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ABSTRACT

Risks of drought complicate decision-making in grass-based livestock systems. Here, we assessed the pertinence of the stochastic viability framework (SV) for making relevant decisions in a system exposed to climate shocks. SV involves maximizing the probability of satisfying predefined constraints over time through adapted decision-making. We applied the approach to the case of Mongolia where climate hazards, combined with high animal densities, regularly cause massive livestock die-offs. We used a livestock system model on which we made preliminary simplifications, based on a thorough understanding of its behaviour, to allow for SV use. Then, we used SV to iteratively identify, based on herd size and plant biomass, the most adapted management decisions. Decisions involve selling/purchasing a certain number of heads of the five local species. We obtained 100-year trajectories satisfying herders' constraints of income and subsistence consumption at a 94% rate. This results from (i) cautious stocking rates reducing die-off frequency and (ii) sales of heads of resistant species to buy heads of fragile species after die-offs to compensate losses of fragile species. These management actions generate resilience, as they mitigate the effects of climate variability and offer reorganization mechanisms after a crisis. We thereby confirm the potential of SV for adaptive decision-making when resilience is at stake.

1. Introduction

Grass, bushes and other herbaceous plants play an important role in livestock production in the global food system. This natural forage serves as the main feed source for herbivores in the subsistence-based systems of Africa, America and Asia (Suttie et al., 2005). It is also a significant source of feed for the less intensive systems of developed countries (Dumont et al., 2013). Such vegetation can grow in drylands unsuitable for crop production (IIASA and FAO, 2021) and is not edible to humans. Therefore, it does not compete with human food sources for space, unlike the grain used by swine and poultry (Mottet et al., 2017; Wilkinson, 2011). This vegetation is also essential to systems providing a wide array of services to society, such as water cycling, biodiversity refuge and landscape cultural identity (Ryschawy et al., 2019).

However, a reliance on natural forage exposes livestock systems to climate hazards, such as droughts (Mace, 1989; Ryschawy et al., 2019). These systems must therefore be resilient enough to absorb hazards and adapt to them to maintain a satisfactory level of performance (Darnhofer, 2014). Decision-making processes adapted to uncertainty and offering sufficient resilience are therefore essential. In this article, we examine the pertinence of viability theory in proposing such decision-making processes. Viability theory has been adapted to quantify resilience (Martin, 2004; Martin et al., 2011; Rougé et al., 2013) and has been successfully applied in extensive livestock systems in Africa (Accatino et al., 2014), South America (Tichit, 2007) and Asia (Sabatier et al., 2017). The theory proposes a mathematical framework used to assess the satisfaction of predefined constraints through a *state-control* approach (Aubin, 1991). This is studied through viable trajectories, defined as successions of *states,* compatible with the satisfaction of predefined constraints (Oubraham and Zaccour, 2018). These states are reached through adapted management decisions called *controls* in the viability terminology. The assessment of constraint satisfaction can be

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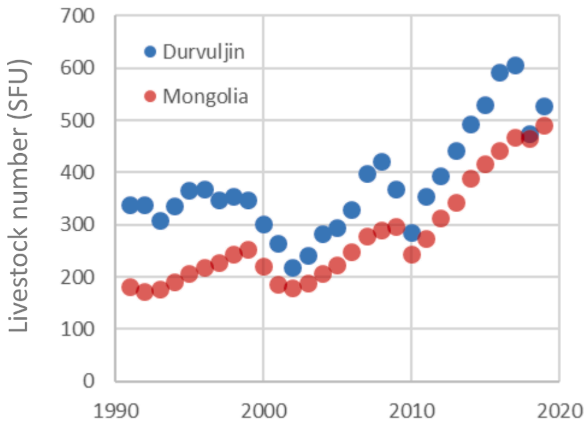

Fig. 1. Total numbers of livestock per household in sheep forage units (SFUs) (from NSOM (2020)).

either binary (yes/no), which is the approach of *robust viability*, or probabilistic, in the case of *stochastic viability* (De Lara and Doyen, 2008; De Lara and Martinet, 2009). This probabilistic aspect is well adapted to situations involving drivers that can only be forecasted through probabilities, such as climate hazards.

We tested the stochastic viability (SV) framework in relation to livestock systems of the desert steppes of Mongolia. These systems are quasi exclusively grass-based with limited possibilities of winter fodder storage. The systems are exposed to climate shocks that can cause, in combination with poor livestock body conditions, severe peaks of livestock mortality called *dzud* (Suttie et al., 2005). The last *dzud* of the winter of 2009–2010 caused economic losses of 345 million USD and killed 10 million animals (23.4% of the total national livestock) (Nandintsetseg et al., 2018). Such events typically take place when high animal densities, droughts, poor pasture conditions and cold temperatures weaken livestock populations, while heavy snowfall complicates access to grass (Joly et al., 2018b; Nandintsetseg et al., 2017, 2018). Mongolian systems are in addition subject to poverty (NSOM, 2015; World Bank, 2009) and pasture degradation (Hilker et al., 2013; Jamsranjav et al., 2018; Liu et al., 2013). Such systems thus face a variety of challenges and hazards, which make them particularly interesting for testing a framework involving stochasticity and the satisfaction of constraints.

To be efficient in this context, SV must propose management decisions ensuring regular and sufficient income to herders, while maintaining pasture conditions. The tool must propose stocking rates (*i.e.* animal densities) high enough to preserve herder incomes but low enough to prevent *dzud* risk and pasture degradation. To test the ability of the SV framework to make appropriate decisions on stocking rates, we used the model previously developed for the Mongolian context by Joly et al. (2018a) and Sabatier et al. (2017). The model simulates the interactions between vegetation, animal and climate dynamics and can be managed through the selling and buying practices of the five local livestock species. Through these practices, the model can adjust the stocking rate and pilot the state of a system. The model can assess the satisfaction of herders' constraints (*e.g.*, income and subsistence consumption) based on the system state and selling and buying decisions.

The model has been previously used to assess the impact of current herder practices on plant underground biomass and the implications of competition between herders (Joly et al., 2018a). It has also been used within the SV framework to propose metrics of resilience for different states, defined by herd size and forage biomass (Sabatier et al., 2017). These metrics concern i) the magnitude of weather perturbations that can be absorbed without compromising constraint satisfaction and ii) the return time to a state enabling constraint satisfaction, if a system has strayed from such a state by a climate shock. These metrics were computed with the help of SV algorithms for states defined as starting points of viable trajectories.

Here, we used these algorithms to derive management decisions preventing deviations from viable trajectories, under randomly generated weather scenarios. From the rate of constraint satisfaction of these trajectories, and comparisons to simpler rules on stocking rates, we assessed the pertinence of SV for the decision-making process. We thus go a step further in the study of the SV framework by testing its pertinence for practical management guidance. We also discuss the technical implications of implementing SV-based decision-making.

2. Material and methods

2.1. Study area

The model is parametrized for the conditions of *Khomyn Tal*, an area of *Durvuljin* district in western Mongolia. We summarize here the area's main characteristics and a full description is given in Joly et al. (2013, 2018a, 2019). The region is characterized by semi-desert steppe vegetation, and the mean annual temperature is 0.42 °C. The mean temperature over the four coldest months is −18 °C (November, December, January and February), and the mean annual precipitation level is 97 mm. Precipitation mostly falls in the form of rain in the summer and its coefficient of variation (CV) is 0.46, denoting a high degree of variability (von Wehrden et al., 2012).

Approximately 50 herder households live in *Khomyn Tal* with the five species of livestock common to Mongolia. In 2019, the national livestock census registered approximately 13,000 goats, 10,000 sheep, 2300 horses, 1400 cattle and 800 camels (NSOM, 2020). Livestock is quasi exclusively fed natural forage exploited through mobile pastoralism. *Khomyn Tal* and surrounding areas suffered two *dzuds* in the winters of 2001/2002 and 2009/2010 (Joly et al., 2018a). In the years between these *dzud* events, herders rebuilt their herds, which caused livestock numbers to fluctuate. This pattern was visible at both the *Durvuljin* and national scales (Fig. 1).

