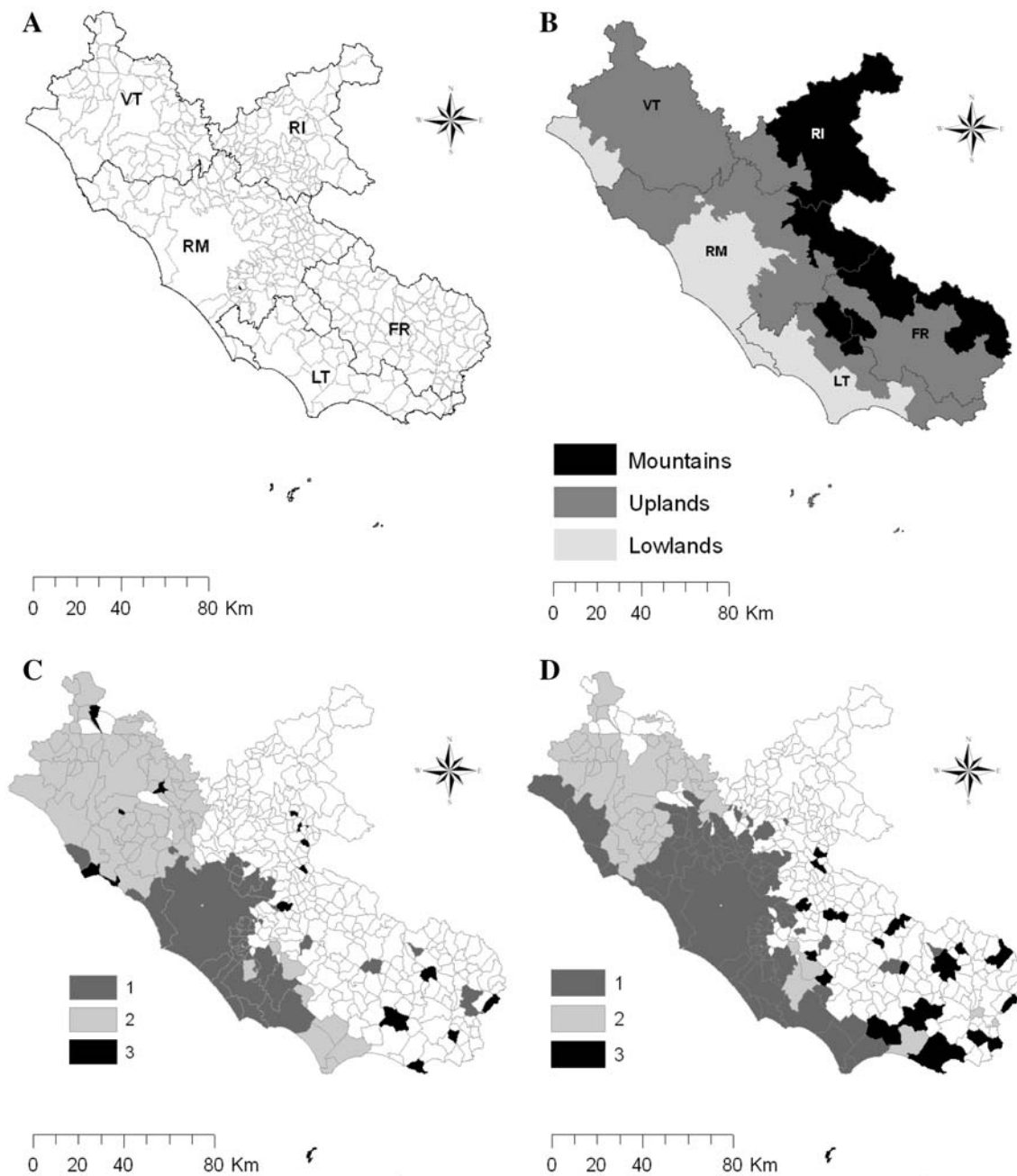

Fig. 2 Distribution of homogeneous regions in Latium by year; (a) boundaries of municipalities (dotted line) and NUTS-3 provinces (filled line)—provinces are indicated as follows: VT: Viterbo, RI: Rieti, RM: Rome, LT: Latina, FR: Frosinone); (b) Elevation zones; (c) Distribution of the three "risky" regions (see Table 7) in 1970 and (d) 2000

