Received: 21 February 2019 | Revised: 9 January 2020 | Accepted: 16 January 2020
DOI: 10.1002/ldr.3559

RESEARCH ARTICLE

WILEY

Updating the MEDALUS-ESA Framework for Worldwide Land Degradation and Desertification Assessment

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Abstract

The environmentally sensitive area (ESA) methodology (originally proposed in the framework of MEDALUS–Mediterranean Desertification and Land Use—a series of international cooperation research projects funded by the European Union) is used worldwide to identify 'sensitive areas' that are potentially threatened by land degradation and desertification (LDD). The distinctive outcome of this approach is a multidimensional index (the ESA index) composed of partial indicators of climate, soil, vegetation, and management quality that are derived from the elaboration of 15 elementary variables. In this study, we propose (a) a major update of the ESA methodology, as presented in the MEDALUS project, for global LDD assessment, (b) a global map of ESAs to LDD, and (c) a global environmentally critical factors map. The results of the updated ESA framework confirm the efficiency and applicability of the ESA methodology in different worldwide areas, allowing for the harmonization of regional/country level studies and applications, and the more efficient use of global level datasets. In this study, we provide examples for analysis of LDD patterns and processes at a global level, as well as for identification of the main risk factors over time and space. Global-ESA and global-environmentally critical factors maps also support regional-scale knowledge on LDD processes and sustainable land management practices for LDD mitigation. High-resolution illustrative maps and other information are available on a dedicated website (http://web.unibas.it/global-esa/).

KEYWORDS
environmentally sensitive areas, global-ESA, land degradation and desertification, MEDALUS, world map

1 | INTRODUCTION

Environmental sensitivity (ES) to land degradation, which is typically related to humid, semi-humid or dry subhumid areas, and desertification, which is typically related to semiarid and arid land, is a broad concept that depends on place-specific socio-ecological conditions, interactions, and adaptation strategies (Reynolds et al., 2007; Helldén & Tottrup, 2008; Maliva & Missimer, 2012; Liu, Wang, Kang, & David, 2014; Karamesouti et al., 2015; Middleton & Sternberg, 2013; Prăvălie, 2016; Kosmas et al., 2016; Prăvălie et al., 2017). A refined knowledge of these interactions is necessary for supporting efficient policy interventions, regional planning, and land management at regional and national levels (Salvati, Gemmiti, & Perini, 2012). The lack of integrated monitoring and assessment procedures has been a major constraint for understanding and combating desertification processes worldwide (Kairis, Karavitis, Kounalaki, Salvati, & Kosmas, 2013; Kelly et al., 2015; Vogt et al., 2011).

Several approaches have been proposed for land degradation and desertification (LDD) analysis by assessing individual variables and indicators and producing complex indices to analyse specific LDD issues (Cheng et al., 2016; Jafari & Bakhshandehmehr, 2016; Kosmas, Tsara, Moustakas, & Karavitis, 2003; Kosmas, Tsara, Moustakas, Kosma, & Yassoglou, 2006; Symeonakis, Karathanasis, Koukoulas, & Panagopoulos, 2016; Tongway & Hindley, 2000; Vogt et al., 2011; Zanchetta & Bitelli, 2017; Zucca, Peruta, Salvia, Sommer, & Cherlet, 2012).

Implementing efficient responses to LDD at different ES levels requires a comprehensive knowledge of the causes underlying these processes (Ferrara, Salvati, Sabbi, & Colantoni, 2014). Several studies have highlighted how sensitivity to LDD is strictly related to the quality of local/regional climate, soil characteristics, vegetation types, socio-economic systems, land management options, and quality/effectiveness of policy responses (Fantechi, Peter, Balabanis, & Rubio, 1995; Incerti, Feoli, Giovacchini, Salvati, & Brunetti, 2007; Montanarella, 2007; Moonen, Ercoli, Mariotti, & Masoni, 2002; Salvati & Zitti, 2008; Wilson & Juntti, 2005). A refined knowledge of socio-economic and biophysical factors underlying LDD processes is also increasingly required when characterising ecosystem dynamics in light of land-use sustainability.

Many authors have emphasized the role of composite indices (or key indicator systems) in the assessment of actual and potential LDD (e.g., 1999; Basso et al., 2000; Ferrara, Salvati, Sateriano, & Nolè, 2012; Kosmas et al., 1999; Sommer et al., 2011). Key indicator systems have been widely used in complex socio-environmental analyses at different spatial and temporal scales (Salvati & Zitti, 2005). As far as LDD is concerned, many candidate indicators, operational frameworks, and processing systems have been proposed (European Environment Agency, 2003, 2006; European Union, 2001; Wascher, 2000). However, the environmentally sensitive area (ESA) index, which was developed in the Mediterranean Desertification and Land Use (MEDALUS) and DESERTLIKS series of European Union research projects (AA.VV, 1999; Brandt, 2004; Kosmas et al., 1999), is one of the most common approaches for estimating land sensitivity to desertification (Salvati, Zitti, & Ceccarelli, 2008; Lavado Contador, Schnabel, Gómez Gutiérrez, & Pulido, 2009, Izzo, Araujo, Aucelli, Maratea, & Sánchez, 2013; Marani Barzani & Khairulmaini, 2013; Mohamed, 2013; Salamani, Hanifi, Hirche, & Nedjraoui, 2013; Bouhata & Kalla, 2014; Wijitkosum, 2014; Bajocco, De Angelis, & Salvati, 2012; Salvati & Ferrara, 2014; Benmessaoud, Chergui, Sahnouni, & Chafai, 2015; Dindaroǯlu, 2015; De Pina Tavares et al., 2015; Zitti, Ferrara, Perini, Carlucci, & Salvati, 2015; Lahlaoi, Rhinane, Hilali, Lahssini, & Moukrim, 2017; Prăvălie et al., 2017: Boudjemline & Semar, 2018; Xu, You, & Xia, 2019; Capozzi et al., 2018). In this regard, a high ESA index value may reflect unbalanced environmental and/or socio-economic conditions, land management and policy options, or an unsustainable mix of these factors for a given land use under specific environmental conditions.

The ESA index, as presented in this framework update, is estimated by a set of 14 elementary variables assessing soil, climate, vegetation, and management quality and based on a summary score index (i.e., the ESA index) through a two-step algorithm (Basso et al., 2000; Ferrara, 2005; Kosmas et al., 1999; Kosmas et al., 1999), where (a) the selection of variables is carried out considering the following requirements (Basso et al., 2000; Ferrara, 2005; Ferrara et al., 2012): (i) correlation with LDD phenomena and/or related environmental issues; (ii) data availability at the appropriate spatial scale; and (iii) data availability for multi-temporal analysis; (b) the two-step algorithm is updated with the following objectives (Basso et al., 2000; Ferrara, 2005, 2012): (i) formulating a simplified and more efficient operational scheme that is applicable to vastly different socio-economic contexts; (ii) presenting a reliable score index derived from an indicator-based monitoring system, characterizing land sensitivity with values ranging from 1 (low sensitivity) to 2 (high sensitivity); (iii) adding (or removing) single variables with the aim of evaluating specific aspects of a given location/area; and (ivs) analysing the multiple relationships among critical factors underlying LDD processes.