2.2. Livestock system modelling

The model takes into account local mobility practices by focusing on grazing areas in the summer as during this season, livestock must accumulate fat reserves to survive the winter. During this season, vegetation is also the most vulnerable to degradation. The model is household based and allocates a portion of land to each household equal to 1/50 of the summer area (based on household numbers). The model simulates the vegetation state through underground biomass because long-term forage renewal depends on underground organs (most of the local plant species are perennial). The model simulates herd size through livestock dynamics and from this, herders' abilities to satisfy their constraints (Fig. 2). To satisfy these constraints, livestock management must offer the following:

i Generate income above the poverty line from live animals and fibre (wool and cashmere)
ii Provide enough animals for subsistence consumption of meat and milk
iii Provide enough transport animals (horses used to herd animals and camels for moving camps)

We used a version of the model that merges the 5 local species into 2 functional types (Sabatier et al., 2017). These types are based on the *bog/bod* traditional Mongolian body size typology (Fijn, 2011). Small

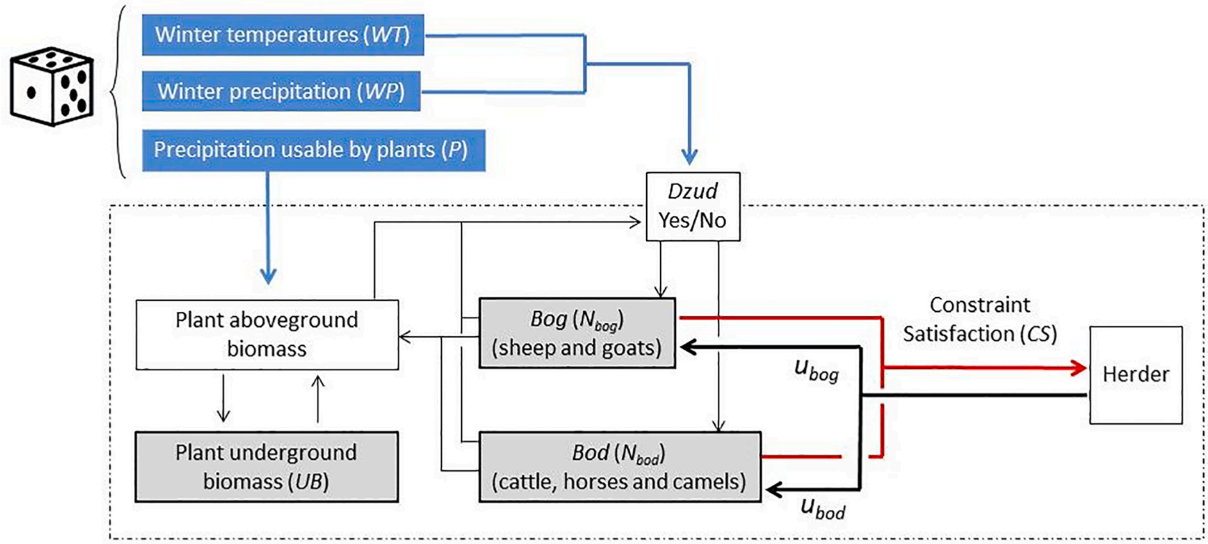

Fig. 2. Conceptual model of the system (bounded by grey dashed lines). Grey boxes denote the system's state, blue arrows denote external drivers (the dice expresses stochasticity), thin black arrows denote internal interactions, bolded black arrows denote herder management options (the sale/purchase of livestock) and red arrow represent the satisfaction of herders' constraints.

animals called *bogs* (sheep and goats) exhibit, on average, more fecundity and are less resistant to *dzud* events than large species called *bods* (horses, cattle, and camels) (Joly et al., 2018a).

2.3. Model dynamics

The model is time discrete, and the state variables are underground plant biomass and *bog* and *bod* herd size (Appendix A). The dynamics of underground biomass depend on the precipitation available for vegetation and the amount of standing aboveground biomass. The renewal of underground organs indeed depends on reserves produced by aboveground photosynthetic leaves, which are themselves impacted by animal grazing (assessed through herd size). Animal dynamics are driven by the death rate, which depends on the occurrence or absence of *dzud* events, animal fecundity that impacts births, the number of old animals culled, and decisions regarding the sale or purchase of other animals.

Animal fecundity in year t depends on the pasture use factor (ratio forage demand/supply) of year $t-1$, which is notably due to the duration of gestation (Joly et al., 2018b). Similarly, survival at the end of the winter of year t is impacted by animal fat reserves, which also depend on the previous summer pasture use of $t-1$. Plant biomass processes in year t are only dependent on rainfall in year t. The dynamics of the model for year t thus depend on events taking place in years $t-1$ and t.

For this reason, we express the state $x(t) \in X = \mathrm{R}^6$ of the system in year t as follows:

$$x(t) = \left(UB(t), N_{bog}(t), N_{bod}(t), UB(t-1), N_{bog}(t-1), N_{bod}(t-1)\right)$$

where $UB(t)$ is underground biomass (kg/ha) and $N_{bog}(t)$ and $N_{bod}(t)$ reflect herd size through *bog* and *bod* numbers (heads), respectively. Animals are allocated to a given surface, which is why $N_{bog}(t)$ and $N_{bod}(t)$ reflect stocking rates (animal number per hectare). $N_{bog}(t)$ and $N_{bod}(t)$ are capped by the maximum number of heads herders can look after (respectively 500 and 90 heads on average) (Joly et al., 2019).

Climate variability $w(t)\ \epsilon\ W = R^6$ is:

$$w(t) = (P(t), WP(t), WT(t), P(t-1), WP(t-1), WT(t-1))$$

where $P(t)$ denotes precipitation available for vegetation, mostly falling in the form of rain, $WP(t)$ denotes winter precipitation falling in the form of snow, and $WT(t)$ is the mean winter temperature. $P(t)$, $WP(t)$ and $WT(t)$ follow the distributions observed in historical series[1], and they are independent from each other in the model for a given year. Therefore, for any year t_1, $P(t_1)$, $WP(t_1)$ and $WT(t_1)$ are independent from each other and are also independent between years, *e.g.,* for any couple of distinct years t_1 and t_2, $P(t_1)$ and $P(t_2)$ are independent. This configuration correctly simulates *dzud* frequency (Joly et al., 2018a).

The control (management action) $u(t) \in U = R^2$ is:

$$u(t) = \left(u_{bog}(t), u_{bod}(t)\right)$$

where $u_{bog}(t)$ and $u_{bod}(t)$ are the sales and purchases of *bog* and *bod*, respectively (heads). When u is positive animals are sold, and when it is negative they are purchased. Contrary to dynamics, it applies to a single year because decisions only influence year t (they cannot apply to past states).

The model's dynamics are expressed by Eq. (1).

$$x(t+1) - x(t) = f(x(t), u(t), w(t)) \tag{1}$$

The model expresses herders' *Constraint Satisfaction* with function $CS(x(t), u(t), w(t))$, which is equal to one when constraints are satisfied and zero otherwise. This function is based on model dynamics, weather and management decisions. The expressions of CS and f are given in Appendix A.

2.4. Stochastic viability

To apply the SV framework, we considered the trajectory of the system during time steps $\{0, \ldots, T\}$. The controls applied during these steps are denoted by $u(\cdot) = \{u(0), \ldots, u(T)\}$, and the climate values are denoted by $w(\cdot) = \{w(0), \ldots, w(T)\}$. The state reached at time t when applying controls $u(\cdot)$ over time period $\{0,\ldots,t\}$, starting from state x_0, is $x_{x_0,u(\cdot),w(\cdot)}(t)$ (Eq. (2)):

$$x_{x_0,u(\cdot),w(\cdot)}(t) = x_0 + \sum_{\tau=0}^{t} f\left(x_{x_0,u(\cdot),w(\cdot)}(\tau), u(\tau), w(\tau)\right) \tag{2}$$

The purpose of relevant strategy u^* in a context of uncertainty is to

[1] P has a Poisson shape type distribution (mean = 80.64, SD =41.47), WP has a normal distribution (mean = 8.17, SD =4.40) and WT has a normal distribution (mean = −12.84, SD =2.14).

