A Multidimensional statistical framework to explore seasonal profile, severity and land-use preferences of wildfires in a Mediterranean country

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Assessing Latent Relationships between Land Degradation Drivers and Candidate Responses to Desertification: A Data Mining Approach

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Abstract

This study investigates the relationship between fine resolution, local-scale biophysical and socioeconomic contexts within which land degradation occurs, and the human responses to it. The research draws on experimental data collected under different territorial and socioeconomic conditions at 586 field sites in 5 Mediterranean countries (Spain, Greece, Turkey, Tunisia and Morocco). We assess the level of desertification risk under various land management practices (terracing, grazing control, prevention of wildland fires, soil erosion control, soil water conservation, sustainable farming, protected areas and financial subsidies to farms) taken as possible responses to land degradation. A data mining approach incorporating principal component analysis, non-parametric correlations, multiple regression and canonical analysis, was developed to identify spatial relationships between land management conditions, local background (assessed using 40 biophysical and socioeconomic indicators) and desertification risk. Our analysis identified distinct relationships between the level of desertification experienced and the underlying socioeconomic context, suggesting that the effectiveness of responses to land degradation is strictly dependent on the local biophysical and socioeconomic context. Assessing the latent relationship between land management practices and the biophysical/socioeconomic attributes characterizing areas exposed to different levels of desertification risk proved to be an indirect measure of the effectiveness of field actions contrasting land degradation.

Key words: Multivariate statistics, Human pressure, Indicators, Response assemblage, Mediterranean region.

1. Introduction

Land Degradation is a complex phenomenon occurring when specific biophysical, economic, social, cultural and institutional factors act synergistically to produce and entrench desertification over the long term (Reynolds et al., 2011). Unsustainable use of natural resources, weak economic development and policy inaction are relevant drivers of land degradation and reflect the complex relationship between local ecological conditions, socioeconomic dynamics and policy action (Bisaro et al., 2013). Desertification results in a progressive decline of land productivity and ecosystem functions, and is a key issue on the global policy agenda (Stringer and Harris, 2014). Desertification has negative impacts on food security, biodiversity and quality of life (Glenn et al., 1998). Abuse or misuse of land, drives to regional disparities in the availability of natural resources and results in a spatially unbalanced development (Johnson and Lewis, 2007).

In the last decades, desertification risk has increased in many parts of the world, with land degradation now becoming severe in both emerging and developed countries (Thomas et al., 2012; Izzo et al., 2013; Yang et al., 2013). In the Mediterranean basin, Land Degradation (LD) is the result of the interplay between natural and socioeconomic systems (Wilson and Juntti, 2005). This process involves a number of biophysical attributes of the landscape (topography, climate, soil, vegetation) and conditions deriving from human activity (e.g. land-use transformations, agricultural intensification, land abandonment, population density, settlement distribution, industry and tourism development).

A large part of the Mediterranean region is vulnerable to LD (Hill et al., 2008). While desert land is relatively scarce, areas with semi-arid climate and socioeconomic conditions which negatively impact soil fertility, biodiversity and ecosystem services are rather common. In such contexts, landscapes have lost part of their ecological and economic potential (Basso et al., 2010). LD processes in the Mediterranean basin are highly variable in time and space, closely influenced by the different speeds of change in environmental and socioeconomic conditions (Ibanez et al., 2008).

Studies that have addressed the most important causes and consequences of LD from a socio-environmental perspective have identified some of the core proximate drivers and underlying factors of change which lead to desertification risk (Zdruli, 2013). Salvati et al. (2015) have proposed an approach to assess the multiple relationships between biophysical factors and socioeconomic attributes in a representative sample of Mediterranean sites, identifying diverging spatial patterns for biophysical and human drivers of LD, with higher variability observed for economic and social indicators. Gaps in knowledge on the role of system complexity in shaping land vulnerability to desertification, however, have often been underestimated (Briassoulis, 2015). Research often focused on single - albeit important - factors such as soil degradation, whilst diachronic approaches which draw on data at a national or regional scale with an adequate spatial resolution are relatively scarce (Kosmas et al., 2015). Indicator-based approaches have been developed mainly for permanent monitoring of biophysical conditions characterizing LD processes (Ferrara et al., 2012). Whilst development of proper indicators and decision support systems to inform mitigation policies is a research priority (Glenn et al., 1998), further investigation is required to identify a comparative framework for assessing the impact of regional-scale drivers, and enable the importance of biophysical and socioeconomic factors to be ranked (Salvati et al., 2015).

Based on the issues discussed above, rethinking a non-reductionist approach to LD in relation to the characteristic territorial dimensions and the most suitable policy responses is imperative (Sabbi and Salvati, 2014). Emphasis should be given to the social, demographic, economic, political and cultural processes that shape LD in any given area, and to the responses that society, in that specific local context, is able to implement (Iosifides and Politidis, 2005). According to Briassoulis (2015), "human response to land degradation can be considered any planned (formal) or unplanned (informal) actions that purport to directly and explicitly tackle it and/or address other individual and collective socioeconomic goals in affected socio-ecological systems". Depending on the prevailing socioeconomic conditions, stakeholders and other actors may have no option but to continue with business as usual (no remedial action), or to engage in resource-intensive activities (negative responses). Conversely, in some local contexts, stakeholders may be able to undertake actions to mitigate soil and land degradation (positive responses). Positive responses contribute to sustainable development of the local system preserving critical ecological functions and relevant socioeconomic attributes (Kelly et al., 2015).

Three key issues should be considered when effective responses to LD are proposed. First, a policy response or the implementation of a policy instrument does not always result in the intended impact in every context. Second, responses may have multiple impacts on the target environment and third, a holistic approach (as opposed to a target-specific or process-specific approach) is required in order to cope with a complex and multifaceted phenomenon such as LD (Salvati et al., 2015). The non-linear, highly-diversified nature of LD processes justifies the implementation of responsive and locally-adaptable policy instruments that are suitable to address place-specific environmental patterns (Wilson and Juntti, 2005). Previous studies have also suggested that the lack of relevant policy, due to *lassez-faire* practices or weak decision-making processes can be considered as tangible policy implementation, although inaction costs have been insufficiently acknowledged and investigated (Ferrara et al., 2012). As a consequence, policy implementation is a relatively fuzzy decision-making spectrum of (more or less) integrated measures, instead of a clear process of well-informed and locally-specific decision-making (Briassoulis, 2005).

In fact, to be effective on the ground, responses have take account of diverse components which are operating at various spatial scales and temporal speeds, and their effectiveness will therefore depend on their ability to respond to the relationships amongst these components. An integrative approach based on the concept of 'response assemblage' was recently proposed with the aim of identifying various types of interventions to combat LD (Briassoulis, 2015). Response assemblages reflect the need for humans to use natural resources sustainably to satisfy societal needs and are intended as "geographically and historically unique, provisional, open, territorial wholes, complex compositions emerging from processes of assembling biophysical and human components" (Briassoulis, 2015). A response assemblage operates at multiple spatial scales and is characterized by specific environmental attributes, land-use regimes and socioeconomic profiles.

Apart from the contribution mentioned above, frameworks identifying responses to LD are still relatively scarce (Thomas et al., 2012; Zdruli, 2013). Understanding place-specific LD processes, and identifying the spatial relationship between drivers of LD at different geographical scales, have allowed designing more effective mitigation strategies (MacDonald et al., 2000; Gellrich et al., 2007; Koulouri and Giourga, 2007; Corbelle Rico et al., 2012). Since place-specific factors and socioeconomic changes at multiple spatial and temporal scales have major impacts on LD responses (Sluiter and De Jong, 2007; Weissteiner et al., 2011; Kairis et al., 2014), stakeholder participation in the design of mitigation responses is crucial in the fight against desertification (Briassoulis, 2005). Iosifides and Politidis (2005) investigated the local context and its impact on individual stakeholder decision-making, and highlighted the importance of an integrated analysis of biophysical and socioeconomic drivers of change in order to identify and understand responses to LD. An in-depth knowledge of the latent relationship between LD drivers and components of the specific local human-biophysical system is an essential baseline when implementing Sustainable Land Management (SLM) strategies (Zdruli, 2013). Salvati et al. (2015) introduced a comprehensive approach to the analysis of the spatial relationship between biophysical and socioeconomic components of a socio-ecological system based on data mining techniques. This framework was applied to a number of rural districts in southern Europe exposed to different levels of desertification risk and allows us to quantify the main environmental and socioeconomic impacts on land. Based on this information, mitigation policies and adaptation strategies for locally-based LD processes have been proposed (Kosmas et al., 2015).

