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Lost in convergence, found in vulnerability: A spatially-dynamic model for desertification risk assessment in Mediterranean agro-forest districts

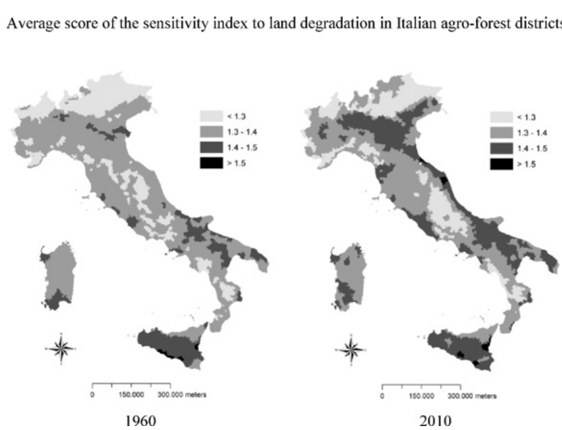
Ilaria Tombolini [a], Andrea Colantoni [b], Gianluca Renzi [a], Adele Sateriano [e], Alberto Sabbi [c], Nathan Morrow [d], Luca Salvati [a,*]

[a] Italian Council for Agricultural Research and Economics (CREA-RPS), Via della Navicella 2-4, I-00184 Rome, Italy
[b] Department of Agricultural and Forestry scieNcEs (DAFNE), Tuscia University, Via S. Camillo de Lellis, I-01100 Viterbo, Italy
[c] Italian National Institute of Statistics (ISTAT), Via C. Balbo 16, I-00184 Rome, Italy
[d] Tulane University, Payson Program in International Development at the School of Law, New Orleans, USA
[e] Via A. Di Tullio 40, I-00136 Rome, Italy

HIGHLIGHTS

- This study illustrates an approach to early-warning assessment of desertification risk.
- We used the ESAI approach to study land vulnerability in Italian agro-forest districts.
- Convergence in Land Vulnerability to Degradation (LVD) was mainly observed in flat districts.
- The average ESAI score converged more rapidly in large districts in respect to smaller districts.
- Spatial convergence in LVD is a key concept in the assessment of land degradation.

GRAPHICAL ABSTRACT



Average score of the sensitivity index to land degradation in Italian agro-forest districts.

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ABSTRACT

This study illustrates an approach to early-warning assessment of desertification risk in Mediterranean agro-forest districts based on the concept of 'spatial convergence' in Land Vulnerability to Degradation (LVD). We investigate long-term and short-term spatial convergence in LVD across 773 agro-forest districts with different biophysical and socioeconomic traits across Italy. We used the standard Environmental Sensitive Area Index (ESAI) based on climate, soil, vegetation and land management attributes as a proxy for LVD. Latitude, elevation and district size are considered as control variables. Results of the analysis show that more than half districts have experienced an increase in the average ESAI score between 1960 and 2010 and present distinct spatial patterns over three time intervals considered in the study: 1960–1990, 1990–2000 and 2000–2010. Convergence in LVD was observed between 1960 and 1990 especially in flat and highly accessible rural districts of northern Italy. The average ESAI score converged more rapidly in large districts in respect to smaller districts. A moderate convergence in LVD was observed in southern and central Italy during 1990–2000 and 2000–2010 respectively.

* Corresponding author at: CREA-RPS, Italy.

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Based on our findings, spatial convergence in LVD is finally proposed as a key concept in the on-going and future assessment of land degradation in rural areas under (increasing) anthropogenic pressure.

1. Introduction

Increased human pressure in dry ecosystems has resulted in a significant expansion of degraded land and a measurable loss of soil quality over the last three decades (Geeson et al., 2002; Montanarella, 2007; Simeonakis et al., 2007). Steep topography, poor soils, low vegetation cover, climate aridity and drought severity, negatively impact land quality, triggering soil degradation processes especially in ecologically-vulnerable areas (Geist and Lambin, 2004; Basso et al., 2012; Bisaro et al., 2014). The negative influence of land degradation on local development, economic performances and social cohesion is also documented, mainly for emerging countries (Glenn et al., 1998), but empirical evidence has been increasingly collected for the wealthiest regions in the world (Juntti and Wilson, 2005; Salvati and Carlucci, 2013; Kelly et al., 2015).

Land Vulnerability to Degradation (LVD) is a dynamic attribute of the landscape (Salvati and Zitti, 2008) and determining the spatial dynamics observed recently at both the global and regional scale requires a continuous monitoring to identify the most relevant contributing factors (Hill et al., 2008). Temporal dynamics and spatial heterogeneity in land degradation drivers are rarely considered together in mitigation and adaptation policies (Gisladottir and Stocking, 2005). By contrast, response interventions to land degradation have been primarily developed with the final objective of reversing (or reducing) the short-term impact of a single factor or a limited set of contributing factors (Sommer et al., 2011). Biophysical and socioeconomic drivers of change have been usually assessed separately (Zdruli, 2014), and therefore policy strategies have also frequently addressed the two dimensions separately (Thomas et al., 2012).

Due to the long-term interaction between nature and man, traditional agro-forest systems dominate Mediterranean landscapes and preserve biodiversity, natural resources, aesthetic and cultural values (Salvati and Ferrara, 2015). Forms of sustainable agriculture were frequently practiced in these districts and provided some protection from land degradation (Biasi et al., 2015). Agro-forest systems are increasingly seen as buffer zones containing soil degradation and desertification risk in vulnerable areas (Bajocco et al., 2015). Agro-forest districts are therefore seen as an appropriate scale for assessment of LVD in Mediterranean Europe (Salvati et al., 2015a). Past experience shows that multidimensional analysis of landscape and socioeconomic transformations in agro-forest systems prove to be relevant evidence base for the development and implementation of integrated land degradation management strategies (Salvati and Zitti, 2009). Additionally, in-depth understanding of complex environmental dynamics in agro-forest systems at the spatio-temporal scales considered in this study contribute essential information for the design of sustainable land management policies (Le Houérou, 1993).

'Convergence' in a given condition or process is a regional system modeling approach commonly applied to indicators of economic growth or income but also used more recently to model a wider variety of sociological and ecological phenomenon (Barro and Sala-i-Martin, 2004). The 'convergence' notion denotes a negative relationship between changes over time in the studied variable and the level of the same variable at the initial observation time (Arbia and Paelinck, 2003). Convergence compares the average change over time to the initial value for an indicator under the implicit assumption that those units with the lowest value will change at a faster rate to those units already near (or above) the mean. If it is assumed that the indicator is rising across the observed units, then there should be a negative relationship between more recent measurements and previous measurements. Then more negative this relationship, the more certainty that values across all units are in fact converging around the mean.

Spatial convergence in economic, demographic and social indicators is well documented in regional and country level assessments (Quah, 1997; Giannias et al., 1999; Manca et al., 2014), but relatively fewer studies focus on convergence of environmental pressure, governance and policy indicators (Iosifides and Politidis, 2005; Aldy, 2006; Ezcurra, 2007). Notwithstanding the relative novelty of the approach, there exists a great demand for research on spatial convergence in ecological (or socio-environmental) variables as a potential evidence base to design policies for the mitigation of land degradation processes driven jointly by biophysical and socioeconomic factors (Bajocco et al., 2015). Spatial convergence is also suggested as a possible early-warning indicator of environmental risk in complex ecological contexts (e.g. Neumayer, 2001).

