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Economic Development as a Determinant of Desertification Risk: Exploring a local-EKC Hypothesis

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Economic Development as a Determinant of Desertification Risk: Exploring a local-EKC Hypothesis

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Abstract

This paper explores the relationship among income and a synthetic index of vulnerability to land degradation (LVI) in Italy. Per-capita value added, crop intensity, industrial and tourism concentration, urban sprawl and other variables estimated over 784 districts were tested as potential drivers of LVI. According to EKC hypothesis, first, second, and third-order polynomial regressions were carried out by using changes (1990-2000) of LVI as dependent variable and socio-economic variables as predictors. The best fit was a linear form incorporating spatial effects where income is inversely associated to land vulnerability. Second- and third-order polynomial forms do not increase goodness of fit.

Key words: Land Degradation, vulnerability, value added, District, EKC, Italy.

Introduction

Understanding causes and effects of economic growth at different temporal and spatial scales as well as its implications on the environment represents an intriguing topic in the whole economic discipline (List and Gallet 1999; Smulders 1999; Cavlovic et al. 2000). This is justified by the finding that many countries/regions have shown marked growth rates over the last century, but this experience could not be longer repeatable in the present (and future) social and ecological conditions (Spangerberg 2001). Investigating the links between development and the environment adds further difficulties to an already complex topic. In this context, indicators of 'de-coupling' and 're-linking' between economic growth and environmental degradation are becoming increasingly popular in detecting and measuring improvements in natural resource efficiency with respect to economic activity (e.g. (Dasgupta et al. 2006; Mukherjee and Kathuria 2006; Caviglia-Harris et al. 2008). As a natural extension of de-coupling analysis, studies on the Environmental Kuznets Curve (EKC) have tried to disentangle this topic from a development perspective (see Dasgupta et al. 2002; Stern 2004; Kahuthu 2006 and references therein). The 'stylised fact' emerging from those analyses suggests the existence of an 'inverted-U' relationship which occurs between indicators of environmental quality (or degradation) and the level of per capita income (Jha and Murthy 2003; Dinda 2004; Galeotti 2007). According to the EKC hypothesis, accelerated wealth creation by economic growth is a precondition for technological progress that in turn would provide a better environment and the means to sustain it. On lower income levels customers prefer commodities other than the environment, resulting in the lack of 'greening' of products and policies (Magnani 2000, 2001; Spangenberg 2001; Bimonte 2002). Although the EKC hypothesis does not originally stems from a theoretical model, recent contributions have started showing how it may be included in formalised economic models (Andreoni and Levinson 2001; Hill and Magnani 2002; Bruvoll et al. 2003; Bretschger and Smulders 2006).

Nowadays EKC studies concentrated on short- and long-term air pollution (e.g. Dinda 2004; Stern 2004; Galeotti 2007 for reviews) and, on a lesser extent, deforestation (e.g. Koop and Tole 1999; Barbier 2001; Culas 2007) and clearcutting (Lantz 2002). Relatively few studies concern other environmental matters, such as water pollution (e.g. Paudel et al. 2005), hazardous waste sites (Wang et al. 1998), pesticides (Managi 2006), farmland conversion (Liu et al. 2008), agricultural land use (James 1999), land cover change (e.g. Skonhoft and Solem 2001), and threatened vertebrate species (McPherson and Nieswiedony 2005), among the others. Only a restricted number of papers addresses the relationship between a synthetic index of environmental quality and income level. Examples of such studies are provided by Zaim and Taskin (2000), Mukherjee and Kathuria (2006) and Caviglia-Harris et al. (2008).

The EKC hypothesis is controversial and has received some critical responses (Heerink et al. 2001; Harbaugh et al. 2002; Galeotti et al. 2006; Chimeli 2007; Muller-Furstenberger and Wagner 2007). Among the several questions addressed in recent studies the most relevant could be synthesised as follows: (i) a continued economic growth is not a sufficient precondition for reducing pressure on the environment without important policy intervention, (ii) the EKC relation has been shown to be valid for few specific environmental processes; (iii) in general, it illustrates the shift from land-intensive to capital-intensive forms of agriculture with growing capital availability and decreasing energy profits in primary sector, but provides little information regarding total environmental impact; and (iv) there are few theoretical grounds for the existence of EKC for land resource depletion (Koop and Tole 1999; Ezzati et al. 2001; Li et al. 2007; Ranjan and Shortle 2007). Notwithstanding the soundness of such criticisms, EKC correctly highlights positive effects of government policies, which are usually more ambitious in high income countries/regions (Barrett and Graddy 2000; Magnani 2000). Therefore, it seems reasonable to hypothesise that the inverted-U relationship is only indirectly linked to income levels. It is instead associated to income through an "induced policy response": in synthesis, as income rises the public will demand more stringent environmental standards (Steer 1998; Munasinghe 1999; Stern 2004).

Recognised as a leading process of natural resource depletion, Land Degradation (LD) includes the effects of both bio-physical and socio-economic drivers (Puigdefabregas and Mendizabal 1998). It reduces soil fertility, often producing worse environmental conditions sometimes evolving in irreversible phenomena of desertification (Thornes 2004; Montanarella 2007). LD occurs in both developing and developed countries: the impact of this process is clearly increasing in Mediterranean basin because of climate change and growing human pressure (Salvati and Zitti 2008a). Notably, few information at the country/region level on the relationship between LD and economic growth are available in this area which cover an adequate time span at disaggregated spatial scale (Wilson and Juntti

2005). Moreover no studies specifically address the EKC for LD to our knowledge[i]. This is likely due to the difficulties in (i) estimating the level of land vulnerability of a certain area due to complex interactions among different factors (e.g. bio-physical, socio-economic, cultural, institutional), (ii) deriving a theoretical relationship between income and LD, and (iii) choosing adequate temporal and spatial scales to explore such relationship.

The aim of this paper is to address (at the district scale) the relationship between economic growth and a proxy for land resource quality and degradation. The study was carried out in Italy, a Southern European country with different levels of land vulnerability and marked regional disparities in per capita income, and covers the whole country at the Travel to Work Area (TTWA) scale. TTWAs are regarded as economically-relevant spatial units able to classify the national territory into sub-regional districts (Baldazzi et al. 1998). They further allow to compare environmental quality indicators with economic variables (e.g. income, production and productivity by sector) estimated from national accounts.

The value added of this paper is manifold. Empirical evidence on possible EKC dynamics for LD is not yet available in Southern Europe, and highly disaggregated data, like those used in this study, are scarcer compared to cross-country analyses even for other environmental processes widely studied from the EKC perspective (Rupasingha et al. 2004; Maddison 2006; Auffhammer and Carson 2008; Ordas Criado 2008). As economic drivers of LD we used per capita value added, then testing the additional effect of process-specific variables such as crop intensity, irrigation, share of industry in total product, urban land use, and tourism concentration, among the others[ii]. We believe that disaggregated analyses at the country level, as the one presented in this paper, can represent a fruitful research direction. Moving from cross-country to single-country studies represents a relatively new line for EKC research which mitigates the problems associated with data comparison from different countries (Vincent 1997; Dean 2002; Paudel et al. 2005). Moreover the analysis carried out in this study highlights the role of spatial effects, which are found to be important in understanding income-environment relationship[iii]. Finally, the analysis suggests policies applicable to other regions with similar economic and ecological characteristics compared to Italy.