Table 1
Characteristics of the 100-year trajectories.

Name	Management type	Constraint satisfaction rate (mean *CS*[1])	Coefficient of variation of the constraint satisfaction rate[2]	Ratio income/ poverty line	*Bog* fecundity	*Bod* fecundity	*Dzud* numbers
Default PovX1	No adjustment rules (livestock numbers are only regulated by *dzud*)	0.19	0.52	1.02	0.74	0.53	11.76
Capping PovX1	Livestock is sold above a threshold of 360 SFU (sheep forage unit)	0.86	0.21	1.79	0.87	0.64	1.65
Viability PovX1	Sale and purchase of livestock are derived from the stochastic viability framework (income is set as ≥ poverty line X1)	0.94	0.07	1.48	0.89	0.65	1.47
Default PovX2	No adjustment rules (livestock numbers are only regulated by *dzud*)	0.08	0.73	1.02	0.74	0.53	11.76
Capping PovX2	Livestock is sold above a threshold of 400 SFU (sheep forage unit)	0.71	0.26	1.97	0.86	0.63	2.29
Viability PovX2	Sale and purchase of livestock are derived from the stochastic viability framework (income is set as ≥ poverty line X2)	0.86	0.12	2.13	0.87	0.63	1.93

[1] *Constraint Satisfaction* (*CS*) is calculated according to the income threshold to satisfy the following: above the poverty line for the 'PovX1' trajectories and over twice this level for the 'PovX2' trajectories.
[2] Expressed as the average of the 1000 mean *CS* values along 100-year trajectories divided by the standard deviation of these 1000 values.

ensure that constraints will be satisfied over time with the highest possible probability. The SV decision-making process must therefore identify controls $u^*_{x_0}(\cdot)$, which starting from state x_0, maximize the expected value of *CS* along time steps $\{0,\dots,T\}$. This approach is formally expressed by Eq. (3).

$$u^*_{x_0}(\cdot) = \arg\left(\underset{u(\cdot)\in U^{T+1}}{max}\ \underset{w(\cdot)\in W^{T+1}}{\mathrm{E}}\left(\prod_{t=0}^{T} CS\left(x_{x_0,u(\cdot),\ w(\cdot)}(t), u(t), w(t)\right)\right)\right) \tag{3}$$

where arg() identifies the specific u value(s) satisfying the condition shown between parentheses, and E() is the expected value of the expression shown between parentheses. Eq. (3) hence indicates that management strategy u^* maximizes the probability that constraints are satisfied over time, and this probability is assessed by the expected value of the product of annual *CS* values.

Identifying this u^* strategy is challenging because it implies, for instance, identifying a series of management options amongst a number of possible candidates that increases exponentially with time (*e.g.,* 10^{20} candidates for 10 yearly possible control options over 20 years). We identified strategy u^* through the backward procedure of dynamic programming applied to stochastic viability, as in Doyen and De Lara (2010). This procedure makes it possible to identify the given strategy by finding recursively, year by year, the best possible decision for a given year. The method applies this approach while maintaining the dynamics between years, as explained below (years connected through Eq. (4) and (5)). By doing so, the procedure solves a very difficult problem concerning a trajectory spanning 20 years (for example) by solving 20 simpler annual sub-problems (Bellman, 2003).

This procedure uses *value function V* that returns, for a given state and year, the highest probability of constraint satisfaction. This probability is obtained by scanning a range of possible u values Eq. (4) and (5). By finding the pair of controls $u_{bog}(t)$ and $u_{bod}(t)$ providing the highest probability of constraint satisfaction, the most adapted decisions for a given year and state are identified. We used this approach to derive our decision-making process.

Using dynamic programming involved two modelling simplifications. The first concerns the dynamics of the system, which depend on the weather of two subsequent years. The dynamic programming algorithm computing V only refers to the weather of a single year (see Eq. (4) and (5)), leading us to approach the pasture use factor of $t-1$ with that of t, because they are closely correlated in the area (Joly et al., 2018b). These simplified dynamics are denoted as f^s and use simplified arguments x^s and w^s (f^s is calculated by replacing $PU(t-1)$ with $PU(t)$ in Eqs. A.3 and A.7: see Appendix A):

$$x^s(t+1) - x^s(t) = f^s(x^s(t), u(t), w^s(t))$$

$$x^s(t) = \left(UB(t), N_{bog}(t), N_{bod}(t)\right)$$

$$w^s(t) = (P(t), WP(t), WT(t))$$

This simplification did not prevent us from using *CS* due to the form of the equations on which it is built (see Appendix A).

Second, to save computing time, we only considered typical weather configurations for $w^s \in W^s$. These configurations are based on cut-off values and distributions of rainfall $P(t)$, and an indicator of winter harshness $WH(t)$ derived from $WP(t)$ and $WT(t)$ (Appendix A). These cut-offs separate $P(t)$ and $WH(t)$ for *dzud* and non-*dzud* years, based on their values in historical series. Values above cut-offs were averaged, and their proportions were calculated. For example, the mean P for *dzud* years is 36.4 mm, and P is below this value for 20% of the years. The mean P value during non-*dzud* years is 91 mm, and P is above this value for 80% of years (values summarized in Appendix A -Table A.2). We obtained in this way four types of years as follows:

$$W^s = \left(w^s_1 = \text{wet} / \text{mild}, w^s_2 = \text{wet} / \text{harsh}, w^s_3 = \text{dry} / \text{mild}, w^s_4 = \text{dry} / \text{harsh}\right)$$

Each type of year w^s_k has a probability $P(w^s_k)$ that is not dependent on t. Hence, for any couple of distinct years t_1 and t_2, $w^s(t_1)$ and $w^s(t_2)$ are independent, which ensures that dynamic programming can be applied. Value function V is expressed through Eq. (4) and (5) and computed for the following ranges of state variables:

The maximum $N_{bog}(t)$ and $N_{bod}(t)$ are 500 and 90 heads, respectively, due to the above explained workforce limits, and the minimum value for both livestock types is 0. Based on trials using these livestock values, $UB(t)$ ranges between 100 and 700 kg/ha. T is set to 20 years for computing time constraints (computing V implies scanning large numbers of states and controls).

With the above simplifications, value function V is computed as follows:

$$\begin{cases} V(\mathrm{T}, x^s) = \underset{u\in U}{\max}\ \underset{w^s\in W^s}{\mathrm{E}}(CS(x^s, u, w^s)) \\ V(t, x^s) = \underset{u\in U}{\max}\ \underset{w^s\in W^s}{\mathrm{E}}(CS(x^s, u, w^s)\cdot V(t+1, x^s + f^s(x^s,\ u, w^s))) \end{cases} \tag{4}$$

Where

$$\begin{cases} \underset{w^s \in W^s}{\mathrm{E}}(CS(x^s,u,w^s)) = \sum_{k=1}^{4} CS(x^s,u,w_k^s)\cdot P(w_k^s) \\ \underset{w^s \in W^s}{\mathrm{E}}(CS(x^s,u,w^s)\cdot V(t+1,x^s+f^s(x^s,u,w^s))) = \sum_{k=1}^{4} CS(x^s,u,w_k^s)\cdot V(t+1,x^s+f^s(x^s,u,w_k^s))\cdot P(w_k^s) \end{cases} \quad (5)$$

2.5. Trajectories

2.5.1. Types of trajectories

To formally assess the pertinence of SV for making management decisions, we built trajectories derived through SV. Then, as mentioned in Introduction, we compared these trajectories to a second type based on a livestock number capping rule. We evaluated in this way the added value of SV relative to a simple adjustment rule. We compared in addition SV trajectories to a third type built without a rule. We assessed this way the baseline performance of no-rule management. In these no-rule trajectories, herders let animal numbers grow until a *dzud* occurs. In the three types of trajectories, apart from animals sold, herders obtain income from fibre and the culling of older animals (see Appendix A). Hence, even in no-rule trajectories, herders obtain an income. The three types of trajectories built are called 'viability', 'capping' and 'default' trajectories (Table 1).

