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Analyzing resource use decisions under global change by agent-based modeling

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Dissertation thesis

Analyzing resource use decisions under global change by agent-based modeling.

submitted by

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University of Osnabrück
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Für meine Eltern

ABSTRACT

Achieving sustainable development to meet the needs of current and future generations is currently on top of the global agenda, both in scientific research as well as global politics. However, achieving sustainable development is still a grand challenge, not least because it is embedded in the context of global change that affects most resource use systems worldwide in multiple ways. Even though many approaches to sustainable management do consider the connection between human activity and environmental dynamics, the role of human behavior as a main driver of system dynamics in coupled human and natural systems is often only poorly addressed.

In this thesis, we aim to contribute to an improved understanding under which conditions human resource use decisions lead to sustainable outcomes, with regard to global change. For this, we will take the perspective of human decision-making and its social, ecological and economic consequences in two different resource use contexts, namely a) pastoralism in drylands and b) disaster risk management with respect to floods. We explicitly consider individual human decision-making as driver of social-ecological system dynamics, investigate the feedbacks between system components, as well as the impact of global change on resource use.

To analyze such complex system dynamics, simulation models have proven to be helpful analysis tools. Particularly agent-based modeling represents a flexible and powerful analysis tool, as it allows us to model the decisions and interactions of individual agents at the micro level, while at the same time observing the outcome of their behavior on a system level. Within three case studies, we develop agent-based simulation models that capture the dynamics and feedbacks of the social-ecological system under consideration in a spatially explicit way. The first study analyzes the performance of disaster management organizations under change. In the second study, we aim to detect the drivers for polarization in a pastoral system in Morocco. The last study investigates behavioral change of pastoralist households and its impact on social, ecological and economic outcome measures. By analyzing a range of scenarios in each study, we determine both the long-term impact of different decision regimes on the state of the social-ecological system as well as the dimensions of change that have the most profound impact on the system dynamics and the sustainability of resource use.

Main results that could be obtained from the modeling experiments include the identification of key resources that have a high influence on the long-term system dynamics. We are also able to show that under the influence of global change, access to certain resources gains in importance, as resources can act as buffer mechanisms to mitigate the adverse effects of global change. Through the operationalization of behavioral theories in model rules and the explicit representation of heterogeneous agent decision making, we could determine under which conditions a more refined representation of human decision making matters, and when a change in behavioral strategies leads to different social-ecological outcomes. Furthermore, all three modeling studies demonstrate the usefulness of stylized agent-based models to gain insights into complex systems.

Overall, this thesis contributes to social-ecological systems research by developing appropriate simulation models to address the problem of sustainable resource use under global change.

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INTRODUCTION

1.1 SUSTAINABLE RESOURCE USE IN THE CONTEXT OF GLOBAL CHANGE

Achieving sustainable development is a grand challenge and on top of the global agenda (see Sustainable Development Goals, 2015). It addresses the problem of satisfying current resource needs of the Earth's population, without compromising the needs of future generations (Brundtland et al., 1987).

With respect to the connected discussions on transformation towards sustainability, it is recognized that human behavior on the individual level is a key component that needs to be taken into account. This includes a) the role of individual behavior and decision-making in natural resource management and b) the factors, values and perceptions that shape individual behavior (International Council for Science (ICSU), 2010). The International Council for Science, for instance, states as one of the five grand challenges that we need to determine "what institutional, economic and behavioral changes can enable effective steps toward global sustainability." (Challenge 4: Responding, International Council for Science (ICSU), 2010).

Understanding decision-making is particularly important in the context of global change, which encompasses several dimensions such as demographic, economic, social and, in particular, climate change. As argued by the World Bank in the 2015 World Development Report, "responding to climate change is one of the defining challenges of our time" (World Bank, 2015, p. 160), especially in face of the growing scientific evidence that human behavior is a main cause for climate change in the last centuries. But also other dimensions of change have a profound effect, such as demographic change (population increase or shrinkage), institutional and political change (liberalization trends, abandonment of traditional institutions) or technological change (new production and communication technologies), just to name a few.

In this thesis, we aim to contribute to an improved understanding under which conditions human resource use decisions are sustainable with regard to specific types of global change. We will take the perspective of human decision-making and its social, ecological and economic consequences in two different resource use contexts, namely pastoralism in drylands and disaster risk management. Both contexts are very different but have in common that (1) individual human decision-making on use of resources in a variable environment, (2) social-ecological feedbacks, and (3) different types of global change have to be taken into account.

We approach these problem contexts by means of simulation models that we developed in the course of this dissertation. These models integrate the mentioned factors and allow a dynamic perspective on these complex systems. In the following sections, we will introduce the underlying conceptual and methodological approaches that we apply in the modeling studies, namely the concept of coupled social and ecological systems, the resource portfolio concept and the approach of agent-based modeling. Finally, we will present the overarching research aims and the methodological motivation for this thesis and introduce the three modeling chapters.

1.2 COUPLED SOCIAL AND ECOLOGICAL SYSTEMS

Humans do not only shape their environment, they also depend on the goods and services it provides. This emphasizes the strong interconnection of the biophysical and social system, and the complexity associated with the task to manage those systems. In general, such complex "integrated system[s] of ecosystems and human society" (Carpenter et al., 2006; Berkes et al., 2008) have been termed as social-ecological systems, driven by nonlinear feedbacks between resources, actors and institutions across multiple scales (Schlüter et al., 2012). Approaches to manage natural resource use systems therefore need to consider not only the ecological and social components of the system, but specifically the link between both. Furthermore, the kinds of social-ecological systems that we consider are characterized by highly variable environmental conditions: strongly fluctuating rainfall, for instance, results in variable resource patterns such as pasture biomass that is available at a certain point in time. This inherent complexity is also reflected in the nonlinearity of the system dynamics and the feedback loops between components of the system. Social-ecological systems have no single equilibrium, but may have alternative stable states (Scheffer et al., 2001) or are characterized as non-equilibrium systems, such as drylands (Vetter et al., 2005). Up to a certain point, the system may be able to withstand change and maintain its function. However, if the system crosses a specific level of change in conditions – called a threshold value – it can change very rapidly and unpredictably into a different stable state. This "rapid reorganization of a system from one relatively unchanging state to another" is called a regime shift (Carpenter et al., 2003; Carpenter et al., 2006). The magnitude of external disturbance that a system can endure without undergoing a regime shift is called resilience (Carpenter et al., 2001; Carpenter et al., 2003). However, resilience does not only encompass the ability to cope with a disturbance, hazardous event, or change and remain functional, but also the ability to reorganize and the capacity for adaptation, learning, and transformation (IPCC, 2014). In this sense, sustainability is not the final state of a social-ecological system that we want to achieve, but rather "a dynamic process that requires adaptive capacity in resilient socio-ecological systems to deal with change" (Berkes et al., 2008). A suitable approach to analyze this dynamic process are simulation models that we will introduce in Section 1.4.

1.3 A CONCEPTUAL VIEW ON RESOURCES AND THE APPLICATION CONTEXTS

1.3.1 *The resource portfolio*

Traditionally, resource economics deals with the demand, supply and allocation of resources, more specifically natural resources, and how to sustainably manage those. Natural resources are "natural assets (raw materials) occurring in nature that can be used for economic production or consumption" (United Nations, 1997), such as water, land, and vegetation, but also sunlight and different forms of energy. Various possibilities to classify natural resources exist, e.g. by origin into abiotic and biotic resources, or into renewable and nonrenewable resources. However, the term "natural resources" is too narrow when we explicitly want to consider humans and their interactions as driving force of resource use. Information, for example, is a key resource that influences human decisions. Furthermore, resources can be prerequisites for decision-making, for example manpower and technical equipment is needed in order to provide flood protection. In this thesis, we therefore use the resource portfolio concept of Gertel and Breuer (Gertel, 2007) that originates from social geography. This concept widens the traditional scope of natural resources and distinguishes resources into four categories: i) incorporated resources, ii) social-institutionalized resources, iii) allocative resources, and iv) monetary resources (see Table 1.1). These four types can be placed along a gradient of convertibility – how easily a resource can be converted into a different form – and persistence – how durable a resource is, once it has been accumulated.

Furthermore, resources can have different functions: primarily, resources constitute assets that can be used by resource users, e.g., human actors. Here, resources are the object of an agent's decision which results in a change of the resource stock, e.g. the decision where and how much to graze changes the amount of biomass on a pasture. Secondly, resources constitute constraints for decisions that may enable or restrict different options for action. Owning a truck, for example, allows a pastoralist to transport livestock, belonging to a certain social group gives access to knowledge or other group resources, such as common grazing grounds.

TABLE 1.1.: Resource portfolio: types of resources and their characterization.

Resource type	Incorporated resources	Social-institutionalized resources	Allocative resources	Monetary resources
Characterization	Directly connected to the physical body. Not transferable to another person.	Connected with a specific person and activated through formal or informal relations, i.e. resources are outcomes of social relationships.	Raw materials (i.e. natural resources), production means and goods. Not connected to a specific person but may be subject to access rights.	All means of payment. Directly exchangeable between persons and convertible into other resources.
Example	Health, education, manpower	Social networks, information	Land, livestock, technical equipment	Cash, savings
Convertibility	Slow	>>>>>>>>>>>>>>>>>>>>>		Fast
Persistence	Inert	>>>>>>>>>>>>>>>>>>>>>		Highly flexible

1.3.2 *Introduction of the resource use contexts*

In this thesis, we consider two different resource use contexts within three modeling studies that are subject to global change on different levels. Even though both contexts are fairly different from another, they are highly relevant in the light of global sustainability, as we will argue in the following:

1) PASTORALISM IN DRYLANDS: Pastoralism – the raising of livestock – is a main way of life in many dryland regions of the world. Drylands cover about 40% of the world's terrestrial surface, of which about 65% constitute rangelands (EMG, 2011) that provide the livelihood for over 1 billion people (Sayre et al., 2013). Because of the general scarcity and high variability of resources, pastoralism is often the most adapted and viable strategy to sustain a household's livelihood. This requires appropriate grazing strategies to avoid an overuse and degradation of resources, specifically of pastures and water. Rangelands cover a wide degree of commercialization, from subsistence-oriented to profit-oriented production. Especially

for subsistence-oriented pastoralists, livestock stands both for a “means of income” and “stores of wealth” (Sayre et al., 2013). Rangelands often carry a negative connotation, e.g. as being “favoured in arid, semi-arid, or other areas of marginal value for crop-based agricultural production” (Silvestri et al., 2012, p. 3). However, rangelands provide many positive environmental services, specifically attributed to pastoralism and the strategic use of livestock mobility, such as the propagation of fodder plants, the manuring of cropland or fostering the regeneration of pastures through explicit non-use, i.e. resting, of pastures (Krätli, 2013). Furthermore, pastoralism plays an important role in biodiversity protection as it is ‘not only critical for maintaining forest areas, but also wildlife populations and the savannah lands they inhabit’ (Abbink et al., 2014, p. 6). In recent years, pastoralism is undergoing several transformations: changes in economic, social and climatic conditions challenge traditional pastoral strategies, and a growing population increases the pressure on the limited resources that the pastures provide.

2) DISASTER RISK MANAGEMENT: Disaster risk management is a core feature for the protection of communities against natural hazards, such as floods. It comprises measures before, during and after a disaster event and is most commonly divided in four phases: i) prevention/mitigation, ii) preparedness, iii) response and iv) recovery (also called the disaster management cycle). In all phases, effective disaster risk management relies heavily on the functioning of emergency forces, e.g. by building and enforcing protective measures before a disaster event, undertaking rescue and protection missions during a disaster as well as providing relief measures after a disaster has taken place. To achieve their tasks, these forces rely on a number of resources such as the availability of helpers (i.e. personnel), technical equipment, and information. Disaster trends of recent years show an increase both in the frequency of disaster events (IPCC, 2012; Schuster, 2013), as well as in the amount of disaster-related losses (Barredo, 2007; Barredo, 2009; Bouwer, 2011). This means that disaster management organizations face a higher demand that they need to cope with and might need to adjust their strategies in order to provide the expected protection.

1.4 METHODOLOGICAL APPROACH: AGENT-BASED MODELING

To address the complex task of understanding and managing social-ecological systems, simulation models have proven to be helpful analysis tools (Schlüter et al., 2012). A main characteristic of simulation models is that they allow to observe system dynamics in time and space, so that we can look at the development of a system both over short as well as long time horizons. This is especially suited when we adopt the viewpoint of sustainability, as we are not interested in a solution that is only adequate in the short term (months, years), but also over the long term (decades, centuries).

A modeling paradigm particularly suited to investigate decision-making is agent-based modeling (ABM). Agents can be defined as bundle of data, attributes, and methods representing an entity residing within the modeled system (Tesfatsion et al., 2006). They can represent a wide range of entities, such as individuals, households, social groups or institutions. Via specified rules and methods, these agents can interact with the environment, as well as with each other and by doing so, create dynamics that can be observed at a higher, e.g. system level. Agents can be heterogeneous in their characteristics, i.e. their attributes and decision rules, allowing it to represent different types of actors within a single model. Furthermore, the behavior of agents can be influenced by adaptation and learning, which allows them to react to changes in their environment.

When we investigate social-ecological systems, the decision-making aspect of the actors in the model is of course of particular importance. An (2012) identified nine types[1] of decision models in agent-based models of coupled human and natural systems, ranging from highly empirically based (statistical) to more mechanistic or process-based models. A major category present micro-economic models, in which the decision of agents is based on some sort of utility function that agents calculate, based on the information available to them. Agents are often assumed to be selfish rational actors that maximize their personal utility, based on stable preferences, perfect knowledge and unlimited cognitive abilities (Monroe, 2001). However, in the real world decisions are often not fully but bounded rational, due to imperfect knowledge and information, context-dependent preferences or limited cognitive abilities to process all information (Bell et al., 1988; Simon, 1984). One main advantage of agent-based modeling is that it allows a more flexible and realistic representation of human decision-making. However, up to now many ABMs still rely on the *Homo Economicus* as “status quo” for decision-making, besides the large body of social science theories on human decision-making that are available. As Groeneveld et al. (2017) have shown in a quantitative review of 134 papers, the decision submodels of the majority of the reviewed models is not explicitly based on a theory, and the single most often used theory is Expected Utility Theory. One reason for this gap lies in the challenge of formalizing social science theories within the scope of a model, as many behavioral theories face ambiguities when we try to translate them into formal equations or model rules (Schlüter et al., 2017). Therefore, to advance the understanding of human decision-making and incorporate more realistic decision models, efforts need to be invested in process-based decision mechanisms (An, 2012). Also, there is still a need for research to compare the impact of different decision-making theories, especially focusing on “the macroscale implications of particular microscale decision-making strategies” (Parker et al., 2003, p. 320).

Besides selecting agent-based modeling as the most suitable method, a second choice made was the use of rather simple, stylized models instead of more realistic, but also highly complicated models. Stylized models exhibit a high level of abstraction, which allows us to quickly implement new ideas and test hypotheses. In this sense, they can be seen as a “virtual lab” (Seppelt et al., 2009), a tool for thinking that allows us to obtain a better mechanistic understanding of the system behavior. Such models have already proven to be useful in studies e.g. by Parker et al. (2008) on a bilateral land market or by Müller et al. (2007a) on resting in pastoral systems. Therefore, the models developed in this thesis are not intended as quantitative prediction tools, but rather as explorative tools for system understanding.

1.5 AIM AND STRUCTURE OF THE THESIS

In this thesis, we aim to explore different contexts of (natural) resource use in the light of global change. We have formulated three overarching research aims and three methodological motivations that guide the analysis of the individual studies. These research aims will be put into concrete terms by specific research questions in each study.

RESEARCH AIMS

a) *Explicitly considering human decision-making as driver of social-ecological system dynamics:*
   Humans increasingly shape their environment, as well as they depend on it. Still, many

[1] These types being: microeconomic models, space theory based models, psychosocial and cognitive models, institution-based models, experience- or preference-based decision models (rules of thumb), participatory agent-based modeling, empirical- or heuristic rules, evolutionary programming, and assumption and/or calibration-based rules (cf. An, 2012).

models that address resource use problems in social-ecological systems do not adequately incorporate the behavior of the resource users. We aim to overcome this gap by putting the main focus on the individual decisions of the resource users.

b) *Investigating the social-ecological feedbacks and their drivers within the different contexts:*
Feedbacks between system components are a well-known characteristic of social-ecological systems. However, their concrete form and the influence factors that drive them are not as obvious, which we will analyze in both resource use contexts.

c) *Analyzing the effect of change within two different resource use contexts:*
Sustainable use of natural resources is a central topic for researchers and practitioners alike. However, the interaction of different dimensions of change increases the complexity of sustainable development. Therefore, a better understanding of how global change affects resource use (at the local level) is needed, which we aim to obtain in this thesis.

METHODOLOGICAL MOTIVATION

d) *Demonstrating the usefulness of stylized agent-based models to gain insights into complex systems:*
The main goal within the three modeling studies in this thesis is to gain a mechanistic understanding of the functioning of the system, with particular focus on resource use decisions of individual actors. For this, we see agent-based modeling in a stylized manner as a particularly suited analysis tool.

e) *Implementing, analysing and comparing models of human decision-making in ABM:*
Even though agent-based modeling is particularly well suited to represent decisions of individual actors, many modelers still assume a rational actor and use Expected Utility Theory as representation of the agent's decision-making. One reason for this lies in its straightforward implementation. In the models developed in this work, we explicitly consider more appropriate concepts of human decision-making, such as bounded rationality, and behavioral theories grounded in social sciences.

f) *Operationalization of the resource portfolio concept within ABM:*
The concept of the resource portfolio originates in social geography. We will use this concept in a dynamic modeling context, which does not only promote modeling, but can also make a positive contribution to theory formation.

1.6 OVERVIEW OF THE MODELING STUDIES

This thesis comprises three modeling studies, two in the context of pastoralism and one in the context of disaster management, that we shortly present in the following. To highlight the similarities as well as differences of these three studies, we compare them in Table 1.2 by means of the dimensions a) which types of resources are considered in the study, b) who is the main actor in the system, c) what kind of change do they face and d) what feedbacks occur between the social and ecological (biophysical) system.

1ST STUDY: CHAPTER 2 "TOWARDS THRESHOLDS OF DISASTER MANAGEMENT PERFORMANCE" Disaster management depends on resources to provide the necessary protection measures to communities at risk. Disaster management organizations such as fire brigades take on a central role, especially when a disaster event such as a flood hits a community and immediate measures are necessary. In this case, the provision of protection is directly

TABLE 1.2.: Overview about the three modeling studies of this thesis. Classification of resources follows the resource portfolio introduced in Section 1.4, I – Incorporated, S – Social-institutionalized, A – Allocative , M – Monetary.

	Study 1: Disaster management, Germany	Study 2: Polarization, Morocco	Study 3: Behavioral change, Drylands (general)
a) Resource	I Manpower S Information A Sandbags, transportation technology	A Livestock, pastures M Monetary resources	S Social norms of pasture resting A Livestock, pastures
b) Actors	Organizations	Households	Households
c) Change	Demographic Climatic Technological	Demographic Climatic Technological Social	Demographic Institutional Social
d) Feedbacks	Social Ecological	Social Ecological	Social Ecological

linked to the operational readiness and performance of disaster management organizations. In this study we analyze how the performance of disaster management organizations changes, and might be at risk, under a) future conditions of availability of resources (including manpower, information and technical resources) under demographic change, and b) changes in climatic conditions, such as an increase in flood frequency. We outline implications for disaster management performance with respect to different geographical settings and scenarios of change.

2ND STUDY: CHAPTER 3 "POLARIZATION IN (POST-)NOMADIC RESOURCE USE IN EASTERN MOROCCO" In recent years, an increased polarization between pastoralists in terms of livestock and monetary resources has been observed in different regions of Morocco, e.g. in the High Plateau in Eastern Morocco. Here, polarization is understood as a division of the household population into clearly opposing factions, namely wealthy pastoralists with large herds and impoverished households that struggle to sustain their herd size. In this study, we analyze how such a polarization can occur. Pastoralist households are the main actors that need to decide where to relocate their herd in each year, given their resource endowment, in order to feed their livestock. The consumption of pasture biomass influences the regrowth of the vegetation which, in turn, determines the future capacity of livestock that can be kept on the pasture. Here, we specifically analyze a) under which conditions initial heterogeneities in resource endowments of households (livestock, monetary resources) can lead to polarization and b) the influence of ecological settings as well as of climate and demographic change on the risk of polarization.