The study reported in this paper contributes to this research frame by illustrating an exploratory framework based on data mining techniques applied to a number of indicators that assesses biophysical and socioeconomic conditions at 586 Mediterranean field sites exposed to variable levels of desertification risk, and where different responses to LD have been implemented. Responses to LD form a set of actions targeting specific environmental problems or coping with undesirable conditions (Bakker et al., 2005; Strijker, 2005; Sluiter and De Jong, 2007). Environmental legislation, economic incentives, customary rules and SLM practices were frequently considered as candidate responses to LD (Thomas et al., 2012; Zdruli, 2013; Kelly et al., 2015). In this study, 8 practical actions covering the abovementioned issues (terracing, grazing control, wildland fire prevention, soil erosion control, soil water conservation, sustainable farming, protected areas, financial subsidies to farms) were selected as relevant examples of candidate responses to LD in the studied areas (Kosmas et al., 2015) and were correlated with the local context profiled using 40 biophysical and socioeconomic indicators (Salvati et al., 2015).

The aims of this study were (i) to investigate spatial occurrence and intensity of candidate responses to LD identifying possible 'response assemblages' at the field scale, (ii) to correlate the occurrence and intensity of candidate responses to LD with the level of desertification risk and (iii) to identify spatial relationships between candidate responses to LD and biophysical/socioeconomic contexts at each field site. The study contributes to the identification of practical actions and policy measures against LD using a statistical procedure which is robust, simple and adaptable to different environmental and socioeconomic conditions. The proposed approach is flexible to changes in background and response indicators. An enriched set of indicators can be used covering relevant candidate responses to LD under different territorial contexts. Data mining is a promising tool for ascertaining the spatial configuration of factors shaping desertification risk (Ferrara et al., 2016) and allows for an indirect evaluation of the effectiveness of land management actions in LD mitigation.

2. Materials and methods

2.1. Study area

A total of 586 field sites were selected in 5 Mediterranean regions. Two areas are situated in European Union (EU) member states (Greece and Spain) and the remaining three areas are in countries which are not part of the EU (Turkey, Tunisia, Morocco). Specifically, the study sites are: (i) Crete island, southern Greece, (ii) Guadalentin basin, south-eastern Spain, (iii) Eskisehir plain, Turkey, (iv) Zeuss Koutine, Tunisia and (v) Mamora Sehoul, Morocco. Each study site covers a surface area ranging between 100 km^2 and 150 km^2 and includes a number of individual field sites.

Field sites were representative of a variety of biophysical and socioeconomic conditions typical of Mediterranean rural landscapes. Data were collected as a part of the extensive fieldwork carried out through the DESIRE research project, financed by European Commission (see Kosmas et al., 2015 and references therein). The field sites are located in areas affected by variable degrees of land degradation, due to their differing levels of soil erosion, salinization, compaction, sealing, contamination, water stress, overgrazing, wildfires and anthropogenic pressures (population growth, tourism development, industrialization, depopulation, land abandonment). In 80% of the study sites, climatic conditions are semi-arid or dry with rainfall ranging between 200 and 600 mm. Reference evapotranspiration > 800 mm (*sensu* Penman) was observed in the majority of field sites. Soils are formed mainly on sedimentary and unconsolidated parent materials. Soil organic matter content in the soil surface has been identified as low to moderate (0.5%-1.5%) in most of the study sites. Dominant vegetation cover types include cereals, olives, vineyards, garden crops and cotton. The agricultural holdings are characterized as owner-farmed in 58% of the sites with farm size ranging from less than 2 hectares to more than 100 ha, and there is a high degree of land fragmentation (Salvati et al., 2015).

2.2. Data collection

Data were collected at the scale of field sites, extending 0.5 to 20 ha and having homogeneous soil, topography and land management (Kairis et al., 2014). Field sites were identified from topographic maps and/or ortho-photographs in 400 m grids by applying a systematic sampling design, with precise location being pin-pointed using a GPS (Ferrara et al., 2016). Most information were collected directly from land owners (Kosmas et al., 2015). A digital questionnaire and guidance notes were compiled defining each elementary variable and assessment methodology with the aim of harmonizing data collection across field sites (see

Salvati et al., 2015 and references therein for technical details). A total of 49 variables with no missing values were derived from information collected on the field.

Values for each variable collected were transformed into a scale indicator (with scores ranging between 1 and 2) describing the (positive or negative) relationship with LD. Increasing scores indicate a higher contribution to land degradation (Kosmas et al., 2015). Existing classification systems (Rubio and Bochet, 1998), reference research frameworks (Lavado Contador et al., 2009) and expert opinion were used to set up the scoring system. Scores are suitable to scale and homogenize the values of the studied variables to a comparable range allowing comparison across space or between different research dimensions (Ferrara et al., 2012).

2.3. Indicators

A comprehensive set of 40 'state' and 'pressure' indicators assessing LD factors and describing biophysical and socioeconomic conditions where remedial interventions are required to prevent desertification risk were prepared according to Kosmas et al. (2015) and Salvati et al. (2015). Candidate indicators were selected by (i) reviewing the existing literature (Rubio and Bochet, 1998; Wilson and Juntti, 2005; Basso et al., 2010; Kairis et al., 2014; Kosmas et al., 2015), (ii) consulting with stakeholders (land users/managers, politicians and research groups working on LD issues at both national and study site level) and (iii) using scientific, technical or planning reports, including National or Regional Action Plans to Combat Desertification. Indicators (list in Table 1, Supplementary materials, and technical details in Table 2, Supplementary materials) were classified into 9 dimensions (4 dimensions assessing biophysical aspects and the remaining 5 dimensions quantifying socioeconomic factors): (a) climate (4 indicators), (b) soil (10), (c) vegetation (3), (d) water runoff and fires (3), (e) agriculture (5), (f) cultivation practices and husbandry (6), (g) land management (10), (h) water use (2) and (i) demography and tourism (4). The overall level of desertification risk in each site was derived according to the Environmentally Sensitive Area (ESA) approach (Lavado Contador et al., 2009), originally produced by EU-funded Mediterranean Desertification and Land Use (MEDALUS) project (Ferrara et al., 2012).

Eight indicators (protected areas, terracing, grazing control, fire prevention, economic subsidies to farms, sustainable farming, soil erosion control and soil water conservation) were used to assess land management practices or policy actions with a (supposed) positive impact on LD (Sabbi and Salvati, 2014). These practices were regarded as important interventions against desertification in the study areas and were classified as candidate responses to LD (Salvati et al., 2015). In this sense, response indicators considered in this study cover a representative set of actions undertaken for sustainable land management, landscape conservation or environmental quality protection (Kosmas et al., 2015). However, the selected response indicators are possibly not exhaustive of the entire set of candidate responses to LD since other practices/actions can be important in different territorial contexts.

2.4. Statistical analysis

A data mining strategy incorporating Principal Component Analysis, Spearman correlations, step-wise multiple regression, non-parametric Mann-Whitney inference and Canonical Correlation Analysis was run on the full sample (n = 586 observations). The multivariate techniques considered here were aimed at (i) assessing variety of local socio-ecological systems, (ii) identifying indicators associated with the level of desertification risk, and (iii) evaluating spatial relationships between candidate responses to LD and the related biophysical/socioeconomic background. The indicators considered in each statistical analysis are listed in Table 1.

To explore multiple spatial relationships between response indicators, a Principal Component Analysis (PCA) was run on a data matrix including values of all response indicators at each of the 586 field sites. Relevant components with eigenvalue > 1 were analyzed. Non-parametric Spearman rank tests were run with the aim of correlating pair-wise response indicators and biophysical/socioeconomic indicators profiling field sites. Significance was set up at $p < 0.05$ after Bonferroni's correction for multiple comparisons.

A multiple linear regression model was run to identify response indicators most associated with the level of desertification risk in each field site. The model was developed using a forward stepwise approach with response indicators as predictors and the level of desertification risk as the dependent variable. Predictors were included in the model when the *p*-level associated to the respective Fisher-Snedecor test was below 0.01. Results of the regression model were illustrated using standardized coefficients and tests of significance for each indicator (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.