We built 1000 simulated trajectories of each type for 100 years and assessed mean constraint satisfaction *CS* for two levels of annual income constraints: above once and twice the poverty line for a household (from parameter $\mathrm{Cons}^{\mathrm{Poverty}}$ multiplied by 1 or 2: see Appendix A). We assessed this way the capacity for SV to handle different income objectives. The income objective is indicated in trajectories by suffixes 'PovX1' and 'PovX2' (Table 1).

2.5.2. Trajectory building

We built the three types of trajectories based on nonsimplified dynamics f and climate distributions w (simplified ones were only used to compute V). We randomly set for each year a value for P, WP and WT according to the same mean, standard deviation and distribution of historical series. Starting point x_0 is defined as $N_{bog} = 252$, $N_{bod} = 36$, and $UB = 500$ for both years of the state based on the most recent surveys (Joly et al., 2018a).

We built 'viability' trajectories by considering for each year t vector $[N_{bog}(t), N_{bod}(t), UB(t)]$. This vector corresponds to simplified state x^s, and we extracted the most adapted control $u^*_{x^s}(0)$ identified when calculating $V(0, x^s)$ (Eq. (4)). This extraction according to x^s makes our SV procedure adaptive. When several values of $u^*_{x^s}(0)$ were possible, we randomly selected one.

We built 'capping' trajectories with a rule involving selling animals when the overall size of the herd in sheep forage units (SFUs) exceeds a threshold. From this overall threshold, we declined *bog* and *bod* thresholds in heads, above which animals were sold. We used 360 and 400 SFU thresholds for PovX1 and PovX2, respectively, as they returned the best *CS* (obtention of these thresholds explained in Appendix B). The capping trajectories also integrate a mechanism of *bog/bod* exchange after a *dzud*. This resilience mechanism practised by herders involves selling resistant *bod* heads after a *dzud,* to buy fragile *bog* heads (Joly et al., 2019).

We finally built our 'default' trajectories by simply setting $u_{bog}(t)$ and $u_{bod}(t)$ to 0. Further details on the trajectory building of the three types are given in Appendix B.

Models were written in Python 3.7.0 with the help of Spyder 3.3.1 (available at https://github.com/fejoly/Stochastic_Viability).

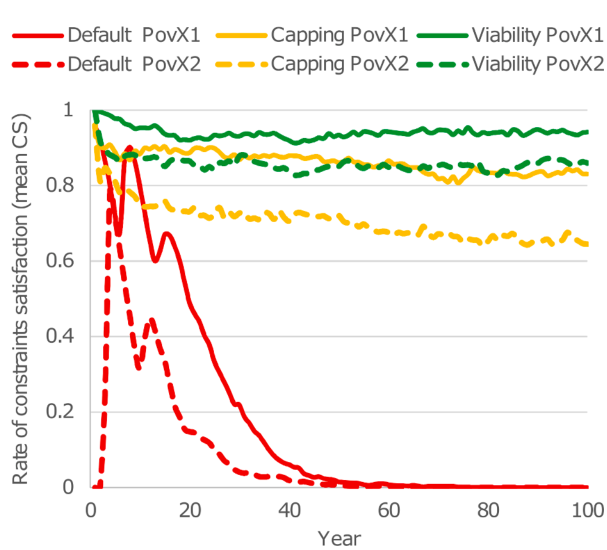

Fig. 3. Rate of trajectory constraint satisfaction (mean *CS*).

3. Results

3.1. Constraint satisfaction of all types of trajectories

For both income objectives (poverty line X1 or X2), mean *CS* increases from default to capping and then to viability (Table 1). Capping and viability trajectories have mean *CS* values ranging from 0.71 to 0.94, whereas mean default *CS* ranges from 0.08 to 0.18. This poor default performance is attributable to the violation of the subsistence consumption constraint. *Bog* and *bod* meats are not substitutable for preservation purposes, and due to the high *dzud* frequency in default trajectories, *bog* livestock is superseded by *bod* livestock (Fig. 4). As a result, *bog* herds fail to satisfy the *bog* meat constraint.

Viability trajectories are thus the most efficient, and they are also the most stable, as illustrated by the *CS* coefficient of variation (Table 1). Such stability is further illustrated by the shape of the trajectories, which reach plateaus for both *CS* and state variables (Figs. 3 and 4). The other trajectories show less stable trends and for example, default trajectories are unable to prevent a decrease in underground biomass. Moreover, capping trajectories are unable to prevent a slight decrease in *CS* over 100 years (Fig. 3). It is of interest to note that the capping and viability trajectories maintain a stable level of underground biomass, close to the starting value (~500 kg/ha). It is also noteworthy to mention that viability trajectories succeeded in providing mean incomes of above the parametrized threshold (Table 1), with the highest *CS* found for viability PovX1 (Table 1). Viability PovX1 trajectories are therefore the most efficient in terms of stability, but viability PovX2 trajectories are the most efficient in terms of income. The difference in *CS* found between the capping and viability trajectories is finally more important for PovX2 ($\Delta = 0.15$) than for PovX1 ($\Delta = 0.08$), which indicates that when the level of constraint increases, the higher efficiency of SV becomes more apparent.

3.2. Factors affecting trajectory efficiency

The better performance of the viability and capping trajectories are due to the reduction in *dzud* frequency, increase in livestock fecundity

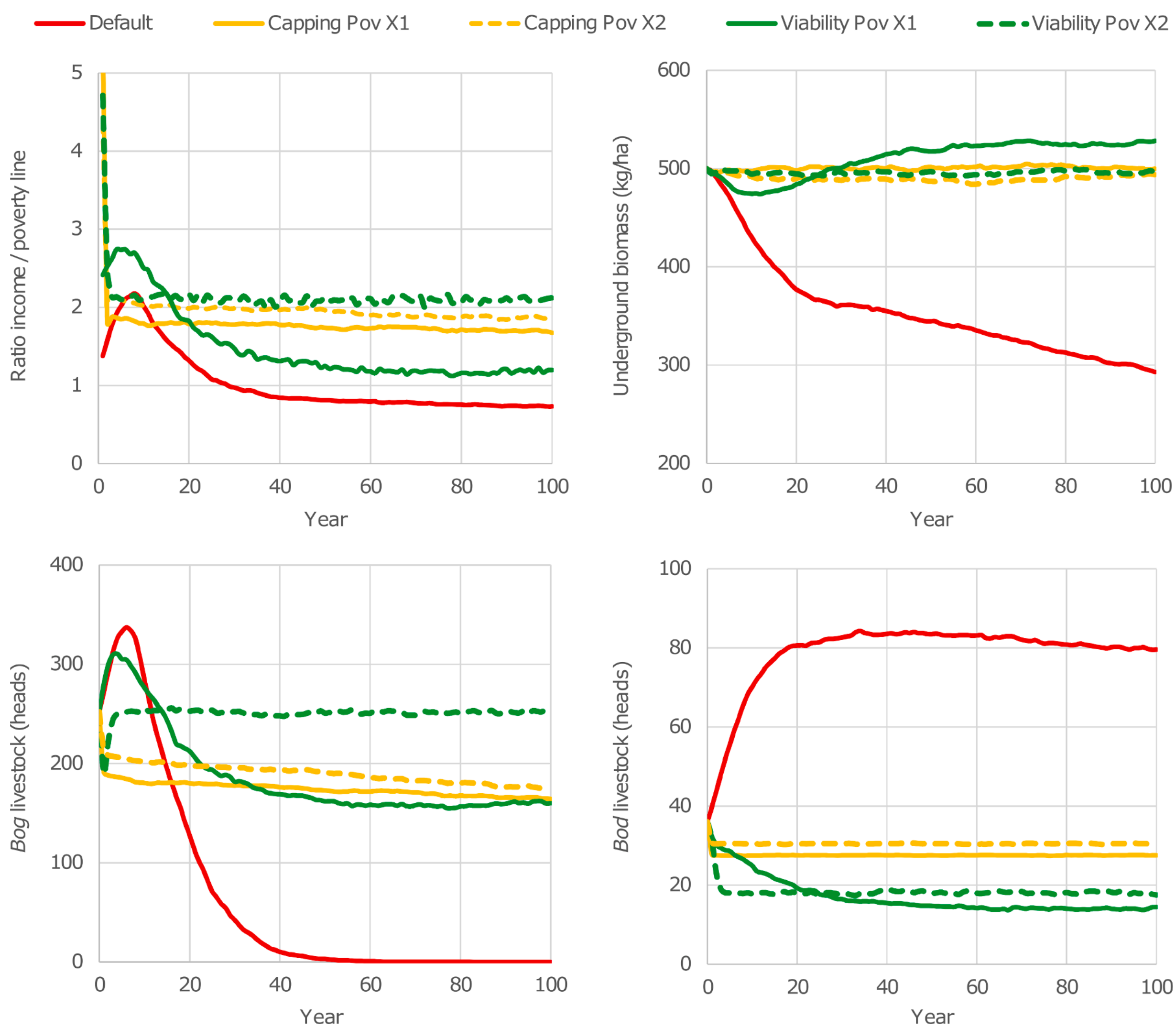

Fig. 4. Income and state variables of the 100-year trajectories (*bog*: sheep + goats, *bod*: horses + cattle + camels).