Salvati and Zitti (2008, 2009) first applied the concept of convergence to LDV and then provided empirical evidence on spatial convergence in LVD at the country scale by identifying the most relevant factors determining convergence among selected ecological and socioeconomic factors in Italy. Salvati et al. (2013) demonstrated that a given territorial system may undergo different (or even contrasting) patterns of land vulnerability (improvement, worsening or stability) in the long-term, amplifying sometimes the heterogeneity in the spatial distribution of land resources (Salvati et al., 2015a). Processes causing spatio-temporal convergence in LVD have been hypothesized to represent a signal of desertification risk (Salvati, 2014). Convergence in LVD may also be used as an organizing concept when developing socio-environmental scenarios for policy implementation (Thornes, 2004). Although a number of candidate indicators, composite indexes and decision support systems assessing desertification risk have been proposed at both global and regional scales, early-warning approaches increasingly require a reduced number of variables and simplified analytical techniques (Salvati et al., 2011).

Meeting these requirements, spatial convergence in LVD is proposed as a promising approach to on-going and future assessment of land degradation in rural areas under (increasing) anthropogenic pressure (Salvati and Zitti, 2009). Convergence or divergence of LVD may prove useful in the assessment of adaption capacity of agro-forest districts to biophysical and human pressures as well as inform specific mitigation strategies (Briassoulis, 2011; Kelly et al., 2015; Salvati et al., 2015a). In the present study we investigate the long-term (1960–2010) spatial convergence of LVD in Italy using a composite index of land vulnerability that integrates environmental and socioeconomic variables at the scale of agro-forest districts. The national coverage of our study makes the results potentially more interesting than a pilot study confined to a limited test area. Analysis of areas experiencing spatial convergence in LVD in Italy provides relevant information for the analysis of land degradation across the northern Mediterranean and may contribute to the evidence-based design of place-specific measures for mitigation of desertification risk and adaptation to rapid socio-environmental changes (Salvati et al., 2015b). The novelty of the approach presented in this study lies in the integration of a widely-used land degradation monitoring system (such as the ESA) into a statistical model incorporating space and selected context variables as relevant predictors of local-scale changes in the level of LVD. Finally, we discuss the relevance of spatial convergence in LVD as an early-warning signal of increased desertification risk at the local scale.

2. Methodology

2.1. Study area

Italy is a northern Mediterranean country divided into three geographical areas (North, Centre, South) and 20 administrative regions with a total land surface that extends 301,330 km^2 (23% lowland, 42% upland and 35% mountains). The distribution of socioeconomic and land resource disparities across Italy reflects millennia of interplay between biophysical factors and human action that is evident in both landscape structure and environmental quality (Salvati and Zitti, 2008). In this study, the Italian territory was partitioned into 773 Agro-forest Homogeneous Districts (AHD) defined by the Italian National Statistical Institute using similarity criteria in climate regime, topography, soil quality and land suitability to cropping, forestry or grazing (Istat, 1958). Agro-forest districts are composed by 5–10 municipalities and are considered robust geographical domains in the analysis of spatially-disaggregated statistical data dealing with the primary sector (Salvati et al., 2015a).

2.2. Data and variables

The Environmental Sensitive Area (ESA) scheme for the identification and prioritization of agricultural areas that require protection can be more broadly applied to the assessment of LVD and desertification risk at both the regional and country scale in southern Europe (Salvati and Zitti, 2009). The fourteen variables considered in the ESA scheme refer to four thematic domains (soil, climate, vegetation, land-use/management) derived from official data sources and made available as spatially-disaggregated continuous layers (Ferrara et al., 2012). A geographic information system was used to operationally manage these layers and to aggregate them into partial indicators quantifying the contribution of each thematic domain to the composite index (Bajocco et al., 2015). Comparable data to fully enumerate the ESA scheme was only available at limited points in time. Therefore, this study will consider a 50-year time period assessing the level of land vulnerability at four specific points in time (1960, 1990, 2000 and 2010).

2.2.1. Soil

Soil quality is a multifaceted concept reflecting the ability of land to sustain agricultural production and natural vegetation (Salvati et al., 2011). By adopting the ESA scheme, four variables (soil texture, depth, parent material and slope) were considered in the assessment of soil quality. Soil data were derived from the European Soil Database at 1 km^2 pixel resolution (Joint Research Center, JRC) and integrated with an Italian database of soil characteristics produced by the Ministry of Agriculture, the Ecopedological map of Italy, a Land System map produced by the National Centre of Soil Cartography (CNCP), and a 20 m Digital Elevation Model (Salvati et al., 2013). A land classification system with scores ranging from 1 to 2 (Salvati et al., 2015b) was developed for each studied variable and applied at the district scale with the aim to homogenize soil variables and define vulnerability classes and thresholds. The score system was derived from statistical analyses and the fieldwork performed by previous authors (Kosmas et al., 2000; Lavado et al., 2009; Salvati et al., 2011). For each elementary spatial unit, a Soil Quality Index (SQI) was estimated as the geometric mean of the scores attributed to each value of the four selected variables, ranging from 1 (the lowest soil vulnerability) to 2 (the highest soil vulnerability). The SQI was then calculated at 1 km^2 resolution for Mediterranean Europe (Colantoni et al., 2015).

SQI is often applied as an operational approach to analyse spatial distribution of soil quality for small areas using diachronic soil mapping but here is treated as a static status variable input to ESA due to limitations in national data coverage (Salvati et al., 2011, 2015b). Although soil depth can vary slightly over longer time intervals and in areas experiencing high levels of soils erosion, the assumption of little average change at the national scale is acceptable due to data availability and cost implications of collecting this data at high spatial resolution (Salvati et al., 2013).

2.2.2. Climate

Three variables were used to assess climate quality in the ESA scheme: average annual rainfall rate, aridity index and aspect. Rainfall and aridity index were both measured as a 10-year average for 4 time windows (1951–1960, 1981–1990, 1991–2000, 2001–2010). Climate variables were derived from spatially-interpolated meteorological data collected in the National Agro-meteorological Database (BDAN) developed by the Italian Ministry of Agriculture for scientific analysis at the country scale in Italy (Bajocco et al., 2015). The BDAN includes daily time series of precipitation, air temperature and humidity, wind (intensity and direction) and solar radiation collected from official (national and regional) networks monitoring weather conditions over the time period between 1951 and 2010. Meteorological data were checked and validated prior to analysis in order to verify temporal and spatial consistency (Colantoni et al., 2015).

Kriging and co-kriging procedures applied to monthly and annual data on precipitation and temperature were used to regionalize the relevant climate variables in the rainfall and aridity index. Ordinary kriging was applied to the spatial distribution of annual rainfall over the investigated time period; monthly temperature regimes were assessed using a co-kriging procedure incorporating the effect of ancillary variables such as elevation and distance to the coast in producing raster maps at 1 km spatial resolution (Salvati and Zitti, 2008). Grid size was chosen based on the density and geographic distribution of gauging stations (Colantoni et al., 2015). The aridity index was calculated as the ratio of cumulated annual rainfalls (mm) to annual reference evapotranspiration (mm). The aridity index ranges from 0 to ∞ with higher values indicating wetter conditions (Incerti et al., 2007). Aspect was finally derived from a Digital Elevation Model (DEM) made available at 20 m-cell size resolution (Salvati et al., 2015a).

