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Short Note

Reporting land degradation sensitivity through multiple indicators: Does scale matter?

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ABSTRACT

This work provides a multi-scale, multi-temporal assessment of the robustness of 6 indicators of land degradation aggregated at various spatial domains relevant to environmental reporting. Based on the Environmentally Sensitive Area (ESA) approach – widely used for environmental reporting of land degradation in Europe – we tested six indicators including (i) the average ESA score, (ii) the maximum ESA score, (iii) the coefficient of variation in the ESA scores, (iv) the normalized range in the ESA scores, as well as the extent of (v) 'fragile' and (vi) 'critical' areas based on a standard land classification developed on behalf of the ESA framework. Statistical robustness and intrinsic stability of these indicators were verified at six spatial domains (administrative regions, provinces, elevation belts, homogeneous economic districts, rural districts, municipalities) separately for three time points (early-1960s, early-1990s, and early-2010s). Results of a mixed parametric/non-parametric correlation analysis indicate that pair-wise relationships between indicators were mostly linear. A Principal Component Analysis identified two non-redundant dimensions associated with the average level of land degradation sensitivity and its intrinsic variability over space; indicators resulted to be associated exclusively with one of these two dimensions for all study years. Average level of sensitivity and variability over space provide, together, a comprehensive and statistically robust assessment of land degradation at vastly different planning levels, irrespective of the territorial domain adopted for environmental reporting.

1. Introduction

Land degradation is a key environmental process with significant socioeconomic implications (Reynolds et al., 2011; Feng et al., 2015; Huang et al., 2020). The United Nations Convention to Combat Desertification (UNCCD) requires permanent monitoring of land degradation sensitivity. According with the sustainability objectives of the 2030 Agenda and, more recently, with the UN zero-net land degradation strategy, a permanent assessment of land degradation sensitivity is a pre-requisite for any soil conservation policy and sustainable development measure in rural areas. Monitoring exposure to desertification risk was carried out through widely differentiated methodologies, based on background socioeconomic contexts and ecological conditions (Colantoni et al., 2015; Gibbs and Salmon, 2015; Dave et al., 2019). In Europe, especially in the Northern Mediterranean region (one of the most significant hotspots in the world for desertification risk included in Annex IV of the UNCCD), permanent monitoring benefited from various approaches and techniques (Vogt et al., 2011; Xu et al., 2019; Xie et al., 2020). However, despite the growing demand for statistically solid and homogeneous indicators to be used in environmental reporting on a continental and national scale (Bajocco et al., 2012), a very heterogeneous set of key variables have been derived from these frameworks - often poorly coordinated, and robust only in specific conditions (Barbero-Sierra et al., 2013; Kelly et al., 2015; Cuadrado-Ciuraneta et al., 2017; Gonzalez-Roglich et al., 2019).