(Table 1) and stabilization of *bog/bod* proportions (Fig. 4). The *bog/bod* proportion was parametrized in the capping trajectories from the maximum possible number of animals, while it was automatically adjusted in the SV trajectories by the viability process. This is notably obtained through a post-*dzud* exchange mechanism of *bogs* and *bods*, illustrated by the relationship between post-*dzud bog* numbers and *bog* sales (Fig. 5). This relationship between livestock numbers and *bog* sales ($u_{bog}(t)$) shows that after a *dzud*, if *bog* herds become too small, SV models buy animals (livestock numbers are assessed here from herd size before culling and sale or purchase; see Appendix A). Solving the associated linear regression indicates that the purchase takes place on average for both SV trajectories when the post *dzud bog* herd falls below 100 heads (Fig. 5). In other words, most of the time, the SV process 'chooses' to buy animals if the *bog* herd falls below 100 heads. This 100-head value is close to that recorded from interviews of local herders (Joly et al., 2019). In addition, the *bog* purchases concern batches of *bogs* of 40 heads or less in 91 and 93% of the *dzud* years for Viable PovX1 and PovX2, respectively (Fig. 5). Finally the post-*dzud* mechanism is further characterized by the relationship between *bog* and *bod* sales ($u_{bog}(t)$ and $u_{bod}(t)$), showing that the purchase of *bogs* is typically associated with a *bod* sale (Fig. 5). In other words, most of the time, the SV process 'chooses' to sell *bods* when it buys *bogs*.

4. Discussion

4.1. Stochastic viability pertinence

Our objective was to assess the ability of the SV approach to define a pertinent stocking strategy in the context of environmental uncertainty. SV provides a mathematical definition for such a strategy through u^* (Eq. (3)), and offers tools with which to translate this strategy into concrete management decisions $u(t)$ (through the dynamic programming of Doyen and de Lara, 2010). By using these tools, we obtained trajectories that clearly demonstrate SV pertinence by ensuring high rates of constraint satisfaction (mean *CS*) and preserving long-term forage potential. We observed this efficiency without a duration limit, as systems are stabilized several decades before the end of the 100-year horizon. In this respect, our results extend beyond studies of agrosystems exposed to environmental stochasticity reported by Oubraham and Zaccour (2018). These studies are either based on a shorter duration (Sabatier, 2010; Sabatier et al., 2012) or stabilize performance less efficiently (Baumgärtner and Quaas, 2009; Tichit et al., 2004).

The comparison of the default and capping trajectories helps illustrate through which drivers strategy u^* is implemented. The comparison shows that post-*dzud bog/bod* exchange, the capping of livestock numbers to reduce *dzud* frequency, and underground biomass stabilization are drivers of efficiency. These drivers generate resilience, as they enable the absorption of climate shocks and reorganization after crises (*dzud*)

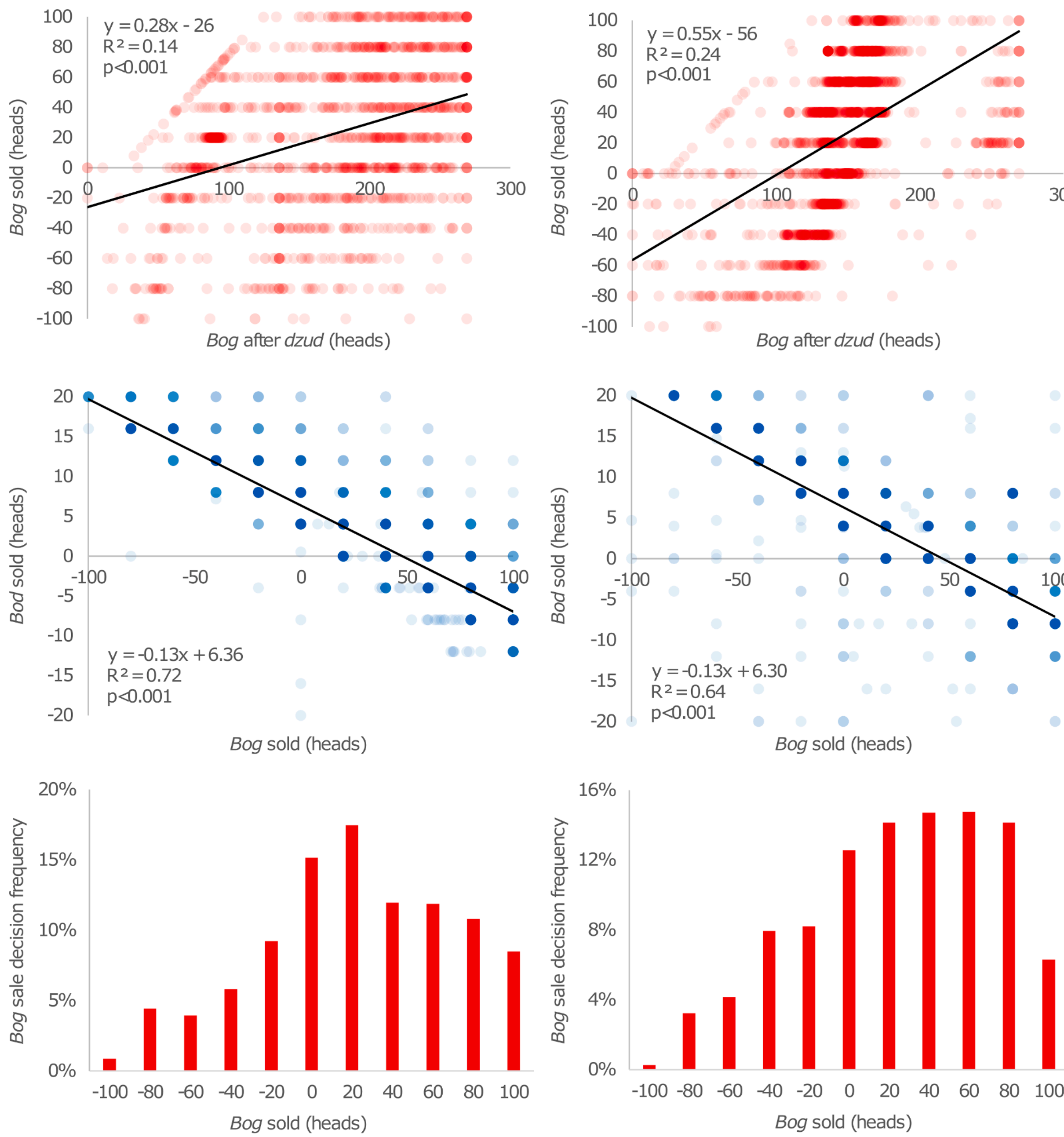

Fig. 5. Characteristics of the post-*dzud* sale or purchase of *bogs* (sheep + goat) and *bods* (horse + cattle + camel) (*dzud* = die-off). Left column: trajectories with programmed income above the poverty line (Viability PovX1). Right column: trajectories with programmed income of over double the poverty line (Viability PovX2).

