Agricultural Systems 149 (2016) 65–74

Contents lists available at ScienceDirect

Agricultural Systems

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

Assessing drought risk in Mediterranean Dehesa grazing lands

Eva Iglesias [c,*], Karen Báez [a], Carlos H. Diaz-Ambrona [b]

[a] Instituto de Desarrollo Agropecuario, Ministerio de Agricultura, Agustinas 1465, Santiago de Chile, Chile
[b] Research Centre for the Management of Agricultural and Environmental Risks, Department of Agricultural Production, Universidad Politécnica de Madrid, Ciudad Universitaria s/n, 28040 Madrid, Spain
[c] Universidad Politécnica de Madrid, Department of Agricultural Economics, Ciudad Universitaria s/n, 28040 Madrid, Spain

ARTICLE INFO

Article history:
Received 7 August 2014
Received in revised form 27 July 2016
Accepted 31 July 2016
Available online xxxx

Keywords:
Drought risk
Bioeconomic model
Rangeland
Grazing livestock
Adaptation strategies

ABSTRACT

Extensive grazing activities in the Mediterranean area will have to confront an increasing risk of drought. This threat poses a challenge to the long-term viability of these activities that play an important role in rural development and have traditionally shaped highly valued ecosystems such as the *Dehesa* landscape in the Iberian Peninsula. The aim of this research is to assess the economic impact of drought on this extensive livestock farming system and evaluate the potential of adaptation strategies such as reducing the stocking rate. A dynamic and stochastic bioeconomic model is developed to account for the complex climatic, ecologic and economic relationships at play during drought.

We simulate the 1999–2010 weather time series to characterize seasonal patterns and evaluate the risk caused by drought spells. We assess the consequences of drought in terms of duration, frequency and intensity, finding that economic losses increase at an increasing rate with long lasting droughts. Our findings reveal different patterns between climate and economic risk variables. The risk of a climate shock concentrates in spring and the beginning of autumn while the risk of suffering economic losses occurs with a 3–4 weeks delay and lasts for a longer period of time. We integrate Monte Carlo routines in our simulation model to assess risk exposure and propose the use of Value-at-Risk to capture downside risk at different thresholds. Our simulation results show that the farmer may have to confront annual economic losses above 22.9% with a 5% probability in the current or baseline scenario. Finally, we use the model as a tool to evaluate the potential of adaptation strategies such as increasing or reducing the stocking rate. We find that the former has rather limited impact on average income as compared to the later but both show significant impacts on risk exposure, which may entail important economic consequences. In particular, we find that increasing the stocking rate by 20% decreases the probability of incurring moderate losses, from 45.0% to 40.6%. Furthermore, it also increases the probability of favourable outcomes, from 50.0% to 52.0%. However, this comes at the expense of a significant increase in the chance of experiencing severe economic impacts, from 5 to 6.9%. On the contrary, reducing the stocking rate by 20% reduces the chance of severe impacts from 5% to 3.7%, but also entails an increase in the probability of moderate losses and a significant drop in the probability of experiencing a favourable outcome.

1. Introduction

The assessment of drought risk on agricultural systems is a research area of main interest given that frequency and severity of drought is expected to increase in the coming decades (IPCC, 2014). Vulnerability to drought in pastures in semi-arid areas can lead to considerable socio-economic and environmental losses in the absence of mitigation and adaptation strategies (Ares, 2007; Morton and Barton, 2002). Practices such as nomadism or transhumance, that once conformed adaptation strategies in the Mediterranean are now in decay (Carmona et al., 2013). Highly variable rainfall patterns is an intrinsic characteristic of Mediterranean grazing lands and has been identified as a major threat to grazing activities. These activities play a key role in the sustainability of highly valued silvo-pastoral ecosystems, which provide a broad array of environmental, cultural and economic services. Surprisingly, despite the relevance of grazing lands at global and local scale, the body of literature that assesses drought risk and analyses the impact of climate variability on grazing ecosystems is relatively limited. Several authors claim that a better understanding of the relationships between climate, ecologic and socioeconomic factors is needed to support decision-making and adaptation strategies (Asner et al., 2004; Iglesias et al., 2007; Thornton et al., 2009 and Jakoby et al., 2014).

The aim of this work is to assess the risk of drought in *Dehesa* grazing activities, which conform a silvo-pastoral ecosystem that extend

* Corresponding author.
E-mail address: eva.iglesias@upm.es (E. Iglesias).

http://dx.doi.org/10.1016/j.agsy.2016.07.017

throughout some 3.6 million hectares in the Southwestern part of the Iberian Peninsula. We address questions such as what is the probability of incurring economic losses and which are the most critical periods of risk. In addition, we evaluate to what extent farm adaptation strategies, such as reducing stocking rate, have an impact on economic risk exposure.

The assessment of drought impact and risk in grazing livestock systems faces several challenges. On the one hand, drought is signalled as a covariate event involving complex spatial and seasonal patterns (Thornton et al., 2009; Tiejten and Jeltsch, 2007; Yurekli and Kurunc, 2006). Yurekli and Kurunc (2006) use an autoregressive moving average (ARIMA) model to estimate weather seasonal patterns and highlight that agricultural drought includes consideration of complex variables that make it impracticable to accurately predict the duration and intensity of agricultural drought. On the other hand, drought is also recognized as a complex socio-environmental phenomenon. Although it is perceived as a climate threat, its effects may be worsened or mitigated by the interaction of various environmental and socioeconomic factors (Kallis, 2008; Thornton et al., 2009; Iglesias et al., 2003, among others). The difficulty of finding a universal definition for drought is highlighted by Zargar et al. (2011) who review 76 different drought indices in the literature. Due to its simplicity, rainfall deficit is the most widely used indicator of drought (Yurekli and Kurunc, 2006; Pratt et al., 1997). Much less frequent is the use of indices or measures involving economic criteria. Among them stands the work of White et al. (1998) who report six core criteria, including farm income and the spatial distribution of the phenomenon together with other biophysical criteria, to assess the extent and severity of drought in grazing lands in Australia.

The review by Thornton et al. (2009) highlights that the interactions of climate variability and climate change in grazing lands is a neglected area of research and pinpoint the lack of data to calibrate and validate bio-economic models as an important backdrop. In the last decade, an emerging body of bio-economic models looked into the sustainability of different grazing management strategies in relation to the phenomenon of drought and the stochastic nature of rainfall (Baumgärtner and Quaas, 2009; Díaz-Solís et al., 2009; Müller et al., 2011; Weikard and Hein, 2011). In this strand, the work of Quaas et al. (2007) analyse farmers' incentives to establish a sustainable grazing management system. Also, Beukes et al. (2002) develop a dynamic bio-economic model that identifies annual rainfall as a key determinant in the decision of whether or not to invest in the implementation of grazing management strategies. These authors advocate more research is needed on the effect of management and structure of the herd stock on farm income. The work of Jakoby et al. (2014) highlights that the first-best strategy in rangeland management differs depending on farmers' characteristics and risk preferences. Their simulation-modelling framework incorporates seasonal weather patterns to evaluate different grazing management options under climate variability. In their work, seasonal patterns are simulated assuming a constant weekly precipitation during the rainy season. In other strand, the work of Lybbert et al. (2004) and Martin et al. (2014) show that risk management behaviour in poor pastoralist populations is clearly influenced by wealth dynamics consideration. While this aspect has received very little attention in the literature on drought and pastoralism, their findings have important policy implications to avoid the poverty trap in vulnerable communities. An innovative approach to risk valuation is the work of Lybbert et al. (2010), who explore the potential of field experiments to better understand how poor valuate drought risk mitigation options in a dynamic context. Linking famers' decision-making and biophysical models in a stochastic context is a computational challenge highlighted by Freier et al. (2011). These authors adopt a Markovian approach and develop an optimization decision-making model in order to identify economic and environmental effects of long persistent drought on extensive livestock systems. Their results show the after-effects of drought last far longer than the meteorological phenomenon itself. To this respect, Wilhite and Glantz (1985) also contend that agricultural drought does not always coincide with periods of meteorological drought.

