Science of the Total Environment 544 (2016) 439–449

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Evaluating the influence of physical, economic and managerial factors on sheet erosion in rangelands of SW Spain by performing a sensitivity analysis on an integrated dynamic model

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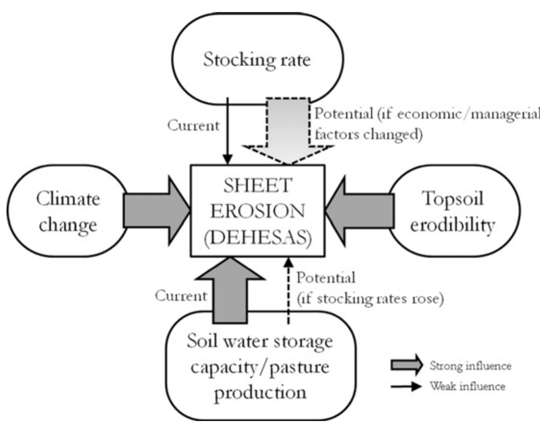
HIGHLIGHTS

- Assessing the influence of diverse factors on soil erosion in dehesa rangelands
- Variance-based sensitivity analysis of an integrated dynamic model
- Climate change will reduce the mean and the variance of long-term erosion rates.
- Economic and managerial factors scarcely influence erosion for the time being.
- Significant increases in erosion rates would be expected if stocking rates rose.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 8 October 2015
Received in revised form 24 November 2015
Accepted 24 November 2015
Available online 4 December 2015

Editor: D. Barcelo

Keywords:
Integrated dynamic model
Sensitivity analysis
Soil erosion
Rangelands
Dehesas and montados

ABSTRACT

An integrated dynamic model was used to evaluate the influence of climatic, soil, pastoral, economic and managerial factors on sheet erosion in rangelands of SW Spain (dehesas). This was achieved by means of a variance-based sensitivity analysis. Topsoil erodibility, climate change and a combined factor related to soil water storage capacity and the pasture production function were the factors which influenced water erosion the most. Of them, climate change is the main source of uncertainty, though in this study it caused a reduction in the mean and the variance of long-term erosion rates. The economic and managerial factors showed scant influence on soil erosion, meaning that it is unlikely to find such influence in the study area for the time being. This is because the low profitability of the livestock business maintains stocking rates at low levels. However, the potential impact of livestock, through which economic and managerial factors affect soil erosion, proved to be greater in absolute value than the impact of climate change. Therefore, if changes in some economic or managerial factors led to higher stocking rates in the future, significant increases in erosion rates would be expected.

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http://dx.doi.org/10.1016/j.scitotenv.2015.11.128
0048-9697/

1. Introduction

Dehesas is the name given to a common landscape created by the clearing of forests in central and SW Spain. The poor soils and adverse rainfall conditions of these areas hardly allow for crops to grow, so their principal uses are livestock rearing (sheep, cattle, pigs and goats) and forestry (cork, wood and charcoal). These landscapes cover approximately 90,000 km^2 in the south-west of the Iberian Peninsula (Gea-Izquierdo et al., 2006).

Dehesas are mostly in private ownership (Plieninger et al., 2003). Traditional uses have formed a landscape pattern of wooded pasturelands and scrublands of variable tree densities. The main tree species are holm oaks (*Quercus ilex rotundifolia*) and cork oaks (*Q. suber*). There are public concerns about the sustainability of this system, which is highly valuable from a socioeconomic and environmental point of view (Pulido and Picardo (Coords.), 2010). Thus, for example, the Spanish National Action Programme to combat Desertification (MAGRAMA, 2008) includes dehesas on the list of socio-ecological systems threatened by land degradation.

Among the diverse threats to dehesas, soil degradation plays a major role. A survey carried out on a large number of farms in the region of Extremadura (SW Spain) indicated that approximately 23% of the area suffers from a high risk of soil degradation, while approximately 60% is prone to degradation processes (Schnabel et al., 2006; Lavado et al., 2009). Soil erosion, which is a primary sign of soil degradation, is observed as sheet erosion on hillsides and as gullying at the bottom of small upland valleys (Schnabel, 1997; Schnabel et al., 1999).

Clearly, it is in the interest of the conservation of dehesas to gain insight into the factors that could cause significant changes in erosion rates in the future. This was the motivation behind the assessment that is reported here.

A factor of special interest is climate change. It can affect erosion rates directly, through changes in the erosive power of rainfall, or indirectly, through changes in plant biomass and vegetation cover. The evaluation of the potential impact of climate change on erosion has been the purpose of various modelling studies to date. Examples are Pruski and Nearing (2002a), Pruski and Nearing (2002b), Nearing et al. (2004), Mullan (2013), Garbrecht et al. (2014) or Routschek et al. (2014). The models utilised in these works are detailed process-based models. Specifically, the first five used the WEPP model (Flanagan and Nearing, 1995) and the last one used EROSION 3D (Schmidt, 1990). In the present study, the expected impacts of nine climate scenarios provided by the Spanish Meteorological Agency on sheet erosion were evaluated.

Other factors of particular interest are the economic and managerial ones. It is commonly believed that overgrazing causes erosion, because grazing reduces biomass, which protects soil against erosion, and trampling reduces soil porosity, thereby creating patches of bare soil and increasing runoff (Mulholland and Fullen, 1991; Aubault et al., 2015). Thus, since economic and managerial factors are drivers of grazing intensity, at least in commercial rangelands, they are seen as human-induced factors in soil erosion. However, there are authors who bring into question the role of overgrazing as a cause of soil erosion, both in reference to Mediterranean rangelands (Perevolotsky and Seligman, 1998) and in general terms (Rowntree et al., 2004). It was thought that the intended assessment might shed some light on this controversy.

Undertaking a comparative evaluation of the influence of many heterogeneous factors on soil erosion in dehesas would require collecting information about a large amount of variables at different locations over very long periods of time. Since this is almost unfeasible in practice, the assessment was carried out by means of a system dynamics model (Forrester, 1961; Sterman, 2000; Kelly et al., 2013). The model was suitable for the task because it integrates variables and processes from the required disciplines and because its parameters constitute the factors being evaluated (Table 1). In this way, the assessment was provided via a thorough sensitivity analysis. However, it must be stressed that, because all model parameters represent meaningful (real) factors, the sensitivity analysis transcends its standard part of a modelling exercise and constitutes a method for gaining insight into one important threat to a valuable socio-ecological system. The originality of this study lies in its integrated nature, and particularly in its taking economic and managerial factors into consideration. Indeed, we have found no other

Table 1
Parameters of the model.

Name	Definition	Range	Units
Climate/weather			
roppm	Surrogate for the capacity of rain to cause runoff, mean	1–4	$cm \cdot cm^{-1}$
roppv	Surrogate for the capacity of rain to cause runoff, CV	0.3–1.5	–
scen	Climate scenario	0–8	–
somoi	Initial soil moisture (=9.7)	Not analysed	cm
Soil			
bdpt	Topsoil bulk density above which pasture does not grow	1.7–1.8	$gr \cdot cm^{-3}$
fcvo	Field capacity (volumetric)	0.2–0.42	[0, 1]
sdhp	Remaining soil depth at which porosity is reduced by half	$5 \cdot 10^{-4}$ - 5	cm
sodpi	Initial remaining soil depth (=23.4)	Not analysed	cm
tseri	Initial topsoil erodibility	$1 \cdot 10^{-6}$ - $5 \cdot 10^{-6}$	$yr \cdot cm^{-1}$
tspoi	Initial topsoil porosity	0.37–0.59	[0, 1]
wpvo	Wilting point (volumetric)	0.05–0.09	[0, 1]
wthr	Weathering rate of the parent rock	$1 \cdot 10^{-3}$ - $5 \cdot 10^{-3}$	$cm \cdot yr^{-1}$
Pasture			
appt	Annual precipitation for pasture yield to be ptyhi	203–826	$mm \cdot yr^{-1}$
pppt	Minimum annual precipitation for pasture growth	0–477	$mm \cdot yr^{-1}$
ptec	Pasture energy content	0.4–0.9	$FU \cdot kg^{-1}$
ptyhi	Initial pasture yield per hectare	75–1916	$kg \cdot ha^{-1} \cdot yr^{-1}$
pyfc	Minimum pasture biomass for full ground cover in a hectare	385–674	$kg \cdot ha^{-1} \cdot yr^{-1}$
rcpc	Parameter relating runoff coefficient to pasture cover	2.5–4.5	–
srhc	Stocking rate causing a 50% area of temporary bare soil	3.53–6.55	$AU \cdot ha^{-1}$
Economic			
ocos	Costs per female other than the cost of supplemental feed	240–3800	$€ \cdot AU^{-1} \cdot yr^{-1}$
prmtm	Price of meat, mean	1.7–2.6	$€ \cdot kg^{-1}$
prmtv	Price of meat, CV	0.064–0.11	[0, 1]
prsfm	Price of supplemental feed, mean	0.22–0.36	$€ \cdot kg^{-1}$
prsfv	Price of supplemental feed, CV	0.09–0.16	d.u.
sinf	Secondary income per breeding female	0–330	$€ \cdot AU^{-1} \cdot yr^{-1}$
subh	Total subsidies per hectare	51–1450	$€ \cdot ha^{-1} \cdot yr^{-1}$
Managerial			
bdfmi	Initial number of breeding females	0.25–2.99	$AU \cdot ha^{-1}$
bfpt	% increase in breading females if EGMF increased by 10%	3.3–7.28	%
bfsr	Ratio of breeding females to stocking rate	0.95–0.98	[0, 1]
dtgm	Average length of the delay to form EGMF	1–11	yr
mtpf	Meat production per breeding female	110–925	$kg \cdot AU^{-1} \cdot yr^{-1}$
rgmf	Reference gross margin per breeding female	150–1000	$€ \cdot AU^{-1} \cdot yr^{-1}$
sfdfi	Initial supplemental feed per breeding female	6–2940	$kg \cdot AU^{-1} \cdot yr^{-1}$
sfec	Supplemental feed energy content	0.28–1.02	$FU \cdot kg^{-1}$
tpcf	Target pasture consumption per breeding female	150–450	$kg \cdot AU^{-1} \cdot yr^{-1}$
Other			
seed	Random seed	0–3	–
Δ	Time step (=0.00390625)	Not analysed	yr

work evaluating a range of factors affecting soil erosion in rangelands to be as in-depth as the one assessed here.

