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Dynamic interactions between vegetation and land use in semi-arid Morocco: Using a Markov process for modeling rangelands under climate change

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Abstract

Integrated scientific assessments of semi-arid agroecosystems with mathematical models are challenging because of computational constraints. These constraints arise from exponentially increasing decision options due to dynamic interactions between the biophysical states of rangeland vegetation and farsighted decisions taken by pastoral stakeholders. This study applies a methodology that integrates these interactions in a computationally feasible manner. We equip a dynamic land use decision model with a detailed representation of biophysical processes by using a Markov chain meta-model of EPIC (Environmental Policy Impact Calculator). Using separate Markov chains for different weather scenarios, we investigate the economic and ecological impacts of droughts on rangeland management in southern Morocco. The drought simulations (two years with 33% less precipitation) show a decrease in profits from pastoralism by up to 57%. Pastoral land use of the rangeland in our model increases surface runoff by 20%, doubles infiltration, and thus influences irrigation agriculture. The economic and ecological impacts of drought in our simulation go substantially beyond its meteorological time horizon.

Keywords: Bioeconomic land use modeling; Dynamic programming; Environmental Policy Impact Calculator (EPIC); Extensive grazing; Irrigation agriculture; Semi-arid pastoralism

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1 Introduction

Pastoralism is the dominant land use in semi-arid and arid areas. These areas occupy 41% of the world's land surface and are inhabited by more than two billion people (Millennium Ecosystem Assessment, 2005). However, in several large-scale economic assessments of global change, semi-arid areas have been found to not play an important role because the overall impacts of climate change are accounted for mostly in terms of the percentage of global gross domestic product (GDP) (e.g. Tol, 2009), and drylands have the lowest GDP per capita (UNCCD, 2007). Hence, the socio-economic effects of climate change in these areas are at present of no great influence in large-scale economic models and the resolution of system properties is low. Furthermore, grazing is not generally considered as part of dynamic global vegetation models (Diaz et al., 2007). Nevertheless, especially in developing countries, pastoralism is a major source of income for large parts of the population (Gertel and Breuer, 2007). At the same time, the social impact of climate change for people living in semi-arid areas has the potential to be quite substantial, since 90% of the affected areas are located in developing countries (Millennium Ecosystem Assessment, 2005) and drylands have the highest infant mortality rates compared to other land use types (UNCCD, 2007). The conflict in the Sudanese Dafur, which can be traced back in part to changes in a pastoral agroecosystem, exemplifies the impacts climate change can have on society (Prunier, 2005). Hence, investigating the effects of climate change in these areas is of great importance.

In order to adequately assess the influence of climate change on large-scale agroecosystems and society, mathematical models can be used. However, these often require very high levels of computational effort, in particular for the integration of vegetation dynamics in combination with decision-making. If human decision-making is farsighted, the number of possible land management plans and related vegetation states can quickly lead to the so-called "curse of dimensionality" (Bellman, 1961), where the computational effort is exponentially related to the number of considered time periods. To overcome this, large-scale land use models use either a static representation of biophysical properties, such as biomass growth, or myopic decision-making, such as prescribed scenarios or exclusion of inter-temporal planning (Lambin et al., 2000; Schaldach and Priess, 2008).

The aim of this study is to quantify the implications of droughts in a medium-scale Moroccan pastoral agroecosystem, and we approach this by estimating the changes in profits from pastoral activities of rural households. In addition, we also assess the relationships between land use intensity and local hydrological and biophysical properties, including the infiltration of water into the groundwater, surface runoff, evapotranspiration (ETP), and albedo. These biophysical parameters might have further implications for land use decisions since, for example, altered hydrological properties can affect downstream oasis agriculture.

To address these aims, we develop an augmented mathematical land use decision model (LDM) that combines a dynamic representation of vegetation with farsighted, profit-oriented decision-making. In this way, it is hoped that our research will help bridge the scientific gap between those existing models that address either the detailed representation of farsighted decision-making on the one hand, or concentrate on describing accurately the biophysical vegetation dynamics on the other. We use a Markov chain to integrate into our LDM the results of an elaborated biophysical soil-vegetation model, as well as parts of its dynamic properties. The applied method is suitable for use at large scales, i.e. for a more adequate representation of dryland agroecosystems in global LDMs, such as GLOBIOM (Havlík, et al., 2010).

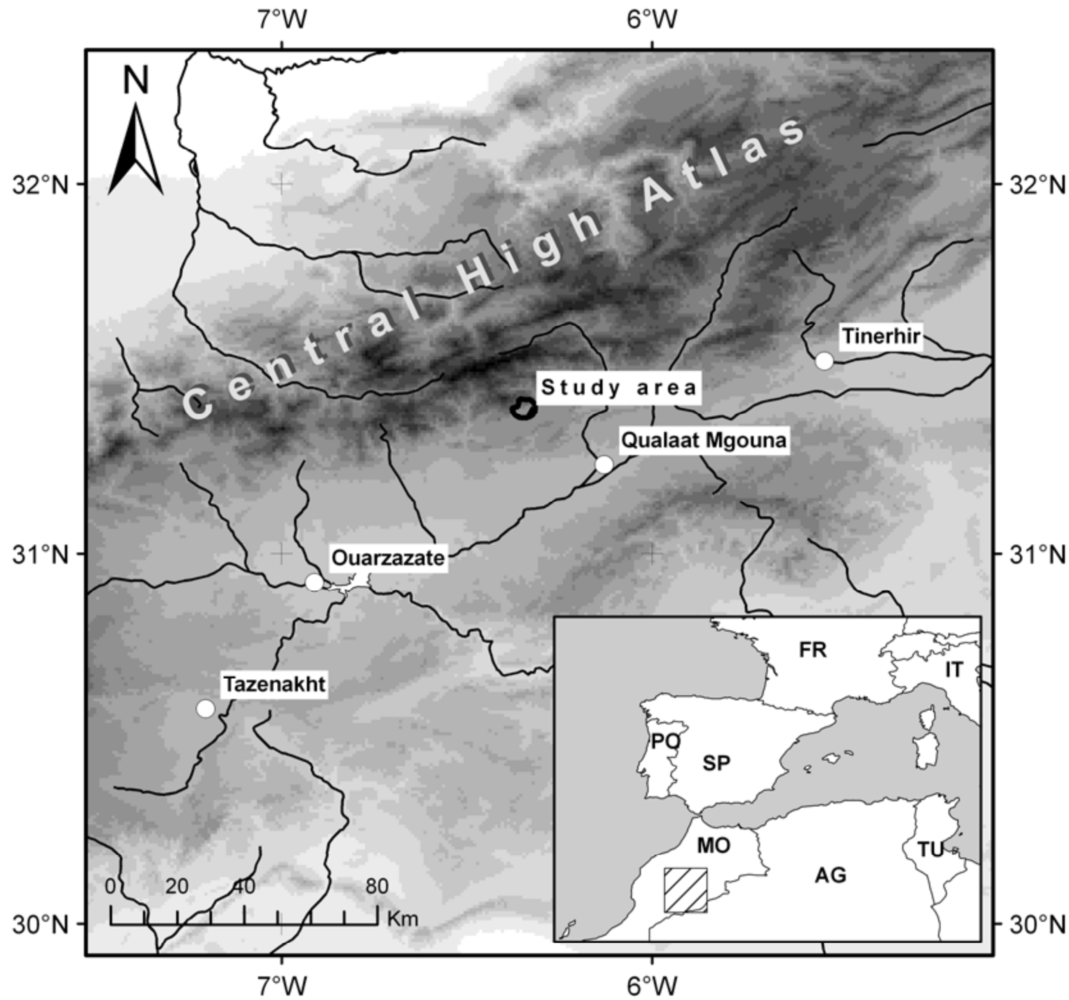

Fig 1 Location of the study area, situated in the Drâa-river catchment and depicted on the map by the bold black boundary line. The lighter black lines represent rivers.