2.2.3. Vegetation

The influence of changes in vegetation cover on the level of LVD was assessed using four variables: plant cover, fire risk, protection from soil erosion, and vegetation drought resistance. Such indicators were obtained from elaboration on CORINE (COoRdination of INformation on the Environment) Land Cover maps produced by the Italian Institute of Environmental Research and Protection (Ispra) for the years 1990, 2000 and 2006 and on a CORINE-like land cover map of Italy produced by Italian Touring Club and National Research Council for 1960 (Salvati et al., 2015a).

2.2.4. Land use and management

Different forms of land use and management, possibly reflecting low or high anthropogenic environmental pressure that influence the level of land vulnerability to degradation, were assessed with respect to population density, demographic growth and land-use intensity. Although indirectly connected with desertification risk in the Mediterranean basin, these variables provides a joint assessment of the local socioeconomic context and anthropogenic land use management impact (Salvati et al., 2011; Salvati, 2014). Population density (inhabitants/km^2) was calculated for 1961, 1991, 2001 and 2011 on the basis of the primary data from the Italian National Census of Population and Households (Salvati and Zitti, 2008). Annual population growth rate was derived from the same dataset and computed separately for 1951–1961, 1981–1991, 1991–2001 and 2001–2011 time intervals (Salvati et al., 2015a). A proxy of land-use intensity was then derived from the four land-use maps mentioned above after a vulnerability score was assigned to each land-use class according to Kosmas et al. (2000).

2.3. Building ESA partial indicators over time

For each point in time, the primary variables assessing climate, vegetation and land-use/management were transformed into vulnerability indicators using a generalized score system based on the estimated degree of correlation with LVD (Salvati and Zitti, 2009). We applied the scores proposed by Salvati and Zitti (2008) and ranging between 1 (the lowest contribution to LVD) and 2 (the highest contribution to LVD). This score system follows standard benchmarks proposed by Kosmas et al. (2000); Geeson et al. (2002); Simeonakis et al. (2007); Lavado Contador et al. (2009); Salvati and Carlucci (2013) and Salvati (2014). Partial indicators of climate, vegetation and land-use/management quality were calculated as the geometric mean of the respective vulnerability indicators' scores for each *i*-th spatial domain. According to the adopted score system, the partial indicators of climate (Climate Quality Index, CQI), vegetation (Vegetation Quality Index, VQI) and land-use/management (Land Management Quality Index, MQI) range between 1 and 2, with larger scores indicating higher land vulnerability (Ferrara et al., 2012). The three partial indicators were spatially overlaid with the SQI illustrated in Section 2.2.1. using a Geographic Information System (Bajocco et al., 2015).

2.4. A multidimensional metric of land vulnerability

Following the original formulation proposed by Geeson et al. (2002) and also considering Karamesouti et al. (2015) and references therein, we calculated the ESA composite index (ESAI) for each *i*-th spatial domain (agro-forest districts) and *j*-th year (1960, 1990, 2000, 2010) as the geometric mean of the four quality indicators (CQI, VQI, MQI, SQI). Based on the score's range defined for each partial indicator, the ESAI assumes values ranging between 1 (the lowest level of LVD) and 2 (the highest level of LVD). Outcomes of the ESA scheme have been extensively validated at several sites in southern Europe (Kosmas et al., 2000; Basso et al., 2012; Ferrara et al., 2012; Bajocco et al., 2015). Lavado Contador et al. (2009) conducted a regional assessment similarly based on heterogeneous geographical datasets with different data quality and spatial resolution and found the ESA scheme as a reliable decision support system for land degradation processes. Ferrara et al. (2012) documented the stability of the ESA index over different temporal and spatial conditions, evaluating the sensitivity to changes in the primary indicators as well as in the composite index. Results of the sensitivity analysis indicate that the ESAI is not affected by spatial and temporal heterogeneity in the underlying indicators. Finally, Salvati et al. (2015b) have identified a number of significant correlations between the ESAI and a vast set of soil degradation indicators in Italy. Despite its acknowledged importance as a tool for monitoring land degradation (Salvati and Zitti, 2009), the ESA scheme also presents some shortcomings since the input variables are oriented towards the description of basic biophysical and socioeconomic attributes of a given area without a formal specification of other socio-political and cultural factors possibly influencing the process of land degradation (Salvati et al., 2015a). However considering the availability of comparable input variables over time and space, the basic specification of the ESA model was considered acceptable for the purposes of the study to investigate diachronic land degradation over a large area and longer timeframe (Salvati and Zitti, 2008).

2.5. Statistical analysis

An average ESAI figure was computed for each agro-forest district and study year, and the corresponding annual rate of change over time was calculated for each relevant time interval: 1960–1990, 1990–2000, 2000–2010. Three types of statistical models were run with the objective to verify convergence over time in the spatial pattern of LVD at the district scale in Italy:

(i) Ordinary Least Squares (OLS) model based on three separate specifications: linear, square and cubic; measuring convergence between the rate of change over time in LVD measured as ΔESAI and the initial level of the target variable measured as the initial mean value of ESAI for the spatial unit,
(ii) OLS model measuring the rate of change over time in LVD and a set of predictors including the initial level of the target variable and a vector of contextual variables, and
(iii) a spatial regression model considering the initial level of the target variable, a vector of contextual variables and space location as predictors.

2.5.1. Convergence analysis

The OLS models mentioned above were estimated as follows:

$$\Delta \mathrm{ESAI}_{(j1-j0,i)} = b_0 + b_1 * \mathrm{ESAI}_{(j0,i)} + e \quad (1)$$

$$\Delta \mathrm{ESAI}_{(j1-j0,i)} = b_0 + b_1 * \mathrm{ESAI}_{(j0,i)} + b_2 * {\mathrm{ESAI}_{(j0,i)}}^2 + e \quad (2)$$

$$\Delta \mathrm{ESAI}_{(j1-j0,i)} = b_0 + b_1 * \mathrm{ESAI}_{(j0,i)} + b_2 * {\mathrm{ESAI}_{(j0,i)}}^2 + b_3 * {\mathrm{ESAI}_{(j0,i)}}^3 + e \quad (3)$$

where $\mathrm{ESAI}_{(j0,i)}$ is the estimated level of LVD for the year j_0 and the *i*-th spatial domain, $\Delta\mathrm{ESAI}_{(j1\text{-}j0,\ i)}$ is the per cent change in the ESAI score observed over a given time interval, and *e* is the error term. Significance was assessed at $p < 0.01$ based on the results of a Fisher-Snedecor F test under the null hypothesis of non-correlation between the dependent variable and the predictor(s). Results report all variables entered in each model with significant coefficients (Salvati and Zitti, 2008). Positive and negative coefficients indicate a tendency of LVD to diverge or to converge respectively (Salvati and Zitti, 2009).

2.5.2. Modeling convergence in the ESAI with contextual attributes

A multiple linear regression model was run to identify the territorial predictors most associated with changes in the level of LVD separately for each time interval. Four predictors were considered (Table 1): the initial level of the target variable (ESAI), the average elevation of each

Table 1
Variables considered in the present study including measurement scale and data source.