3RD STUDY: CHAPTER 4 "IMPLICATIONS OF BEHAVIORAL CHANGE ON THE SOCIAL, ECOLOGICAL AND ECONOMIC DIMENSIONS OF PASTORAL SYSTEMS" Social norms about pasture resting have been a central element to sustainable rangeland management in many pastoral regions of the world. Such a norm can be considered as a resource, as it regulates the access of pastoralists to pastures. However, many of these regions are strongly affected by change: liberalization processes, for instance, have led to an opening of national economies and markets, giving rise to the privatization of land and property. Alongside this economic transformation, many countries are undergoing serious demographic transitions, leading to population growth and higher competition for resources also in pastoralist territories. The combination of these processes causes a change in strategies of pastoralist households, including an increasing non-compliance with traditional norms. In this study, we analyze how changes in household behavior influence the long-term conditions of resources, such as livestock and pasture, in a stylized semi-arid common property rangeland system.

The thesis is structured into three parts (Chapters 2 – 4) that comprise the three different modeling studies, followed by an overall discussion (Chapter 5) of the results and conclusion at the end.

2

TOWARDS THRESHOLDS OF DISASTER MANAGEMENT PERFORMANCE UNDER DEMOGRAPHIC CHANGE: EXPLORING FUNCTIONAL RELATIONSHIPS USING AGENT-BASED MODELING

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2.1 ABSTRACT

Effective disaster management is a core feature for the protection of communities against natural disasters such as floods. Disaster management organizations (DMOs) are expected to contribute to ensuring this protection. However, what happens when their resources to cope with a flood are at stake or the intensity and frequency of the event exceeds their capacities? Many cities in the Free State of Saxony, Germany were strongly hit by several floods in the last years and are additionally challenged by demographic change with an ageing society and out-migration leading to population shrinkage in many parts of Saxony. Disaster management which is mostly volunteer-based in Germany is particularly affected by this change, leading to a loss of members. We propose an agent-based simulation model that acts as a "virtual lab" to explore the impact of various changes on disaster management performance. Using different scenarios we examine the impact of changes in personal resources of DMOs, their access to operation relevant information, flood characteristics as well as differences between geographic regions. A loss of DMOs and associated manpower caused by demographic change has the most profound impact on the performance. Especially in rural, upstream regions population decline in combination with very short lead times can put disaster management performance at risk.

2.2 INTRODUCTION

When floods hit a community, disaster management and emergency services have to act as quickly and effectively as possible to safeguard people and property. However, effective disaster management depends on several conditions, e.g., the availability of resources for protection, the number of helpers and their skills, the existence of plans for emergency and evacuation (Kirschenbaum, 2002), and the effectiveness of communication and coordination (Kreibich et al., 2016; O'Sullivan et al., 2012; Comfort et al., 2004). Another crucial aspect is time: if lead time (i.e. time between warning of an imminent flood and its occurrence, Werner et al., 2005) is too short or the time needed to put all necessary measures into place – the coping time (i.e. effective response time) – is too long, disaster management might be unable to provide the necessary support and protection. Although disaster management has developed practical and well-tested routines over many years of service, these routines might come under pressure under changing context conditions such as increasing flood intensities, limited resources or changes in organizational structures (Kuhlicke, 2013). Worldwide disaster statistics show a strong increase in extreme events. Especially, weather-related events such as floods, storms and droughts have been occurring more frequently in the last decades (Schuster, 2013; IPCC, 2012). Likewise, an increase in disaster-related losses has been observed. However, the causes for this increase are controversially discussed. Many studies show that anthropogenic changes are main drivers for an increase in disaster losses (Bouwer, 2011; Barredo, 2009; Barredo, 2007), especially due to increases in exposure caused, for example, by a rising number of properties in flood-prone areas (Fuchs et al., 2015; Jongman et al., 2014). In just eleven years the Free State of Saxony, Germany, has experienced three extreme flood events (2002, 2010 and 2013), of which two (2002, 2013) have exceeded the statistical return rate of 1 in 100 years and caused damages of several billion Euro (DKKV, 2015, p. 32; Mechler et al., 2003). Besides this, a large proportion of the flood-prone area in this region is currently undergoing major demographic transitions with an aging society, out-migration and low birth rates leading to significant population shrinkage (BBSR, 2014). This shrinkage comes along with an economic decline, cutbacks in municipal finances, demolition of houses and loss of urban functions, e.g. in the area of infrastructure. However, this shrinkage does not take place uniformly: as Schulz (2012) is able to show in her case study on the Free State of Saxony, there is hardly any correlation between shrinkage and the demolition of the built environment, which often takes place in outer districts, and the reduction of exposure to flood risk on the other hand side. Additionally, Kuhlicke et al. (2012) show that for those shrinking cities we can observe a decline in adaptive and coping capacity, as the provision of essential public and private services (e.g. flood protection) is not possible anymore due to budget constraints. Therefore, in most cases shrinkage leads to no significant reduction of the communities' vulnerability to floods. This also affects disaster management as, on the one hand, disaster management organizations (DMOs) are more often confronted with extreme events and need to provide higher degrees of support and protection. On the other hand, they need to fulfill their services with shrinking resources, not only in monetary terms, but especially in terms of manpower (Steinführer et al., 2014). Disaster management in Germany is largely on an organized but still voluntary basis (*Ehrenamt*) and is especially affected by a loss of members. This trend is strongest in the East German federal states, where, for example, voluntary fire brigades (*Freiwillige Feuerwehr*) have suffered a decline in numbers of active members of about 20000 (9%) between 1997 and 2007 (Albrecht et al., 2010). Additionally, the functioning of DMOs might be negatively affected by changes in the employment situation of their members: even if in theory the operational units are still fully equipped, the actual operational readiness is often impeded by larger distances between workplace and hometown and a lower willingness of employers to grant their employees a release from their work (Metzmann, 2006). This can lead to understaffing of DMO units during a disaster event. This study addresses the effect of the mentioned processes of change on disaster management performance, using two regions in Saxony as exemplary study sites. Although we selected the Free State of Saxony as an example region for our study, the just stated developments apply to other regions in Germany as well. Moreover, this region is very heterogeneous, so not every part is affected in the same magnitude of change. We will therefore also address the question of how disaster management performance is affected, depending on the local settings. To make this more explicit, we characterize each case site along two dimensions that affect the strength of impact of the floods on a community, namely the geographic (including hydrologic) and demographic settings.

Analyzing how change in a single aspect affects the functioning of DMOs might be possible with a pen and paper exercise. However, when changes occur in parallel and in different intensity, their combined effects are not as easily foreseeable anymore. We therefore develop and apply a simulation model to determine the impact of change on the performance of disaster management, and estimate which conditions can lead to performance thresholds that put community protection at risk, for example, under which circumstances a certain lead time threshold might not be reached anymore.

Several modeling studies exist that address natural hazards and their influence on community functioning, ranging from pre-disaster to post-disaster assessments. The complexity of these models ranges from more simple or conceptual models to very complex models that are often used for prediction purposes. Models like the Life Safety Model (Lumbroso et al., 2011) or MASSVAC (Hobeika et al., 1985), for example, aim at predicting exact evacuation times for a specific disaster event or the expected loss of life. Dawson et al. (2011) developed a very detailed model of flood incident management to determine the risk of people being flooded under different hydrological and defense conditions and evacuation strategies. However, to achieve a good predictive power, these models require accurate input data. Other models are more conceptual or address specific issues of disaster management like information sharing between emergency personnel (Zagorecki et al., 2010) and the reliability of information in disaster relief operations (Kostoulas et al., 2008), post-disaster recovery (Nejat et al., 2012) with focus on housing recovery and how it relates to homeowners' decision making or to the recovery of critical services and community capital over time (Miles et al., 2011; Miles et al., 2006).

The model presented in this paper is not intended as a quantitative prediction tool but rather as an explorative tool in a "what-if" manner, comparable to a flight simulator that is used to evaluate the performance and capacity of reaction of a pilot, both under normal and altered or extreme conditions, without putting pilots or passengers at risk. Likewise, disaster management organizations and other emergency services cannot exercise extreme events in real life: they can only plan for certain expectations (e.g., flood magnitude, resources needed) and develop action strategies in accordance with these expectations. When conditions change and these expectations fall short, the functioning of the organizations might not be guaranteed anymore. Our "flight simulator" approach is to develop a rather simple, stylized "virtual lab" (Seppelt et al., 2009) that allows us to quickly implement new ideas and test hypotheses, to obtain a better mechanistic understanding of the system behavior. We therefore use a spatially explicit, agent-based modeling approach, as it allows us to incorporate, explicitly, the micro-level decision making of actors and observe their joint emergent behavior on a macro or system level (Holland, 1992) in their respective geographic context. Thus, agent-based models (ABMs) are suited to model the behavior of individual actors such as disaster management units that act independently to solve a common goal, i.e., protecting a community.

We apply the model to two exemplary case sites in Saxony – Leipzig, as an example for an urban area, and the Neisse region, representing a more rural region – and try to answer the following questions:

1. Which dimension of change has the most profound influence on the performance of disaster management?

2. Can we identify bottlenecks or critical thresholds for the capacities of disaster management to ensure protection?

3. How do these thresholds depend on the regional geographic and demographic setting?

2.3 METHODS

In this section, we will first describe the model structure, i.e. entities, processes, model rules and data used. Second, we explain how we measure performance of disaster management in the model. We then present a characterization of the geographic and demographic settings. The section ends with a description of the scenarios that we used to demonstrate the functionality and robustness of the model.

2.3.1 *Description of the agent-based model*

The description of the model loosely follows the ODD+D protocol structure (Müller et al., 2013). A complete model description can be found in the Appendix (Appendix A.1), which also includes technical implementation details and model assumptions (Appendix A.2).

2.3.1.1 *Overview*

PURPOSE The purpose of the model is to analyze the performance of disaster management and understand how it is affected by change (e.g. demographic, climatic, or technological). The model is designed for both scientists and stakeholders, as an exploratory tool to understand the functioning of disaster management under change and as a discussion tool to illustrate these results to experts, address possible shortcomings and highlight options for improvement.

ENTITIES, STATE VARIABLES, AND SCALES There are three main entities in the model: DMOs, disaster sites and sandbag reserves. We have selected the case of sandbag logistics as an exemplary task that is conceptually simple, yet crucial for the flood protection of a community. DMO agents represent a group of members or distinct units of a disaster management organization that can work independently and autonomously to perform certain tasks that are assigned to them. Each agent is characterized by certain properties, e.g. group size, and is associated with a transportation vehicle that is characterized by a given sandbag transportation capacity (ranging from small trucks to low-loaders). Disaster sites and sandbag reserves are stationary entities with which DMO agents interact, e.g. via filling and distributing sandbags. Space is explicitly included, the spatial setting of rivers, flood-prone areas and the street network are based on GIS data. Time is modeled in discrete intervals with one unit (tick) representing 1 min. There is no fixed time horizon; a model run stops after all tasks are finished. A conceptual diagram of the model is shown in Fig. 2.1.

PROCESS OVERVIEW AND SCHEDULING At the beginning of each simulation, each DMO agent is assigned a task. In the current model version, it is either to fill sandbags, transport sandbags or distribute sandbags. DMO agents will identify their nearest target site, which can either be a disaster site or a sandbag reserve (using the A* search algorithm, Goldberg et al., 2005; Hart et al., 1968), move there and perform the required tasks. Agents can switch between tasks when necessary, for example, when more helpers are needed for either filling or distributing sandbags. The simulation stops when the required number of sandbags is present and distributed at all disaster sites. A flow chart of the general sequence of model processes is displayed in Fig. 2.2.

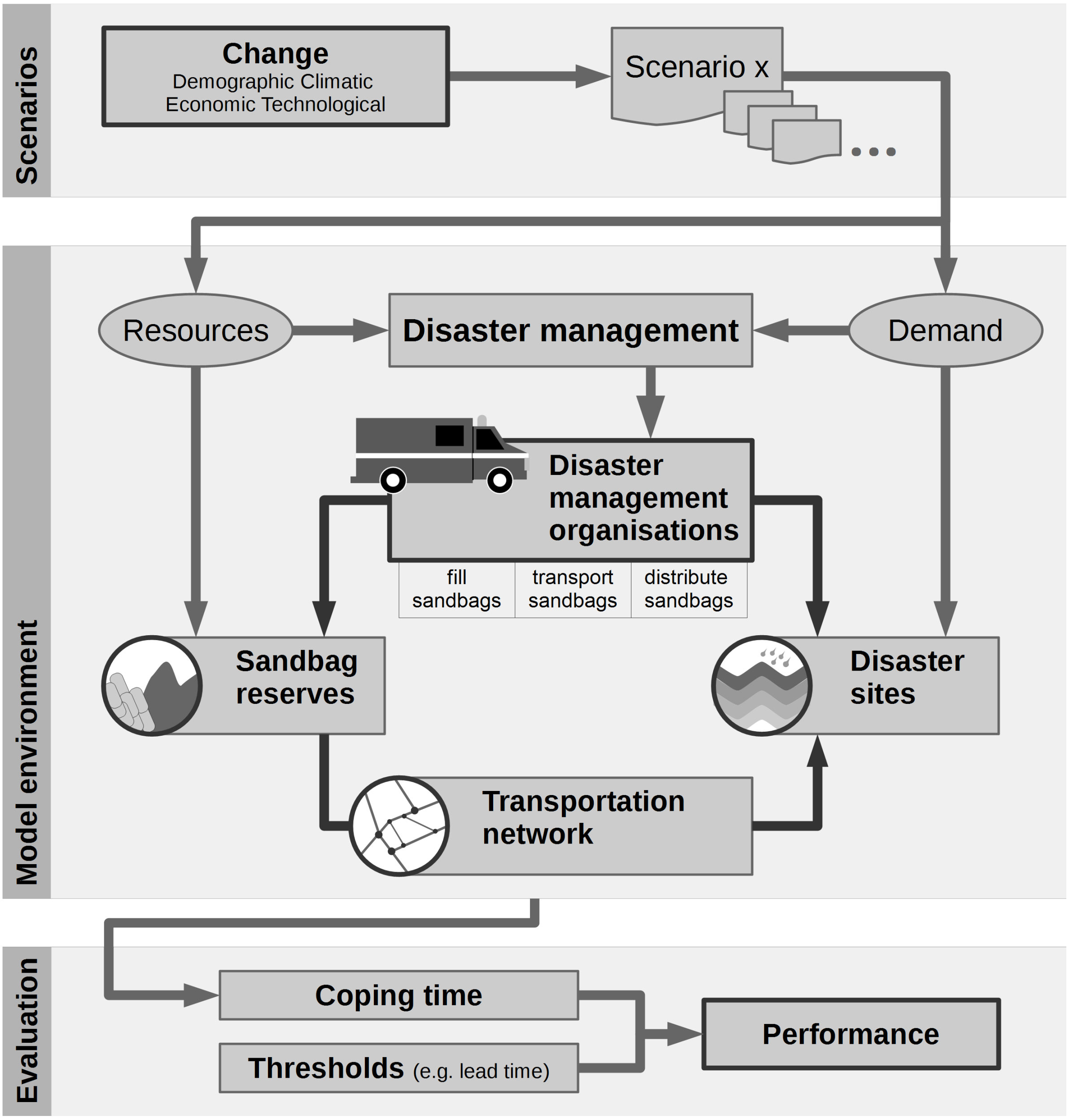


FIGURE 2.1.: Conceptual diagram of the model. The model environment shows the entities and their relationships that are simulated in the model. The influence of change is incorporated via scenarios that allow us to change resources (e.g. available DMO units), demand (e.g. required amount of protection) and other boundary conditions. The performance of disaster management for each scenario is subsequently evaluated with respect to critical time thresholds (e.g. lead time).

2.3.1.2 *Design concepts*

The model has been developed in order to depict the case of flood protection and disaster management in Saxony. DMO agents have to make decisions about which disaster site should be handled in which order, based on their information access. Agents can switch between tasks, either when they completed their current subtask or when more helpers are needed for a different task. DMO agents have full knowledge about the spatial settings of the model. This means they know the location of all target sites (disasters and sandbags reserves). However, each DMO agent has a certain level of information access about the state of each site: full knowledge indicates that they have complete knowledge about the state of all disaster sites at all

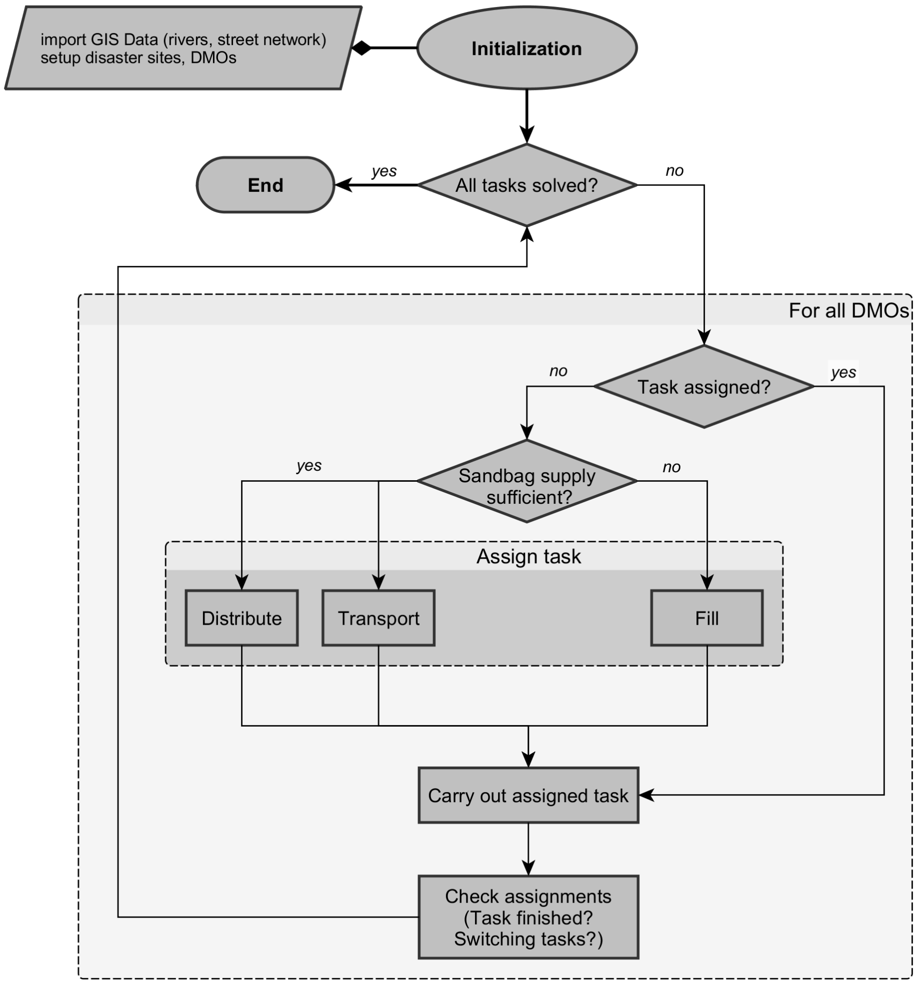


FIGURE 2.2.: Model flow chart showing the general temporal sequence of processes. Processes in the dashed box are carried out in each time step for each DMO (disaster management organization) agent.

times, i.e. how many sandbags are needed at which site and when tasks at a certain site or all sites are completed. The second level, partial knowledge, implies that they can only acquire their knowledge through direct contact, i.e. when they are at a site; after having acquired knowledge, agents remember it from then onwards. Direct interaction between agents does not take place in the current model version. However, agents interact indirectly in several ways: they are aware of where resources are needed and where not, e.g. they know if a disaster site is successfully protected. In regards to heterogeneity, currently, within any single simulation all DMO agents are homogeneous in their properties. Disaster sites are randomly distributed at the beginning of each simulation. The order in which DMO agents act in each time step is determined randomly by the NetLogo 'ask' command. For each simulation, the time needed to fulfill all tasks – the coping time – is measured as the main indicator of performance. When the model is run interactively (using the graphical interface), several variables can be monitored during a simulation run, e.g. the current distribution of tasks onto the DMO agents or the degree to which tasks are fulfilled.

