Chapter 21

A Model for Evaluating Soil Vulnerability to Erosion Using Remote Sensing Data and A Fuzzy Logic System

Ignacio Meléndez-Pastor, Jose Navarro Pedreño,
Ignacio Gómez Lucas and Antonis A. Zorpas

Additional information is available at the end of the chapter

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Abstract

Soil vulnerability is the capacity of one or more of the ecological functions of the soil system to be harmed. It is a complex concept which requires the identification of multiple environmental factors and land management at different temporal and space scales. The employment of geospatial information with good update capabilities could be a satisfactory tool to assess potential soil vulnerability changes in large areas. This chapter presents the application of two land degradation case studies which is simple, synoptic, and suitable for continuous monitoring model based on the fuzzy logic. The model combines topography and vegetation status information to assess soil vulnerability to land degradation. Topographic parameters were obtained from digital elevation models (DEM), and vegetation status information was derived from the computation of the normalized difference vegetation index (NDVI) satellite images. This spectral index provides relevance and is updated for each scene, evidences about the biomass and soil productivity, and vegetation density cover or vegetation stress (e.g., forest fires, droughts). Modeled output maps are suitable for temporal change analysis, which allows the identification of the effect of land management practices, soil and vegetation regeneration, or climate effects.

Keywords: soil vulnerability, fuzzy logic, remote sensing, soil erosion, soil degradation

1. Introduction

Soil is considered a nonrenewable resource, and it is essential for food security and for our sustainable future and is defined as the top layer of the earth's crust formed by mineral particles, organic matter, water, air, and living organism [1]. Desertification associated to soil erosion processes is the main topic to protect and maintain soils. Moreover, desertification and land degradation are terms that are used in order to indicate ecosystem productivity and are associated with loses of vegetation covered [2]. The United Nations program against desertification is crucial as it focuses on fighting hunger and poverty, foresting stability, and building resilience to climate change in some of the world's most vulnerable areas [3]. Soil erosion, water-holding capacity, salinity, sodicity, losses of nutrients, etc. are common indicators used to categorize land degradation [1]. The genesis of soil is a long process, and the formation of a layer of 30 cm depth takes from 1000 to 10,000 years [4]. This scenery created between soil degradation and the long process of formation gives us few alternatives about soil conservation, which is essential for humans.

Soil vulnerability is the capacity of one or more of the ecological functions of the soil system to be harmed, i.e., biomass production, filtering, buffering and transformation medium, gene reserve, and protection of flora and fauna [5]. In other words, it is the sensitivity of soil against degrading processes.

The most important degrading process worldwide related to desertification, among others, is soil erosion as a result of climate change. Climate change is one of the major drivers of an ecosystem shift in a decertified state [6]. The vegetation plays a key role protecting soil. Moreover, soil erosion is associated to biomass production which has an important role in the future energy situation [7]. There are several factors affecting soil erosion. However, vegetation and topography play a crucial role in the vulnerability of soil. The first one is the most important source of organic matter to soil, protecting it against rain and wind (water and wind erosion) [8]. The second one determines and facilitates the losses of soil due to erosive processes and transport.

Soils with low vegetation cover and high slopes are more vulnerable against degrading processes. For this reason, it is very important to know these factors to establish the vulnerability of a soil in order to protect it, prevent erosion, and keep resources for a sustainable future use.

Many countries like Cyprus, Greek Islands, Spain, and Italy are affected by soil erosion, and there are many problems to access or obtain soil data because of the orography, accessibility, or other environmental factors. It is estimated that more than 115 million hectares which represents 12% of European total land are subject to erosion [9]. Moreover, it is estimated that, in the Mediterranean area (consists of a vulnerable area due to climate change effects), water erosion could affect the loss of 20/40 ton/ha of soil after a single cloudburst, and in extreme cases, the erosion could be even more than 100 ton/ha [10, 11]. For this reason, it is important to have techniques that facilitate the creation and population of spatial information. These techniques are englobed in digital soil mapping (DSM) which are systems composed by numerical models inferring the spatial and temporal variations of soil types and soil properties from soil observation and knowledge and from related environmental variables [12]. It is important to have an overview of the state and properties of soils for decision-makers and to facilitate the population and access to soil data. We cannot forget that land and water resources are central to agriculture and rural development and are intrinsically linked to global challenges of food insecurity and poverty, climate change adaptation and mitigation, as well as degradation and depletion of natural resources that affect the livelihoods of millions of rural people across the world. [13].

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The use of easy models that can be applied by administration for decision-making plays a key role for resource conservation and people. In this sense, the models based on remote sensing data and mathematical models as those based on fuzzy logic systems can be helpful.

The models based on fuzzy logic systems are related to fuzzy set theory which plays a primary role in fuzzy logic. Zadeh developed the theoretical basis of this theory and defined the concept of fuzzy sets as "A fuzzy set A in X is characterized by a membership function fA(x) which associates with each point in X a real number in the interval [0, 1], with the value of fA(x) at x representing the 'grade of membership' of x in A. The nearer the value of fA(x) to unity, the higher the grade of membership of x in A" [14]. The more interesting property is that fuzzy sets work well with data uncertainties. A strict categorization (with discrete classes) of environmental/soil factors falls within subjectivity and carelessness of uncertainties (e.g., error measurements, selection of decimals, missed data, etc.). Fuzzy sets are used for classifications where the classes do not have sharply defined boundaries [15]. This approach is easily applied for environmental phenomena study, such as soil nutrient losses, atmospheric pollutant dispersion, forest productivity, etc., due to the great spatial variability and possible discontinuity of those phenomena.

Fuzzy theory provides a rich mathematical basis for understanding decision problems and for constructing decision rules in multi-criteria evaluation and combination [16]. A wide variety of fuzzy logic approaches have been developed in order to expand the concept of fuzzy sets. Fuzzy measure refers to any set of function which is monotonic with respect to set membership [17]. The variety of functions that can be applied is great. In fact, a fuzzy function is a generalization of the concept of a classical function. A classical function f is a mapping (correspondence) from the domain D of definition of the function into a space S; $f(D) \subseteq S$ is called the range of f. Different features of the classical concept of a function can be considered fuzzy [18]. Fuzzy measures include Bayesian probabilities, beliefs and plausibilities of Dempster-Shafer theory, and membership grades of fuzzy sets, providing a framework for the methodologies of uncertainty studies [19].