Acronym	Variable name	Measurement scale	Data source
ESAI	Environmentally Sensitive Area Index	Average score ranging from 1 to 2	Elaboration on CQI, SQI, VQI, MQI
CQI	Climate Quality Index	Average score ranging from 1 to 2	Italian agro-meteorological database
SQI	Soil Quality Index	Average score ranging from 1 to 2	Joint Research Centre (Ispra)/EEA[a]
VQI	Vegetation Quality Index	Average score ranging from 1 to 2	Elaboration on CLC[b] maps
MQI	Land-use/management Quality Index	Score ranging from 1 to 2	Elaboration on pop. census/CLC maps
Lat	Latitude (north-south gradient)	0: northern and central Italy districts; 1: southern Italy districts	ISTAT[c] territorial statistics
Ele	Elevation	m	ISTAT Atlas of Italian municipalities
Area	District's surface area	km^2	Elaboration on ISTAT (1958)

[a] European Environment Agency.
[b] Corine Land Cover.
[c] Italian National Institute of Statistics.

district (Ele), a dummy variable (Lat) classifying districts based on the geographical position in Italy with '0' given for districts situated in northern and central Italy and '1' for districts situated in southern Italy, and district's surface area (Area). Model's outcomes are reported using regression coefficients and tests of significance for each variable as well as an overall Fisher-Snedecor's F-statistic testing for the null-hypothesis of non-significant model and a Student's *t*-statistic testing for the null hypothesis of non-significant regression coefficient. A Durbin-Watson statistic testing for the null hypothesis of serially uncorrelated errors was applied separately to regression residuals.

2.6. Exploring spatial convergence in the ESAI with a Geographically Weighted Regression

A Geographically Weighted Regression (GWR) model (Fotheringham et al., 2002) was finally used to identify spatio-temporal convergence in

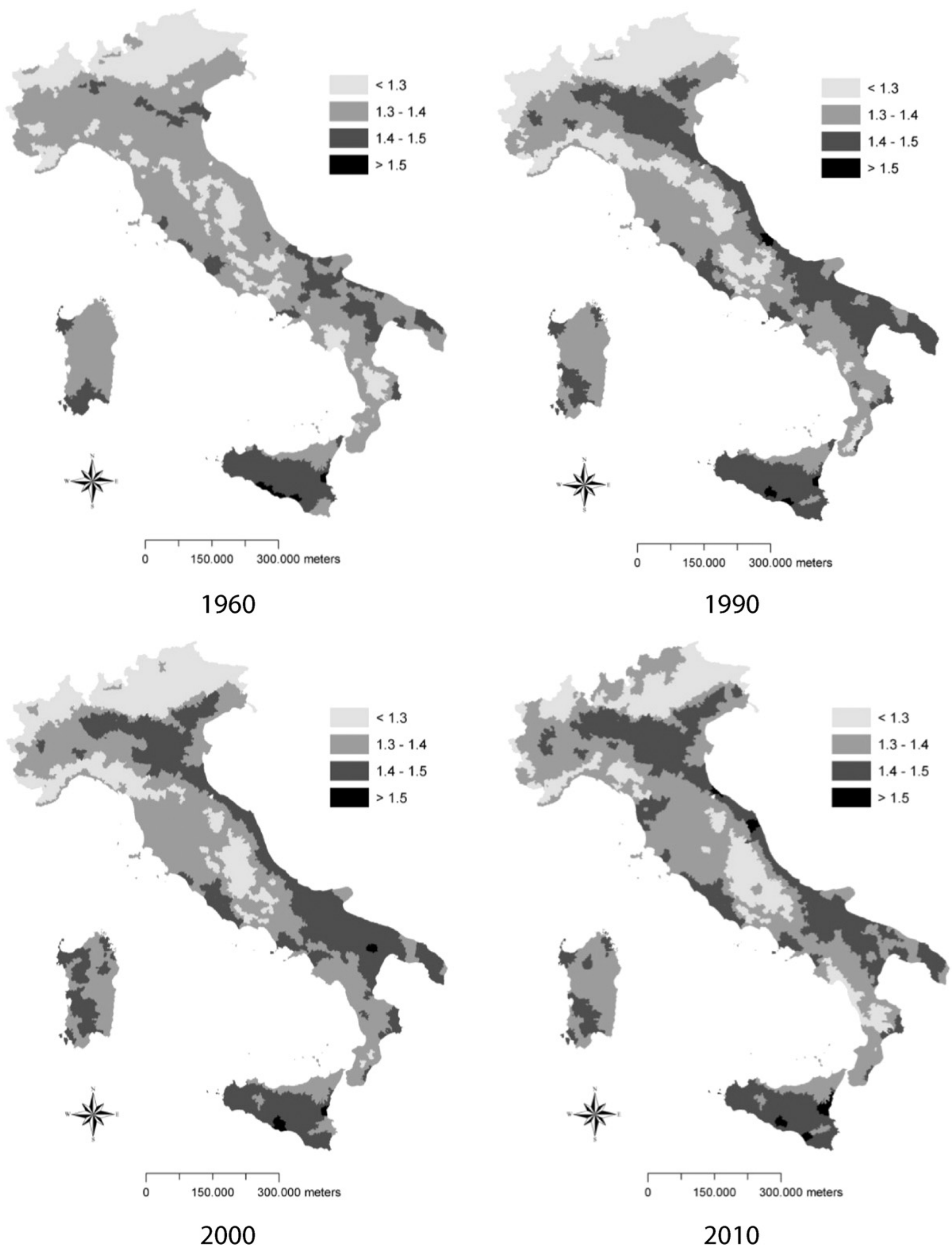

Fig. 1. Spatial distribution of the average ESAI score by agro-forest district in Italy by year.

LVD taking into account the initial level of the ESAI, the four predictors mentioned above (ESAI, Ele, Lat, Area) and space. The specification of a basic GWR model for the *i*-th spatial domain is:

$$y_{(i)} = x_{(i)} * b_{(i)} + e_{(i)} \tag{4}$$

where $y_{(i)}$ is the dependent variable, $x_{(i)}$ is the row vector of predictors, $b_{(i)}$ is the column vector of regression coefficients, and $e_{(i)}$ is the random error, all estimates being calculated at location *i*. Regression parameters were estimated at each agro-forest district by weighted least squares and may vary in space. We used a bi-square nearest neighbour kernel function modeling socioeconomic processes that are non-stationary in space (Manca et al., 2014) to derive the spatial distribution of locally-weighted regression parameters based on model (4). The highest weights were attributed to the observations close to the *i*-th location.

3. Results

Spatio-temporal changes in the distribution of the average ESAI score in the Italian agro-forest districts are shown in Fig. 1. The observed variations in the ESAI suggest that the environmental conditions contributing to LVD worsen throughout Italy over the study period. Nearly half Italian districts showed an increase in the average ESAI score over all investigated time periods. The largest rates of growth in the ESAI score were observed in the Po valley (northern Italy), along the Adriatic coast (central Italy), and in some districts of Apulia and Sicily, southern Italy. Identifying a 'critical' level of land vulnerability to degradation, the average ESAI score in southern Italy was nearly 1.4 in 2010 (Basso et al., 2012). Soil and vegetation quality contributed the most to the spatial distribution of the ESAI score (Fig. 2). SQI and VQI showed, on average, the highest scores (respectively 1.53 and 1.47) on a vulnerability scale ranging from 1 to 2. VQI scores increased in Italy by 3% between 1960 (1.47) and 2010 (1.50). The CQI showed the largest increase across the country (+7%) with the average score moving from 1.09 in 1960 to nearly 1.20 in 2010. Finally, MQI was relatively stable over time (1.31 for 1960 and 1.30 for 2010).