2 Methodology

2.1 Study site and setup

The study site is located in the Moroccan province of Ouarzazate, on the southern slopes of the High Atlas mountain range (Fig. 1). The region is characterized by a semi-arid to arid climate and a strong precipitation gradient (200 mm to more than 700 mm per year), which exists because of a similarly steep altitudinal gradient (Schulz and Judex, 2008). Climate projections for this region differ greatly and indicate large uncertainty in the direction of precipitation development (Sillmann and Roeckner, 2008; Born et al., 2008;

Huebener and Kerschgens, 2007). Precipitation is currently the limiting factor for agricultural activities in this region, and a likely scenario for the future is characterized by increased water scarcity and increased interannual variability of precipitation. To cope with variable precipitation levels and a low average value, a mixed system of irrigation agriculture in river oases and livestock grazing on natural rangelands is traditionally used to secure livelihoods (Barrow and Hicham, 2000). Traditional livestock grazing takes the form of transhumance, i.e. the variability in rainfall is mitigated by the mobility of pastoralists. However, developments in recent decades and expectations of the herders indicate that this traditional system is changing more and more towards the use of sedentary flocks (Breuer, 2007; Davis, 2006).

For this study, we develop an augmented LDM on a landscape level. The data for parameterization, calibration and validation of the model were collected in the surroundings of the rural village of Taoujgalt (6.322203° W, 31.38994° N). The village is situated approximately 100 km north of the provincial capital Ouarzazate and consists of 37 households (pers. comm. El Moudden). The mean annual temperature is 14 °C, and annual precipitation (2001–2008) is relatively variable at 270 ± 70 mm. The parent material for the soil is Jurassic limestone and red siltstones (couches rouges) covered by Calcisols. The dominant vegetation (pasture) consists of *Artemisia herba-alba – Stipa parviflora* steppes. Meteorological data are taken from the recordings of a meteorological station under the IMPETUS project, situated 2 km from the village (Schulz et al., 2010). Similarly, vegetation data, recorded annually by the BIOTA project on permanent monitoring plots inside and outside an exclosure experiment (BIOTA, 2010), are used. Soil and surface properties of the study region are retrieved from the IMPETUS database (IMPETUS, 2010). The pastures surrounding the settlement are located at altitudes of between 1800 and 2400 m above sea level. Our simulations relate to the pastures around the village, which are in reach for the sedentary livestock (goats and sheep). The livestock are kept in stables overnight in the village, and the ranges of livestock herds, as determined by collar data, does not exceed more than 3 km and 400 m in altitude per day (Mahler, 2010). In total, the investigated area covers 2500 hectares.

2.2 The LDM

Bioeconomic LDMs are used to assess the economic and ecologic impacts of land use changes, environmental developments and relevant policies (Janssen and van Ittersum, 2007). These models are applied at very different scales, ranging from the plot level to global studies. For the present study, we developed a LDM to depict extensive grazing management in a semi-arid area under variable precipitation conditions. The agricultural activities simulated by the model include a range of different intensities of grazing and a constant demand of firewood.

2.2.1 General structure

Our LDM is a mathematical optimization model that jointly depicts farsighted land use decision-making, livestock, and biophysical vegetation dynamics. The biophysical vegetation dynamics were derived from simulations using the Environmental Policy Impact Calculator (EPIC; Williams et al, 1989). We parameterized EPIC with local monitoring data from the study site and included it as a Markov chain meta-model into the LDM. The model uses homogenous response units (HRUs; Skalsky et al., 2008) to portray different land qualities, which themselves aggregate raster-based GIS data to avoid repeated calculations of spatial units with similar physical properties (soil type, slope, and altitude).

In order to model human decision-making it is necessary to make certain behavioral assumptions. Following a utilitarian approach, we assume people are rational and make their strategic decisions based on a maximization of utility. In aggregated agricultural assessments (landscape to global), it has been shown that the assumption of profit maximization mostly holds (Lambin et al., 2000). Therefore, the objective function of our LDM is formulated as given in Eq. 1.

$$Max \sum_{t,l,c} (Ns_{t,l,c} \cdot p_{t,l,c}) \tag{1}$$

where $Ns_{t,l,c}$ is the number of livestock sold in year t and p is the corresponding producer price on the local market. The livestock in our model includes two species (index l: goats and sheep) and three age classes (index c: less than one year old, 1–2 years old, and more than 2 years old). The price is not constant over time, as livestock producer prices in Morocco are usually lower during droughts (Hazell et al., 2001; Skees et al., 2001). $Ns_{t,l,c}$ needs to be non-negative, and for simplicity we assume that selling takes place at the end of the year, with the units as heads of animals per year. The total number of animals at the end of year t equals the sum of animals sold and animals kept for the following year (Eq. 2).

$$Ne_{t,l,c} = Nb_{(t+1),l,c} + Ns_{t,l,c} \;\; \forall \; t,l,c \tag{2}$$

where $Ne_{t,l,c}$ is the number of animals at the end of a year t and $Nb_{t,l,c}$ is the number of animals at the beginning of the following year $t+1$.

The number of animals per year is subject to various constraints, as represented in general by Eq. 3.

$$\sum_{l,c} (Ne_{t,l,c} \cdot a_{l,c,j}) \leq b_{t,l,c,j} \quad \forall \; t,j \tag{3}$$

where $b_{t,l,c,j}$ are j times t different constraints on the number of animals, which may be different for each livestock and age class. Technical coefficients ($a_{l,c,j}$) relate the livestock variables $Ne_{t,l,c}$ to the individual constraints, which include resource endowments such as the maximum availability of fodder for the animals.

The general structure of the livestock growth module is given in Eq. 4.

$$\sum_{c} Nb_{t,l,c} \cdot g_{t,l,c,\hat{c}} \geq Ne_{t,l,\hat{c}} \;\; \forall \; t,l,\hat{c} \tag{4}$$

where the factor $g_{t,l,c,\hat{c}}$ maps the number of living animals at the beginning of each year onto the number of animals at the end of the year. The indices c and $\hat{c}$ separate the "source" and "destination" of age classes. For instance, the source age classes for lambs are all mature age classes, and the source age class for the one-year-olds is the previous year's lambs. The factor $g_{t,l,c,\hat{c}}$ includes reproduction and survival rates of the livestock and is calculated by several other equations. The livestock growth rate is limited by the availability and quality of fodder. If fodder is scarce, $g_{t,l,c}$ declines in order to fulfill the energetic needs of the remaining ewes. If fodder is too scarce to fulfill the basic energy demands of the animals, growth stops entirely and animals must be sold to prevent starvation. Thus, the growth module is still linear technically, but behaves like a typical sigmoid growth function. Goats and sheep are treated separately because in relation to body weight, the maximum dry-matter consumption of goats is up to 40% higher than for sheep. This makes it possible for goats to tolerate a diet with lower energy content (Le Houerou, 1980).

An important class of variables in the LDM are land use variables, which indicate the land use management (intensity and pattern of grazing, firewood collection) within the individual HRUs. The land use variables control the removed biomass within a HRU, as given in Eq. 5.

$$\sum_{m,s} X_{t,HRU,m,s} \cdot EPIC\_yield_{HRU,m,s} = RB_{t,HRU} \quad \forall t, HRU \qquad (5)$$

where $X_{t,HRU,m,s}$ are the land use variables with m possible management alternatives and s possible vegetation states. The states of vegetation are needed to represent the dynamic behavior of vegetation. $EPIC\_yield_{HRU,m,s}$ is the productivity data per unit area of a HRU dependent of management and state and is precalculated by the EPIC model. The parameter $RB_{t,HRU}$ represents the total amount of removed biomass (dry-matter), which is gathered from a HRU in year t by applying management m. This removed biomass includes fodder for livestock and firewood for households. The fodder is one of the j constraining factors $b_{t,l,c,j}$ of Eq. 3. For every HRU the sum of land use variables has to equal the area of the HRU, i.e. a HRU can be subdivided into a maximum of s times m sub-units. Since HRUs are the smallest spatial units in our LDM, these sub-units cannot be localized spatially.

2.2.2 Planning horizon and recursivity

A dynamic program simultaneously determines the optimal decisions for all considered time steps t (Eq. 1). The solution can be interpreted as the optimal trajectory for a decision maker in order to achieve the highest utility over the entire planning horizon T. When simulating an agroecosystem, one needs to consider that strategic decision-making is normally constrained to a certain finite time horizon. Furthermore, decision-making is influenced at all time steps by updated information. For instance, future weather conditions can only be estimated, while for the current year decisions are based on actual precipitation and temperature. To incorporate this feature into our model, we use a mixed recursive-dynamic specification, similar to that developed by Barbier and Bergeron (2001).