A key point in the ESA methodology, and the main difference from other approaches used for evaluating LDD processes, is that the composite index is intended to be used as an integrated tool for complex system analysis because the ESA index score is not a unique model outcome; rather, the ESA index is the basis for further investigation of the extent, nature, and characterization of the ES of an area (Ferrara, 2005; Bajocco, Salvati, & Ricotta, 2011; Recanatesi et al., 2016). The strength of the combined variable/score system and computing algorithm lies in the original formulation of the ESA index, which is constructed as a relative index (contrasting with composite indices that produce absolute scores). This system aims to build a reference framework based on the specific type and characteristics of any study area (Colantoni, Ferrara, Perini, & Salvati, 2015). In other words, the ESA framework is flexible and adaptable to a wide range of spatial contexts, and different data sources and variables can be used for a more effective evaluation of the characteristics of any given spatial context (Basso et al., 2000; Ferrara, 2005; Kosmas et al., 1999). In addition, the ESA framework can be used for time-series analysis by using multi-temporal datasets to evaluate trends overtime in the ESA index, as well as for future predictions of land sensitivity, for example, by delineating appropriate projections of each input variable under different scenarios. The ESA methodology has been extensively tested and applied worldwide, and the methodology demonstrates efficiency, reliability, and flexibility in the choice of relevant indicators and the inherent capability of integrating data from different official sources (Imeson & Cammeraat, 2002; Manuchehr & Mahbobeh, 2007; Lavado Contador et al., 2009; Bouhata and Kala Bouhata & Kalla, 2014; De Pina Tavares et al., 2015; Jafari & Bakhshandehmehr, 2016).

This paper aims to present a coherent and complete reference framework regarding the use of global datasets that are available for scientific analysis or technical documents for public administrations or decision makers based on ESA methodology. This study will provide (a) a simpler and faster application of the ESA methodology on a regional/country scale by using the proposed variable/score system and algorithms; (b) a reliable and worldwide consistent definition of new variable/score systems when based on different datasets at different scales by using this framework as guidance. More specifically, this study (a) develops a comprehensive methodology and a global level reference framework for mapping sensitivity to LDD processes based on global datasets featuring climate, soil, vegetation, and management components, (b) establishes the first global ESA framework that incorporates ESA and environmentally critical factors (ECFs) maps, as a new informative and relevant outcome of the ESA methodology, and (c) provides examples illustrating the potential of the ESA methodology applied for regional-scale LDD analysis and monitoring.

2 | MATERIALS AND METHODS

2.1 | Study area

The study area includes the entire world surface area, as derived from the ESA CCI land cover map referring to the year 2015 (Table 1). Water bodies, urban areas, permanent snow and ice, and the Antarctic region were excluded from the analysis because these areas that have insufficient data coverage. Statistical analysis was carried out using a random sample of 20,444 observations corresponding to land pixels extracted from the 1-km map using a 100-km step regular grid.

2.2 | The original ESA approach

The main reference for variable selection and framework establishment is the 'Manual on key indicators of desertification and mapping environmentally sensitive areas to desertification' (Kosmas et al., 1999, Basso et al., 2000, OECD, 2004, and subsequent works), where the ESA methodology was developed for the Mediterranean region and was later tested and applied in many other regions of the world. The original methodology was based on a comprehensive analysis of 15 variables and a two-phase computational approach. All the variables were grouped according to four characteristics 'qualities' (climate, soil, vegetation, and management, the latter intended as 'degree of human induced stress'—Kosmas et al., 1999, p. 45). In the first step, the values of each elementary map area (i.e., pixels in a raster map) in each variable were reclassified according to a variable/score classification system, and a generalized evaluation was carried out to produce four quality indicators (soil quality, SQI; vegetation quality, VQI; climate quality, CQI; and management quality, MQI), which were estimated as the geometric mean of the respective scores of pertinent variables. In the second step, the ES of each elementary unit was derived by computing the geometric mean of the corresponding quality indicators (Figure S1 in the Supporting Information).

2.3 | Key aspects of the ESA index and the ECF maps

The main strengths of the ESA methodology are as follows: (a) the adoption of variables of different nature (raster, vector, and numerical), type (continuous, discrete, and ordinal) and spatial scale as system inputs; (b) the potential for excluding some variables depending on their availability or adding other variables in relation to investigation needs, for example, characterising aspects of particular local interest. Changes in some of the input variables may impact the ESA index, and thus, a careful establishment of each new class/score scheme is required. In this regard, the present update provides a unique methodological reference framework that uses several global datasets that were recently made available, allowing for more efficient comparison of regional/country scale results as far as LDD monitoring is concerned. This updated framework can be also used as a guideline for setting up, with ease and speed, new variable/score systems when using other different datasets/variables (by changing or adding into the ESA system or by relating them into statistical analyses), also at different scales. The ECF map represents an additional tool for summarising the contribution of input variables to the definition of ES levels as delineated by the ESA index. In other words, this map can be used to assess variations in the composition and structure of the ESA score (e.g., two locations with the same ESA score can result from many different values of sensitivity or the result of values near the scale limits).

2.4 | Updating the ESA algorithm to a global scale

Starting from the two-step approach proposed in the original MEDALUS framework, the ESA algorithm was updated to overcome the problem of missing data in global datasets. The algorithm was adapted to evaluate the geometric mean of each quality indicator by using the variables with available information for any elementary analysis unit (Equation 1). In other words, when the information was missing in a given elementary unit of any single variable, the related quality score was computed, for that pixel, by using the scores of the remaining variables (defined hereafter as 'active variables'), as follows:

$$Quality\_x_{ij} = \left(variable\_1_{ij} \cdot variable\_2_{ij} \cdot variable\_3_{ij} \cdot \ldots \cdot variable\_n_{ij}\right)^{1/n_{ij}}, \quad (1)$$

where i,j = rows and columns of a single elementary pixel of each variable; n = number of active variables for each elementary unit; x = the four qualities referring to soil, climate, vegetation, and management.

The final ESA index was computed according to the original procedure as a geometric mean of the four quality values recorded at each location (i.e., in each elementary pixel; Equation 2):

$$ESA_{ij} = \left(SQI_{ij} \cdot VQI_{ij} \cdot CQI_{ij} \cdot MQI_{ij}\right)^{1/4}, \quad (2)$$

where i,j = rows and columns of a single elementary pixel of each quality.

If specific information on a pixel was missing for all the input variables of a given quality indicator, the corresponding ESA index was not computed, and that pixel was classified as 'NoData.' To overcome unsatisfactory or missing information in some areas, two source datasets were combined when establishing each individual variable (Table S1). It is worth noting that, with this updated procedure, elementary units with missing information represent a negligible part of