2.3.1.3 *Details*

The model is implemented in NetLogo (Wilensky, 1999). A screenshot of the model interface with a sample simulation run is shown in Fig. 2.3.

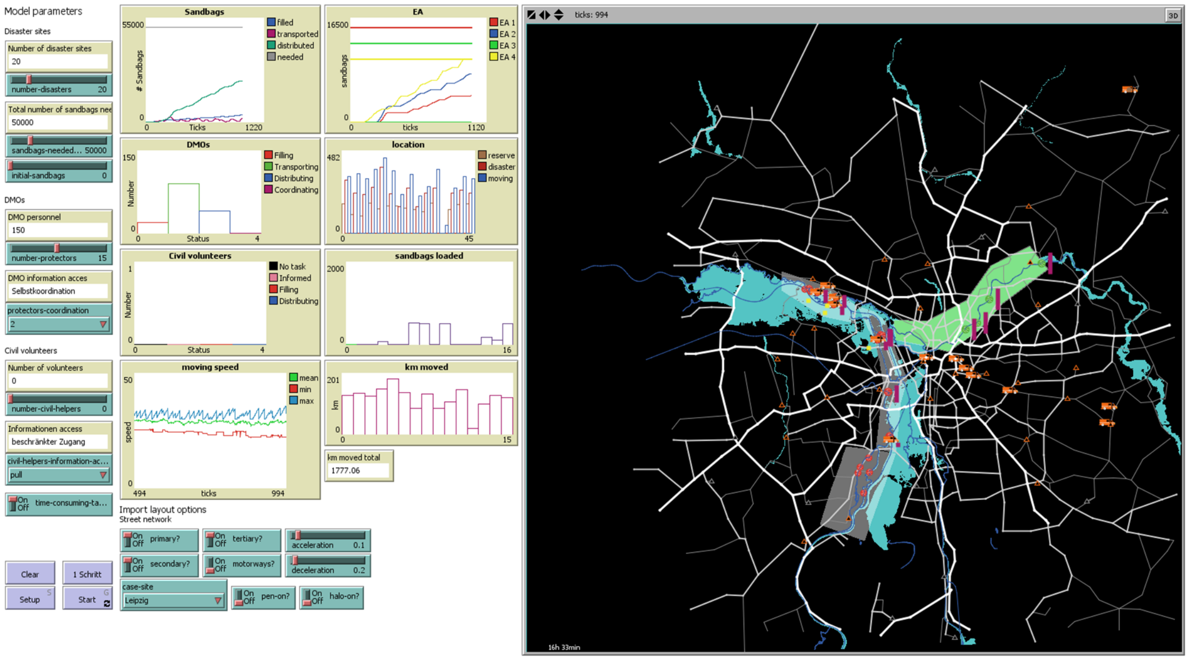


FIGURE 2.3.: Screenshot of the NetLogo model interface. The map shows a snapshot of a running simulation, with DMO agents moving along the street network and disaster sites in various states of protection. The green shaded area depicts a river section that is already protected whereas in the grey shaded areas sandbags are still needed at various sites.

FLOOD CHARACTERISTICS AND SANDBAG DEMAND The model only includes the location of rivers and flood-prone areas but does not employ a hydrologic model to simulate flood flow through the river. We translate flood intensity implicitly into a number of disaster sites and a total demand of sandbags that need to be distributed. Based on this total demand (e.g., 100,000 sandbags), the number of sandbags needed at each disaster site is calculated.

DMO MOVEMENT AND DECISION MAKING DMO agents have to decide a) which task and b) which target site to choose. In reality, DMOs rarely have the time to derive an optimal decision; they mostly rely on certain routines and past experiences (Kuhlicke, 2010). In our model, DMO agents therefore employ simple heuristics in their decision making, based on their level of information access (partial or full knowledge) and their available resources (e.g. whether sandbag supply is sufficient or not). An example for a heuristic used by DMO agents is as follows:

If sandbags are loaded onto the transport vehicle, locate the nearest target site X and calculate the route there. Then, move to the target site X. Finally, unload all sandbags and distribute sandbags. If all tasks at site X are completed, mark site as finished; otherwise, remember current state of the site.

The times needed for certain tasks, e.g., the filling or distribution of sandbags, is calculated based on estimates that serve as a calculation basis in disaster management. For example, one helper can fill about 80 sandbags h^{-1} (taken from *Taschenkarte Deichverteidigung*, THW Ortsverband Emden, 2007). Likewise, estimates for traveling speeds of transport vehicles (minimum, maximum and average speed) are included in the model (a detailed table is available in the Appendix A.2). DMO agents can move along the transportation network to their target sites. Here, the model uses the A* search algorithm (Goldberg et al., 2005; Hart et al., 1968) to determine the shortest paths to target sites within the spatial environment of the model. The algorithm is an extension of the popular Dijkstra search algorithm (Dijkstra, 1959) but is significantly faster.

INITIALIZATION AND INPUT DATA Currently, there are two study sites implemented in the model, the city of Leipzig and the Neisse region. For both areas, spatial data for rivers, flood-prone areas and the street network are imported from preprocessed GIS data layers. River and street network data are pulled from OpenStreetMap (Geofabrik, 2014), including road categories and associated speed limits. Flood-prone areas are extracted from data of the Saxony State Office for Environment, Agriculture and Geology (LfULG (Landesamt für Umwelt, Landwirtschaft und Geologie), 2012). All data is initially simplified in ArcGIS to reduce complexity (e.g. reducing the number of nodes or approximating arcs with straight lines).

2.3.2 *Measuring performance*

The functioning and performance of disaster management, i.e., the provision of protection against the negative impacts of a flood, is a central part of making a community resilient, i.e., able to cope with a flood event and maintain its functioning (IPCC, 2014). To measure the performance of the disaster management and its capacity to cope with a single disaster event, we use the coping time t_{cope}. During a disaster operation, the degree to which protection measures are realized increases (Fig. 2.4A, black line) until all measures are put into place. We define this time span as the coping time t_{cope} (Fig. 2.4A, bold light grey line). Only if this time is below a certain threshold (in most cases the flood lead time t_{lead}, see Fig. 4A, bold dark grey line) is the communities' protection guaranteed. Depending on the available resources, the coping time t_{cope} can change, reflecting an increase or decrease in coping capacity. Additionally, the demand posed onto the organizations, e.g., in terms of the intensity of the flood, can change too. If available resources decrease and demand increases, it is less likely that coping time stays below a given threshold.

For every scenario of change (detailed in Section 2.3.4) we can measure coping time t_{cope} and evaluate it with respect to the lead time t_{lead} (or other critical time) threshold. A lower coping capacity leads to a slower realization of protection measures, represented by a slower rise of the protection measure fulfillment curve (Fig. 2.4B, black dashed line). If the coping time t_{cope} exceeds the lead time threshold t_{lead} (Fig. 2.4B, bold light grey dashed line), the community might be at risk as realized protection measures are below 100% when t_{lead} is reached. Therefore, coping time t_{cope} reflects a measure of resistance with regard to a concrete flood event. In our analysis, we therefore measure the coping time t_{cope} in each simulation, where one simulation represents the realization of one disaster event based on the boundary conditions and resource and demand settings of the current scenario.

If we consider disaster management as a social-ecological system by itself that is subject to change (demographic, climatic, technological), we can adopt a resilience perspective and analyze under which conditions the capacity of DMOs to cope with flood events (i.e. to have a coping time below a given threshold) can still be ensured. However, as in the definition given by the IPCC (2014), resilience comprises not only the "capacity [...] to cope with a hazardous event or trend [...], responding or reorganizing in ways that maintain their essential function" but also includes "the capacity for adaptation, learning, and transformation" (IPCC, 2014,

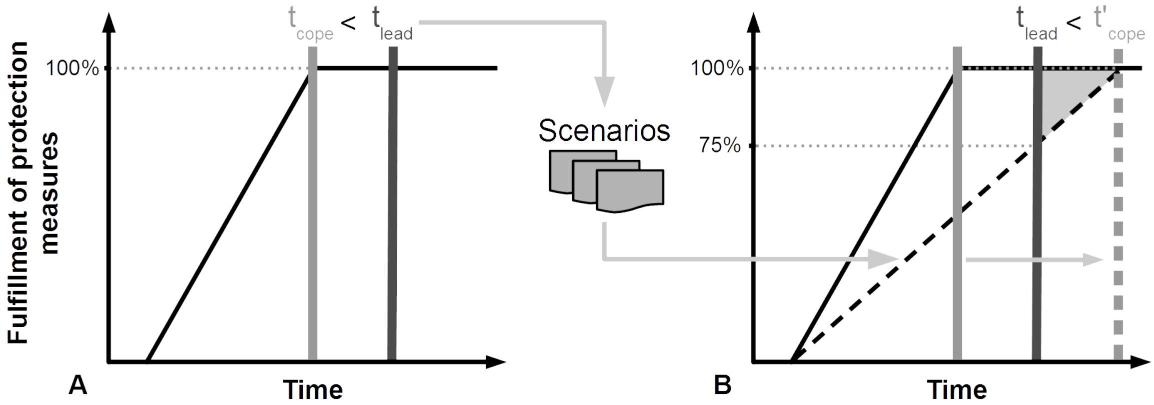


FIGURE 2.4.: Measuring the performance of disaster management. Coping time t_{cope} refers to the time needed to put all protection measures into place (light grey lines). Whether coping time is above or below the lead time threshold t_{lead} (dark grey lines) determines whether community protection can be ensured or not. The black lines present the degree of fulfillment of protection measures.

Annex II, p. 1772). Thus, in our analysis we also focus on steps of adaptation or reorganization that can improve coping time and might be necessary to maintain the functioning of DMOs.

2.3.3 *Characterization of the geographic and demographic settings*

The selected study region, the Free State of Saxony, is very heterogeneous in both its geographic (including hydrologic) and demographic situation. Therefore, the impact of change can be different, depending on the specific local settings of the community of interest. This in turn can have different effects on disaster management performance.

TABLE 2.1.: Characterization of geographic and demographic settings and comparison across the two study sites.

Setting		Characteristics	Urban area Leipzig	Rural region Neisse
Geographic	Topography	Mountainous/hilly or flat land/lowland Elevation	Lowland	Lowland
	River location	Upstream / Downstream	Downstream	Downstream
	Flood setting	Flash floods or plain floods	Plain floods	Plain floods
Demographic	Size	Town size Number of inhabitants	Large city $>$ 500.000	Small towns $<$ 5.000
	Population growth rate	Growing/shrinking	Significantly growing	Shrinking
	Migration	In- and out-migration trends	Influx of young people	Departure of young people, leading to an aging society

The geographic location of a community has strong implications for the occurrence of the flood, e.g. its lead time and the associated resources needed for flood protection. In the upper reaches, flash floods are more prominent occurring with relatively short lead times and high force and velocity, whereas downstream plain floods are more prominent often associated with longer lead time, lower low velocity, but much longer duration.

The population size and its growth or shrinking rate are indicators for the availability of manpower for disaster management. In small towns or rural areas, the number of helpers that are deployable is usually lower than in urban areas. Additionally, rural areas are often affected by both population decline and aging, whereas opposite trends can be observed in urban regions.

To account for these differences, we characterize each case site along these two dimensions, as shown in Table 2.1. By taking these two dimensions as a basis, we can identify further combinations of settings that are relevant for the study region (e.g., rural and urban areas, towns along the upper or lower reaches of the rivers). Additionally, we can draw some inferences from these settings, such that urban areas usually have a dense transportation network that reduces travel times of disaster management, which is often the opposite in rural regions. When we compare disaster management performance with respect to change, we can then draw implications as well on these regional levels.

2.3.4 *Scenario description*

Change mainly affects two components of the system: disaster management and its capacities, e.g. via the number of available helpers or resources, and the disaster event, e.g. flood intensities that result in changed demand. We also structure our scenario analysis along these two dimensions, so that in scenario 1) we analyze how a given flood event can be handled under changing organizational settings. In scenario 2) we then investigate the effects of changes in the flood and demand settings. Table 2.2 shows a list of the change processes, their impacts on the system level and the affected model parameters with their range of variation.

Furthermore, all analyses from scenarios 1) and 2) were carried out in scenario 3) for two different spatial settings: a) the city of Leipzig in the north west of Saxony and b) the rural Neisse region between Zittau and Görlitz in the east of Saxony, adjacent to the border to Poland (see also Table 2.1). These two sites have been selected as examples of an urban and a rural region that are affected differently by change, e.g., demographic change leading to either population growth or shrinkage. Additionally, this comparison serves as a test of robustness, to see if the model is applicable to different spatial settings. For each parameter combination, 100 simulations have been run. The model results have been evaluated using the R Statistical Environment (R Core Team, 2015).

2.4 RESULTS

2.4.1 *The influence of the number of DMOs*

For all conducted simulations, we measured the coping time t_{cope} as an indicator of how well disaster management can cope with a certain disaster event. At first, we take a closer look at the relationship between coping time t_{cope}, the number of DMO agents and their properties in scenario 1) while leaving the flood settings constant (Section 2.4.1). Here, we can could observe a decline of coping time t_{cope} with increased number of organizations N_{DMO} (see Fig. 2.5).

TABLE 2.2.: Scenario overview, showing change processes, their impact and affected model parameters. All analyses carried out for scenarios 1) and 2) have been carried out for two different spatial settings in scenario 3). Flood lead times represent a flood characteristic; however they are mostly determined by geographical and hydrological settings as well as river morphology, not by climate change. Therefore, no process is associated to it.

Scenario		*Process*	*Impact*	*Affected model parameters*	*Range of variation*
3) Spatial heterogeneity Spatial layout of rivers, flood prone areas and the transportation network. Two case sites: Leipzig, Neisse	*1) DMO properties*	Demographic change	Population decline	Number of DMOs N_{DMO}	5–100
		Technological change	Transportation improvements	Capacity of DMOs (# sandbags / DMO unit)	250–2000
			Better information availability	DMO information access (knowledge of disaster sites)	partial knowledge full knowledge
	2) Flood characteristics	Climate change	Increased flood intensity	Required total number of sandbags $N_{Sandbags}$	50000–100000
				Number of disaster sites $N_{Disaster}$	5–80
		–	Differences in lead times	Flood lead time threshold t_{lead} [hours]	12 – 48

This general relationship held across all parameter combinations and became especially evident on a double logarithmic scale: coping time t_{cope} and number of disaster management organizations N_{DMO} are apparently linked by a power law relationship, i.e.:

$$t_{cope} \propto \frac{1}{N_{DMO}} \tag{2.1}$$

The number of DMO agents N_{DMO} is therefore a main determinant of the coping time t_{cope}. Decreasing DMO numbers, e.g. due to demographic change, lead to increasing coping times. These coping times might exceed the flood lead time t_{lead}, depending on the flood characteristics and geographical location of the community at risk. In Fig. 2.5, we have superimposed three different lead time t_{lead} thresholds (72, 48 and 24 hours) to illustrate this relationship: to achieve a coping time below a 72 hour lead time threshold, at least 10 DMO agents were needed in this setting. However, when this lead time threshold was only 24 hours, 33 DMO agents were needed to stay under this threshold.

This strong relationship between coping time t_{cope} and number of DMOs N_{DMO} can be explained by the link between transportation capacity of DMOs and the time needed per trip to a target site, i.e. one trip from a sandbag reserve to a disaster site (and back). This results in a total number of trips that is split upon the number of DMOs present, thus the power law relationship. Based on these observations, we can reformulate this relationship as follows:

$$t_{cope} = c \times \frac{1}{N_{DMO}{}^{(1-\epsilon)}} \tag{2.2}$$

$$\log t_{cope} = y_1 - (1-\epsilon)\log N_{DMO} \tag{2.3}$$

where ϵ and $y_1 = \log c$ are parameters that can be derived by fitting the relationship to the data extracted from the simulation runs. Once the fitting formulas are determined, they can be used for calculating the critical minimum coping time t_{crit} that results for a given number of DMOs or, vice versa, calculating the minimum number of DMOs needed N_{DMO}^{min} to achieve a certain coping time below the flood lead time t_{lead}. Results for this are presented under in 2.4.3.

2.4.2 *Scenario 1: Variation of DMO properties*

The general power law relationship between the number of DMO agents and coping time that we showed in the previous section was found to be robust when we changed properties of the DMOs. This is evident from the results presented in Figure 2.6 (on a double logarithmic scale) and the similarity of the fitted linear slope. However, quantitatively we observed large differences in the coping time when we varied a) the capacity and b) the information access of the DMO agents, for a given flood demand setting. With a larger capacity (panels A-D),

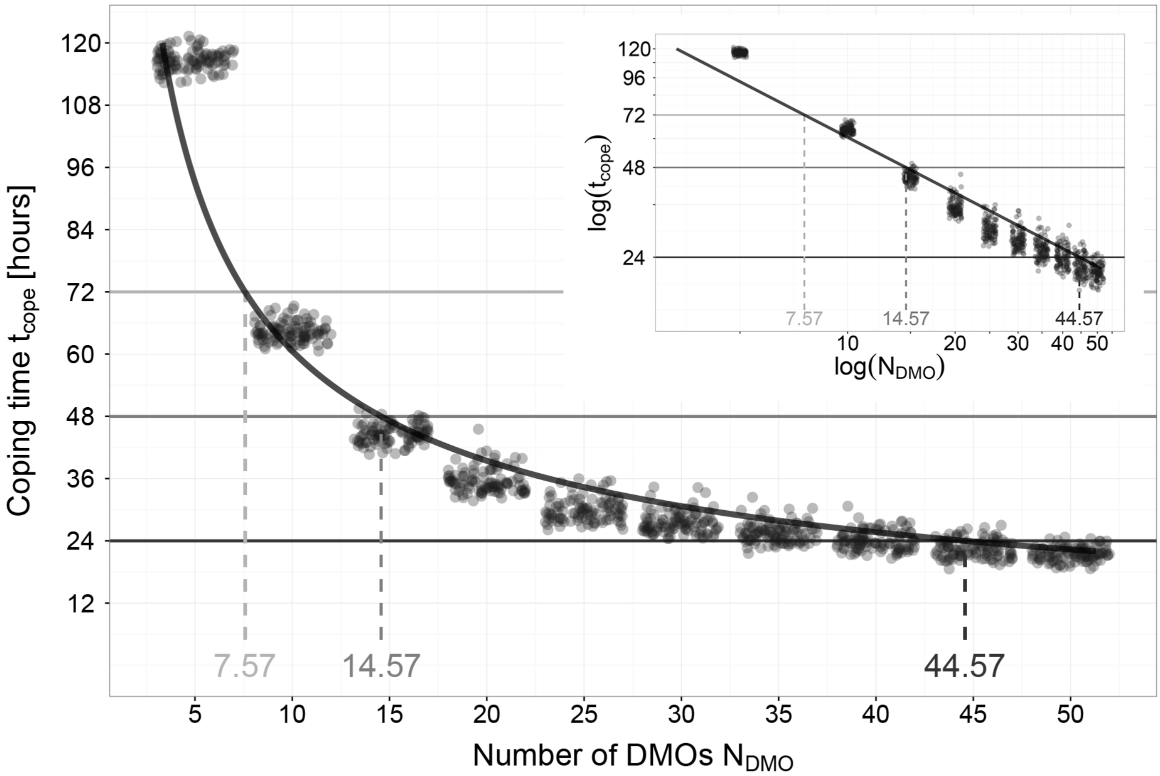


FIGURE 2.5.: General qualitative relationship between coping time t_{cope} and number of DMOs N_{DMO}. Coping time decreases with increasing number of DMOs following a power law relationship (as depicted in the smaller inset plot, showing the same data on a log-log scale). Dots represent results of single simulations, where overlapping dots result in darker colors. Black curve shows the fitted power law and the intersection with the 24, 48 and 72 hour threshold yields the minimum number of DMOs necessary to achieve that coping time. Results correspond to a flood setting of 40 disaster sites and a total demand of 50000 sandbags.

more sandbags can be transported in one round, i.e. one trip from sandbag reserve to disaster site and back, which effectively reduces the number of rounds that are needed to achieve protection at one site. For a given number of DMOs, this reduced the coping time t_{cope}. However, increasing the capacity also had its limits. The largest reduction of coping time was achieved for the doubling of the capacity from 250 to 500 sandbags (Fig. 2.6A and B), whereas the subsequent capacity increases to 1000 and 2000 sandbags only achieved a smaller reduction (Fig. 2.6C and D). This suggests that there is a marginal utility where the costs involved in improving the capacity of a single DMO agent are not worth the obtained performance increase. Increasing the number of DMO agents was more effective; especially for high numbers of DMOs, an increase in capacity resulted in almost no reduction in coping time (e.g., N_{DMO} = 80 and an increase in capacity from 1000 to 2000 sandbags).