The Environmentally Sensitive Area (ESA) framework has proved to

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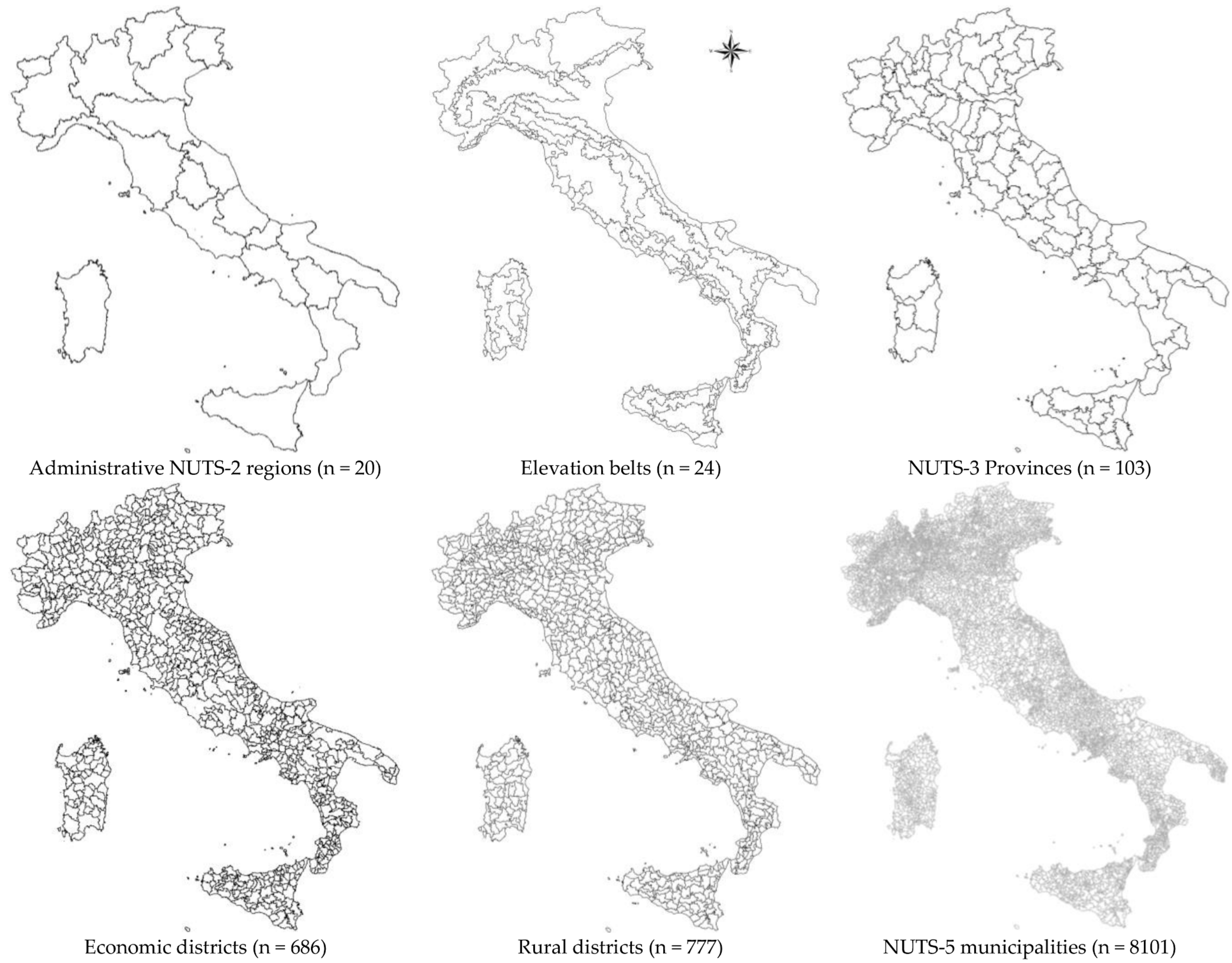

Fig. 1. The six geographical partitions of Italy considered in this study.

be a widely used approach for environmental reporting at continental level (e.g. European Environment Agency), being occasionally adopted in national and regional monitoring exercises throughout Europe (Ferrara et al., 2016; Giger et al., 2018; Karamesouti et al., 2018), especially in Mediterranean countries. Initially oriented towards research and development applications, the ESA(I), a multi-level, diachronic Indicator of the degree of sensitivity to land degradation of a given territory (Delfanti et al., 2016), has also been successfully applied in other contexts (Eastern Europe, Middle East, Central Asia, Latin America), and more recently adopted to draw up a holistic mapping of land degradation risk worldwide (Ferrara et al., 2020).

The ESA approach has significant advantages for environmental reporting of desertification risk, being statistically stable and easily derivable from freely available data sources with high spatial resolution both in advanced countries and in emerging economies (Salvati and Zitti, 2007). ESAI results are also easily readable over time at the desired spatial scale thanks to a classification of the territory based on intuitive levels of exposure to land degradation, directly linked to basic drivers underlying degradation processes (climate, soil quality, vegetation cover, land-use, human pressure). The extreme flexibility of the composite indicator and the possible application to different spatial and temporal scales, as demonstrated by Salvati et al. (2008), delineates ESAI as an excellent approach for integrated environmental reporting of land degradation. The simplicity of calculation and ease of application in different environmental contexts makes the indicators deriving from the ESA approach particularly useful from a spatial planning and natural resource management perspectives (Briassoulis, 2019; Akbari et al., 2020; Prăvălie et al., 2020). However, to our knowledge, no study has so far investigated the appropriateness and stability of possible indicators derived from the ESA approach for environmental reporting.

By proposing a novel experimental design, such a study could help design of suitable indicators to inform national and regional strategies addressing the zero-net land degradation objective and, more generally, the sustainable development targets of the 2030 Agenda (Sommer et al., 2011; Torres et al., 2015; Fleskens and Stringer, 2014). The fact that some indicators resulting (directly or indirectly) from the ESA philosophy have occasionally been used for environmental reporting in European Union countries, justifies the urgent need of an explicit validation approach assessing redundancy and robustness at varying spatial levels.