TABLE 1 List of datasets used in the 2015 Global-ESA map

Quality	Variable	Reference database	Source res.	Source	References
Soil	Parent material	Lithological map of the World (LiMW_GIS 2015.gdb.zip). Based on Global lithology map database v1.1–2012	Vector	http://ccgm.org/en/home/168-lithological-map-of-the-world-9782917310250.htmls	Hartmann & Moosdorf, 2012
	Slope grade	Derived from ESRI grids Altitude 30 arc-sec - 02.2000	30 arc-s	http://www.worldclim.org/current	ESRI Grids (2000)
	Soil texture	Harmonized World Soil Database HWSD version 1.21–07.03.2012	30 arc-s	http://webarchive.iiasa.ac.at/Research/LUC/External-World-soil-database/HTML/index.html?sb=1	FAO/IIASA/ISRIC/ISSCAS/JRC, 2012
		DSMW–Digital Soil Map of The World. Version 3.6–02.28.2007	Vector	http://www.fao.org/geonetwork/srv/en/metadata.show?id=14116	FAO/UNESCO, 2007
	Drainage Rock fragments Soil groups	Harmonized World Soil Database HWSD version 1.21–07.03.2012	30 arc-s	http://webarchive.iiasa.ac.at/Research/LUC/External-World-soil-database/HTML/index.html?sb=1	FAO/IIASA/ISRIC/ISSCAS/JRC, 2012
Climate	Rainfall	CRU TS 4.01 Precipitation (as mean 2013–2017)	0.5 deg	https://crudata.uea.ac.uk/cru/data/hrg/	Harris, Jones, Osborn, & Lister, 2014
	Aridity index, AI_U	Calculated from CRU TS 4.01 Precipitation and CRU TS 4.01 Potential Evapotranspiration using Penman-Monteith (as mean 2013–2017)	0.5 deg	https://crudata.uea.ac.uk/cru/data/hrg/	Harris et al., 2014
Vegetation	Fire risk Drought resistance Erosion protection	ESA CCI–land cover map v2.0.7–2015	300 m	http://maps.elie.ucl.ac.be/CCI/viewer/download.php	ESA Climate Change Initiative - Land Cover led by UCLouvain (2017)
	Plant cover	Calculated from USGS LCI. MODIS MOD13A3.006 based. $NDVI_{MVC}$ Maximum Value Composite (as mean 2013–2017)	30 arc-s	https://e4ftl01.cr.usgs.gov/MOLT/MOD13A3.006/	Didan, 2015
Management	Land use intensity	ESA CCI–land cover map v2.0.7–2015	300 m	http://maps.elie.ucl.ac.be/CCI/viewer/download.php	ESA Climate Change Initiative—Land Cover led by UCLouvain (2017)
	Population density	Gridded Population of the World (GPW), UN-Adjusted Population Density, v4 - 2015	30 arc-s	http://beta.sedac.ciesin.columbia.edu/data/set/gpw-v4-population-density-adjusted-to-2015-unwpp-country-totals/data-download	CIESIN, 2015 Doxsey-Whitfield et al., 2015
Administrative boundaries (for analyses at country level)	Global Administrative Areas (GADM) (*gadm36.gbk.zip*) 2018		Vector	https://gadm.org/download_world.html	ESRI (2015)

Abbreviation: ESA, environmentally sensitive area.

the global dataset. Specifically, these points account for less than 0.01% of the total land surface. In any case, in very particular spatial conditions and analyses, it is always possible to exclude those units that do not satisfy defined criteria.

2.5 | Selecting the global level variables

To adapt and upscale the original ESA framework to the global scale, the following criteria were considered when selecting the input variables (Kosmas et al., 1999): (a) consistency with the original ESA approach (Kosmas et al., 1999); (b) time-series data availability and regularity for multi-temporal mapping and indicator estimates; and (c) data source quality and reliability for future updates and refined time-series analysis. Based on these criteria, 14 variables were selected in this study (Table 1).

The updated framework presents some changes to the methodology proposed in Kosmas et al. (1999a), as follows: (a) the 'slope aspect' variable was removed from the climate quality assessment because it had no internal consistency under global-scale coverage, (b) the 'soil depth' variable was replaced with a more comprehensive variable assessing 'soil groups/types' because of the inherent differences between the variable classes available at the global scale and the original classes of the ESA methodology, and (c) population density was used as a proxy of human pressure on the environment (Otto, Krusi, & Kienast, 2007; Salvati et al., 2008; Tanrivermis, 2003). Other minor changes included the use of (a) the UNEP (1992) aridity index instead of the Bagnouls–Gaussen index because of the easy computation procedure and full data coverage at the global scale; (b) the MODIS-NDVI maximum value composite for refined vegetation cover detection; and (c) the land-use intensity variable based on the ESA CCI land cover map (Haberl et al., 2007; Bajocco et al., 2011; Recanatesi et al., 2016).

2.6 | Setting up the variable dataset

All variables were downloaded from their official websites, converted to the appropriate raster format, resampled to a spatial resolution of 1 km when necessary, and registered using the EPSG geographic projection system 4,326 (WGS84). To ensure that the different datasets were coherent in both spatial distribution and content, missing variable values across sea coastlines were replaced by averaging the nearest neighbour unit values using geographic information systems. Thus, pixels that were missing due to the different spatial coverage of the original variables were estimated. Water bodies, urban areas, permanent snow, and ice areas were also excluded from all intermediate maps using the same procedure as the one adopted for coastlines. Intermediate and final maps were produced at a resolution of 1 km. The 2015 ESA CCI land cover map resampled at a 1-km spatial resolution was selected as the final reference map (Table 1). Data were processed using RStudio and QGIS software (RStudio Team, 2018; QGIS Development Team, 2018). The selected maps and the final adopted resolution of 1 km^2 are functional to the development of the ESA methodology update presented in this study. They have a large field of applicability, but it is possible to use other datasets at a higher resolution level for more local investigation, that is, for soil data, slope grade, climatic data, or the same 2015 ESA CCI land cover map at its original resolution.

2.7 | Updating the ESA scores

The scores of each single variable were defined following Kosmas et al. (1999) and were based on the level of correlation between each selected variable class and the different sensitivity levels to LDD at the global scale, as evaluated in earlier studies (UNEP, 1997; Rubio & Bochet, 1998, Kosmas, Poesen, & Briassouli, 1999; 1999; Kosmas, Danalatos, & Gerontidis, 2000, Kosmas et al., 2003, Kosmas et al., 2006; Basso et al., 2000; Maliva & Missimer, 2012; Ochoa et al., 2016; Moreira, Vaz, Catry, & Silva, 2009; Salvati & Zitti, 2008; Kairis, Karavitis, Salvati, Kounalaki, & Kosmas, 2015; Panagos et al., 2015; IUSS, 2015; Calviño-Cancela, Chas-Amil, García-Martínez, & Touza, 2016). The complete score/class nomenclature is susmmarised in Table 2, and further details are reported in Table S1. Maps of the input variables are illustrated in Figure S6. The ESA ranges that identify the distinct land sensitivity types to LDD are reported in Table S2a.

2.8 | The ECFs index

The ECF index and the related global map are an original output derived from the elaboration of the ESA dataset, and this output aims to provide complementary information associated with the ESA index. The ECF index was obtained by counting, for each pixel, the number of variables with an ESA index score > 1.425 (Equation 3), which corresponds to the C2 “critical” threshold, as reported in Table S2a.

$$ECF_{ij} = \sum_{n=1}^{14} f\left(variable_{ijn}\right), \tag{3}$$

where *i,j* = rows and columns of a single elementary pixel of each variable, and *f(x)* is the characteristic function of the threshold, equal to 1.425:

$$f(x) = \begin{cases} 1, if\ x > 1.425 \\ 0, if\ x \leq 1.425 \end{cases}.$$

This indicator outlines the importance of factors most likely associated with ES to LDD in a given area. Because land classified with the same ESA score can have very different sensitivity scores among the input variables—therefore being influenced by different drivers of land sensitivity—the combined use of the ESA index and the ECF index allows for a more comprehensive and simple assessment of land sensitivity levels in a given area with respect to the original ESA framework.