We contribute to the literature with a stochastic and dynamic bio-economic model that focuses on the multifaceted nature of drought spells and integrates seasonal weather patterns in order to gain a deeper understanding of the complex relations at play during drought. In addition, we use Monte Carlo techniques to assess economic drought risk at the farm level based on three key elements: (i) probability (ii) potential economic losses and (iii) timeframe being considered. We propose the use of Value-at-Risk, a widely used measure in financial risk assessment to capture downside risk. The methodological approach is presented in the next section where we describe fieldwork, summarize the characteristics of the study site and lay down the bio-economic model. In the third section we present and discuss results while in the final section we establish the main conclusions of the research.

2. Methodology

2.1. Study site: grazing livestock in Iberian Dehesa ecosystem

The production system under analysis is that of a traditional *Dehesa* farm, in the Southwestern part of the Iberian Peninsula (see Fig. 1). The region has a continental Mediterranean climate with mild winters and very hot summers. The annual rainfall is between 600 and 650 L/m^2 and usually peaks in autumn and spring.

The model was parameterized, calibrated and validated using face-to-face field survey, a review of technical information and local studies, satellite data and in situ field data obtained in a representative *Dehesa* grazing farm located in Pozoblanco (Pedroches Valley). Field work was conducted between May 2010 and June 2012 on two plots of land, 60 m × 60 m in size, with grazing and no grazing activities respectively. Pasture growth was measured at monthly intervals, with wet weight and dry matter measured in three random sample cuts on each plot. Soil water content was also measured[1] at three random points and at three cumulative depths (20 cm, 40 cm and 60 cm) during the vegetation activity period. Meteorological daily data on air temperature, rainfall and solar radiation was obtained from the closest weather station,[2] while rainfall was also measured in situ.[3]

A face-to-face survey was conducted with experts and farmers in the area to characterize farm management and strategies to mitigate drought impacts. This information was also complemented with a review of local studies and technical information. The extensive grazing farm has a livestock density of 0.3 livestock units (LSU) per hectare and is focused on the rearing of beef cattle. Management of livestock is heavily dependent on pasture availability and the breeding calendar of the herd is the main adaptation strategy to confront highly variable seasonal weather patterns. The breeding calendar is illustrated in Table 1 in supplementary material. The mating period usually runs from January to May and calving takes place between the months of October and February to coincide with the main pasture growth period, which reaches its peak in spring.[4] The usual fertility ratio of a livestock farm in the area is 0.85 and farmers sell young at approximately 6 months of age when the animal has reached the required weight. Grazing provides the main component of the herd's diet on the farm and livestock usually graze for the whole year, except for the months of August and September when there is not enough pasture growth and their diet must therefore be supplemented. The increase in

[1] Soil water content in volume percentage was determined using a direct measure taken with TDR (Time Domain Reflectance) sensor (Soil moisture Equipment Corp 6050 × 1 Trase System I).

[2] Hinojosa del Duque (38° 29′ 53″ N, 5° 6′ 51″ W, 543 masl).

[3] Measures were recorded with an automatic pluviometer HOBO-200.

[4] Beef cattle go through different physiological stages during the production cycle resulting in different nutritional needs for each period t. The breeding calendar of the herd is detailed in Table 1 in the supplementary material.

Fig. 1. Location of the Pedroches Valley.

supplementation feed costs was identified as the most relevant impact of drought during the field survey.

The economic component of the model also considers the direct costs associated with the rearing of the herd, the number, weight and sale price of animals as well as the subsidies granted to the farmer by the Common Agricultural Policy (CAP). Farm income is heavily determined by the costs of supplementing the animals' diet, which depends on the availability of pasture throughout the season. The historical series of fodder and forage prices as well as the sales of livestock have been obtained from the statistical records of the Ministry of Agriculture, Food and Environment and the markets in the area under study.

2.2. The bio-economic model

In order to analyse the economic risk faced by a grazing livestock farm in *Dehesa* lands, a dynamic and stochastic bio-economic model has been developed. The model incorporates climate variables, ecological and soil factors that characterize pasture growth, livestock characteristics, farm management strategies and the economic information on market prices and CAP subsidies. The model has been developed in @Risk, risk analysis software that characterize random variables using density functions and the implementation of Monte Carlo routines. Model simulation is based on daily weather data corresponding to the 1999–2010 period. The model has a dynamic and recursive structure and integrates several timeframes. Pasture growth is simulated on a daily basis, which will be denoted by subscript *i*, while pasture availability, grazing and feed supplements are computed for 10-day periods,[5] and will be denoted with subscript *t*. This means that 36 such periods are studied per year. The mathematical model approach is structured in four main equations (see Fig. 2). The first reflects pasture growth, the second equation determines the nutritional needs of the livestock, and the third is the state equation that reflects the dynamics of the pasture ecosystem. Finally, the fourth equation reflects the economic outcome of the farm. Functions and variables are listed in Table 2.

Eq. (1) is detailed as follows and describes the relationships that determine pasture growth in each period t according to the vector of daily weather variables $[\tilde{\beta}_i]$, which includes average rainfall $\tilde{R}_i$, average air temperature $\tilde{T}_i$, and solar radiation $\tilde{S}_i$; and the remaining pasture in previous period, $\tilde{B}_{t-1}$. This equation takes into account a set of parameters characterizing soil properties and the composition of the pasture (see Table 3).

$$\phi\left(\left[\tilde{\beta}_i\right],\tilde{B}_{t-1}\right) = \sum_{i=1}^{10} \min\left(\left(1-e^{-k_e\tilde{\beta}_{t-1}/k_f}\right)\tilde{S}_i k_p k_r\,\varphi\left(\tilde{T}_i\right),\tilde{W}_i k_a \varphi\left(\tilde{T}_i\right)\right)k_h \quad (1)$$

The pasture growth function has been adapted from the *Dehesa* model (Etienne et al., 2008), and follows the approach of Hanson et al. (1994) and Corson et al. (2006). Accumulated pasture growth in each 10-day period is the sum of daily estimates based on interception of solar radiation, soil water availability $\tilde{W}_i$ and air temperature. This function becomes determined by the minimum of two limiting factors. In the first term, light interception is modelled as an exponential function of the leaf area index and the coefficient of solar radiation extinction k_e. Leaf area index is defined as the biomass in the previous period, divided by the constant specific leaf area k_f. Light interception is then multiplied by the solar radiation, by the ratio photo-synthetically active radiation k_p, and by the radiation use efficiency of the pasture k_r. In the second term, soil water availability for pasture growth is calculated from a simplified soil water balance $\tilde{W}_i = \theta(\tilde{W}_{i-1},\tilde{R}_i,\widetilde{ET}_i)$, taking into account soil property parameters such as field capacity k_{fc}, permanent wilting point k_{wp}, percentage of soil pedregosity k_{pg} and soil depth z; daily rainfall and daily pasture evapotranspiration ET_i (see details in Huang et al., 2011). Then soil water availability is multiplied by the water use efficiency k_a. In both terms, pasture growth is also limited by the effect of the air temperature according to $\psi(\tilde{T}_i)$ which is a piece-wise linear function defined as follows: $\psi(\tilde{T}_i) = \{-1+0.2T_i\ if\ 5\le T\le 10; 1\ if\ 10\le T\le 20; 5-2T_i\ if\ 20\le$

[5] For the shake of simplicity, months with 31 days are represented by two periods of 10 days and a third last period of 11 days. Hence, monthly data are easily computed by aggregating 3 periods. We generically refer to 10-day periods.