Methods

Logical framework

According to the EKC hypothesis, vulnerability to LD should be associated to increasing income, having a peak at intermediate (country/regional) income levels. This is likely due to increasing human pressure on the environment when income rises due to crop intensification, population growth, urban sprawl, forest conversion to agricultural and urban land uses, industrial and tourism concentration, and other minor factors (Puigdefabregas and Mendizabal 1998; Rubio and Bochet 1998; Basso et al. 2000). However, at higher income levels, vulnerability to LD should decrease as the economy itself change (e.g. by increasing share of services in total product with a consequent reduction in agricultural and industrial impacts on the environment).

According to this framework, Figure 1 illustrates the EKC hypothesis applied to land vulnerability in a developed country like Italy. Following EKC, we expect to identify an inverse relationship between income and land vulnerability over the entire range of observed income. The relationship can be studied at regional and local levels. Notably, site-specific determinants generally complicate the evaluation at the (strictly) local scale. Different approaches are therefore needed to discriminate the impact of income and production on the environmental conditions leading to LD at that scale (Wilson and Juntti 2005). The approach used here is appropriate for a sub-regional scale of observation (e.g. provinces, local districts) and proceeds through analysis of the relationship between income and a synthetic index describing the level of vulnerability to LD of each spatial unit.

Such a relation could be linear (de-coupling hypothesis) or polynomial (re-linking hypothesis). In the former case, income growth has beneficial effects on land vulnerability over the entire range of observed income. In the latter one, income growth shows a beneficial effects on LD at lower/intermediate income levels only, whereas a 're-linking' process (income growth coupled with increasing LD vulnerability) is expected at higher income. More complex patterns (e.g. third or higher order polynomials) may highlight site-specific responses of land vulnerability as income rises[iv].

The aim of EKC analysis is to estimate a vector of coefficients, each linked to a single driver of a specified environmental process, by using a reduced form:

$$E = f(Y, A) \quad (1)$$

where E represents the environmental process under study, Y is the income driver, and A is a set of additional drivers.

There is only a partial consensus on how to specify the EKC relationship. A widely used way is to adopt first-, second- and third-order polynomials, comparing different specifications for relative robustness (Mukherjee and Kathuria 2006). However, neither the linear, nor quadratic or cubic functions can be considered fully realistic representations of the income-environment relationship (Maddison 2006). All these specifications arise estimation problems and underline specific economic aspects. The use of the first-order income factor only, without quadratic and cubic terms, collapses EKC to the basic de-coupling analysis (Mazzanti et al. 2008). The quadratic specification implies that environmental degradation will move towards a plus or minus infinity as income increases. Third (or higher levels) polynomial could also lead to N rather than U shaped curves (Shobee 2004), opening new issues in understanding the income-environment relationship for policy-making. In the present study different specifications are estimated for both income alone and income with additional covariates. They include the linear income descriptor only (de-coupling baseline case), linear and squared income terms (EKC usual case), and linear, squared, and cubic income terms. Then, the additional covariates are introduced and tested as linear terms.

In synthesis, the analytical scheme carried out in this paper is as follows. After having selected appropriate data, study period, as well as the spatial domain for analysis, a *proxy* for land quality and degradation (appropriately addressing the specificity of the study area) was identified. Several variables taken as potential drivers of LD were then selected and classified into three groups according to their effects on the process under study. The EKC relationship was verified, at a first stage, through regressions between the environmental index and per-capita value added alone based on different specifications (e.g. linear, quadratic, cubic equations). The best form was chosen by using standard diagnostics. The LD-income relationship was then controlled by entering additional variables to the specifications mentioned above and by checking for spatial effects. Results were finally analysed by comparing coefficient estimates obtained through different specifications.

Study area

The Italian peninsula has a surface of *ca.* 301.330 km^2 and its coastline (including the islands) extends for *ca.* 7,375 km. Its mountain topography, latitudinal extension, and proximity to the sea account for a marked deal of variation in Italy's climate. Average annual rainfall ranges from *ca.* 350 mm in Sicily to *ca.* 1,500 mm in north-east regions. The Italian territory therefore represents an intriguing case study from both the environmental and socio-economic perspectives, as it shows a complex pattern of land resource distribution and economic development. As a matter of fact, northern Italy represents one of the most developed regions in Europe, while southern Italy still shows locally low levels of per-capita income and a higher share of agriculture in total product (11%) compared to the European average (nearby 3%). The country is divided (2001 census) into twenty NUTS-2 administrative regions and 103 NUTS-3 provinces. For more detailed analyses, Italian Statistical Office individuated more than 700 local districts (the so called Travel To Work Areas, TTWAs) to study labour market and economic conditions. TTWAs were identified on the basis of data relative to daily labour mobility from 1981, 1991, and 2001 Population Census data (ISTAT 1997). They reflect districts of economic interest and are generally used to analyse regional differentiation in Italian development. TTWAs were recently used for regional analysis of district specialisation in agriculture and are regarded as adequate spatial domains to analyse the possible interaction between economic and environmental processes (Giusti and Grassini 2007). We used the 784 TTWA districts identified from the 1991 census data (Figure 2) to assure temporal and spatial comparability over time among selected indicators.

Data and indicators

General consensus about the best environmental indicators for EKC analysis has not been achieved. Different measures have different implications and interpretations. However, the use of composite indexes should be preferred, as more suitable to illustrate complex environmental phenomena than the traditional (single process) EKC literature (Mukherjee and Kathuria 2006; Caviglia-Harris et al. 2008). In this paper a composite index estimating the level of vulnerability to LD was computed as dependent variable in the models[v]. This *proxy* variable for vulnerability to LD is set up through a standard approach, i.e. the Environmental Sensitive Area (ESA) methodology (Basso et al. 2000). A synthetic index (the so called ESAI) is usually derived from this procedure. ESAI can be regarded as an 'early warning' indicator of the level of vulnerability to LD. Salvati et al. (2008) proposed an original ESAI-like index of vulnerability to LD (the so called LVI). LVI is better suited to account for some peculiar characteristics of the Italian landscape and circumvents data limitations at high-resolution scales (Salvati and Zitti 2008b). LVI is composed of three thematic indicators of climate, soil properties, and land use which produce a ranking of vulnerability to LD on a municipality or district basis. In this study, LVI was computed for two time slices (1990 and 2000). See Appendix 1 for a detailed description of LVI.

There is no consensus about the type and number of explanatory factors introduced as potential drivers of the environmental degradation: notably, some studies use income variables only. The choice depends on both data availability and research objectives. Significant drivers of LD may include policy factors, socio-economic aspects, and site-specific variables. The empirical analysis provided by Salvati et al. (2008b) suggests that agricultural intensification, industrial concentration, tourism pressure, and urban sprawl are important factors affecting land vulnerability. Moreover, according to Wilson and Juntti (2005), various hypotheses were claimed to explain the process of LD in the Mediterranean basin, including (i) 'human pressure' hypothesis, (ii) 'agricultural impact' hypothesis, and (iii) 'environmental factors' hypothesis. Based on these findings, we identified three classes of predictors at the district level, namely (i) socio-economic variables, (ii) agricultural variables, and (iii) environmental/control variables. Suitable variables were chosen according to findings illustrated in previous works (Puigdefabregas and Mendizabal 1998; Rubio and Bochet 1998; Tanrivermis 2003; Montanarella 2007)[vi]. Apart from district per-capita income[vii] (GDP), socio-economic variables (SOC) include six variables: share of agriculture (AGP) and industry (IND) in total product, land productivity (LAN), labour productivity in services (SER), as well as two dummies, respectively identifying urban (URB) and tourist (TOU) districts. Agricultural variables (AGR) include five variables: percentage of agricultural land on the total district area (SAU), variation of agricultural land surface over a ten-year horizon (LOS), percentage of irrigated agricultural land (IRR), percentage of economically marginalised farms (MAR), as well as an index of crop intensity (INT). Environmental/control variables

(ENV) include five variables: LVI score measured at the beginning of the study period (LVI), district elevation (ELE), surface (SUR), population density (POP), and a dummy for the geographical area (North/Centre and South[viii]: GEO).