TABLE 2 Elementary variables composing the environmentally sensitive area index and the related sensitivity scores

Parent material

Type	Score
SU	1.0
VB; SS; PB; EV	1.2
SM	1.4
VI; PI; MT	1.5
PA; VA	1.6
SC	1.7
PY	2.0

Slope grade, %

Ranges	Score
< 3	1.0
3 < 6	1.1
6 < 12	1.2
12 < 18	1.3
18 < 24	1.4
24 < 30	1.5
30 < 36	1.7
>= 36	2.0

Soil texture

Type	Score
CL; L; SCL; SL; LS	1.0
SiCL; SiL; SC	1.2
C(h); SiC; C(l); Si	1.6
S	2.0

Drainage

Type	Score
Well	1.0
Moderately well	1.2
Imperfectly	1.4
Somewhat excessive	1.7
Poor; very poor; excessive	2.0

Rock fragments, %

Type	Score
>= 60	1.0
40 < 60	1.1
30 < 40	1.3
20 < 30	1.5
10 < 20	1.7
< 10	2.0

Soil groups

Type	Score
AN; CH; CM; FL; HS	1.0
GR; KS; NT; PH	1.1
AC; AT; FR; GL; LV; PZ; RG; VR	1.3
AL; LX; PD ; PL	1.5
CL	1.6
AR; PT	1.7
GY; LP; SC; SN; RK; DS; ST	2.0

		Drought resistance	Fire risk	Erosion protection	Land Use Intensity
Code	Type	Scores			Score
10	Cropland, Rainfed	1.5	1.4	1.7	1.7
11	Herbaceous cover	1.6	1.4	1.8	1.7
12	Tree or shrub cover	1.3	1.2	1.6	1.4
20	Cropland, irrigated or post flooding	1.4	1.4	1.4	1.6
30	Mosaic cropland (>50%) / natural vegetation) (<50%)	1.5	1.5	1.5	1.5
40	Mosaic natural vegetation (>50%) / cropland (<50%)	1.5	1.4	1.4	1.5
50	Tree cover, broadleaved, evergreen, closed to open (>15%)	1.0	1.3	1.0	1.1
60	Tree cover, broadleaved, deciduous, closed to open (>15%)	1.1	1.4	1.1	1.2
61	Tree cover, broadleaved, deciduous, closed (>40%)	1.0	1.3	1.0	1.0
62	Tree cover, broadleaved, deciduous, open (15-40%)	1.2	1.7	1.4	1.3
70	Tree cover, needleleaved, evergreen, closed to open (>15%)	1.1	1.5	1.1	1.1
71	Tree cover, needleleaved, evergreen, closed (>40%)	1.1	1.3	1.0	1.1
72	Tree cover, needleleaved, evergreen, open (15-40%)	1.2	1.2	1.3	1.2
80	Tree cover, needleleaved, deciduous, closed to open (>15%)	1.2	1.3	1.3	1.1
81	Tree cover, needleleaved, deciduous, closed (>40%)	1.3	1.3	1.5	1.5
82	Tree cover, needleleaved, deciduous, open (15-40%)	1.3	1.3	1.5	1.5
90	Tree cover, mixed leaf type (broadleaved and needleleaved)	1.0	1.1	1.0	1.0
100	Mosaic tree and shrub (>50%) / herbaceous cover (<50%)	1.4	1.5	1.2	1.2
110	Mosaic herbaceous cover (>50%) / tree and shrub (<50%)	1.3	1.4	1.3	1.5
120	Shrubland	1.5	1.4	1.6	1.7
121	Shrubland evergreen	1.2	1.6	1.2	1.5
122	Shrubland deciduous	1.4	1.4	1.6	1.6
130	Grassland	1.6	1.3	1.4	1.5
140	Lichens and mosses	1.0	1.0	1.1	1.2
150	Sparse vegetation (tree, shrub, herbaceous cover) (<15%)	1.6	1.3	1.7	1.8
151	Sparse tree (<15%)	1.5	1.2	1.6	1.6
152	Sparse shrub (<15%)	1.5	1.2	1.6	1.6
153	Sparse herbaceous cover (<15%)	1.6	1.3	1.7	1.7
160	Tree cover, flooded, fresh or brackish water	1.0	1.0	1.0	1.3
170	Tree cover, flooded, saline water	1.0	1.1	1.2	1.2
180	Shrub or herbaceous cover, flooded, fresh/saline/brackish water	1.1	1.1	1.2	1.3
200	Bare areas	2.0	1.0	2.0	2.0
201	Consolidated bare areas	2.0	1.0	2.0	2.0
202	Unconsolidated bare areas	2.0	1.0	2.0	2.0
190; 210; 220	Urban; Water; Permanent snow and ice	Excluded			Excluded

Plant cover, $NDVI_{MVC}$

Ranges	Score
= >0.80	1.0
0.72 < 0.80	1.1
0.62 < 0.72	1.2
0.50 < 0.62	1.3
0.38 < 0.50	1.4
0.26 < 0.38	1.5
0.18 < 0.26	1.6
0.13 < 0.18	1.7
0.11 < 0.13	1.8
0.10 < 0.11	1.9
< 0.10	2.0

Population density, inhabitants/km^2

Ranges	Score
< 4	1.0
4 < 30	1.1
30 < 80	1.2
80 < 170	1.3
170 < 300	1.4
300 < 500	1.5
500 < 850	1.6
850 < 1400	1.7
1400 < 2000	1.8
2000 < 2700	1.9
≥ 2700	2.0

Aridity Index, AI_U

Ranges	Score
>=1.00	1.00
0.75 < 1.00	1.05
0.65 < 0.75	1.15
0.50 < 0.65	1.25
0.35 < 0.50	1.35
0.20 < 0.35	1.45
0.10 < 0.20	1.55
0.03 < 0.10	1.75
< 0.03	2.00

Precipitation, mm yr^{-1}

Ranges	Score
>=650	1.00
570 < 650	1.05
490 < 570	1.15
440 < 490	1.25
390 < 440	1.35
345 < 390	1.50
310 < 345	1.65
280 < 310	1.80
<280	2.00

Note: See source links in Table 1 and Table S1 for a full explanation of the acronyms.

2.9 | Evaluating global ESA framework reliability and performance

Setting up a composite index requires the identification of a target objective (i.e., LDD processes in this study), a set of variables composing the index and practical aggregation rules (Eyles & Furgal, 2002; Von Schirnding, 2002; Liu et al., 2014). In addition, the ESA framework provides a relative reference basis (based on the notion of 'ECF') to be used for further analysis. A key point is that the ESA index does not represent a unique predictive variable. Rather, it is a composite score value that indicates, for each elementary unit, the convergence towards a critical state (score 1 = *lowest sensitivity*; score 2 = *highest sensitivity*), where the intermediate values represent all possible combinations of sensitivity among variables and scores. Thus, the ESA index, together with individual variables, the intermediate qualities, and the ECF index, can be regarded as a complete reference framework from which to start a more complete analysis, thus providing an operational assessment and contextual information tool for complex LDD processes analyses (Basso et al., 1999).

The efficiency and reliability of the ESA framework when estimating different levels of land sensitivity to LDD processes in broadly different environments and socio-economic contexts was documented in earlier studies (Ferrara et al., 2012; Lavado Contador et al., 2009; Manuchehr & Mahbobeh, 2007; Salvati & Ferrara, 2014; Zambon, Benedetti, Ferrara, & Salvati, 2018). A reliability analysis evaluating the uncertainty, performance, and ambit of the updated ESA index is proposed in this work.