This paper is structured as follows. Section 2 is devoted to outline the model. In Section 3 the procedure followed for the sensitivity analysis is detailed. The results are presented and discussed in Sections 4 and 5, and summarized in Section 6.

2. Model overview

The model used in this study is an update of that presented in Ibáñez et al. (2014). In that paper the reader may find a full characterisation of the model (conceptualisation, appropriateness of the modelling approach, data availability and validation) and a description of all those equations that have remained unaltered to date. The changes made for the present study, along with other details, are justified and described in a Supplementary document. The overview given in this Section is mainly focused on showing the great diversity of factors whose effects on soil erosion were assessed and on clarifying the causal relationships involved.

Fig. 1 shows the causal diagram of the model, and Tables 1 and 2 provide the lists of parameters and equations, respectively. Both tables should be consulted when reading this section. The parameters are classified into six categories: climate/weather, soil, pasture, economic, managerial and others (Table 1).

2.1. Level of description of the model

The model has an annual time scale and is lumped spatial (Kelly et al., 2013). The area modelled is an ideal area of dehesa with homogeneous topographical, biophysical and managerial characteristics. This area is positioned on the top of a hillside, so that it does not receive flows of material from upper areas. In this study, the area was assumed to be one hectare for the sake of simplicity.

Because of the annual time scale of the model, short-term processes, i.e. those determining soil moisture (Fig. 1), evolve over the time steps of the model, whose size was fixed at 0.00390625 yr (around 1.43 days). A justification for this number is given in the Supplementary document.

With the above-mentioned temporal and spatial scales, the model could only make a high-level description of the dehesa system. This was convenient because it permitted the building of an integrated dynamic model on the basis of a relatively small amount of data, and with dimensions that made it possible to perform an effective, though computationally costly, sensitivity analysis, which was the main goal of this study.

A high-level description entails a loss of precision, but in compensation, and in accordance with Levins (1966), extreme attention was paid to build a model which maximizes generality and realism. This must be stressed. On the one hand, because on these two features rests the capacity of the model to provide insight into dehesas, even though it neglects processes that are relevant at a lower-level description. On the other, because maximizing generality and realism requires building a robust model, and this was necessary to prevent any simulation in the sensitivity analysis from crashing. The latter was successfully achieved: none of the 245,300 simulations crashed, even though most parameters varied within wide ranges.

2.2. Influence of climate/weather parameters on soil erosion within the model

Parameters roppm and roppv are, respectively, the mean and coefficient of variation (CV) of ROPP (Eq. (1); Fig. 1). This is a gamma random variable which serves as a surrogate for the overall capacity of rainfall to cause runoff during a time step, i.e. it reflects the variability of factors such as rainfall intensity during storms, duration of storms or rainfall distribution. Thus, roppm and roppv are positively related to the mean and variance of the runoff coefficient over time steps, respectively. Through this variable both parameters are involved in determining the rates of infiltration and surface runoff (Eqs. (8), (9) and (10) and Supplementary document). And the square of surface runoff is a factor in the equation of erosion rate (Eq. (20)), in line with the erosion models found in Kirkby (1971), Morgan (1980; 1995), Band (1985) or Thornes (1990).

The parameter ‘climate scenario’ (scen) is used to specify what the climate scenario is for a given simulation. There are nine possible preset climate scenarios to be chosen. Table 3 shows statistics on them and the value of scen for each one. One climate scenario consists of three time-series data on precipitation, reference evapotranspiration (ET_o) and annual precipitation (Table 2). The size of these time series matches the number of time steps in 90 years (annual precipitation takes the same value over the time steps of a given year).

The climate scenarios were derived from nine preliminary datasets that were taken from the collection of local-scale projections available in the repository of the Spanish Meteorological Agency (http://escenarios.aemet.es). Preliminary datasets included daily data on precipitation and temperature corresponding to the cities of Cáceres and Badajoz (Extremadura, SW Spain) and covering the period 2011–2100. One dataset included time series recreating the control period from 1961 to 1990, so that it formed the basis for our no-change climate scenario (scen = 0). The other eight included climate-change

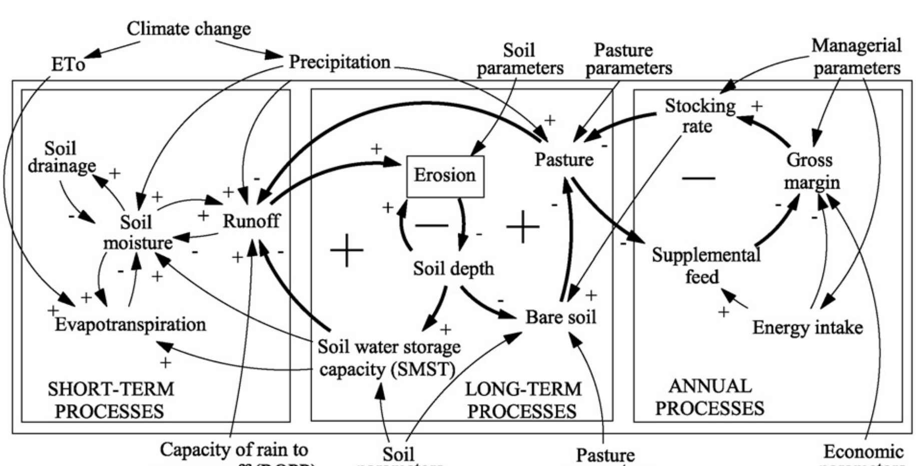

Fig. 1. Causal diagram of the model. Arrows go from explanatory to response variables. A plus/minus sign indicates that the two variables involved in the relationship correlate positively/negatively.

Table 2
Model variables and equations[a].

Precipitation [$cm \cdot \Delta^{-1}$]	
PCPT: Its scenario is fixed by the parameter scen (Table 3)	
Annual precipitation [$mm \cdot yr^{-1}$]	
ANPP: Its scenario is fixed by the parameter scen (Table 3)	
Reference evapotranspiration [$cm \cdot \Delta^{-1}$]	
RFET: Its scenario is fixed by the parameter scen (Table 3)	
Surrogate for the capacity of rain to cause runoff [$cm \cdot cm^{-1}$]	
ROPP = GAMMA{roppm; roppv}	(1)
Price of meat [$€ \cdot kg^{-1}$]	
PRMT = [b] if t = INTEGER{t} then NORMAL{prmtm; prmtv} else PRMT(t − Δ)	(2)
Price of supplemental feed [$€ \cdot kg^{-1}$]	
PRSF = [b] if t = INTEGER{t} then NORMAL{prsfm; prsfv} else PRSF(t − Δ)	(3)
Soil moisture [cm]	
SOMO(t + Δ) = SOMO + Δ × (IFTR − SODR − ACET)	(4)
SOMO(0) = somoi	(5)
Actual evapotranspiration [$cm \cdot yr^{-1}$]	
ACET = MIN{RFET; IFTR + (SOMO − SMWP)}/Δ	(6)
Soil drainage [$cm \cdot yr^{-1}$]	
SODR = MAX{0; SOMO − SMFC}	(7)
Minimum runoff coefficient [$cm \cdot cm^{-1}$]	
MROC = MIN{1; ROPP} × EXP{−rcpc × GRCV}	(8)
Infiltration [$cm \cdot yr^{-1}$]	
IFTR = MIN{(1 − MROC) × PCPT; SMST − SOMO}/Δ	(9)
Surface runoff [$cm \cdot yr^{-1}$]	
SFRO = PCPT/Δ − IFTR	(10)
Remaining soil depth [cm]	
SODP(t + Δ) = SODP + Δ × (wthrf − ERRT)	(11)
SODP(0) = sodpi	(12)
Topsoil porosity [d.u.]	
TSPO = [(2)] tspoi × PODF	(13)
Soil porosity distribution factor [$cm^2 \cdot cm^{-2}$]	
PODF = [(2)] SODP × (α + sodpi)/[sodpi × (α + SODP)]	(14)
α = 0.5 × sodpi × sdhp/(0.5 × sodpi − sdhp)	(15)
Topsoil bulk density [$gr \cdot cm^{-3}$]	
TSBD = 2.65 × (1 − TSPO)	(16)
Soil moisture at saturation [cm]	
SMST = [d] tspoi × (α + sodpi) × [SODP + α × LN{α/(α + SODP)}] / sodpi	(17)
Soil moisture at field capacity [cm]	
SMFC = fcvo × SMST/tspoi	(18)
Soil moisture at wilting point [cm]	
SMWP = wpvo × SMST/tspoi	(19)
Erosion rate [$cm \cdot yr^{-1}$]	
ERRT = [c,e] tseri × PODF × $SFRO^2$	(20)
Permanent bare soil area [$ha \cdot ha^{-1}$]	
PBSA = MIN{1; INTEGER{TSBD/bdpt}	(21)
Potential area for pasture growth [$ha \cdot ha^{-1}$]	
PPTA = 1 − PBSA	(22)
Actual area for pasture growth [$ha \cdot ha^{-1}$]	
APTA = PPTA × srhc/(srhc + BDFM/bfsr)	(23)
Pasture yield in a hectare without bare soil (where APTA = 1) [$kg \cdot ha^{-1} \cdot yr^{-1}$]	
PTYH = ptyhi × MAX{0; ANPP – pppt}/(appt − pppt)	(24)
Actual pasture yield (in APTA) [$kg \cdot ha^{-1} \cdot yr^{-1}$]	
PTYD = APTA × PTYH	(25)
Annual representative ground cover [$ha \cdot ha^{-1}$]	
GRCV = MIN{APTA; (PTYD – PTCF × BDFM/bfsr)/pyfc}	(26)
Pasture consumption per breeding female [$kg \cdot AU^{-1} \cdot yr^{-1}$]	
PTCF = MIN{tpcf; bfsr × PTYD/BDFM}	(27)
Energy intake per breeding female [$FU \cdot AU^{-1} \cdot yr^{-1}$]	
EINF = sfec × sfdfi + ptec × tpcf	(28)
Supplemental feed per breeding female [$kg \cdot AU^{-1} \cdot yr^{-1}$]	
SFDF = (EINF − PTCF × ptec)/sfec	(29)
Gross margin per breeding female [$€ \cdot AU^{-1} \cdot yr^{-1}$]	
GMGF = PRMT × mtpf + sinf + subh/BDFM – PRSF × SFDF − ocos	(30)
Expected gross margin per breading female [$€ \cdot AU^{-1} \cdot yr^{-1}$]	
EGMF(t + Δ) = EGMF + Δ × [GMGF − EGMF]/dtgm	(31)
EGMF(0) = rgmf	(32)
Number of breeding females [$AU \cdot ha^{-1}$]	
BDFM = bdfmi × $[MAX\{0; EGMF\}/rgmf]^{\rho}$	(33)
ρ = LN{1 + bfpt/100}/LN{1.1}	(34)