This variables' specification appears suitable in high heterogeneity datasets (like the one used here) compared to more aggregated datasets, like provincial and regional ones, in order to analyse possible decentralised, local-level interactions between environment and economic drivers and related policy strategies (Briassoulis 2004). Moreover, the use of various sets of variables, considered together and separately, represents an (indirect) sensitivity exercise when analysing coefficient stability. Socio-economic, agricultural, and control variables were estimated from national accounts and census data provided by the Italian National Institute of Statistics (ISTAT 2006) and refer to the year 2000. Average values of each considered variable were reported in Table 1.

Statistical analyses

Before testing EKC, an explorative analysis was carried out on the selected predictors in order to correctly specify econometric models, by avoiding redundancy and collinearity among variables which could bias model estimates[ix]. The analysis included (i) computation of a correlation matrix among predictors (by using both Pearson moment coefficient and Spearman rank correlation coefficient) and preliminary stepwise OLS regressions among the dependent variable and the three classes of predictors (SOC, AGR, ENV) alone and pooled together. This step is necessary as, at our knowledge, a strictly EKC relationship among LD and income was never formulated for Mediterranean countries and most of the variables considered in this study as predictors were never introduced in EKC models studying other environmental processes. Based on this approach, four variables (AGP, AUA, MAR, SER) were excluded from the analysis due to correlation with the other predictors[x]. EKC hypothesis was then tested by specifying different (reduced) forms starting with the simplest one, relating change in LVI over the investigated period as dependent variable (ΔLVI) and district per capita value added (or its logarithm) as the main economic driver (GDP). The vector X_i, which include ancillary variables referring to other, possible LD drivers was then added to the core hypothesis as control. Table 2 reports possible hypotheses on the form of the relationship illustrated in Figure 1. At first stage, the following equation was estimated:

$$\Delta LVI = b_0 + b_1(GDP) + b_2(GDP)^2 + b_3(GDP)^3 + \mathbf{e} \qquad (2)$$

where b_0 is the intercept and $b_{(\bullet)}$ are the coefficient terms. The vector X_i which includes the three classes of (additional) variables (SOC, AGR, and ENV) was then incorporated in the selected form as follows:

$$\Delta LVI = b_0 + b_1(GDP) + b_2(GDP)^2 + b_3(GDP)^3 + b_m(X_i) + \mathbf{e} \qquad (3)$$

Equations (2-3) were preliminary estimated through OLS standard regression. Collinearity among variables was checked throughout by way of variance inflation factor and condition index. Outputs report variables which entered each model with significant coefficients and standard errors. Notably, OLS regression assumes spatial randomness which indicates that any grouping of high or low values of the study variable in space would be independent. If this assumption is not true, *i.e.* a spatial structure exists in the variable as detected by the presence of spatial correlation, standard OLS estimates are inefficient (Rupasingha et al. 2004). We therefore studied spatial variation in both the dependent variable (ΔLVI) and the main predictor (GDP) through exploratory spatial data analysis techniques.

Central to the spatial framework is the choice of the matrix that describes the interaction structure of the cross sectional units, i.e. the definition of proximity. For each spatial unit a relevant neighbouring set must be defined consisting of those units that potentially interact with it. Although in regional data analysis proximity is usually defined in terms of contiguity, if the basic units are defined by administrative boundaries this definition may not be appropriate, because partitions of the territory based on administrative criteria may not coincide with the one based on the study's target criteria. An alternative approach is used in this paper, *i.e.* a spatial weight matrix based on Euclidean distances between the gravitational centres of the different areas[xi]. As little is known about the spatial distribution of ΔLVI in Italy, potential interactions between locations were summarised by the matrix $W = \{ w_{ij} \}$ where $w_{ij} = 1$ if districts i and j are within a fixed distance, d, of each other and 0 otherwise. We consider eight values of d ranging from 25 to 200 kilometres with a span of 25 kilometres. By increasing d incrementally, it is possible to assess how far the links between spatial units extend[xii], i.e. spatial correlation. It can be defined as the coincidence of value similarity with location similarity (Anselin 2001). In this paper, the assessment of global spatial autocorrelation was carried out through Moran's I and Geary's c statistics (Cliff and Ord 1981). Along with the test statistics, the standardised z-value for each statistic, the associated significance level, p_1, assuming the (asymptotic) distributions of I and c are normal, and an alternative indicator of statistical significance (p_2)[xiii], were calculated.

However, Moran's I and Geary's c tests provide only a general measure of spatial correlation. To model spatial correlation in association with the explanatory variables, two levels of variation should be modelled: large-scale changes in the mean due to spatial location or other explanatory variables, and small scale variation due to interactions with neighbours. To address these matters, two approaches were considered here. First, a spatial regression model was developed in the following form:

$$Z_i = \mu_i + \delta \quad (4)$$

where Z_i is the random process at location i (i.e. ΔLVI), μ_i is the mean at the same site, which is a linear, square or cubic model with (i) GDP alone (i.e., the restricted model), and (ii) all the covariates (i.e. the full model), $\delta \sim N(0, \Sigma)$ and Σ is the covariance matrix of random variables at all locations. The small scale variation is modelled by fitting two different covariance models to Σ, including conditional spatial autoregression (CAR) and moving average (MA) structures. The spatial weight matrix introduced in these models was chosen according to the results of Moran's and Geary's statistics.

The second approach arise from consideration that socio-economic processes are usually not constant over space, bearing a certain amount of spatial non-stationarity. If the data generating process is non-stationary over space, global statistics (and model fitting) which summarise major characteristics of a given spatial data configuration (and the relationship among variables) might be locally misleading due to a bias in the estimates[xiv]. Different types of (local) techniques were developed in order to deal with spatial non-stationarity, including the Geographically Weighted Regression (GWR) proposed by Fotheringham et al. (2002)[xv]. The methodological framework underlying GWR is quite similar to that of local linear regression models, as it uses a kernel function to calculate weights for the estimation of local weighted regression models. In GWR, kernel weighting is applied to observations in geographical space and the methodological focus is concerned with assessing local variation in the regression coefficients, rather than data smoothing as in a-spatial local regression techniques. In contrast to the standard regression model, where the regression coefficients are location invariant, the specification of a basic GWR model for each location s = 1, …, n, is:

$$y(s) = X(s)b(s) + \mathbf{e}(s) \quad (5)$$

where y(s) is the dependent variable at location s, X(s) is the row vector of explanatory variables at location s, b(s) is the column vector of regression coefficients at location s, and **e** (s) is the random error at location s. Hence, regression parameters, estimated for each location by weighted least squares, vary in space implying that each coefficient in the model is a function of s, a point within the geographical space of the study area. As a result, GWR gives rise to a distribution of local estimated parameters. The weighting scheme is expressed as a kernel function that places more weight on the observations closer to the location s. In this study we adopted one of the most commonly used specifications of kernel function, which is the bi-square nearest neighbour function (Fotheringam et al. 2002)[xvi].