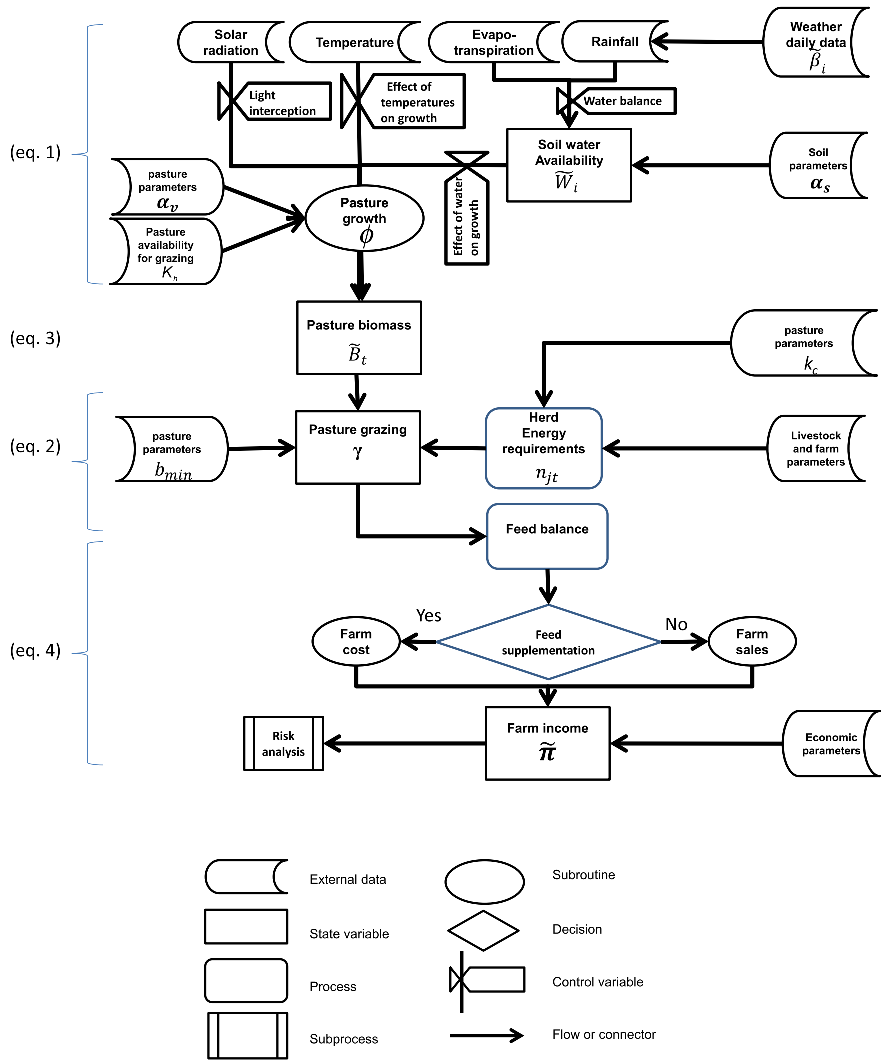

Fig. 2. Model scheme.

$T \le 25$; and 0 otherwise } with units in °C. Finally, coefficient K_h represents the ratio of the pasture that is grazed by animals. Parameter values and their respective sources are detailed in Table 3.

$$\gamma(X, X_{jt}) = \min\left(\sum_j \left(n_{jt}\frac{X_{jt}}{a}\right)\frac{1}{d_t}, \left(\tilde{b}_{t-1}k_{s_t} + \phi\left(\left[\tilde{\beta}_i\right], \tilde{b}_{t-1}\right) - b_{\min}\right)\right) \quad (2)$$

Eq. (2) estimates pasture grazing, as the minimum between livestock nutritional needs and the biomass availability for each 10 day-period t. The first term represents biomass demand as determined by the number of animals in each state j and period t X_{jt}, according to the decision of the farmer with regards to the calving calendar and use of forage resources, and the energy requirements of the livestock in each physiological state n_{jt}, and is divided by a, which is the farm grazing area and by d_t representing the values of energy density of the pasture in each period t (see Table 4). The second term represents available biomass as determined by biomass from previous period corrected by the coefficient of pasture senescence $k_{s\,t}$ plus pasture growth and detracting $b_{\min}$ which is the biomass that remains and cannot be grazed by the herd.

$$\tilde{B}_t = \tilde{B}_{t-1}k_s + \phi\left(\left[\tilde{\beta}_i\right], \tilde{B}_{t-1}\right) - \gamma(X, X_{jt}) \quad (3)$$

Eq. (3) is the state equation that simulates the dynamics of pasture availability and establishes that biomass in period t depends on the biomass of the previous period taking into account the corresponding senescence coefficient, plus pasture growth in period t minus biomass grazed by animals in period t.

Finally, Eq. (4) defines the stochastic annual farm income $\tilde{\pi}$ as the difference between total revenue and farm costs. We assume the farmer always satisfies livestock energy requirements with feed supplements when not enough pasture is available. The first two components of the equation reflect market revenues and CAP subsidies respectively, while the last two components represent feed costs and other farm costs. In this equation p is livestock sale price, r the ratio of births, X the number of cows and s_w the livestock weight at sale. In the second term, y represents CAP subsidies while in the third term, $\tilde{C}_t$ is feed price, c_v represents other costs of the farm (such as labour, veterinary

Table 2
Variables and functions.

Variables and functions	Definition
Daily weather variables $[\tilde{\beta}_i]$	
$\tilde{T}_i$	Temperature
$\tilde{S}_i$	Solar radiation
$\tilde{R}_i$	Rainfall
$\tilde{W}_i$	Water balance
$\tilde{B}_t$	Biomass availability
$\phi([\tilde{\beta}_i], \tilde{B}_{t-1})$	Pasture growth function
$\gamma(X, X_{jt})$	Pasture grazing function
$\pi(X, X_{jt})$	Annual farm income function
X	Livestock density

Table 3
Vegetation and soil parameters.

	Parameter	Definition	Units	Value	Source
Vegetation parameters [α_v]	k_r	Radiation use efficiency	g/MJ	1.62	Wight and Skiles (1987)
	k_a	Water use efficiency	kg/ha mm^{-1}	12.97 (1.0–20.1)	Martín Polo et al. (2003)
	k_p	Ratio of photo-synthetically active radiation		0.5	Connor et al. (2011)
	k_f	Specific leaf area	m^2/kg	22	Sheehy et al. (1979)
	k_e	Coefficient of solar radiation extinction		0.4	Loomis and Williams (1969)
	k_h	Ratio of pasture grazed by animals		0.45	White and Troxel 1995
Soil param.[α_s]	k_{pg}	Percentage of rock cover	%	5.9	Rosa et al. (1984)
	k_{fc}	Field capacity	%	25	Rosa et al. (1984)
	k_{wp}	Permanent wilting point	%	10	Rosa et al. (1984)
	z	Depth of soil	m	0.6	Rosa et al. (1984)

Table 4
Farm management and economic model parameters.