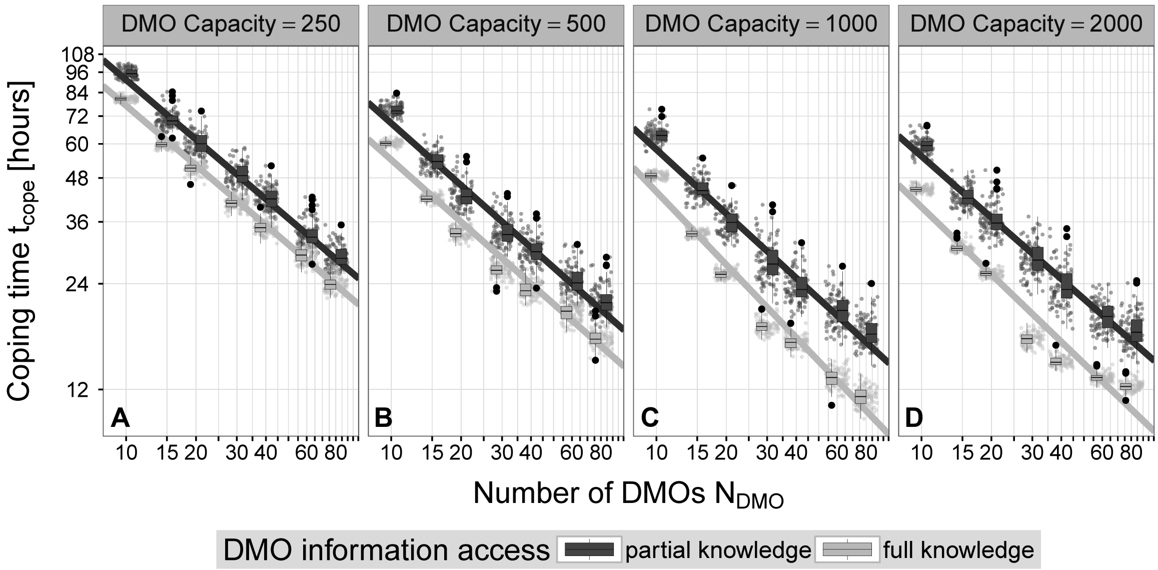


FIGURE 2.6.: The distribution of coping time depending on DMO properties: i) DMO transportation capacity (panels from left to right), ii) the number of DMOs (x axis) and iii) their information access (dark grey/light grey). Dots represent results of single simulations, where overlapping dots result in darker colors, and superimposed box plots show the distribution of the results. Thick line shows the fitted power law. Results are presented on a double logarithmic scale. Results correspond to a flood setting of 80 disaster sites and a total demand of 50000 sandbags.

The way that DMOs have access to information about disaster sites also influenced the coping time. With only partial knowledge, DMOs recognize the (demand) state of a disaster site only when they visit it. This potentially leads to unnecessary trips to sites. With full knowledge, DMOs know the state of all disaster sites at all times, so they avoid such unnecessary trips. Coping time t_{cope} was therefore always lower when DMOs had better information access. We could even observe cases where better information access had the same effect as doubling the number of DMO agents, e.g. for N_{DMO} = 40 and a transportation capacity of 500 sandbags (Fig. 2.6B), the average coping time for DMOs with full knowledge was equal to the coping time of 80 DMO units with the same capacity but only partial knowledge. For a DMO capacity of 1000 and 2000 sandbags (Fig. 2.6C and D), the slope of the power law fit for DMOs with full knowledge is steeper than for those with only partial knowledge. This indicates that the combination of full information access and high transportation capacity is more effective (i.e., leads to higher reduction in coping time) than just a higher capacity alone. However, results were not significantly different to prove that point, based on the current simulation results.

2.4.3 *Scenario 2: Variation of the flood characteristics*

Changed flood settings can be translated in either a higher demand for resources or manpower or in shorter lead times, or in shorter lead times. Here, we first tested the performance of DMOs for different levels of demand in terms of a) the number of disaster sites and b) the total number of sandbags that need to be distributed (Fig. 2.7). We saw that coping time increased both with increasing total demand, $N_{Sandbags}$, as well as with a higher number of disaster sites, $N_{Disasters}$. At first, we saw that a doubling of the total demand (Fig. 2.7A and B) does not lead to the same doubling of the coping time t_{cope}. Rather, coping time increase was between 79% and 98%, depending on the number of disaster sites, as well as the information access of DMOs. Here, we saw a clear difference in how strongly coping time increased between simulations where DMOs had partial knowledge, compared to full knowledge. Whereas for partial knowledge and a total demand $N_{Sandbags} = 50000$ (Fig. 2.7A) an increase from 5 to 80 disaster sites leads to a prolongation of the coping time t_{cope} of nearly 11 h (from 19 h to 29 h 45 min), it resulted only in a 3 h 30 min longer coping time when DMOs had full knowledge (from 19 h 30 min to 23 h). For a total demand of 100000 sandbags (Fig. 2.7B), the increase of coping time and also the difference depending on the information access was comparable. Thus, better information access of DMOs can mitigate, to some degree, the additional demand posed by the increased number of disaster sites.

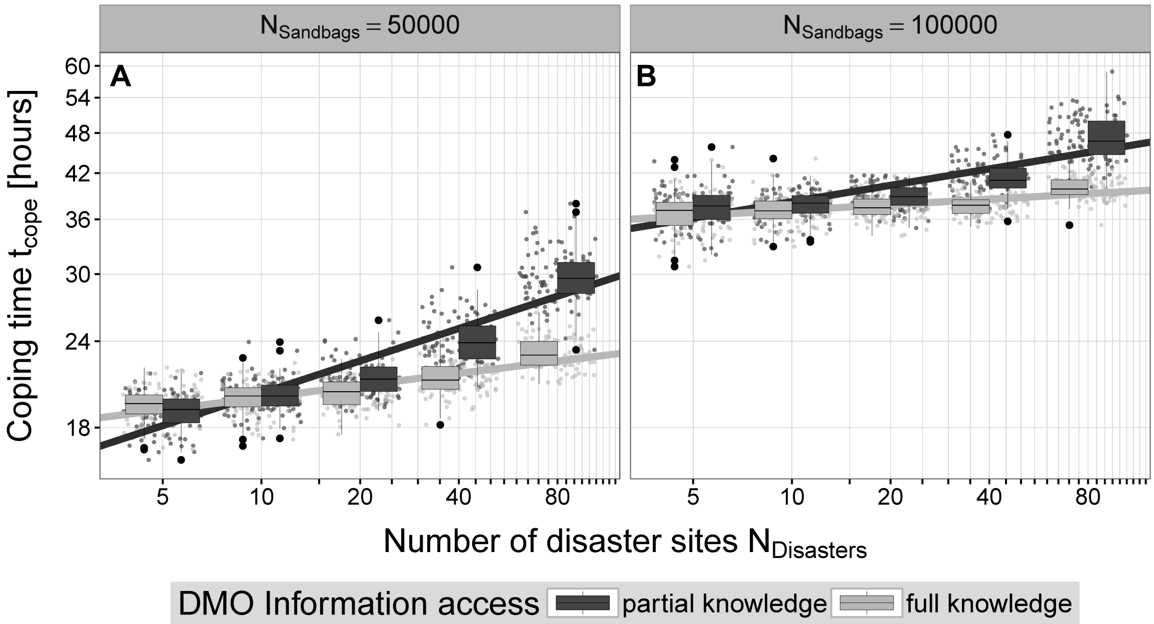


FIGURE 2.7.: The distribution of coping time depending on flood characteristics: i) the total demand of sandbags $N_{Sandbags}$ that need to be distributed (left and right panel), and ii) the number of disaster sites $N_{Disasters}$ (x-Axis). Results are additionally split by the information access of DMOs (dark grey/light grey). Dots represent results of single simulations, where overlapping dots result in darker colors, and superimposed box plots show the distribution of the results. Thick line shows the fitted power law. Results are presented on a double logarithmic scale. Results correspond to a setting with $N_{DMO} = 40$ and a DMO capacity of 500 sandbags.

Variations in flood lead times have been considered in terms of the minimum number of DMOs N_{DMO}^{min} needed to achieve a certain lead time t_{lead}. We determined this number from fitting equation 2.3 to the coping times obtained from the simulation. Results for this analysis are displayed in Fig. 2.8. Here, we first analyze panels A-C, whereas the comparison of both panels A-C and D-F will be presented in the following section.

We saw that, in general, the minimum number of DMOs N_{DMO}^{min} increases increased when the lead time threshold t_{lead} increased as well (Fig. 2.8B and C). This is not surprising, as with lower lead times, the same number of tasks need to be solved in shorter time. However, this increase was nonlinear: for high to medium lead times (48 h–24 h), the increase in DMOs needed was only subtle. However, once we crossed the threshold to very short lead times below 24 hours, the numbers increased sharply. In such areas, e.g. cities in the upper reaches of rivers, the number of disaster management organizations is the crucial factor that determines the performance of disaster management.

In line with the previous analyses, the increase did also depends on a) the demand posed onto the DMOs, here in terms of the number of disaster sites, as well as b) the capabilities of the DMOs, in terms of their transportation capacity and information access. When we compare Fig. 2.8A and B, we see that the curves show a much steeper increase when DMOs only had partial knowledge (Fig. 2.8A). Also, lower capacity (thin lines) and a higher number of disaster sites (orange and red lines) lead to an increase in the minimum number of DMOs needed. However, when we look at Fig. 2.8B, where DMOs had full knowledge (i.e., they know the status of all disaster sites at all times), this increase was much more subtle. The role of information access is also reflected in the average distances moved by DMO agents (not displayed here): while for full knowledge, higher numbers of disaster sites lead to no noticeable rise of the distance moved, partial knowledge showed a strong increase here. A reason for this rise lies in the unnecessary extra trips that DMO agents carry out when their information about disaster sites is not up to date. Of course, the number of such trips increases with a higher number of disaster sites. This shows again that information access can play a large role to overcome either increased demands (higher number of disaster sites, shorter lead times) or shortcomings in resource supply (the number of DMOs = manpower). Especially the combination of full knowledge and high transportation capacity effectively eliminated the need for more DMO agents when the number of disaster sites increased, which becomes apparent from the overlapping bold lines in Fig. 2.8B. Full knowledge (Fig. 2.8B, thin lines) or high transportation capacity (Fig. 2.8A, bold lines) alone did not achieve this effect.

2.4.4 *Scenario 3: Regional comparison*

The two case study sites that we compared for this scenario, a) an urban area and b) a rural region, roughly have the same spatial extent (a) 35 km x 31 km and b) 35 km x 23 km, but are very different in their geographic location, their demographic situation and their infrastructure; e.g., the transportation network is much more dense in the urban area than in the rural region (see the maps in Fig. 2.8A and D). When we compare the performance of DMOs across both regions it should be noted that the general qualitative behavior of the model did not change, similarly as shown before, which confirmed that the model performance is robust also under different spatial settings. Comparing both regions quantitatively revealed some interesting results. At first, because of the differences in the transportation network, we would have expected larger differences in the average distance moved of the DMO agents. However, there was no noticeable difference in the full knowledge scenario, and we observed a difference for large numbers of disaster sites only for partial knowledge, e.g., for $N_{Disasters} = 80$, one DMO agent moved on average 250 km in the urban case and 300 km in the rural region (in one simulation run). We compared the increase of minimum DMO numbers, N_{DMO}^{min}, depending on the lead time between both spatial settings and saw that the general pattern is very similar in both regions, with only subtle increases of N_{DMO}^{min} for the full knowledge scenario (compare

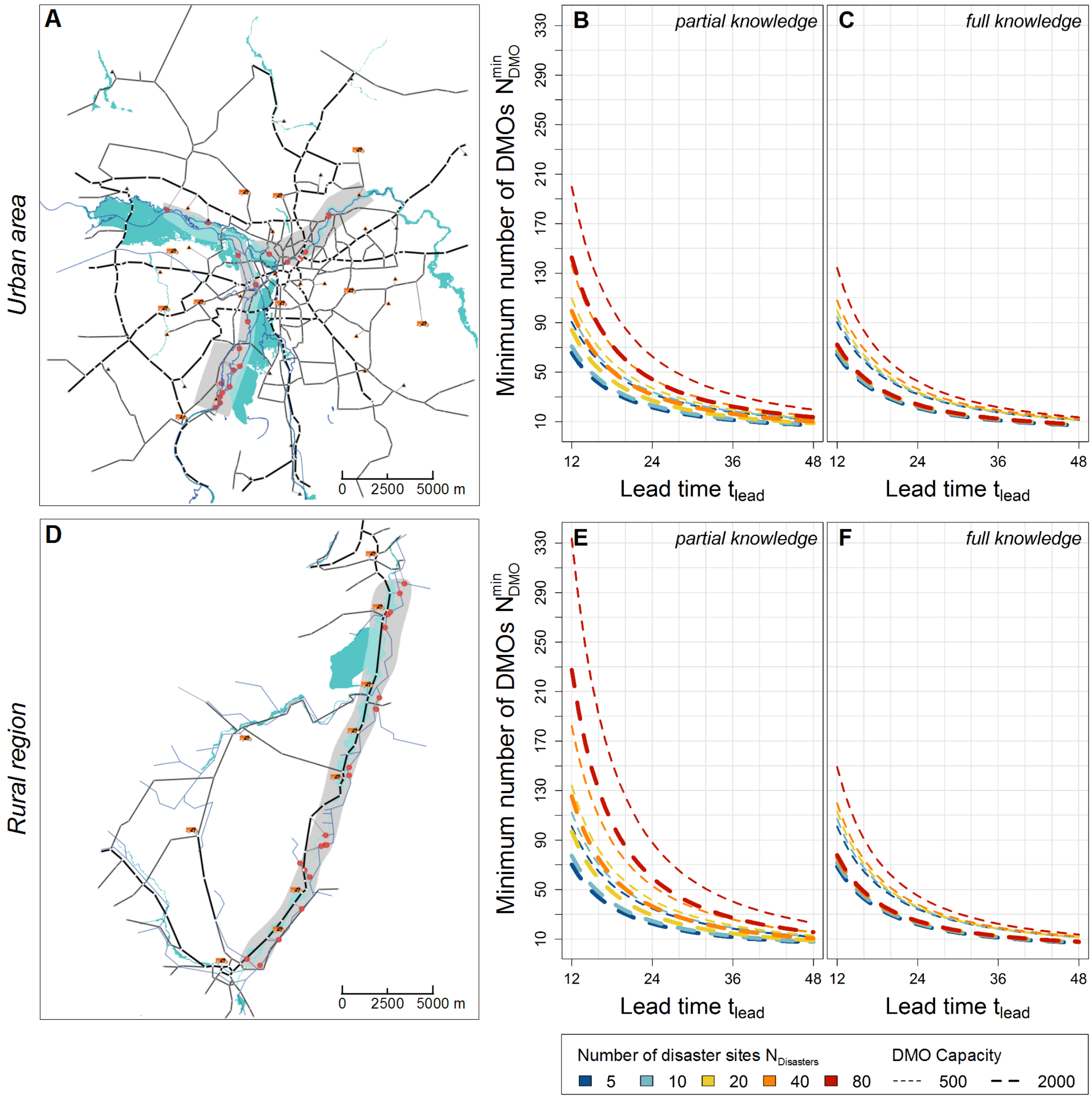


FIGURE 2.8.: Minimum number of DMOs N_{DMO}^{min} in dependence of the flood lead time t_{lead}. The results are depicted for two spatial settings, an urban area (A-C) and a rural region (D-F). The maps for each region (A,D) show rivers (blue lines), flood-prone areas (blue shaded area) and the transportation network (black and grey lines). The lines in the main graphs B, C and E, F are color-coded according to the number of disaster sites and their thickness shows the transportation capacity of the DMO agents.

Fig. 2.8C and 2.8F). However, a more substantial increase could be seen in the rural region for the partial knowledge scenario, and at very short lead times (Fig. 2.8E). Here, the limits in infrastructure seemed to amplify the bottleneck of the number of DMOs needed. Particularly low transportation capacity of the DMO agents and a high number of disaster sites showed a significantly larger number of DMO agents needed when compared with the urban area: whereas approximately 200 DMO agents were needed to ensure protection at 80 disaster sites and stay below a lead time of 12 hours in the urban area, the same task required more than 330 DMO agents in the case of the rural region, an increase of 65%.

2.5 DISCUSSION

In this work, we present a "virtual lab" approach in the form of an agent-based simulation model in combination with a geographical information system to assess performance of disaster management under change in a spatially explicit way. As a main result we show that future performance of disaster management depends to a large degree on the demographic development, as manpower remains the most important resource, especially if flood lead times are very short (< 24 hours). Technological advances such as better information access or improved transportation capacities of DMOs can help to overcome performance deficiencies, but only up to a certain degree.

2.5.1 *Implications for disaster management*

The performance of disaster management is at stake when demand for protection and resources to cope and attain this protection are at a mismatch. Our model has shown that change can lead to such a mismatch on different levels. This becomes evident in our study region where we can observe a coincidence of change particularly in two dimensions: demographic change, leading to a decline in the number of disaster management organizations at hand, and climatic change, leading to an increase in flood frequency. Throughout all analyses demographic change has emerged as the factor with the strongest influence on the performance. In other words, under a "loss in DMOs scenario", the performance that is expected from disaster management may no longer be guaranteed and even well-established and tested routines might then fall short. Therefore, disaster management performance depends strongly on the differences in the demographic development, as well as in the flood characteristics due to geographical conditions. Though we only compared two geographic settings that are examples for lowland and downstream regions, our parameter variation (e.g. the variation of the lead time threshold) allows us to draw implications beyond the two case sites (see Table 2.3).

While performance is likely to be ensured in urban and downstream regions (with lead times of often more than 24 hours), performance could be at risk in rural, upstream regions where lead times are short (12 – 24 h, or even shorter) and population shrinkage leads to a decline in DMO numbers. However, shrinkage does not necessarily lead to a reduction of exposure to flood risk, as areas of demolition rarely overlap with flood-prone areas. Also, the capacity to cope with and adapt to flood risk is very much restricted for communities in rural areas, due to both limited financial means and a loss of public services, which renders them highly vulnerable with respect to flood risk. Deficiencies in manpower can partly be substituted with technological advances such as better information availability or increased transportation capacity. Therefore, especially in regions where disaster management performance is at risk, a focus should be put, for example, on efficient communication and coordination strategies as a possibility for a transformation that could enhance the resilience of disaster management on the long term. If we link these results back to our case study area of Saxony, a combination of short lead times and more rural areas can be found, for example, in the upstream area of the Mulde river. A more in-depth analysis of disaster management performance, its drivers and possible improvement options should therefore focus on this region.