In this process, fuzzy sets and soil erosion are combined in order to facilitate decision-making based on easy criteria that can be applied by administration. Desertification, climate change, and soil productivity have to be considered. The need of global understanding of local processes and the possibilities of the computers and remote sensing techniques are the bases of this methodology. For these environmental, social, and economic reasons, it is necessary to have a tool for taking decisions. On the one hand, decision theory is concerned with the logic by which one arrives at a choice between alternatives [20]. On the other hand, the procedure by which one selects among different alternatives is enabled by a decision support system (DSS). The study of decision support systems is an applied discipline that uses knowledge and especially theory from other disciplines [21]. In this case, the knowledge of soil science and mathematical modeling helps us build an effective DSS.

A type of decision support system widely used is the multi-criteria evaluation (MCE) based on multi-criteria analysis (MCA) of analytical hierarchy process (AHP) [22, 23]. The AHP analysis is based on three basic principles as indicated by Zorpas and Saranti [22], and those include the preferences configuration, the interruption of the problem into subproblems, and finally the pair-wise comparison of criteria/subcriteria with the proposed alternative scenarios. The MCA [22, 23] focuses on four main stages starting with recognition of the problem (if possible to split in subproblems) and the formation of a hierarchical structure, followed by the pair-wise comparison of decision elements used to derive normalized absolute scales of numbers whose elements are then used as priorities, and continued with the control of the priorities set (to solve the problem) and finally the assessment and the evaluation of the alternative scenarios to solve the specific problem. This methodology can be used from decision-makers, engineers, consultants, researchers, and governmental and local authorities in order to evaluate or propose specific solution in a specific problem [21].

The MCE explores how to combine the information from several criteria to form a single index of evaluation using discrete or continuous factors [21–23]. For this purpose in environmental sciences, thematic information aggregation procedures are used in the process of criteria combination. Two traditions of aggregation procedures have been extensively used for MEC [24]: (1) Boolean overlay where all criteria are assessed by thresholds of suitability to produce Boolean maps using logical operators such union, intersection, or negation and (2) weighted linear combination (WLC) where continuous criteria are standardized (generally by a simple linear transformation) to a common numeric range and then combined by weighted averaging. Both aggregation criteria are rather inflexible as consequence of their inherent logic aggregation (type of operators and properties).

Aggregation operations on fuzzy sets are operations by which several fuzzy sets are combined in a desirable way (assuming some rules and operators) to produce a single fuzzy set [25]. Fuzzy measures provide a theoretical base to explore an expand understanding of MCE processes and the design of new aggregation operators [24]. Two traditions of logic operators have been extensively used since decades [26]: (1) MIN and MAX operators for Boolean overlay and fuzzy membership aggregation and (2) averaging operator for weighted linear combination. Jiang and Eastman [24] suggested the use of weighted linear combinations as a fuzzy set membership operator together with the MIN and MAX operators, in the framework of fuzzy measures. This is a very flexible approach for fuzzy set aggregations. In this chapter, the proposed soil vulnerability model related to soil erosion is based on this approach for fuzzy set aggregation and easy functions for the analysis.

2. A fuzzy logic model to evaluate soil vulnerability

Soil erosion may be considered the most important degradation processes in this approach, and the vulnerability of soils is based on the most important criteria affecting this process. Two types of information used by this model are (1) topographic parameters and (2) vegetation. Remote sensing techniques allow us to have data from any part of the Earth. For instance, digital elevation models (DEMs) which can describe the topography of any region can be derived from data obtained by the Shuttle Radar Topography Mission of NASA [18] and many other platforms. Remote sensing techniques can also provide vegetation status data for the analysis. For instance, data obtained from Landsat missions [27] or other programs facilitate the calculus or vegetation index like normalized difference vegetation index (NDVI).

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The analytical capabilities derived from the use of DEM are enormous, ranging from basic topographic feature estimation, to flood simulations, and others. Moreover, remote sensing has a great potential to obtain imagery from optical, thermal, and microwave spectral regions across wide regions of the planet with a great temporal frequency, enough accuracy, and open source. Image processing methods of remotely-sensed data could extract valuable and specialized information of selected targets (e.g., soils, vegetation, waters, etc.). An added value of image processing techniques is the capability to analyze temporal series of data which can be useful to study the vulnerability and changes occurred in soils along time.

The proposed model is based on a set of three initial inputs, selected considering the previous indications (**Figure 1**):

- Slope: This topographic parameter could be derived from a DEM, and it is defined as the variation of altitude between two points in relation with the distance that separate them. Slope parameter reports information about the roughness of the territory and plays a key role in soil erosion because it could increase or reduce the effect of water [28]. The universal soil loss equation (USLE), and derived equations from this, considers slope parameter as a key factor for superficial soil water erosion [29].
- Aspect: This topographic parameter could be derived from a DEM. It reports information about the geographic orientation of the slopes. As a general rule (in the north hemisphere), a slope closer to a north aspect presents lower temperature and higher moisture levels