(Walker et al., 2004). SV management uses these drivers more efficiently, especially when income constraints are high, which is attributable to the dynamic programming procedure. This procedure helps obtain these states that ensure the highest probability of constraint satisfaction over time, which obviously contributes to improved long-term performance. The procedure also makes decisions adaptively, *i.e.* based on the state of the system. Our results thus demonstrate that SV, through its long-term focus and adaptive approach, makes it possible to derive a decision-making process pertinent in the context of climate variability.

Our results also illustrate interesting aspects of the SV framework itself. First, they show that the simplifications made to the weather distribution (from W to W^s) and to system dynamics (from f to f^s) did not prevent building trajectories with high rates of constraint satisfaction. These simplifications were made because of the complexity of the system and based on a thorough knowledge of its dynamics. This illustrates that dynamic programming applied to stochastic viability can be used in complex systems following relevant simplifications. The fact that trajectories are stable over 100 years, despite training over 20 years (V computed over 20 years), illustrates an additional level of robustness. This shows that an initial momentum ensuring sustainability can be given to the system. Second, our use of different levels of income constraints and identification of different levels of constraint satisfaction represent a quantitative application of the viability framework, showing that the focus can be placed on income (Viability PovX2) or stability (Viable PovX1). This indicates that trade-offs can be studied through viability theory, even though this was not its initial purpose (Aubin, 1991). Finally, we focused on assessing SV efficiency to manage stochasticity around a mean and therefore did not take climate change into account. However, it could be possible to integrate this process and in this case, for a given starting state, the management and value functions (u and V) would depend on an initial date. A climate trend could be this way integrated in V computation.

4.2. Towards the development of a decision-making tool

From a technical perspective, decision-making tools could be built from the applied SV procedure. They would involve defining management decisions according to the system state, as modelled here. The state would be defined by herd size, which is easily accessible to herders, and underground biomass, which is more difficult to measure but can be assessed through plant cover (Joly et al., 2018a). *Bog* number, *bod* number and underground biomass values could be sent through SMS or smartphone applications to a server, and control values (the sale or purchase of animals) could be returned. This control extraction method is fast once value function *V* has been computed, *i.e.*, over <20 s on our regular laptop computer (while *V* computation over 20 years took several hours). The control value could then be sent back to a phone through a mass messaging system similar to that developed in Mongolia to warn of weather hazards (People in Need, 2018).

From a nontechnical perspective, these decision-making tools would have both advantages and disadvantages. A first advantage is that income levels can be parametrized, which offers interesting options. Viability povX2 is in this regard particularly interesting and could be chosen by herders who have bank cash saving mechanisms (IFRC, 2017). Herders might, for this reason, be more interested in the mean level of income over time than in the annual satisfaction of the poverty line. A second advantage is that some of the controls applied by the SV procedure are in line with a resilience mechanism found in traditional pastoral societies of Africa and Asia. Post-disaster animal exchange is indeed commonly practised within multispecies herds. As mentioned above, the method is practised in Khomyn Tal and is based on a portfolio of species with distinct traits, such as resistance to hazards to provide a safety net, and high fecundity to provide a growth asset (Blench and Marriage, 1999; Joly et al., 2019; Mace, 1989). By continuously adjusting the numbers of animals of the different species types, herders maintain stable performance despite hazards and die-offs. The 100 head threshold above which models and herders restock their *bog* herd (*i.e.,* choosing to buy animals) suggests that this mechanism is very similar in SV trajectories and real systems.

Regarding the disadvantages of the SV process, viable trajectories first have a *dzud* avoidance approach that differs from pastoralist practices. Pastoralists indeed commonly maximize their herd numbers as part of a risk mitigating strategy to accumulate wealth in anticipation of hardship (Hendricks et al., 2004; Naess and Bardsen, 2013; Roe, 1998; Rota, 2009; Thrift and Ichinkhorloo, 2015). By using small herds, SV trajectories do the opposite and following an SV strategy would require herders to change their risk perceptions. This is a challenge because smaller herds involve an immediate and visible loss of earnings through reduced annual income from fibre and culled animals. Oppositely, gains are less tangible as they are obtained through fecundity increases, which may be difficult to assess, and through *dzud* frequency reductions, *i.e.,* on a certain time horizon in a probabilistic manner. Reducing numbers may therefore be perceived by herders as gambling on hypothetical gains. A second disadvantage is that applying SV management implies a fluid market. The approach requires the presence of a pool of animals that can be purchased and a demand that can absorb animals for sale. The availability of *bogs* to purchase after a *dzud* and their price might be the most acute problem, as most people may need animals at the same time. However, restocking animals could be transported from less to more severely impacted areas, as *dzuds* have variable intensity across Mongolia (Nandintsetseg et al., 2017). The number of animals purchased were, in addition, most of the time in our models below 40, which is close to transactions locally observed (Joly, 2015). Purchasing enough animals may therefore not be a problem. A final difficulty of this decision-making process is that livestock of several households can mix between seasonal camps. This could affect the assessment of the size of herds grazing in a seasonal area and reduce the precision of the management decision made. However, it may be possible to solve this problem by using the tool at the scale of community groups, such as those already established in the country (Ulambayar et al., 2016).

This above list of pros and cons hence suggests that there may be more sociocultural, market, and land governance obstacles than technical difficulties for the adoption of SV-based decision-making tools. These factors should be addressed before considering large-scale application. The integration of SV processes with other pastoral management tools, such as mobility, should also be addressed.

4.3. Precision livestock farming

Beyond the Mongolian context, our results can contribute to research on livestock precision farming (PLF). To date, PLF is mostly applied to indoor industrial contexts (Shalloo et al., 2018), for example to adjust levels of feed to individual animal needs and prevent the systematic use of medicine (Shalloo et al., 2018; Tullo et al., 2019). Our SV management approach could be used as part of a PLF scheme in outdoor, grass-based systems. It would be relevant in the case of herds involving a diversity of animals with distinct traits (species or races), as using such diversity for resilience is one of the principles of agroecology applied to livestock farming systems (Dumont et al., 2013). The approach we used with *bogs/bods* could hence be extrapolated to any kind of diversity. Such support would be valuable since diverse livestock systems are more complex to manage than simple ones (Martin et al., 2020). In addition, the ergonomics of agroecological practices are receiving interest (Joly et al., 2021), which justifies the investigation of tools that could be used to ease their implementation. Our results therefore illustrate how models and computer decision-making tools could be used in an agroecological context.

5. Conclusion

We demonstrated in this article the potential for SV to be used to make pertinent decisions in a complex system exposed to environmental shocks. SV decisions generate trajectories that are more effective and resilient than those proposed by a simple livestock number capping rule through a long-term and adaptive approach. Our use of SV was possible due to specific modelling simplifications based on a thorough comprehension of the studied system. We thereby illustrated that the benefits of SV are not only theoretical but also practical, from the possibility of deriving a concrete decision-making process.

Regarding applicability to Mongolia, we identified several developments that would be needed to implement our decision-making process:

- Add a climate change trend in the value function calculation
- Study the fluidity of the livestock market to confirm the possibility of buying enough *bog* heads after a *dzud*
- Assess the attitudes of herders towards livestock number reduction as a risk avoidance strategy
- Assess the possibility of implementing decisions at the community level
- Incorporate the process into a broader decision framework integrating pastoral mobility

CRediT authorship contribution statement

Frédéric Joly: Conceptualization, Methodology, Software, Formal analysis, Writing – original draft, Visualization. **Rodolphe Sabatier:** Conceptualization, Methodology, Software. **Laurent Tatin:** Writing – review & editing. **Claire Mosnier:** Writing – review & editing. **Ariell Ahearn:** Writing – review & editing. **Marc Benoit:** Writing – review & editing. **Bernard Hubert:** Writing – review & editing. **Guillaume Deffuant:** Conceptualization, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Model dynamics

Vegetation submodel

$UB(t)$ is modelled according to Eq. (A.1), which describes how biomass allocation from underground biomass enables aboveground biomass (AB) to grow at the beginning of the growing season, when photosynthesis has not yet started (Müller et al., 2007). It describes how *UB* requires regular biomass reallocation from AB to compensate for biomass previously used. This reallocation from AB compensates for *UB* natural mortality. Without this reloading, *UB* is slightly depleted.