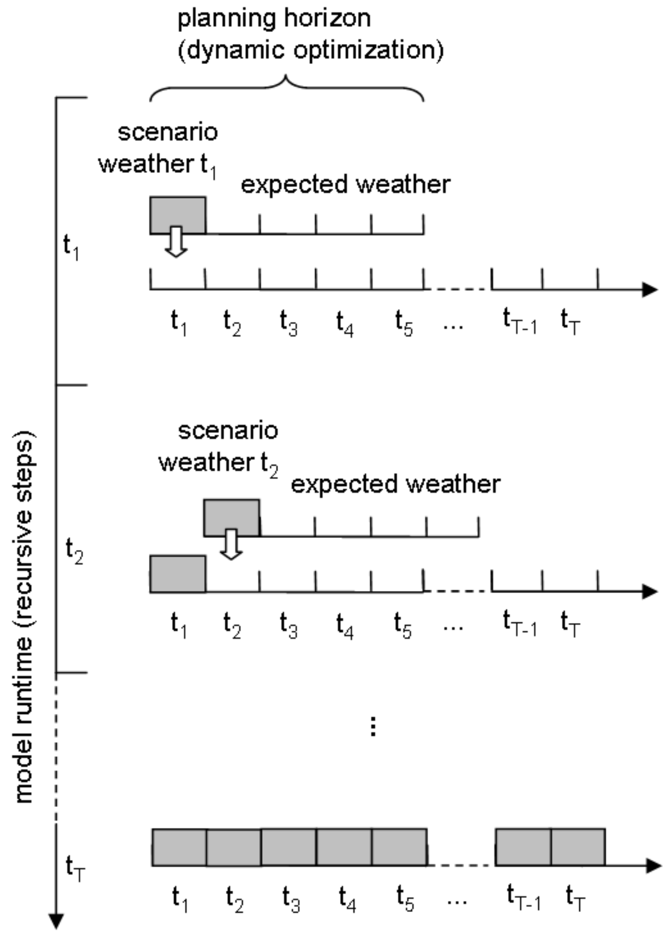

Fig 2 Mixed recursive-dynamic LDM with a planning horizon of five years. The indices t_1 to t_T represent individual years of the entire model runtime. Grey boxes represent the results of the first years of dynamic optimization, which are used as initial conditions for the next time step and results of the recursive model.

Figure 2 depicts the recursive-dynamic setup, where a forward-looking planning horizon of 5 years is used. As shown in the top part of Fig. 2, the optimization of the first recursive step t_1 is calculated based on initial data. A weather scenario is prescribed for the first year of the optimization, while some expected weather is used for the remaining years of the planning horizon. After calculating the optimal combination of land use options, the results of the first year of the optimization are recorded. Parts of the results, such as the numbers of livestock (Eq. 2) and the values of all land use variables (Eq. 5) are used to initiate the model at the next recursive step t_2 (Fig. 2, middle). Specifically, the combined impacts of each year's management and weather regime is used recursively to update the initial vegetation state and herd size for the following year's planning process. This procedure is repeated for every year of the entire model runtime (Fig. 2, bottom).

In economic models, discounting future profits expresses the time preferences of decision makers (a sheep now is more valuable than a sheep in ten years). The higher the discounting rate the less future profits or losses are taken into account, i.e. the more myopic the behavior. In our model, a shortening of the planning horizon to two years results in a less farsighted behavior of the model, as the state of vegetation in the third year and beyond is no longer accounted for in the model. A longer planning horizon, on the other hand, leads to a more sustainable behavior, as in this case the model will take more care for the future wellbeing of its resource base. Hence, adjusting the length of the planning horizon in our dynamic-recursive LDM is similar in its effect to the widely applied discounting of profits in dynamic LDMs. In order to keep things simple, we do not use an additional discounting of the profits in our optimization procedure, since it is difficult to assess which discounting rate the pastoralists are using

within a planning horizon. Instead, the model is calibrated to observed time preferences by manually adjusting the length of the planning horizon (see section 2.2.7).
To prevent unrealistic activity planning in the last year of each optimization, we use terminal values for the livestock. These values represent the benefits of livestock remaining beyond the end of the model's planning horizon. We parameterize terminal values by averaging shadow prices of livestock of a model run with a 20-year planning horizon.

2.2.3 Vegetation dynamics

In representing extensive grazing in semi-arid rangelands, the main dynamic entities in our model are livestock and vegetation. Both are linked and controlled by biophysical constraints and human management. Capturing the dynamics of vegetation and livestock, as well as their interactions under different climate scenarios, is our main interest in developing this model. Hence, the fodder endowment in our LDM is not an exogenous parameter, but instead depends on management and the weather of current and previous years. The variable used as a proxy for the state of vegetation is above ground plant material (AGPM) in tons per hectare. AGPM is an explicit parameter in the EPIC model, is frequently measured in field experiments, and reflects the productivity of pastures under certain weather and management regimes (Wiegand et al., 2004; Navarro et al., 2006; Schlecht et al., 2009). The fraction of AGPM utilized for fodder and firewood corresponds to the removed biomass of pastures. The longer a herd stays in an area and the bigger the herd, the more fodder they consume and the less AGPM they leave at the end of the season. Since productivity of a pasture is correlated to AGPM, the fodder consumption and firewood extraction of one year influences the productivity of the pasture in the following year. Adequate representation of this relationship in LDMs causes a computational problem similar to that described by Schneider (2007) for carbon sequestration. In particular, to maximize the utility from land use decisions over a multi-period planning horizon (Eq. 1), the dynamic model has to find the optimal management trajectory with corresponding states of vegetation. For example, if a farmer could choose between 10 alternative grazing intensities in each year, he would face 10 alternatives in year one, 10^2 combinations of current and future land use alternatives over two years, 10^3 over three years, and so forth. It is easy to see how an approach that includes every possible trajectory as an individual choice can become computationally very expensive. For example, suppose a dynamic model depicts six regions, two soil types, two livestock classes, three livestock cohorts, 10 different grazing intensities, and five time periods. The total number of possible decision paths would equal $12 \cdot 60^5$ ($\sim 9 \cdot 10^9$) alternatives. Such a dynamic decision model would require a huge amount of calculations, even though it is not yet that big. In addition, for every possible management decision path, one would have to compute the biophysical impacts upon vegetation with EPIC.
To overcome these computational hurdles, we classify discrete states of vegetation and calculate future states by a given current state and a transition probability between old and new states (Markov process). We assume that this property holds true in our context, i.e. that the impacts of past management and climate are sufficiently contained in the current state of vegetation expressed as AGPM. In this way, we reduce the necessary computational effort by several orders of magnitude. At the same time, we are able to

include biophysical simulation results and dynamic properties of EPIC into the augmented LDM. This technique, referred to as “meta-modeling” (Wei et al., 2009), is described in the following section.

2.2.4 EPIC simulations

To address the requirements of a Markov chain formulation of dynamic properties of vegetation, we use a state index *s* for the land use variable $X_{t,HRU,m,s}$ (Eq. 5). The state index *s* represents different discrete states of AGPM. The transition probabilities between the individual AGPM states are derived from vegetation development functions calculated beforehand by EPIC. These calculations are carried out for all soil types, climate scenarios, and alternative managements (grazing pattern and intensity). In our case, we start from an existing set of plant parameters in EPIC called "rangeland" developed for semi-arid areas in the United States. The default rangeland parameterization is adapted to observed values in our study region regarding plant growth height, maximum leaf area index (LAI), and the necessary heat units for plant maturity. Furthermore, we prescribe soil and terrain properties (slope) and weather (from meteorological data). The management impact is given as a set of arbitrary variations in grazing intensities and number of grazing days per year, which should cover a range of theoretically possible intensities. The EPIC simulations are automatically prepared and executed using a PYTHON-based program. To investigate different climate conditions, we use a precipitation scenario according to the observed average for the period 2002–2008 as a basis for comparison, which we will refer to hereafter as "average weather". To investigate droughts and to validate our model with observed data, we use dryer- or wetter-than-average precipitation data from individual years in the period 2002–2008.