Despite the individuality of the spatial structure of the different study regions, the model results indicate strong robustness and therefore a certain transferability of the qualitative findings to other regions of the same type. The reason is that the spatial processes (here: transport) are averaging out the effects of small-scale spatial heterogeneities, which is a well-known effect from spatial systems dynamics (Banitz et al., 2016; Frank et al., 2002; Fahse et al., 1998). In consequence, rules of thumb for management can be derived (Frank, 2004).

TABLE 2.3.: Possible implications for disaster management performance in dependence of demographic and geographic settings.

Disaster management performance	Demographic & geographic setting
Performance ensured	*Urban areas*: high population density, population largely growing, dense infrastructure → high number of DMOs with availability of helpers ensured *Downstream, lowland*: plain floods, long flood lead times → sufficient preparation time to carry out protection measures Performance of DMOs is likely to be ensured.
Performance uncertain	*Small to medium sized towns*: no clear population growth / shrinking trend → DMO number depends on the specific town *Downstream / middle reaches*: mostly plain floods, medium flood lead times. Performance of disaster management depends on the specific local settings. Possible bottlenecks could be overcome by, for example, better information access or higher transportation capacity of DMOs.
Performance at risk	*Rural regions / small towns*: low population density, population shrinking, sparse infrastructure → low number of DMOs, availability of helpers likely to decrease *Upstream, mountainous*: flash floods, short flood lead times → limited timespan to install protection measures. Performance of DMOs is likely to be at risk as resources (e.g. DMO numbers) are decreasing and demand (e.g. flood frequency) is likely to increase.

Even though further analysis would be needed to provide reliable heuristics, one such rule could be that securing the availability of members should be a top priority to ensure operational readiness of disaster management. A second rule could stem from the interchangeability of information access and transportation capacity, i.e. that better information access can compensate for lower transportation capacity.

2.5.2 *Model limitations and future extensions*

Of course, the developed model is a simplification of the reality and is based on a number of strong assumptions. We only focus on one task in the current model – the filling, transportation and distribution of sandbags – and omit a range of other tasks such as the evacuation of people or the protection and maintenance of critical infrastructure. This task of filling and distributing sandbags was chosen as it a) is relatively simple to represent in the model and b) demands a large number of resources (both technical as well as manpower) during a flood event. The model also omits more complex control structures such as management authorities or operation control that are responsible for the coordination of all DMOs and their tasks in a real disaster event. Including all these elements and processes would lead to a highly complex model that might more accurately represent reality, but makes understanding key elements that drive the system performance nearly impossible (Sorenson, 2002). However, understanding these key elements and processes is the main goal of our model in the sense of a "virtual lab" approach. Highly complex models are also difficult to communicate, both to other researchers as well as to stakeholders and experts in disaster management. The virtual lab approach enables "computational experimentation" known as promising way of enhancing social learning, exploring chances and risks of upcoming developments, and assessing the effectiveness of potential counteractivities (Chapin et al., 2010; Folke et al., 2010).

In the context of disaster management, agent-based modeling is still relatively new, but a couple of innovative models have emerged in recent years. The ABM developed by Zagorecki et al. (2010) puts an explicit focus on information exchange and cooperation between organizations and conclude that more flexible communication and information sharing between agents leads to a more efficient response. It is especially notable that information sharing between lowest level agents is more efficient than only between high level agents (e.g., managers). This relates well to our assumption of "full information" where DMO agents have instant knowledge about the state of all disaster sites, which could be compared to a very flexible and efficient information sharing between agents. While Zagorecki et al. (2010) focus on one very specific aspect of disaster management, the model of Dawson et al. (2011) addresses flood incident management of an entire coastal town. Their model is very detailed and allows a variation of hazard and defense characteristics as well as evacuation strategies. However, the model does only include citizens as agents and simulates their movement in response to flood warnings, not disaster management organizations. One strength of their model lies in the usage of only publicly available datasets so that the model is easily adaptable to other case sites. Even though less dependent on data, our model also only uses data from publicly accessible sources, facilitating an adaptation to a different regional setting. Including another case site that resembles a rural, upstream region would be a sensible next step.

Besides a spatial adaptation, the modular setup of the ABM allows for an easy extension of regarding additional entities (e.g., management structures) or processes (e.g., evacuation). One planned extension of the model (with an existing prototype version) addresses a fairly recent process of change: the fast development of the internet and mobile communication technologies has made information exchange very easy and fast. Moreover, the rise of social networks such as Facebook or Twitter has enabled civilians to exchange knowledge and organize relief efforts besides or in addition to official practices carried out by DMOs. This has been especially visible during the 2013 flood where a surge of so-called "free helpers" (*ungebundene Helfer*) that do not belong to any formal organization either followed the call for help or even organized themselves to help mitigating the consequence of the flood (DKKV, 2015, p. 166 ff). However, this self-coordination can also have unanticipated effects when helpers betake themselves to wrong sites or carry out tasks single-handedly that might be unnecessary or impede other tasks. Furthermore, the response of unbound helpers did not have the same intensity in every region: bigger cities benefited much more from the willingness to help, whereas small towns or rural regions depended much more on DMOs alone. Therefore, the next-planned extension focuses on the effective coordination of unbound helpers, to determine when such helpers are useful to enhance the performance of disaster management and when not. Furthermore, we would like to include the possibility of infrastructure breakdown (e.g., road closures, bridge collapse) that can have significant impact on the performance as well as on the attainability of certain protection goals. These extensions can contribute to making the model more realistic; still, the current model has already proven to be both a robust as well as illustrative tool to investigate the impact of change on disaster management and highlight which future conditions might put its performance at risk.

2.6 DATA AVAILABILITY

All data used in this publication was obtained from publicly accessible sources. River and street network data are pulled from OpenStreetMap (Geofabrik, 2014). Flood-prone areas are extracted from data of the Saxony State Office for Environment, Agriculture and Geology (Landesamt für Umwelt, Landwirtschaft und Geologie, LfULG (Landesamt für Umwelt, Landwirtschaft und Geologie), 2012). Raw data and preprocessed model input data is available at `dx.doi.org/10.6084/m9.figshare.4056663.v1`.

3

POLARIZATION IN (POST-)NOMADIC RESOURCE USE IN EASTERN MOROCCO: INSIGHTS USING A MULTI-AGENT SIMULATION MODEL

3.1 ABSTRACT

Mobile pastoralist strategies have evolved over centuries and are well-adjusted to the variable climatic conditions of semi-arid regions. However, recent decades have brought about changes in economic, social and climatic conditions, as well as a number of technical advancements such as truck transportation that impact on the livelihood of pastoralist households.

An increased inequality, between wealthy pastoralists that are able to raise large herds, and impoverished households that experience decreasing herd sizes, has been observed in recent years, for example, on the High Plateau in Eastern Morocco. And whereas wealthy pastoralists possess the financial means to use trucks to transport their herds across large distances, the group of impoverished households is mainly limited to the range that they can travel by foot. This phenomenon can be described as polarization, as the household population is divided into clearly opposing factions.

The reasons that lead to this polarization, however, are not well understood so far. In this study, we have developed a multi-agent simulation model to examine the economic, ecological, climatic and demographic driving factors of polarization. The model captures the feedbacks between pastoralist households, their herds and the pastures that they use in a common property grazing system. Using this model we can show that heterogeneities in household assets (namely livestock and monetary resources) are only one reason for polarization. Changes of ecological conditions and the impact of climate and demographic change can also cause polarization, even if households are completely homogeneous in their characteristics.

3.2 INTRODUCTION

Pastoralism, a major way of life and highly adapted land use practice in many societies worldwide, is under transformation (Gertel, 2015). Mobile pastoralist strategies such as nomadism or transhumance that are adjusted to the variable climatic conditions of semi-arid regions have evolved over centuries. However, these strategies now face several major challenges caused by changes in economic, social and climatic conditions, as well as by the increased technological progress that has given pastoralists access to basic amenities such as electricity, but also trucks or cell phones.

An increased inequality between pastoralists has been observed in recent years, for example on the High Plateau in Eastern Morocco: On the one hand, certain households are able to raise large herds and accumulate financial resources. Technological progress has led to a replacement of dromedaries as traditional means of transport (Rachik, 2000) by trucks. These provide households with the necessary means to move their herds, fodder, and water across large distances. At the same time, they want to profit from amenities in town (education and health infrastructure) and settle down. On the other hand, impoverished households experience decreasing herd sizes and financial means and their grazing area is mainly defined by the distance that they can travel by foot. Thus, we cannot just observe an increasing inequality between households, but rather a polarization of households, especially in economic terms. Here, we understand polarization as a division of the household population into opposing factions (Random House Kernerman Webster's College Dictionary, Random House, 2010).

Analysts mainly argue that polarization is driven by changes in the economic settings, which include a) a rising monetization due to the change from camel to truck transport and b) the self-reinforcing effect of heterogeneities in household's assets. Based on household survey data of the High Plateau in Eastern Morocco, Mahdi (2007) points out that the ability to invest into motorized mobility is one crucial factor that determines whether households succeed in pastoralism or succumb, despite the spatio-temporal environmental variability that is characteristic for drylands. Likewise, Bourbouze et al. (2009) refer to the decades from 1950 on as "the era of the truck" in which "flocks belonging to the big farmers are transported by truck and take over the area to the detriment of smaller flocks." (Bourbouze et al., 2009, p. 250).

However, even though these empirical observations indicate reasons for polarization, the exact mechanisms and influencing factors that determine polarization processes are not well understood. In this study, we consider polarization as social-ecological phenomenon and aim at a closer examination of its economic, ecological, climatic and demographic driving factors and mechanisms. Here, household behavior plays an essential role, as individual decisions of the households depend both on the resources available to the household (e.g. its monetary resources), as well as the resources provided by the ecosystem (e.g. pasture biomass). Household behavior therefore provides a social-ecological feedback mechanism between the household's assets and the underlying resource use system and is also a driving factor of polarization.

Simulation models are an powerful tool to disentangle the effect of such different influence factors. We specifically use a multi-agent simulation model in order to identify the main drivers of polarization between pastoralists. Agent-based models allow us to incorporate, explicitly, the micro-level decision making of the individual pastoral households. This enables us to represent households with their behavior and assets, to account for their feedback with the utilized natural resources (here: pastures) as well as to explore their joint emergent behavior on a macro or systems level (Holland, 1992).

Agent-based modeling has proven to be useful in generating new insights in the context of pastoralism. Okayasu et al. (2010), for instance, use a multi-agent model to determine a mechanism that allows coexistence of wealthy and poor herders in a mobile pastoralist system in Mongolia. In a model of communal livestock production in South Africa, Rasch et al. (2016) investigate the effect of a social norm on the stability of the system and the emergence of cooperation between agents.

We develop a spatially explicit, multi-agent simulation model that represents the dynamics of households and feedbacks between them, their livestock and the pastures. The development of the model is guided by qualitative empirical knowledge of the High Plateau in Eastern Morocco. We use this model in an explorative way, i.e. as a "virtual lab" (Seppelt et al., 2009; Zurell et al., 2010), as we do not intend to give quantitative predictions. The model is, rather, intended as a tool of thinking that allows us to identify key determinants and to make qualitative statements. Using the model, we address the following questions:

1. Under which conditions can a heterogeneous initial distribution of assets between households lead to polarization?

2. To what extent can ecological settings and their impact already be a cause for polarization?

3. How do climate change and demographic change affect the risk of polarization?

Our study is structured as follows: in the next section we introduce the developed agent-based model as well as the simulation experiments that we conduct and the outcome measures that we use. We will then present the results, in correspondence to the three formulated research questions. The final section discusses the results and draws conclusions.

3.3 METHODS

In the following, we describe the model in a structured form, based on the ODD+D protocol (Müller et al., 2013).

3.3.1 *Model purpose and background*

The model depicts a common property natural resource use system in which households can use their assets to raise livestock as their source of income. The biophysical properties of the model, i.e. precipitation, vegetation growth and the spatial configuration of the pastures, are represented in a stylized form but approximate the conditions of the High Plateau in Eastern Morocco, which we use an empirical example to guide the model development. The aim of this model is to understand how polarization can occur in such a system, i.e. a split of the households into opposing groups with respect to their livestock and monetary resources. Specifically, we want to analyze whether and how economic, ecological, demographic or climatic factors can lead to such polarization.

3.3.2 *Entities, state variables and scales*

Here, we describe the main model entities and state variables. An overview about all state variables is given in Table 3.1 and a conceptual diagram of the model entities and their relationships is shown in Fig. 3.1.

HOUSEHOLDS H AND LIVESTOCK L There is a single type of agents, each representing a pastoralist household H. There are N_H households in the system. Households are characterized by two main assets: the livestock L that it owns and its monetary resources M. Each household possesses one herd of sheep from which it can generate income by selling animals, which accumulates monetary resources M. From his monetary resources M, each household has to cover living costs C_{living} and potentially mobility costs $C_{mobility}$ to relocate their herds. Each household starts with an initial herd of size L_{init} and initial monetary resources M_{init}. Livestock L graze on the vegetation that is provided by pastures. Fodder uptake per animal and year is given as a fixed amount of biomass *intake* needed, and livestock reproduces with a fixed deterministic birth rate b.

PASTURES P The basic spatial unit of the common property natural resource used is a pasture P which is represented in the model as a hexagonal patch with a size of 400 ha. A series

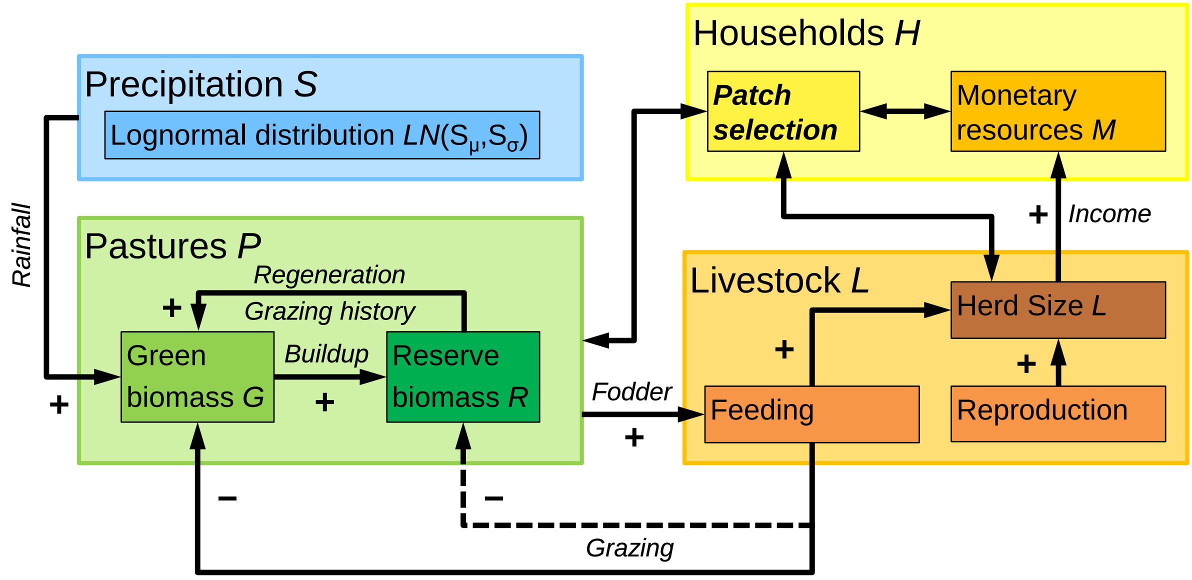


FIGURE 3.1.: Conceptual diagram of the model showing the entities (households H, livestock L, pastures P and precipitation S) and their relationships. Plus/minus signs (+/-) indicate the type of feedback between the different model elements. Double-sided arrows going from/to 'Patch selection' indicate that there is an influence in both directions, which can be positive or negative.

of these patches is laid out on a grid to form the virtual landscape (see Fig. 3.2a) upon which households H can move with their livestock L and have access to. The distances between patches follow an exponential model that is based on empirical observations (Kreuer, private communication, see Fig. 3.2b): next neighbor patches are assumed to be within walking distance, whereas patches further away usually require some means of transport, e.g. trucks, and therefore cause mobility costs $C_{mobility}$.

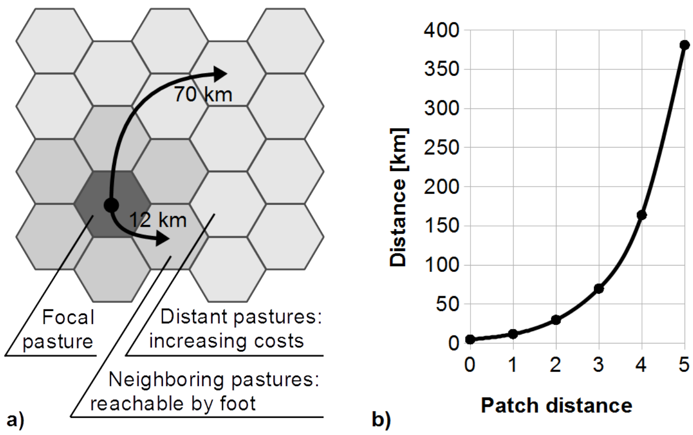


FIGURE 3.2.: Spatial layout of the model. a) Virtual landscape and b) exponential relationship of patch distances to distances in km.

Each pasture patch P contains vegetation which is modeled by two functional parts: green biomass G, which comprises all photosynthetic active plant parts and serves as the main fodder for the livestock, and reserve biomass R, which summarizes the storage parts of the plant below and above ground.

PRECIPITATION S The most important climatic driver of green biomass growth is precipitation S. Our study area is characterized by a semi-arid climate where rainfall is low on average but highly variable, so that both years of extreme drought as well as above than average rainfall are possible. We use stochastic rainfall and rainfall events are drawn from a lognormal distribution. The model uses discrete annual time steps. We assume a long term perspective with a time horizon T of 200 years as standard value.

TABLE 3.1.: Overview on the set of state variables in the model.

Entity	State variable	Symbol	Unit
Households	Monetary resources	M	[Dh]
Livestock	Herd size	L	[sheep]
Pastures	Green biomass	G	[kg/ha]
	Reserve biomass	R	[kg/ha]
Precipitation	Annual rainfall	S	[mm/a]

3.3.3 *Process overview and scheduling*

In every year, precipitation and subsequent growth of green biomass on each pasture takes place first. After that, livestock reproduces with a fixed birth rate and all households pay their annual living costs. A main process constitutes the pasture selection process that is carried out by each household sequentially, and in random order of the households in each time step. Households try to find a pasture that suits their needs based on the available biomass and distance of the pastures, the current herd size of their livestock and their current monetary resources and movement costs. After the selection has taken place, livestock will feed immediately. At the end of the year, the regeneration of reserve biomass takes place. A complete flow chart of the model processes can be found in Appendix B.

3.3.4 *Individual decision-making*

Household decision making on its resource use is assumed to be bounded rational and to follow a simple decision tree, as depicted in Fig. 3.3. In each time step (year), a household has to pay fixed annual living costs C_{living} at the beginning of the year. In case its monetary resources M drop below zero, the household tries to destock and sell animals, in order to alleviate his debts. However, households will not destock below a critical threshold of livestock L_{crit}, which represents a minimum viable herd size necessary to secure the household's livelihood. If the households monetary resources are then still below zero, it can no longer pay for mobility and is, therefore, restricted to movements to its immediate neighboring patches that are reachable by foot (i.e. that do not cause any costs). Based on his current herd size L and monetary resources M, the available fodder on the pasture patches and associated mobility costs, the household then calculates a suitable best patch on which it relocates its herd for the current year. In case no better patch was found, it will remain on its current patch, e.g. because no other patch has higher fodder availability or because the household cannot afford to move to any other patch. Depending on the available biomass on the patch selected in the end, households might still need to destock and sell animals, which could involve destocking below the critical livestock threshold L_{crit} (otherwise animals would die as they would not find enough fodder). After one household has completed the selection process and livestock feeding has taken place, the next household will act.