[a] The symbol (t), meaning at time t, is omitted except when variables refer to t + Δ, t–Δ and t = 0.
[b] INTEGER returns the largest integer smaller than or equal to its argument.
[c] Note that PODF = 1 when SODP = sodpi.
[d] Definite integral of TSPO between 0 and SODP, with the boundary condition SODP(0) = 0.
[e] Substituting Eq. (13) into Eq. (16) and solving for PODF gives PODF = (2.65 − TSBD) / (2.65 − TSBD(0)).

Table 3
Statistics on the climate scenarios evaluated in this work. The scenario to be used in a simulation is fixed through the parameter scen. DP = Average daily precipitation; RDY = Average number of rainy days per year; PRD = Average precipitation per rainy day; AAP = Average annual precipitation; DP95 and DP99 = 95th and 99th percentiles of daily precipitation, respectively; DET = Average daily ET_o.

Scenario	scen	DP	RDY	PRD	AAP	DP95	DP99	DET
No-change	0	1.41	91.37	5.63	514.68	9.3	23.9	2.7
CGCM2_FIC_A2	1	1.1	77.13	5.21	401.98	7	18.5	2.9
CGCM2_FIC_B2	2	1.17	79.32	5.39	427.83	7.5	19.5	2.81
CGCM2_INM_A2	3	1.42	156.52	3.3	517.19	8	14	2.87
CGCM2_INM_B2	4	1.48	159.61	3.37	538.39	8.5	14	2.78
ECHM4_FIC_A2	5	0.88	61.99	5.18	321.19	6	17.5	3.29
ECHM4_FIC_B2	6	0.91	64.67	5.14	332.23	6	17.5	3.22
ECHM4_INM_A2	7	0.75	112.41	2.42	272.25	4.5	10.5	3.44
ECHM4_INM_B2	8	0.84	120.66	2.54	306.77	5	11	3.35

projections corresponding to two Coupled Atmosphere–Ocean General Circulation Models (CGCM2 and ECHAM4), two downscaling methods (AnalogINM and AnalogFIC) and two emissions scenarios (A2 and B2). They formed the basis for the eight climate-change scenarios used in the study (scen = 1 to 8). See the Supplementary document for details on the preliminary datasets and how they were adapted to serve as inputs to the model.

Table 3 shows that the climate-change scenarios considered in this work predict higher evapotranspiration rates and rainfall decreases, both in intensity per rainy day and in the frequency of extreme events. On the one hand, higher evapotranspiration rates and lower rainfall amounts imply a drier soil, and thus less runoff. On the other, a drier soil entails less pasture biomass, and thus more runoff. Hence the impacts of the climate scenarios on erosion were unclear before carrying out this study.

The parameter 'initial soil moisture' (somoi) can hardly affect erosion in the long term, so it was not included in the sensitivity analysis.

2.3. Influence of soil parameters on soil erosion within the model

The parameter 'initial topsoil erodibility' (tseri) has a direct positive influence on erosion rate because it is a constant factor in its equation (Eq. (20)). As soil is lost by erosion, topsoil porosity gets lower (topsoil bulk density gets higher) so that topsoil erodibility decreases from its initial value. If soil runs out, porosity becomes zero (bulk density becomes 2.65 $g \cdot cm^{-3}$) and topsoil erodibility falls to zero. In this way erosion drives a negative feedback loop in the long term involving soil depth (Fig. 1). The specific course of the decline in topsoil erodibility is determined by the factor PODF (Eq. (20)). The parameter 'remaining soil depth at which porosity is reduced by half' (sdhp) specifies the shape of PODF, i.e. the distribution of porosity over the soil profile (Eq. (13)–(15)), and thus whether the decline in topsoil erodibility will happen rather abruptly when only a relatively small amount of soil is left (sdph low) or be more evenly distributed over time (sdph high).

Soil moisture at saturation, i.e. soil water storage capacity, equals the total pore space in the soil at a given time step (Eq. (17)). The difference between such a volume and the level of soil moisture determines the potential rate of infiltration at the time step (Eq. (9)). Therefore, as soil is lost through erosion and soil water storage capacity diminishes, surface runoff and thus erosion rates increase on average. Hence, in this case, erosion drives a self-accelerating positive feedback loop in the long term (Fig. 1). Its consequences will be deferred if parameters 'initial topsoil porosity' (tspoi) or 'initial remainig soil depth' (sodpi) take high values, or if the parameter sdhp (see above) takes a low value. This is because of the sign of their relationships with soil water storage capacity: positive for the first two and negative for the third one.

The parameter 'field capacity' (fcvo) is involved in determining soil drainage (Eqs. (7) and (18)) and the parameter 'wilting point' (wpvo) in determining actual evapotranspiration (Eqs. (6) and (19)). Through these variables they influence soil moisture over time (Eqs. (4)–(5)) and thus infiltration rates, surface runoff and, eventually, erosion rates.

As already explained, topsoil bulk density (Eq. (16)) increases as erosion removes layers of soil. If topsoil bulk density exceeded the value of the parameter 'topsoil bulk density above which pasture does not grow' (bdpt) the whole area modelled would become permanent bare soil (Eq. (21) and Supplementary document). If this were the case, the potential area for pasture growth would drop to zero (Eq. (22)). This would cause erosion rates to rise on average, since ground cover limits surface runoff (Eq. (8)). In this way, erosion might drive a second self-accelerating positive feedback loop in the long term (Fig. 1).

The parameter 'weathering rate of the parent rock' (wthr) is the rate of soil formation (Eq. (11)). It does not affect erosion rate but counterbalances it to a certain extent.

Finally, the parameter 'initial remaining soil depth' (sodpi) (Eq. (12)) was excluded from the sensitivity analysis to allow the amounts of soil lost in all the simulations to be compared in absolute terms. It was fixed at 23.4 cm, the average soil depth over the available field data.

2.4. Influence of pasture parameters on soil erosion within the model

The parameter 'stocking rate causing a 50% area of temporary bare soil' (srhc) reflects the capacity of pasture species to resist livestock trampling. The larger its value, the smaller the area of temporary bare soil caused by a given stocking rate in one year, or, conversely, the larger the area for pasture growth (Eq. (23) and Supplementary document).

Pasture yield (in the area for pasture growth) linearly depends on annual precipitation as long as it exceeds a minimum threshold amount (Sullivan and Rohde, 2002) (Eqs. (24)–(25)). This pasture production function is expressed in terms of meaningful parameters that depends on pasture characteristics, namely 'initial pasture yield per hectare' (ptyhi), 'annual precipitation for pasture yield to be ptyhi' (appt) and 'minimum annual precipitation for pasture growth' (pppt).

The amount of pasture being left at the end of the dry period of a given year, when ground cover is at its minimum, is used as the 'annual representative ground cover' (GRCV) (Eq. (26) and Supplementary document). Therefore, this variable depends on the area of bare soil (and thus on bdpt and shrc), on pasture yield (and thus on ptyhi, appt and pppt) and on the parameters affecting livestock consumption of pasture, which will be explained later. Following Elwell and Stocking (1976), GRCV limits surface runoff, and thus erosion rates, by means of an exponential function involving parameter rcpc ('Parameter relating runoff coefficient to pasture cover') (Eq. (8)). The larger its value, the more the soil is protected from erosion by a given level of ground cover.

The parameter 'minimum pasture biomass for full ground cover in a hectare' (pyfc) allows for the converting of amounts of pasture biomass into ground cover. The larger its value, the larger the amount of biomass needed for ground cover to be 1 (100%) in a whole hectare.

The parameter 'pasture energy content' (ptec) will be explained in the next Section.