To establish the vegetation development functions for the computation of state transition probabilities, each EPIC simulation starts with two extreme initial conditions: i) a minimum AGPM value of zero; and ii) a maximum AGPM value, in our case the value after 15 years of zero grazing management. All EPIC simulations span a 15-year horizon under constant management to ensure that the model comes close to a steady state for a certain regime. Since EPIC uses a random daily weather generator, based on the monthly averages for observed meteorological data, we use at least 20 ensemble runs to calculate state transition probabilities. The ensemble runs of EPIC are averaged and standard deviations calculated. Figure 3 shows the simulated AGPM values for two different management options under 2002–2008 average precipitation. The observed variability of AGPM is classified into 12 states. For each state, climate and management, parameters such as average value and standard deviation of plant transpiration, surface runoff, and LAI are written to a data file for subsequent usage in the augmented LDM.

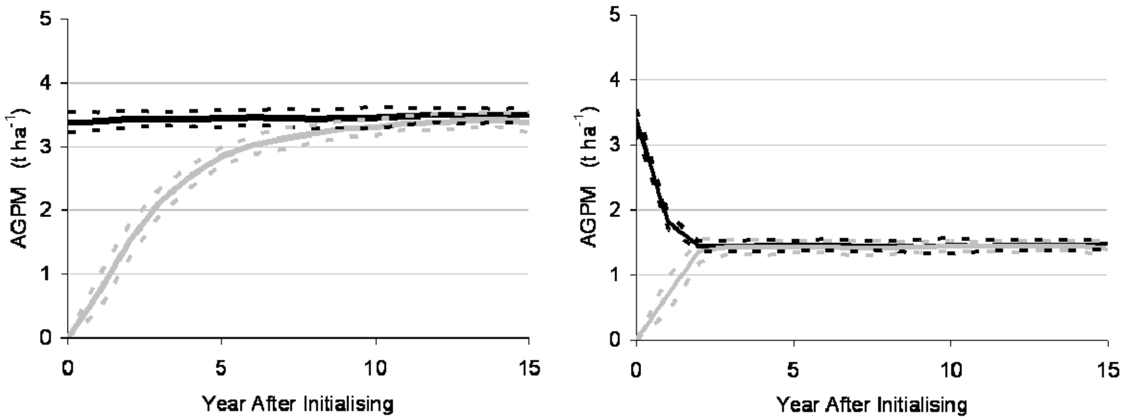

Fig 3 Results of the EPIC ensemble runs (n=20) for zero grazing management (left) and medium intensity grazing management (right). *AGPM* is the above ground plant material at the end of the year in $t \cdot ha^{-1}$. Black solid lines represent the results of initializing with the maximum *AGPM* values, grey solid lines of initializing with a zero *AGPM*, and dotted lines depict the interval of standard deviation for the correspondingly colored ensemble runs.

2.2.5 State transition probabilities

The vegetation development functions from the EPIC simulations (Fig. 3) are approximated by polynomial functions between the initial state and the steady state. Beyond the steady state, constant values are used. To transform the polynomial functions into transition probabilities for Markov chains, the parameter space for AGPM is classified into 12 states (the same states as used to record plant transpiration, LAI etc.). The transition probabilities are arranged within a transition probability matrix (TPM), where the initial state corresponds to rows and the subsequent state after one time step to columns (Table 1). Such a TPM is established for each HRU, management and climate regime. Each cell contains the probability of a particular transition and lies between 0 and 1. The row sum in the TPM has to equal one as the system is conservative.

Table 1: Example of a vegetation state transition probability matrix for a given HRU, management and climate regime (rows: old state, columns: new state).

	State 1	State 2	State 3	…	State 12
State 1	0	0.65	0.35	…	0
State 2	0	0	1	…	0
…	…	…		…	
State 12	0	0	0	…	0

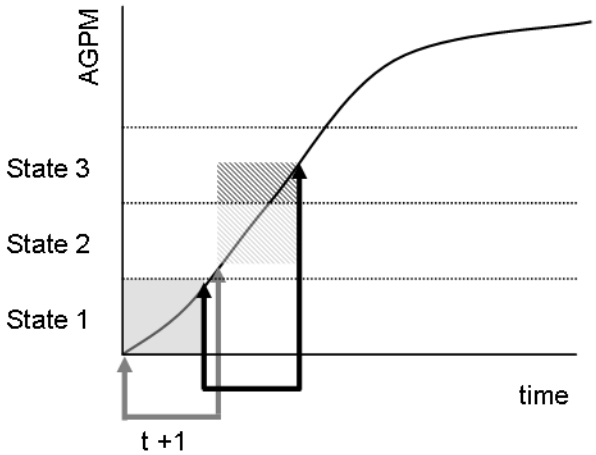

Fig 4 Determination of transition probabilities between states of AGPM for a given HRU, management and climate regime. AGPM is displayed against time. Grey arrowed lines measure one time step starting from the lower boundary of vegetation state 1, and black arrowed lines measure one time step starting from the upper boundary of vegetation state 1. Heights of the shaded squares indicate the range of possible vegetation states after one time step.

The determination of transition probabilities is illustrated by Fig. 4 for the case of transitions from state 1 to follow-on states. The black polynomial starting at the origin describes a development function of AGPM (y-axis) for a certain regime as calculated by EPIC. It passes the state boundaries at certain points in time. For both the lower and upper boundary of state 1 (grey and black arrows, left part), we determine the point on the polynomial that is reached after exactly one year (grey and black arrows, right). The probabilities of the transitions are calculated by comparing the share of individual new states to the range covered by all new states together. Thus, for all possible starting points within state 1 (filled square, 100%), the new state after one time step will be within the range depicted by the shaded squares covering a portion of state 2 and state 3. The specific probability of reaching either state 2 or state 3 from state 1 is proportional to the shares of the shaded square that lies below (shaded grey square) or above (shaded black square) the boundary between state 2 and state 3, respectively. In our example, starting from state 1, 65% of the vegetation will be in state 2 after one year and 35% will be in state 3. The result of this calculation is then written into the TPM (Table 1). The described procedure is then repeated to calculate the transition probabilities between all 12 states for all HRUs, managements and climate regimes. More details on the numerical computation of the TPM are given in Schneider (2007).

2.2.6 Integration into the LDM

To include the dynamic interaction between land management and vegetation, the TPM is used in an inter-temporal balancing equation of vegetation states (Eq. 6). This equation assures that vegetation states are influenced by past weather and management.

$$\sum_{m} X_{t,HRU,m,s} = \sum_{m,\hat{s}} \left(X_{t-1,HRU,m,\hat{s}} \cdot TPM_{t-1,m,\hat{s}\to s} \right) \quad \forall \; t, HRU, s \qquad (6)$$

where $X_{t,HRU,m,s}$ are the land use variables, s is the index for the classified states of vegetation, and m the applied management (grazing intensity and pattern). The index for the states of land use variables in the period $t\text{-}1$ is given by $\hat{s}$. $TPM_{t-1,m,\hat{s}\to s}$ is the TPM, which describes all transitions from old states $\hat{s}$ to new states s given the applied management m. It is time-dependent since it is specific for the weather scenario chosen in each year.

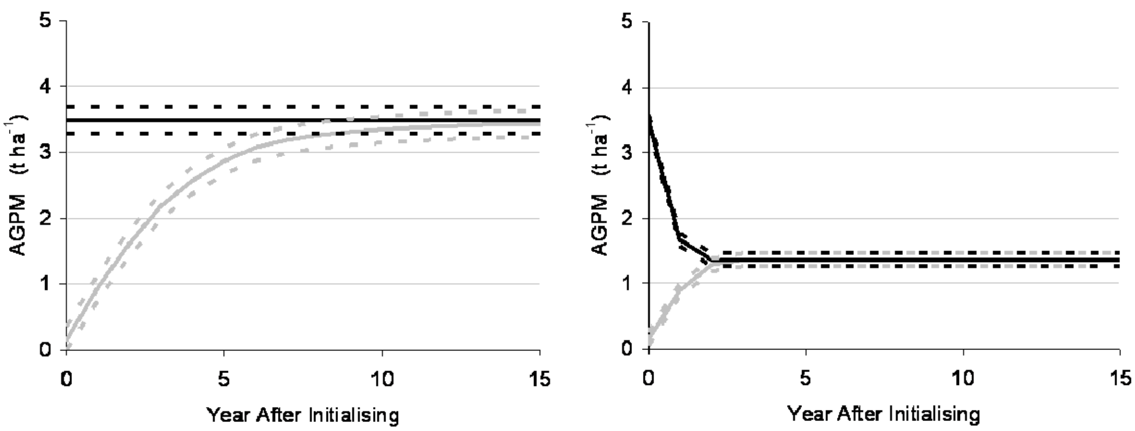

Fig 5 AGPM trajectories simulated with our augmented LDM using transition probability matrices. For comparability with EPIC results (Fig. 3), we forced zero grazing management (left) and medium grazing management (right) over 15 years starting from both minimum and maximum AGPM values. Dotted lines give the 90 percent confidence intervals derived from the EPIC deviations.