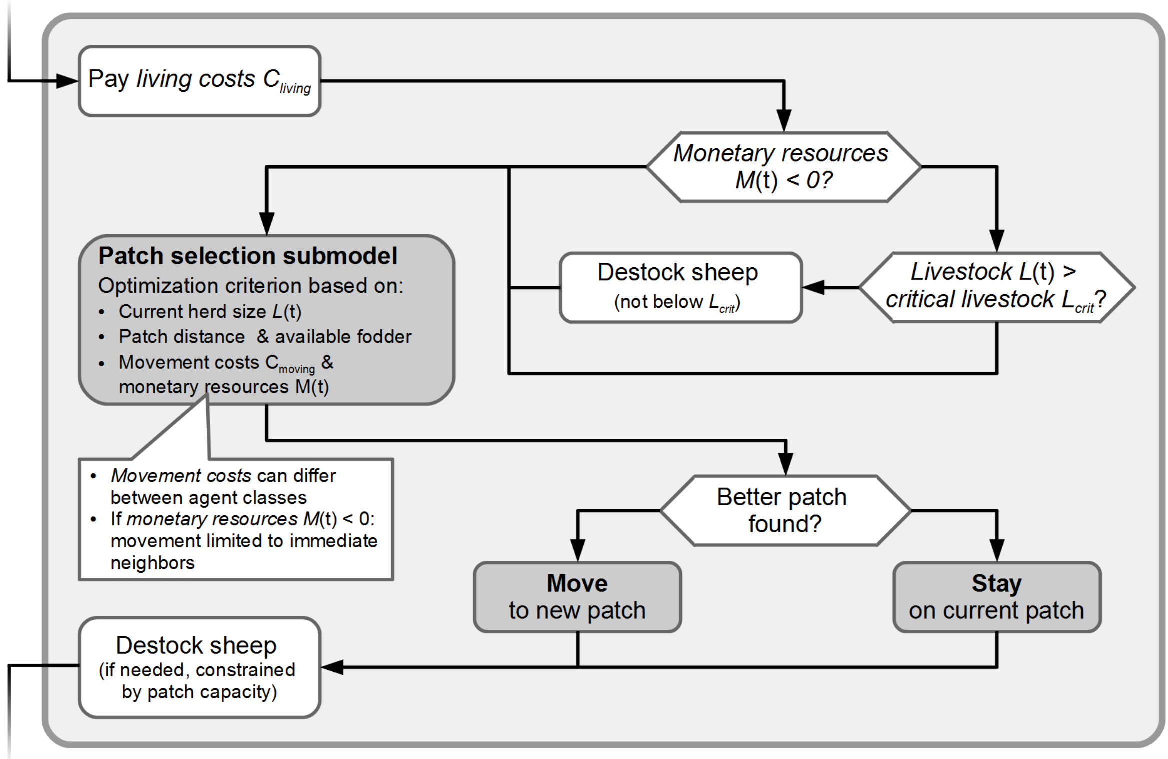


FIGURE 3.3.: Flow chart of the decision process of one household in one time step. Snapshot of the complete model flowchart, indicated by the arrows going in/out of the box.

3.3.5 *Individual sensing, interaction and heterogeneity*

Households sense the state of the vegetation on all pastures, i.e. the amount of available green and reserve biomass. Because agent decision making is sequentially, households sense the actions of other households indirectly by perceiving the grazing state of each pasture when they make their decision. The sensing is not erroneous, i.e. households always perceive the true biomass amounts. Interactions between households are indirect as they perceive the state of the pastures, and therefore the relocation of herds of other households, and can take these into account when deciding where to move. Each household has an individual home pasture to which they return at the end of every year. If we assume two classes of households, each class can vary in their initial conditions of herd size L_{init} or monetary resources M_{init}, as well as in their level of movement costs $C_{mobility}$. Otherwise households are assumed to be homogeneous in their decision making, i.e. all households follow the same decision rules (as described in Section 3.3.4).

3.3.6 *Details*

The model was implemented in C++, using the Qt application framework version 5.5.0 (compiler MinGW 64 5.1.0). The model simulation results have been evaluated using the R Statistical Environment (R Core Team, 2015). An overview about all parameters and their standard values is shown in Table 3.2.

TABLE 3.2.: List of parameters and their standard values. MAD is the international currency code of Moroccan Dirham, 1 Dh ≈ 0.09 €(as of 28.09.2016). If only one group of households H is used, N_H denotes their number. If two groups H_1 and H_2 are used, their numbers are given by $N_{H,1}$ and $N_{H,2}$ respectively.

Parameter	Symbol	Unit	Standard value	Reference
Number of households	N_H ($N_{H,1}$ / $N_{H,2}$)	Unitless	18 (9 / 9)	–
Number of pastures	N_P	Unitless	20	–
Pasture size	*area*	[ha]	400	Fieldwork D. Kreuer
Time horizon	T	years [a]	200	–
Number of simulations	n_{sim}	Unitless	500	–
Mean annual rainfall	S_μ	[mm/a]	200	Linstädter et al. (2013)
Standard deviation of annual rainfall	S_σ	[mm/a]	100	Linstädter et al. (2013)
Biomass growth rate	w	Unitless (rate)	0.8	Dressler et al. (2012)
Rain use efficiency	*rue*	[kg G · (kg R · mm)-1]	0.002	Steinschulte (2011)
Green biomass growth limit, relative to reserve biomass	λ	Unitless (ratio)	0.5	Steinschulte (2011)
Growth limit of reserve biomass	R_{max}	[kg/ha]	1500	Dressler et al. (2012)
Reserve biomass mortality	m	Unitless (rate)	0.05	Dressler et al. (2012)
Grazing harshness on green biomass	gr_1	Unitless (rate)	0.5	Dressler et al. (2012)
Direct grazing take-off rate of reserve biomass	gr_2	Unitless (ratio)	0.1	Dressler et al. (2012)
Initial reserve biomass	R_0	Unitless	0.25 x Rmax	–
Livestock birth rate	b	Unitless (rate)	0.8	Chaarani et al. (2009)
Fodder intake of sheep	*intake*	[kg/a]	640	Lazarev (2008)
Sheep price	P_S	Moroccan Dirham (MAD) [Dh]	500	Chaarani et al. (2009)
Mobility costs	$C_{mobility}$	[Dh/km]	10	Fieldwork D. Kreuer
Annual living costs of households	C_{living}	[Dh/a]	25000	Fieldwork D. Kreuer
Critical herd size	L_{crit}	[sheep]	30	–
Initial herd size	L_{init}	[sheep]	100	–
Initial monetary resources	M_{init}	[Dh]	100000	Müller et al. (2015)

3.3.6.1 *Households*

Each household is characterized by some assets (herd size L, monetary resources M) relevant for decision-making on livestock management and pasture use as well as its current patch location. At the beginning of the simulation, each household is initialized with a distinct pasture patch, which represents its home patch. Households start their patch selection in each year on their home patch. The calculation of mobility costs is therefore always relative to the distance of the selected patch to the household's home patch. Depending on the considered scenarios, households H can either be completely homogeneous, i.e. all households are initialized with the same initial conditions and parameters, or in the heterogeneous case they can belong to one of two groups H_1, H_2, with respective numbers of households $N_{H,1}$, $N_{H,2}$. These groups can then vary either in their initial assets (herd size L_{init} and monetary resources M_{init}) or in their mobility costs $C_{mobility}$.

3.3.6.2 *Vegetation and climate*

The vegetation model is based on the model in Müller et al. (2007a) and Dressler et al. (2012) and captures the main biomass dynamics relevant for the research question. Biomass on each pasture patch is represented as an abstract perennial plant type, characterized by two functional parts: green biomass G and reserve biomass R. In each annual time step t, biomass is modeled using two difference equations:

$$G(t) = G(t-1) + S(t) \times rue \times R(t-1) \text{ with } G(t) \leq \lambda \times R(t-1) \tag{3.1}$$

$$\begin{aligned} R(t+1) = R(t) + w \times \{gr_1 \times (G(t) - G_{over}(t)) + G_{over}(t)\} \times \left(1 - \frac{R(t)}{R_{max}}\right) \\ - \{(m_r + gr_{2,t}) \times R(t)\} \end{aligned} \tag{3.2}$$

Green biomass G represents the main fodder of the animals and is fully available to grazing. Reserve biomass R represents all plant storage parts that can only partly be consumed, and only if green biomass is not sufficient. Reserve biomass buildup depends on green biomass and is controlled by the growth rate w. However, only green biomass that is not consumed, termed green biomass over G_{over}, can contribute fully to the growth of reserve biomass. The effect of grazing is incorporated by two parameters that determine grazing harshness: gr_1 reflects the regeneration capacity of reserve biomass under grazing. If effectively reduces the contribution of grazed green biomass to reserve biomass buildup. The parameter gr_2 determines the part of reserve biomass that can additionally be consumed by the animals. Both parameters can be adjusted to resemble more or less harsh grazing conditions and influence reserve biomass buildup. Thus, reserve biomass is an indicator for the long-term ecological state of the system. The growth of green biomass G, in turn, is driven by reserve biomass R as well as precipitation S. Rainfall values are drawn individually for each pasture from a lognormal distribution LN with a given mean S_μ and standard deviation S_σ.

In this simplified version, spatial heterogeneities related to topography and soil characteristics are not taken into account.

3.3.7 *Simulation experiments and outcome measures*

To systematically analyze under which conditions polarization occurs in our system, we have structured our analysis into three main scenarios. First, we will analyze under which economic conditions polarization between households can occur by analyzing the impact of heterogeneities in their resource endowments and costs for herd mobility. In the second scenario, we will focus on the ecological properties of the underlying vegetation system to determine whether changes in the ecological conditions can also lead to polarization, even if households are completely homogeneous in their resource assets. The third scenario then focuses on the effects of climatic and demographic change. For each of these scenarios, we systematically vary selected parameters that we have listed in Table 3.3.

TABLE 3.3.: List of parameters that have been varied in the different scenarios. Light grey shading indicates parameters that are kept constant under a specific scenario, dark grey shading indicates parameters that have been varied and the range of variation. If heterogeneous household groups are assumed, they are marked with H_1 and H_2, their group size is given by $N_{H,1}$ and $N_{H,2}$, respectively. Otherwise, only H and N_H are used.

Group	Parameters	Scenario			
		1) Impact of household heterogeneities		2) Change of ecological conditions	3) Climate and demographic change
Economic		H_1	H_2	H	
	Initial herd size L_{init} [sheep]	100	5 – 100	100	
	Initial monetary resources M_{init} [Dh]	100000	0 – 100000	100000	
	Mobility costs $C_{mobility}$ [Dh/km]	10	10 – 200	0	
Ecological	Grazing harshness gr_1	0.5		0 – 1	0.5
	Biomass growth rate w	0.8		0 – 1	0.8
Climatic	Mean annual rainfall S_μ [mm/a]	200			10 – 350
	Standard deviation of annual rainfall S_σ [mm/a]	100			0 – 200
Demographic	Number of households N_H	18 ,		18	15 – 20
		$N_{H,1} = 9$	$N_{H,2} = 9$	no classes	no classes

The focus of our analysis lies on the emergence of polarization between household groups in terms of their economic assets, namely livestock and monetary resources. As livestock depends on pasture biomass for feeding, the condition of the pastures is of importance as well. Therefore, as outcome measures three variables are of interest: herd size L and monetary resources M as economic indicators and reserve biomass R as indicator of the ecological state of the system. Based on the two economic indicators, we derive a measure for polarization based on the concept of Esteban et al. (1994), who define a population as polarized if it can be grouped into significantly-sized clusters, where attributes (e.g. income, livestock) of the members within a certain cluster are similar but between clusters dissimilar. Likewise, we define a population of households to be polarized, if households can be grouped into distinct classes based on their herd size and monetary resources. As we have defined a critical threshold of livestock L_{crit} (an indicator for the minimal viable herd size), we define a simple classification based on herd size as follows:

$$Class_L = \begin{cases} s_{zero} & L(T) = 0 \\ s_{crit} & L(t) \leq L_{crit} \\ s_{larger} & L(T) > L_{crit} \end{cases} \tag{3.3}$$

with T indicating the final time step of the simulation. Based on the share of households that fall into these classes, we can calculate a degree of polarization. We have based this measure of polarization on the Herfindahl-Hirschmann index H (Hirschmann 1964) that measures market concentration and the equality of market shares of firms. It is defined as

$$H = \sum_{i=1}^{N} s_i^2 \tag{3.4}$$

where s_i denotes the market share of firm i and N is the number of firms. A normalized version of the index that is scaled between 0 and 1 can be calculated as H^*:

$$H^* = \begin{cases} 1 & N = 1 \\ \frac{H-\frac{1}{N}}{1-\frac{1}{N}} & N > 1 \end{cases} \tag{3.5}$$

A low Herfindahl-Hirschmann index indicates an equal distribution of shares among all firms, whereas a high index corresponds to a maximum concentration around one firm. If we define s_i as the share of households in herd size class i, with $i \in \{s_{zero}, s_{crit}, s_{larger}\}$, and N as the number of observed herd size classes ($N \in \{1, 2, 3\}$), we can calculate the degree of polarization Δ_{pol} as:

$$\Delta_{pol} = 1 - H^* \tag{3.6}$$

$$\Delta_{pol} = 1 - \begin{cases} 1 & N = 1 \\ \dfrac{\left[\left(\frac{|s_{zero}^2|}{N_H}\right)^2 + \left(\frac{|s_{crit}^2|}{N_H}\right)^2 + \left(\frac{|s_{larger}^2|}{N_H}\right)^2\right] - \frac{1}{N}}{1 - \frac{1}{N}} & N > 1 \end{cases} \tag{3.7}$$

3.4 RESULTS

3.4.1 *Basic system dynamics – one random run*

For an overview on the general model dynamics, we present temporal dynamics of the ecological and economic state variables for a baseline parameter set (see Table 3.1) in Fig. 3.4. This scenario represents a moderately dense population of completely homogeneous households. Livestock dynamics show an initial peak around 180 animals (all households start with an initial herd size $L_{init} = 100$), followed by a decline to an average level L_μ of approximately 75 animals. However, even though average livestock does not change after this initial spinup phase of ca. 60 years, individual herd sizes of a given household can still fluctuate between years, as a result of the current climatic (amount of rainfall) and ecological (available pasture biomass) conditions. As households generate income by destocking animals and selling livestock, but only have to pay constant annual living costs C_{living} (no mobility costs under baseline conditions), monetary resources M_μ steadily increase for all households and reach quite high numbers. Reserve biomass R_μ starts at an intermediate level ($\approx 450kg/ha$) and then slowly declines, reaching a level of $250kg/ha$ on average at the end of the simulation. This decline is similar to the qualitative course of livestock, and reflects the grazing state of the system – as reserve biomass represents the storage parts of the plants and its buildup is mainly driven by green biomass, it is an indicator of the long-term ecological state of the system.

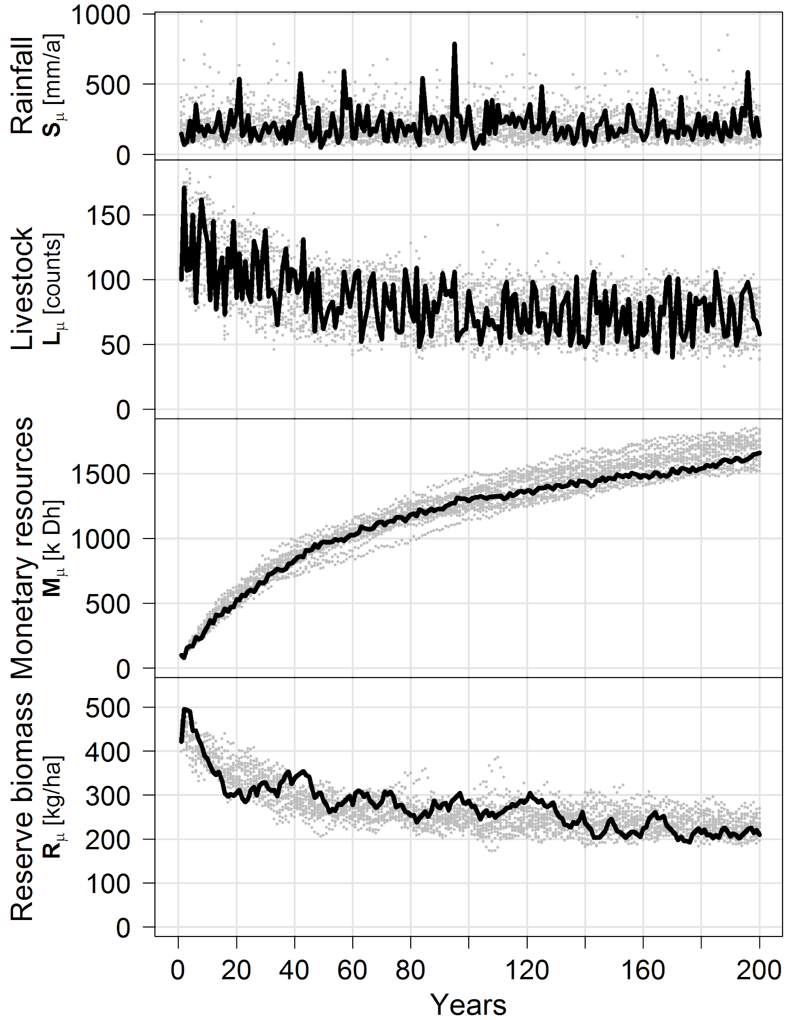


FIGURE 3.4.: Temporal dynamics of a single simulation run for the baseline parameter set. Black bold line highlights one selected household H, respectively pastures P, while grey dots show the results of all households ($N_H = 18$) and pastures.

3.4.2 *Scenario 1: The impact of household heterogeneity*

In a first analysis, we focus on the economic properties of the household and analyze the extent to which differences in initial household endowments (herd size L_{init}, monetary resources M_{init}) and costs for mobility $C_{mobility}$ lead to polarization of households. We have structured this analysis into three steps: first, we consider the dynamics of livestock L and monetary resources M of all households on the level of single simulations, to determine conditions that lead to polarization. Based on these qualitative observations, we propose an analytical calculation to derive whether polarization between households occurs, based on the initial

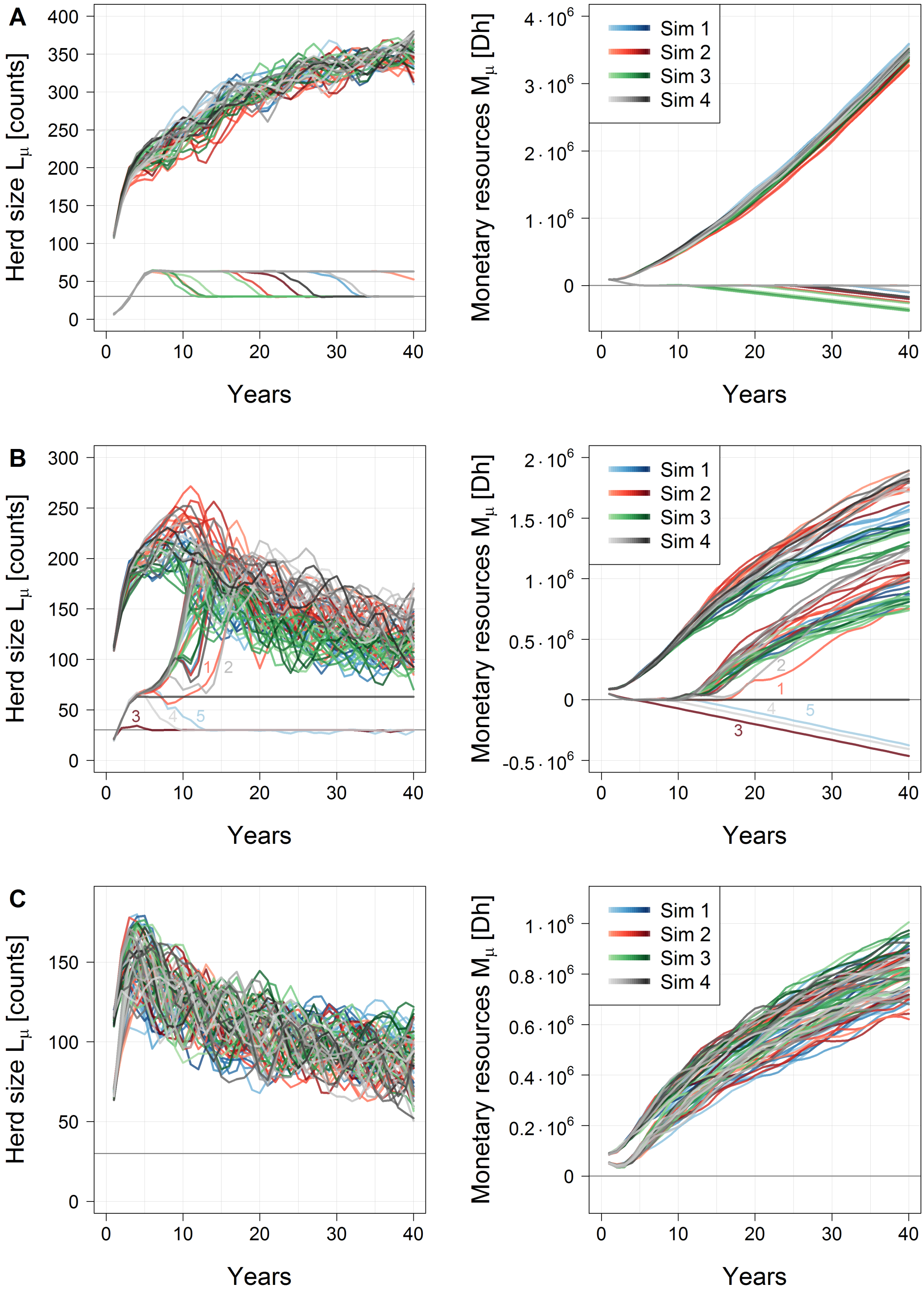


FIGURE 3.5.: Herd size and monetary resources of four exemplary simulation runs. Number of households $N_H = 18$, with $N_{H,1} = N_{H,2} = 9$. Each line corresponds to one household, the shading of the lines has been varied over one color for each simulation. Horizontal lines correspond to L_{crit} (= 30 sheep) and zero monetary resources, respectively. A) Initial herd size $L_{init} = 8$ sheep for household class H_2, initial monetary resources $M_{init} = 91000\,Dh$ for household class H_2 B) $L_{init} = 20$ sheep, $M_{init} = 50000\,Dh$. C) $L_{init} = 60$ sheep, $M_{init} = 60000\,Dh$. For household class H_1, initial conditions are identical in all three scenarios, $L_{init} = 100$ sheep and $M_{init} = 100000\,Dh$.

conditions of the households, and verify this calculation with simulation results. In the third step, we analyze the effect of mobility costs on the extent of polarization.