Table 8 Cross-year classification of municipalities in Latium by region membership (percent values) and average ISD

1970|2000	1	2	3	4	%	ISD
1	6.9	0.5	–	0.8	8.2	0.454
2	5.1	11.5	–	2.2	18.8	0.395
3	–	–	3.2	1.0	4.2	0.366
4	4.8	1.1	6.4	56.5	68.8	0.330
%	16.8	13.1	9.6	60.5	377	
ISD	0.408	0.332	0.351	0.300		

observed over 1970–2000. Region 1, originally spreading over the coastal rim and lowland municipalities close to Rome, grew in 2000 by including several municipalities in Latina and Viterbo provinces. By contrast, the spatial distribution of region 2 was quite similar in both years. Due to its typical features, area 3 included not-contiguous municipalities, confirming the point distribution of soil erosion phenomena in both years. In 1970 the surface area potentially at risk (Regions $1 + 2 + 3$) amounted to 56% of the investigated area. This increased to 63% in 2000. Considering the major causes of LD risk, 41% of the total regional surface was primarily affected by soil sealing (coupled with landscape fragmentation and fire risk) in 1970, increasing to 47% in 2000 (Region 1); 11% of the land was exposed to soil salinization due to agricultural intensification, falling to 8% in 2000 (Region 2), and 4% of the land was prone to soil erosion risk, increasing to 8% in 2000 (Region 3). Changes in region membership, as revealed by the number of municipalities classified into different clusters between the two investigated periods, are illustrated in Table 8. This analysis provides an illustration of LD trends and the possible drivers causing shifts between the different "risky" regions. In general, 78% of the Latium municipalities showed a stable cluster membership between 1970 and 2000. Only 4% of the municipalities belonging to a "risky" region in 1970 clustered into a non-risky region in 2000, while 12% of the municipalities showed the reverse pattern.

Discussion

Environmental changes causing uncertainty in variable trajectories (Thornes 2004) and hence, increasing ecological risk (Quaas and others 2007), are key to knowledge processes attempting to disentangle the interactions among ecological factors, economic performance, social dynamics, and political actions (Ibanez and others 2008). Discussing some of the most important aspects of LD risk, taken as an emblematic environmental process, and raising issues related to socio-economic matters in order to achieve

a sustainable development in the Mediterranean basin are meaningful tools for both monitoring strategies and policy implementation (Dumanski and Pieri 2000; Zalidis and others 2002, 2004; Veron and others 2006).

The multivariate strategy presented in this article is able to estimate the importance and spatial distribution of the main indicators of LD risk and follows those changes over time. This approach does not classify land according to a synthetic evaluation of its level of risk. The procedure, instead, tries to identify, based on an indirect approach, the functional drivers determining LD risk and their severity at the local scale, thus providing more complete outputs useful for policy prescriptions. The method is easy to implement and can be applied to a large ensemble of environmental indicators when available. In the present study, two groups of indicators were chosen, representing the economic and ecological aspects of LD in a certain area (Dumanski and Pieri 2000; Huby and others 2007; Siche and others 2008). The socio-economic dimension is broadly conceived and includes indicators describing the impact of the main economic sectors on the environment through specific variables such as industrial concentration, tourism pressure, agricultural intensification, and relevant information on population growth and density (e.g., Patterson and others 2004). The bio-physical dimension considers the impact of climate, soil properties, and land use on soil quality and its potential deterioration.

Indicator choice was influenced by the (limited) availability of high-resolution data over long time periods; nevertheless, we believe that the selected indicators may adequately quantify environmental conditions and LD risk in the study area. A wider availability of both bio-physical and socio-economic variables at the same spatial and temporal scales will allow the various aspects of this complex phenomenon to be more accurately depicted at both the regional and local level (Dumanski and others 1998; Niemeijer 2002; Montanarella 2007).