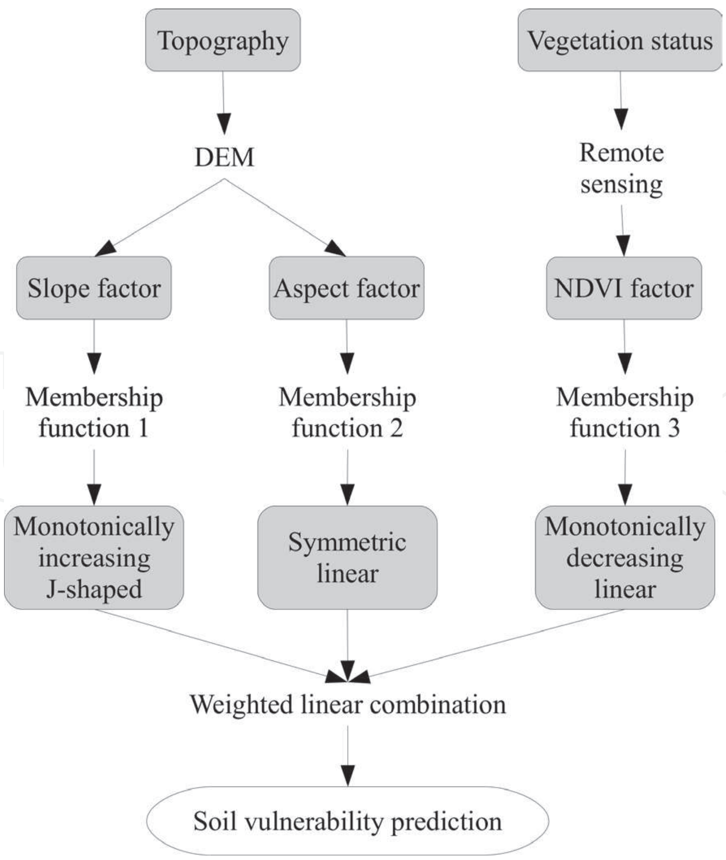

Figure 1. Flowchart of the fuzzy logic model to soil vulnerability evaluation.

(lower incident radiation levels). This parameter could suggest information about soil moisture, water availability by plants, etc. This general rule could be dismissed in special local situations (e.g., for places where wet maritime winds impact against slopes closed to a south aspect). This factor is of great importance in plant distribution and growth and soil development and properties [30].

- Normalized difference vegetation index (NDVI) is computed as a normalized ratio between near infrared (NIR) and red spectral bands of remotely-sensed imagery. NDVI values range between −1 and +1. This vegetation index is strongly related with several vegetation parameters such as changes in biomass and chlorophyll content [31, 32]. NDVI is related with other vegetation parameters too [33] such as leaf water content, CO_2 net flux, absorbed photosynthetically active radiation (APAR), and leaf area index (LAI), among others. A high NDVI value (usually over 0.3–0.5) indicates a vigorous and dense vegetal coverage.

Slope, aspect, and NDVI are the parameters computed in our model and could be extracted for wide regions from remote sensing data. Those parameters are computed following the flowchart as **Figure 1** presents, with an easy function that can be implemented. The simplicity of the model may be the limiting factor because only three inputs are taken into account.

However, this tool is good enough to have an overview of the soil erosion and could be a good tool for regional soil vulnerability assessment and long-term monitoring with a low economic cost. A near real-time monitoring of soil vulnerability, depending on the availability of data from satellite, could be performed and used by land managers and scientist. The main advantage in this sense is that field campaign to check soil, vegetation status, slope, and other filed parameters is initially not necessary. Moreover, the centered field work in determined areas reduces the cost of large field campaigns of wide territories.

The proposed model considers input parameters as fuzzy sets (factors) to be standardized by the definition of individual membership functions. A great variety of fuzzy set membership functions have been developed.

Based on Eastman [16], fuzzy set membership functions can be defined by three parameters:

- Shape of the function that provides three possible options: (1) monotonically increasing which begins at 0 and then rise and stay at 1, (2) monotonically decreasing which is opposite to the previous one, and (3) symmetric which firstly rise and then fall again
- Control points that govern the shape of the curve
- Type of function with three possible options: (1) sigmoidal produced by a cosine function, (2) J-shaped produced by a sine function, and (3) linear produced by a linear function

The definition of these parameters provides a great number of possibilities to define the effect of individual factors in the observed phenomena. The shape and type of membership functions should be defined according to the knowledge of environmental phenomena. Weighted linear combination is used for the standardized aggregation factors. This method allows the possibility to assign equal or differential weights to factors in function of experts' knowledge about their relative importance for the studied phenomena. Finally, it is important to mention that this simple model approach could be completed with other factors to be considered in

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the aggregation process or in other stages of the model. Equilibrium must be found between model simplicity and valuable obtained data to soil conservation.

3. Soil vulnerability under high slope changes: a case study

A test of soil vulnerability evaluation of this model after a fire event was done, considering that the area to test the model has many changes in slope and is close to the sea, affected from marine breeze and moisture. The selected area is located on the south-east coast of Spain (Alicante province) in the area of “La Granadella” (38.73°N, 0.19°E). This test site supported a fire event from 26 to 30 on August 2000. The topography is characterized by a highly rough relief (cliffs above the sea of more than 150 m) and a wet Mediterranean climate (700–1000 mm/year of rainfall). This is an interesting test area which combines a wet climate and a complex and precipitous relief and exhibits a great recurrence of fires.

The hypothesis to verify with the fuzzy logic model is that vegetation regeneration has a primary role in soil vulnerability reduction. The potential advantage for the use of fuzzy sets with respect to other methods of factor combination must be owed to their great flexibility derived from the defined membership functions.

Vegetation status information was obtained from two satellite scenes acquired by the multispectral advanced spaceborne thermal emission and reflection radiometer (ASTER): (http://asterweb.jpl.nasa.gov/) sensor. The first scene was acquired 4th October in 2000, some days after the forest fire, while the second scene was acquired 7th June in 2003, being a reasonable period for a substantial evolution in the landscape.

ASTER sensor is composed of three subsystems in function of their spectral and spatial resolution characteristics: visible near-infrared radiometer (VNIR) with 15 m of spatial resolution and stereoscopic capability, short-wave infrared radiometer (SWIR) with 30 m of spatial resolution, and thermal infrared radiometer (TIR) with 90 m of spatial resolution [34]. Only VNIR system bands were employed for our analyses. Both scenes were in origin preprocessed to an ASTER high-level product denominated AST_07 which contain data of surface reflectance [35].

Topographic information was obtained from a high-resolution digital elevation model (**Figure 2**) that was computed using the previous vector cartography (scale 1:10,000). Triangulated irregular network (TIN) polygons were computed with the nodes of the vector cartography and used to develop the raster DEM. The spatial resolution of the DEM was adjusted to ASTER-VNIR imagery (15 m). Satellite images were geometrically corrected using the high-resolution DEM and additional cartography in order to minimize the positional errors among the different sources of information. The root-mean-square error (RMSE) of the geometric correction was less than half a pixel for both ASTER scenes.