3.1. Convergence analysis

The relationship between state and changes in the level of LVD observed in each agro-forest district is illustrated in Table 2. We run linear, square and cubic models of convergence to investigate the relationship between change in the average ESAI over three time intervals (1960–1990, 1990–2000, 2000–2010) and the respective ESAI score at the beginning of the studied time interval (1960, 1990, 2000). A square convergence pattern was observed for 1960–1990 with moderately high adjusted-R^2 and a significant Spearman non-parametric correlation coefficient. The rate of change in LVD increased with the level of land vulnerability up to a peak estimated ESAI = 1.4 while decreasing in districts classified at high initial ESAI score. Convergence patterns between the investigated variables were non-significant in the subsequent time intervals (1990–2000 and 2000–2010).

3.2. Modeling convergence in the level of the ESAI with contextual attributes

A multiple regression analysis estimating convergence in the level of LVD was run separately for each time interval including 4 predictor variables (Table 3). A moderately significant convergence pattern was found over 1960–1990 (adjusted $R^2 = 0.26$). Elevation is the most relevant variable associated to convergence in the LVD. This result indicates that flat areas are more sensitive to rapid increases in the ESAI with respect to hilly and mountainous districts. Weak signals of convergence were observed for the time period between 1990 and 2000 (adjusted $R^2 = 0.10$) with the average ESAI score, latitude and elevation affecting negatively LVD. The ESAI coefficient was not significant during 2000–2010, indicating lack of convergence in the spatial pattern of LVD. Latitude and elevation were the only significant variables producing a model with adjusted $R^2 = 0.17$. LVD in northern Italian districts grew much more rapidly in respect to southern Italy. Moreover, LVD increased much more rapidly in upland and mountain districts than in flat areas, indicating a distinct spatial pattern from what was observed in the preceding time intervals.

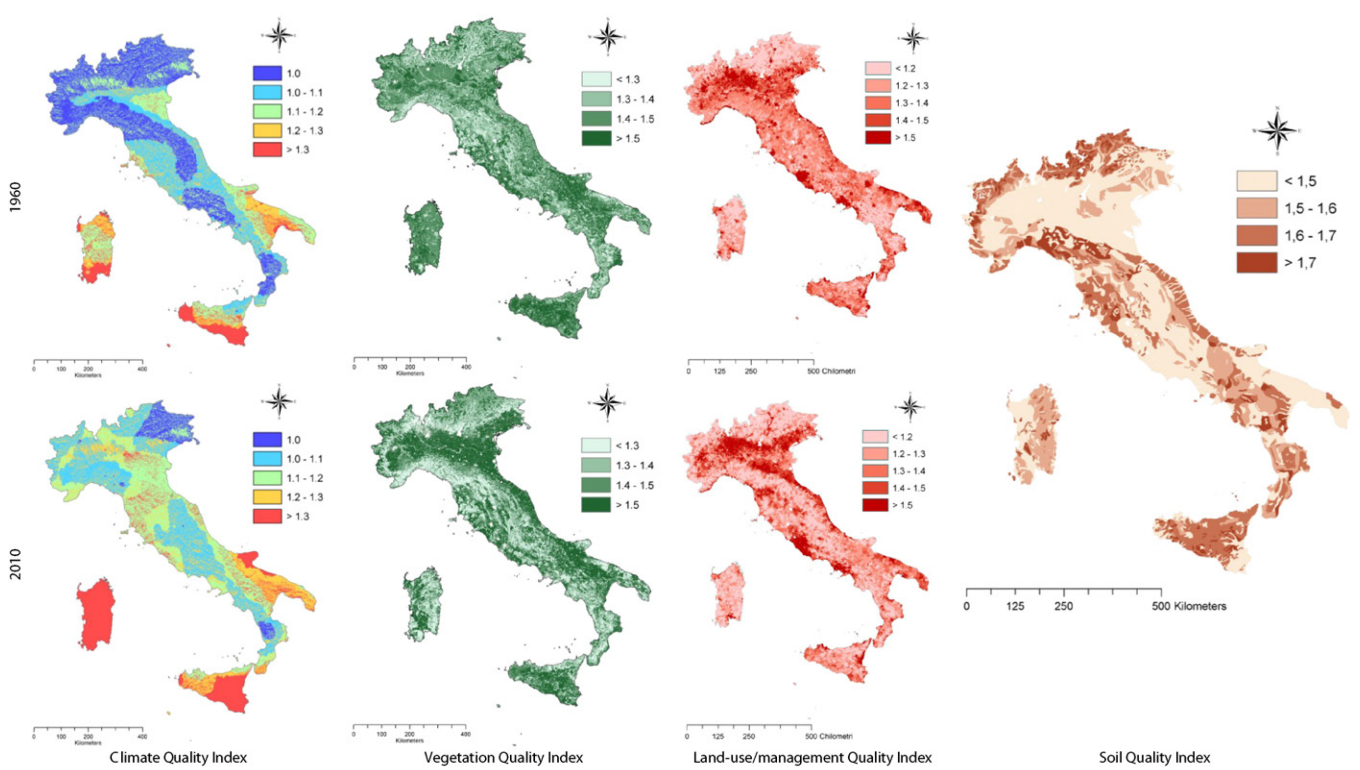

Fig. 2. Spatial distribution of the average ESA scores of the four partial indicators (CQI, VQI, MQI, SQI) in Italy at the beginning and the end of the study period.

Table 2
First-, second- and third-order polynomial regression for the convergence analysis of change in the average ESAI score at the spatial level of agro-forest districts by time interval in Italy (*significance at $p < 0.05$).

Variable	1960–1990			1990–2000			2000–2010		
	Linear	Square	Cubic	Linear	Square	Cubic	Linear	Square	Cubic
Intercept	0.12	−13.17	−41.64	0.17	−4.85	74.33	0.26	3.86	19.98
ESAI	−0.13	19.39	82.08	−0.09	7.33	−168.02	0.15	5.46	−41.05
ESAI^2		−7.11	−53.04		−2.74	126.49		1.96	28.10
ESAI^3			11.21			−31.69			−6.39
Adj-R^2	0.01	0.10*	0.10	0.002	0.01	0.02	0.00	0.01	0.01
Spearman ρ	0.18*			−0.01			−0.09		
n	773								

3.3. Exploring spatial convergence in the level of land vulnerability to degradation with a Geographically Weighted Regression

The results of the GWR models (Fig. 2) outline convergence in LVD between 1960 and 1990 (adjusted $R^2 = 0.41$) with the highest R^2 observed in northern and central Italy. The impact of the (negative) ESAI coefficient on model's structure is particularly evident in north-eastern Italy. The impact of district's surface area and latitude is also higher in north-eastern districts than elsewhere in Italy. The GWR model for 1990–2000 results in a weaker relationship (adjusted $R^2 = 0.22$) with the highest local-R^2 concentrated in southern Italian districts. A negative ESAI coefficient was also observed in southern Italy. Elevation and latitude are additional variables influencing changes in LVD in southern Italy. Finally, the GWR model for 2000–2010 resulted in a relatively weak relationship (adjusted $R^2 = 0.27$) with the highest R^2 observed in central Italy. Negative ESAI coefficients were observed in central Italy in this time period with elevation and district size influencing negatively the dependent variable in the same spatial unit (Fig. 3).