2.5. Influence of economic, managerial and other parameters on soil erosion within the model

In brief, all the economic and managerial (EM) parameters, except 'target pasture consumption per breeding female' (tpcf), influence soil erosion by means of the stocking rate and ground cover. Indeed, such parameters ultimately govern the evolution of stocking rate over time which, as already explained, affects ground cover through pasture consumption and the formation of temporary bare soil. Parameter tpcf, which depends on farming practices, i.e. on the amount of time that animals are allowed to graze, also affects ground cover, but not through stocking rate (Eqs. (26)–(27)).

Going into some detail, since the model represents a commercial rangeland, stocking rate depends on expected profitability, which is measured by the expected annual gross margin per breeding female (Eq. (30) to (34); see Ibáñez et al. (2014) for details on how farmer's expectations are modelled and how they relate to stocking rate). Therefore, it is by means of the annual gross margin per breeding female (GMGF) (Eq. (30)) that most of the EM parameters drive the stocking rate.

Thus, all the economic parameters and the parameter 'meat production per breeding female' (mtpf) affect GMGF directly. The latter has been classified as managerial because it depends on a farmer's decisions regarding the breeds of livestock and slaughter weights. Parameters 'initial supplemental feed per breeding female' (sfdfi), 'supplemental feed energy content' (sfec) and tpcf (see above), which also depend on a farmer's decisions, and the parameter 'pasture energy content' (ptec), which is a pasture parameter whose explanation was deferred, affect GMGF by determining the target energy intake and the amount of supplemental feed supplied per animal (Eqs. (28)–(29)).

In years when pasture is scarce, so that livestock cannot attain the target pasture consumption, animal production is maintained by increasing supplemental feed, and thus by reducing GMGF. In this way, the stocking rate can be involved in a self-regulating negative feedback loop (Fig. 1). However, the speed at which such a regulation is made depends on the farmer's behaviour, specifically on how fast he/she perceives changes in profit conditions and how reactive his/her stocking strategy is (Anderies et al., 2002; Higgins et al., 2007). These managerial factors are represented, respectively, by parameters 'average length of the delay to form expectations about gross margins' (dtgm) and 'percentage increase in breading females if the expected gross margin per breeding female increased by 10%' (bfpt). Note that a conservative farmer following a constant stocking strategy has a high value of dtgm and a low value of bfpt. For this farmer, the mentioned self-regulating feedback loop hardly applies.

Within the group of other parameters, the parameter 'random seed' (seed) serves to change the values generated for the three stochastic variables of the model. These are ROPP (Section 2.2) and the average annual prices of meat and supplemental feed, which are randomly sampled from normal distributions each year (Eqs. (2)–(3)). The means (prmtm and prsfm) and CVs (prmtv and prsfv) of such distributions are in the group of economic parameters.

3. Sensitivity analysis

There are many available sensitivity analysis (SA) methods. Saltelli et al. (2008) and Gan et al. (2014) provide comprehensive surveys of them. These methods can be classified into two broad categories: local and global. A local SA evaluates the changes in an output Y by varying an input X_i while keeping constant the other inputs. Therefore, a local SA is only informative at a single nominal point in the parameter space, unless the model is linear or additive. On the contrary, a global SA estimates the effect of X_i on Y by varying all inputs at the same time. An SA of this kind leads to robust estimates, since it is based on information gathered from a number of points scattered over the whole parameter space, and is model-free, since it does not rely on the assumptions of linearity and additivity. As a drawback, a global SA is computationally more expensive than a local SA, meaning that it requires a much greater number of model simulations.

Variance-based methods are the most common global SA. They are based on a decomposition of the variance of the output, V(Y), into terms corresponding to the different inputs and their interactions (Sobol, 2001; Cariboni et al., 2007; Saltelli et al., 2008; Saltelli and Annoni, 2010; Glen and Isaacs, 2012; Gan et al., 2014). A first order sensitivity index is defined as:

$S_i = V(E[Y/X_i]) / V(Y)$.

where X_i is the i-th input ($i = 1, 2,..., k$). S_i measures the expected reduction in V(Y) if X_i were fixed; hence a large value is evidence of an important input. First order sensitivity indices are the appropriate measures when the aim of an SA is factor prioritization, as it is in this case..

The contributions to V(Y) of the interactions between factors are captured by higher-order sensitivity indices. However, the number of interactions increases exponentially with the number of factors so, when this is large, only the first order sensitivity indices are usually estimated. For example, in the present case where $k = 34$ (Table 1), only the second order effects amount to 1122.

The total sensitivity index is defined as:

$S_{Ti} = E(V[Y/X_{\sim i}]) / V(Y)$.

where $X_{\sim i}$ denotes all factors except X_i. S_{Ti} measures the expected portion of V(Y) that would remain if all factors but X_i were fixed. Thus, the total sensitivity index measures the total contribution to V(Y) due to X_i, including its first-order effect plus all higher-order effects due to interactions. Hence a very small value of S_{Ti} is evidence of a non-influential factor that could be fixed at any value within its range of variation without influencing the output Y. Total sensitivity indices are the appropriate measures when the aim of an SA is factor fixing or model simplification.

Due to their computational cost, variance-based methods may be unfeasible for models with many parameters or taking a long time to run. The model used in this study only takes 2–3 s per run but 34 parameters is a rather large number to perform a variance-based method. For example, Cariboni et al. (2007) and Saltelli et al. (2008) advise that k should be less than 20. Therefore, a preliminary parameter screening was carried out with the aim of detecting non-influential factors that could be omitted from a variance-based analysis. The Elementary Effect (EE) method (Morris, 1991) was followed for this initial screening. This method is effective in cases where the number of parameters moderately exceeds that allowing the use of a variance-based technique (Campolongo et al., 2007; Cariboni et al., 2007; Saltelli et al., 2008).

Suppose initially that all inputs X_i ($i = 1,..., k$) are uniformly distributed over [0, 1]. This range of variation is discretised in p levels so that each X_i can only take values from $\{0, 1/(p - 1), 2/(p - 1),..., 1\}$. The elementary effect of X_i on output Y is defined as:.

$EE_i = Y(X_1, ..., X_i + \delta, ..., X_k) - Y(X_1, ..., X_i, ..., X_k) / \delta$.

where δ is a predetermined multiple of $1/(p - 1)$, normally $p/2(p - 1)$ if p is even. In brief, Morris's method exploits a total of $r(k + 1)$ simulations to obtain a sample of r values of every EE_i and then calculate its sample mean μ_i and standard deviation σ_i. The former evaluates the overall influence of X_i on Y and the latter, the extent to which X_i is involved in interactions and/or has non-linear effects. Campolongo et al. (2007) explain that μ_i is vulnerable to Type II errors, i.e. failing to detect an influential factor, and they propose replacing it with the sample mean of the absolute values of EE_i, called μ_i^*, which solves the problem. In addition, these authors show that μ_i^* is a good proxy for the total sensitivity index S_{Ti}. For this reason, μ_i^* was used to detect non-influential parameters in the model..

The sampling of the r values of EE_i requires generating r random starting points in the input space ω (a k-dimensional p-level grid), and then deriving r trajectories from them. The details can be seen in Morris (1991). This author proposes obtaining each starting point by simple random sampling. In this study, Latin Hypercube Sampling (LHS) was preferred since it allows the sample points to be spread more evenly over ω. Campolongo et al. (2007) propose a sampling method that also ensures a good scanning of ω, but it requires many computations. Moreover, these authors show the advantage of their method over random sampling but not over LHS.

Although no theoretical assumption of independence between factors is made in the EE method, sampling independently the r points in ω when the factors are not independent, i.e. without taking into account their joint distribution, leads to the calculation of some elementary effects at points that are unlikely in reality. However, this does not seem to be a major problem if the method is exclusively aimed at detecting non-influential factors, as it is in this study. Indeed, a factor is non-influential if it proves to be so after evaluating likely and unlikely points in ω. Therefore, the question of the independence between factors was neglected in the preliminary screening.

The output Y in this analysis was the remaining soil depth after a lapse of 90 years, hereafter $SODP_{90}$. Also, p equalled 4, as recommended by Saltelli et al. (2008), and r equalled 50, which is the maximum of its typical range (Campolongo et al., 2007). The parameter scen was excluded. Estimating the sensitivity of soil erosion to possible future climate scenarios is one of the concerns of this work so scen would never be omitted from the variance-based procedure. Instead, the EE method was applied to each climate scenario so 15,300 simulations were run in total (1700 simulations per value of scen).

Parameter values were assumed to be uniformly distributed over their ranges of variation. Thus, any value initially sampled within [0, 1], $X_{i[0,1]}$, was transformed into a value of the factor X_i, with range of variation $[m_i, M_i]$, by making:

$X_i = m_i + (M_i - m_i) \times X_{i[0,1]}$.

Ranges of variation, which are shown in Table 1, reflect the uncertainty about the factors existing in the study area (see the Supplementary document for details).

Table 4 shows the results of the application of the EE method. Initially, the criterion for omitting a parameter from the variance-based procedure was it having an average value of μ_i^* (last column) less than 1% of the largest one, which was 2.5271 (parameter tseri). However, it was decided to retain parameter srhc (stocking rate causing a 50% area of temporary bare soil) because its average value of μ_i^* (0.0241) was very close to the limit. The seven omitted parameters (in bold in Table 4) were fixed at the values used in the original model (see Ibáñez et al., 2014, for the sources of data).

27 parameters remained, which is still a rather large number for a variance-based method, in accordance with Cariboni et al. (2007) and Saltelli et al. (2008). The next step in the SA was to check whether this reduced set of parameters included correlated factors. When this is the case, the estimation of sensitivity indices requires the following of special procedures (Saltelli and Tarantola, 2002; Jacques et al., 2006; Saltelli et al., 2008; Da Veiga et al., 2009).