By exploiting a diachronic ESA database realized for Italy, a country included in the Annex IV of the UNCCD with large areas at risk of desertification (Salvati and Zitti, 2009), the experimental scheme proposed in this work develops an indirect validation of a large set of candidate indicators of the level of land degradation calculated for 6 administrative and geographical levels (from regions to municipalities) at three historical periods (early-1960s, early-1990s, early-2010s) characteristic of different socioeconomic contexts and environmental conditions (Salvati et al., 2016). By adopting parametric and non-parametric techniques within a multivariate exploratory approach, the present work identifies the most appropriate indicators of land degradation and represents an operational scheme validating other indicators' systems for environmental reporting at multiple spatial scales of interest for development policies and regional planning.

2. Methodology

2.1. Study area

The study area encompasses the whole of Italy (301.330 km^2), a Mediterranean country included (together with Portugal, Spain, and Greece) in the Annex IV of the UNCCD as a hotspot for land degradation and desertification risk in Southern Europe. Italy shows extensive socioeconomic disparities between Northern and Southern regions, with the latter being classified as marginal, disadvantaged and mostly at risk of desertification (Delfanti et al., 2016). Wealthier areas of the country (per-capita income higher than 25,000 Euros) concentrated in Northern Italy (Chelli et al., 2016). Economically disadvantaged districts (per-capita income lower than 15,000 Euros) were mostly found in rural

Table 1
Pair-wise correlation analysis between land degradation indicators in Italy by year, spatial partition and coefficient type (Pearson, Spearman); significant coefficients at $p < 0.05$ after Bonferroni's correction for multiple comparisons are shown.

Year/	Pearson coefficient					Spearman coefficient					Pearson coefficient					Spearman coefficient				
Indicator	m	h	d	r	f	m	h	d	r	f	m	h	d	r	f	m	h	d	r	f
Administrative regions											*Elevation belts*									
1960																				
h	0.76					0.72					0.85					0.86				
d																				
r		0.84					0.87													
f	0.95					0.98					0.96					0.97				
c	0.77					0.84	0.84				0.78					0.79				
1990																				
h	0.86					0.83					0.79					0.72				
d																				
r																				
f	0.93					0.90					0.95	0.75				0.96	0.76			
c	0.79	0.77				0.90	0.85				0.77	0.74				0.78	0.74			
2010																				
h	0.87					0.82					0.80					0.81				
d																				
r																				
f	0.92					0.91					0.94	0.76				0.95	0.77			
c	0.78	0.84				0.83	0.87				0.76	0.74				0.77	0.75			
Provinces											*Economic areas*									
1960																				
h	0.73					0.69					0.81					0.78				
d																				
r													0.60					0.55		
f	0.70	0.69				0.72	0.70				0.69	0.67				0.70	0.68			
c	0.69	0.61				0.70	0.62				0.66	0.63				0.65	0.64			
1990																				
h	0.74					0.73					0.80					0.78				
d																				
r			0.61					0.60					0.67					0.62		
f	0.71	0.68				0.72	0.70				0.70	0.68				0.71	0.67			
c	0.70	0.60				0.69	0.61				0.67	0.64				0.68	0.64			
2010																				
h	0.72					0.72					0.77					0.77				
d																				
r			0.72					0.69					0.67					0.62		
f	0.70	0.67				0.69	0.68				0.69	0.65				0.68	0.64			
c	0.67	0.60				0.66	0.60				0.62	0.60				0.62	0.60			
Rural districts											*Municipalities*									
1960																				
h	0.84					0.83					0.82					0.79				
d																				
r													0.84					0.82		
f	0.89	0.74				0.93	0.84				0.79	0.70				0.81	0.65			
c	0.67	0.61				0.74	0.83			0.72	0.68	0.65				0.69	0.66			
1990																				
h	0.84					0.80					0.81					0.80				
d																				
r			0.71					0.65					0.86					0.82		
f	0.89	0.61				0.93	0.73				0.80	0.62				0.81	0.64			
c	0.68	0.66				0.77	0.92			0.67	0.68	0.66				0.70	0.67			
2010																				
h	0.79					0.79					0.81					0.81				
d																				
r			0.73					0.67					0.86					0.83		
f	0.84	0.59				0.91	0.68				0.76	0.61				0.82	0.62			
c	0.69	0.62				0.84	0.92			0.69	0.70	0.63				0.71	0.64			

m: average ESAI score; h: maximum ESAI score; d: ESAI coefficient of variation; r: ESAI normalized range; f: per cent share of 'fragile' land in total landscape; c: per cent share of 'critical' land in total landscape.

