REGIONALISING DPSIR: A MULTIDIMENSIONAL APPROACH FOR ESTIMATING LAND DEGRADATION VULNERABILITY

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Abstract

Although several studies based on the calculation of composite indexes of Land Degradation (LD) were recently carried out in southern Europe, relatively few papers tend to address the impact of specific determinants of LD at the local scale. In this contribution a simple, computational approach is proposed to define homogeneous, vulnerable regions and the main factors acting as potential drivers of LD at that scale. The procedure was applied to a dataset composed of ten environmental indicators available at the municipality scale in 1970 and 2000 and depicting ecological conditions at the regional level (Latium, central Italy). The procedure consists of three steps: a principal component analysis is carried out on the original data matrix extracting latent patterns and simplifying data complexity. Then, a *k-means* cluster analysis is applied on a restricted number of meaningful, latent factors extracted by PCA in order to produce a classification of the study area into homogeneous regions. A stepwise discriminant analysis is finally performed to determine which indicators mostly contributed to define regional clusters. Five regions are identified among which three are considered at risk of LD, representing half of the whole Latium surface in 1970 and clearly increasing in 2000. The three regions classified at risk are mainly affected by (i) soil sealing and related processes, (ii) soil salinisation due to agriculture intensification and (iii) soil erosion mainly due to depopulation and loss in cultivated land. Based on these findings, specific mitigation strategies at the regional scale may be delineated.

Introduction

Defining the concept of geographical region needs to attempt a general consideration of the whole question of regional science. The recognition, quantification, and spatial representation of ever-varying aspect of the land may benefit by a division in homogeneous areas. The availability of Geographic Information Systems (GIS) that facilitate the use of cluster analysis for geographic regions has raised end-user expectations and demands for data, appropriate spatial tagging and consistency in area definitions. The interest in such procedures for analysing several possible local and regional situations arises in geographic and ecological topics (Salvati and Zitti 2008a). The complexity of the environmental phenomena and their interaction with social and economic processes needs a multidisciplinary approach based on the analysis of the various driving forces involved in such processes (Basso et al. 2000, Rubio and Bochet, 1998). The DPSIR framework is applicable to these issues (Fig. 1). DPSIR implementation is based on the use of a multiplicity of indicators (e.g. Rubio and Bochet 1998), which can be aggregated into composite indexes through various computational procedures (e.g. Salvati and Zitti 2008b).

Taken as an emblematic environmental process, different problems emerge in the evaluation of Land Degradation (LD) risk including (i) the choice of relevant indicators, (ii) the method used to normalise the indicators themselves, and (iii) the weighting techniques. A multidimensional approach able to consider both time and space dimensions may clarify latent patterns and trends of the main factors affecting land sensitivity to degradation (e.g. Salvati and Zitti, 2008c). Among the different procedures to built-up composite indicators of environmental sensitivity, the ESA (Environmental Sensitive Area) index appears yet to be the most largely applied in the Mediterranean basin, due to its simplicity in model building and its flexibility in the use of relevant indicators (Basso et al., 2000). Formulating an approach alternative to ESA is sometimes problematic due to the impossibility of positing hypotheses that are free of subjective, *ex-ante* choice (e.g. Salvati et al., 2008). However, there is certainly scope for investigating empirical ways of relaxing the mentioned assumptions. The aim of this paper is therefore to illustrate an alternative procedure to assess LD risk over time.

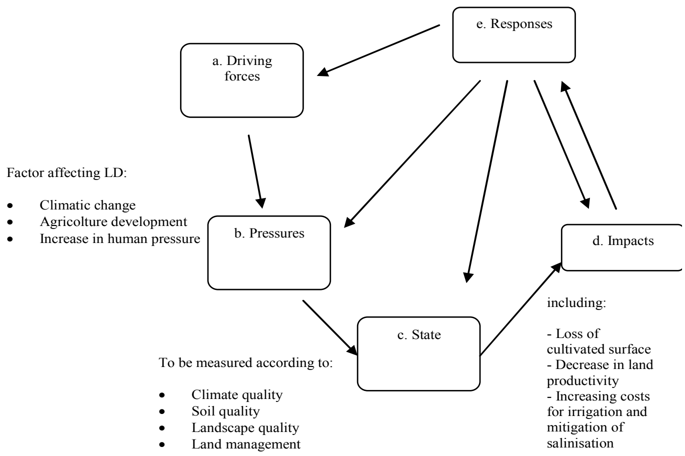

Figure 1 – A simplified DPSIR scheme illustrating the factors involved in LD at the local level in Latium.