4. Discussion

This paper investigates spatio-temporal convergence as a composite index of land vulnerability to degradation to serve as an evidence base for on-going and future assessment of desertification risk. We run an exploratory data analysis on indicators derived from a comprehensive dataset evaluating environmental and socioeconomic dynamics of >700 homogeneous agro-forest districts over 50 years (1960–2010). Evidence for spatial convergence of LVD in Italy reflects a latent increase in desertification risk, at least in defined socioeconomic contexts and time periods, as observed in the agro-forest districts situated in northern and central Italy between 1960 and 1990.

Our findings suggest that convergence in LVD depends on a limited set of factors contributing to land degradation. These factors may represent a target for specific (formal) responses against desertification (e.g. environmental and agro-environmental policies, developmental policies and, more generally, an integrated strategy for sustainable management of vulnerable land). Convergence analysis provides a rich information base suitable (i) to identify long-term trends in LVD (Montanarella, 2007), (ii) to develop reliable projections of future trends in land degradation risk (Onate and Peco, 2005) and, finally, (iii) to design efficient mitigation strategies (Thomas et al., 2012).

The findings of our study indicate that land surface exposed to degradation processes has increased heterogeneously during the studied time interval as a result of distinct patterns of convergence in the level of land vulnerability to degradation between Italian regions. In other words, convergence processes have progressively consolidated the environmental gap between highly vulnerable areas from less vulnerable areas (Bajocco et al., 2015). The spatially-heterogeneous increase in LVD observed in Italy reflects the complex interplay of local development factors, latent transformations in the socioeconomic context and ecological conditions changing over time (Safriel, 2009; Giménez-Morera et al., 2010; Yang et al., 2013). Agro-forest districts in northern and central Italy have shared a high or moderately high land quality exposed to a relatively high anthropogenic environmental pressure. Southern Italy districts have shown, on average, a lower-quality natural capital (climate, soil, vegetation) with higher spatial heterogeneity in respect to the agro-forest districts situated in northern and central Italy. The territorial conditions at the start of this analysis act as relevant factors in determining a lack of convergence in LVD and, possibly, a moderate or negligible increase in the level of land vulnerability at the district scale (Simeonakis et al., 2007; Lavado Contador et al., 2009; Karamesouti et al., 2015; Salvati and Ferrara, 2015).

Table 3
Multiple regression models for convergence in the average ESAI score by time interval in the agro-forest districts of Italy.

Variables	Beta	Std. err.	B	Std. err.	$t_{(768)}$	p-Level
1960–1990: adjusted $R^2 = 0.26$, $F_{(4768)} = 70.2$, $p < 0.0001$						
Intercept			0.6930	0.0893	7.7596	0.0000
Lat	0.1129	0.0352	0.0196	0.0061	3.2064	0.0014
Ele	−0.6080	0.0367	−0.1088	0.0066	−16.5833	0.0000
ESAI	−0.2911	0.0412	−0.4708	0.0666	−7.0697	0.0000
Area	0.0788	0.0314	0.0068	0.0027	2.5056	0.0124
1990–2000: adjusted $R^2 = 0.10$, $F_{(4768)} = 22.7$, $p < 0.0001$						
Intercept			0.8187	0.1404	5.8326	0.0000
Lat	0.3470	0.0380	0.0931	0.0102	9.1240	0.0000
Ele	−0.1842	0.0469	−0.0508	0.0129	−3.9259	0.0001
ESAI	−0.2882	0.0508	−0.5829	0.1027	−5.6741	0.0000
Area	−0.0347	0.0348	−0.0046	0.0046	−0.9971	0.3190
2000–2010: adjusted $R^2 = 0.17$, $F_{(4768)} = 39.7$, $p < 0.0001$						
Intercept			0.1062	0.1569	0.6770	0.4986
Lat	−0.3833	0.0382	−0.1195	0.0119	−10.0388	0.0000
Ele	−0.1597	0.0452	−0.0512	0.0145	−3.5333	0.0004
ESAI	0.0048	0.0501	0.0110	0.1146	0.0958	0.9237
Area	−0.0733	0.0333	−0.0113	0.0051	−2.1984	0.0282

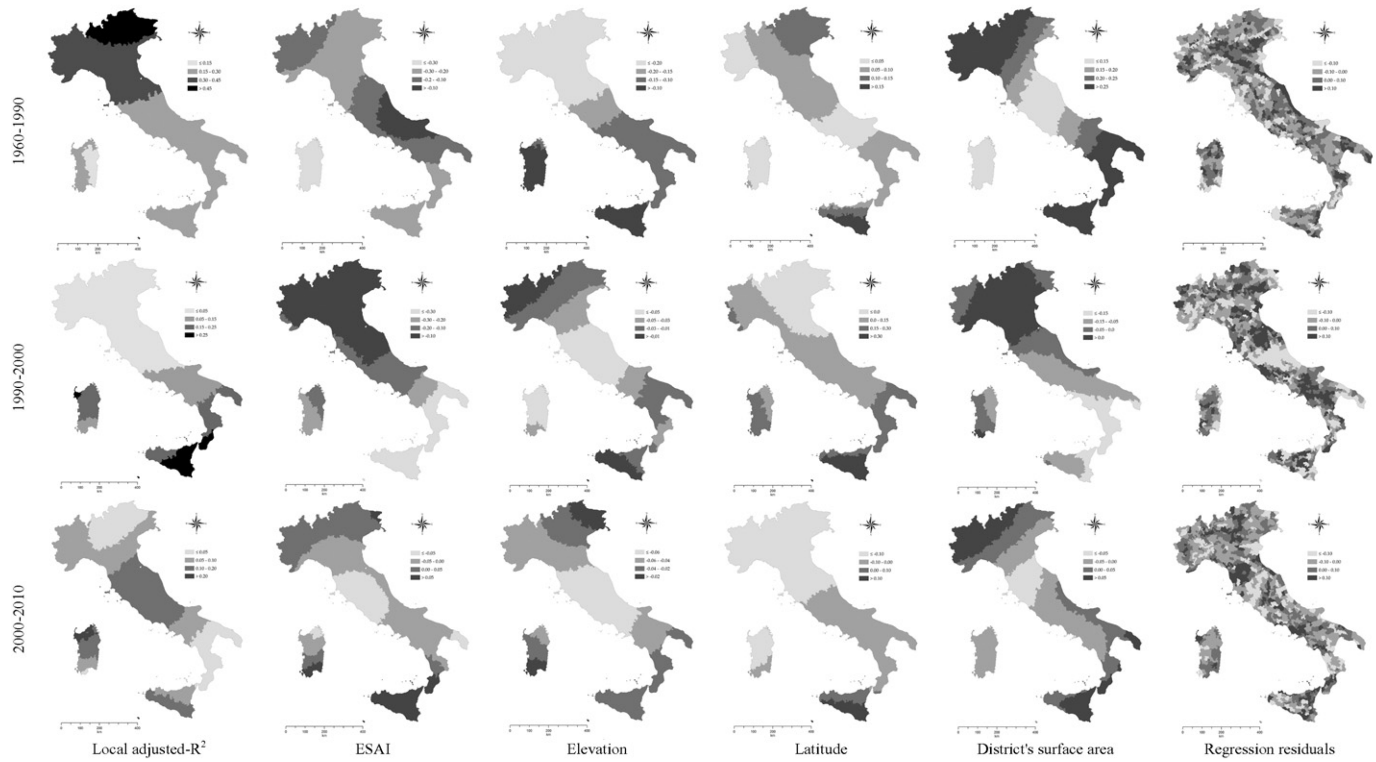

Fig. 3. Geographically Weighted Regression models for convergence in the average ESAI score in Italy by time interval.