A sample of 20,444 sites was extracted, and data mining procedures, including multivariate statistical techniques and neural networks, were applied to better explore the spatial patterns and the latent relationship among the indicators, with the additional objective of controlling for redundancy and multicollinearity among variables. Principal component analysis (PCA) was applied to the matrix composed of the 14 input variables and the four qualities and the composite ESA index as supplementary variables. This analysis aims to (a) identify the most important 'latent' factors describing the spatial pattern of the elementary variables at the global level and (b) correlate these factors to the spatial distribution of the ESA index and, thus, sensitivity to LDD at the global level (Salvati & Zitti, 2009a). Hierarchical clustering was carried out on the ESA index and the first three PCA components using Ward's agglomeration method and Euclidean distance as the amalgamation rule according to the spatial level of countries. This analysis aimed to identify the spatial patterns of the elementary variables and the composite index by clustering world countries into homogeneous groups as far as sensitivity to LDD was concerned (Salvati & Zitti, 2009b). The results of this approach provide an example of the ESA methodology potential when investigating latent LDD patterns and processes. A neural network (self-organizing map with holdback casual validation) was applied to the complete dataset of 14 variables. This analysis aimed to (a) assess the internal coherence and reliability of the ESA estimates based on the elementary variables, (b) evaluate the stability of the ESA index over changing conditions in the composite variables (n = 14) and qualities (CQI, SQI, VQI, and MQI), and (c) identify the potential outliers affecting the ESA index at the elementary spatial unit level. Neural network techniques are a particularly suitable analysis for coping with big data with an unknown statistical distribution or with variables presenting more or less evident deviations from normal distributions (Salvati, Ferrara, & Chelli, 2018). Statistical analyses were carried out using STATISTICA and JMP® software (STATISTICA, v.7.0; JMP®, v.13).

3 | RESULTS AND DISCUSSION

3.1 | Identification of ESAs worldwide

Major outcomes of the global ESA methodology include the Global-ESA map (Figure 1) and the Global-ECF map (Figure 2), both of which refer to the year 2015. High-resolution illustrative maps are available, together with other supporting information, on a dedicated website (http://web.unibas.it/global-esa/). Map types and map legends are reported in Table S2. The world areas with the highest sensitivity to LDD include large pre-desert areas in the Saharan region, a relatively large zone spanning from the Middle East to Mongolia and China, the southwestern part of Africa, a relatively large part of Western Australia, a relatively restricted land strip from Chile to Patagonia, Argentina, and a larger—but more heterogeneous—area between Mexico and the western United States, that is, from California to Texas. The geography of the land that is sensitive to LDD only partly coincided with areas bordering desert land, but this land included a large portion of fringe land between desert and savannah or other transitional/pre-desert vegetation types. A relatively small part of sensitive land was found in Europe (mainly in southern Spain) and in North-eastern Brazil. All these areas were characterized by different ECFs, as reported in Figure 2. The outcomes of this map substantially resemble those obtained from the ESA map but enhance our knowledge of individual factors characterizing sensitive land. Accordingly, vegetation and climate are the most frequent critical factors shaping land sensitivity to LDD worldwide.

Figure S2 illustrates the spatial distribution of the ECFs related to the four different quality indicators (climate, vegetation, soil, and management). Although climate and vegetation showed a substantially similar spatial distribution, soil and management were critical factors with a particularly scattered spatial distribution across the globe.

Two specific examples of the usefulness of integrating spatial knowledge from the ESA and ECF indices are provided in Figure 3, which shows land classification in a pre-desert area with a high sensitivity to LDD (Nile Delta, Egypt, a) and in a less sensitive district experiencing rapid deforestation (Amazonia, Brazil, b). The two maps (upper panel) demonstrate that critical factors in the Nile Delta are spatially heterogeneous (right) even if the overall land sensitivity levels are comparable (left). More specifically, the green area coinciding with the right dot in Figure 3 (a pictures) is classified as sensitive (ESA index = 1.527 with an ECF index = 5) because of the synergistic action of 5 critical factors (with 5 high scores) associated with climate aridity, soil quality, and management (agricultural intensification). The surrounding, pre-desert district, coinciding with the left dot, experiences the same level of sensitivity (ESA index = 1.525). However, this

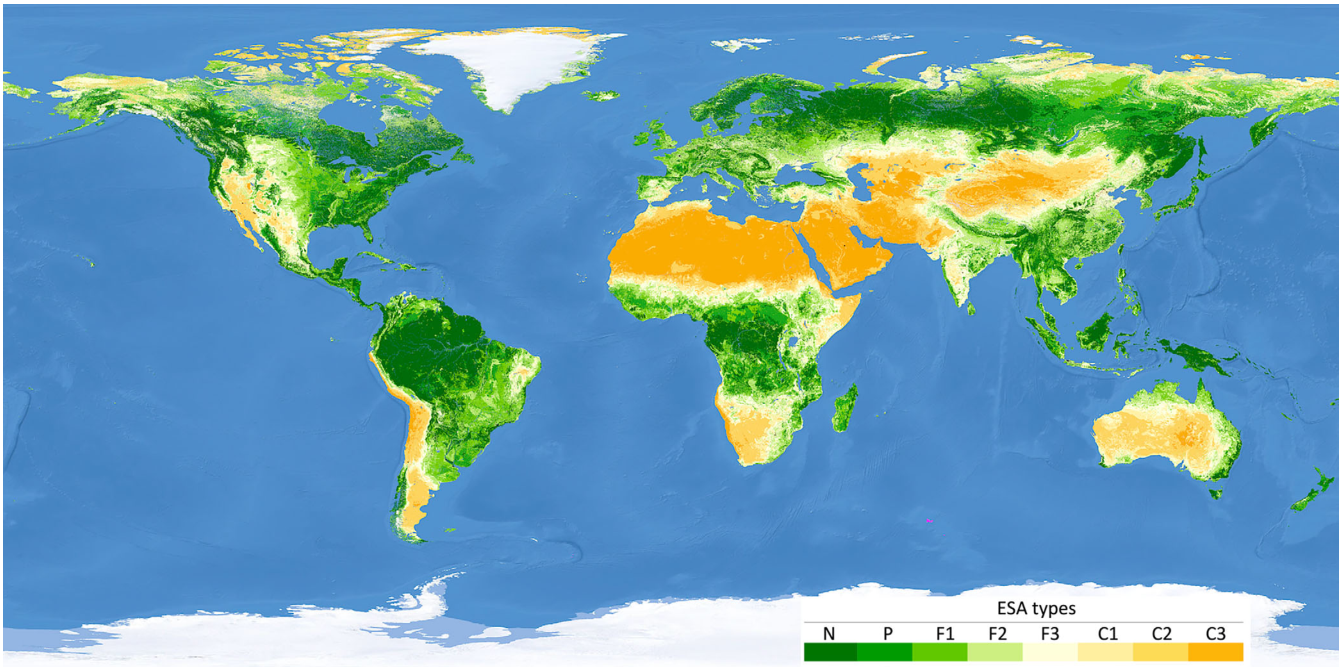

FIGURE 1 Environmentally sensitive areas map at the global level (Global-ESA) for 2015. See Table S2a in the Supporting Information for further details on ESA types. ESA, environmentally sensitive area [Colour figure can be viewed at wileyonlinelibrary.com]