regions of Southern Italy (Ciommi et al., 2017). Ecological conditions also vary significantly along latitudinal and elevation gradients (Colantoni et al., 2015), with semi-arid landscapes with Mediterranean vegetation, temperate-dry climate regimes, and medium–low human pressure concentrated in Southern Italy (Zambon et al., 2018). The spatial distribution of precipitation follows the latitudinal gradient in Italy, passing from about 1500 mm in the North-east of Italy to about 400 mm in the South of Sicily; temperatures in turn follow the elevation gradient (Scarascia et al., 2006).

2.2. Elementary spatial units

The study area was partitioned adopting 6 different layers (Istat, 2006) with administrative or geographical relevance (Fig. 1): (i) 20 NUTS-2 administrative regions, (ii) 24 territorial ambits derived from the spatial intersect of five macro-regions (North-West, North-East, Centre, South, and the two major islands) and five elevation belts (lowlands, coastal upland, interior upland, coastal mountains, interior mountains), (iii) 103 NUTS-3 provinces, (iv) 686 economically homogeneous districts (the so called 'local labour systems' in use for statistical reporting and conceptually similar to the 'Travel-To-Work Areas' derived from a spatial analysis of commuting patterns based on population census data), (v) 777 homogeneous agricultural areas delineating rural districts of relevance for spatial planning and, finally, (vi) 8101 NUTS-5 municipalities (Istat, 2006). These spatial domains represent homogeneous economic, institutional, and territorial units relevant to environmental reporting and specifically addressing the informative needs of local and regional Action Plans to combat desertification, in line with the directives provided by UNCCD.

2.3. Data and indicators

The analysis is based on a pre-existing dataset developed as a part of a long-term study on the evolution of land degradation in Italy from the early 1960s to the present days (Salvati et al., 2016). This study was grounded on the Environmental Sensitive Area (ESA) philosophy, developing a diachronic cartography of the ESA index covering the whole country at three time points (early-1960s, early-1990s, early-2010s). The ESA procedure calculates a composite indicator assessing the level of sensitivity to land degradation based on 14 elementary variables grouped in 4 dimensions (climate, soil, vegetation/land-use, human pressure). Suitably classified in standard scores (Salvati and Zitti, 2008), each variable contributes through a system of weights to the final indicator calculated by geometric mean in each spatial unit (Salvati and Zitti, 2009). The ESA index assumes continuous values from 1 (the lowest level of sensitivity to degradation) to 2 (the highest level of sensitivity). In this work, ESA raster maps at 1 km^2 spatial resolution (Salvati et al., 2016) have been used; Ferrara et al. (2020) provided additional technical details.

Six indicators of land degradation derived from ESA maps have been calculated separately for each time point and spatial domain, forming 6 (indicators) $\times$ 3(years) matrices for each spatial domain, having variable sample size each (ranging from 20 domains for the 'administrative regions' level to 8101 domains for the 'municipality' level). Each indicator was computed adopting a 'zonal statistics' approach within the ArcGIS software (Redlands, CA) by overlying the respective ESA raster map with a shapefile representing the polygons that form the geometry of each selected domain in the study area (e.g. administrative regions, …, municipalities). Indicators tested in this work include (i) the average ESA score (delineating the mean degree of land sensitivity to degradation in a given spatial domain, hereafter 'm'), (ii) the maximum ESA score (taken as a proxy of desertification risk, 'h'), (iii) the coefficient of variation (standard deviation/mean*100) in the ESA scores (outlining spatial heterogeneity in the level of land sensitivity, 'd'), (iv) the normalized range ((max–min)/mean) in the ESA scores (another indicator of spatial variability in land degradation that takes account of the extreme conditions of risk through computation of the highest and the lowest score in each domain, 'r'), and the per cent land surface classified as (v) 'fragile' ('f') or (vi) 'critical' ('c') in total landscape based on a standard nomenclature system ('fragile' areas: $1.225 < \text{ESA} < 1.375$; 'critical' areas: $\text{ESA} > 1.375$; Kosmas et al., 2016). These two measures were used to indicate moderate and high sensitivity to land degradation (Karamesouti et al., 2015). Taken together, these indicators were assumed to reflect the territorial profile of land degradation, being widely adopted as reliable measures of desertification risk in both scientific literature and official environmental reports (Delfanti et al., 2016). The experimental design of the present study was aimed at verifying statistical stability across space and redundancy of the indicators' set, with the aim at proposing few appropriate indicators for environmental reporting of land degradation at the desired operational/planning scale.