$$UB(t+1) - UB(t) = -\mathrm{m} \cdot UB(t) \cdot (1 + \mathrm{d} \cdot UB(t)) + \mathrm{w_{res}} \cdot \left(\mathrm{w_{gr}} \cdot P(t) \cdot UB(t) - Co(t)\right) \cdot (1 - \mathrm{d} \cdot UB(t)) \tag{A.1}$$

where m is a natural mortality rate and d is a density dependence parameter (the higher the level of underground biomass is, the slower it is replenished and the faster it dies). $\mathrm{w_{res}}$ denotes the proportion of AB allocated to *UB* replenishment, and $\mathrm{w_{gr}}$ is a factor of rain use efficiency accounting for run-off and evapotranspiration. $P(t)$ is precipitation occurring over the first 8 months of the calendar year considered usable by vegetation. It accounts for the soil moisturizing effect of winter precipitation in the spring at the time vegetation starts growing (Nandintsetseg and Shinoda, 2011). $Co(t)$ is the livestock consumption of aboveground biomass per ha and reduces the amount of plant standing foliage of plants (Eq. (A.2)).

$$Co(t) = \mathrm{ConsSU} \cdot \sum_{i=\mathrm{bog,bod}} N_i(t) \cdot \mathrm{SFU_i} \cdot \eta / \sigma \tag{A.2}$$

where ConsSU is the mean daily amount of forage consumed by a sheep, and SFU_i is a coefficient that converts the daily forage intake of type *i* into an equivalent in SFU. η is the stay duration in the summer zone (day), and σ is the area used by one household (ha).

Livestock submodel

The livestock submodel distinguishes *dzud* and non-*dzud* years with the help of index $Idzud(t)$. The index illustrates how a low availability of forage and a cold and snowy winter result in a *dzud* (Eq. (A.3)).

$$Idzud(t) = PU(t-1) \cdot WH(t)$$

$$\text{with } WH(t) = WP(t) \cdot Max(0, (\mathrm{WT_{threshold}} - WT(t))) \cdot \theta \tag{A.3}$$

where $PU(t-1)$ is the pasture use ratio of forage consumed to available forage and $WH(t)$ is an indicator of winter harshness. We used the pasture use of year $t-1$ to express the $Idzud(t)$ value of year *t* because *dzud* mortality occurs at the end of the winter during the first months of the year, as a consequence of the previous year's conditions. $WP(t)$ is the cumulative precipitation of the six coldest months of years $t-1$ and *t* (October to December of year $t-1$ and January to March of year *t*), representing the snow water equivalent for the winter (used to quantify snow abundance.) $WT(t)$ is the mean temperature of the six coldest months of years $t-1$ and *t* (October to December of year $t-1$ and January to March of year *t*). $\mathrm{WT_{threshold}}$ is a temperature threshold and θ is a coefficient making $Idzud(t)$ equal to 1 to separate *dzud* from non-*dzud* years in simulations. $PU(t)$ is expressed by Eq. (A.4):

$$PU(t) = Co(t) \cdot \sigma \Big/ \left(\mathrm{w_{gr}} \cdot P(t) \cdot UB(t) \cdot \sigma + \Phi_{\mathrm{reserve}}\right) \tag{A.4}$$

where Φ_{reserve} is a local riverbed forage used for reserve grazing and is expressed by a constant because this vegetation is less prone to degradation than desert steppes, as it is not used continuously, and it is abundantly watered by the river water table.

Dynamics of animal type *i* are expressed by Eq. A.5:

$$N_i(t+1) - N_i(t) = -N_i(t) \cdot L_{Idzud(t),i} + B_i(t) - SubsOrCul_i(t) - u_i(t) \tag{A.5}$$

where $L_{Idzud(t),i}$ is the death rate of a type *i* animal according to the occurrence or absence of a *dzud*. $B_i(t)$ represents the number of born animals, $SubsOrCul_i(t)$ denotes the number of old animals either slaughtered for subsistence consumption or culled, and $u_i(t)$ is the control term that defines the number of animals sold or purchased. When it is positive, animals are sold, and when the value is negative, animals are purchased.

$B_i(t)$ is expressed by Eq. (A.6):

$$B_i(t) = N_i(t)\cdot\left(1 - L_{Idzud(t),i}\right)\cdot\%\mathrm{fem_i}\cdot\left(\left(\mathrm{Acul_i} - \mathrm{Arep_i}\right) / \mathrm{Acul_i}\right)\cdot Prod_{Idzud(t),i,t} \quad (A.6)$$

where $\%\mathrm{fem_i}$ is the percentage of females, $\mathrm{Arep_i}$ is the age at which gravid females give birth for the first time, $\mathrm{Acul_i}$ is the age of culling for subsistence or the sale of old animals, and $Prod(t)_{Idzud(t),i}$ is the productivity assessed by the number of young born animals per female of breeding age. This value depends on *dzud* occurrence because females can miscarry during such a disaster and on $PU(t-1)$, which affects body condition at the time of reproduction (especially at the time of gestation) (Joly et al., 2018b). The value is expressed according to Eq. (A.7) and bounded by $\mathrm{MinProd_i}$ and $\mathrm{MaxProd_i}$.

$$\begin{cases} \text{If } \mathrm{Idzud(t)} < 1 : \mathrm{Prod_{Idzud(t),i,t}} = \gamma_\mathrm{i}\cdot(1 - \mathrm{PU(t-1)}) + \psi_\mathrm{i} \\ \text{If } \mathrm{Idzud(t)} \geq 1 : \mathrm{Prod_{Idzud(t),i,t}} = \delta_\mathrm{i} \end{cases} \quad (A.7)$$

where γ_i and ψ_i are coefficients and δ_i is a constant.

$SubsOrCul_i(t)$ is equal to the proportion of animals culled if it is higher than the number of animals that herders consume in year t and corresponds to the renewal rate of species i in the herd. If this rate is too low to satisfy subsistence consumption, herders slaughter more animals (Eq. (A.8)).

$$SubsOrCul_i(t) = \max\left(\left(N_i(t)\cdot\left(1 - L_{Idzud(t),i}\right) + B_i(t)\right) / \mathrm{Acul_i}; \mathrm{Cons_i^{subs}}\right) \quad (A.8)$$

where $\mathrm{Cons_i^{Subs}}$ represents the number of heads needed for subsistence consumption.

Constraints

The constraints are expressed for convenience according to variable $N_i^{bcs}(t)$ that describes livestock numbers before culling and sale or purchase (Eq. (A.9)). This variable is also used to study the relationships between livestock numbers and the number of *bog* heads purchased after a *dzud*.

$$N_i^{bcs}(t) = N_i(t)\cdot\left(1 - L_{Idzud(t),i}\right) + B_i(t) \quad (A.9)$$

The first two constraints concern the availability of animals for subsistence consumption of *bog* and *bod* meat before culling (Ineq. A.1 and A.2). Both types are distinguished because they are not substitutable: *bogs* are consumed during the warm months when they have enough body fat, and *bods* are consumed in the winter when their carcasses can be frozen outside of herders' camps. *Bods* are slaughtered at the beginning of the season, and *bog/bod* consumption practices ensure a year-round availability of meat.

$$N_{bog}^{bcs}(t) \geq Cons_{\mathrm{bog}}^{\mathrm{Subs}} \quad \text{(Ineq. A.1)}$$

if

$$N_{bod}^{bcs}(t) \geq Cons_{\mathrm{bod}}^{\mathrm{Subs}} \quad \text{(Ineq. A.2)}$$

The third constraint refers to the subsistence consumption of milk and milk products, and its expression depends on livestock productivity, as females that produce milk are only those that have given birth (Ineq. A.3).

$$\sum_{i=bog,bod} N_i^{bcs}(t)\cdot Prod(t)_{Idzud(t),i}\cdot\mu_\mathrm{i} \geq \mathrm{Cons^{SubsMilk}} \quad \text{(Ineq. A.3)}$$

where $\mathrm{Cons^{SubsMilk}}$ is the milk consumption threshold and μ_i the amount of milk produced by a head of livestock, accounting for the age and sex structure of the herd.