The population of households is divided into two equally sized groups H_1 and H_2 ($N_{H,1} = N_{H,2} = 9$) that are equipped with different initial herd sizes and mobility costs at the beginning of the simulation. For simplicity, we only varied parameters for one group (H_2), while keeping the parameters of the other group (H_1) fixed with $L_{init} = 100$ sheep and $M_{init} = 100000\,Dh$. In our first analysis, we explored single simulation runs to determine which qualitative patterns can emerge from different combinations of initial herd size L_{init} and monetary resources M_{init}. We have explored a wide range of parameter combinations (see Table 3.3, Scenario 1), but only found three main qualitative patterns that we show in Fig. 3.5. When the initial herd sizes or monetary resources of households in group H_2 are markedly below those in group H_1, we observe that households in group H_2 do not reach the same herd size levels as households in group H_1, but are rather bound to the critical herd size threshold L_{crit} (= 30 sheep), to which their herd size declines, after an initial increase (see Fig. 3.5A). The effect that initializing households with very different initial assets will lead to polarization is not unexpected. However, not all differences in initial conditions do lead to the same splitting effect: In Fig. 3.5B, we see that, in one simulation run, some households of group H_2 are able to increase their herd size to a level above the critical herd size threshold L_{crit}, whereas other households drop down to L_{crit} after 10 to 15 years. When we look at the corresponding course of monetary resources, we see that households which are able to reach a herd size above L_{crit} (Fig. 3.5B, lines 1, 2) have positive monetary resources, i.e. they accumulate savings, while households that drop to L_{crit} (Fig. 3.5B, lines 3, 4, 5) also drop below zero for monetary resources and therefore incur debts. Households with negative monetary resources are restricted to their next neighbor patches for mobility; the results therefore indicate that this mobility restriction is one cause for the occurrence of polarization. Finally, we can observe combinations of initial settings for which no polarization occurs, and in which initial differences are compensated after approximately 10 years (Fig. 3.5C). After this short initial period, both groups are not distinguishable anymore.

Based on these different qualitative behaviors, we want to understand exactly when such a split occurs and therefore we derive an analytical threshold in the following. Given an initial endowment of monetary resources, a household can survive for a given number of years and pay his annual living costs, without the need of destocking animals to make money. However, once households have depleted their initial endowments, they need to earn money from selling (destocking) livestock in order to be able to pay their living costs. Once this point in time is reached, they need to have accumulated a viable herd size, i.e. a herd that produces enough offspring to increase their herd size, taking into account the possibly needed selling of animals to pay living costs. If we assume that initial herd size is rather small so that no destocking needs to take place to match with the pasture capacity and that households do not have to pay costs for mobility, we can calculate herd size L and monetary resources M in year t as follows:

$$L(t) = (1+b)^t \times L_{init} \tag{3.8}$$

$$M(t) = M_{init} - t \times C_{living} \tag{3.9}$$

where b is the deterministic sheep birth rate and C_{living} are the annual living costs. As living costs are constant, we can calculate the year $\hat{t}$ in which households need to have accumulated a viable herd as

$$\hat{t} = \frac{M_{init}}{C_{living}} + 1 \tag{3.10}$$

We can then use Equations 3.8 - 3.10 to formulate the following inequality:

$$\underbrace{(1+b)^{\hat{t}} \times L_{init}}_{\text{Herd size in year } \hat{t}} - \underbrace{\frac{C_{living}}{P_S}}_{\substack{\text{Living costs} \\ \text{(in sheep equivalents)}}} > \underbrace{(1+b)^{\hat{t}-1} \times L_{init}}_{\text{Herd size in year } \hat{t}-1} \tag{3.11}$$

where P_S is the sheep price for selling one sheep. Only if the left hand side of Equation 3.11 is larger than the right hand side, households will be able to increase their herd size and avoid falling back onto the critical herd size L_{crit}. We can now calculate the level of livestock needed in year $\hat{t}$ to reach a viable herd size, which we call the critical initial herd size $\hat{L}_{init}$ as

$$\hat{L}_{init}(\hat{t}) = \frac{\frac{C_{living}}{P_S}}{\left[(1+b)^{\hat{t}} - (1+b)^{\hat{t}-1}\right]} \tag{3.12}$$

Substituting Equation 3.10 into Equation 3.12 yields then the final equation:

$$\hat{L}_{init}(\hat{t}) = \frac{\frac{C_{living}}{P_S}}{\left[(1+b)^{\frac{M_{init}}{C_{living}}+1} - (1+b)^{\frac{M_{init}}{C_{living}}}\right]} \tag{3.13}$$

Given an initial endowment of monetary resources M_{init}, we can use Equation 3.12 to calculate the threshold level of critical initial herd size $\hat{L}_{init}(\hat{t})$, which we have plotted in Fig. 3.6A. To confirm this threshold, we conducted a full parameter variation of initial herd size L_{init} and monetary resources M_{init} using the same setup of household groups H_1 and H_2 as above. In Figure 3.6B, we show the degree of polarization Δ_{pol} between both groups that we have

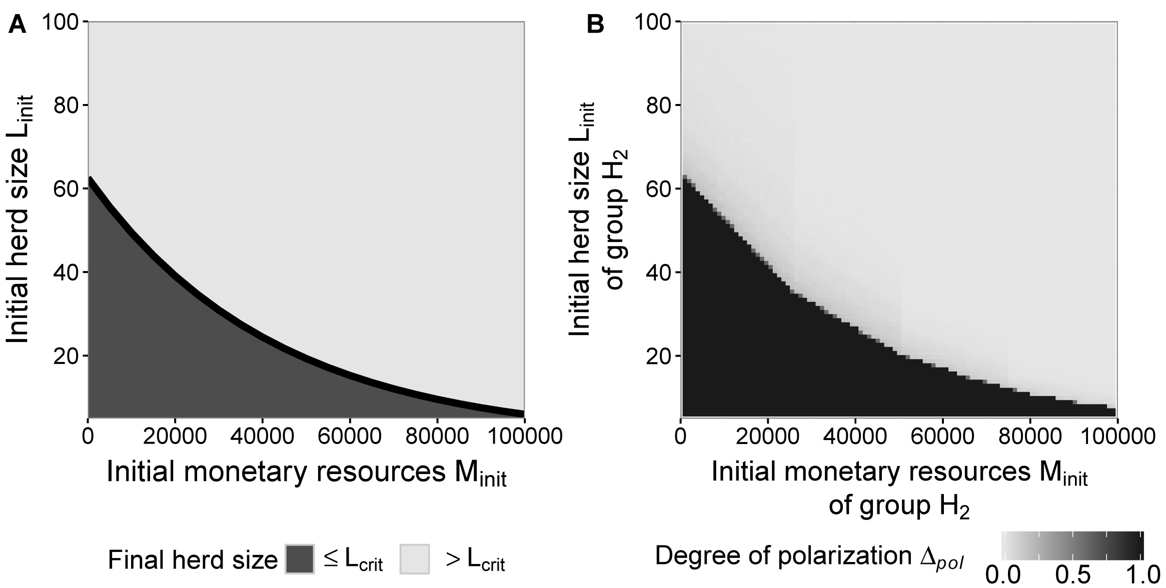


FIGURE 3.6.: Effect of initial conditions (initial monetary resources M_{init}, initial herd size L_{init}) on final state T. A) Analytical threshold $\hat{L}_{init}\left(\hat{t}\right)$, calculated from Eq. (6) (black line). Light shaded area represents all initial conditions for which households reach a herd size above the critical livestock threshold L_{crit}, dark shaded area represents initial conditions for which households fall at or below the critical livestock threshold L_{crit} B) Simulated results: Degree of polarization Δ_{pol} between two household groups (H_1 and H_2), given their initial conditions. For H_1, initial herd size $L_{init} = 100$ sheep and initial monetary resources $M_{init} = 100000\,Dh$.

calculated from the distribution of households over the herd size classes $Class_L$. Here, we can confirm our observations from the qualitative analysis: we can mostly observe two behaviors, either both household groups end with the same level of livestock and no polarization occurs ($\Delta_{pol} = 0$, light grey area) or group H_2 drops to the critical livestock threshold L_{crit}, whereas herd size of H_1 is strictly larger than L_{crit} ($\Delta_{pol} = 1$, dark grey area). Only for some parameter combinations, we observe a pattern similar to Fig. 3.5B, in which not all households of group H_2 drop to L_{crit}, leading to a degree of polarization $0 < \Delta_{pol} < 1$. From multiple simulation runs, however, we have seen that not always the same households suffer from that herd size crash which indicates that not only the rule of restricted mobility can be the cause for the observed polarization, but also other factors need to be analyzed.

In a final step, we analyzed the effect of mobility costs $C_{mobility}$ (see Fig. 3.7). Here, both household groups H_1 and H_2 start with the same level of initial endowments ($L_{init} = 100\,Dh$, $M_{init} = 100000$ sheep). Households in group H_1 have a low level of mobility costs $C_{mobility}$ as we assume these households already have access to a truck and only have to cover variable costs, e.g. for gas. On the other hand, households in group H_2 do not own a truck and therefore have to cover a much higher level of mobility costs that includes fixed costs, e.g. for renting a truck and paying a driver. We vary the level of mobility costs $C_{mobility}$ for group H_2, whereas costs of group H_1 are fixed. Here, we also see that the degree of polarization Δ_{pol} increases with higher mobility costs $C_{mobility}$. However, we never observe a full polarization ($\Delta_{pol} = 1$) where both household groups belong to two different herd size classes, as we have previously seen for the initial conditions. Even for mobility costs $C_{mobility}$ of 200 Dh/km that are twice as high as the average level of mobility costs for households that do not own a truck, Δ_{pol} stays below 1.

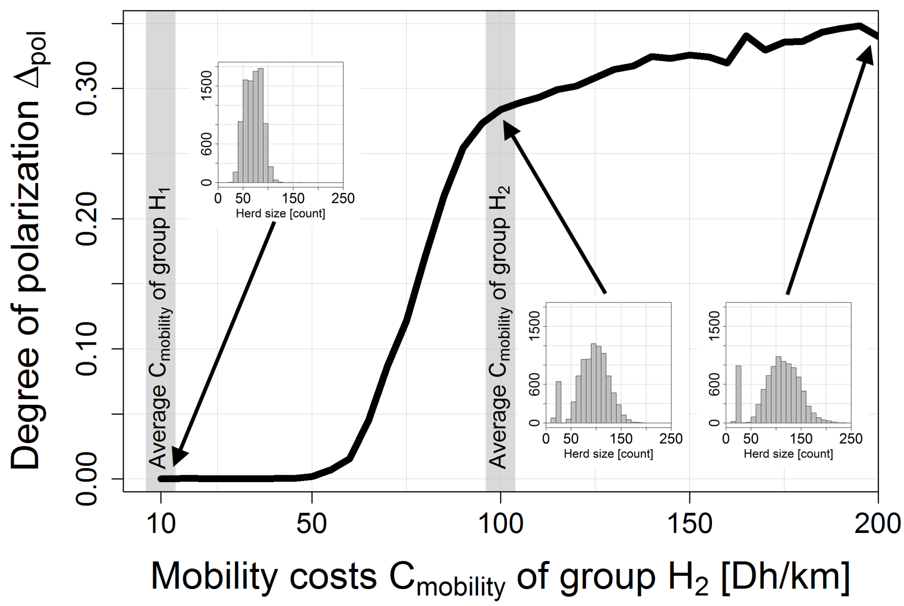


FIGURE 3.7.: Degree of polarization depending on the mobility costs $C_{mobility}$ of the households. Grey shaded areas highlight the average of mobility costs derived from empirical observations for households in groups H_1 and H_2. Whereas group H_1 is assumed to already own a truck and thus only has to pay variable costs (e.g. gas), group H_2 has to pay both variable and fixed costs (e.g. costs for renting or buying a truck). Superimposed histograms depict the herd size distribution over 500 simulation runs for three selected mobility costs $C_{mobility}$ (10 Dh, 100 Dh, 200 Dh).

This is also evident from the observed herd size distributions that we exemplarily added for three different levels of mobility costs $C_{mobility}$ (see the three superimposed histograms in Fig. 3.7): for low costs ($C_{mobility} = 10\,Dh/km$), the distribution of herd sizes exhibits only a single peak, whereas for high costs ($C_{mobility} = 100\,Dh/km$ and $C_{mobility} = 200\,Dh/km$), the distribution has a second, albeit smaller, peak that corresponds to households at or below the critical herd size threshold L_{crit}. From this, we can see that mobility costs do not have an equally strong influence on polarization as initial herd size or monetary resources.

3.4.3 *Scenario 2: A variation of ecological conditions*

We have seen that heterogeneities between households – in initial conditions as well as costs for mobility – can cause polarization. In this section, we explore whether differences in the ecological conditions of the system, such as an altered growth rate of the vegetation (w) or an increased grazing harshness (gr_1), can also lead to polarization, even when households are completely homogeneous in their properties. This means that all households start with the same initial herd size L_{init} and the same amount of monetary resources M_{init}. Furthermore, we assume that mobility costs $C_{mobility}$ are zero; hence distances between pastures do not play a role. We first focus on the effect of grazing harshness gr_1, which reflects the regeneration capacity of the reserve biomass under grazing: It determines the share of grazed green biomass that can still contribute to reserve biomass buildup as the time till complete grazing is sufficient for photosynthesis (i.e. a higher value of gr_1 signifies a lower grazing harshness).

In Fig. 3.8, we compare the effect of three different values of grazing harshness gr_1 on the three outcome measures livestock L, monetary resources M and reserve biomass R. Under a moderate grazing harshness ($gr_1 = 0.5$), we see that no polarization occurs as only one level for average herd size L_μ ($\approx$ 75 sheep) and monetary resources M_μ ($\approx 2000\,k\,Dh$) emerges. Already a slight increase of the grazing harshness ($gr_1 = 0.4$) reveals a different course: until $t = 75$ years, both livestock L_μ and monetary resources M_μ decline steadily (besides a small peak of M_μ at $t = 25$). At this point, a split into two groups occurs. The first group's herd size collapses at the critical livestock level L_{crit} and its monetary resources decline below zero. Contrary to that, herd size and monetary resources of the second group increases tremendously, reaching peak herd size levels of $L_\mu = 480$. This polarization cannot be explained by differences in household properties, as all households are identical in their properties.

Under more severe grazing conditions (grazing harshness), biomass regeneration is impeded, which leads to a strong degradation of pastures – when comparing reserve biomass for $gr_1 = 0.4$ and $gr_1 = 0.5$, we see that it was only half of the amount at $t = 75$. This, in turn, affects herd sizes and monetary resources, as less sheep can be kept on the pastures and, thus, the income of households by selling animals declined as well. If then a household's monetary resources fall below zero, their mobility is limited to next neighbor patches and in each year they will destock and sell animals, as they try to reduce their debts. This leads to an effective reduction of grazing harshness and therewith to a recovery of biomass (R_μ increased from 125 kg/ha to 1300 kg/ha), from which all other households were able to benefit. However, which households fall into the group with critical (≤ 30) or larger (> 30) herd sizes was not determined by initial conditions. For an even further increase of grazing harshness ($gr_1 = 0.3$), the system broke down almost completely, evident from the extremely low level of reserve biomass R_μ. Under these conditions, we could even observe households that completely lost their herd, i.e. $L(T) = 0$. Polarization of households into two groups could be observed as well under these settings, however, households that fall into the group with higher livestock numbers at the end were also not able to accumulate a significant amount of livestock, with $L(T) < L_{crit}$.