	Parameter	Definition	Units	Value	Source
Farm management parameters	a	Farm grazing land	ha	200	Field survey
	X	Number of breeding cows (Baseline scenario)	LSU	50	Field survey
	r	Calving rate		0.85	Field survey
	n_{jt}	Energy requirements of dry cows	UFL/LSU	6.58	Terradillos et al. (2004)
	n_{jt}	Energy requirements of gestating cows	UFL/LSU	8.19	Terradillos et al. (2004)
	n_{jt}	Energy requirements of lactating cows	UFL/LSU	9.82	Terradillos et al. (2004)
	n_{jt}	Energy requirements of bulls	UFL/LSU	9.09	Terradillos et al. (2004)
	n_{jt}	Energy requirements of calves for heifers	UFL/LSU	6.58	Terradillos et al. (2004)
	n_{jt}	Energy requirements of calves	UFL/LSU	8.26	Terradillos et al. (2004)
	d_t	Energy density of pasture	UFL/kg dry matter	0.5–0.99[a]	Terradillos et al. (2004)
Economic parameters	c_v	Farm costs other than supplements	€/LSU	234	Field survey
	c_t	Average forage price	€/UFL	0.19	Junta de Andalucia[b]
	p	Sale price of livestock	€/kg live weight	2.3	Field survey
	s_w	Sale weight of livestock	kg	200	Field survey
	y	CAP subsidies	€/LSU	328	Junta de Andalucia

[a] Energy density value for each period of the year can be found in Table 4 provided as supplementary material.
[b] Junta de Andalucia. Agricultural Statistics. Available at: http://www.juntadeandalucia.es/agriculturaypesca/portal/servicios/estadisticas/.

costs, etc.) and a is available grazing farm land in hectares (see Table 4). Feed price is considered a random variable. Based on market data we assume it follows a triangular distribution function with min = 0.16, most likely = 0.19 and max = 0.22.

$$\pi(X, X_{jt}) = prs_w X + yX - \tilde{C}_t \left(\sum_{t=1}^{36} \left(\sum_j n_{jt} X_{jt} \right) - a\,\gamma(X, X_{jt}; n_{jt}) \right) - c_v X \quad (4)$$

Based on observed daily weather data during the 1999–2010 period, Monte Carlo simulation is used to assess main sources of risk and to characterize the probability distribution function of annual farm income. In addition, we explore the role of farm adaptation strategies such as the livestock density to reduce vulnerability to drought. To this end, we assess the impact of three different farm stocking rate scenarios on its economic risk exposure.

Pasture growth was calibrated and validated using fieldwork and in situ data collection as described in Section 3. Water use efficiency parameter was used as a fine tuning factor for calibration purposes. The parameter value was set at 12.97 kg DM/ha mm, within the value ranges provided by Martín Polo et al. (2003) for the study area.[6] The results of a sensitivity analysis of pasture growth to this parameter are included as supplementary material. Correlation among observed and simulated pasture growth was $R^2 = 0.6$. In addition, time series NDVI[7] (Normalized Difference Vegetation Index) was used to validate the model economic outcomes for 2000–2012 years. This index is highly correlated with drought impacts and is currently used in weather insurance to monitor drought impact and trigger indemnities. The variable of annual cost deviation relative to historic average was regressed against the annual sum of NDVI deviations obtaining a correlation coefficient $R^2 = 0.57$. An alternative regression model, also including a quadratic term, was tested in order to account for nonlinear trends. Under this specification both coefficients were significant at 1 and 5%, with $R^2 = 0.74$. Further model details are provided as supplementary material.

3. Results and discussion

3.1. Characterization of drought: intensity, frequency and duration

The model is used to simulate 10-day pasture growth, 10-day feeding costs as well as annual farm income under the 1999–2010 climatic scenario. Our results show that main feeding costs are incurred during

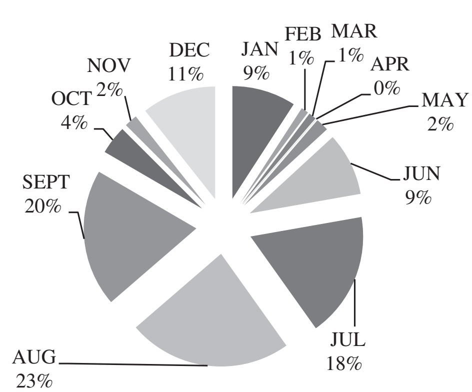

Fig. 3. Relative importance of monthly feeding costs throughout the farming calendar. Source: Own simulation results.

[6] Martín Polo et al. (2003, pag. 39) measured the productivity and use of rain water in two Dehesa grassland with different soil and grass species, their results go from 1.0 kg MS ha^{-1} mm^{-1} to 20.1 kg MS ha^{-1} mm^{-1}.
[7] Source: NASA, MOD13Q1 NDVI (250 m); selected area: 2.25 ∗ 2.25 km, centered location point: Lat [38,38025346650464] Lon [−4,757487773895264]. Time series: February 2000 to July 2012. Data frequency: 16 days. Pixel number and size: 81 (250 ∗ 250 m). Land uses selected: grassland and woody savannas.

Table 5
Descriptive statistics of monthly feeding costs (€/LSU).

Months	Average	Std.dev.	CV	Variance	Max	Min	Median	Asymmetry
January	17.6	9.0	0.5	80.9	33.8	5.7	17.3	0.3
February	2.0	3.2	1.5	10.0	8.8	0.0	0.0	1.1
March	2.1	6.0	2.9	36.5	18.9	0.0	0.0	2.5
April	0.0	0.0	.	0.0	0.0	0.0	0.0	.
May	3.6	6.9	1.9	47.3	17.6	0.0	0.0	1.4
June	17.4	21.5	1.2	461.3	55.4	0.0	7.0	0.8
July	34.5	18.2	0.5	331.8	48.2	0.0	48.2	−0.9
August	45.2	6.3	0.1	40.0	49.4	32.5	48.8	−1.3
September	38.0	9.1	0.2	82.5	45.8	16.9	43.3	−1.3
October	7.9	9.8	1.2	95.6	30.5	0.0	7.6	1.3
November	3.6	4.3	1.2	18.1	12.3	0.0	1.7	0.9
December	20.5	8.2	0.4	67.5	29.0	2.0	23.0	−1.1

Source: Own simulation results.

the summer months of July, August and September (see Fig. 3). However, as descriptive statistics in Table 5 illustrate, higher variability happens in February–March, May–June and October–November. These results highlight the distinction between aridity, as a usual condition of low rainfall when corresponding average feed costs are high but there is no or little variability, and drought risk, where average feeding costs are low but variability is high. Despite climate variability, farmers never incur extra feeding costs during April. The results are consistent with our fieldwork where surveyed farmers pinpointed the beginning and end of spring and beginning of autumn as the most critical periods in regard to drought effects.

Fig. 4 illustrates feeding costs in relation to the historic average value and illustrates highly variable inter and intra-annual patterns for the simulated 1999–2010 time series. The bars with values greater than zero correspond to costs above the average of that period and are thus associated with periods in which less pasture is available due to drought spells. Based on these simulation model results, the risk of drought is characterized in terms of its frequency, intensity and duration, as illustrated in Table 6. We build histograms in order to estimate the frequency and assess the magnitude of drought accounting for those periods when the farmer incurs feeding costs above the historical period average. We distinguish three possible situations with feeding cost above average during: (a) one ten-day period (b) two consecutive ten-day periods and (c) 3 or more consecutive ten-day periods. We can see that periods of drought lasting ten days are the most common and occur once or twice a year, while droughts lasting for two consecutive ten-day periods are much less common, occurring twice every three years. Finally, droughts lasting three or more consecutive ten-day periods occur every two years. It is important to highlight that the average economic impact per ten-day period is similar for periods of drought of one or two ten-day periods. However, for long lasting drought spells the costs increase at an increasing rate.