The fourth constraint refers to the availability of transport animals for household $\mathrm{Cons^{Ride\&Draft}}$, *i.e.,* the availability of horses used for herd management and camels used for draft (Ineq. (A.4)).

$$N_{bod}^{bcs}(t) \geq \mathrm{Cons^{Ride\&Draft}} \quad \text{(Ineq. A.4)}$$

$$N_{bod}(t) \geq \mathrm{Cons^{Ride\&Draft}}$$

Both N_{bod}^{bcs} and N_{bod} are considered as draft animals are used year-round.

The fifth constraint refers to household revenue. Three types of income were taken into account, and overall household income was calculated by summing the income values and subtracting the mean herding cost. The difference had to be superior to poverty line $\mathrm{Cons^{Poverty}}$ at the household scale (Ineq. A.5).

$$InFibre(t) + InLive(t) + InSkinHide(t) - \mathrm{HC} \geq \mathrm{Cons^{Poverty}} \quad \text{(Ineq A.5)}$$

where *InFibre(t), InLive(t)*, and *InSkinHide(t)* are, respectively, the annual incomes generated through the sale of fibre, live animals and skins/hides of animals slaughtered for subsistence. HC denotes the herding costs, and $\mathrm{Cons^{Poverty}}$ represents the poverty line value. As herders use very few inputs, such as fodder or concentrates per head of livestock (Joly et al., 2019), we considered HC to be constant.

The different incomes were quantified according to Eqs. (A.10) – (A.12):

$$InFibre(t) = \sum_{i=\text{bog,bod}} N_i^{bcs}(t) \cdot \mathrm{I_i^{Fibre}} \tag{A.10}$$

$$InLive(t) = \sum_{i=\text{bog,bod}} \left(\max\left(0; \left(\frac{N_i^{bcs}(t)}{\mathrm{Acul_i}} - Cons_i^{Subs}\right)\right) + u_i(t) \right) \cdot \mathrm{I_i^{Live}} \tag{A.11}$$

$$InSkinHide(t) = \sum_{i=\text{bog,bod}} \mathrm{Cons_i^{Subs}} \cdot \mathrm{I_i^{SkinHide}} \tag{A.12}$$

where I_i^{Fibre}, I_i^{Live} and $I_i^{SkinHide}$ are the annual incomes generated by one head of animal of type i for each kind of product.

If Ineqs A.1 to A.5 hold true, constraint satisfaction function CS is equal to 1 and is equal to 0 otherwise (if only one ineq. is wrong, $CS = 0$).

The parameters used in Appendix A and their values are given in Table A.1.

Table A.1
Parameters of the model (from Joly et al. (2018a) and Sabatier et al. (2017)).

Parameter	Value	Parameter	Value
m	0.058 (unitless)	γ_{bog}	0.63 (unitless)
d	0.0011 ha • kg^{-1}	γ_{bod}	0.56 (unitless)
w_{res}	0.74 (unitless)	Ψ_{bog}	0.35 (unitless)
w_{gr}	0.0045 (mm^{-1})	Ψ_{bod}	0.17 (unitless)
ConsSU	1.38 kg • day^{-1}	δ_{bog}	0.40 (unitless)
SFU_{bog}	0.94 (unitless)	δ_{bod}	0.32 (unitless)
SFU_{bod}	6.33 (unitless)	$Cons_{bog}^{Subs}$	25 heads
η	150 days	$Cons_{bod}^{Subs}$	2 heads
σ	1800 ha	$Cons^{Subsmilk}$	764 litres
$\Phi_{reserve}$	160,000 kg	$Cons^{Ride\&Draft}$	10 heads
$WT_{threshold}$	−10 °C	$Cons^{Poverty}$	4657,268 MNT *
θ	0.06 (unitless)	μ_{bog}	8 l • head^{-1}
$L_{Idzud(t),bog}/\ Idzud(t) < 1$	0.03 (unitless)	μ_{bod}	66 l • head^{-1}
$L_{Idzud(t),bod}\ /\ Idzud(t) < 1$	0.03 (unitless)	HC	769,000 MNT
$L_{Idzud(t),bog}/\ Idzud(t) \geq 1$	0.53 (unitless)	I_{bog}^{Live}	114,435 MNT • head^{-1}
$L_{Idzud(t),bod}\ /Idzud(t) \geq 1$	0.26 (unitless)	I_{bod}^{Live}	804,248 MNT • head^{-1}
$\%fem_{bog}$	0.53 (unitless)	I_{bog}^{Fibre}	10,252 MNT • head^{-1}
$\%fem_{bod}$	0.51 (unitless)	I_{bod}^{Fibre}	5821 MNT • head^{-1}
$Acul_{bog}$	7 years	$I_{bog}^{SkinHide}$	17,105 MNT • head^{-1}
$Acul_{bod}$	14 years	$I_{bod}^{SkinHide}$	25,512 MNT • head^{-1}
$Arep_{bog}$	2 years		
$Arep_{bod}$	3 years		
$MaxProd_{bog}$	0.97 (unitless)		
$MaxProd_{bod}$	0.74 (unitless)		
$MinProd_{bog}$	0.36 (unitless)		
$MinProd_{bod}$	0.28 (unitless)		

* Mongolian tugrik (local currency)

Table A.2
Simplified weather configurations.

Weather configuration	$P(w^s)$	$P(t)$	$WH(t)$
w_1^s (wet year/mild winter)	0.53	91.0	0.7
w_2^s (wet year/harsh winter)	0.27	91.0	3.5
w_3^s (dry year/mild winter)	0.13	36.4	0.7
w_4^s (dry year/harsh winter)	0.07	36.4	3.5

Appendix B. Trajectory building

Trajectories derived from SV

For animal type i, $u_{x^s}^*(0)$ is capped by $N_i(t) \cdot (1 - L_{Idzud(t),i}) + B_i(t) - SubsOrCul_i(t)$ to avoid selling more animals than is available. This can happen for the most extreme values generated from nonsimplified weather space W, since u^* is based on a simplified W^s.

Trajectories derived from a capping number rule

The capping trajectories are based on a maximum livestock number (Eq. (B.1)).

$$\mathrm{N}_{\mathrm{i,max}} = \mathrm{SFU}_{\mathrm{max}} \cdot \rho_{\mathrm{i}} / \mathrm{SFU}_{\mathrm{i}} \tag{B.1}$$

where $\mathrm{SFU}_{\mathrm{max}}$ is the overall herd size in SFU (*bog*+*bod*), $\mathrm{N}_{\mathrm{i,max}}$ is the maximal number in heads of type *i* and ρ_{i} is the proportion of i in SFU within $\mathrm{N}_{\mathrm{i,0}}$. From $\mathrm{N}_{\mathrm{i,max}}$, controls *u* were derived (Eq. (B.2)).

$$\begin{cases} u_{bog}(t) = -r_{Idzud(t)} \cdot \left(N^{bcs}_{bog,t} - SubsOrCul_{bog,t}\right) + \max\left(0, \left(1 + r_{Idzud(t)} \cdot \left(N^{bcs}_{bog,t} - SubsOrCul_{bog,t}\right) - \mathrm{N}_{\mathrm{bog,max}}\right)\right. \\ u_{bod}(t) = r_{Idzud(t)} \cdot \left(N^{bcs}_{bod,t} - SubsOrCul_{bod,t}\right) + \max\left(0, \left(1 - r_{Idzud(t)} \cdot \left(N^{bcs}_{bod,t} - SubsOrCul_{bod,t}\right) - \mathrm{N}_{\mathrm{bod,max}}\right)\right. \end{cases} \tag{B.2}$$

where $r_{Idzud(t)}$ is an adjustment ratio designed to exchange *bog* heads against *bod* heads after a *dzud*. The value is equal to zero for $Idzud(t) < 1$ and $(L_{Idzud(t),\ bog} - L_{Idzud(t),\ bod})/2$ for $Idzud(t) \geq 1$.

To assess the $\mathrm{N}_{\mathrm{i,max}}$ that returned the best *CS*, for both types of income objectives PovX1 and PovX2, we scanned values of between 0 and 1500 SFU.

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