Although the necessary data to quantify correlations was lacking, it is likely that there are only two groups of correlated factors in the set of 27 parameters. The first one includes the six parameters related to soil water storage capacity and the pasture production function (tspoi, fcvo, wpvo, appt, pppt and ptyhi). The existence of correlations within this group has been widely reported (e.g. Greenwood and McKenzie, 2001; Whalley et al., 2008; Glab, 2013). The second group includes the two parameters characterising the farmer's responsiveness when facing economic changes (dtgm and bfpt) (Section 2.5). Although we do not know of any study addressing this issue, it can be assumed that these parameters would be negatively correlated in both conservative and responsive farmers.

Given that the correlated factors of the model could be split into uncorrelated groups of factors, it was possible to follow the simple procedure proposed by Jacques et al. (2006) that consists in estimating combined sensitivity indices for these groups, thereby neglecting the estimation of the impact of every single factor within them. For this purpose, two multidimensional factors were defined: the soil-water-storage-capacity-pasture-production factor (wspt), which condenses the first group of parameters, and the farmer-behaviour factor (frbh), which condenses the second one. As a result, there remained $k = 21$ factors (19 one-dimensional and 2 multidimensional) that could be considered uncorrelated.

Glen and Isaacs (2012) compare 12 pairs of estimators of S_i and S_{Ti} for accuracy and precision using the G function (Sobol, 2001) as a model. Half of the estimators require $N(k + 2)$ model simulations and the other half require $N(2\,k + 2)$, where N is the sample size. The pair of estimators labelled as B_3 by these authors was used to estimate S_i and S_{Ti} in this study. Such pair of estimators is one of the two pairs that reached the best performance among those requiring $N(k + 2)$ model simulations. See Glen and Isaacs (2012) for details. Output Y

Table 4
μ* values obtained in the Elementary Effects method for each value of the parameter scen (climate scenario). In bold, the 7 parameters omitted from the variance-based procedure.

scen	0	1	2	3	4	5	6	7	8	Mean
seed	0.0789	0.0412	0.0647	0.0222	0.026	0.0367	0.0505	0.0513	0.028	0.0444
roppm	0.7231	0.5514	0.6514	0.3597	0.4554	0.6141	0.6864	0.3254	0.4566	0.5359
roppv	1.0006	0.9075	0.7559	0.5997	0.6504	0.8354	0.8528	0.3976	0.5025	0.7225
bdpt	0.0507	0.0192	0.0029	0.0021	0.0064	0.0013	0.0031	0.001	0.0025	**0.0099**
fcvo	0.0595	0.0306	0.032	0.0509	0.0554	0.0043	0.0069	0.0052	0.0062	0.0279
sdhp	0.3022	0.1356	0.1426	0.1162	0.135	0.0644	0.0674	0.0329	0.039	0.115
tseri	4.2248	2.9496	3.3461	2.6285	2.6304	2.2256	2.4087	1.0941	1.2358	2.5271
tspoi	0.3007	0.2479	0.2659	0.229	0.2344	0.0705	0.068	0.0441	0.0564	0.1685
wpvo	0.0578	0.0412	0.0382	0.0331	0.0425	0.0102	0.0127	0.0107	0.0087	0.0283
wthr	0.3714	0.3684	0.3629	0.3595	0.3625	0.3673	0.3674	0.3583	0.366	0.3649
appt	1.2235	0.504	0.9551	0.8542	0.4561	0.5465	0.5764	0.2687	0.2458	0.6256
pppt	1.257	1.395	0.9622	0.8536	0.8015	1.7956	1.7838	0.8891	0.6055	1.1493
ptec	0.0028	0.0014	0.0011	0.0035	0.0095	0.001	0.0005	0.003	0.0022	**0.0028**
ptyhi	1.7288	0.4279	0.9052	0.5638	0.7168	1.0875	0.5865	0.4827	0.4377	0.7708
pyfc	0.1397	0.0629	0.0337	0.049	0.0372	0.0833	0.1137	0.0352	0.0593	0.0682
rcpc	0.6296	0.1403	0.1328	0.1492	0.1184	0.1877	0.1464	0.0875	0.0632	0.1839
srhc	0.0676	0.0176	0.0249	0.0336	0.0235	0.0253	0.0098	0.0037	0.0109	0.0241
bdfmi	0.7715	0.2729	0.1706	0.2231	0.2219	0.1152	0.153	0.0788	0.155	0.2402
bfpt	0.0835	0.0445	0.0248	0.0566	0.0658	0.0325	0.0192	0.0136	0.0103	0.039
bfsr	0.006	0.0013	0.008	0.0032	0.0118	0.0118	0.0329	0.0034	0.0023	**0.009**
dtgm	0.1846	0.1322	0.0625	0.0141	0.0457	0.0733	0.0564	0.0678	0.0422	0.0754
mtpf	0.5902	0.2833	0.1479	0.3409	0.1538	0.2718	0.2174	0.086	0.1405	0.248
rgmf	0.1012	0.0437	0.1125	0.1258	0.127	0.1562	0.0523	0.043	0.0419	0.0893
sfdfi	0.0751	0.0851	0.0629	0.132	0.066	0.1332	0.0785	0.0187	0.0841	0.0817
sfec	0.0772	0.0021	0.0073	0.0601	0.0027	0.0068	0.0364	0.009	0.0011	**0.0225**
tpcf	0.1086	0.1031	0.1742	0.0365	0.0594	0.0443	0.0388	0.1223	0.05	0.0819
ocos	0.854	0.5212	0.4831	0.3964	0.4019	0.3298	0.3757	0.211	0.1781	0.4168
prmtm	0.0884	0.0136	0.0424	0.0598	0.0379	0.0603	0.0927	0.0598	0.0231	**0.0531**
prmtv	0.0126	0.0086	0.0013	0.0015	0.0051	0.0022	0.0031	0.0027	0.0131	**0.0056**
prsfm	0.0104	0.0214	0.0055	0.0109	0.0801	0.0213	0.0243	0.0121	0.0098	**0.0217**
prsfv	0.0003	0.004	0.0036	0.0034	0.007	0.0006	0.0283	0.0172	0.0003	0.0072

again was the variable $SODP_{90}$. LHS was applied and N was fixed at 10,000, hence a total of 230,000 simulations were run. The estimates of S_i and S_{Ti} can be seen in Table 5 along with other statistics (see below).

4. The three leading parameters affecting sheet erosion in dehesas

The boxplot of the 230,000 values of $SODP_{90}$ obtained for the variance-based SA (VBSA) can be seen at the rightmost part of Fig. 2.

Table 5
Results of the variance-based sensitivity analysis. S_i and S_{Ti} = Estimates; SBCI = Size of the 95% CI; LCBD = 95% Lower confidence bound of the difference between couples of consecutive indices; LCBI = 95% Lower confidence bound of ST_i. All CIs were calculated with the bootstrap percentile method (1000 resamples).

	S_i [SBCI]	LCBD		S_{Ti} [SBCI]	LCBI	LCBD
tseri	0.248 [0.033]	0.006	wspt	0.391 [0.059]	0.361	−0.003
wspt	0.217 [0.039]	−0.023	scen	0.361 [0.061]	0.329	−0.020
scen	0.214 [0.036]	0.169	tseri	0.347 [0.078]	0.307	0.231
ocos	0.024 [0.018]	−0.008	ocos	0.089 [0.095]	0.041	0.031
roppv	0.021 [0.012]	0.004	roppv	0.041 [0.098]	−0.008	−0.006
roppm	0.011 [0.009]	0.000	mtpf	0.034 [0.098]	−0.015	−0.006
wthr	0.006 [0.005]	−0.005	bdfmi	0.028 [0.094]	−0.020	−0.010
mtpf	0.005 [0.010]	−0.007	roppm	0.026 [0.097]	−0.023	−0.004
bdfmi	0.005 [0.011]	−0.005	subh	0.021 [0.097]	−0.028	0.002
subh	0.004 [0.008]	−0.004	sfdfi	0.011 [0.098]	−0.038	−0.004
rcpc	0.003 [0.005]	−0.003	tpcf	0.009 [0.098]	−0.041	−0.005
sfdfi	0.002 [0.006]	−0.004	rgmf	0.008 [0.097]	−0.040	−0.004
rgmf	0.002 [0.006]	−0.004	rcpc	0.007 [0.099]	−0.043	−0.004
tpcf	0.001 [0.005]	−0.003	frbh	0.007 [0.097]	−0.042	−0.004
frbh	0.001 [0.005]	−0.003	wthr	0.007 [0.099]	−0.043	−0.002
pyfc	0.001 [0.003]	−0.002	prmtm	0.005 [0.097]	−0.044	0.000
prmtm	0.001 [0.005]	−0.002	sinf	0.002 [0.098]	−0.047	−0.002
sinf	0.000 [0.003]	−0.001	pyfc	0.002 [0.098]	−0.048	−0.002
srhc	0.000 [0.002]	−0.001	sdhp	0.002 [0.097]	−0.048	−0.001
seed	−0.001 [0.002]	−0.001	seed	0.001 [0.097]	−0.049	−0.002
sdhp	−0.001 [0.003]	–	srhc	0.001 [0.097]	−0.048	−0.003

Given that the initial soil depth was the same in all simulations (23.4 cm), we will alternatively refer to the accumulated loss of soil over 90 years (in cm), namely $ACLS_{90} = 23.4 – SODP_{90}$. Thus, $ACLS_{90}$ ranged between −0.38 cm (a 1.6% gain of soil depth) and 9.93 cm (a 42.4% loss) over the VBSA simulations. The median was 1.23 cm (a 5.26% loss) and the sample mean 1.52 cm (a 6.5% loss). Hence $ACLS_{90}$ showed a right-skewed distribution (and $SODP_{90}$ a left-skewed one). It is noted that soil horizon A, the most productive one, has an average depth of 10 cm in the available field data.