Topographic parameters (slope and aspect) were computed using the DEM. Both parameters were quantized as degrees. Normalized difference vegetation index is derived from a spectral band transformation between near-infrared and red bands. The original NDVI formulation has been attributed to Rouse et al. [36] and their research with early Landsat images. The original NDVI formulation has been adapted to subsequent sensors whose spectral characteristics are

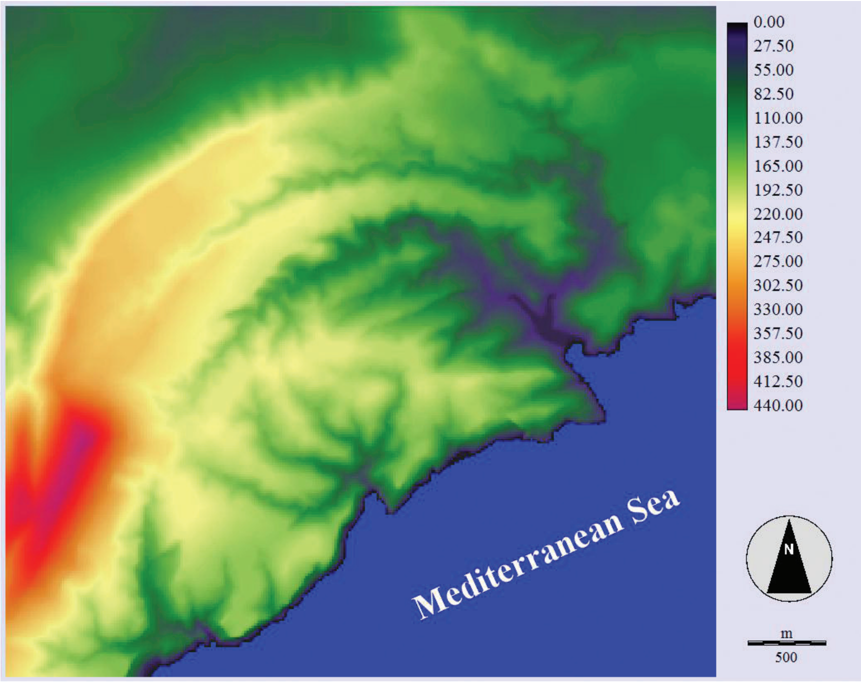

Figure 2. Digital elevation model (DEM) of "Sierra de Escalona" test site.

different among them. The following equation is the adaptation of NDVI for ASTER spectral bands (Eq. (1)):

$$\mathrm{NDVI} = \frac{\rho_{\mathrm{VNIR3}} - \rho_{\mathrm{VNIR2}}}{\rho_{\mathrm{VNIR3}} + \rho_{\mathrm{VNIR2}}} \tag{1}$$

where ρ_{VNIR2} is the spectral reflectance for the second band of the ASTER-VNIR subsystem and ρ_{VNIR3} is the spectral reflectance for the third band of the same subsystem. The computation of NDVI is more suitable with surface reflectance data (like AST_07 high-level ASTER product) in order to minimize differential wavelength-dependent atmospheric disturbances. NDVI was computed in the same way for the 2000 and 2003 scenes (**Figure 3 (a)** and **(b)**).

Soil vulnerability estimations were computed for both 2000 and 2003 scenarios. Individual fuzzy set membership functions are characterized by their shape and type and were defined for each of the considered soil vulnerability factors (i.e., slope, aspect, and NDVI). In this sense, **Table 1** provides a synthesis of model parameters used with the fuzzy logic model. The proposed model employed the following membership function for input variables: (1) NDVI, a monotonically decreasing linear function; (2) slope, a monotonically increasing J-shaped function; and (3) aspect, a symmetric linear function. Membership functions required the definition of several control points (CP) for a potential model generalization.

Fuzzy membership functions were combined weighting the relative importance of each one using a linear system. Jiang and Eastman [24] suggested the use of weighted linear combinations as a fuzzy set membership operator together with the MIN and MAX operators, as a very flexible approach for fuzzy set aggregations.

This weighting process considers the relative importance of each variable in the modeling process. Vegetation and slope were considered the most important factors for the soil vulnerability model.

Further details of the definition of membership functions and model calibration are available in Melendez-Pastor et al. [37]. Finally, a temporal change analysis of soil vulnerability was computed using the percentage of change procedure employing the following formulation (Eq. (2)):

$$\text{Temporal change }(\%) = \frac{(t_2 - t_1)}{t_1} \cdot 100 \tag{2}$$

where t_1 and t_2 are the soil vulnerability estimations for 2000 and 2003, respectively.

The application of the fuzzy logic model for this study area covers two environmental facts, an (almost) invariant one associated to the slope and orientation (which are mainly determined by the geomorphology of the landscape) and a highly changing parameter as the vegetation through NDVI. Landscape topography greatly affects soil profile formation [30, 38], while vegetation status and dynamics are highly related with the quality of the soils [39]. The DEM analysis revealed that the study area has a mean slope value of 16 degree, with a maximum slope value of 78 degrees. Relief is mainly configured on a NE-SW direction with preferential slope orientation to the SE direction. NDVI mean values varied from 0.31 (standard deviation of 0.12) on 2000 to 0.38 (standard deviation of 0.09) on 2003.

Soil vulnerability simulations (**Figure 3 (c)** and **(d)**) revealed the severe impact of the forest fire on vegetation. The model marks the importance of vegetation dynamics, the relation with the presence of soil although both are limited to the position as the model indicates (slope and