2.4. Statistical analysis

An exploratory analysis was run, separately for each spatial domain and year, with the aim at delineating the pair-wise relationship between indicators, and their intrinsic redundancy. Pair-wise correlations between indicators were analysed using parametric (Pearson, product-moment coefficients) and non-parametric (Spearman co-graduation coefficients) approaches. Testing for significance at $p < 0.05$ (after Bonferroni's correction for multiple comparisons), Pearson and Spearman coefficients respectively identify linear and non-linear correlations between two sensitivity indicators (Duvernoy et al., 2018). A significant Pearson coefficient coupled with a similar Spearman coefficient (irrespective of the p-value) indicates a linear correlation (Pili et al., 2017). A significant Spearman coefficient together with a non-significant Pearson coefficient indicates a non-linear correlation (Salvati and Zitti, 2007). A Principal Component Analysis was subsequently run separately for each spatial level ($n = 6$) and year ($n = 3$) on the $6 \times n$ matrix containing the value of each indicator at each spatial domain, where n is the sample size varying from 20 (regions) to 8101 (municipalities). This multivariate technique was adopted to quantify indicators' redundancy and to identify few (independent) dimensions relevant to environmental reporting (Serra et al., 2014). Components with eigenvalue > 1 have been selected and further analysed considering loadings of each indicator separately on each component (Salvati and Serra, 2016). Loadings $> |0.8|$ or between $|0.5|$ and $|0.8|$ indicate very strong or moderately strong association of a given indicator with the respective component.

3. Results

Table 1 compares the results of pair-wise Pearson's parametric and non-parametric Spearman correlations for six land degradation indicators at the different spatial scales adopted in this work. With very few exceptions, statistically significant pair-wise relationships were stable over time and space. Almost all the tested correlations are linear, as both coefficients (Pearson and Spearman) were found significant with comparable sign and intensity. Only one case of non-linear correlation was identified for the relationship between the per cent share of 'fragile' and 'critical' land in total landscape, being restricted to few geographical partitions.

The strongest linear correlations (i.e. the highest (positive) coefficients, found at all territorial partitions and for all time periods) were observed between (i) the average ESA score and the maximum ESA score, (ii) the average ESA score and 'fragile' areas, (iii) the average ESA score and 'critical' areas. Other significant correlations in most of the territorial partitions and time periods were observed between (iv) the maximum ESA value and 'fragile' areas, (v) the maximum ESA value and 'critical' areas, and (vi) the ESA coefficient of variability and the ESA normalized range. Results of a Principal Component Analysis run separately by territorial partition and year on the matrix containing land

Table 2
Results of a Principal Component Analysis run on indicators of land degradation by year and spatial partition; component loadings > |0.6| are shown.

Year/	Adm. regions		Elevat. belts		Provinces		Econ. areas		Rural districts		Municipalities	
Variable	PC1	PC2	PC1	PC2	PC1	PC2	PC1	PC2	PC1	PC2	PC1	PC2
1960												
m	0.93		0.81		0.78		0.66		0.95		0.79	
h	0.91		0.93		0.92		0.92		0.78		0.91	
d		0.60		0.83		0.70		0.68		0.93		0.80
r		0.68	0.80			0.70		0.69		0.86		0.84
f	0.86		0.81		0.82		0.82		0.88		0.80	
c	0.77		0.78		0.79		0.78		0.74		0.75	
Exp.Var.	*63.7*	*18.7*	*71.5*	*18.6*	*55.1*	*30.9*	*55.4*	*32.5*	*53.7*	*24.6*	*62.9*	*32.0*
1990												
m	0.93		0.85		0.81	−0.81	0.82		0.97		0.98	
h	0.96		0.95		0.89		0.87		0.91		0.91	
d		0.73		0.98		0.68	0.81	0.63		0.89		0.95
r		0.72		0.79		0.60	0.75	0.67		0.92		0.97
f	0.85		0.79		0.84				0.83		0.80	
c	0.79		0.75		0.77				0.75		0.72	
Exp.Var.	*65.7*	*18.7*	*57.3*	*25.2*	*46.9*	*40.7*	*47.4*	*42.3*	*49.6*	*32.4*	*50.1*	*45.2*
2010												
m	0.91		0.83		0.94		0.98		0.98		0.65	
h	0.95		0.96		0.75		0.84		0.82		0.95	
d		0.87		0.84		0.80		0.86		0.80		0.86
r		0.84		0.62		0.84		0.90		0.86		0.85
f	0.83		0.78		0.80		0.8		0.84		0.80	
c	0.86		0.75		0.78		0.74		0.72		0.71	
Exp.Var.	*67.5*	*19.4*	*50.7*	*28.3*	*49.3*	*41.1*	*45.3*	*44.1*	*51.1*	*30.0*	*52.3*	*42.9*