Response indicators were analyzed separately using non-parametric Mann-Whitney U statistics testing for significant differences ($p < 0.05$) in the two EU countries (Greece and Spain) compared with the three Mediterranean countries outside of the EU (Morocco, Tunisia, Turkey). This statistic analyzes the occurrence and intensity of different land management actions/practices within and outside the European Union, providing an indirect evaluation of the effectiveness of some EU policies relevant to LD (e.g. farm subsidies). A Canonical Correlation Analysis (CCA) was finally run to investigate the spatial relationship between the 20 biophysical indicators (or the 20 socioeconomic indicators) and the 8 response indicators at the spatial scale of field site. The general objective of the CCA is to combine two sets of indicators (e.g. biophysical indicators *vs* land management actions; socioeconomic indicators *vs* land management actions) into a common structure formed by few factors (roots) that explain a high proportion of the matrices' variance. The roots' structure was analyzed on the basis of the correlation coefficients with input indicators. The final aim of the CCA was to summarize the results derived from previous analysis' steps providing a comprehensive overview of the complex spatial patterns within the studied indicators, and the spatial relationship between desertification risk, local context and candidate responses to LD.

3. Results

3.1. Principal Component Analysis

The PCA run on the 8 response indicators at the spatial scale of field site extracted 3 relevant components explaining together more than 65% of the total variance (Table 1). Component 1 accounts for 28.5% of the total variance and was correlated positively with soil erosion control measures, soil water conservation measures and the extent of protected areas. Component 2 accounts for 19.5% of the total variance with positive loadings assigned to terracing and farm subsidies and a negative loading assigned to fire prevention. Component 3 accounts for 17% of the total variance and outlines the counter-correlation between sustainable farming and grazing control. Figure 1 illustrates the position of each field site over the factorial plane based on components 1 and 2. Component 1 discriminates field sites mainly within non-EU countries (Tunisia, associated with negative or slightly positive scores; Morocco and Turkey associated exclusively with highly positive scores); component 2 discriminates field sites in EU countries (Greece and Spain, receiving positive scores on average) from sites situated in non-EU countries (receiving negative scores on average).

3.2. Non-parametric correlations

A non-parametric correlation analysis investigating pair-wise relationships between the spatial distribution of response indicators and biophysical or socioeconomic attributes was illustrated in Table 3(Supplementary materials). The level of desertification risk in each field site was correlated positively with the extent of protected areas, fire prevention and grazing control. The remaining 5 response indicators were not associated with desertification risk. Fire prevention was the response indicator with the largest number of significant correlations with biophysical and socioeconomic indicators at the field site scale (78%) preceding sustainable farming (68%) and protected areas (58%). Responses totaling an intermediate number of significant correlations with context indicators were grazing control (54%) and farm subsidies (49%). Soil water conservation measures (46%), terracing (44%) and soil erosion control measures (42%) showed a lower percentage of significant correlations in respect to the other response indicators. Level of fire prevention was found relatively high in field sites with medium-high population density and positive demographic growth rate, tourism intensity and net farm income. By contrast, level of fire prevention was low in areas characterized by semi-arid climate, poor soils, moderate-low plant cover, land fragmentation and small farm size. Based on these evidences, level of fire prevention seems to increase in wealthier rural contexts with suitable conditions for cropping. Similar results were found for sustainable farming, a practice frequently observed in contexts with good climate conditions and farms with young owners and high returns. Protected areas were associated to contexts with good soil and climate quality, being the highest in sites with considerable soil depth and water storage capacity and medium-high plant cover. Protected areas were preferentially observed in areas with stable or moderately increasing population growth, sustainable farming (depending on tillage depth, intensity and direction) and moderate-low rate of land abandonment.

Grazing control was a practice more frequently observed in semi-arid and arid land with low-quality soils and in local contexts with high grazing intensity, land abandonment and fragmentation. Farm subsidies were associated with biophysical and socioeconomic indicators reflecting place-specific factors more evidently than regional environmental conditions. Soil water conservation measures were especially observed in rural sites with a young population structure and where sustainable farm practices are routinely applied. Terracing was mainly observed under semi-arid and arid climate regimes and in socioeconomic contexts with intense grazing, high land ownership rate, low tourism intensity and high land abandonment rates. Finally, soil erosion control measures were preferentially observed in areas with high risk of soil erosion, low plant cover, high grazing intensity, parallel employment of farmers in non-agricultural sectors, depopulation and land abandonment.

3.3. Multiple regression model

Results of a step-wise multiple regression with level of desertification risk as the dependent variable and response indicators as predictors are illustrated in Table 2. The best regression model incorporates four predictors with adjusted $R^2 = 0.25$ and a significant Fisher-Snedecor F test. Model's outcomes are in partial agreement with the findings collected from the non-parametric Spearman analysis (section 3.2). Protected areas and grazing control were the predictors with the highest regression coefficient, preceding terracing and farm subsidies. Desertification risk was higher in field sites with extensive terraces and economic subsidies, decreasing in sites with protected areas and high grazing control.

3.4. Non-parametric inference

Results of the pair-wise non-parametric Mann-Whitney U test comparing the spatial distribution and intensity of response indicators in EU (n = 276 sites) and non-EU countries (n = 310 sites) indicate that 4 indicators out of 8 were highly different ($p < 0.0001$) in the two groups of countries (grazing control: adj-Z = 11.5; fire prevention: adj-Z = 21.5; farm subsidies: adj-Z = -14.1; protected areas: adj-Z = 7.1). Frequency of sustainable farming (adj-Z = -3.3) and terracing (adj-Z = 3.9) was different ($0.001 < p < 0.05$) between EU and non-EU countries. Two indicators (soil erosion control measures: adj-Z = 0.2; soil water conservation measures: adj-Z = -1.7) show a homogeneous distribution ($p > 0.05$) in both EU and non-EU countries.

3.5. Canonical correlation analysis

A separate Canonical Correlation Analysis (CCA) was run on the standardized data matrices respectively composed of 20 biophysical indicators (Table 3) and 20 socioeconomic indicators (Table 4), each contrasted with the 8 response indicators observed at the spatial scale of field site. The CCA assessing biophysical indicators extracted 7 roots respectively with 59.6% (left set of input variables) and 94.2% (right set of input variables) in total variance. Each root identified specific response indicators associated with a restricted number of context indicators. Root 1 (respectively 12% and 21% in total variance) was correlated positively with fire prevention and negatively with farm subsidies. The biophysical indicators correlated with Root 1 were soil texture and soil water storage capacity (positive coefficients), potential evapotranspiration and rainfall erosivity (negative coefficients). Root 2 (13% and 16% in total variance) was correlated positively with terracing, grazing control, soil drainage and 4 climate indicators (rainfall, aridity index, potential evapotranspiration and rainfall seasonality). The loading's structure of this root suggests that grazing control and terracing are actions strictly dependent on the biophysical context. Root 3 (12% and 19% in total variance) was correlated positively with soil erosion control measures and sustainable farming, in turn associated with the overall degree of soil erosion and runoff water storage (positive coefficients), rainfall and aridity index (negative coefficients). The structure of root 3 indicates that application of soil erosion control measures is dependent on the overall degree of soil erosion. Root 4 (6% and 12% in total variance) was correlated positively with farm subsidies, grazing control and rainfall erosivity. Negative coefficients to root 5 (8% and 13% in total variance) were assigned to soil water conservation measures and vegetation cover. Root 6 (5% and 6% in total variance) outlines the association between extent of protected areas and dominant use of land at each site: protected areas were typically associated with priority habitats including forests, high-biodiversity pastures and crop mosaics. Finally, root 7 (5% and 7% in total variance) identified a negative relationship between soil erosion and terracing, confirming that this traditional land management option is an indirect response to biophysical factors triggering erosion risk.

The CCA assessing socioeconomic indicators extracted 8 roots respectively with 64.6% (left set of input variables) and 100% (right set of input variables) in total variance. Each root identified one-to-three response indicators in turn associated with a restricted number of contextual indicators. Root 1 (15% and 22% in total variance) was correlated negatively with farm subsidies and positively with fire prevention and grazing control. Three socioeconomic indicators correlated negatively with root 1 (impervious surface area, population growth, aging index). Farm subsidies and sustainable farming were negatively correlated with Root 2 (14% and 15% in total variance), together with 3 socioeconomic indicators (land fragmentation, aging index and land abandonment). Root 3 (14% and 15% in total variance) was associated with grazing control and grazing intensity (negative coefficients) and land abandonment (positive coefficient). Root 4 (6% and 15% in total variance) indicated that impact of farm subsidies (negative coefficient) and sustainable farming (positive coefficient) is counter-correlated in the sample, with population density and net farm income associated with Root 4 with positive and negative sign, respectively. A negative coefficient to root 5 (10% and 10% in total variance) was assigned to both soil water conservation measures and percentage of irrigated arable land.

Protected areas (root 6), soil erosion control measures (root 7) and terracing (root 8) were not correlated with any socioeconomic indicator.