Our approach also provides an empirical solution that relaxes the previously mentioned weaknesses of the ESA framework and, in general, of several composite indices (Ronchi and others 2002; Lawn 2003; Morse 2008). Changes in the environmental conditions observed in Latium were explored in more detail through this analysis when compared to the findings of previous studies using composite indices of land vulnerability calculated over the same region and time span (e.g. Salvati and Zitti 2008b).

It was illustrated that functional drivers of LD act differently along elevation and urban gradients, thus confirming the hypothesis introduced in previous studies (Salvati and Zitti 2007). This was mainly due to different economic performances characterizing the investigated area in the last fifty years. The metropolitan area of Rome represents one of the most developed regions in Italy, while marginal, inland areas show disadvantaged conditions with

low levels of per-capita income and high shares of agriculture in total product. A visual comparison of the distribution of "risky" regions identified in this study (Fig. 2) and other LD maps produced at the regional level (Salvati and Zitti 2005, 2008b) suggests that a substantial similarity exists in the results produced by different procedures aimed at depicting vulnerable areas. In all studies, vulnerable lands were found in lowlands and neighboring uplands, especially in those provinces (i.e. Viterbo, Rome, Latina) showing dry climatic conditions, agricultural intensification, and growing population density.

Based on *k-means* clusters, DFA indicated that climate and soil variables are crucial in discriminating among "risky" regions. This suggests that such factors play a key role in determining the level of LD, which is increasing over time (e.g., Puigdefabregas and Mendizabal 1998; Sharma 1998; Sivakumar 2007). The results of DFA also suggest that some socio-economic factors significantly contribute to the determination of LD risk, especially CROPINT and POP-DENS. As a matter of fact, crop intensification, growth of mechanization (with a consequent risk of soil compaction), and low-efficiency irrigation contribute to the overexploitation of water resources and soil degradation especially in drier areas, thus enhancing LD. Moreover, population growth affects the phenomenon of soil sealing by human expansion into productive lands, again incrementing LD risk (Salvati and Zitti 2005). Although recent studies confirm this framework (Diodato and Ceccarelli 2004; Montanarella 2007; Salvati and Zitti 2008b), a deeper investigation of underlying causes of soil degradation is needed.

To conclude, although the importance of composite indices in the environmental sciences is not under discussion, the procedure presented here (i) increases knowledge on LD from both bio-physical and socio-economic perspectives, (ii) integrates data from different sources, and (iii) provides stakeholders with tools to define the characteristics of environmental "risky" regions. Based on these considerations, the proposed framework could be applied to other complex environmental problems featuring basic information collected at different temporal and spatial scales.

References

Atis E (2006) Economic impacts on cotton production due to land degradation in the Gediz Delta, Turkey. Land Use Policy 23:181–186

Basso F, Bove E, Dumontet S, Ferrara A, Pisante M, Quaranta G, Taberner M (2000) Evaluating environmental sensitivity at the basin scale through the use of geographic information systems and remotely sensed data: an example covering the Agri basin—Southern Italy. Catena 40:19–35

Bathurst JC, Sheffield J, Leng X, Quaranta G (2003) Decision support system for desertification mitigation in the Agri basin, southern Italy. Physics and Chemistry of the Earth 28:579–587

Casadio-Tarabusi E, Palazzi P (2004) An index for sustainable development. BNL Quarterly Review 299:185–206

Claval P (1987) The region as a geographical, economic and cultural concept. International Social Science Journal 39:159–172

D'Angelo M, Enne G, Madrau S, Percich L, Previtali F, Pulina G, Zucca C (2000) Mitigating land degradation in Mediterranean agro-silvo-pastoral systems: a GIS-based approach. Catena 40:37–49

Diodato N, Ceccarelli M (2004) Multivariate indicator Kriging approach using a GIS to classify soil degradation for Mediterranean agricultural lands. Ecological Indicators 4:177–187

Dumanski J, Pieri C (2000) Land quality indicators: research plan. Agriculture, Ecosystems & Environment 81:93–102