Results

Descriptive statistics for district value added and the level of vulnerability to LD

Spatial distributions of vulnerability to LD (ΔLVI) and district value added (GDP) were mapped in Figure 3. Concerning GDP, northern Italy represents one of the most developed European regions, while southern Italy is regarded as a disadvantaged area, as per-capita income is about half of that observed in northern regions. In this area only few districts (generally from Apulia or Basilicata) featuring industrial concentration and high-yield agriculture, showed per-capita income higher than 10.000 euros, which is lower than Italian (14.300 euros) average. From LVI scores, sensitive areas concentrated mainly in three specific areas, including (i) the two major islands and Apulia in the southern part of the country, (ii) few dry, coastal areas close to Rome and along Adriatic sealine in central Italy, and (iii) lowlands of Po plain in northern Italy. In the latter area, potential drivers of LD include severe drought episodes, crop intensification, industrial concentration, and urban sprawl. Population growth, tourism pressure, and fragmentation of the rural landscape usually play a major role inducing LD phenomena along the coasts in central Italy. Finally, serious phenomena of soil sealing, salinisation, and erosion are locally observed in southern Italy in connection with poor climate and soil quality as well as urban sprawl and summer fires.

Results of standard OLS regression

The pair-wise relationship between the two variables at country level was described in Table 3 by using different specifications. For comparative purposes, we first estimated models with per-capita value added (in its squared or third order value) alone (i.e. Equation 2), without spatial correction. Then we estimated the same form by introducing spatial effects and including other covariates (i.e. Equation 3). Based on log-GDP, squared and third-order polynomial regressions between ΔLVI and GDP gave a goodness of fit similar to the linear form[xvii]. Lower values of GDP were linearly associated to higher level of land vulnerability with $b_1 = -0.038$.

Exploratory spatial analysis for GDP and ΔLVI and results of spatial regression

Table 4 reports Moran's *I* and Geary's *c* statistics for ΔLVI and GDP based on spatial matrices corresponding to selected geodesic distances. These tests provide evidence of positive spatial autocorrelation across TTWA districts for both variables. Areas with relatively high (low) ΔLVI (or GDP) are located close to other areas with relatively high (low) ΔLVI (or GDP) more often than it would be observed if their locations were purely random. Both statistics are highly significant irrespective of the chosen inference strategy at all distances considered. Standardised test statistics, especially Geary's *c*, suggest that spatial linkages are strongest when 'close' areas (125 and 150 km respectively for ΔLVI and GDP) are considered.

Based on log-GDP term alone (Equation 2), the linear form incorporating spatial effects gave better results than squared and third-order (not shown) forms (Table 5)[xviii]. Lower values of GDP were linearly associated to higher ΔLVI with $b_1 = -0.038$ (CAR model) or -0.023 (MA model). GWR provides similar results indicating that ΔLVI is linearly associated to GDP with $b_1 = -0.037$. Elasticity of ΔLVI to GDP[xix] was rather stable through the various specifications considered: $\eta_{ld/gdp}$ amounted to -0.88, -0.90, and -0.86 by considering standard OLS, CAR, and GWR models, respectively.

Estimating the full model

Estimates for Equation (3) based on various regression models are presented in Table 6. An inverse, linear relationship between GDP and ΔLVI was observed in all models[xx]. On average, high-income districts experienced lower growth rates of LVI irrespective of the other variables considered. Coefficients for GDP are stable in all the models considered (-0.023). A positive relation with INT, IRR, and GEO and a negative relation with LVI were found. LAN, ELE and POP were found (weakly) significant (with negative coefficients) in MA and GWR models only.

Discussion

Addressing the multiple interaction among ecological processes and economic growth at the regional scale helps in developing more effective policies aimed at mitigating land resource depletion in Mediterranean-type ecosystems (Wilson and Juntti 2005). A coherent multi-disciplinary approach addressing the synergic effects of bio-physical and socio-economic drivers of LD is needed to fill this objective. This paper provides an example of integration and analysis of environmental variables available at fine resolution with economic information estimated at the district scale.

The analysis presented here explores a possible income-LD relation in Italy through an empirical approach. Results indicate that a relationship exists among land vulnerability and economic growth of local districts, providing (indirect) evidences in favour of EKC. However, the best fit was a linear form where income is associated to decreasing LVI over time. Classical, second order polynomial forms do not increase significantly goodness of fit. Notably, the signs and significance of income term remained unchanged in all models[xxi]. Recent studies verifying EKC have used higher order specifications instead of quadratic (Mukherjee and Kathuria 2006). Researchers have argued that one of the reasons for getting a peak outside the estimated function is due to quadratic specification, which may be restrictive in this context (Lantz 2002). In the present study, however, regression analysis indicates that third-order specifications do not increase the proportion of explained variance.

Finally, spatial effects are found to be important in understanding the relationship among land vulnerability and socio-economic drivers. By incorporating the spatial dimension in regression analysis, global fits indicated that a linear model including income, additional socio-economic variables and spatial effects represents a sound specification of the income-environment relation specific for LD processes[xxii].

Taken together, our results suggest that an induced policy response could be possible at the income levels observed in both northern/central and southern regions (e.g. Briassoulis 2004). However, environmental measures had generally different impacts on land quality and vulnerability in the two areas. This is likely because determinants of LD act differently in northern and southern Italy according to the different development paths which have characterised the two regions in the past (Salvati and Zitti 2008a). Regression analyses indicate that other variables (e.g. site-specific factors) may as well influence the relationship among economic growth and LD, but their contribution seems to be (rather) limited as compared to that of (district) income[xxiii]. This means that income represents a synthetic index which may depict – better than other variables – the economic, social, and environmental transition in both developed and disadvantaged southern European regions. Different factors may be invoked to explain the relationship between vulnerability to LD and economic growth, including (i) increasing levels of education and environmental awareness in more involved agents (e.g. farmers); (ii) more open systems of local governance, and (iii) high income elasticity for environmental quality. Therefore, it is reasonable to evoke a mechanism where higher development generates positive externalities acting in the mitigation of land vulnerability.

There are several practices widely diffused in high income districts that could (partly) explain the observed pattern. The efficient application of agro-environmental schemes, sustainable irrigation in dry areas, dissemination of good farming practices in highly intensified agricultural districts, spreading of technologies able to reduce soil pollution and protect land quality, and coherent monitoring/control activities carried out by regional environmental agencies (Glenn et al. 1998; Cacho 2001; Tanrivermis 2003) may all represent examples of good practices with positive feedback on the level of land vulnerability. This suggests that the establishment of policy targets at the source would be needed. A first step will be to incorporate these measures in strategies aimed at mitigating LD by supporting their implementation in economically-disadvantaged, dry areas. This should help the income-environmental relationship reversal into a negative elasticity, with a potential process of 'tunneling through' the exogenously determined EKC (Munasinghe 1999).