4. Discussion

Research, participatory processes, tools for policy makers and local-scale responses are seen as key components of an integrated strategy to fight desertification in the Mediterranean basin (Reynolds et al., 2011). The positive (research) and normative (policy) interest in human responses to LD usually focuses on sectoral policies and single-target measures that are designed to mitigate environmental degradation in affected or vulnerable areas (Omuto et al., 2013). Conversely, actions targeting either the resources impacted and/or the drivers and proximate causes of degradation are considered 'best practices' in strategies designed to mitigate LD. Policy implementation in different socioeconomic and biophysical contexts necessitates responses which support adaptive management and effective local governance (Thomas et al., 2012), because human responses to LD are inevitably context-specific and contingent (Wilson and Juntti, 2005).

The study reported in this paper contributes to the debate on the characterization of candidate responses to LD, trying to identify specific 'response assemblages' based on spatial convergence of different land management practices across a range of local contexts. The approach proposed here contributes to a decision support system that can be used by various stakeholders for joint monitoring drivers and candidate responses of land degradation in local contexts characterized by different environmental and socioeconomic conditions. The approach is distinctively based on the exploratory analysis of a comprehensive set of indicators collected in 586 field sites identifying (apparent or latent) relationships between LD drivers and candidate responses, depending on the intimate characteristics of each local context. In this sense, our results outline the role of 'state' and 'pressure' variables of a local system (e.g. climate dryness, soil quality, vegetation cover, land abandonment), confirming the results of earlier studies (Basso et al., 2010; Kosmas et al., 2015; Salvati et al., 2015). The evident complexity in the system of relationships between drivers and candidate responses to LD allows distinguishing biophysical factors (often characterized by one-to-one relationships between drivers and responses) from socioeconomic factors (more frequently characterized by relationships among multiple drivers and one response), corroborating the interpretative framework provided in Salvati et al. (2015). Evidences of this study may encourage more refined research applied to the comprehensive analysis of a local system (Stavi et al., 2015) and its evolution in terms of ecological aspects (e.g. soil quality, geo-diversity and vegetation) or socioeconomic conditions (e.g. changes in the social and economic base with impact on the produced value added).

Candidate responses to LD can be classified as 'broad' or 'narrow' spectrum based on the observed correlation with the local background and the overall level of desertification risk (e.g. Salvati and Zitti, 2009). Fire prevention, sustainable farming and protected areas were identified as broad-spectrum actions (Kosmas et al., 2015). Grazing control and farm subsidies were classified as medium-spectrum actions since they operate at the farm scale with indirect impact on LD in terms of economic and environmental sustainability. By contrast, soil conservation measures and terracing practices are intended to cope specifically with soil degradation processes and are correlated primarily with soil indicators. Results of non-parametric inference confirm the local-scale target of soil conservation measures - possibly less relevant in EU policy in respect with actions classified as 'broad-spectrum', such as farm subsidies or land protection, or in national/regional strategies in respect with sectoral measures such as fire prevention, grazing control, sustainable farming or terracing.

Moreover, the candidate responses investigated in this study show distinct spatial relationships depending on the level of desertification risk and the underlying territorial context (Salvati et al., 2015). These evidences may outline divergent responses of the socio-environmental local systems to ecological disturbances, highlighting possible mismatches between single-action responses and the related biophysical conditions prevailing at the time (Garcia-Orenes et al., 2010) For example, our data indicate that measures for soil conservation were more frequently adopted in regions with high soil quality. Whilst most sites experienced a single-action response in our sample, the analysis of the spatial relationship between responses indicates a diversified set of candidate 'response assemblages' based on the co-existence of different actions with positive (or negative) feedbacks within the local context. Although practices considered in this study are seen as particularly important in the field sites investigated, different practices/actions can be relevant in other socioeconomic contexts or better suited to mitigate LD in other environmental conditions. An improved knowledge of latent relationships between local contexts and a comprehensive set of actions/practices seen as candidate responses to LD is therefore a key issue to inform policy strategies which target desertification (Bisaro et al., 2013).

In this sense, the approach illustrated in this paper may inform the development of practical tools for (i) analysis of response indicators derived from a comprehensive set of LD indicators, (ii) assessment of spatial relationships between context and response indicators and, based on this background, (iii) characterization of 'response assemblages' to LD at both local and regional scales. Data mining is a promising tool to classify field sites and candidate responses into homogeneous groups according to specific territorial conditions.

PCA results indicate both convergent and divergent patterns characterizing the spatial distribution of response indicators, identifying three homogeneous sets of actions/practices respectively coping with (i) soil conservation, (ii) sustainable farm management and (iii) natural vegetation protection. Measures impacting soil degradation (containing soil erosion or improving soil water conservation) were more frequently observed in sites where a considerable proportion of land is protected, indicating a high level of environmental policy enforcement (Kosmas et al., 2015). While suggesting that measures of soil conservation are more frequently applied in protected areas compared with other measures protecting natural habitats, such as fire prevention, our evidences contribute to shed light on the multiple spatial relationships between candidate LD responses. However, these results need further empirical verification against a larger sample of sites representative for vastly different land-use, socioeconomic and environmental conditions.

Measures contributing to farm sustainability (sustainable farming, grazing control) were found uncorrelated with soil conservation and fire prevention actions in the studied sites. This evidence suggests how candidate responses are critically influenced by short- and long-term land-use decisions, acting with a variable intensity on a (more or less) wide spectrum of land cover types and landscapes (Salvati et al., 2015). In this sense, measures specifically designed to protect natural vegetation (e.g. fire prevention) were demonstrated to be spatially associated with specific measures dealing with sustainable management of farmland (i.e. terracing and farm subsidies). These evidences are in agreement with earlier studies (Weissteiner et al., 2011; Kelly et al., 2015; Kosmas et al., 2015). Economically-disadvantaged rural districts preserving high-diversity crop mosaics may benefit from a set of actions against LD that include protection of natural vegetation, economic subsidies and interventions for land consolidation supporting traditional cropping systems (Ferrara et al., 2016). Such correlation patterns may indicate a process of spatial divergence in the studied actions/practices, shaping the effectiveness of candidate 'response assemblages' at the local scale. Spatial convergence of different environmental measures is an interesting issue in the analysis of responses to LD requiring further investigation on theoretical frameworks and empirical evidences from representative environments (Salvati and Zitti, 2009).

Although data mining techniques provide useful information to improve our knowledge on the multiple relationships characterizing complex socio-environmental systems, there are limitations to this approach because correlation and similarity patterns do not necessarily imply causation processes (Kosmas et al., 2015). As many other quantitative exercises based on a large number of input variables, our approach proposes a standardized selection and classification of biophysical and socioeconomic indicators in fixed groups based on objective - but possibly questionable - criteria and value's thresholds (Salvati et al., 2015). In this sense, a mixed framework integrating exploratory quantitative approaches with a qualitative and descriptive analysis based on a deep knowledge of test areas through bibliographic analysis, interviews with local stakeholders and field observation is adequate to improve knowledge of complex socio-environmental systems (Kelly et al., 2015).

5. Conclusions

Our study suggests how land management actions/practices, intended as candidate responses to LD, are largely dependent on the local context. Mitigation plans and SLM strategies are increasingly committed to promote a policy shift from single-driver and process-specific targets to a more comprehensive set of practical actions integrating responses adapted to local contexts. In this way, research is required to indicate mechanisms involving stakeholders in problem analysis and solution-finding for application of adaptable and context-specific responses to LD. Since stakeholders have different perceptions of desertification risk, establishing (or intensifying) dialogue between stakeholders, policy-makers and the general public will contribute to increase effectiveness of land management actions in LD containment. An improved analysis of environmental indicators assessing practical actions combating or reversing LD and investigation on the effectiveness of joint responses to LD at various spatial scales is hence essential to design mitigation strategies based on the identification of appropriate response assemblages.

6. References

Bakker, M.M., Govers, G., Kosmas, C., Vanacker, V., Oost, K.V., Rounsevell, M. 2005. Soil erosion as a driver of land-use change. Agriculture, Ecosystems and Environment 105: 467–481.

Basso, B., De Simone, L., Ferrara, A., Cammarano, D., Cafiero, G., Yeh, M., Chou, T. 2010. Analysis of contributing factors to desertification and mitigation measures in Basilicata region. Italian Journal of Agronomy 5(3S): 33-44.

Bisaro, A., Kirk, M., Zdruli, P., Zimmermann, W. 2013. Global drivers setting desertification reseach priorities: insights from a stakeholder consultation forum. Land Degradation and Development. Land Degradation and Development, Doi: 10.1002/ldr.2220.

Briassoulis, H. 2005. Policy integration for complex environmental problems. Aldershot: Ashgate.