Dumanski J, Pettapiece WW, McGregor RJ (1998) Relevance of scale dependent approaches for integrating biophysical and socio-economic information and development of agroecological indicators. Nutrient Cycling in Agroecosystems 50:13–22

Duran BS, Odell PL (1974) Cluster analysis. Springer-Verlag, New-York

Feoli E, Gallizia Vuerich L, Zerihun W (2002) Evaluation of environmental degradation in northern Etiopia using GIS to integrate vegetation, geomorphological, erosion, and socio-economic factors. Agriculture, Ecosystems & Environment 91:225–313

Feoli E, Giacomich P, Mignozzi K, Oztürk M, Scimone M (2003) Monitoring desertification risk with an index integrating climatic and remotely-sensed data: an example from the coastal area of Turkey. Management of the Environmental Quality 14:10–21

Harman HH (1976) Modern factor analysis. University of Chicago Press, Chicago

Hein L (2007) Assessing the costs of land degradation: a case study for the Puentes catchment, southeast Spain. Land Degradation and Development 18:631–642

Hubacek K, van den Bergh JCJM (2006) Changing concepts of 'land' in economic theory: from single to multi-disciplinary approaches. Ecological Economics 56:5–27

Huby M, Owen A, Cinderby S (2007) Reconciling socio-economic and environmental data in a GIS context: an example from rural England. Applied Geography 27:1–13

Ibanez J, Martinez Valderrama J, Puigdefabregas J (2008) Assessing desertification risk using system stability condition analysis. Ecological Modelling 213:180–190

Incerti G, Feoli E, Giovacchini A, Salvati L, Brunetti A (2007) Analysis of bioclimatic time series and their neural network-based classification to characterize drought risk patterns in south Italy. International Journal of Biometeorology 51:253–263

ISTAT (2006) Atlante statistico dei comuni. Istituto Nazionale di Statistica, Rome

Kok K, Patel M, Rothman DS, DeGroot R (2004) Multi-scale scenario development within Medaction. In: Gagliardo P (ed) Desertification: actors, research, policies. Società Geografica Italiana, Studi e Ricerche, no. 14, Rome, Italy

Kosmas C, Danalatos NG, Gerontidis S (2000a) The effect of land parameters on vegetation performance and degree of erosion under Mediterranean conditions. Catena 40:3–17

Kosmas C, Gerontidis S, Marathianou M (2000b) The effect of land use change on soil and vegetation over various lithological formations on Lesvos. Catena 40:51–68

Lawn PA (2003) A theoretical foundation to support the Index of Sustainable Economic Welfare (ISEW), Genuine Progress Indicator (GPI), and other related indexes. Ecological Economics 44:105–118

Le Houerou HN (1993) Land degradation in Mediterranean Europe: can agroforestry be a part of the solution? A prospective review. Agroforestry Systems 21:43–61

Loumou A, Giourga C, Dimitrakopoulos P, Koukoulas S (2000) Tourism contribution to agro-ecosystems conservation; the case of Lesbos island, Greece. Environmental Management 26:363–370

Montanarella L (2007) Trends in land degradation in Europe. In: Sivakumar MV, N N'diangui N. (eds) Climate and land degradation. Springer, Berlin

Morse S (2008) On the use of headline indices to link environmental quality and income at the level of the nation state. Applied Geography 28:77–95

Mouat D, Lancaster J, Wade T, Wickham J, Fox C, Kepner W, Ball T (1997) Desertification evaluated using an integrated environmental assessment model. Environmental Monitoring and Assessment 48:139–156

Nader MR, Salloum BA, Karam N (2008) Environment and sustainable development indicators in Lebanon: a practical municipal level approach. Ecological Indicator (in press)

Niemeijer D (2002) Developing indicators for environmental policy: data-driven and theory-driven approaches examined by example. Environmental Science and Policy 5:91–103

Nir D (1990) Region as a socio-environmental system. An introduction to a systemic regional geography. Kluwer, Dordrecht

Nourry M (2008) Measuring sustainable development: some empirical evidence for France from eight alternative indicators. Ecological Economics 67(3):441–456