Interestingly, the income-LD relationship seem to be not complicated by 're-linking' at higher income levels, as observed for other processes. The underlying mechanism could be as follows: the richest districts in northern Italy tend to be more innovative in terms of technology, environmental monitoring, and new institutional/policy approaches. There is no evidence that LD is more severe in that region because of feedbacks from economic drivers. However, the positive effect needs time to be effective as it depends largely on a systemic reaction of the whole system at different economic/ecological stages (Bruvoll et al. 2003)[xxiv].

Considering the explorative approach of this analysis, it seems valuable (i) to reproduce the study in other southern European countries based on data collected at detailed observation scales, and (ii) to collect additional information at the local scale to confirm the results or provide alternative interpretations of the observed relationship. Previous studies have shown that vulnerability to LD varies over time, thus suggesting that LD is a dynamic concept in time and space (Salvati and Zitti 2008b). However, the lack of spatial data has restricted the analysis for longer periods in this study. Despite data limitations, the study covers a period when important changes in all the variables considered occur in Italy and vulnerability to LD increased throughout southern Europe (Salvati and Zitti 2008a). We are therefore confident that the results of this study, although interpreted with caution, may be regarded as representative of environmental conditions at a defined time and space and might produce reliable inference for the future. This confirms the importance of making available estimates of LD vulnerability over a long time span, which would allow to implement more sophisticated statistical techniques, as usually carried out in several other studies concerning the EKC hypothesis.

Conclusion

The results presented here are, at our knowledge, the first evidence supporting EKC for LD. This is particularly important as these findings are obtained through a sub-regional cross-section analysis of a developed country rather than a cross country analysis. Results suggest that a disaggregated within-country analysis is sound in economic terms and may provide a robust statistical ground. Cross-country analyses, even if focused on homogeneous areas, could be misleading since they capture only the average effect. When exploiting the within-country heterogeneity (especially in a disaggregated spatial domain, like the one considered in this paper) different relationships among the environmental processes and the economic drivers may arise, calling for differentiated policy strategies (Briassoulis 2004). The state-specific situation remains a crucial issue to address at the European level, where environmental policies are often implemented assuming that single country conditions are similar regarding the ecological issue (Neumayer 2001). If national situations differ with respect to the point at which the country lies along the EKC development dynamic, more heterogeneity in national, regional, and local policies could be claimed. Empirical analysis on single countries could provide more information to policy makers on those directions, but a common ground research effort should be carried out in Mediterranean Europe in order to disentangle common spatial and temporal trends in the studied relationship. The claimed ground could benefit from the wide literature produced in the framework of the major research programmes concerning desertification monitoring and mitigation (e.g. Puigdefabregas and Mendizabal 1998; Rubio and Bochet 1998; Basso et al. 2000).

What kind of policy suggestions arise from this study? Following the original EKC hypothesis, structural changes reflected in higher income and lower share of agriculture in total product positively affect land quality thus reducing vulnerability to LD (Dasgupta et al. 2006). However, policies supporting income alone cannot be considered as sufficient to mitigate LD processes, as additional drivers act to reverse the positive effect of income rise. Some of them are identified in the present analysis acting at a regional scale and thus need (environmental) policy response. As an example, environmental measures aimed at reducing agricultural impacts especially in terms of intensification, excessive mechanisation, and unsustainable irrigation are to be coupled with (general) pro-growth policies (Briassoulis 2005). To integrate policy measures acting at different spatial scales (*e.g.* environmental measures at farm level, social measures at the municipality level, economic policies at regional or higher scales) is a coherent response to the most important LD drivers individuated in this paper. According to income disparities observed in Italy, this study provides interesting insight from a regional perspective. We have seen that Italy represents a clear example of a possible increasing gap, fuelled by the income-driven, endogenous dynamics of de-coupling/re-linking, that emerges between low- and high-income areas. It suggests that the role of mitigation-oriented policies and their impact on the environmental degradation is different in northern and southern regions. In such a context, a coordination of multi-scale (environmental) policies is expected to really improve the effectiveness of LD mitigation in the light of both sustainable development and reduction of regional disparities (Briassoulis 2004). Implementing coordination of specific measures (e.g. environmental, social, economic) with the final aim to avoid a downward spiral between environmental degradation and (lower) income may correctly address the problem in economically disadvantaged regions.

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Figure 1. A global EKC curve describing Land Degradation-income relationship and the possible position of Italy on it.

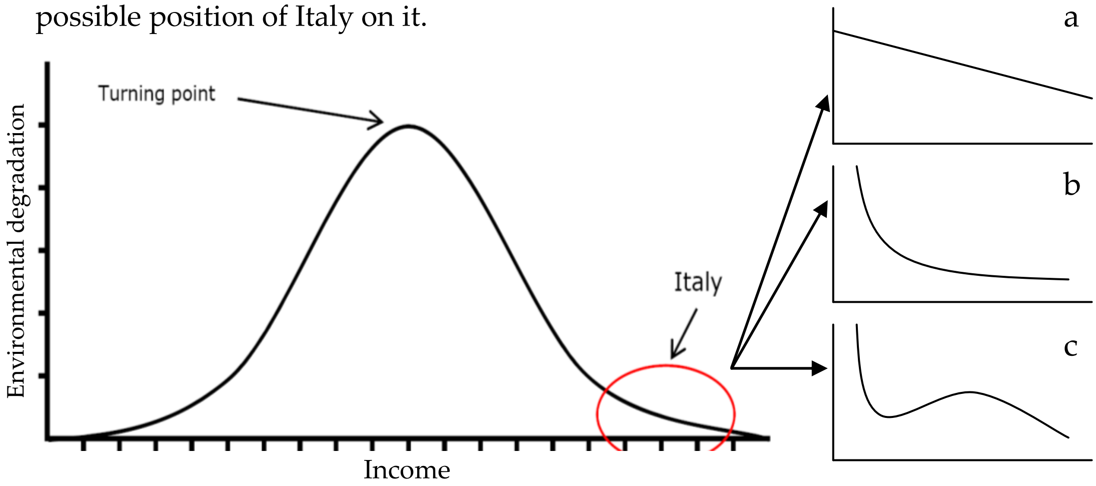

Figure 2. Map of the study area indicating the spatial domain considered (black line depicts NUTS-2 region boundaries, grey line indicates local district boundaries).

Figure 3. Vulnerability to Land Degradation (expressed as the distribution of LVI score by quartiles: arrow depicts increasing vulnerability; left panel) and district value added (expressed in Euros per-capita; right panel) both estimated in 2000 over the Italian territory.