Briassoulis, H. 2015. The Socio-ecological Fit of Human Responses to Environmental Degradation: An Integrated Assessment Methodology. Environmental Management, DOI 10.1007/s00267-015-0584-z.

Corbelle-Rico, E., Crecente-Maseda, R., Sante-Riveira, I., 2012. Multi-scale assessment and spatial modelling of agricultural land abandonment in a European peripheral region: Galicia (Spain). Land Use Policy 29(3): 493–501.

Ferrara, A., Salvati, L., Sateriano, A., Nolè, A. 2012. Performance Evaluation and Costs Assessment of a Key Indicator System to Monitor Desertification Vulnerability. Ecological Indicators 23: 123-129.

Ferrara, A., Kelly, C., Wilson, G., Nolè, A., Mancino, G., Bajocco, S., Salvati, L. 2016. Shaping the role of 'fast' and 'slow' drivers of change in forest-shrubland socio-ecological systems. Journal of Environmental Management 169: 155-166.

García-Orenes, F., Cerdà, A., Mataix-Solera, J., Guerrero, C., Bodí, M.B., Arcenegui, V., Zornoza, R. Sempere, J.G. 2010. Effects of agricultural management on surface soil properties and soil-water losses in eastern Spain. Soil and Tillage Research 109(2): 110-115.

Gellrich, M., Baur, P., Koch, B., Zimmermann, N.E. 2007. Agricultural land abandonment and natural forest re-growth in the Swiss mountains: a spatially explicit economic analysis. Agriculture Ecosystems and Environment 118: 93–108.

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. Environmental Science & Policy 1(2): 71-78.

Hill, J., Stellmes, M., Udelhoven, T., Roder, A., Sommer, S. 2008. Mediterranean desertification and land degradation: Mapping related land use change syndromes based on satellite observations. Global & Planetary Change 64: 146-157.

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

Iosifides, T., Politidis, T. 2005. Socio-economic dynamics, local development and desertification in western Lesvos, Greece. Local Environment, 10, 487-499.

Izzo, N., Araujo, P.P.C., Aucelli, A., Maratea A., Sánchez, A. 2013. Land sensitivity to desertification in the Dominican republic: an adaptation of the ESA methodology. Land

Degradation and Development 24(5): 486–498.

Johnson, D.L., Lewis, L.A. 2007. Land degradation – Creation and destruction. Lahnam: Rowman & Littlefield.

Kairis, O., Karavitis, C., Kounalaki, A., Fasouli, V., Salvati, L., Kosmas, K. 2014. The effect of land management practices on soil erosion and land desertification in an olive grove. Soil Use and Management 29: 597–606.

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: A case study in Gorgoglione, Basilicata region, Italy. Land Use Policy 46: 11-20.

Kosmas, C., Kairis, O., Karavitis, C., Acikalin, S., Alcalá, M., Alfama, P., Atlhopheng, J., Barrera, J., Belgacem, A., Solé-Benet, A., Brito, J., Chaker, M., Chanda, R., Darkoh, M., Ermolaeva, O., Fasouli, V., Fernandez, F., Gokceoglu, C., Gonzalez, D., Gungor, H., Hessel, R., Khatteli, H., Khitrov, N., Kounalaki, A., Laouina, A., Magole, L., Medina, L., Mendoza, M., Mulale, K., Ocakoglu, F., Ouessar, M., Ovalle, C., Perez, C., Perkins, J., Pozo, A., Prat, C., Ramos, A., Ramos, J., Riquelme, J., Ritsema, C., Romanenkov, V., Sebego, R., Sghaier, M., Silva, N., Sizemskaya, M., Sonmez, H., Taamallah, H., Tezcan, L., de Vente, J., Zagal, E., Zeiliguer, A., Salvati, L. 2015. An Exploratory Analysis of Land Abandonment Drivers in Areas Prone to Desertification. Catena 128: 252-261.

Koulouri, M., Giourga, C. 2007. Land abandonment and slope gradient as key factors of soil erosion in Mediterranean terraced lands. Catena 69: 274–281.

Lavado Contador, J.F., Schnabel, S., Gómez Gutiérrez, A., Pulido Fernández, M. 2009 Mapping sensitivity to land degradation in Extremadura, SW Spain. Land Degradation and Development 20(2): 129–144.

MacDonald, D., Crabtree, J.R., Wiesinger, G., Dax, T., Stamou, N., Fleury, P., Lazpita, J.G., Gibon, A. 2000. Agricultural abandonment in mountain areas of Europe: environmental consequences and policy response. Journal of Environmental Management 59: 47–69.

Omuto, C. T., Balint, Z., Alim, M.S. 2013. A framework for national assessment of land degradation in the drylands: a case study of Somalia. Land Degradation and Development, doi: 10.1002/ldr.1151

Reynolds, J.F., Grainger, A., Stafford Smith, D.M., Bastin, G., Garcia-Barrios, L., Fernandez, R.J., Janssen, M.A., Jürgens, N., Scholes, R.J., Veldkamp, A., Verstraete M.M., von Maltitz, G., Zdruli, P. 2011. Scientific concepts for an integrated analysis of desertification. Land Degradation and Development, DOI: 10.1002/ldr.1104.

Rubio, J.L., Bochet, E. 1998. Desertification indicators as diagnosis criteria for desertification risk assessment in Europe. Journal of Arid Environments 39: 113–120.

Sabbi, A., Salvati, L. 2014. Seeking for a Downward Spiral? Soil Erosion Risk, Agro-forest landscape and Socioeconomic Conditions in Italian local communities. Land Use Policy 41: 388-396.

Salvati, L., Zitti, M. 2009. Convergence or divergence in desertification risk? Scale-based assessment and policy implications in a Mediterranean country. Journal of Environmental Planning and Management 52(7): 957-971.

Salvati, L., Kosmas, C., Kairis, O., Karavitis, C., Acikalin, S., Belgacem, A., Solé-Benet, A., Chaker, M., Fassouli, V., Gokceoglu, C., Gungor, H., Hessel, R., Khatteli, H., Kounalaki, A., Laouina, A., Ocakoglu, F., Ouessar, M., Ritsema, C., Sghaier, M., Sonmez, H., Taamallah, H., Tezcan, L., de Vente, J. 2015. Unveiling Soil Degradation and Desertification Risk in the Mediterranean Basin: A Data Mining Analysis of the Relationships between Biophysical and Socioeconomic Factors in Agro-forest Landscapes. Journal of Environmental Planning and Management 58(10): 1789-1803.

Sluiter, R., De Jong, S.M. 2007. Spatial patterns of Mediterranean land abandonment and related land cover transitions. Landscape Ecology 22: 559–576.

Stavi, I., Fizik, E., Argaman, E. 2015. Contour bench terrace (shich/shikim) forestry systems in the semi-arid Israeli Negev: Effects on soil quality, geodiversity, and herbaceous vegetation. Geomorphology 231: 376-382.

Strijker, D. 2005. Marginal lands in Europe – causes of decline. Basic and Applied Ecology 6: 99–106.

Stringer, L.C., Harris, A. 2014. Land degradation in Dolj county, southern Romania: environmental changes, impacts and responses. Land Degradation and Development, doi: 10.1002/ldr.2260

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. Environmental Science & Policy 16, 122–135.

Weissteiner, C.J., Boschetti, M., Böttcher, K., Carrara, P., Bordogna, G., Brivio, B.A. 2011. Spatial explicit assessment of rural land abandonment in the Mediterranean area. Global and Planetary Change 79: 20–36.

Wilson, G.A., Juntti, M. 2005. Unravelling desertification. Wageningen: Wageningen University Press.

Yang, L., Wu, J., Shen, P. 2013. Roles of science in institutional changes: The case of desertification control in China. Environmental Science & Policy 27: 32-54.
Zdruli, P. 2013. Land resources of the Mediterranean: status, pressures, trends and impacts on future regional development. Land Degradation and Development, DOI: 10.1002/ldr.2150.

Table 1. Principal Component Analysis loadings (> |0.5|).

Variable	PC 1	PC 2	PC 3
Farm subsidies		0.50	
Protected areas	0.69		
Fire prevention		-0.65	
Sustainable farming			0.67
Soil erosion control	0.71		
Soil water conservation	0.50		
Terracing		0.60	
Grazing control			-0.52
Explained variance (%)	*28.6*	*19.5*	*17.0*

Figure 1. Principal Component score plot of the 586 field sites investigated in the present study by country (PC 1: x-axis *vs* PC 2: y-axis).