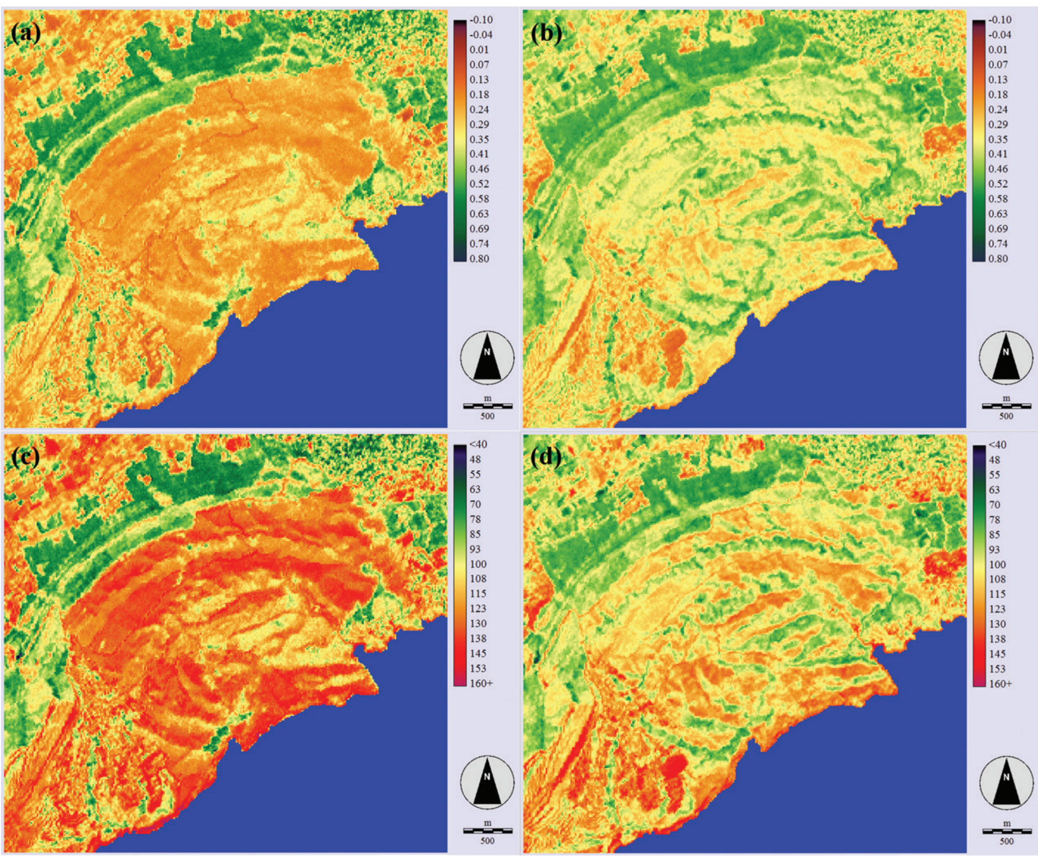

Figure 3. NDVI estimations for 2000 (a) and 2003 (b). Soil vulnerability estimations for 2000 (c) and 2003 (d). Soil vulnerability results area in 8 bits of quantization.

Factors		Slope	Aspect	NDVI
Membership functions	Shape	Monotonically increasing	Symmetric	Monotonically decreasing
	CP 1	0	0	0
	CP 2	90	180	1
	CP 3	No	180	No
	CP 4	No	360	No
	Type	J-shaped	Linear	Linear
Weights		0.35	0.05	0.6

Table 1. Model parameters for the soil vulnerability factors slope, aspect, and NDVI.

aspect). A characteristic pattern of soil vulnerability mitigation by intense vegetation regeneration could be advertised along the valleys where NDVI has increased faster since 2000. The temporal change estimation of soil vulnerability simulations (**Figure 4**) remarks the local high postfire ecosystem regeneration. Change rates are up to a 30% of less soil vulnerability within burned area. Soil vulnerability change map also highlighted areas where soil vulnerability has increased. Those changes correspond to land use conversions to urban (change rates up to a 30% of more soil vulnerability) and vegetation status variations.

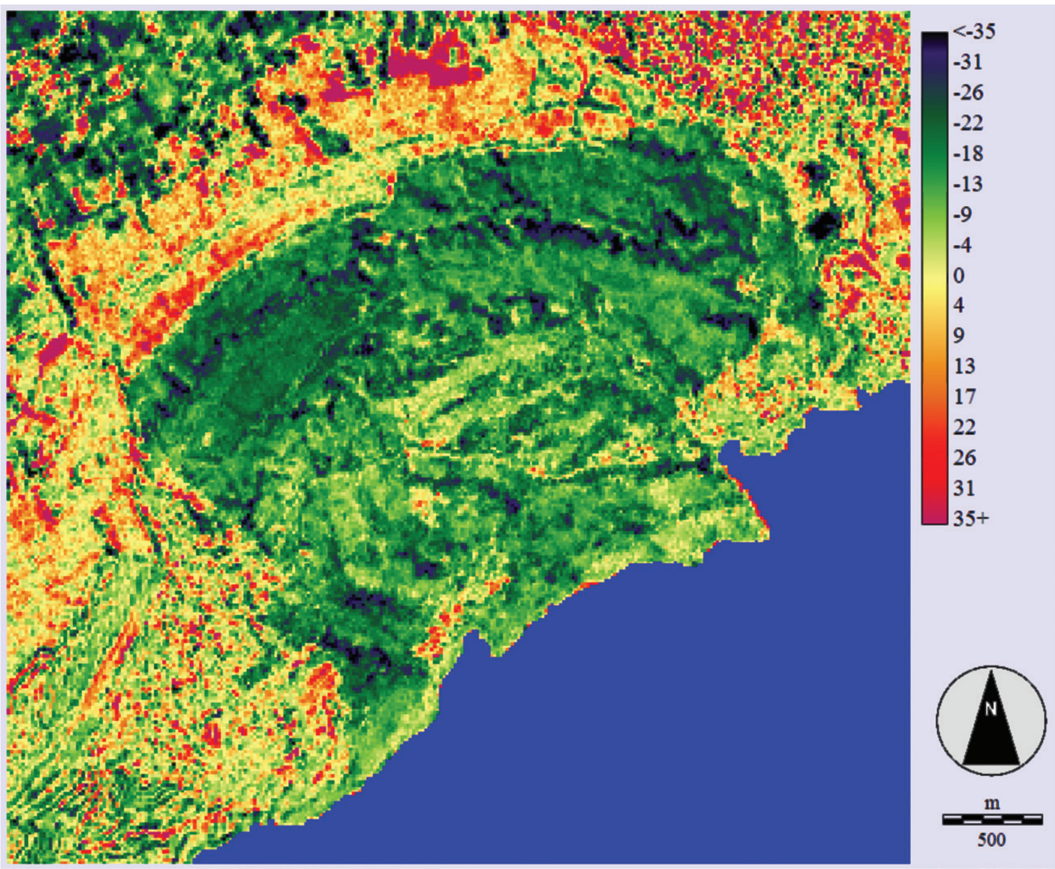

Figure 4. Temporal change (%) of soil vulnerability estimation. Green pixels correspond to less vulnerable areas on 2003.