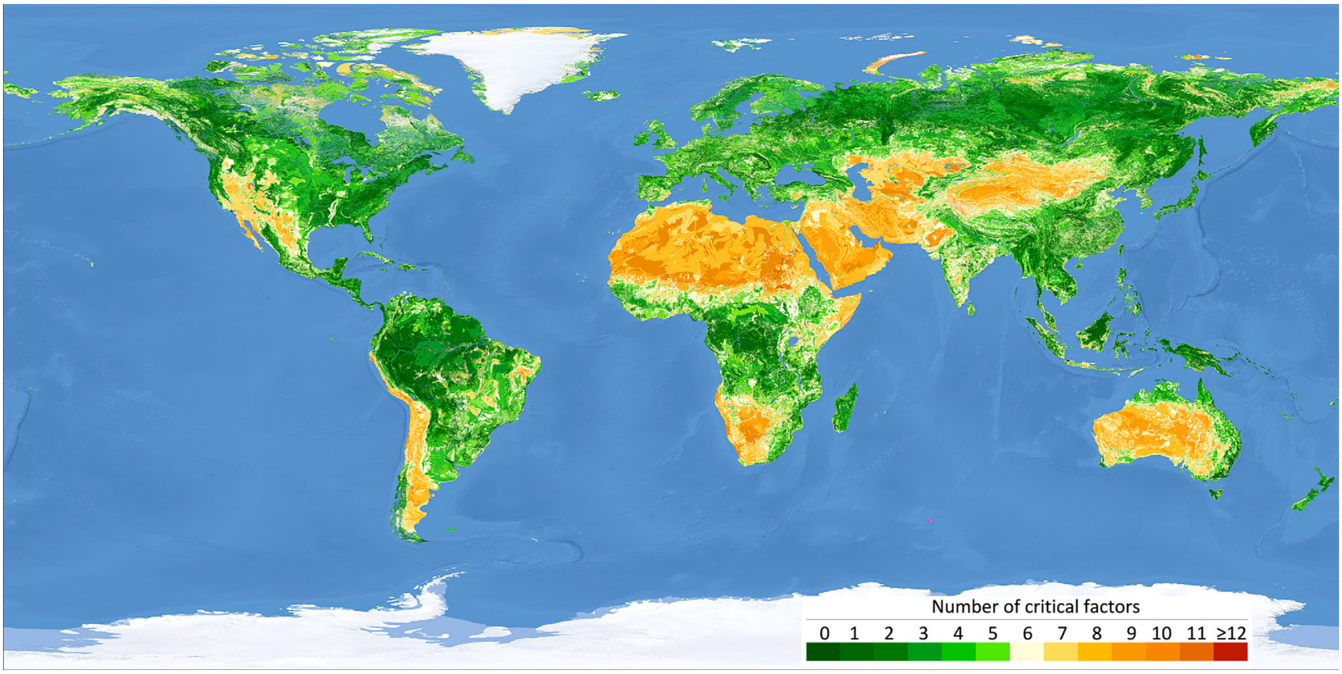

FIGURE 2 Environmentally critical factors map at the global level (Global-Environmentally critical factor) for 2015 (a factor is considered critical if the ESA score > 1.425) [Colour figure can be viewed at wileyonlinelibrary.com]

area shows an ECF index equal to 7, which is associated with the critical conditions for vegetation, climate, soil, and management. The reverse conditions were observed in Amazonia, Brazil, where some environmentally critical hotspots were observed, mainly in areas experiencing intense deforestation. These sites represent a sort of 'ignition point' for land degradation if background conditions worsen (e.g., increased soil aridity because of higher anthropogenic pressure due to the increase in population density, infrastructural development, and transformation into more intensive land-use types).

An integrated interpretation of the ESA and ECF maps demonstrates that the ESA framework allows for a particularly comprehensive analysis of the regional environmental and socio-economic

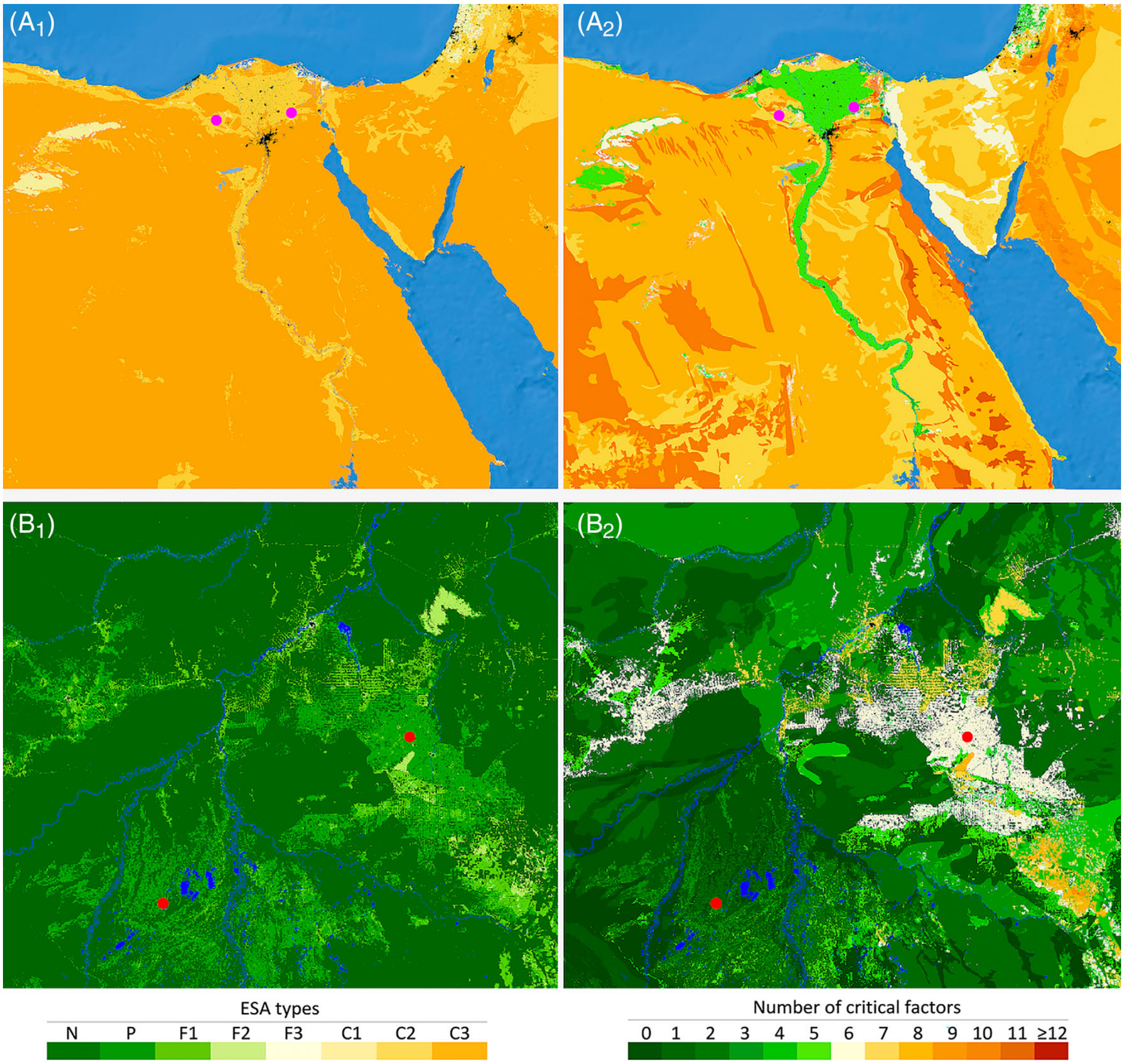

FIGURE 3 Examples of the integrated use of environmentally sensitive area (ESA; left) and environmentally critical factor (right) maps when assessing the overall level of land sensitivity to land degradation and desertification processes. (a) Nile Delta, (b) Amazon rainforest [Colour figure can be viewed at wileyonlinelibrary.com]

contexts underlying the different levels of sensitivity to land degradation, as detailed in the following sections.