In this sense, distinct spatial patterns of convergence are the result of different drivers of land degradation in northern and southern Italian districts (Salvati et al., 2013). Salvati (2014) showed how socioeconomic drivers of change prevail in northern and central Italy with place-specific increases in the level of land vulnerability more rarely driven by biophysical factors (Salvati, 2014). Joint biophysical and socioeconomic factors are more frequently involved in land degradation processes in southern regions than elsewhere in Italy (Bajocco et al., 2015).

Salvati and Zitti (2009) demonstrated that spatially-diverging trends in LVD reflect socioeconomic processes that tend to consolidate regional disparities in the quality of soil, vegetation and climate capitals. For example, anthropogenic pressures and socioeconomic transformations in the northern Mediterranean region have impacted coastal and flat areas more intensively than economically-marginal and mountainous land (Salvati and Zitti, 2008). Soil salinization and compaction are examples of degradation processes typical of coastal areas with a negative impact caused by population growth, urban sprawl, crop intensification and poor water management (Giménez-Morera et al., 2010; Biasi et al., 2015; Kelly et al., 2015). By contrast, the decrease of workers in the primary sector and the abandonment of agricultural land may trigger wildfire risk and soil erosion in economically-marginal and remote districts of northern and central Italy (Le Houérou, 1993; Iosifides and Politidis, 2005; Salvati and Carlucci, 2013; Bisaro et al., 2014).

Salvati (2014) suggests that the implementation of regional- and local-scale policies identifying land degradation processes benefit from a multi-temporal assessment of relevant socio-ecological variables and monitoring the short-term evolution of local agricultural systems. Based on this assumption, a comprehensive, regional-scale strategy for mitigation of and adaptation to the increased land degradation risk in the Mediterranean basin is increasingly required to consider the different socioeconomic attributes of a number of target areas together (Sommer et al., 2011), assuming spatial heterogeneity at the local scale as a relevant predictor of land degradation risk (Basso et al., 2012). For example, it was demonstrated that the increased spatial heterogeneity in the ESAI is closely related with the formation or consolidation of land degradation hotspots (Bajocco et al., 2015). Land degradation hotspots require specific land protection measures that target the relevant factors shaping spatial heterogeneity and the level of land degradation (Salvati et al., 2015a). However, methodologies identifying current hotspots or predicting the spatial distribution of future hotspots are relatively scarce or specifically designed for local-scale studies (Zdruli, 2014). Our approach may fill this gap identifying LVD-converging or diverging areas and assessing the intensity of convergence or divergence at the country scale and help to identify and clarifying the role of factors driving the observed changes. Adaptation policies especially benefit from a such monitoring approach (Briassoulis, 2011); for example, strategies promoting adaptation to increased levels of desertification risk may be specifically prioritized and adopted in areas with a more rapid convergence in LVD with respect to the neighbouring districts. In this sense, spatial convergence in LVD can be regarded as an early-warning indicator of desertification risk.

5. Conclusions

Understanding factors responsible for spatial convergence in LVD requires a multidisciplinary approach capable to (re)connect the recent landscape dynamics of local agro-forest systems to a comprehensive analysis of sustainable development, socio-ecological changes and the conservation of renewable land resources at the regional scale (Akhtar-Schuster et al., 2011). The methodology illustrated in this paper provides an informative tool for on-going and future assessment of (changing) environmental conditions at homogeneous spatial units, such as agro-forest systems or other relevant analysis domains at the local scale (Gisladottir and Stocking, 2005). In this sense, our findings potentially could provide an evidence base to plan and implement dedicated conservation policies for agro-forest systems experiencing landscape transformations. This study also demonstrates the relevance and importance of freely-available, updated and high-resolution data sources for environmental monitoring and risk surveillance. The proposed methodology in this study allows for disaggregation of the component factors used in an ESA analysis and this is desirable for policy development, targeting and programme design. Data availability and access remain a primary concern in monitoring and assessing LVD and a continuous effort from official sources is needed to produce appropriate diachronic layers with the highest spatial precision and comparability, limit the impact of data inaccuracies and between-source differences, and ensure public access to these vital information to inform local and regional mitigation and adaptation strategies. Finally, further investigation is required to clarify the importance of joint changes in economic and environmental factors determining convergence in land vulnerability to degradation.

References

Akhtar-Schuster, M., Thomas, R.J., Stringer, L.C., Chasek, P., Seely, M., 2011. Improving the enabling environment to combat land degradation: institutional, financial, legal and science-policy challenges and solutions. Land Degrad. Dev. 22 (2), 299–312.

Aldy, J.E., 2006. Per capita carbon dioxide emissions: convergence or divergence? Environ. Resour. Econ. 33 (4), 533–555.

Arbia, G., Paelinck, J.H., 2003. Spatial econometric modeling of regional convergence in continuous time. Int. Reg. Sci. Rev. 26 (3), 342–362.

Bajocco, S., Salvati, L., Smiraglia, D., Ceccarelli, T., Perini, L., 2015. Planning for sustainable agro-forest systems: protected areas and soil degradation hotspots in Italy (1990–2010). Soil Sci. Plant Nutr. 61, 404–413.

Barro, R.J., Sala-i-Martin, X., 2004. Economic Growth: MIT Press. Massachusettes, Cambridge.

Basso, B., De Simone, L., Cammarano, D., Martin, E.C., Margiotta, S., Grace, P.R., Chou, T.Y., 2012. Evaluating responses to land degradation mitigation measures in Southern Italy. International Journal of Environmental Research 6 (2), 367–380.

Biasi, R., Brunori, E., Smiraglia, D., Salvati, L., 2015. Linking traditional tree-crop landscapes and agro-biodiversity in Central Italy using a database of typical and traditional products: a multiple risk assessment through a data mining analysis. Biodivers. Conserv. 24 (12), 3009–3031.

Bisaro, A., Kirk, M., Zdruli, P., Zimmermann, W., 2014. Global drivers setting desertification research priorities: insights from a stakeholder consultation forum. Land Degrad. Dev. 25 (1), 5–16.

Briassoulis, H., 2011. Governing desertification in Mediterranean Europe: the challenge of environmental policy integration in multi-level governance contexts. Land Degrad. Dev. 22 (3), 313–325.

Colantoni, A., Ferrara, C., Perini, L., Salvati, L., 2015. Assessing trends in climate aridity and vulnerability to soil degradation in Italy. Ecol. Indic. 48, 599–604.

Ezcurra, R., 2007. Is there cross-country convergence in carbon dioxide emissions? Energy Policy 35 (2), 1363–1372.

Ferrara, A., Salvati, L., Sateriano, A., Nolè, A., 2012. Performance evaluation and costs assessment of a key indicator system to monitor desertification vulnerability. Ecol. Indic. 23, 123–129.

Fotheringham, A.S., Brunsdon, C., Charlton, M., 2002. Geographically Weighted Regression. The Analysis of Spatially Varying Relationships. Wiley, Chichester.