4. Soil vulnerability and vegetation as a limiting factor

The proposed model was also engaged in a research of soil vulnerability evaluation in a semiarid area in the south of Alicante province (Spain). This study area is located in a portion of the "Sierra de Escalona" (37.97°N, 0.86°W), an area with altitudes ranging from 80 to 340 m.a.s.l., a semiarid Mediterranean climate with hot summers and scarce precipitations (less than 250–300 mm), and fragile soils severely affected by erosion and land degradation processes. Dominant land cover classes are intensive agriculture (citrus and almond trees) at low to medium slopes, xerophytic shrubs in abandoned fields and marginal areas, and sparse *Pinus halepensis* stands at the highest slopes. A large reservoir fed by a transbasin diversion is located in the north of the study area. This is an interesting test area which combines a semiarid climate, intensive exploitation of soil resources by agriculture, and high erosion rates resulting transport of sediments and nutrients to the reservoir.

The hypothesis to verify with this fuzzy logic model application is that soil vulnerability is enhanced during drought periods when vegetation status is less protective against land degradation drivers. The engagement of satellite images allowed the estimation of soil vulnerability changes within a drought period and between hydrologic years with different precipitation patterns (drought vs. normal year).

A comparison of the changes regarding soil vulnerability between late spring/early summer and late summer for different hydrologic years was included in this research. The selections of the dates were based on meteorological information and satellite image availability. Meteorological information for the nearby Pilar de la Horadada town meteorological stations was obtained from the Spanish Agroclimatic information System for Irrigation (Ministry of Agriculture and Fisheries, Food and Environment). Precipitation data indicated that the 2000 water year was characterized by a severe drought (169.8 mm), while 2003 was a more regular hydrologic year (253.0 mm). This information was the starting point for the compilation of vegetation and topography datasets.

Four satellite scenes acquired by the multispectral ASTER sensor were employed to obtain vegetation information. Two scenes were acquired for the 2000 hydrologic year (June 30 and August 1) and two other images for the 2003 water year (May 22 and August 10). The first images correspond to the end of spring and early summer, while the second scenes correspond with the end of summer. Only VNIR system bands (15 m of spatial resolution) were employed for our analyses. Both scenes were in origin preprocessed to the ASTER high-level product of surface reflectance (AST_07).

Topographic information was obtained from a high-resolution digital elevation model (**Figure 5**) that was computed using the previous vector cartography (scale 1:10,000). Triangulated irregular network (TIN) polygons were computed with the nodes of the vector cartography and used to develop the raster DEM in the same way as the previous case study. The spatial resolution of the DEM was adjusted to ASTER-VNIR imagery (15 m). Satellite images were geometrically corrected using the high-resolution DEM and additional cartography in order to minimize the positional errors among the different sources of information. The root-mean-square error (RMSE) of the geometric correction was less than half a pixel for both ASTER scenes.

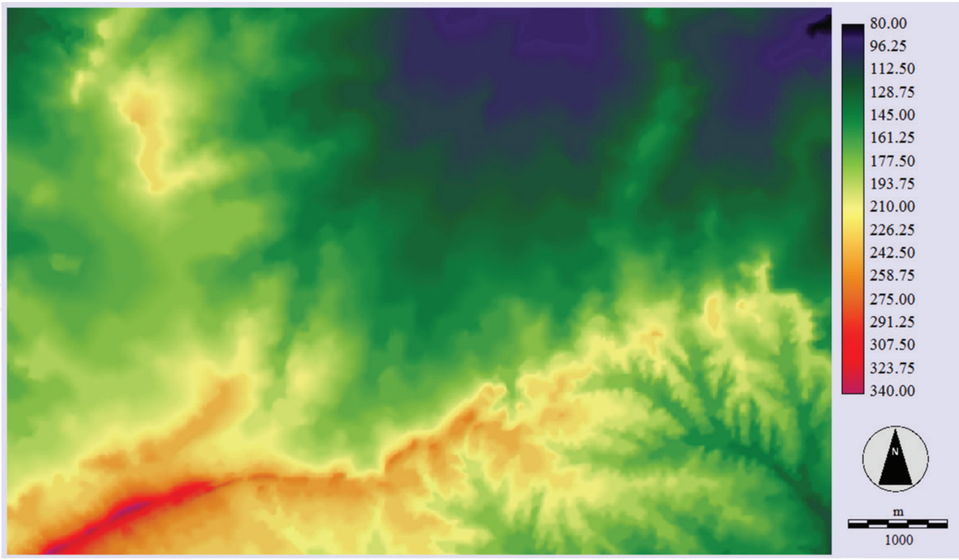

Figure 5. Digital elevation model (DEM) of "La Granadella" test site.

Slope and aspect were computed using the DEM and quantized as degrees. Normalized difference vegetation indices were computed with the surface reflectance data spectral band transformation between near-infrared and red bands according to Eq. (1). Soil vulnerability estimations were computed for the four dates of the ASTER scenes (**Table 2**). The proposed model employed the following membership function and weights for input variables: (1) NDVI, a monotonically decreasing linear function with a weight value of 0.4, (2) slope, a monotonically increasing J-shaped function with a weight value of 0.4, and (3) aspect, a symmetric linear function with a weight value of 0.2. Membership function control points were the same of the previous case study. Further details of the definition of membership functions and model calibration are available in Melendez-Pastor et al. [40]. Finally, a temporal change analysis of soil vulnerability was computed using the percentage of change procedure employing the formulation of Eq. (2). Temporal change analyses were done between different seasons for the same year estimations (E01 vs. E02 and E31 vs. E32) and between the same seasons for different years (E01 vs. E31 and E02 vs. E32).