Methods

The statistical procedure introduced benefit from a mixed strategy of multivariate analysis to obtain homogeneous 'risky' regions. The multivariate strategy includes a principal component analysis directly conducted on the original data matrix (variables · municipalities) extracting latent patterns and simplifying the complexity of original matrix. Then, a *k-means* cluster analysis was applied on a limited number of important latent factors extracted by PCA in order to produce a classification of the study area based on homogeneity in the variables considered. The final number of clusters was chosen according to statistical criteria. Finally, a stepwise discriminant analysis was conducted to determine which variables are more significant in discriminating 'risky' regions. Indicators used in this exercise are illustrated in Table 1.

Table 1 - Thematic indicators used in the assessment of LD risk, related research theme, unit of measure, and relation with LD.

Theme	Indicator	Unit of measure and relation with LD
Socio-economic	Population density	People km^{-2} (+)
	Demographic variation	% (+)
	Tourism concentration	Workers km^{-2} (+)
	Industrial concentration	Equiv. km^{-2} (+)
	Agriculture intensification	% (+)
Geo-physical	Loss in cultivated surface	% (-)
	Woodland cover	% (-)
	Aridity index	mm/mm (-)
	Available Water Capacity	mm (-)
	Estimated erosion rate	T ha^{-1} y^{-1} (+)

Results

Based on the results of the multivariate analyses, we aggregate clusters into different regions according to the average values of the indicators considered, elevation, and distance to Rome (Figure 2); additional information are used at this stage to identify the major drivers of LD caused by the local environmental and socio-economic configuration in each region. Two classes of regions were identified: (i) areas potentially at risk, (ii) areas with good environmental conditions and moderate human impact, regarded as not vulnerable to LD in the short term. The drivers of LD are generally different in the 'risky' regions: (i) soil sealing, fragmentation of traditional agricultural land, and fire risk are the main causes of land vulnerability in region 1. In region 2, the causes of LD risk are mainly due to agriculture intensification. Soil salinisation and compacting due to heavy mechanisation, water shortage, and unsustainable irrigation practices are the major threats to rural land in a context of marked reduction in rainfall amount and severe drought. The region 3 could be regarded as a 'depopulation and soil erosion' area. Here is active a downward environmental 'spiral' due to a defined causal chain involving rural depopulation, land abandonment, loss in cultivated surface, soil erosion, and enhanced economic marginalisation in a context of increasing rainfall intensity and drought episodes.

Conclusion

This paper illustrates a simple procedure to assess LD risk which is alternative to the use of composite indexes (e.g. Salvati and Zitti 2008c). The method is easy to implement and can be applied to a larger ensemble of variables when available. In the present study, two groups of variables were chosen referring to the economic and ecological aspects of LD of a certain area (Salvati et al. 2008). The results also suggest that the proposed framework could be applied to other complex ecological problems featuring different basic information collected at different time and spatial scales. We therefore suggest to integrate the use of composite indexes and data mining approaches like the one presented in this paper in order to achieve complete information from (limited) available time-series and spatial data.

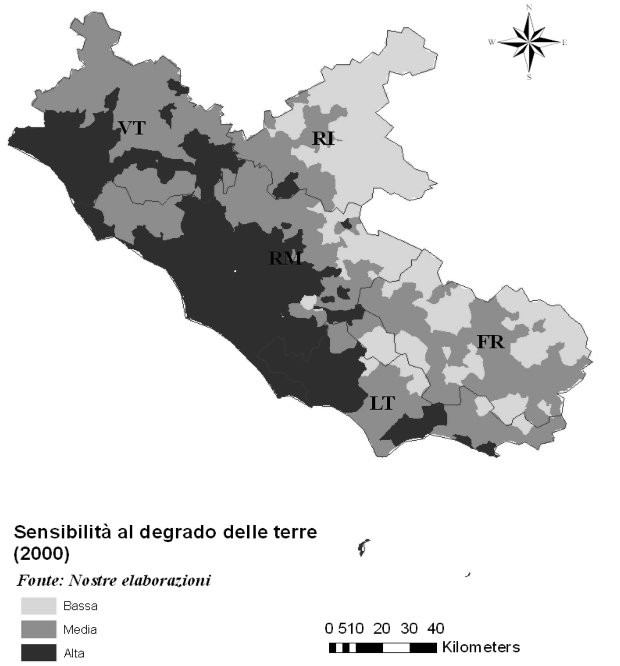

Figure 2 – Environmental vulnerable regions in Latium, central Italy: an example applied to LD.

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