3.2 | Assessment of the contribution of individual qualities to the ESA index

A preliminary analysis of the spatial patterns of the ESA index and the related quality indicators (CQI, SQI, VQI, and MQI) was carried out using a moving average of the values of each indicator in the sample, assessing the individual contribution of the quality indicators to the ESA index. Higher or lower scores in the ESA index indicated a negative (worsening) or positive (improving) contribution to the overall levels of land sensitivity to LDD. Figure 4 presents the spatial trend between the ESA index and the combined quality indicators (assessing soil, climate, vegetation, and management). Climate was the factor most likely to determine the level of land sensitivity above the selected 'critical' threshold (ESA index > 1.425). The vegetation factor also followed the same direction but had a milder intensity. Soil conditions contributed to land sensitivity only under relatively good climate, vegetation, and management conditions, that is, for land classified as 'not affected' or 'potentially affected.' Management moderately influenced the overall level of land degradation only in a restricted range of ESA scores that corresponded to land classified as 'fragile.' In other words, climate and vegetation were the two factors most likely to be associated with critical conditions of land sensitivity to LDD processes. Management was the factor that most likely determined the 'fragile' conditions to LDD, although the impact of vegetation and climate factors was low. Soil quality was a factor rarely associated with particularly high values of land sensitivity to LDD, but it played an important role in defining areas where sensitivity could shift towards critical levels because of the impact of multiple environmental factors.

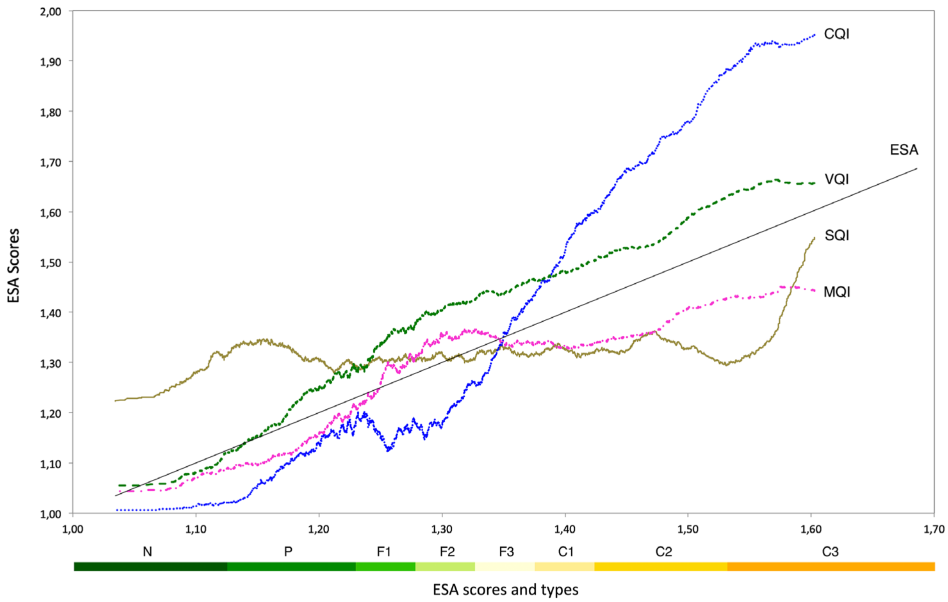

FIGURE 4 Relationship between average ESA (x-axis) and quality scores (y-axis). See Table S2a for further details on ESA types. CQI, climate quality; ESA, environmentally sensitive area; MQI, management quality; SQI, soil quality; VQI, vegetation quality [Colour figure can be viewed at wileyonlinelibrary.com]

3.3 | Evaluating the spatial pattern of individual ESA index variables

PCA was conducted on the individual variables comprising the ESA index (Table 3) at the sampling sites extracted in Section 2.9, and three components explained more than 60% of the total variance (Table S3). The data shown in Figure 5 highlight how PCA discriminated the critical factors into three main components. Component 1 (37.2%) is associated with vegetation (loading = 0.90) and climate (loading = 0.87) variables. Component 2 (12.8%) is exclusively associated with soil variables. Finally, Component 3 (10.0%) is associated with population density, which was used as a proxy for human pressure in MQI. Taken together, the results indicate that (a) climate and vegetation factors contributed synergistically to determine higher levels of land sensitivity to LDD and that (b) soil and management were factors that shaped land sensitivity to LDD independently from climate and vegetation.

The spatial distribution of the factor scores (Figure S3) classifies countries according to the dominant environmental factors characterizing the overall level of land sensitivity. Axis 1 distinguished Saharan countries in Africa and the Middle East, as well as selected countries from central Asia from the rest of the world. These countries can be considered as typically pre-desert, with the worst climate and vegetation conditions. These conditions represent the base of early desertification processes. Factor 2 was mainly associated with southern African countries, India, Australia, and countries in Latin America; specifically, Factor 2 discriminated for land conditions associated with low-quality and high-quality soils. Finally, Factor 3 identified countries with high anthropogenic pressure, mainly in Europe, India, and central Africa. Similarities in the spatial patterns characterizing environmental factors worldwide were studied by considering the results from hierarchical clustering as previously described. By producing a two-way dendrogram (Figure S4), cluster analysis allows for the discrimination of countries based on similarities in the distributions of individual factors that determine a more or less intensity level of land sensitivity to LDD. According to the results shown in the PCA, countries with the highest sensitivity to LDD, such as those in Africa and central Asia, were grouped into a unique cluster. Other affected countries around the world were clustered together.

TABLE 3 Results of a principal component analysis applied to the individual variables composing the ESA index

Variable	PC 1	PC 2	PC 3
Rock	−0.13	**0.74***	0.05
Texture	0.15	**0.51***	−0.14
Drainage	−0.08	0.42	−0.40
SoilGroup	0.49	−0.13	−0.18
Slope	−0.15	−0.47	0.09
Parent	−0.19	**−0.73***	−0.03
AI	**0.85***	0.04	−0.06
Precipitation	**0.76***	−0.11	−0.36
PlantCover	**0.91***	−0.06	−0.13
Drought	**0.90***	0.01	0.29
ErosionProt	**0.87***	0.05	0.36
Fire	**−0.61***	0.10	0.37
LUI	**0.88***	0.05	0.36
Pop	−0.15	0.10	**0.74***
§SQI	0.12	0.24	−0.32
§CQI	**0.87***	−0.05	−0.25
§VQI	**0.90***	0.03	0.30
§MQI	**0.68***	0.10	**0.66***
§ESA	**0.96***	0.05	0.08

Note: * as bold, indicates relevant factors with loadings >0.5; § indicates supplementary analysis variables.
Abbreviations: CQI, climate quality; ESA, environmentally sensitive area; MQI, management quality; PC, principal component; SQI, soil quality; VQI, vegetation quality.