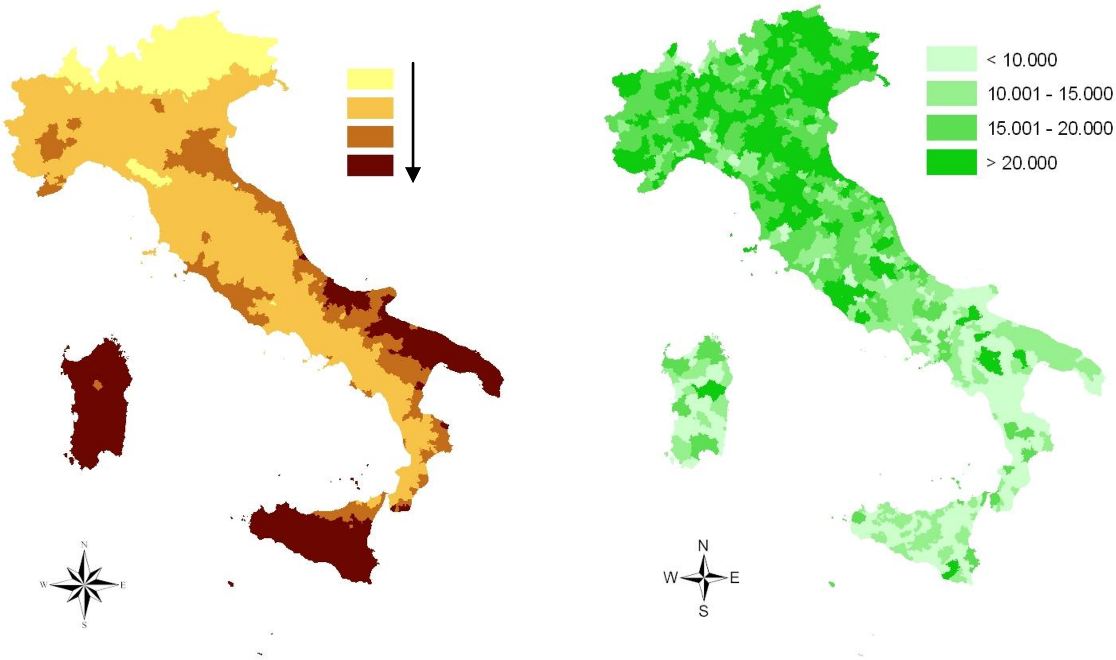

Table 1. Average (and standard error) values of dependent and independent variables considered in this study.

Variable (Acronym)	Average (± SE)	Source
Number of districts	784	ISTAT (1997)
Change in land vulnerability over time (ΔLVI, %)	11.7(0.1)	This paper
Socio-economic variables (SOC)		
District value added (GDP, euros *per head*)	14,300(215)	ISTAT (2006)[a]
Share of industry in total product (IND, %)	26.9(0.4)	ISTAT (2006)[a]
Share of agriculture in total product (AGP, %)	8.1(0.2)	ISTAT (2006)[a]
Tourism districts (TOU)	9.1[g]	ISTAT (2006)[b]
Urban districts (URB)	4.9[g]	ISTAT (2006)[b]
Land productivity (LAN, euros per hectare of UAA)	1,905(29)	ISTAT (2006)[c]
Labour productivity of service (SER, euros *per worker*)	46,666(645)	ISTAT (2006)[a]
Agricultural variables (AGR)		
Crop intensity (INT)	0.68(0.01)[h]	ISTAT (2006)[d]
Agricultural Utilised Area (UAA, %)	44.1(0.7)	ISTAT (2006)[d]
Change in agricultural surface (LOS, %)	90.4(0.7)	ISTAT (2006)[d]
Irrigated land (IRR, %)	14.7(0.7)	ISTAT (2006)[d]
Economically marginalised farms (MAR, %)	13.7(0.5)	ISTAT (2006)[d]
Environmental and control variables (ENV)		
Land Vulnerability Index in 1990 (LVI)	0.39(0.002)[i]	This paper
District elevation (ELE)	40.6[l]	ISTAT (2006)[e]
District surface (SUR, km^2)	384.3(13)	ISTAT (1997)
Population density (POP, inhabitants km^{-2})	183.2(10)	ISTAT (2006)[f]
Geographical sector (GEO)	46.6[m]	ISTAT (1997)

[a] National accounts; [b] Elaborations from ISTAT (1997); [c] National accounts and census of agriculture; [d] Census of Agriculture; [e] Our elaborations based on a 250 m Digital Elevation Model provided courtesy of L. Perini (CRA-CMA) and integrated with data from ISTAT (2006); [f] Census of Population and Households; [g] percentage of tourism and urban districts on the total number of districts in that area; [h] INT ranges from 0 to 1; higher values indicate increasing crop intensity; [h] LVI ranges from 0 to 1; higher values indicate increasing vulnerability to LD; [l] percentage of mountain districts (with average ELE > 650 m); [m] percentage of southern districts. All variables refer to 2000.

Table 2. Hypotheses on equation coefficients and their meaning in economic terms (see also Figure 1).

Coefficient	Hypothesis
$b_1 = b_2 = b_3 = 0$	No relationship between LD and per capita income
$b_1 > 0$ and $b_2 = b_3 = 0$	A monotonic decreasing relationship between LD and per capita income
$b_1 < 0$ and $b_2 = b_3 = 0$	A monotonic decreasing relationship between LD and per capita income (panel A)
$b_1 > 0$, $b_2 < 0$ and $b_3 = 0$	An inverted U-shaped relationship
$b_1 < 0$ and $b_2 > 0$ and $b_3 = 0$	An U-shaped relationship (panel B)
$b_1 < 0$, $b_2 < 0$ and $b_3 > 0$	A N-shaped relationship
$b_1 < 0$, $b_2 > 0$ and $b_3 < 0$	Opposite to the N-shaped relationship (panel C)

Table 3. Results of the standard OLS regression analysis among vulnerability to LD (ΔLVI) and per-capita value added (GDP) of local districts in Italy (standard errors of the estimates are reported in brackets).

	Linear	Quadratic	Cubic
b_0	0.201(0.009)**	0.104(0.185)	0.104(0.186)
GDP	-0.038(0.002)**	0.010(0.090)	0.010(0.091)
GDP^2		-0.006(0.011)	-0.006(0.012)
GDP^3			~0.000
Adj-R^2	0.263	0.262	0.261
F	278.0**	139.0*	139.0*
df	1, 778	2, 777	2, 777

Stars indicate the probability level of *t* test associated to each regression coefficient as follows: * $0.001 < p < 0.05$, ** $p < 0.001$.

Table 4. Measures of global spatial autocorrelation, DLVI and GDP; spatial weight matrix: geodesic distance < *d* km.

	ΔLVI				GDP			
				Moran global I				
d	*I*	*z(I)*	*p*1	*p*2	*I*	*z(I)*	*p*1	*p*2
25	0.6155	24.40	0.0000	0.0000	0.7626	30.22	0.0000	0.0000
50	0.5131	41.01	0.0000	0.0000	0.7109	56.77	0.0000	0.0000
75	0.4554	52.66	0.0000	0.0000	0.6794	78.48	0.0000	0.0000
100	0.4224	63.02	0.0000	0.0000	0.6588	98.17	0.0000	0.0000
125	0.4048	73.19	0.0000	0.0000	0.6452	116.50	0.0000	0.0000
150	0.3870	81.87	0.0000	0.0000	0.6244	131.90	0.0000	0.0000
175	0.3723	89.76	0.0000	0.0000	0.6032	145.20	0.0000	0.0000
200	0.3624	97.99	0.0000	0.0000	0.5926	160.00	0.0000	0.0000
				Geary global c				
d	*c*	*Z(c)*	*p*1	*p*2	*c*	*Z(c)*	*p*1	*p*2
25	0.3737	-15.71	0.0000	0.0000	0.3571	-16.13	0.0000	0.0000
50	0.4608	-21.90	0.0000	0.0000	0.3642	-30.93	0.0000	0.0000
75	0.5214	-23.17	0.0000	0.0000	0.3745	-30.29	0.0000	0.0000
100	0.5616	-23.37	0.0000	0.0000	0.3797	-33.07	0.0000	0.0000
125	0.5867	-23.30	0.0000	0.0000	0.3854	-34.65	0.0000	0.0000
150	0.6060	-22.08	0.0000	0.0000	0.3909	-44.80	0.0000	0.0000
175	0.6222	-22.06	0.0000	0.0000	0.3990	-35.09	0.0000	0.0000
200	0.6338	-21.26	0.0000	0.0000	0.4049	-34.56	0.0000	0.0000

Table 5. Results of spatial regression (both Conditional Autoregressive model, CAR, and Moving Average model, MA: spatial weight matrix: *d* = 50 km) and Geographically Weighted Regression (GWR) analyses among vulnerability to LD (ΔLVI) and per-capita value added (GDP) of local districts (N = 784) in Italy (standard errors of the estimates are reported in brackets).