As already explained, the purpose of the VBSA was decomposing the variance of $SODP_{90}$ or $ACLS_{90}$ (which is the same) into terms corresponding to the different factors and their interactions. The estimates of S_i (Table 5) show that only three factors account for 68% of such a variance. They are topsoil erodibility (tseri; 24.8%), the multidimensional

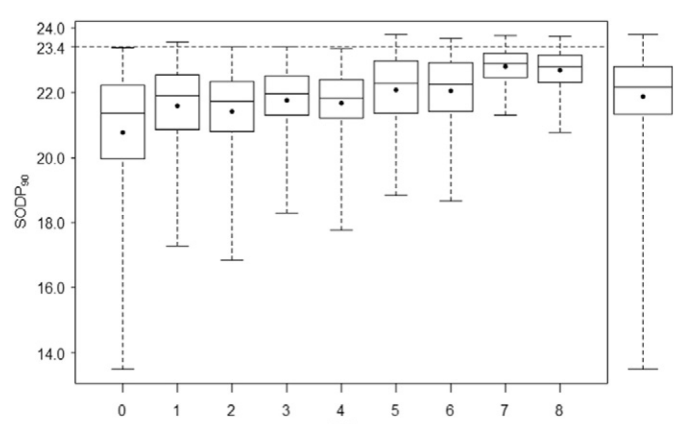

Fig. 2. Boxplot of the remaining soil depth after 90 years ($SODP_{90}$) vs. climate scenario (scen) resulting from the 230,000 simulations of the variance-based SA. The boxplot at the rightmost part of the figure corresponds to the marginal distribution of $SODP_{90}$. The initial soil depth was 23.4 cm in all simulations.

soil-water-storage-capacity-pasture-production factor (wspt; 21.7%) and climate scenario (scen; 21.4%). The percentage of the fourth parameter in order of importance decreases substantially (ocos; 2.4%). If S_{Ti} values are considered, the same group of three leading parameters is prominent, though they seem to be arranged differently. Also, it turns out that $S_{Ti} > S_i$ in all cases, so factors are involved in interactions. This was expected, since the model is nonlinear and nonadditive.

The bootstrap percentile method (1000 resamples) (e.g. Hersterberg et al., 2003) was used to estimate CIs for the sensitivity indices and to check whether their places in the rankings were statistically significant. Table 5 shows the sizes of such intervals in brackets. They were less than 18% of the respective estimates of S_i, and less than 23% of those of S_{Ti}, for the three leading parameters.

The 95% lower confidence bounds of the differences between couples of consecutive indices (LCBD) were also obtained, again using the bootstrap percentile method; they can be seen in Table 5. These statistics allow for checking in which cases the place of a factor in a ranking is statistically significant. For example, the first place of tseri in the S_i ranking is statistically significant because the corresponding LCBD value (CI of the difference between the S_i values of tseri and wspt) is positive (0.006). However, the positions of wspt and scen in the same ranking remain uncertain since the corresponding LCBD value is negative (−0.023). Thus, now it can be seen that despite the three leading parameters are sorted differently in both rankings, their relative positions are uncertain in most cases. Nevertheless, the top position of the whole group of leading parameters is statistically significant in both rankings.

Finally, Table 5 includes the 95% lower confidence bounds of all the S_{Ti} values (LCBI). They are positive only for wspt, scen, tseri and ocos, meaning that only for these factors the hypothesis of no influence on $SODP_{90}$ or $ACLS_{90}$ is rejected. However, the significance of ocos, whose LCBI value is only 0.04, is much less than those of the other three parameters, whose LCBI values are 0.36, 0.33 and 0.31, respectively.

Although the values of the sensitivity indices of the leading parameters are relatively similar, the uncertainty about soil erosion added by each of them is different. Topsoil erodibility (tseri) and soil water storage capacity (one of the components of wspt) can be relatively well known, so the uncertainty added by them can be reduced considerably in practice. In turn, the uncertainty about the pasture production function (the other component of wspt) is chiefly due to that of climate change. Indeed, if this change was not expected, the pasture production function might be taken as fixed and could be relatively well known (at least for the next 90 years). However, climate change affects the pasture production function. For example, increases in atmospheric carbon dioxide concentrations cause changes in plant production and transpiration rates (Rosenzweig and Hillel, 1998). Hence, climate change is the main source of uncertainty about soil erosion in dehesas.

The sample means of $SODP_{90}$ obtained for the climate scenarios in the VBSA simulations are marked with points in the boxplots shown in Fig. 2. It can be seen that all sample means corresponding to the climate-change scenarios (scen ≠ 0) were greater than that corresponding to the no-change scenario (scen = 0). Besides, all differences of means in relation to the latter were statistically significant (p-values $<2.2 \times 10^{-16}$; Welch's t-tests).

The sample means of $SODP_{90}$ under the nine climate scenarios were regressed against each of the variables included in Table 3, using only one explanatory variable per regression to safeguard degrees of freedom. The best fit ($R^2 = 0.86$) was achieved when the regressor was '95th percentile of daily precipitation'. Its regression coefficient was negative, as expected (p-value = 0.0003). Therefore, the frequency of days of extreme rainfall would be the best explanatory variable of the changes in sheet erosion caused by the climate scenarios. This result agrees with those found in other related studies that utilised models specifically intended to assess the direct impacts of changes in rainfall and temperature on erosion (Pruski and Nearing, 2002a; Pruski and Nearing, 2002b; Nearing et al., 2004; Garbrecht et al., 2014). When using 'average daily ET_o' as regressor, only a slightly worse fit was achieved ($R^2 = 0.84$). The coefficient was positive in this case (p-value = 0.0005), again as expected. This indicates that the rise in ET_o predicted by climate-change scenarios also had an important influence on the reductions in soil erosion they led to.

Fig. 2 reveals that the sample variances of $SODP_{90}$ under the climate-change scenarios were less than its sample variance under the no-change scenario. All differences in relation to the last one were statistically significant (p-values $<2.2 \times 10^{-16}$; Brown-Forsythe test). Therefore, the climate change scenarios analysed in this study seem to reduce uncertainty about sheet erosion in the study area.

5. The influence of economic and managerial factors on soil erosion

All the EM factors showed little influence on the variance of $SODP_{90}$ or $ACLS_{90}$. The same result was obtained for the two factors related to the capacity of rain to cause runoff (ROPP).

As already mentioned, the EM factors influence soil erosion by way of stocking rate and ground cover. However, given that neither of these variables can be negative, the influence of the EM factors on erosion was restricted in this study, so their sensitivity indices turned out to be low.

Note that, in this case, the total sensitivity index S_{Ti} of a factor X_i measures how large $E(V[SODP_{90}/X_{\sim i}])$ is in relation to $V(SODP_{90})$, where $/X_{\sim i}$ denotes "when all factors are fixed except X_i". Suppose that X_i is an EM factor and that, among all the other factors being fixed, some of them (normally other EM factors) take values resulting in a soil that is permanently denuded of pasture regardless of the value of X_i. For example, suppose that X_i is the price of meat and that the fixed factors include high subsidies that make it profitable to rear large livestock numbers that denude soil of pasture even when the price of meat stays at the lower limit of its range of variation. In cases like this, $SODP_{90}$ will be relatively small (accumulated soil loss will be large) and will not vary between simulations in which only the value of X_i is changed, because in all of them soil is permanently bare regardless of X_i (and ground cover cannot be negative). Hence, $V[SODP_{90}/X_{\sim i}]$ will equal zero (the variance refers to the range of variation of X_i). An instance of this kind of situation is illustrated by curve C1 in Fig. 3.

Other combinations of values of the fixed factors might result in a soil that is bare only if X_i is within a certain subset of its range of variation. Here, $SODP_{90}$ will not vary between simulations in which X_i takes values within that subset while the rest of parameters are held constant; hence $V[SODP_{90}/X_{\sim i}]$ will be rather reduced.

Similarly, there might be cases in which some EM factors other than X_i are fixed at values which make it unprofitable to rear livestock, regardless of the value of X_i. For example, X_i might be the price of meat and the fixed factors might include very high costs per breading female

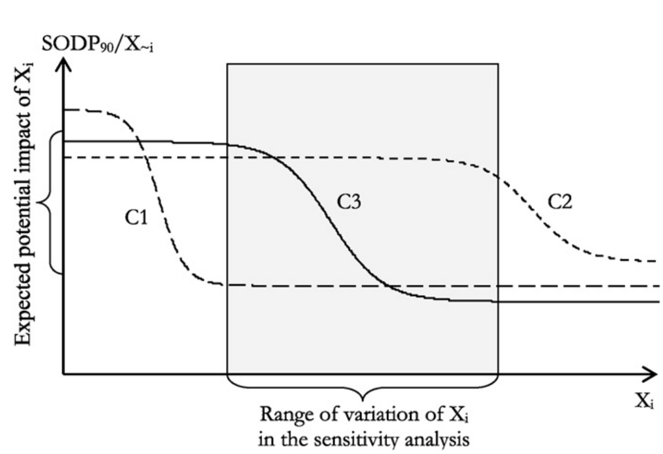

Fig. 3. Three instances of the influence of an economic or managerial factor (X_i) on the remaining soil depth after 90 years ($SODP_{90}$) when all factors except X_i are fixed ($X_{\sim i}$).

making the livestock business unprofitable even when the price stays at the upper limit of its range of variation. In cases like this, the stocking rate will be null regardless of the value of X_i (it cannot be negative), so $SODP_{90}$ will be relatively large and will not vary between simulations in which only X_i is changed, thereby equalling $V[SODP_{90}/X_{\sim i}]$ to zero. Curve C2 in Fig. 3 is not far from representing an example of this kind of situation. Other combinations of the fixed EM factors might result in no stocking rate only if X_i is within a subset of its range of variation. In these cases, $V[SODP_{90}/X_{\sim i}]$ will be reduced to some degree. Curve C2 in Fig. 3 is indeed an instance of this situation.