3.2. Exploring seasonal patterns and main sources of risk

We use Monte Carlo techniques to identify main sources of risk. Farm income is influenced by various stochastic factors including the availability of pasture in the different months and the price of forage and feed supplements. Monte Carlo simulation is a reiterative process of analysis, which uses repeated samples from the inputs distribution and produces a distribution of possible farm income values. A correlation analysis is then conducted to identify main sources of risk. The Tornado diagram in Fig. 5 ranks these stochastic factors or inputs according to their Spearman correlation coefficient revealing the direction and magnitude of their influence on the farm economic output. According to these results, main sources of risk are encountered for required supplemental feeding during the months of July and June. Forage price also shows a significant impact on farm risk exposure. Although main climate risk periods occur during spring -March and May-, feed supplementation costs during this period show the lowest correlation with farm income risk.

A complementary insight into seasonal patterns is illustrated in the upper and lower graphs in Fig. 6, which shows the average and standard deviation of pasture growth and feeding costs, respectively. The X-axis represents the periods of the agricultural calendar starting in autumn (September). Standard deviation reflects volatility of outcomes and is used as a proxy for risk. Although the most significant pasture growth occurs between periods 18 and 22 (March–April), the line that

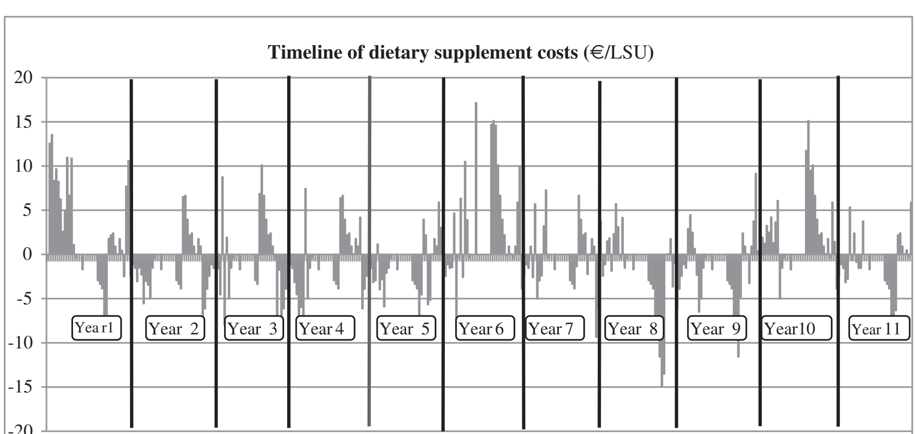

Fig. 4. Evolution per ten-day period of the feed cost of a representative beef cattle farm in Pedroches Valley (Spain) in 1999–2010.
Source: Own simulation results.

Table 6
Duration, frequency and intensity of periods of drought.

Duration	Intensity (€/LSU)	Frequency
1 ten-day period	7.6	Between once or twice every year
2 ten-day periods	15.2	Twice every three years
3 or more ten-day periods	30.0	Once every two years

Source: Own results.

represents the standard deviation shows that risk occurs at several critical points: the highest risk is found between the 21–24 periods (April to May) exhibiting a linear increasing trend and is followed by a second period of high risk at the beginning of autumn. The peak in period 27 also reflects the uncertainty on the starting point of the dry season.

The analysis of monthly average costs of feeding supplements throughout the year shows there is no risk during the 21st–23rd periods. We find a significant delay in relation to climate risk since economic risk does not start to peak until late spring and lasts till the beginning of summer (24th–31st periods). A declining trend in risk is identified as summer progresses. This analysis confirms greatest expenditure occurs during the summer months, however with no or little risk associated. We find a peak in risk at the beginning of the agricultural year, corresponding to simultaneous risk in pasture growth. In this case, climate patterns may have an immediate effect since there is little or no pasture over the ground at this time of the year. During late autumn and early winter average feed costs increase in parallel to economic risk. This risk-increasing trend again reveals a delayed response to the beginning of autumn climate risk.

3.3. Characterizing farm risk exposure under stoking rates scenarios

As illustrated in Fig. 7, risk exposure is assessed by estimating the probability of incurring a certain range of economic losses within a year timeframe. We use Monte Carlo techniques to estimate the probability density function of farm income as given by the 1999–2010 weather daily data. The logistic function was selected according to goodness of fit test (chi square = 0.8182), with an average of 136.6 €/ha. The left tail area is used to assess the frequency and severity of drought impacts.

We compute Value-at-Risk (VaR) to assess downside risk. This is, how large are drought economic losses that occur with a 5% probability. Our results show that the farmer confronts potential economic outcome below 105.3 €/ha, which represent losses larger than 23% in relation to historical average income. This result is in line with Lybbert et al. (2004) classification of > 25% as severe losses. We define and compute the probability of moderate drought as the probability of farm income falling within the range 136.6–105.3 €/ha, which represent the historical average and the VaR 5% respectively, and is given by the integral of this variable's density function over that range. Table 7 presents Value-at-Risk at other probability levels in order to provide a comprehensive picture of downside risk. Our simulation results show that droughts occurring with a 10% probability, impose economic loses above 17,1%, while drought related loses above 8,5% may be expected with a probability of 25%, i.e. once in four years. Our results are somewhat more moderate than those obtained by Freier et al. (2011) who explore drought impact in Morocco grazing lands finding a profit loss of 25% as a result of one-year drought, defined as a year with 33% lower than average precipitation levels. A more wealthy Dehesa farmers' situation may account for these plausible differences. We further note that comparison is not straight forward, while their risk approach is normative in that they define the risk scenario, we follow a positive approach and evaluate risk exposure under historical weather patterns. This is one differential feature as compared to other works found in the literature review.

In this line, we further inquire how different stocking rates scenarios affect farm exposure to risk. In particular, we analyse and compare two different scenarios corresponding to a 20% reduction (LOW scenario) and a 20% increase (HIGH scenario) in stocking rate relative to the baseline or current scenario (see Fig. 8 and Table 8). We find that the impact of increasing the stocking rate on average income is three times lower as compared to the impact of decreasing the stocking rate and has opposite sign. Increasing the stocking rate increases expected income by < 1% but involves significant impact in the shape of the probability density function and entails important risk consequences. In particular, our results show that when increasing the stocking rate by 20%, the probability of experiencing moderate adverse outcome decreases from 45.0% to 40.7%. In addition the probability of being above the average income increases to 52.2%. However, this comes at the expense of increasing the left tail-end risk; the probability of experiencing economic outcomes below the severe drought impact threshold notably rises, from 5.0% to 6.9%.