NDVI estimations highlighted the critical importance of hydrologic year accumulated precipitation for the maintenance of vegetation status for nonirrigated areas. In **Figure 6 (a)** and **(b)**,

Estimation	**Year**	**Season**	**ASTER scene**	**Accumulated precipitation**
E01	2000	Spring summer	06-30-2000	167.2
E02	2000	Late summer	08-01-2000	167.8
E31	2003	Spring summer	05-22-2003	246.4
E32	2003	Late summer	08-10-2003	250.0

Table 2. Soil vulnerability estimations and employed ASTER scenes. Hydrologic year accumulated precipitation for Pilar de la Horadada meteorological station is shown.

the largest portion of the study area corresponds with nonirrigated crops, sclerophyllous vegetation, and some coniferous forest areas. They had very low NDVI values, while irrigated areas and some wet ravines exhibited quite high NDVI values (0.4–0.6). These NDVI images correspond with an intense drought water year with less than 168 mm of accumulated precipitation.

Climatic conditions for the hydrologic year 2003 were very different with almost 50% more precipitation. Greener areas in **Figure 6 (c)** and **(d)** correspond with the irrigated crops and also with some coniferous forest and dense sclerophyllous vegetation areas. More intense NDVI changes for irrigated crops were associated with the harvest of seasonal crops.

High values of soil vulnerability estimations were obtained for almost the whole study area in all the scenes (**Figure 7**), due to the abrupt orography and the lack of vigorous vegetation cover. Southern slopes with high slope values are shown as the most vulnerable areas since its vegetation cover, and edaphic development is very scarce. The lowest soil vulnerability estimations were obtained for some crop fields with permanent crops in flat areas.

Temporal change analyses between different seasons for the same year estimations were done. **Figure 8 (a)** corresponds with the change in 2000 (E01 vs. E02), and **Figure 8 (b)** is for the change in 2003 (E31 vs. E32). The most remarkable changes were associated with the irrigated crops. Temporal crops had been collected within the period of time of the change analysis, and the soil vulnerability increased by the elimination of the vegetation cover. On the other hand, temporal change between the same seasons but for different years (2000 vs. 2003) was analyzed. **Figure 8 (c)** corresponds with the change analysis for late spring-early summer (E01 vs. E31), while **Figure 8 (d)** corresponds with the change analysis for late summer (E02 vs. E32).

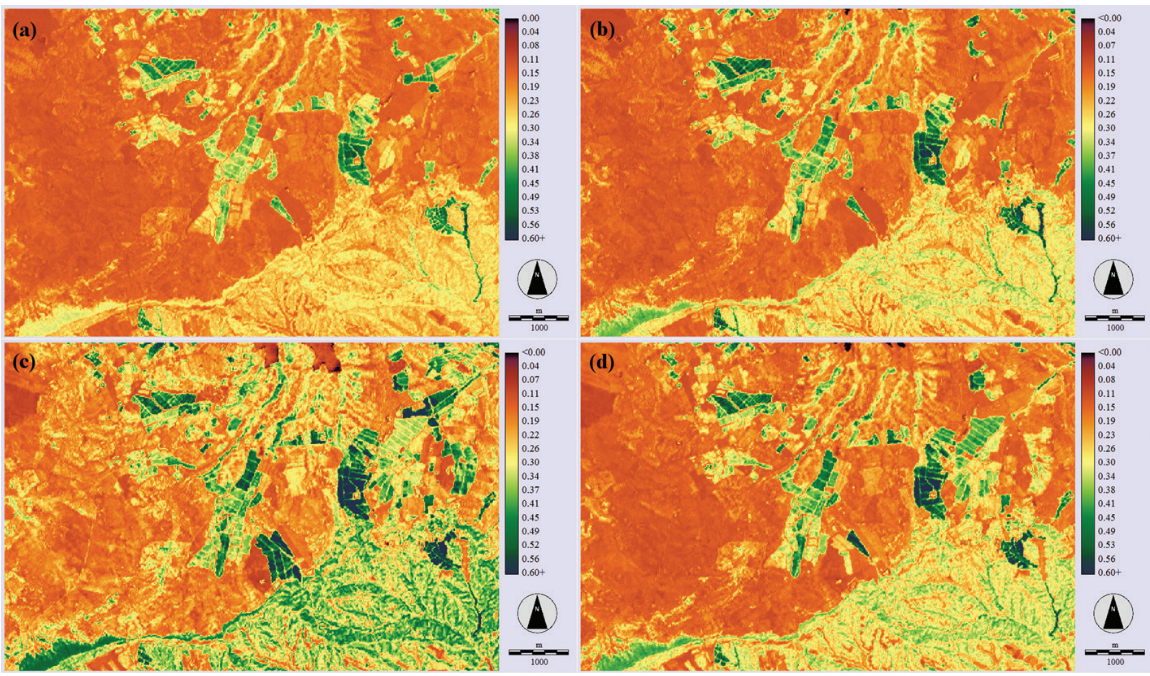

Figure 6. NDVI images for the estimations E01 (a), E02 (b), E31 (c), and E32 (d).