By using Eq. 6, our augmented LDM is able to approximate the dynamics of vegetation as simulated by the EPIC model, since vegetation is influenced by past management and past weather events. An example is given in Fig. 5, where we display some AGPM values from our augmented LDM against time. We use the same constant management intensities and weather as for the EPIC example in Fig. 3. It is immediately evident that the graphs in Fig. 4 are virtually the same as those in Fig. 3, which demonstrates the correct implementation of the Markov chain in our augmented LDM. The accuracy of the reproduction of the EPIC results is determined by the number of classes chosen to characterize the state space. The more states chosen, the more accurate the Markov chain representation. By using 12 sates, the correlation with the EPIC output is very high, with $R^2 > 0.99$ (except for the steady state segments, where the correlation is affected more by the chosen class-width).

2.2.7 Model parameterization and calibration

Both the EPIC model and our augmented LDM are parameterized with observed data. Most data were made available by the IMPETUS project (Schulz and Judex, 2008) and the BIOTA Maroc project (Finckh et al., 2007), which were active in the region of our study site in the period 2001–2009. A summary of the data sources for parameterization is provided in Table 2.

Table 2: Parameters and data sources used for EPIC and the augmented LDM.

Model	Parameters	Source
EPIC	Soil: carbon, texture, bulk density, depth, pH, coarse fragment, $CaCO_3$ content	IMPETUS database (IMPETUS, 2010)
	Elevation, slope	IMPETUS database (IMPETUS, 2010)
	Vegetation: above ground plant material (AGPM), leaf area index (LAI), heat units, growth height, rooting depth	BIOTA-Maroc Database (Finckh et al., 2010) and Baumann (2009)
EPIC/LDM	Meteorological data (monthly averages): Maximum temperature, minimum temperature, precipitation, relative humidity, solar radiation, wind velocity	IMPETUS database (IMPETUS, 2010)
LDM	Livestock: prolificacy, fertility, live weights, energy consumption, energy consumption for pregnancy and lactation, survival rates, survival rates for new born, maximum daily dry-matter consumption	Boudiab (1981), Guessous et al. (1989), Hossaini-Hilali and Benlamlih (1995), and Hossaini-Hilali and Mouslih (2002) Kamphues et al. (2004), Le Houerou (1980)
	Energy content of vegetation	Le Houerou (1980), Heneidy (1996) and Bryl (2009)
	Luzerne production in oasis	Kirscht (2008), El Moudden (2004), Hayek et al. (2009)
	Household consumption of firewood	El Moudden (2004)
	Price data for livestock	Own fieldwork, livestock Market at Ait'Toumert, May 2009

The EPIC model is parameterized with observed field data on plant growth height, rooting depth, LAI, and the necessary heat units for the plants to reach maturity. Using zero grazing management, the model is calibrated to match the observed value of 3.2 t per ha AGPM in 2008 after eight years of livestock exclosure (Baumann, 2009, pers. comm. Akasbi). For calibrating the EPIC output to the observed AGPM value, we use the plant population density as a tuning parameter (since EPIC cannot calculate plant population dynamics). Data for calibration are retrieved from the monitoring database of the BIOTA-Maroc project (BIOTA, 2010). To calculate the TPMs with EPIC, five HRUs are established for the study site, which are characterized by three slope classes (less than 5%, 5–15%, and more than 15%) and two altitude ranges (less than 2000 m and 2000–2400 m).

Weather scenarios for the augmented LDM are generated from observed daily data for the period 2002–2008, and the mean annual precipitation (MAP) of "average weather" is 270 mm. For validation of our model, we calculate TPMs with reduced or increased mean precipitation corresponding to the observed values for the individual years. To address our research questions, we use a 33% reduction of precipitation (which corresponds to 180 mm MAP) in order to simulate a two-year drought. We prescribe the actual sequence of years to be used by our augmented LDM in a separate weather file.

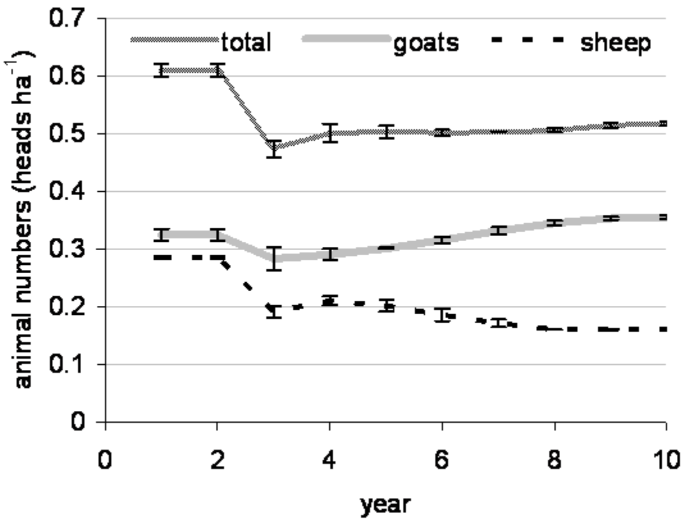

Fig 6 Stocking rates (at the beginning of a season) and composition of flocks for average weather with 270 mm precipitation (years 1 and 2) and 180 mm precipitation (later). Error bars indicate 90% confidence intervals over ensemble simulations (n = 6).

The objective function specification and the length of the planning horizon are the only tuning parameters outside of EPIC in our augmented LDM, which are used to match observed AGPM results under grazing and flock composition. The specification of the objective function in the augmented LDM poses a two-fold challenge. First, we need to assume the objective(s) that drive farmers' decisions, i.e. concerning the stocking rates of their animals. Possible preferences may include individual objectives such as the maximization of annual profits or utility from livestock herds, but also their combinations. Second, we need to assume the farmers' planning horizon and expectations about weather conditions for the years ahead. Since we want to model aggregated behavior of pastoralists, we do not base the decision-making in our model on a survey of individuals, but instead try to calibrate our objective function by hand and compare the output to observed behavior. The model output, for example concerning the different mixing ratios of sheep and goats in the flocks, is very sensitive to the expected weather in the following year(s). For instance, if a sequence of dry years is always expected, sheep are slowly disappearing. On the other hand, the conditions of the pastures (i.e. AGPM state) are influenced little by flock composition in our model and thus can be interpreted well independently of it. Hence, we chose our utility function and the length of the planning horizon manually in a way to a) fit to observed values of AGPM for the year 2009 under applied grazing and average weather (2002–2008 average), and b) fit to observed livestock compositions of the flocks as reported in a census (Schulz and Judex, 2008). Satisfying a) and b), we use a maximization of profits over a five-year horizon as the objective function. Furthermore, within the planning horizon, the weather, as described by the weather file, is taken for the first year of optimization. The same weather is then expected for years two and three, and for years four and five average weather is expected, i.e. the seven-year average. To show the sensitivity of flock composition in our model to weather shifts, we display the reaction of animal numbers *Nb* to a shift from average weather at the beginning to 33% less precipitation (Fig. 6). The shift to a dryer weather regime (from year 3 on) leads to lower stocking rates and the composition of the flock changes towards more goats. This agrees well with observations from dryer areas adjacent to our study site (Heidecke and Roth, 2008).