	CAR spatial regression		MA spatial regression		GWR	
	Linear	Quadratic	Linear	Quadratic	Linear	Quadratic
b_0	0.200(0.009)**	0.108(0.185)	0.141(0.011)**	0.230(0.164)	0.197(0.010)**	0.118(0.161)
GDP	-0.038(0.002)**	0.008(0.091)	-0.023(0.003)**	-0.067(0.080)	-0.037(0.002)**	0.002(0.079)
GDP^2		-0.006(0.011)		0.005(0.010)		-0.005(0.010)
Adj-R^2					0.241	0.240
Log-L	824.8	824.9	935.8	935.9		

Stars indicate the probability level of *t* test associated to each regression coefficient as follows: * 0.001 < *p* < 0.05, ** *p* < 0.001.

Table 6. Results of regression analysis among vulnerability to LD (ΔLVI), per-capita value added (GDP), and additional drivers in the Italian local districts (N = 784; standard errors of the estimates are reported in brackets).

	OLS	CAR	MA	GWR
b_0	0.186(0.016)**	0.181(0.016)**	0.146(0.015)**	0.141(0.017)**
GDP	-0.023(0.004)**	-0.023(0.004)**	-0.023(0.004)**	-0.023(0.004)**
GEO	0.011(0.001)**	0.011(0.001)**	0.015(0.002)**	0.006(0.001)**
LVI	-0.084(0.009)**	-0.082(0.009)**	-0.097(0.013)**	-0.083(0.009)**
INT	0.011(0.002)**	0.010(0.002)**	0.010(0.002)**	0.004(0.002)*
IRR	0.009(0.003)**	0.009(0.003)*	0.014(0.003)**	0.006(0.002)*
LAN	-0.006(0.002)*	-0.006(0.002)*	-0.002(0.002)	-0.001(0.002)
ELE	-0.003(0.001)*	-0.003(0.001)*	-0.001(0.001)	-0.000(0.001)
POP	-0.004(0.002)	-0.004(0.002)	-0.007(0.002)*	-0.004(0.002)*
SUP	0.002(0.001)	0.003(0.001)	0.002(0.001)	0.002(0.001)
IND	-0.010(0.004)	-0.010(0.004)	-0.012(0.004)	-0.007(0.005)
URB	-0.000(0.002)	-0.000(0.002)	-0.000(0.002)	-0.002(0.002)
TUR	-0.004(0.002)	-0.003(0.002)	-0.001(0.001)	-0.002(0.002)
LOS	-0.003(0.002)	-0.003(0.002)	-0.003(0.002)	-0.000(0.002)
Adj-R^2	0.377			0.278
Log-L		889.2	1007.0	

Results of the full model expressed in linear terms are reported; OLS means standard a-spatial regression, CAR indicates Conditional Autoregressive spatial regression model, MA means Moving Average spatial regression model and GWR indicates Geographically Weighted Regression model (see text for specification and technical details). Stars indicate the probability level of *t* test associated to each regression coefficient as follows: * $0.001 < p < 0.05$, ** $p < 0.001$.

Appendix 1. Land Vulnerability Index (LVI)

As proposed by Salvati et al. (2008), in this study we used the Land Vulnerability Index (LVI) as indicator of the level of vulnerability to LD in Italy. LVI was composed of three thematic indicators describing climate, soil properties, and land use quality, which produce a ranking of vulnerability to LD on a municipality or district basis (Salvati and Zitti 2008b). Climate variables include aridity index, average annual rainfall, rainfall variability and concentration, as well as the average number of rainy days (all measured over a thirty-years period). Soil variables include soil depth and texture, available water capacity, organic carbon content, and erosion risk. Finally, land use variables include proxies for vegetation quality, land use intensity, as well as population concentration and growth over a ten-year horizon. LVI allows (i) to estimate the importance of the indicators supposed as underlying causes of LD of which the synthetic index is composed and (ii) to analyse changes in the investigated variables. It employs a multiway data analysis to assign weights to each considered variable. In this study the methodology was applied at two time slices (early-nineties and early-2000).

The procedure to calculate LVI is detailed in this paragraph. As a first step, data from all the variables were converted to a regular spatial grid covering the whole investigated area in order to make available consistent information from different scales. Grid size was chosen according to the resolution of the variables used in land vulnerability evaluation. A 30 km random grid was built-up in order to extract data over a total of 299 grid nodes covering the whole country. The value of each variable was estimated as a mean of a circle plot (500 m radius) centred on the coordinates of each grid node (e.g. Basso et al., 2000). All the variables were computed through a cardinal scale and transformed into a 0-1 range as follows:

$$X_{t,i,j} = (x'_{t,i,j} - x'_{t,min,j})/(x'_{t,max,j} - x'_{t,min,j}) \qquad \text{(A1)}$$

$$X_{t,i,j} = 1 - [(x'_{t,i,j} - x'_{t,min,j})/(x'_{t,max,j} - x'_{t,min,j})] \qquad \text{(A2)}$$

where $x'_{t,i,j}$ represents the observed value for the variable *i* measured over the spatial unit *j* in the year *t*, and $x'_{t,min,j}$ and $x'_{t,max,j}$ respectively represent the minimum and maximum values for the variable *i* measured in all the spatial units. Equation 1 was applied to the variables showing a positive relationship with LD, equation 2 to the variables which showed a negative association to LD. Each transformed variable ranges from 0 (the lowest contribution to land vulnerability) to 1 (the highest contribution to land vulnerability).

A Multiway Data Analysis (MDA) was then performed in order to depict changes over time of the indicators entered the LVI. MDA is a generalisation of Principal Component Analysis (PCA) whose goal is to explore large sets of quantitative variables collected on the same set of observations. The structure of the variable dataset was analysed by computing loadings, i.e. the correlation among variables and MDA axes allowing to assess the main variations in the position of the single variables over the factorial plane. In this study MDA was therefore applied, to the matrices composed by the *x*-th variables (n = 14) measured over the *y*-th years (n = 2) on the *z*-th available spatial units (n = 299). A weight was attributed to each variable by multiplying its contribution (V_i) to the m most important factorial axes with their proportion of explained variance (C_k). The *m* most important axes were chosen as explaining more than 10% of the total variance. The sum of these products for all the *m* selected axes represents the weight (W_i) attributed to each variable:

$$W_i = \frac{\sum_{k=1}^{m} (V_i \bullet C_k)}{\sum_{j=1}^{n} \sum_{k=1}^{m} (V_i \bullet C_k)} \qquad \text{(A3)}$$

Weights are expressed in percentages and range between 0 and 100. Finally, the average weight of each thematic indicator was obtained as the sum of the variables' weights computed over the entire study period and divided by the number of variables entered in each theme. The final index was evaluated for each spatial unit as the indicators' weighted average:

$$LVI_j = \sum_{i=1}^{n} (W_i \bullet X'_{i,j}) \qquad \text{(A4)}$$

LVI scores range between 0 (the lowest land vulnerability) and 1 (the highest land vulnerability). Following the indications provided by Basso et al. (2000) for ESAI, final LVI maps were produced after the single layers were registered and referenced to an elementary pixel size of 1 km^2. Changes in LVI calculated over each of TTWA districts between early-nineties and early-2000 is the variable entered regression models. In the remaining four districts, the lack of data concerning some variables prevents us to compute a reliable figure for the LVI. Computation was based on the use of original 1 km^2 LVI raster maps. An average figure of LVI was attributed to each district on the basis of the 'zonal statistics' tool available through GIS software. Vulnerability estimates were further validated in Italian sample areas by field enquiries.