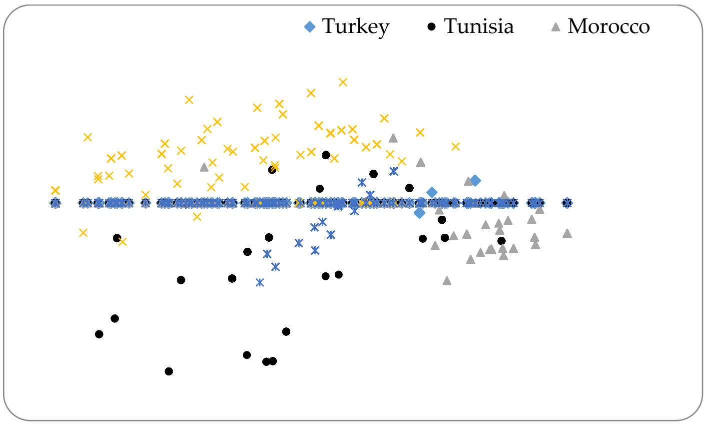

Table 2. Results of the step-wise multiple linear regression with desertification risk as the dependent variable and the 8 response indicators to land degradation (predictors) observed at each of the 586 plots investigated in the present study (adjusted R^2 = 0.248, $F_{(4,581)}$ = 49.3, p < 0.001).

Variable	Beta	Std.Err.	*t*(581)	*p*-level
Intercept	0.000	0.030	1.342	0.180
Protected areas	0.442	0.038	11.624	0.000
Grazing control	0.277	0.039	7.030	0.000
Terracing	-0.186	0.039	-4.790	0.000
Farm subsidies	0.128	0.039	3.321	0.001

Table 3. Canonical analysis run between biophysical indicators and response indicators in the 586 plots investigated in the present study (bold indicates significant correlations with coefficient > ǀ0.5ǀ).

Variable	Root 1	Root 2	Root 3	Root 4	Root 5	Root 6	Root 7
			Biophysical indicators				
% variance	*0.12*	*0.13*	*0.12*	*0.06*	*0.08*	*0.05*	*0.05*
Degree of erosion	-0.07	-0.06	**0.52**	0.21	-0.42	0.13	**-0.50**
Major land use	0.08	0.01	-0.17	0.41	0.05	**0.66**	0.23
Vegetation cover type	0.41	0.29	0.47	0.30	-0.11	0.05	-0.14
Rainfall	0.37	**-0.51**	**-0.56**	0.24	-0.14	-0.07	-0.08
Aridity index	0.21	**-0.50**	**-0.54**	-0.21	-0.39	-0.24	0.05
Potential evapotranspiration	**-0.66**	**-0.51**	-0.22	0.13	-0.25	0.00	-0.12
Rainfall seasonality	-0.11	**0.78**	-0.40	-0.15	0.05	0.14	0.21
Rainfall erosivity	**-0.51**	0.30	-0.01	**0.52**	0.25	0.27	0.00
Parent material	-0.19	-0.26	-0.05	0.18	-0.08	0.09	-0.12
Rock fragments	0.12	-0.06	-0.16	-0.14	0.11	-0.16	0.11
Slope aspect	-0.09	-0.06	0.23	0.06	0.16	0.13	-0.42
Slope gradient	-0.43	0.26	-0.06	-0.01	-0.04	0.37	-0.29
Soil depth	0.14	0.04	0.03	0.27	-0.47	-0.02	-0.15
Soil texture	**0.56**	0.16	-0.22	0.21	0.03	0.04	-0.24
Soil water storage capacity	**0.50**	0.25	-0.17	0.00	-0.49	0.33	-0.08
Exposure of rock outcrops	0.30	-0.09	0.12	0.48	-0.10	-0.20	-0.14
Organic matter surface horizon	0.49	-0.29	-0.30	-0.05	-0.20	0.25	-0.04
Plant cover	0.18	-0.36	0.06	-0.05	**-0.53**	0.17	-0.23
Drainage density	0.09	**-0.70**	0.47	-0.03	0.22	-0.01	-0.26
Runoff water storage	0.33	-0.10	**0.71**	0.03	-0.44	0.16	0.24
			Response indicators				
% variance	*0.21*	*0.16*	*0.19*	*0.12*	*0.13*	*0.06*	*0.07*
Farm subsidies	**-0.59**	-0.43	0.40	**0.54**	0.10	-0.02	0.03
Protected areas	0.48	0.03	0.47	-0.35	-0.16	**0.62**	-0.04
Fire prevention	**0.94**	-0.30	-0.02	0.07	-0.12	0.00	-0.03
Sustainable farming	0.10	0.11	**0.80**	-0.43	0.10	-0.31	0.09
Soil erosion control	0.16	0.29	**0.67**	0.02	-0.47	-0.14	-0.25
Soil water conservation	-0.05	0.40	0.04	0.07	**-0.79**	-0.06	-0.02
Terracing	0.09	**0.54**	0.11	0.33	-0.22	-0.02	**0.68**
Grazing control	0.42	**0.66**	0.13	**0.51**	0.27	-0.03	-0.17

Table 4. Canonical analysis run between socioeconomic indicators and response indicators in the 586 plots investigated in the present study (bold indicates significant correlations with coefficient > |0.5|).

Variable	Root 1	Root 2	Root 3	Root 4	Root 5	Root 6	Root 7	Root 8
				Socioeconomic indicators				
% variance	*0.15*	*0.14*	*0.10*	*0.06*	*0.10*	*0.05*	*0.02*	*0.02*
Impervious surface area	**-0.69**	-0.32	-0.18	-0.01	0.34	-0.02	-0.08	-0.14
Burned area	-0.27	0.22	-0.27	-0.16	-0.15	0.35	0.29	0.03
Farm ownership	-0.07	0.38	-0.57	-0.08	-0.25	-0.16	-0.01	0.09
Farm size	-0.40	0.30	0.15	-0.30	0.34	0.41	-0.05	0.00
Land fragmentation	-0.44	**-0.67**	0.11	0.14	-0.24	-0.11	-0.21	0.01
Net farm income	-0.01	0.22	0.33	**-0.54**	-0.29	0.08	-0.17	-0.26
Parallel employment	0.40	-0.33	0.41	0.05	-0.28	-0.38	0.02	0.21
Tillage operations	0.20	-0.31	0.34	0.12	0.42	0.28	0.04	0.04
Tillage depth	0.28	-0.38	0.21	0.16	0.25	0.29	-0.26	-0.03
Tillage direction	0.07	-0.45	0.22	-0.05	0.44	0.20	0.22	0.01
Grazing intensity	0.46	0.16	**-0.72**	0.05	-0.19	0.18	-0.02	0.14
Land use intensity	-0.16	-0.49	-0.03	0.04	0.14	0.44	0.04	-0.06
Period of existing land use	0.34	-0.44	0.00	-0.30	0.28	0.02	0.03	-0.31
Irrigation percentage of arable land	0.21	0.39	0.23	0.33	**-0.69**	-0.04	0.02	0.23
Tourism intensity	0.12	0.19	0.23	-0.20	0.17	0.12	-0.13	0.20
Aging index	**-0.64**	**-0.64**	-0.06	-0.31	-0.13	-0.02	0.01	-0.06
Population density	-0.02	0.30	-0.33	**0.61**	0.46	0.11	-0.12	-0.19
Population growth	**-0.93**	0.07	-0.20	-0.13	0.00	0.10	0.01	0.04
Frequency of tillage	0.09	0.12	0.25	0.05	0.07	0.22	-0.38	0.04
Land abandonment	-0.11	**-0.52**	**0.52**	-0.01	-0.34	-0.08	0.11	-0.25
				Response indicators				
% variance	*0.22*	*0.15*	*0.15*	*0.15*	*0.10*	*0.06*	*0.06*	*0.11*
Farm subsidies	**-0.57**	**-0.53**	-0.03	**-0.57**	-0.23	-0.04	0.01	-0.10
Protected areas	0.46	-0.26	0.31	0.41	-0.25	**0.53**	-0.33	-0.06
Fire prevention	**0.89**	0.10	0.36	-0.18	-0.18	-0.08	-0.02	-0.05
Sustainable farming	0.16	**-0.75**	0.09	**0.58**	0.00	-0.20	0.14	-0.04
Soil erosion control	0.24	-0.41	-0.32	0.28	-0.37	-0.31	**-0.58**	-0.14
Soil water conservation	-0.07	0.32	-0.24	0.49	**-0.71**	-0.11	0.08	-0.27
Terracing	0.12	0.03	-0.48	0.06	0.11	0.03	-0.04	**-0.86**
Grazing control	**0.55**	-0.09	**-0.77**	-0.09	-0.07	0.19	0.19	0.05

SUPPLEMENTARY MATERIALS

Table 1. List of the indicators used in the data mining approach presented in this study (see Table 2(Supplementary materials), for a complete description of variables including technical details).