However, in order to match observations, we had to introduce two further constraints in our model. First, as fuel for cooking and heating is collected by the people of Taoujgalt from the surrounding pastures, we introduce an additional demand for biomass (taken from low quality fodder). This demand is parameterized based on household data and the average origin of firewood (pers. comm. El Moudden). Second, following empirical evidence by Le Houerou (1980), our model does not permit sheep production on a pure browse diet because the energy content of fodder plants is insufficient, especially for the high energy demand of gestation and lactation. Therefore, to match observations, we introduce the possibility of using Lucerne produced in the oasis as additional fodder. This modification makes it possible for the model to simulate lamb production. The parameterization for the production of Lucerne is taken from the average crop mix in the region (Kirscht, 2008) and the cultivated area in the oasis.

Price data for our augmented LDM were gathered from informal interviews performed in May 2009 at the livestock market in Ait'Toumert, which is the closest market to our study site. Average local prices for one-year-old sheep and goats in good years were 60 € and 40 € per head, respectively. During droughts prices are on average 50% lower than during good years.

2.2.8 Validation of the model

The LDM is validated against a time series of observed AGPM data from the study site. Figure 7 shows the precipitation values for every year in the period 2002–2009, data which are used as an external weather file for our augmented LDM. Figure 8 shows the results of our model for AGPM with zero grazing management and measured values of AGPM from the BIOTA project at fenced sites, which excluded grazing. Figure 9 compares results from our augmented LDM with grazing management and corresponding values from the BIOTA database, which were measured outside the fence.

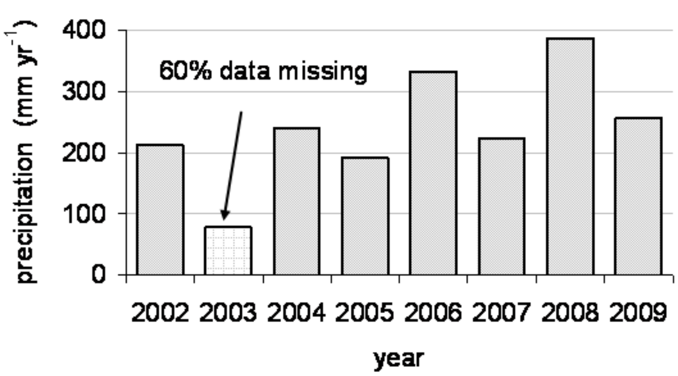

Fig 7 Measured precipitation at the study site, used as an external weather file in the augmented LDM.

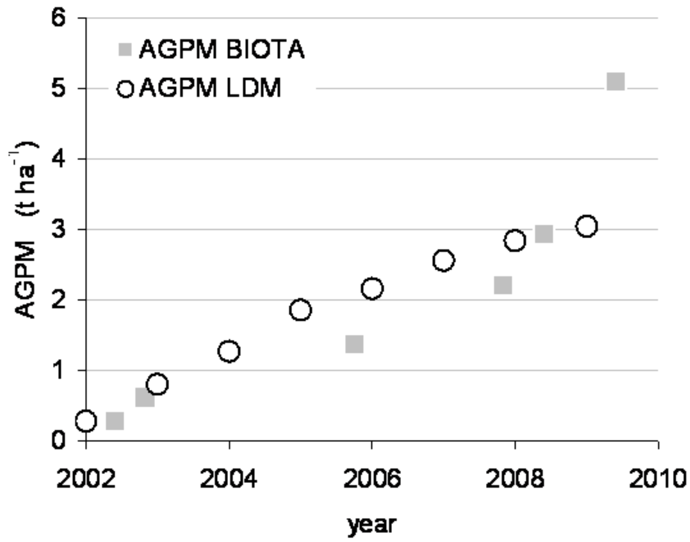

Fig 8 AGPM under zero grazing management. Comparison of observed (BIOTA) and modeled values (LDM).

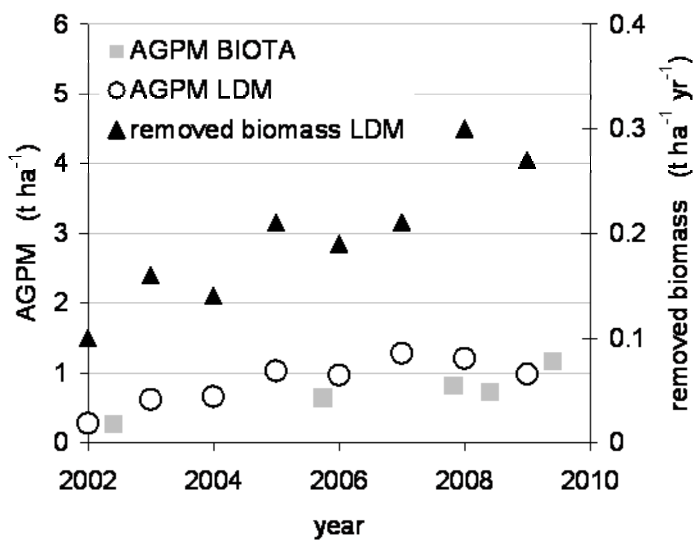

Fig 9 AGPM with grazing. Comparison of observed (BIOTA) and modeled values (LDM). The amount of removed biomass as calculated by the LDM is given on a secondary x-axis (to the right).

As seen in Figs. 7–9, our model fits relatively well to the observed values of AGPM. However, the model performs better at sites with grazing than at sites without grazing; in particular, the most recent value of AGPM under zero grazing (summer 2009) deviates notably from modeled results. This might be due to the fact that plant population dynamics are not included. As data from the BIOTA Maroc project reveal, the relatively wet winter of 2008/2009 has led to a 12% increase in plants per square meter. EPIC and

the meta-model of it are not capable of simulating plant population dynamics, which is a clear limitation. However, we achieve a relatively good fit from our model for the remaining years and especially under grazed conditions. Furthermore, the quite low AGPM values under grazing for 2006 and 2008 indicate, both for the model and for the observations, a delayed impact of the low precipitation years 2005 and 2007. This reflects the appropriateness of including vegetation dynamics in our augmented LDM.
The simulated results for stocking rates from our augmented LDM can be compared to empirical livestock data. A census conducted in early summer of 2009 revealed a stocking rate of 0.5 heads per hectare in the area around Taoujgalt, which is close to the lower boundary of our estimates (0.6–0.96). Since there was no evidence of institutional regulation of animal numbers, the deviation may be due to the fact that only herds from the village were included and counted. However, transhumant pastoralists pass the region several times a year and substantially increase the stocking rate during these times. A regional agricultural census for the investigated area revealed a huge variation of between 1 and 60 heads per hectare (Heidecke and Roth, 2008). As our simulations show, the upper section of this range may not be realistic.

3 Simulation results

To investigate the effects of drought in our agroecosystem of interest, we simulate two years with 33% less precipitation. The overall time horizon is ten years, with years 4 and 5 experiencing the drought. The remainder years are simulated with average weather. We use an ensemble of six model runs to separate the effects of droughts from the effects of the model's initial state. The 90% confidence intervals of the individual runs are shown by error bars in Figs. 10–12.

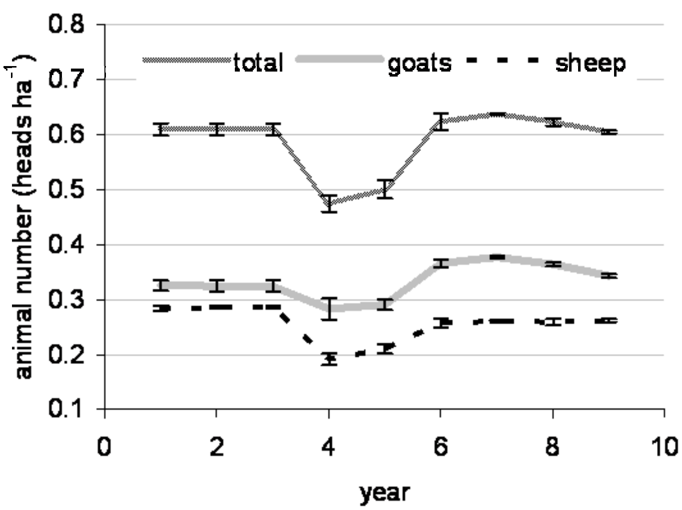

Fig 10 Stocking rates as given by our augmented LDM. Drought is simulated in years 4 and 5. Error bars indicate 90% confidence intervals over the ensemble simulations (n = 6).