FOOTNOTES

[i] See also Salvati and Zitti (2008c) for a preliminary analysis of LD-income relationship in Italy.
[ii] The conceptual framework of EKC has been widened over time with studies that incorporate new variables (also analysing complex, multidimensional processes) into regression models (Rupasingha et al. 2004). However, to our knowledge, the large part of the explanatory variables used in this paper was not incorporated in previous works.
[iii] Although quite neglected in EKC studies up to early 2000, the importance of spatial effects in environmental-income relationship was clearly pointed out in more recent papers and needs to be further clarified for specific ecological processes.
[iv] The mechanisms through which income acts (positively or negatively, directly or indirectly) are not completely clear by now (Wilson and Juntti 2005). However, starting from the evidence provided by previous studies (Perez-Trejo and Clark, 1996; Walpole et al. 1996), we have selected a number of socio-economic variables as potential drivers of LD, in order to clarify the role of income in influencing land quality and thus vulnerability.
[v] It should be noted that degradation of land quality regards environmental management, whereas the endowments of land resources are mostly driven by geographical location and prevailing ecological context. The effects of these two components (i.e. 'land resource management' and 'endowments' in terms of land quality) can be separated by calculating changes in land quality with reference to a base year. As instance, comparing climate and soil quality between northern and southern Italy may show northern regions standing apart from southern ones, but it will be erroneous to conclude that environmental policies of northern Italy are better than southern ones. This is because southern Italy is endowed, on average, with lower land quality (e.g. due to harsh climate and lower quality soils). However, if we look at changes in land quality over a study period, one can infer about the process of LD and its impact on land conservation practices.
[vi] Note that we exclude from our study some variables which are commonly used as predictors in EKC literature as they are relevant at country-level, but meaningless at district-level (i.e., within the same country).
[vii] District-level published income data refer to GDP before the deduction of production taxes. Therefore, all the data are, strictly speaking, estimates of gross value added.
[viii] Classification of the Italian territory in two areas follows an economic rationale related to EU funding strategy. For a long term, EU structural funds divided Italy into eight economically disadvantaged target regions (Abruzzo, Molise, Campania, Apulia, Basilicata, Calabria, Sicily, and Sardinia) and twelve developed regions (Aosta Valley, Piedmont, Lombardy, Liguria, Trentino-Alto Adige, Veneto, Friuli Venezia Giulia, Emilia Romagna, Tuscany, Umbria, Marche, and Latium). This classification had implications for socio-economic policies at the national level but yet reflects income disparities among northern and southern regions. Notably, the classification has rationale also in environmental analysis of land vulnerability (Salvati and Zitti 2008a).
[ix] The analysis also takes into account results presented in a preliminary form by Salvati and Zitti (2008d) and based on a multivariate analysis of income, sensitivity to LD and ancillary variables in Italy covering the most recent years at detailed spatial scale.
[x] Concerning endogeneity, Rupasingha et al. (2004) hypothesised a possible simultaneous bias between environmental indicators, per-capita income and education variables, which are not included in our models. Moreover, the exploratory analysis carried out on the original set of predictors may reduce the risk of endogeneity when estimating equation parameters.
[xi] Notably, other choices of the weighting matrix are possible in an EKC context (e.g. Rupasingha et al. 2004). Patacchini (2008) discusses different methods to construct an appropriate weight matrix in countries like Italy with specific environmental and economic characteristics. In the present case, as the final objective of this empirical study is to identify economic drivers of a typical environmental phenomenon such as LD, which is influenced by the geodesic distance, our choice seems reasonable.
[xii] In this way, the analysis of spatial dependence exhibited by given variables (i.e. ΔLVI and GDP) using alternative definitions of neighbourhoods (i.e., varying the d distance) conveys information about the spatial configuration that maximises the intensity of interactions between districts.
[xiii] See Patacchini (2008) for further details.
[xiv] As model parameter estimates relate to the study area as a whole and inference on these might lead to poor understanding of the relationship investigated if this exhibits significant local spatial variation.
[xv] Spatially varying coefficient models have also been developed in the statistical literature following a Bayesian approach (Gelfand et al., 2003), but so far their scope has proved to be limited (Wheeler, 2007).
[xvi] Geographically Weighted Regression models were developed by using GWR 3.0 provided by the National Centre for Geocomputation (Maynooth, Ireland).

xvii Similar results (data available on request) were found by using absolute (district) GDP.

xviii Similar results (data available on request) were found by using absolute (district) GDP.

xix Based on the linear form: $\Delta LVI = b_0 + b_1(GDP)$, the elasticity of ΔLVI to GDP ($\eta_{ld/gdp}$) was computed as:

$$\eta_{ld/gdp} = \frac{\frac{d(\Delta \mathrm{LVI})}{dGDP}}{\frac{\Delta \mathrm{LVI}}{GDP}} = \frac{b_1}{b_0 + b_1 GDP} \qquad \text{(n1)}$$

and calculated at a defined income which coincides with the average (district) value added (14,300 euros). Income figures are computed as per-capita, logarithmic values and refers to 2000.

xx Second- and third-order polynomial forms showed, in all considered specifications, a goodness of fit systematically lower than the linear model and thus were neither reported in tables nor discussed in the main text (data available on request).

xxi The estimated level of income coinciding with a stable land vulnerability over time is higher than the maximum value observed at the district level. Such an evidence does not depend on the specification of the form, remaining valid also when adding different covariates to the estimation equation.

xxii Concerning the spatial coverage of the study, it was recently pointed out that data from a wide, homogeneous region or from a single country may often provide a more reliable set of statistical units than cross-country analysis (Vincent 1997, Dean 2002). Although the limited data variability is an intrinsic feature of such datasets, the relevancy for policy-making purposes could be higher (e.g. Mazzanti et al. 2008). To improve the quality of our results as opposed to both cross-country quantitative analysis and qualitative case studies of local interest (Wilson and Juntti 2005), we have used a dataset based on information available at the district level over the whole Italian territory.

xxiii This result differs from some previous EKC studies, where ancillary variables, in addition to income, play a key role in determining degradation levels (Dinda 2004; Stern 2004; Galeotti 2007).

xxiv Therefore the existence of effective LD-mitigating effects might be better detected on long time series at disaggregated geographical level, and the short length of our district-level study period does not allow us to perform such a detailed case by case analysis over time. Improvements in this direction are especially needed in a context of increasing impact of LD on Mediterranean ecosystem.