In the LOW scenario (20% decrease of the stocking rate) average income decreases by 3% while the probability of extreme adverse impacts notably decreases. In particular, the probability of trespassing severe impact threshold drops from 5.0% to 3.7%. This comes at the expense of an increased probability of incurring moderate impact and also at the expense of a significant decrease of experiencing favourable situations. We find that the probability of moderate impacts increases from

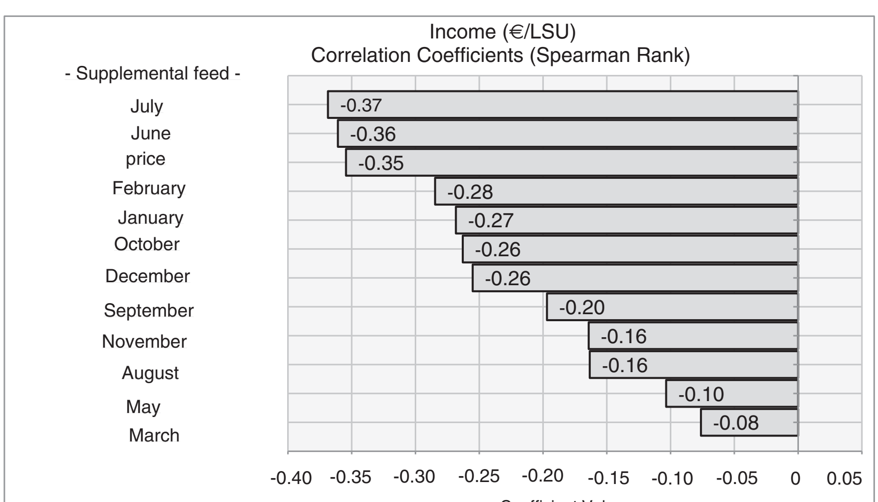

Fig. 5. Factors that determine the risk.
(Source: own results).

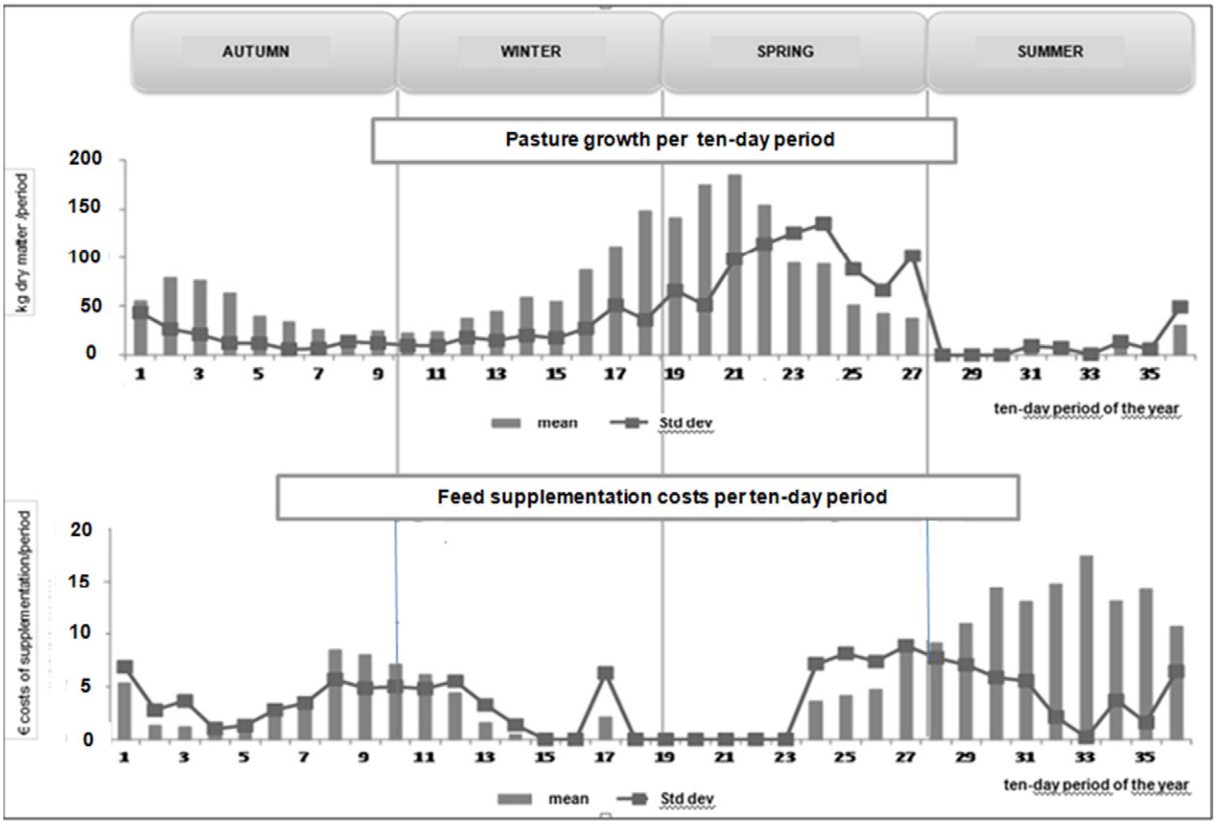

Fig. 6. Relationship between pasture growth and feed supplementation cost.
Source: Own simulation results.

45.0% to 57.9% while the probability of being above this threshold significantly decreases from 50.0% to 38.5%. This is, decreasing the stocking rate reduces vulnerability to extreme drought spells but the farmer incurs opportunity costs or foregone benefits when good climate conditions happen. This result may explain while most farmers may be reluctant to adopt a lower stocking rate. On the other hand, only farmers who pursue income maximization, i.e. no or very little risk aversion, would choose a higher stocking density option. In line with Jakoby et al. (2014) who argue that farmers' decision-making may be guided by different risk preferences, this model may provide a useful tool to assess

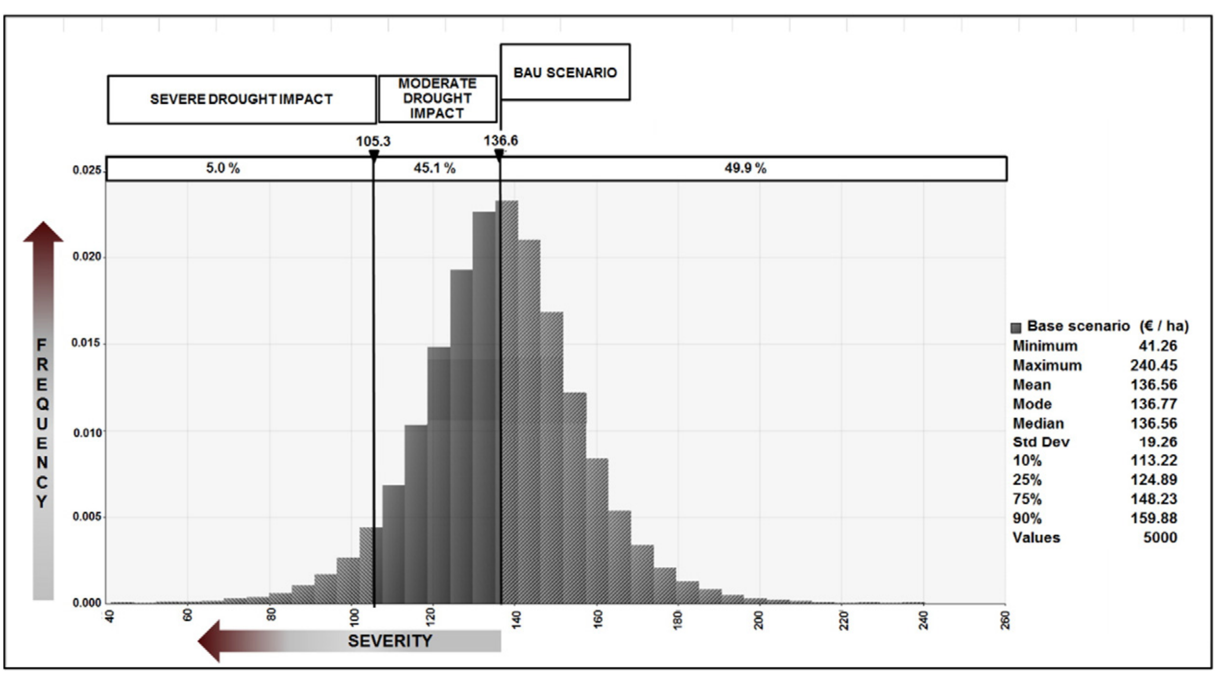

Fig. 7. Probability density function of farm income (€/ha).
Source: Own simulation results.