The neural network was finally applied to the complete dataset (Figure S5). Based on the sample selected in Section 2.9, the internal coherency and reliability of the ESA estimates were confirmed by the high goodness-of-fit of the neural network with the empirical data. In

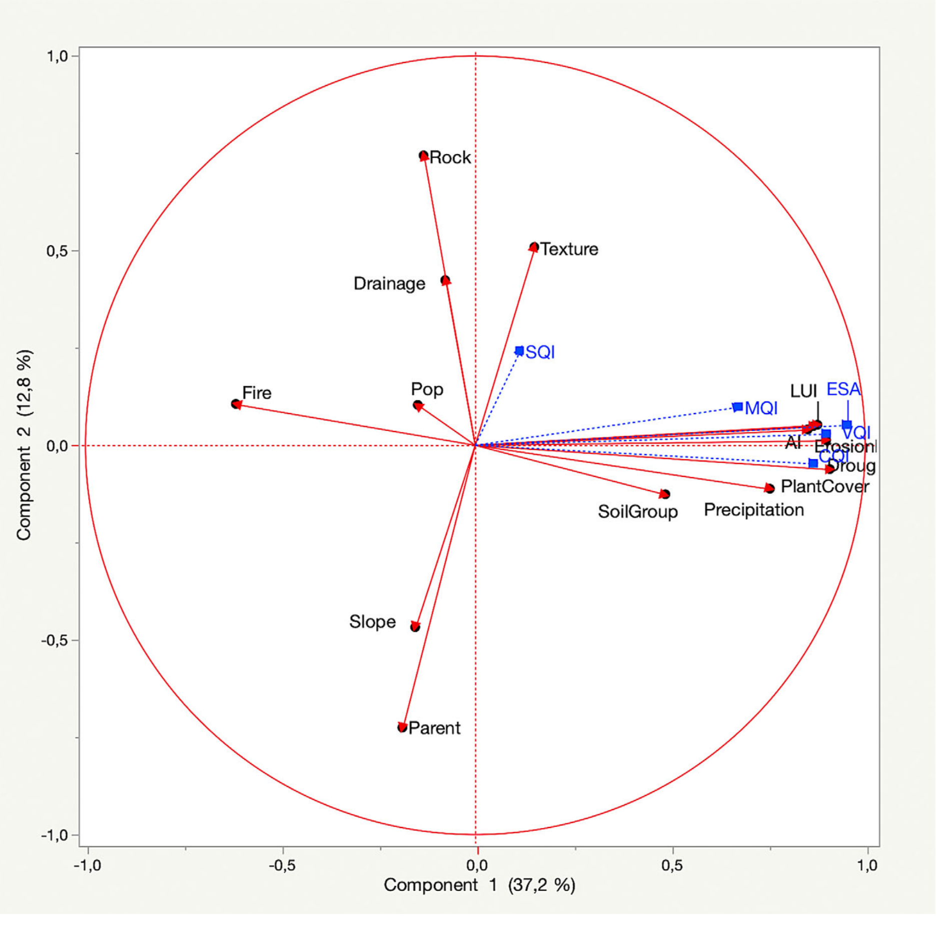

FIGURE 5 Principal component analysis loadings. Coloured variables indicate supplementary analysis variables. CQI, climate quality; ESA, environmentally sensitive area; MQI, management qualitys [Colour figure can be viewed at wileyonlinelibrary.com]

fact, training and validation were highly satisfactory for the ESA index (R^2 close to .99 in both phases), indicating the absence of variable outliers. The ESA index was also demonstrated to be stable over changing conditions in the composite variables and qualities (SQI, CQI, VQI, and MQI), and they were robust to different values of the qualities of the composite index. In other words, the variability of the composite index was quite constant at varying levels of environmental sensitivity, thus confirming the validity of this ESA framework update.

4 | CONCLUSIONS

Based on a common reference framework, the ESA update presented in this study allows analysing, in a robust operational scheme, the main LDD drivers in different areas worldwide. This objective was achieved by adopting a reliable set of key indicators to evaluate the level of land sensitivity to degradation and the multidimensional relationship among critical LDD factors. The originality of the ESA framework lies in the fact that land sensitivity is interpreted as the intimate combination of soil, climate, vegetation, and socio-economic aspects causing environmental degradation and/or unsustainable land management options. According to this perspective, the original ESA index and the new ECF composite index contribute to the analysis of the direct causes of LDD, allowing for a better understanding of the latent relationships underlying those processes.

Main outcomes of this study are as follows: (a) a newly updated framework (new variables, new class/score system, and new computing algorithm) for analysing and characterising LDD processes in different areas worldwide; (b) a methodological approach assessing ECFs of LDD and the spatial relationship among them; and (c) a reference framework for a better identification of site-specific factors shaping land sensitivity to LDD on local scales. These outcomes were specifically designed to support the development and implementation of sustainable policies and land management options to combat LDD at both regional and national spatial levels. The overall results from both Global-ESA and Global-ECF maps are in line with earlier assessments of land vulnerability to desertification worldwide (e.g., the World Atlas of Desertification, the USDA (1998) global desertification vulnerability map, Helldén et al., Helldén & Tottrup, 2008; Lu, Wang, & McCabe, 2016). At the same time, our approach provides a comprehensive assessment framework for evaluating the different LDD processes at a very detailed spatial scale (1-km^2 grid), with global coverage and the possibility of developing local scale applications within a coherent framework worldwide. Because an essential condition for the selection of the input variables was the availability of comparable and homogeneous time-series data with global coverage, the selected climate, soil, vegetation, and management variables together with this updated framework easily contribute to the setup of a dynamic monitoring system based on changes in the ESA index. From this perspective, the selection of the variables and the preparation of the maps were based on the ESA-CCI 2015 global land cover map, to calculate the ESA index for multiple time intervals.

However, the proposed update of the MEDALUS ESA framework has some shortcomings, assumptions, and innovations, which should be addressed by future research directions. It might be interesting

1. to define its performance in a multi-temporal analysis aimed at investigating the impacts of variable changes on socio-ecological systems in different areas of the world. In this ambit, further investigation could reduce shortcomings derived from the use of heterogeneous data sources over time and space. Additional studies are also needed to improve quality, temporal coherence, and spatial reliability of input variables, especially those related to climate and soil variables. Future research could also contribute to a better understanding of the relationships between the variable's rate of change and the rapidity of induced permanent changes in the different worldwide socio-ecological systems;
2. to evaluate the effects on the ESA and ECF indices due to adding (or removing) input variables, which is an often used characteristic of the ESA methodology in many site-specific applications. In this regard, further investigation could analyse the impacts of this assumption by better defining the context and significance of these changes, as well as their limits (e.g., the criteria for defining the score/class system of the new, used variables; the compatibility of their spatial scale with regards to the spatial context; the effects of these changes on the intermediate and final indices);
3. to better explore the role of other human-related factors (institutional, socio-economic, and cultural) within the ESA framework. In this update, the population variable efficiently summarizes many of the aspects of the human-induced stress on socio-ecological systems and ensures the availability and regularity of long time-series datasets. A diversified characterization of the human component within site-specific applications could be an interesting area for research insights;
4. to investigate the applicability and the performance of the new ECF map in analysing the LDD processes. The joint use of the ESA and the ECF maps represents a significant improvement of the overall MEDALUS ESA model's fit and prediction's quality and a promising ambit for future research.

ACKNOWLEDGMENTS

The authors acknowledge the valuable comments made by anonymous reviewers that greatly helped to improve the text and the excellent support of the editorial board in the reviewing process.

CONFLICT OF INTERESTS

The authors declare no conflicts of interest.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

How to cite this article: Ferrara A, Kosmas C, Salvati L, Padula A, Mancino G, Nolè A. Updating the MEDALUS-ESA Framework for Worldwide Land Degradation and Desertification Assessment. *Land Degrad Dev*. 2020;31:1593–1608. https://doi.org/10.1002/ldr.3559