Patterson T, Gulden T, Cousins K, Kraev E (2004) Integrating environmental, social and economic systems: a dynamic model of tourism in Dominica. Ecological Modelling 175:121–136

Puigdefabregas J, Mendizabal T (1998) Perspectives on desertification: western Mediterranean. Journal of Arid Environment 39:209–224

Quaas MF, Baumgärtner S, Becker C, Frank K, Müller B (2007) Uncertainty and sustainability in the management of rangelands. Ecological Economics 62:251–266

Ronchi E, Federico A, Musmeci F (2002) A system oriented integrated indicator for sustainable development in Italy. Ecological Indicators 2:197–210

Rubio JL, Bochet E (1998) Desertification indicators as diagnosis criteria for desertification risk assessment in Europe. Journal of Arid Environment 39:113–120

Salvati L, Zitti M (2005) Land degradation in the Mediterranean basin: linking bio-physical and economic factors into an ecological perspective. Biota 5:67–77

Salvati L, Zitti M (2007) Territorial disparities, natural resource distribution, and land degradation: a case study in southern Europe. GeoJournal 70:185–194

Salvati L, Zitti M (2008a) Regional convergence of environmental variables: empirical evidences from land degradation. Ecological Economics 68(4):162–168

Salvati L, Zitti M (2008b) Assessing the impact of ecological and economic factors on land degradation vulnerability through multiway analysis. Ecological Indicators 9:357–363

Salvati L, Macculi F, Toscano S, Zitti M (2007) Comparing indicators of intensive agriculture from different statistical sources. Biota 8:51–60

Sharma KD (1998) The hydrological indicators of desertification. Journal of Arid Environment 39:121–132

Siche JR, Agostinho F, Ortega E, Romeiro A (2008) Sustainability of nations by indices: comparative study between environmental sustainability index, ecological footprint and the emergy performance indices. Ecological Economics 66(4):628–637

Simeonakis E, Calvo-Cases A, Arnau-Rosalen E (2007) Land use change and land degradation in southeastern Mediterranean Spain. Environmental Management 40:80–94

Sivakumar MVK (2007) Interactions between climate and desertification. Agricultural and Forest Meteorology 142:143–155

Tanrivermis H (2003) Agricultural land use change and sustainable use of land resources in the Mediterranean region of Turkey. Journal of Arid Environment 54:553–564

Thornes JB (2004) Stability and instability in the management of Mediterranean desertification. In: Wainwright J, Mulligan M (eds) Environmental modelling: finding simplicity in complexity. Wiley, Chichester, UK, pp 303–315

Trakhtenbrot A, Kadmon R (2006) Effectiveness of environmental cluster analysis in representing regional species diversity. Conservation Biology 20:1087–1098

Trouvè A, Berriet-Solliec M, Depres C (2007) Charting and theorising the territorialisation of agricultural policy. Journal of Rural Studies 23:443–452

van Delden H, Luja P, Engelen G (2007) Integration of multi-scale dynamic spatial models of socio-economic and physical processes for river basin management. Environment Modeling & Software 22:223–238

Veron SR, Paruelo JM, Oesterheld M (2006) Assessing desertification. Journal of Arid Environment 66:751–763

Williams CL, Hargrove WW, Liebman M, James DE (2008) Agro-ecoregionalization of Iowa using multivariate geographical clustering. Agriculture, Ecosystems & Environment 123:161–174

Yli-Viikari A, Hietala-Koivu R, Huusela-Veistola E, Hyvonen T, Perala P, Turtola E (2007) Evaluating agri-environmental indicators (AEIs)—use and limitations of international indicators at national level. Ecological Indicators 7:150–163

Zalidis G, Stamatiadis S, Takavakoglou V, Eskridge K, Misopolinos N (2002) Impacts of agricultural practices on soil and water quality in the Mediterranean region and proposed assessment methodology. Agriculture, Ecosystems & Environment 88:137–146

Zalidis GC, Tsiafouli MA, Takavakoglou V, Bilas G, Misopolinos N (2004) Selecting agri-environmental indicators to facilitate monitoring and assessment of EU agri-environmental measures effectiveness. Journal of Environmental Management 70:315–321