Variable	Class	PCA	SRC	MLR	MWU	CA
Desertification risk	D		●	●		
Degree of erosion	B		●			●
Major land-use/cover	B		●			●
Vegetation cover type	B		●			●
Rainfall	B		●			●
Aridity index	B		●			●
Potential evapotranspiration	B		●			●
Rainfall seasonality	B		●			●
Rainfall erosivity	B		●			●
Parent material	B		●			●
Rock fragments	B		●			●
Slope aspect	B		●			●
Slope gradient	B		●			●
Soil depth	B		●			●
Soil texture	B		●			●
Soil water storage capacity	B		●			●
Exposure of rock outcrops	B		●			●
Organic matter surface horizon	B		●			●
Plant cover	B		●			●
Drainage density	B		●			●
Runoff water storage	B		●			●
Impervious surface area	S		●			●
Burned area	S		●			●
Farm ownership	S		●			●
Farm size	S		●			●
Land fragmentation	S		●			●
Net farm income	S		●			●
Parallel employment	S		●			●
Tillage operations	S		●			●
Tillage depth	S		●			●
Tillage direction	S		●			●
Grazing intensity	S		●			●
Land use intensity	S		●			●
Period of existing land use	S		●			●
Irrigation percentage of arable land	S		●			●
Tourism intensity	S		●			●
Population aging index	S		●			●
Population density	S		●			●
Population growth	S		●			●
Frequency of tillage	S		●			●
Land abandonment	S		●			●
Farm subsidies	P	●	●	●	●	●
Protected areas (policy enforcement)	P	●	●	●	●	●
Terracing	P	●	●	●	●	●
Grazing control	P	●	●	●	●	●
Fire prevention	P	●	●	●	●	●
Sustainable farming	P	●	●	●	●	●
Soil erosion control	P	●	●	●	●	●
Soil water conservation	P	●	●	●	●	●

D = dependent variable; B = biophysical context variables; S = socioeconomic context variables; P = policy-relevant indicators assessing the intensity of land management actions. PCA = Principal Component Analysis (results in Table 1, Figure 1), SRC: Spearman Rank Correlation analysis (results in Table 3, Supplementary materials); MLR: Multiple Linear Regression (results in Table 2); MWU = Mann-Whitney U-test (results in main text, section 3.4); CA = Canonical Analysis (results in Tables 3 and 4).

Table 2. List of indicators with class ranking and the related score.

CLIMATE								
Annual rainfall (mm)	<280	280-650	650 -1000	>1000				
	2	*1.6*	*1.3*	*1.0*				
Aridity index	<50	50-75	75-100	100-125	125-150	>150		
	1.0	*1.2*	*1.4*	*1.6*	*1.8*	*2.0*		
Annual potential evapotranspiration (mm)	<500	500-800	800-1200	1200-1500	>1500			
	1.0	*1.2*	*1.5*	*1.8*	*2.0*			
Rainfall seasonality	<0.19	0.20-0.39	0.40-0.59	0.60-0.79	0.80-0.99	1.00-1.19	>1.20	
	1.0	*1.2*	*1.4*	*1.6*	*1.8*	*1.9*	*2.0*	
Rainfall erosivity (mm/h)	<60	60 - 90	91-120	121-160	>160			
	1.0	*1.2*	*1.5*	*1.8*	*2.0*			
SOIL								
Parent material	Limestone-marble	Acid Igneous	Sandstone, flysh	Marl, clay, conglomerates	Basic Igneous	Shale Schist	Alluvium, colluvium	
	2.0	*1.8*	*1.6*	*1.3*	*1.4*	*1.2*	*1.0*	
Rock fragments on soil surface (%)	<15	15-40	40-80	>80				
	2.0	*1.0*	*1.6*	*1.8*				
Slope aspect	N, NW, NE	S, SW, SE	Plain					
	1.0	*2.0*	*1.0*					
Slope gradient (%)	<2	2 - 6	6-12	12-18	18-25	25-35	35-60	>60
	1.0	*1.2*	*1.4*	*1.6*	*1.7*	*1.8*	*1.9*	*2.0*
Soil depth (cm)	<15	15-30	30-60	60-100	100-1500	>150		
	2.0	*1.8*	*1.6*	*1.4*	*1.2*	*1.0*		
Soil textural class	Very coarse	Coarse	Medium	Moderate fine	Fine	Very fine		
	2.0	*1.8*	*1.6*	*1.2*	*1.3*	*1.4*		
Soil water storage capacity (mm)	<50	50-100	100-200	200-300	>300			
	2.0	*1.8*	*1.5*	*1.3*	*1.0*			
Exposure of rock outcrops (%)	None	2-10	10 -30	30-60	>60			
	1.0	*1.3*	*1.5*	*1.8*	*2.0*			
Organic matter of surface horizon(%)	High >6.0	Medium 2.1-6.0	Low 2.0-1.1	Very low <1.0				
	1.0	*1.3*	*1.6*	*2.0*				
Degree of soil erosion	None	Slight	Moderate	Severe	Very severe			
	1.0	*1.2*	*1.5*	*1.8*	*2.0*			
VEGETATION								
Major land-use	Agriculture	Pasture	Shrubland	Forest	Mining	Recreation		
	1.5	*1.6*	*1.4*	*1.0*	*2.0*	*1.2*		
Agricultural cover type	Cereals	Olives	Vines	Almonds	Oranges	Vegetables	Cotton	
	2.0	*1.0*	*1.4*	*1.3*	*1.6*	*1.8*	*1.5*	
Plant cover (%)	<10	10-25	25-50	50-75	>75			
	2.0	*1.8*	*1.5*	*1.3*	*1.0*			

WATER RUNOFF							
Drainage density (km of channels per km²)	Coarse <5 km	Medium 5-10 km	Fine 10-20 km	Very fine >20 km			
	1.0	*1.3*	*1.7*	*2.0*			
Impervious surface area (ha/10 km² of territory / 10 years)	Low <10 ha	Moderate 10-25 ha	High 26-50 ha	Very high >50 ha			
	1.0	*1.3*	*1.7*	*2.0*			
Burnt area (ha burnt land over 10years/10km² of territory)	Low (<10 ha)	Moderate (10 - 25 ha)	High (26 - 50 ha)	Very high (>50 ha)			
	1.0	*1.3*	*1.7*	*2.0*			
AGRICULTURE							
Farm ownership	Owner – farmed	Tenant – farmed	Shared – farmed	State – farmed			
	1.0	*2.0*	*1.5*	*1.7*			
Farm size (ha)	<2	2 – 5	5 – 10	10 – 30	30 - 50	50 – 100	>100
	2.0	*1.8*	*1.6*	*1.5*	*1.3*	*1..1*	*1.0*
Land fragmentation (Number of parcels)	1-3	4-6	7-9	10-12	13-15	16-19	>19
	1.0	*1.2*	*1.4*	*1.6*	*1.8*	*1.9*	*2.0*
Net farm income	Low (<Local mean - St.	Moderate (>Local mean -	High (> Local Mean < Local	Very high (> Local Mean + St.			
	2.0	*1.7*	*1.3*	*1.0*			
Parallel employment	NO	Industry	Tourism	State	Municipality		
	1.0	*2.0*	*1.4*	*1.7*	*1.5*		
CULTIVATION PRACTICES AND HUSBANDRY							
Tillage operations	NO	Plowing	Disking, harrowing	Cultivator			
	1.0	*2.0*	*1.7*	*1.4*			
Frequency of tillage (number)	NO	1	2	3	4		
	1.0	*1.2*	*1.4*	*1.7*	*2.0*		
Tillage depth (cm)	NO	<20	20-30	30-40	>40		
	1.0	*1.1*	*1.3*	*1.7*	*2.0*		
Tillage direction	Down-slope	Up-slope	Parallel to Contour up-	Parallel to Contour down-	Down-slope Oblique	Up-slope Oblique	Other (No tillage)
	2.0	1.4	1.2	1.5	1.8	1.3	1.0
Grazing intensity (livestock density, SR, vs. grazing capacity, GC, in each site)	Low (SR<GC)	Moderate SR=GC to	High (SR>1.5GC)				
	1.0	*1.5*	*2.0*				
LAND-USE							
Land-use intensity (% class area of intense use of land)	Low (< 25%)	Medium (25-75%)	High (> 75%)				
	1.0	*1.5*	*2.0*				
(Period) of existing land use	< 1 year	1-5 years	5-10 years	10-20 years	30-50 years	> 50 years	
	2.0	*1.8*	*1.6*	*1.4*	*1.2*	*1.0*	
Land abandonment (10ha/years/10km²)	Very high (> 50)	High (26-50)	Moderate (10-25)	Low (< 10)			
	2.0	1.6	1.3	1.0			
WATER USE							
Irrigation percentage of arable land	< 5	5-10	10-25	25-50	> 50		
	2.0	*1.8*	*1.6*	*1.3*	1.0		
Runoff water storage	No	Low	moderate	adequate			
	2.0	1.8	1.4	1.0			