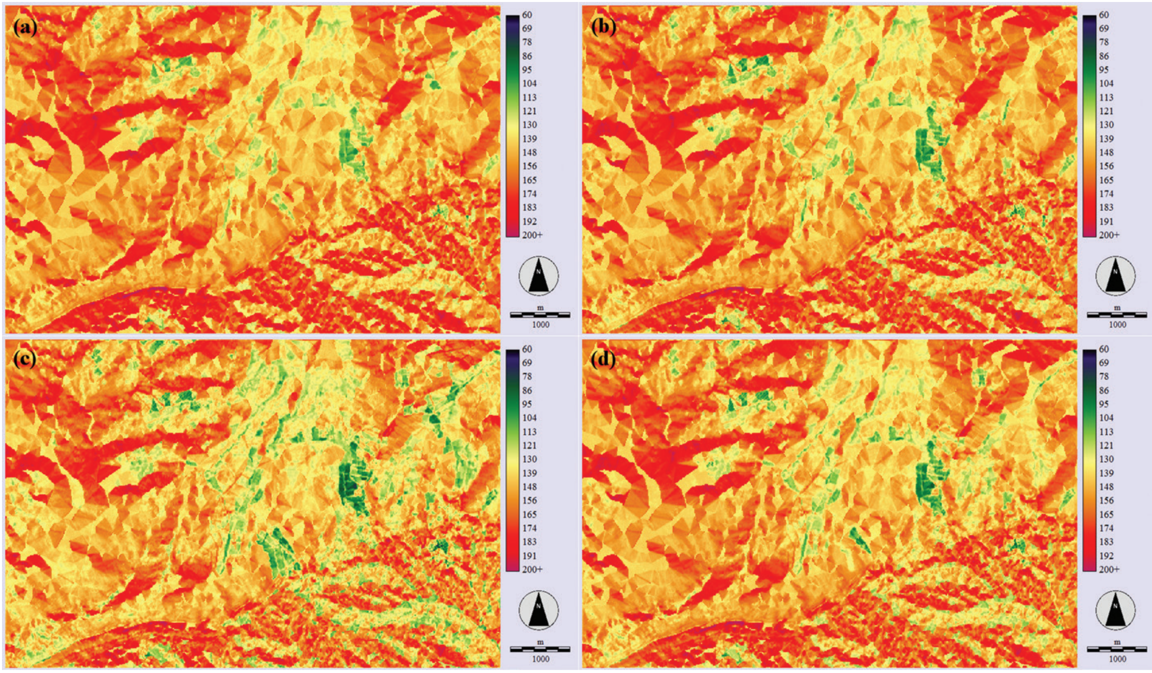

Figure 7. Soil vulnerability estimations E01 (a), E02 (b), E31 (c), and E32 (d).

The intense effect of drought mitigation in soil vulnerability values was estimated. This effect was more intense for the change analysis of late spring-early summer when very few areas exhibited an increase of soil vulnerability estimations. **Figure 8 (c)** indicated a large increase of soil vulnerability in areas of the center and east of the image, which are produced by crop

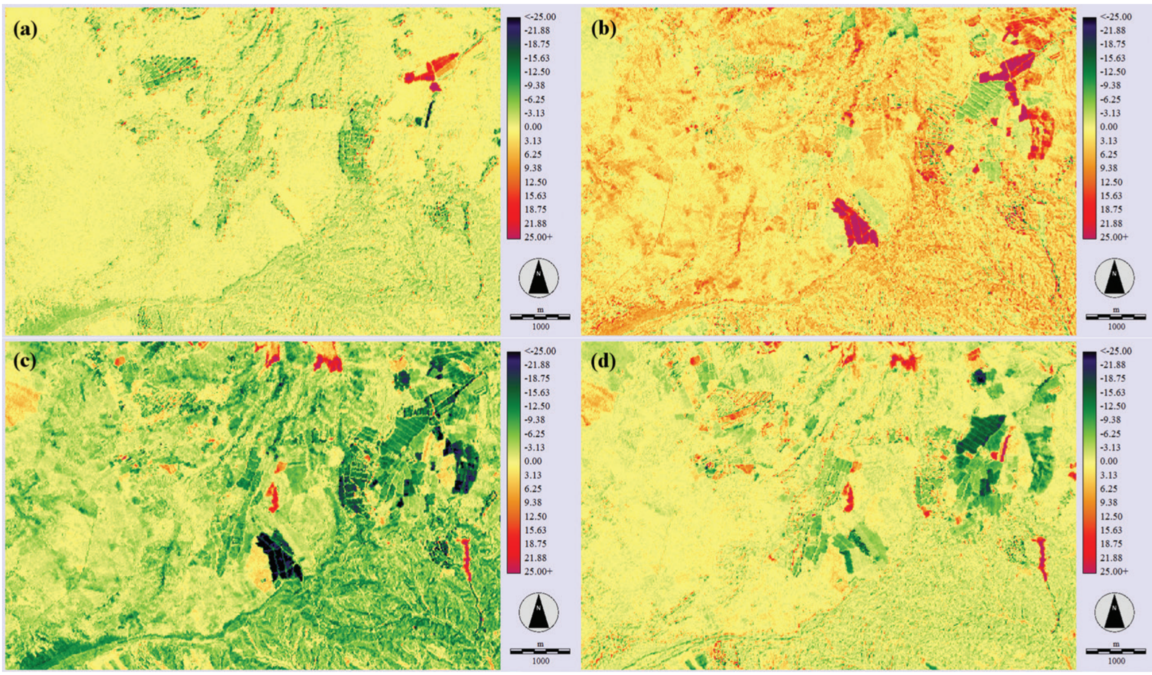

Figure 8. Temporal change (%) of soil vulnerability estimation E01 vs. E02 (a), E31 vs. E32 (b), E01 vs. E31 (c), and E02 vs. E32 (d).

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replacements. Two higher soil vulnerability areas in the north of the image are part of the reservoir basin without a soil profile. Late summer temporal changes were less evident for the nonirrigated areas by the absence of precipitations in 2000 and 2003. Soil vulnerability reductions were associated to irrigated areas less affected by the typical summer drought of the study area.

5. Conclusions

The main advantage of the proposed model is the fact that it is associated to the easy data collection and computation, which can be used to evaluate soil vulnerability and erosion. The tests applied as an example remarks the great potential of the proposed approach and its great sensitivity to evaluate the actual state and detect temporal changes of soil vulnerability as a dynamic key parameter which plays significant role for soil conservation.

Our studies verified the utility of this simple and easy tool to update with satellite images and fuzzy logic model approach. The applicability of this approach for large and sparsely populated areas with limited field information could be useful in order to promote better land management strategies and more in-depth analysis of soil degradation processes. Decision support systems for local and regional authorities and land management can be tools that help decision-makers arrive to an adequate response for environment, society, and sustainable future.

Author details

Ignacio Meléndez-Pastor[1], Jose Navarro Pedreño[1]*, Ignacio Gómez Lucas[1] and Antonis A. Zorpas[2]

*Address all correspondence to: jonavar@umh.es

1 Department of Agrochemistry and the Environment, Miguel Hernández University of Elche, Elche, Spain

2 Faculty of Pure and Applied Sciences, Environmental Conservation and Management, Laboratory of Chemical Engineering and Engineering Sustainability, Cyprus Open University, Nicosia, Cyprus

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