Finally, for some combinations of values of $X_{\sim i}$, an EM factor X_i might show, over the range of variation used in the VBSA, its potential influence on $SODP_{90}$, i.e. the largest value of $V[SODP_{90}/X_{\sim i}]$ for a given combination of values of $X_{\sim i}$. An example of this is curve C3 in Fig. 3.

Thus, for each EM factor X_i, the parameter space of $X_{\sim i}$ in the VBSA might contain two regions for which $V[SODP_{90}/X_{\sim i}]$ is either zero or somewhat reduced. Since S_{Ti} is directly proportional to the mean of $V[SODP_{90}/X_{\sim i}]$ over such a parameter space, if at least one of those regions were large for an EM factor, the value of its total sensitivity index S_{Ti} would be significantly diminished. And, given that $S_i \leq S_{Ti}$, the value of its first order sensitivity index would also be diminished. One of those regions is due to the fact that ground cover cannot be negative no matter how unfavourable conditions may be for pasture. Let us call this restriction on the influence of the EM factors on erosion, the GC (ground-cover) restriction. The other region is due to the fact that stocking rate cannot be negative no matter how unprofitable the livestock business may be. Let us call this the SR (stocking-rate) restriction.

In order to assess the extent to which the GC and SR restrictions affected the estimation of the sensitivity indices of the EM factors in this study, the variable 'number of breeding females at the end of the VBSA simulations', hereafter $BDFM_{90}$, was used. This was the best available proxy for the average stocking rate with which each simulation was run.

$BDFM_{90}$ ranged between 0 and 16.28 $AU \cdot ha^{-1}$ and showed a right-skewed distribution with a sample mean equal to 0.77 $AU \cdot ha^{-1}$. Thus, in 101,082 (44%) of the simulations $BDFM_{90}$ equalled 0 $AU \cdot ha^{-1}$ while in only 8598 (3.74%) was it greater than 3 $AU \cdot ha^{-1}$. This fitted well with the available data on the number of breeding females per hectare, which ranged between 0.25 and 15.76 $AU \cdot ha^{-1}$ (this last value was rejected as outlier when fixing the range of variation of bdfmi; Table 1). The sample mean of our observations (which did not include non-grazed enclosures) was 1.5, and that of $BDFM_{90}$, once excluded the zero values, was 1.25.

The high frequency of zeros in $BDFM_{90}$ is not a surprising result for dehesas. A zero stocking rate at the end of one simulation indicates that the combination of (constant) values of the EM factors used in such a simulation resulted in permanent or very frequent negative gross margins. In reality, the EM factors may change over time so there is a specific combination of their average values each year. Therefore, the percentage of simulations that ended up without livestock in the VBSA estimates the probability of getting negative annual gross margins in the study area. This economic weakness of the livestock business in dehesas has been pointed out by numerous experts (Pulido and Picardo (Coords.), 2010) and is well known by farmers. It is also illustrated by the fact that many farms in dehesas include enclosures that are never grazed and are usually used for forestry and hunting.

What is relevant here is that the high proportion of zeros in $BDFM_{90}$ indicates that, in all likelihood, the SR restriction had a high incidence in the estimation of the sensitivity indices of the EM factors. The low proportion of high values of $BDFM_{90}$ would indicate that the incidence of the GC restriction was much lower, though this is somewhat less clear. Nevertheless, there is a valid reason for why the EM factors showed scant influence on sheet erosion in this study.

A restriction similar to the GC and SR ones affects the influence of the two factors related to ROPP on erosion (roppm and roppv; Section 2.2). Indeed, if soil is saturated, runoff coefficient is one whatever the ROPP may be. And note that the modelled soil is a shallow soil which saturates easily. Besides, ROPP causes little changes in erosion rates when soil is well covered by pasture (e.g. in years without a drought). Thus, there also exist equally as good reasons to explain the low sensitivity indices shown by the factors related to ROPP.

It is important to note that the sensitivity indices estimated for the EM factors and factors related to ROPP are not deceptive. Nevertheless, they have to be interpreted adequately. Sensitivity indices give statistical accounts of the losses of soil resulting from simulating an ample range of possible variations on a simplified dehesa (given by different likely values of the endogenous factors) under a wide range of possible scenarios (given by different likely values of the exogenous factors). It turned out that the influence of the EM factors and factors related to ROPP was null or restricted in a large proportion of such simulations. Hence, the low values of the sensitivity indices of these factors indicate that it is unlikely to find them influencing soil erosion in the study area, not that such factors cannot affect soil erosion.

Indeed, the sensitivity indices of a factor do not necessarily assess its potential impact. This refers to the expected impact of the factor when it varies over its widest possible range of variation, which does not necessarily coincide with that used in the VBSA. Thus, in the present study, supposing that the effect of a factor X_i is monotonic, its potential impact could be estimated by the difference between the means of $SODP_{90}$ or $ACLS_{90}$ calculated at two very extreme possible values of X_i (Fig. 3). If such a difference of means is calculated at the two extremes of the range of variation used in the VBSA, and this is not the widest possible range, the result would not estimate the potential impact of the factor but would resemble the assessment provided by the sensitivity indices. For example, if there were a great proportion of situations like those illustrated by curve C_1 in Fig. 3, the difference of means would be small, like the value of the sensitivity indices.

In this study, the ranges of variation of the EM factors reflected the uncertainty about them existing in the study area, but they did not encompass all their possible values. Hence, their potential impacts on sheet erosion could not be estimated on the basis of the VBSA simulations. However, the potential impact on sheet erosion of stocking rate, through which the EM factors affect soil erosion, could be estimated since the VBSA simulations included extreme values of it.

Thus, the sample mean of $ACLS_{90}$ in those simulations where $BDFM_{90}$ equalled 0 $AU \cdot ha^{-1}$ was 1.42 cm. And the same mean in those simulations where $BDFM_{90}$ was greater than 10 $AU \cdot ha^{-1}$ was 3.09 cm. So the expected potential impact of livestock on $ACLS_{90}$ is 1.67 cm. This impact is greater in absolute value than the impact evaluated for climate change. Indeed, the sample mean of $ACLS_{90}$ under the climate-change scenarios was 1.38 cm, while the same mean under the no-change climate scenario was 2.62 cm. Hence the expected impact of climate change on $ACLS_{90}$ is -1.24 cm. The greatest difference between the sample mean of $ACLS_{90}$ under a climate-change scenario and that under the no-change scenario was -2.03 cm (scen $= 7$; Fig. 2).

To sum up, if an initially non-grazed enclosure became grazed with a stocking rate greater than 10 $AU \cdot ha^{-1}$, a high impact on erosion is to be expected, even greater in absolute value than the expected impact of climate change, which has proved to be one of the most important factors in sheet erosion in dehesas. However, it is unlikely to find the combination of EM factors leading to the aforementioned increment of stocking rate in the study area, at least for the time being, while climate change is underway.

As a last remark, it must be said that the high importance showed by the soil-water-storage-capacity-pasture-production factor (wspt) in the VBSA was due to the fact that the stocking rate was low in many simulations. The importance of such a factor would not be that high if the stocking rate had ranged between higher limits, simply because the amount of pasture biomass would have been smaller, on average. To check this point, a VBSA was carried out on a simplified version of the model representing a perfectly constant stocking strategy. To accomplish this, the variable 'number of breeding females' (BDFM) was substituted for the parameter bdfmi, thereby detaching the stocking rate from any explanatory variable. This model contained 13 parameters, since most of the EM factors were removed, and the VBSA was based on 30,000 simulations ($N = 2000$). The parameter bdfmi was assumed to be uniformly distributed in the range of 0.25 to 15.76.

In this VBSA, parameters scen ($S_i = 0.39$) and tseri ($S_i = 0.34$) remained at the top of the S_i ranking. The S_i value of the third parameter in order of importance (roppv) fell to 0.056. Parameter bdfmi showed scant relevance ($S_i = 0.029$). In all likelihood, this was caused by the GC restriction since bdfmi was greater than 5 $AU \cdot ha^{-1}$ in 69% of the simulations and greater than 10 $AU \cdot ha^{-1}$ in 37% of them. As expected, the S_i value of wspt fell to 0.008. This ability of the stocking rate to reduce the (beneficial) influence of pasture in sheet erosion provides further evidence that the potential impact of livestock on erosion is high for dehesas.

6. Conclusions

In this modelling study, topsoil erodibility, climate change and a combined factor related to soil water storage capacity and the pasture production function proved to be the most important factors affecting sheet erosion in dehesas. Economic and managerial factors demonstrated scant influence, but this simply means that it is unlikely to find them influencing soil erosion in the study area for the time being. The low profitability of the livestock business is maintaining stocking rates at low values in general, so therefore they are not affecting ground cover substantially. However, this study has shown that the potential impact of livestock, the means of influence of economic and managerial factors on soil erosion, is greater in absolute value than the impact of climate change. Therefore, concerns about the sustainability of dehesas should rise, if stocking rates were to rise in the future because of generalized changes in some economic or managerial factors.

Acknowledgements

This work was developed within the AMID research project (CGL2011-23361), financed by the Spanish Ministry of Economy and Competitiveness. This support is gratefully acknowledged. Also, thanks to the creators and developers of the R software, with which all the computations and statistical analyses of this study were performed.

Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.scitotenv.2015.11.128.

References

Anderies, J.M., Janssen, M.A., Walker, B.H., 2002. Grazing management, resilience and the dynamics of a fire-driven rangeland system. Ecosyst. 5, 23–44.
Aubault, H., Webb, N.P., Strong, C.L., McTainsh, G.H., Leys, J.F., Scanlan, J.C., 2015. Grazing impacts on the susceptibility of rangelands to wind erosion: the effects of stocking rate, stocking strategy and land condition. Aeolian Res. 17, 89–99.
Band, L.E., 1985. Field parameterization of an empirical sheetwash transport equation. Catena 12, 281–290.
Campolongo, F., Cariboni, J., Saltelli, A., 2007. An effective screening design for sensitivity analysis of large models. Environ. Model. & Softw. 22, 1509–1518.
Cariboni, J., Gatelli, D., Liska, R., Saltelli, A., 2007. The role of sensitivity analysis in ecological modelling. Ecol. Model. 203, 167–182.
Da Veiga, S.D., Wahl, F., Gamboa, F., 2009. Local polynomial estimation for sensitivity analysis on models with correlated inputs. Technometrics 51, 439–451.
Elwell, H.A., Stocking, M.A., 1976. Vegetal cover to estimate soil erosion hazard in Rhodesia. Geoderma 15, 61–70.
Flanagan, D.C., Nearing, M.A., 1995. USDA — Water Erosion Prediction Project (WEPP) Hillslope Profile and Watershed Model Documentation. National Soil Erosion Research Laboratory, USDA — Agricultural Research Service, West Lafayette, IN., USA.
Forrester, J.W., 1961. Industrial Dynamics. The MIT Press, Cambridge Massachusetts.
Gan, Y., Duan, Q., Gong, W., Tong, C., Sun, Y., Chu, W., Ye, A., Miao, C., Di, Z., 2014. The role of sensitivity analysis in ecological modelling. Environ. Model. & Softw. 51, 269–285.
Garbrecht, J.D., Nearing, M.A., Douglas Shields, Jr., F., Tomer, M.D., Sadler, E.J., Bonta, J.V., Baffaut, C., 2014. Impact of weather and climate scenarios on conservation assessment outcomes. J. Soil Water Conserv. 69, 374–392.
Gea-Izquierdo, G., Cañellas, I., Montero, G., 2006. Acorn production in Spanish holm oak woodlands. Investig. Agrar.-Sist. Recur. F. 15, 339–354.
Glab, T., 2013. Impact of soil compaction on root development and yield of meadow-grass. Int. Agrophysics 27, 7–13.
Glen, G., Isaacs, K., 2012. Estimating Sobol sensitivity indices using correlations. Environ. Model. & Softw. 37, 157–166.
Greenwood, K.L., McKenzie, B.M., 2001. Grazing effects on soil physical properties and the consequences for pastures: a review. Aust. J. Exp. Agric. 41, 1231–1250.
Hersterberg, T., Monaghan, S., Moore, D.S., Clipson, A., Epstein, R., 2003. Bootstrap methods and permutation tests. In: Farace, P. (Ed.), The Practice of Business Statistics. W.H. Freeman and Company, New York.
Higgins, S.I., Kantelhardt, J., Scheiter, S., Boerner, J., 2007. Sustainable management of extensively managed savanna rangelands. Ecol. Econ. 62, 102–114.
Ibáñez, J., Lavado Contador, J.F., Schnabel, S., Pulido Fernández, M., Martínez Valderrama, J., 2014. A model-based integrated assessment of land degradation by water erosion in a valuable Spanish rangeland. Environ. Model. & Softw. 55, 201–213.
Jacques, J., Lavergne, C., Devictor, N., 2006. Sensitivity analysis in presence of model uncertainty and correlated inputs. Reliab. Eng. and Syst. Saf. 91, 1126–1134.
Kelly (Letcher), R.A., Jakeman, A.J., Barreteau, O., Borsuk, M.E., ElSawah, S., Hamilton, S.H., Henriksen, H.J., Kuikka, S., Maier, H.R., Rizzoli, A.E., van Delden, H., Voinov, A.A., 2013. Selecting among five common modelling approaches for integrated environmental assessment and management. Environ. Model. & Softw. 47, 159–181.
Kirkby, M.J., 1971. Hillslope process-response models based on the continuity equation. In: Brunsden, D. (Ed.), Slopes Form and Process 3. Institute of British Geographers, Special Publication, pp. 15–30.
Lavado, J.F., Schnabel, S., Gómez, S., Pulido, M., 2009. Mapping sensitivity to land degradation in Extremadura. SW Spain. Land. Degrad. Dev. 20, 129–144.
Levins, R., 1966. The strategy of model building in population ecology. Am. Sci. 54, 421–430.
MAGRAMA, 2008. Programa de acción nacional contra la desertificación. MAGRAMA-Ministerio de Agricultura, Alimentación y Medio Ambiente, Madrid. http://www.unccd.int/ActionProgrammes/spain-spa2008.pdf.
Morgan, R.P.C., 1980. Soil Erosion. Longman Group, Essex.
Morgan, R.P.C., 1995. Soil Erosion and Conservation. Longman, Essex.
Morris, M.D., 1991. Factorial sampling plans for preliminary computational experiments. Technometrics 33, 161–174.
Mulholland, B., Fullen, M.A., 1991. Cattle trampling and soil compaction on loamy sands. Soil Use Manag. 4, 189–192.
Mullan, D., 2013. Soil erosion under the impacts of future climate change: assessing the statistical significance of future changes and the potential on-site and off-site problems. Catena 109, 234–246.
Nearing, M.A., Pruski, F.F., O'Neal, M.R., 2004. Expected climate change impacts on soil erosion rates: a review. J. Soil Water Conserv. 59, 43–50.
Perevolotsky, A., Seligman, N.G., 1998. Role of grazing in Mediterranean rangeland ecosystems. Bioscience 48, 1007–1017.
Plieninger, T., Pulido, F.J., Konold, W., 2003. Effects of land-use history on size structure of holm oaks stands in Spanish dehesas: implications for conservation and restoration. Environ. Conserv. 20, 61–70.
Pruski, E.E., Nearing, M.A., 2002a. Climate-induced changes in erosion during the 21st century for eight U.S. locations. Water Resour. Res. 38 (12), 1298. http://dx.doi.org/10.1029/2001WR000493.
Pruski, E.E., Nearing, M.A., 2002b. Runoff and soil loss responses to changes in precipitation: a computer simulation study. J. Soil Water Conserv. 57, 7–16.
Rosenzweig, C., Hillel, D., 1998. Climate Change and the Global Harvest. Potential Impacts of the Greenhouse Effect on Agriculture. Oxford University Press. Inc., New York.
Routschek, A., Schmidt, J., Kreienkamp, F., 2014. Impact of climate change on soil erosion. A high-resolution projection on catchment scale until 2100 in Saxony/Germany. Catena 121, 99–109.
Rowntree, K., Duma, M., Kakembo, V., Thornes, J., 2004. Debunking the myth of overgrazing and soil erosion. Land Degrad. Dev. 15, 203–214.
Saltelli, A., Annoni, P., 2010. How to avoid a perfunctory sensitivity analysis. Environ. Model. & Softw. 25, 1508–1517.
Saltelli, A., Tarantola, S., 2002. On the relative importance of input factors in mathematical models: safety assessment for nuclear waste disposal. J. Am. Stat. Assoc. 97, 702–709.
Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., Saisana, M., Tarantola, S., 2008. Global Sensitivity Analysis. The Primer. John Wiley & Sons Ltd., Chinchester.
Schmidt, J., 1990. A mathematical model to simulate rainfall erosion. Catena Suppl. 19, 101–109.
Schnabel, S., 1997. Soil erosion and runoff production in a small watershed under silvo-pastoral landuse (dehesas) in Extremadura, Spain. Geoforma Ediciones, Logroño.
Schnabel, S., Gómez, D., Ceballos, A., 1999. Extreme events and gully erosion. In: Coelho, C. (Ed.), Proceedings on the International Seminar on Land Degradation and Desertification. International Geographical Union, Lisbon, pp. 17–26.
Schnabel, S., Lavado, J.F., Gómez, A., Lagar, D., 2006. La degradación del suelo en las dehesas de Extremadura. In: Consejería de Infraestructura y Desarrollo Tecnológico (Ed.), Gestión Ambiental y Económica del Ecosistema Dehesa en la Península Ibérica. Junta de Extremadura, Mérida, pp. 63–72.
Sobol, I.M., 2001. Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates. Math. Comput. Simulat. 55, 271–280.
Sterman, J.D., 2000. Business Dynamics: Systems Thinking and Modelling for a Complex World. Irwin McGraw-Hill, Boston.
Sullivan, S., Rohde, R., 2002. On non-equilibrium in arid and semi-arid grazing systems. J. Biogeogr. 29, 1595–1618.

Thornes, J.B., 1990. The interaction of erosional and vegetational dynamics in land degradation: spatial outcomes. In: Thornes, J.B. (Ed.), Vegetation and Erosion: Processes and Environments. John Wiley & Sons, Chichester, pp. 1–53.
Whalley, W.R., Watts, C.W., Gregory, A.S., Mooney, S.J., Clark, L.J., Whitemore, A.P., 2008. The effect of soil strength on the yield of wheat. Plant Soil 306, 237–247.
(Coords.) (19 authors)Pulido, F., Picardo, A., 2010. El libro verde de la dehesa. Documento para una estrategia ibérica de gestión. [The green book of dehesas. Document for an Iberian management strategy]. Available online at: http://www.uco.es/integraldehesa/index.php/especiales/libro-verde-de-la-dehesa.