DEMOGRAPHY AND TOURISM						
Population aging index (population >65 / total population = R, %)	Low R<5	Moderate R=5-10	High R=10-20	Very high R>20		
	1.0	*1.3*	*1.7*	*2.0*		
Population density (inhabitants / km²)	Low <50	Moderate 50-100	High 100-300	Very high >300		
	1.0	*1.3*	*1.7*	*2.0*		
Population growth rate (% per year)	Low <0.2	Moderate 0.2-0.4	High 0.4-0.6	Very high >0.6		
	1.0	*1.3*	*1.7*	*2.0*		
Tourism intensity (number of overnight stays /10 km² =R)	Low R<0.01	Moderate R=0.01-0.04	High R=0.04-0.08	Very high R>0.08		
	1.0	*1.3*	*1.7*	*2.0*		
RESPONSE INDICATORS						
Fire prevention (land protected from fires in total area)	NO	Low < 25%	Moderate 25-50%	High 50-75%	Very high > 75%	
	2.0	*1.8*	*1.6*	*1.3*	*1.0*	
Grazing control	NO	Sustainable number of	Fencing	Avoidance of soil compaction (wet soil)	Fire Protection	
	2.0	*1.0*	*1.2*	*1.4*	*1.3*	
Sustainable farming	No sustainable	No tillage	Minimum tillage	Inducing plant cover	Up-slope tillage	Minimum ploughing
	2.0	*1.0*	*1.3*	*1.1*	*1.4*	*1.5*
Soil erosion control (% area protected in total area, %, excluding terracing)	NO	Low, <25% protected	Moderate, 25-75% protected	Adequate, >75% protected		
	2.0	*1.7*	*1.4*	*1.0*		
Soil water conservation	Weed control	Mulching	temporary storage	inducing vapor adsorption	No	
	1.0	*1.0*	*1.0*	*1.2*	*2.0*	
Terracing (% area under terracing)	No area	Low, <25%	Moderate, 25-50%	High, 50-75%	Very high, >75%	
	2.0	*1.7*	*1.5*	*1.2*	*1.0*	
Farm subsidies (by motivation)	NO	Environmental protection	Per-area subsidies	Per-animal subsidies	Per-product	
	1.2	*1.0*	*2.0*	*2.0*	*2.0*	
Protected areas (policy enforcement)	Adequate > 75% of the area	Moderate (25-75% of the area)	Low (< 25% of the area)	No		
	1.0	*1.4*	*1.7*	*2.0*		

Table 3. Non-parametric Spearman pair-wise rank correlation analysis between biophysical (or socioeconomic) indicators and response indicators to land degradation in the 586 plots investigated in the present study (bold indicates significant correlations tested at $p < 0.05$ after Bonferroni's correction for multiple comparisons).

Variable	Grazing control	Fire prevention	Sustainable farming	Soil erosion control measures	Soil water conservation measures	Terracing	Farm subsidies	Protected areas
Desertif risk	**0.21**	**0.26**	0.06	0.07	-0.06	-0.07	-0.08	**0.30**
Degree of erosion	0.01	-0.05	**0.21**	**0.40**	**0.18**	-0.06	**0.29**	**0.16**
Major land use	**0.40**	0.14	**-0.41**	0.03	0.16	**0.22**	-0.01	-0.01
Veget. cover type	**0.50**	**0.31**	**0.28**	**0.38**	**0.23**	**0.23**	-0.05	**0.34**
Rainfall	-0.15	**0.59**	**-0.31**	**-0.19**	-0.13	**-0.19**	-0.17	-0.03
Aridity index	**-0.46**	**0.22**	**-0.41**	**-0.24**	-0.07	**-0.20**	-0.16	**-0.19**
Pot. evapotransp.	**-0.55**	**-0.38**	**-0.30**	**-0.20**	0.00	**-0.28**	**0.48**	**-0.45**
Rain seasonality	**0.36**	**-0.21**	**-0.22**	-0.11	**0.18**	**0.44**	**-0.41**	-0.09
Rainfall erosivity	**0.22**	**-0.54**	-0.06	-0.03	-0.14	**0.28**	**0.48**	**-0.36**
Parent material	**-0.22**	**-0.21**	-0.12	-0.11	0.00	**-0.18**	**0.34**	**-0.22**
Rock fragments	-0.09	0.14	0.00	-0.09	-0.12	-0.06	-0.13	-0.05
Slope aspect	0.02	-0.10	0.08	0.12	-0.11	-0.12	**0.18**	0.05
Slope gradient	-0.01	**-0.46**	-0.09	-0.05	0.12	0.03	0.11	-0.06
Soil depth	0.13	0.13	0.02	**0.18**	**0.33**	0.01	-0.10	0.14
Soil texture	**0.40**	**0.48**	-0.12	0.08	-0.03	0.08	**-0.35**	**0.18**
Soil water storage	**0.27**	**0.42**	-0.01	**0.21**	**0.36**	0.06	**-0.44**	**0.45**
Expos. rock outcrops	**0.22**	**0.35**	0.07	**0.17**	0.00	0.06	0.14	0.04
Org. matt. surf. horiz.	-0.07	**0.58**	**-0.26**	-0.12	-0.06	-0.10	**-0.32**	**0.22**
Plant cover	**-0.23**	**0.27**	-0.07	0.15	0.09	**-0.24**	-0.02	**0.21**
Drainage density	**-0.32**	**0.18**	**0.27**	0.04	**-0.30**	**-0.47**	**0.37**	0.14
Impervious surf area	**-0.30**	**-0.64**	**0.30**	0.07	**-0.22**	0.00	**0.62**	**-0.26**
Burned area	0.12	**-0.29**	**-0.29**	-0.16	0.14	0.05	0.14	**-0.21**
Farm ownership	**0.37**	**-0.17**	**-0.34**	0.11	**0.33**	**0.22**	-0.05	**-0.29**
Farm size	**-0.26**	**-0.21**	**-0.44**	**-0.41**	**-0.23**	-0.03	0.10	**-0.29**
Land fragmentation	**-0.28**	**-0.53**	**0.47**	**0.24**	-0.04	-0.15	**0.57**	0.01
Net farm income	-0.16	**0.36**	**-0.44**	-0.16	-0.02	-0.10	0.06	-0.04
Parallel employment	-0.09	**0.34**	**0.45**	**0.26**	-0.04	**-0.26**	-0.01	**0.37**
Tillage operations	-0.04	**0.23**	**0.26**	-0.09	**-0.36**	-0.11	-0.10	**0.23**
Tillage depth	-0.04	**0.21**	**0.35**	0.00	**-0.32**	-0.15	-0.08	**0.35**
Tillage direction	-0.06	0.12	**0.32**	-0.12	**-0.40**	-0.13	0.06	0.13
Grazing intensity	**0.76**	**0.22**	-0.07	**0.27**	**0.21**	**0.36**	**-0.28**	0.11
Land use intensity	0.01	**-0.22**	**0.29**	0.03	**-0.19**	0.00	**0.28**	0.07
Period exist. land use	0.05	0.11	0.09	0.00	**-0.41**	0.06	0.16	0.00
Irr. % arable land	-0.01	**0.28**	-0.07	0.09	**0.49**	**-0.22**	**-0.37**	**0.32**
Runoff water storage	0.09	**0.40**	**0.41**	**0.41**	0.15	0.08	0.04	**0.53**
Tourism intensity	-0.11	**0.21**	**-0.21**	**-0.19**	**-0.19**	**-0.23**	-0.10	0.05
Pop. aging index	**-0.26**	**-0.63**	**0.25**	0.10	**-0.18**	-0.08	**0.81**	**-0.30**
Pop. density	0.16	**-0.19**	0.02	-0.04	**0.18**	**0.32**	**-0.47**	0.05
Pop. growth rate	**-0.41**	**-0.82**	**-0.24**	**-0.21**	0.08	-0.06	**0.56**	**-0.56**
Freq. tillage	**-0.30**	0.13	-0.04	**-0.25**	-0.15	**-0.32**	**-0.27**	**0.27**
Land abandonment	**-0.34**	0.00	**0.46**	**0.18**	-0.15	**-0.27**	**0.39**	**0.23**