Table 7
Annual farm income: Value-at-Risk.

Probability	Potential economic outcomes	Potential economic losses (VaR)
5%	<105.3 €/ha	>22.9%
10%	<113.2 €/ha	>17.1%
25%	<124.9 €/ha	>8.5%

Source: Own simulation results.

decision making, evaluate the impact of adaptation strategies and guide the design of drought mitigation measures (Table 8).

Table 8
Farm Income (€/ha) in different stocking rate scenarios.

	Scenarios		
Statistics	Stocking rate − 20%	Base scenario	Stocking rate + 20%
Minimum	56.49	41.26	23.46
Maximum	210.16	240.45	254.62
Mean	132.63	136.56	137.8
Mode	132.13	136.77	136.55
Median	132.63	136.56	137.8
Std Dev	15.16	19.26	22.69

Source: own results.

4. Conclusions

We presented a dynamic and stochastic bio-economic model to assess the economic risk of drought in grazing activities that sustain *Dehesas*, a highly valued silvo-pastoral ecosystem in the Southwestern part of the Iberian Peninsula. Field surveys, expert assessment and literature review were used to parameterize the model. Simulated pasture growth and economic model outcomes were validated by performing comparison against fieldwork and observed satellite NDVI data respectively. The model is based on a relatively limited amount of technical data and we claim that use of widely available satellite information for calibration and validation purposes may help to apply the model in other semi-arid areas.

Our modelling framework contributes to the literature with several distinguished features. First, it allows for both inter-annual and intra-annual variability in order to better understand how climate risk translates into economic losses. Our results reveal complex patterns and show that, while climate risks concentrate at the beginning of spring and autumn, economic risk usually occurs later and lasts longer. These results are in line with previous research work that reports a delay between climate risk and its economic consequences (Freier et al., 2011; Wilhite and Glantz, 1985). We further characterized impacts and assessed episodes of drought in terms of duration, frequency and intensity revealing that the economic impact of a prolonged period of drought increase in a non-linear fashion. In addition, identifying critical factors and main sources of risk offers useful insights and may provide guidelines for the design of assistance, relief or other drought risk mitigation measures, such as insurance policy.

Second, our framework incorporates Monte Carlo techniques to estimate the probability density function of farm incomes and propose the use of Value-at-Risk (VaR) to assess farm vulnerability to drought and as a tool to control the level of farm risk exposure. This approach avoids the need to overcome highly computational burden as signalled in Freier et al. (2011) and conveys relevant information to assess farmers' decision and policy makers as we illustrated through the assessment of different stocking management options. We find that the stocking rate has important implications in risk exposure. In particular, we show that lowering the stocking rate may significantly reduce vulnerability and decrease the chance of worst outcomes, but also entails opportunity costs in favourable weather circumstances which may explain farmers' reluctance to adopt them. On the other hand, increasing stocking provide little gains in terms of expected farm income which suggests that coupling sustainable stock density requirements with agricultural support measures would prevent intensification without imposing a significant welfare loss to farmers. From a policy perspective, preventing intensification is less costly that promoting further extensification options.

Our model relies on historical daily climate data but could be extended to simulate and assess the impact of climate change scenarios. This is a promising research area that could shed light on the impact of climate change scenarios but also assess costs and benefits of mitigation measures providing a holistic picture of farmers risk exposure.

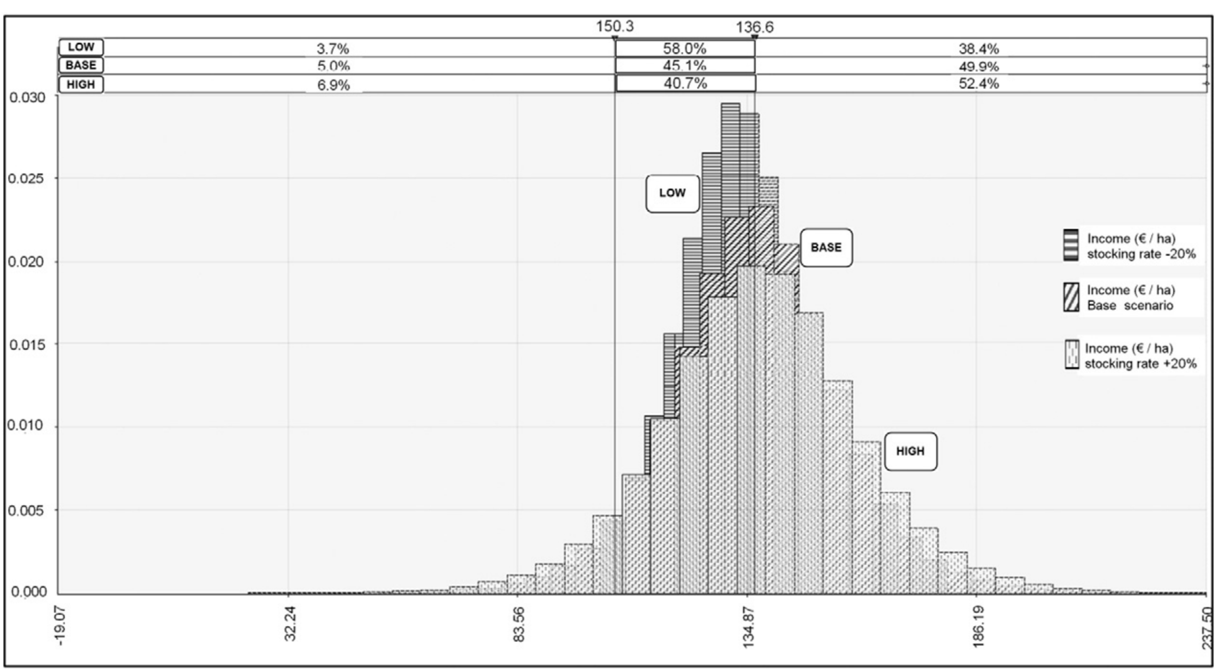

Fig. 8. Annual Farm Income (in €/ha) under stocking rate scenarios.
Source: Own results.

Acknowledgements

This study was partly funded by CEIGRAM, ENESA(P100220C346) (Analysis and integration of agricultural and zoo-technical information obtained "in situ" with satellite data in order to improve drought index insurance in grazing lands 2010–2012 Project) and by the AGRISOT Ref S2013/ABI-2717 Sistemas agrarios sostenibles: Manejo de carbono, nitrógeno y agua para optimizar producción y calidad. Eva Iglesias thanks colleagues at University of Maryland for their helpful comments during the review process.

Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.agsy.2016.07.017.

References

Ares, J., 2007. Systems valuing of natural capital and investment in extensive pastoral systems: lessons from the Patagonia case. Ecol. Econ. 62 (1), 162–173.

Asner, G.P., Elmore, A.J., Olander, L.P., Martin, R.E., Harris, A.T., 2004. Grazing systems, ecosystem responses, and global change. Annu. Rev. Environ. Resour. 29, 261–299.

Baumgärtner, S., Quaas, M.F., 2009. Ecological-economic viability as a criterion of strong sustainability under uncertainty. Ecol. Econ. 68 (7), 2008–2020.

Beukes, P.C., Cowling, R.M., Higgins, S.I., 2002. An ecological economic simulation model of a non-selective grazing system in the Nama Karoo, South Africa. Ecol. Econ. 42 (1–2), 221–242.