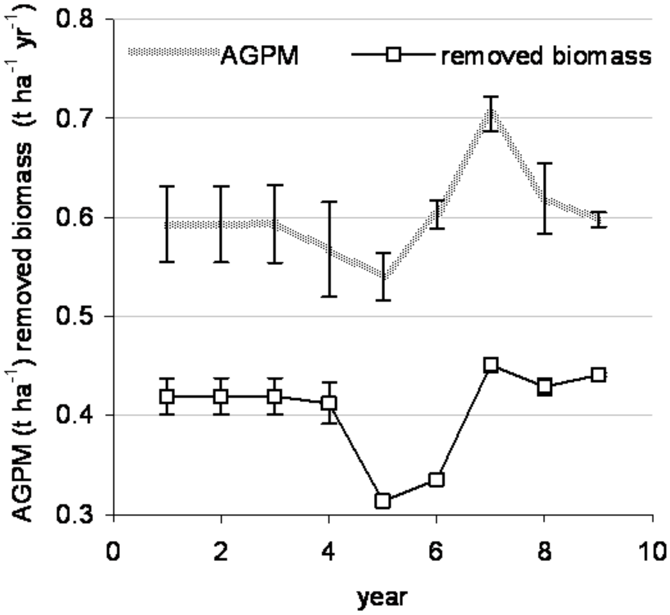

Fig 11 AGPM and removed biomass as given by our augmented LDM. Drought is simulated in years 4 and 5. Error bars indicate 90% confidence intervals over the ensemble simulations (n = 6).

The augmented LDM simulations show for the first three years with average weather conditions an optimal stocking rate of 0.6 (± 0.01) total animals per hectare at the beginning, and 0.96 (± 0.01) at the end of a grazing season. The stocking rates for the beginning of a season are displayed in Fig. 10. The resulting AGPM under average weather is on average 0.60 (± 0.04) t ha^{-1} (Fig. 11). Total biomass consumption of grazing livestock averages 0.42 (± 0.02) t ha^{-1} yr^{-1} DM (Fig. 11). At the beginning of the drought in year 4, stocking rates are reduced by 20% (Fig. 10). During the first year of the drought, the model projects more animal sales than usual because the drought is expected to last longer than one year. However, because prices decrease by about 50% in years with low precipitation, the profit from sold livestock drops by 25% (Fig. 12).

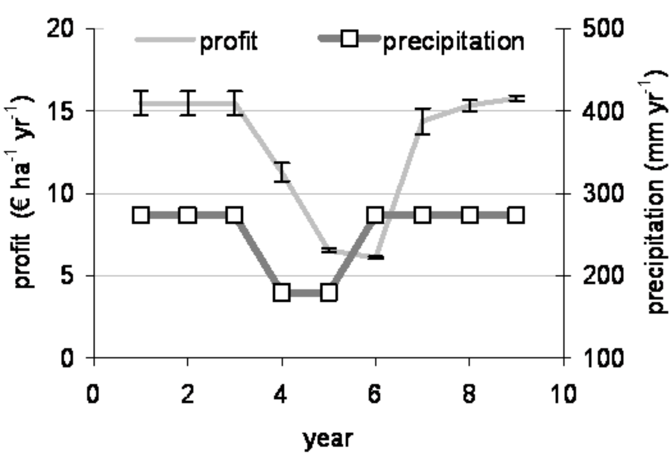

Fig 12 Relationship between precipitation and income as calculated by our augmented LDM. Drought is simulated in years 4 and 5. Error bars indicate 90% confidence intervals over ensemble simulations (n = 6).

In the second year of the drought, the profits decrease further to 43% of normal values (Fig. 12). This is due to low prices in the second year of the drought and a low potential for removing biomass from pastures, which reaches a minimum of about 0.3 tones per hectare and year (Fig. 11). The simulation of reduced precipitation leads to economic and ecological impacts, which go substantially beyond the meteorological time horizon of the drought. For instance, even though precipitation is back to normal levels and animal prices are high in year 6, removed biomass of the pasture and profits remains at low levels (Figs. 11 and 12).

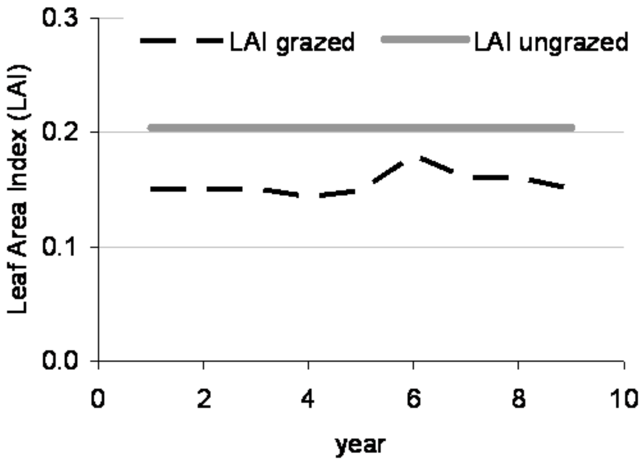

Fig 13 Leaf area index under the assumption of a two-year drought (years 4 and 5) with grazing (dashed, black line) and without (grey, solid). The six ensemble simulations do not show deviations in this parameter.

The model results also indicate that continued grazing in areas affected by a drought may lead to substantial variation in LAI over the years (Fig. 13). Since LAI is an important factor for local climatic processes, this implies the existence of dynamic interactions between human management and radiative properties of the steppes.

The pastures studied in our research are situated within the catchment of the oasis of Taoujgalt. Therefore, it is of interest how hydrological properties of the landscape are affected by human management under given weather scenarios. As we are unable to calibrate our model output with observed data, we instead refer to relative differences in our results (Figs. 14–16). Evapotranspiration (ETP; Fig. 14) is almost unaffected by grazing in our augmented LDM. The model indicates very high rates of evaporation, and therefore the effect of grazing on plant transpiration is of less significance to changes in total ETP. However, under average weather conditions, groundwater recharge of grazed pastures is 20% higher than the recharge of abandoned pastures (Fig. 15). During a drought, the simulated infiltration with grazing is still higher than without. The most pronounced effect of human management is shown by our model as being surface runoff. This parameter doubles relative to fully developed vegetation if grazing is applied (Fig. 16). During drought, surface runoff is heavily reduced, with the influence of human management further enhancing the decrease. It can be seen from Figs. 14–16 that human management is in general less important to hydrological properties of the landscape than precipitation. However, human management is important for infiltration and surface runoff, which further influences the availability of irrigation water in the oasis.

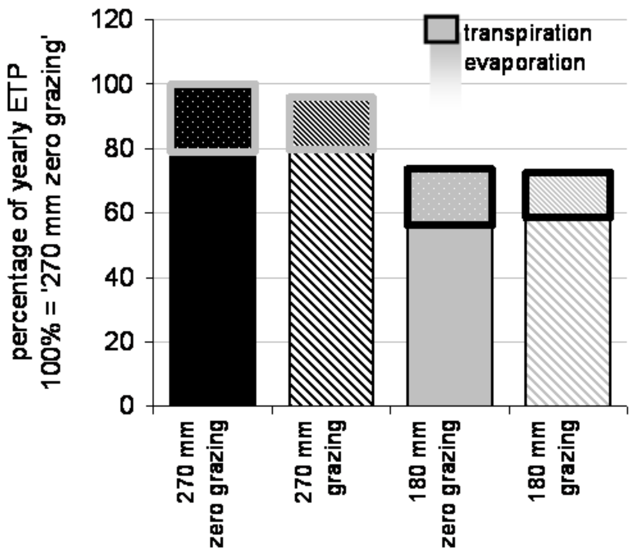

Fig 14 Simulated total annual ETP as the sum of plant transpiration (framed, upper part) and evaporation (lower part of bar). Average weather (270 mm annual precipitation) and 33% reduction of precipitation are investigated (180 mm).