Geeson, N.A., Brandt, C.J., Thornes, J.B., 2002. Mediterranean Desertification: A Mosaic of Processes and Responses. Wiley, Chichester.

Geist, H.J., Lambin, E.F., 2004. Dynamic causal patterns of desertification. Bioscience 54 (9), 817–829.

Giannias, D., Liargovas, P., Manolas, G., 1999. Quality of life indices for analysing convergence in the European Union. Reg. Stud. 33 (1), 27–35.

Giménez-Morera, A., Sinoga, J.D., Cerdà, A., 2010. The impact of cotton geotextiles on soil and water losses from Mediterranean rainfed agricultural land. Land Degrad. Dev. 21 (2), 210–217.

Gisladottir, G., Stocking, M., 2005. Land degradation control and its global environmental benefits. Land Degrad. Dev. 16, 99–112.

Glenn, E., Stafford Smith, M., Squires, V., 1998. On our failure to control desertification: implications for global change issues, and a research agenda for the future. Environ. Sci. Pol. 1 (2), 71–78.

Hill, J., Stellmes, M., Udelhoven, T., Röder, A., Sommer, S., 2008. Mediterranean desertification and land degradation: mapping related land use change syndromes based on satellite observations. Glob. Planet. Chang. 64 (3), 146–157.

Incerti, G., Feoli, E., Salvati, L., Brunetti, A., Giovacchini, A., 2007. Analysis of bioclimatic time series and their neural network-based classification to characterise drought risk patterns in South Italy. Int. J. Biometeorol. 51, 253–263.

Iosifides, T., Politidis, T., 2005. Socio-economic dynamics, local development and desertification in western Lesvos, Greece. Local Environ. 10 (5), 487–499.

Istat, 1958. Circoscrizioni statistiche agrarie. Istituto Nazionale di Statistica, Roma.

Juntti, M., Wilson, G.A., 2005. Conceptualizing desertification in Southern Europe: stakeholder interpretations and multiple policy agendas. Eur. Environ. 15 (4), 228–249.

Karamesouti, M., Detsis, V., Kounalaki, A., Vasiliou, P., Salvati, L., Kosmas, C., 2015. Land-use and land degradation processes affecting soil resources: evidence from a traditional Mediterranean cropland. Catena 132, 45–55.

Kelly, C., Ferrara, A., Wilson, G.A., Ripullone, F., Nolè, A., Harmer, N., Salvati, L., 2015. Community resilience and land degradation in forest and shrubland socio-ecological systems: evidence from Gorgoglione, Basilicata, Italy. Land Use Policy 46, 11–20.

Kosmas, C., Danalatos, N.G., Gerontidis, S., 2000. The effect of land parameters on vegetation performance and degree of erosion under Mediterranean conditions. Catena 40, 3–17.

Lavado Contador, J.F., Schnabel, S., Gomez Gutierrez, A., Pulido Fernandez, M., 2009. Mapping sensitivity to land degradation in Extremadura, SW Spain. Land Degrad. Dev. 20 (2), 129–144.

Le Houérou, H.N., 1993. Land degradation in Mediterranean Europe: can agroforestry be a part of the solution? A prospective review. Agrofor. Syst. 21 (1), 43–61.

Manca, G., Attaway, D.F., Waters, N., 2014. Program assessment and the EU's agrienvironmental measure 214: an investigation of the spatial dynamics of agrienvironmental policies in Sardinia, Italy. Appl. Geogr. 50, 24–30.

Montanarella, L., 2007. Trends in land degradation in Europe. In: Sivakumar, M.V., N'diangui, N. (Eds.), Climate and Land Degradation. Springer, Berlin.

Neumayer, E., 2001. Improvement without convergence: pressure on the environment in European union countries. J. Common Mark. Stud. 39 (5), 927–937.

Onate, J.J., Peco, B., 2005. Policy impact on desertification: stakeholders' perceptions in Southeast Spain. Land Use Policy 22 (2), 103–114.

Quah, D.T., 1997. Empirics for growth and distribution: stratification, polarization, and convergence clubs. J. Econ. Growth 2 (1), 27–59.

Safriel, U., 2009. Deserts and desertification: challenges but also opportunities. Land Degrad. Dev. 20 (4), 353–366.

Salvati, L., 2014. A socioeconomic profile of vulnerable lands to desertification in Italy. Sci. Total Environ. 466–467, 287–299.

Salvati, L., Carlucci, M., 2013. The estimated impact of Mediterranean land degradation on agricultural income: a short-term scenario. Land Use Policy 32, 302–308.

Salvati, L., Ferrara, A., 2015. Profiling agro-forest landscape types at the wildland–urban interface: an exploratory analysis. Agrofor. Syst. 89 (2), 291–303.

Salvati, L., Zitti, M., 2008. Regional convergence of environmental variables: empirical evidences from land degradation. Ecol. Econ. 68, 162–168.

Salvati, L., Zitti, M., 2009. Convergence or divergence in desertification risk? Scale-based assessment and policy implications in a Mediterranean country. J. Environ. Plan. Manag. 52 (7), 957–971.

Salvati, L., Bajocco, S., Ceccarelli, T., Zitti, M., Perini, L., 2011. Towards a process-based evaluation of land vulnerability to soil degradation in Italy. Ecol. Indic. 11 (5), 1216–1227.

Salvati, L., Ceccarelli, T., Bajocco, S., Perini, L., 2013. Amplifying (or consolidating) territorial disparities in the quality of the environment: the case of land degradation in Italy. Prof. Geogr. 65 (4), 647–663.

Salvati, L., Colantoni, A., Mavrakis, A., Ferrara, A., 2015a. Complex adaptive systems, soil degradation and land sensitivity to desertification: a multivariate assessment of Italian agro-forest landscape. Sci. Total Environ. 521-522, 235–245.

Salvati, L., Ferrara, C., Corona, P., 2015b. Indirect validation of the environmental sensitive area index using soil degradation indicators: a country-scale approach. Ecol. Indic. 57, 360–365.

Simeonakis, E., Calvo-Cases, A., Arnau-Rosalen, E., 2007. Land use change and land degradation in southeastern Mediterranean Spain. Environ. Manag. 40, 80–94.

Sommer, S., Zucca, C., Grainger, A., Cherlet, M., Zougmore, R., Sokona, Y., Hill, J., Della Peruta, R., Roehrig, J., Wang, G., 2011. Application of indicator systems for monitoring and assessment of desertification from national to global scales. Land Degrad. Dev. 22 (2), 184–197.

Thomas, R.J., Akhtar-Schuster, M., Stringer, L.C., Marques, M.J., Escadafal, R., Abraham, E., Enne, G., 2012. Fertile ground? Options for a science–policy platform for land. Environ. Sci. Pol. 16, 122–135.

Thornes, J.B., 2004. Stability and instability in the management of Mediterranean desertification. In: Wainwright, J., Mulligan, M. (Eds.), Environmental Modelling: Finding Simplicity in Complexity. Wiley, Chichester, pp. 303–315.

Yang, L., Wu, J., Shen, P., 2013. Roles of science in institutional changes: the case of desertification control in China. Environ. Sci. Pol. 27, 32–54.

Zdruli, P., 2014. Land resources of the Mediterranean: status, pressures, trends and impacts on future regional development. Land Degrad. Dev. 25 (4), 373–384.