Carmona, C.P., Azcárate, F.M., Oteros-Rozas, E., González, J.A., Peco, B., 2013. Assessing the effects of seasonal grazing on holm oak regeneration: implications for the conservation of Mediterranean dehesas. Biol. Conserv. 159, 240–247.

Connor, D., Loomis, R.S., Cassman, K.G., 2011. Crop Ecology: Productivity and Management in Agricultural Systems. second ed. Cambridge University Press, Cambridge, United Kingdom.

Corson, M.S., Skinner, R.H., Rotz, C.A., 2006. Modification of the SPUR rangeland model to simulate species composition and pasture productivity in humid temperate regions. Agric. Syst. 87 (2), 169–191.

Díaz-Solís, H., Grant, W.E., Kothmann, M.M., Teague, W.R., Díaz-García, J.A., 2009. Adaptive management of stocking rate to reduce effect of drought on cow-calf production systems in semi-arid rangelands. Agric. Syst. 100 (1–3), 43–50.

Etienne, A., Valderrama, J.M., Díaz-Ambrona, C.H., 2008. Productive model of evergreen oak and annual pastures in Extremadura (Spain). Options. Méditerranéennes A 79, 65–68.

Freier, K.P., Schneider, U.A., Finckh, M., 2011. Dynamic interactions between vegetation and land use in semi-arid Morocco: using a Markov process for modeling rangelands under climate change. Agric. Ecosyst. Environ. 140 (3–4), 462–472.

Hanson, J.D., Baker, B.B., Bourdon, R.M., 1994. Documentation and users guide for SPUR2. GPSR Technical Report No. 1. USDA Agricultural Research Service, Great Plains Systems Research Unit, Ft. Collins, CO.

Huang, G., Liu, Y., Huang, R., 2011. The interannual variability of summer rainfall in the arid and semiarid regions of northern China and its association with the northern hemisphere circumglobal teleconnection. Adv. Atmos. Sci. 28 (2), 257–268.

Iglesias, E., Garrido, A., Gómez-Ramos, A., 2003. Evaluation of drought management in irrigated areas. Agric. Econ. 29 (2), 211–229.

Iglesias, E., Garrido, A., Gómez-Ramos, A., 2007. Economic drought management index to evaluate water institutions' performance under uncertainty. Aust. J. Agric. Econ. 1 (3), 17–38.

IPCC, 2014. Climate change 2014: impacts, adaptation, and vulnerability. In: Field, C.B., Barros, V.R., Dokken, D.J., Mach, K.J., Mastrandrea, M.D., Bilir, T.E., Chatterjee, M., Ebi, K.L., Estrada, Y.O., Genova, R.C., Girma, B., Kissel, E.S., Levy, A.N., MacCracken, S., Mastrandrea, P.R., White, L.L. (Eds.), Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA 1132 pp.

Jakoby, O., Quaas, M.F., Müller, B., Baumgärtner, S., Frank, K., 2014. How do individual farmers' objectives influence the evaluation of rangeland management strategies under a variable climate? J. Appl. Ecol. 51 (2), 483–493.

Kallis, G., 2008. Droughts. Annu. Rev. Environ. Resour. 33, 85–118.

Loomis, R.S., Williams, W.A., 1969. Productivity and the morphology of crop stands. In: Eastin, J.D., Haskin, F.A., Sullivan, C.Y., Van Bavel, C.H.M. (Eds.), Physiological Aspects of Crops Yield. Madison, Wisconsin, American Society of Agronomy, pp. 27–47.

Lybbert, T.J., Barrett, C.B., Desta, S., Layne Coppock, D., 2004. Stochastic wealth dynamics and risk management among a poor population. Econ. J. 114 (498), 750–777.

Lybbert, T.J., Galarza, F.B., Mcpeak, J., Barrett, B., Boucher, S.R., Carter, M.R., Chantarat, S., Fadlaoui, A., Mude, A., 2010. Dynamic field experiments in development economics : risk valuation. Agric. Resour. Econ. Rev. 39 (2), 176–192.

Martín Polo, J.L., Valle Gutiérrez, C.J., Blanco de Pablos, A., Sánchez Rodríguez, M.E., 2003. La dehesa y los recursos forrajeros: fertilización laboreo y siembra. II. Productividad y utilización del agua de lluvia. Span. J. Agric. Res. 1 (1), 35–42.

Martin, R., Linstädter, A., Frank, K., Müller, B., 2014. Livelihood security in face of drought e assessing the vulnerability of pastoral households. Environ. Model. Softw. 75, 414–423.

Morton, J., Barton, D., 2002. Destocking as a drought – mitigation strategy: clarifying rationales and answering critiques. Disasters 26 (3), 213–228.

Müller, B., Quaas, M., Frank, K., Baumgärtner, S., 2011. Pitfalls and potential of institutional of rangeland management. Ecol. Econ. 70 (11), 2137–2144.

Pratt, D.J., Le Gall, F., De Haan, C., 1997. Investing in pastoralism – sustainable natural resource use in arid Africa and the Middle East. Technical Paper 365. The World Bank.

Quaas, M.F., Baumgärtner, S., Becker, C., Frank, K., Müller, B., 2007. Uncertainty and sustainability in the management of rangelands. Ecol. Econ. 62 (2), 251–266.

Rosa, D., Baños, C., Mudarra, J.L., Barahona, E., Moreira, J.M., Gago, R., Puertas, J.M., Ramos, A., 1984. Catálogo de suelos de Andalucía. In: Agencia de Medio Ambiente. In: de Andalucía, J. (Ed.) Serie Monografías del Medio Ambiente Vol. 3.

Sheehy, J.E., Cobby, J.M., Ryle, G.J.A., 1979. The growth of perennial ryegrass: a model. Ann. Bot. 43 (3), 335–354.

Terradillos, A., García, A., Arana, M., 2004. Alimentación del ganado. Manual Práctico Para Explotaciones Lecheras y ganadería Ligada a la Tierra. Consejería de Agricultura y Pesca de Andalucía. Servicio de Publicaciones y Divulgación.

Thornton, P.K., van de Steeg, J., Notenbaert, A., Herrero, M., 2009. The impacts of climate change on livestock and livestock systems in developing countries: a review of what we know and what we need to know. Agric. Syst. 101 (3), 113–127.

Tiejten, B., Jeltsch, F., 2007. Semi-arid grazing systems and climate change: a survey of present modelling potential and future needs. J. Appl. Ecol. 44, 425–434.

Weikard, H., Hein, L., 2011. Efficient versus sustainable livestock grazing in the Sahel. J. Agric. Econ. 62 (1), 153–171.

White, L.D., Troxel, T.R., 1995. Balancing forage demand with forage supply. Texas Agricultural Extension Service, p. B-1606.

White, D.H., Howden, S.M., Walcott, J.J., Cannon, R.B., 1998. A framework for estimating the extent and severity of drought, based on a grazing systems in south-eastern Australia. Agric. Syst. 57 (3), 259–270.

Wight, J.R., Skiles, J.W., 1987. SPUR, simulation of production and utilization of rangelands: documentation and user guide. In: USDA-Agricultural Research Service (Ed.)ARS Series Vol. 63.

Wilhite, D.A., Glantz, M.H., 1985. Understanding the drought phenomenon: the role of definitions. Water Int. 10 (3), 111–120.

Yurekli, K., Kurunc, A., 2006. Simulating agricultural drought periods based on daily rainfall and crop water consumption. J. Arid Environ. 67 (4), 629–640.

Zargar, A., Sadiq, R., Naser, B., Khan, F.I., 2011. A review of drought indices. Environ. Rev. 19, 333–349.