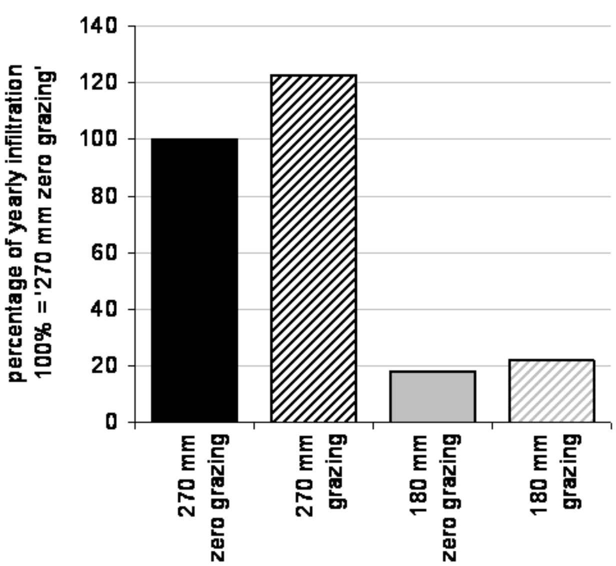

Fig 15 Simulated total annual groundwater recharge (infiltration). Average weather (270 mm annual precipitation) and 33% reduction of precipitation are investigated (180 mm).

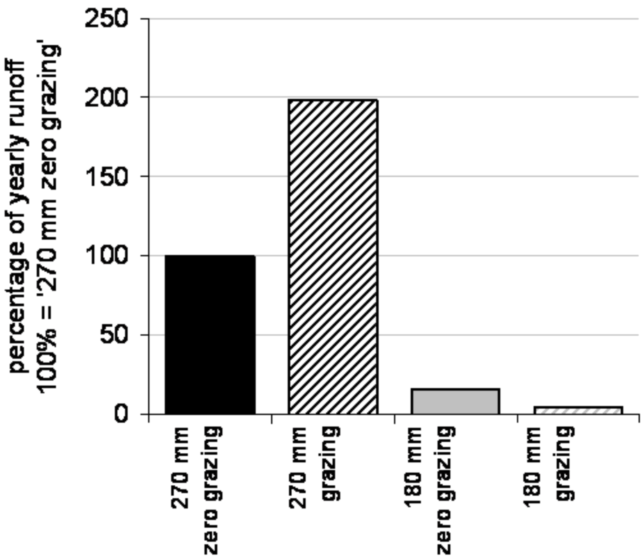

Fig 16 Simulated total annual surface runoff. Average weather (270 mm annual precipitation) and 33% reduction of precipitation are investigated (180 mm).

4 Discussion

The Markov-chain-based integration of EPIC with an economic LDM has succeeded in providing a more accurate picture of the complex land use system dynamics than the two modeling components alone. However, the reduction of EPIC to a single-state-variable-based Markov chain is not cost-free. We assume that the entire land management history of a certain site is fully captured by the value of a single state variable, namely AGPM. In reality, the grazing and precipitation history affects many other factors, including species composition, plant morphology, plant population density, and soil structure. The impact on these other factors is not considered explicitly in our augmented LDM, and thus biases our results. To overcome this deficiency, one could introduce more state variables at the expense of increased computation and calibration requirements. Furthermore, we assume that transitions do not occur between different vegetation types, and we justify that by the observation that pastoral agroecosystems, especially in the Mediterranean, are characterized by a long and continuous grazing history. Therefore, transitions between different vegetation types are limited (Navaro, 2006; Diaz et al. 2007). For this reason, we use only a single state variable and calibrate the model against measured AGPM data. This represents a compromise between simplicity of the model and accuracy of the model output, as given in Figs. 7–9.

The major advantage of our augmented LDM is the joint representation of farsighted decision-making and vegetation dynamics, even though both components are simplified. The combined modeling of human decision-making and environmental processes leads to new insights. For instance, in a transdisciplinary study for southern Morocco, de Jong et al. (2008) demonstrated a conceptual model of the importance of human land use management for evaluating the impact of climate change. In their study, the authors exogenously prescribed land use management. Our augmented LDM provides quantitative results on human impacts on hydrological parameters under altered climate, while using land use management as an internal variable. Thus, using Markov-chain-based replications of biophysical models within economic models increases the explanatory power of such models. Due to non-exponential computational requirements over explicit time periods, the method can be used for regional or global models.

The results from applying our augmented LDM to investigate a Moroccan agroecosystem demonstrate clearly the importance of dynamic vegetation for evaluating the socio-economic effects of droughts with mathematical models. As Fig. 10 shows, the stocking rates of goats and sheep themselves are not sufficient to explain the drought-induced changes. Hence, the interplay between stocking rates and dynamic vegetation must be responsible for the observation of longer-lasting effects of a drought on parameters such as profit and AGPM (Figs. 11–12).

Concerning the social effects of droughts, a close look at the results of our augmented LDM demonstrates the problem of increasing long-term social inequality, i.e. making poorer farmers poorer and richer farmers richer. Since we use only one aggregated agent for the entire village of Taoujgalt, the model has the option to suspend livestock selling in the year after the drought (Fig. 12) in order to restock the pastures and apply optimal management (Fig. 10). However, disaggregating the model to a higher resolution of agents would certainly lead to farmers with lots of animals and farmers with few animals. At a certain threshold of animal numbers, the latter would be forced to sell a substantial part of their herd after the drought in order to sustain their livelihoods. In this way, their future profits would be reduced due to delayed restocking. Wealthier farmers, on the other hand, might take advantage of the situation, since proportionally more fodder would be available for their animals after the drought and restocking would result in greater profits for them later. Hence, the dynamics displayed by our model demonstrate the polarizing effect of droughts. A more detailed representation of farmers in our augmented LDM could therefore make it possible to better investigate the social impacts of droughts in semi-arid areas. Instead of calculating the loss of GDP, a further developed LDM could assess the risk of impoverishment of rural people. Furthermore, land use policy options could be investigated, which reduce the risk of emerging social inequality due to repeated occurrence of droughts.

However, in order to apply such an augmented LDM to real-world problems, empirical data for calibration and validation of the model are essential (see Figs. 7–9). Especially for developing countries, time series of vegetation and biomass dynamics in semi-arid areas under consideration of human land use are scarce. The application of our augmented LDM to the investigation of social effects of land use policies in semi-arid areas emphasizes the singular value of ecological long-term monitoring campaigns, such as those carried out under the BIOTA Maroc and IMPETUS projects.

Surface water runoff and groundwater recharge in our augmented LDM are influenced by land use decisions in ways that fit with experimental studies (e.g. Murphy et al., 2004, Le Maitre et al., 2007). In our model, during normal years, livestock husbandry increases water availability for downstream oasis agriculture. This might be an important influence of landscape management on irrigation agriculture: the observation of relatively high grazing pressure around oases could be attributed to the evolutionary success of coupling high intensity grazing with concentrated irrigation agriculture. Therefore, an agricultural decision model for such regions should depict this relationship. Similarly, climate-relevant parameters such as LAI are influenced by human management (25% less under grazing management in our model), which certainly has implications for regional climate and predictions of it.

5 Conclusion

The methodology presented in this paper allows a computationally feasible integration of a complex biophysical model into an economic LDM. The dynamic interactions between land management and vegetation in semi-arid areas can be more accurately depicted. The Markov-chain-based approximation of the biophysical impacts reduces drastically the computational requirements compared to a direct coupling with explicit land use management trajectories. By using separate Markov chains for different weather scenarios, locations, and management regimes, we are able to investigate the economic and environmental effects of a drought, including the likely adaptation of management.

Our simulations show that a 33% decrease in precipitation reduces profits from pastoralism by up to 57%, although losses in the first year can be kept at relatively low levels. Through the inclusion of a dynamic vegetation module, the relationship between precipitation and profits in our model becomes history-dependent, i.e. the impact of reduced precipitation on profits depends on the grazing management of previous years. Furthermore, our model results indicate that, for the studied agroecosystem, human land use increases surface runoff and infiltration to the groundwater relative to undisturbed conditions, but decreases LAI. This shows the importance of including physical relationships into socio-economic models, or vice-versa, including human management adaptation into biophysical models. The exclusion or exogenous specification of land use management can bias the results and conclusions of agroecological and climate models. The insights from our interdisciplinary modeling approach emphasize the need for ecological long-term monitoring campaigns in order to be able to parametrize and validate bioeconomic land use models.

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