m: average ESAI score; h: maximum ESAI score; d: ESAI coefficient of variation; r: ESAI normalized range; f: per cent share of 'fragile' land in total landscape; c: per cent share of 'critical' land in total landscape.

degradation indicators are reported in Table 2, illustrating indicators' loadings on the extracted components.

PCA results were consistent for all the territorial partitions, as two components that satisfy the basic requirement (eigenvalue > 1) were stably extracted. The percentage of variance explained by the first two components varied across territorial partitions, being systematically higher than 80% of the overall variance. On the basis of the extracted loadings, the structure of the two components was stable over time and space. The first component was associated with the average ESA (m), maximum ESA (h), 'fragile' areas (f) and 'critical' areas (c), albeit with variable loadings. In general, 'm' and 'h' indicators received the highest loadings on Component 1, with positive signs. Component 2 was associated with the ESA coefficient of variation (d) and the ESA normalized range (r), displaying positive and moderately high loadings.

4. Discussion and conclusion

Our study identified non-redundant indicators of the level of sensitivity to land degradation for environmental reporting, testing statistical stability, information completeness, and relevance at various spatial scales, from regional to local. The statistical analysis of land degradation indicators at three time periods that reflect different socioeconomic contexts and environmental conditions in Italy, highlighted the presence of two non-redundant dimensions for all the spatial domains: (i) the overall, 'average' level of sensitivity and (ii) the spatial variability in the level of sensitivity. Assuming these two dimensions as statistically independent, each indicator tested here was found associated exclusively with one dimension. The average ESA score and the ESA coefficient of variation – both calculated on defined spatial domains – were the indicators most associated with these two dimensions. The robustness of these two indicators was also demonstrated across spatial scales over a sufficiently long time horizon. The statistical analysis also documented how average and maximum ESA scores provided substantially similar information for environmental reporting. On the basis of these considerations, the joint use of the average ESA and the related coefficient of variation provides non-redundant and statistically robust information to the environmental reporting of land degradation both for aggregate spatial domains (e.g. administrative regions, elevation ranges) and when a greater geographical detail is needed (e.g. rural districts, municipalities). Various stakeholders may benefit from such an indicators' system, from spatial planning authorities (at all governance levels, from countries to local scales) to individual practitioners interested in assessing the environmental impact assessment of a specific action on a given affected landscape (Briassoulis, 2019).

The use of such indicators for environmental reporting at the most appropriate spatial scale (e.g. regions and, by generalization, countries) can finally inform integrated sustainable development policies (Agenda 2030) and, more specifically, the zero-net land degradation strategy (Akhtar-Schuster et al., 2017; Jiang et al., 2019; Huang et al., 2020). To track the evolution of land degradation, this strategy requires a set of indicators that are stable over time and space, with the final aim at evaluating the effectiveness of mitigation and adaptation policies (Graves et al., 2015; Cao et al., 2018; Cheng et al., 2018). Future research should assess – through comparative approaches – the reliability and statistical efficiency of these indicators at an even more aggregate spatial scale (e.g. countries, homogeneous groups of countries, continents), possibly starting from an ESA-based, global assessment of land degradation.

CRediT authorship contribution statement

Samaneh Sadat Nickayin: Funding acquisition, Resources, Writing - review & editing. **Giovanni Quaranta:** Conceptualization, Supervision. **Rosanna Salvia:** Conceptualization, Validation, Writing - review & editing. **Sirio Cividino:** Data curation, Investigation, Visualization. **Pavel Cudlin:** Formal analysis, Methodology, Writing - original draft. **Luca Salvati:** Project administration, Software, Writing - original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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