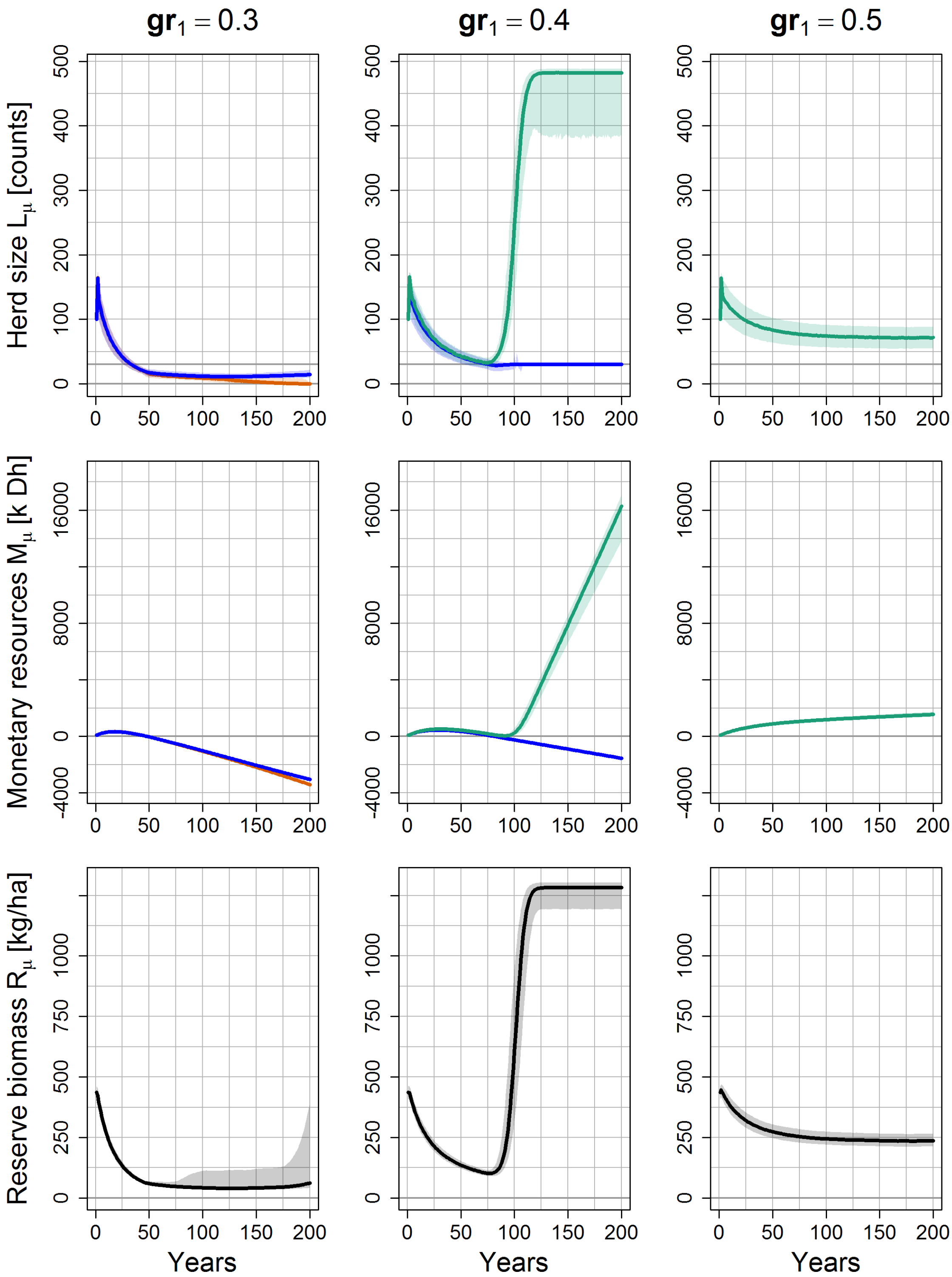


FIGURE 3.8.: Occurrence of polarization in dependence on the grazing harshness gr_1. For mean herd size L_μ and mean monetary resource M_μ results have been grouped according to the herd size classes $Class_L$ at the end of the simulation ($t = 200$), i.e. s_{zero} ($= 0$, red), $s_{critical}$ ($\leq L_{crit} = 30$, blue), larger ($> L_{crit}$, green). Shaded area represents upside/downside standard deviation σ_{up} / σ_{down} around the calculated means.

In a second step, we carried out a sensitivity analysis for two ecological parameters simultaneously: The growth rate w that reflects the recovery of reserve biomass based on green biomass and the grazing harshness gr_1 that we have just explored exemplarily (see Fig. 3.9). We could observe distinct areas of parameter combinations for which no polarization occurs: for ecosystems with fast growing plant types or where grazing has little impact, households were always able to achieve herd sizes above the critical livestock threshold L_{crit} (top right triangle of Fig. 3.9). In contrast, for a biomass growth rate $w < 0.15$, households were unable to accumulate any livestock, independent of the grazing harshness. Under such harsh ecological conditions, pastoralism is not viable. In between these two extremes, we observed two cases of polarization: for a large parameter range, a split into household groups with either zero or critical herd sizes occurred, whereas only for a rather narrow band of parameter combinations polarization took place between households stuck at the critical level of livestock L_{crit} and households above that level (compare large versus narrow dark grey shaded areas in Fig. 3.9). Both these areas are separated by a likewise narrow band of no polarization where all households belong to the critical herd size class.

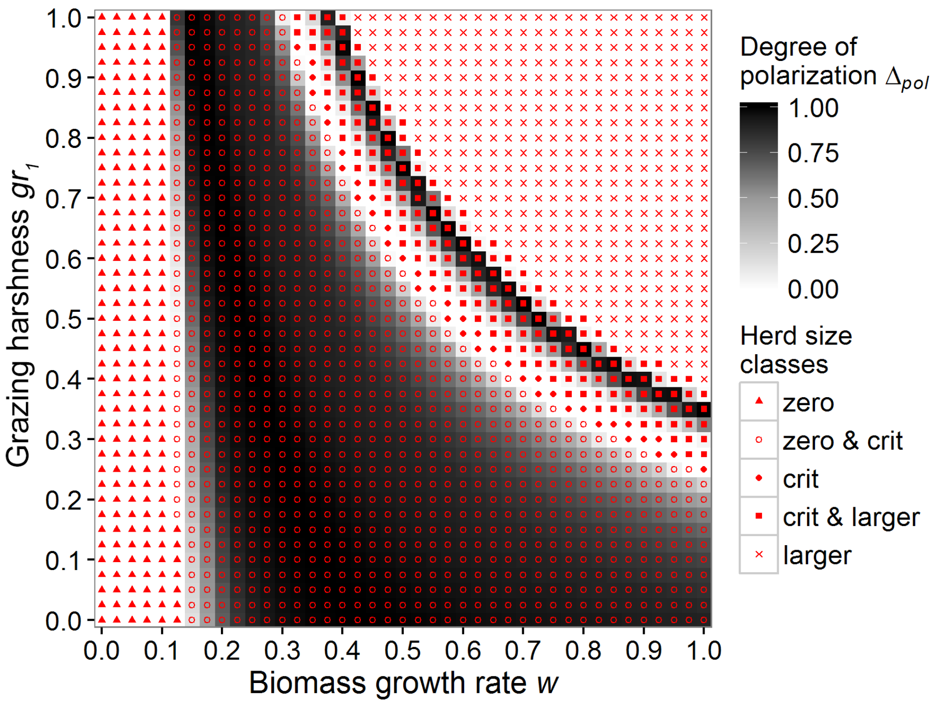


FIGURE 3.9.: Degree of polarization Δ_{pol} in dependence on biomass growth rate w and grazing harshness gr_1. The greyscale shading depicts the degree of polarization Δ_{pol}, with $\Delta_{pol} = 0$ representing no polarization (a single herd size class) and $\Delta_{pol} = 1$ representing full polarization of households into two groups. The superimposed symbols depict the herd size classes that occur for each parameter combination, i.e. s_{zero} $(= 0)$, $s_{critical}$ $(\leq L_{crit} = 30)$, larger $(> L_{crit})$. There can either be a single class or two classes occurring simultaneously.

3.4.4 *Scenario 3: The influence of climate and demographic change*

In the final scenario, we explored two different processes of change: demographic change, depicted in a changing number N_H of households in the system, and climate change, expressed in a variation of the rainfall pattern. We conducted a similar sensitivity analysis as in the preceding section for mean rainfall S_μ and standard deviation S_σ, for three different initial numbers of households N_H (see Fig. 3.10). Also in this analysis, we could observe two parameter ranges in which polarization occurs, bordered and separated by a range of no polarization. In general, higher mean rainfall leads to improved conditions for the households (i.e. less households in lower herd size classes). For a given amount of rainfall, however, an increase in rainfall variability led to a higher chance of polarization occurring, e.g. increasing rainfall variability by $50\,mm/a$ in the standard scenario ($N_H = 18$ and $S_\mu = 200\,mm/a$, Fig. 3.10, middle panel) already pushed the system into a highly polarized state. A similar effect was caused by a change in the number of households N_H. An increase ($N_H = 20$, Fig. 3.10, bottom panel) caused polarization to occur at climatic conditions that were not prone to polarization before. A decrease ($N_H = 16$, Fig. 3.10, top panel), on the other hand, had the opposite effect, as expected.

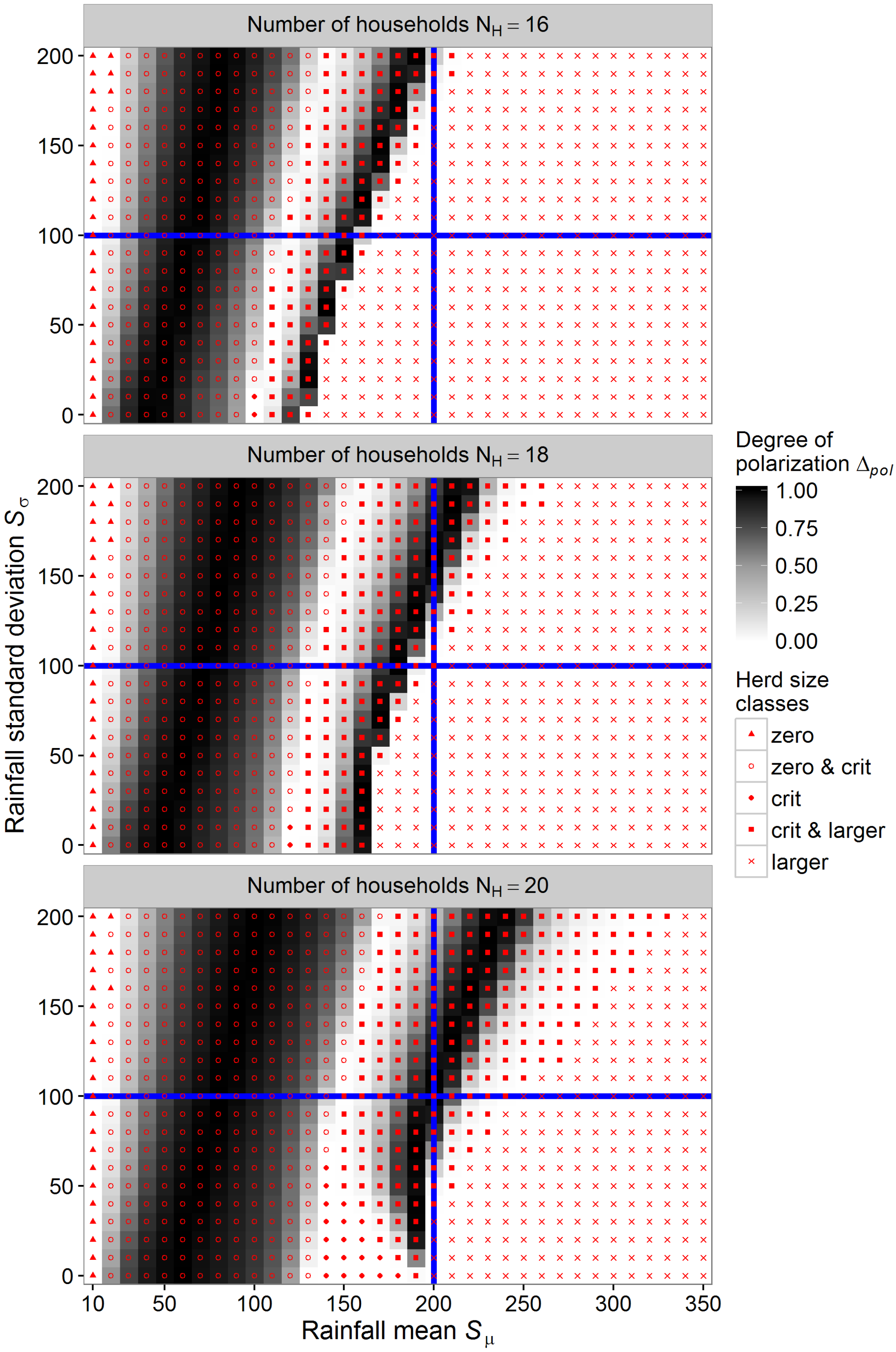


FIGURE 3.10.: Degree of polarization Δ_{pol} depending on climatic and demographic conditions. Each panel corresponds to one value for number of households N_H. The greyscale shading depicts the degree of polarization Δ_{pol}, with $\Delta_{pol} = 0$ representing no polarization (a single herd size class) and $\Delta_{pol} = 1$ representing full polarization of households into two groups. Standard rainfall parameters ($S_\mu = 200\,mm/a$, $S_\sigma = 100\,mm/a$) are highlighted with blue lines. The superimposed symbols depict the herd size classes that occur for each parameter combination.

3.5 DISCUSSION

3.5.1 *Causes for polarization are manifold*

In our study, we have shown that polarization between households can stem from different sources (see Fig. 3.11). In the following, we will discuss these sources with respect to our case study, the High Plateau in Eastern Morocco, and draw some implications for pastoral systems in general. We have seen that not only differences in household's assets, such as livestock or monetary resources, or the advantage of having lower mobility costs for households that own a truck to move their herd, can lead to a polarization between households. Independent of household characteristics, changes in ecological, climatic and demographic settings can also drive polarization. This shows that the occurrence of polarization has to be considered as social-ecological phenomenon. However, whereas differences in initial conditions of households allow it to predict which households end in which herd size class (see Section 3.5.2), given that polarization occurs, this is not possible for conditions that are inherent to the biophysical system (see Section 3.5.3).

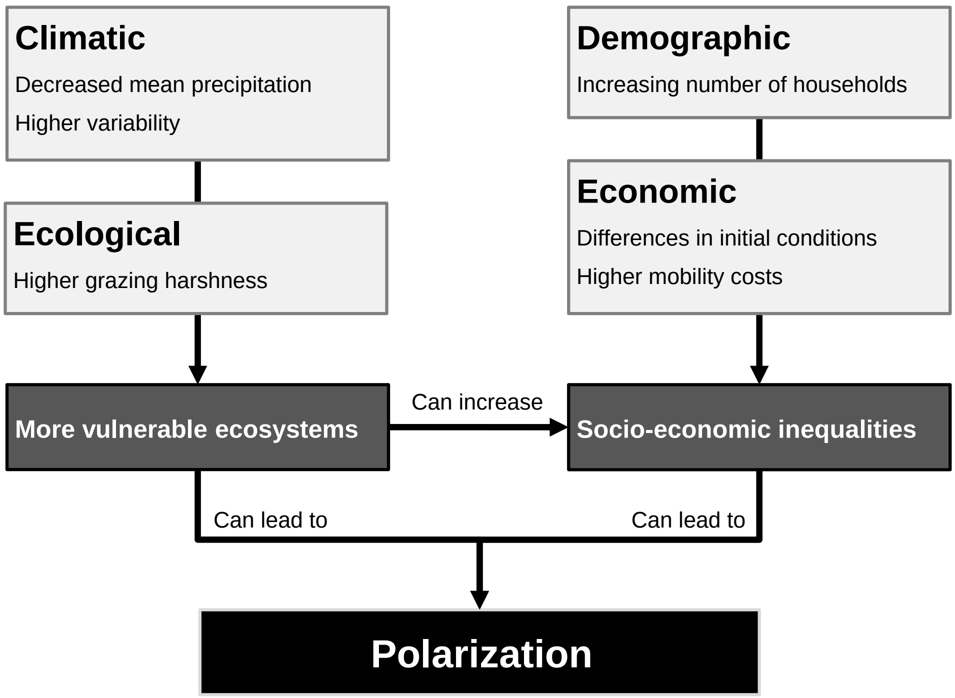


FIGURE 3.11.: Mechanisms that can lead to polarization.

3.5.2 *Differences in household assets can lead to poverty traps*

A variation of the initial conditions of households showed that large differences in resource assets between households can lead to polarization. In particular, we showed that reaching a viable herd size, i.e. a herd size that is able to produce enough offspring to increase or maintain the current herd size, while taking into account the need to cover household living costs. Reaching such a level is necessary to be able to stay above the critical livestock threshold L_{crit} in the long term. The importance to maintain a certain minimum herd size in order to avoid poverty is stated e.g. by Toth (2015) who identifies a poverty trap threshold of about

5 TLU[1] per household member, based on empirical data from pastoralists in Northern Kenya. Households which fall below that threshold are unable to engage in mobile pastoralism, and in turn generate a lower income. The role of mobility is also emphasized in our model, as we have included a threshold for household mobility : if a household's monetary resources fall below zero, herd relocation is restricted to next neighbor patches that are reachable by foot. This restriction was found to be a crucial factor to explain the occurrence of polarization in the model. However, such a model assumption can be empirically justified: from empirical observations we see that distances of herd movement are significantly different between poor and wealthy households. A household survey by Kreuer (2011) in Eastern Morocco shows that, when comparing the lower and upper quartile of herd owners (with respect to herd size), only 1% of the smallest herd owners possess a truck, while 58% of the largest herd owners do. Also, Breuer (2007) shows an empirical relationship between herd size and distance of herd displacement (see Fig. 3.12), which further supports our assumption.

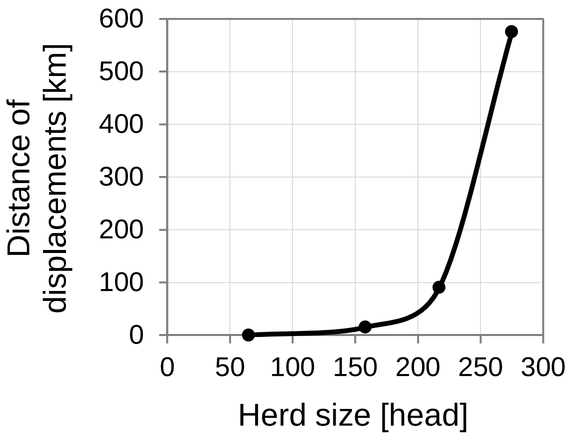


FIGURE 3.12.: Relationship between herd size and distance of herd displacement of the Ait Oussikis Nomads, High Atlas Mountains, Morocco. Data taken from Breuer (2007).

From a critical viewpoint, the effect that large differences in household's initial conditions can lead to polarization might not be too surprising. However, differences in household's assets might not just be attributed to initial settings. A household that suffers an immense shock, e.g. a herd disease or a loss of work force due to illness or death of household members, can also experience a sudden loss of their assets. If such a shock is too large, the household might not be able to recover and thus end up in a *poverty trap*. We could then ask what magnitude of shocks a household can endure before being trapped in poverty. Here, the derivation of an analytical threshold, although simplistic, represents a step towards an indicator to determine the fate of a household: to some extent, such an indicator can be used to predict whether households are more likely to end in a poverty trap or not, given their endowments.

Whereas illnesses or the death of livestock are shocks that hit households individually, another frequent type of shock are droughts that affect the livelihood of households on a larger scale. However, Martin et al. (2016), who assess livelihood security in the face of drought for transhumant pastoralist households in the High Atlas Mountains, Morocco, find that drought by itself is often not the main driver to threaten livelihood security. Instead, household characteristics such as income needs or the choice of a mobility strategy have a much more profound impact on household vulnerability.

1 TLU = Tropical Livestock Unit, 1 TLU is equivalent to 10 sheep.

3.5.3 *Ecological conditions by themselves can trigger polarization*

Whereas the effect of household heterogeneity leading to polarization might not come as a big surprise, the profound influence of ecological system conditions was rather striking. Here, initial conditions did not determine which household would emerge on a high or critical livestock level, as all households had the same properties. From our analysis of biomass growth rate and grazing harshness, however, we have seen that within a certain parameter range already small changes in parameter values can lead to polarization: the transition from an ecosystem that is able to provide enough fodder for all herds present, and one where polarization between households stuck at the critical herd size level L_{crit} and others with larger herds, resembles a tipping point behavior. At this point, the fate of a household is rather dependent on stochastic effects: on the one hand side, rainfall variability on each pasture leads to differences in fodder availability. On the other hand, the order in which households select pastures is randomized in each time step, so that households that move first have a wider range of pastures to select from, compared to households that move last. Of course, these stochastic processes operate as well under different system conditions; however, their effect becomes important here in particular, as the change in ecological settings leads to a higher risk of pasture degradation. Thus, the degradation of the natural resources represents a source for economic polarization of the households.

The parameter changes that we have analyzed can have several reasons: a decrease of the growth rate could for example be caused by a change in plant composition due to land use or climate change. Grazing harshness, which is inherently a property of the ecological system and describes the regeneration capacity of the biomass under grazing, can also be influenced by land tenure regimes: traditional land management strategies such as the *agdal* (Dominguez et al., 2012), for example, guarantee a resting of pastures at the beginning of the season, where newly grown green biomass can contribute to reserve biomass regeneration. However, the importance of such traditional regimes is fading, and new pastoralists entering the system tend to violate access rules (Fernández-Giménez, 2000; Ruttan et al., 1999), which increases the grazing harshness on these pastures. These findings indicate that a social-ecological perspective is indispensable to obtain a comprehensive understanding of the driving forces of polarization.

3.5.4 *Global change increases the danger of polarization*

Changes in demographic and climatic conditions have also shown to be factors that can cause polarization. More harsh climatic conditions are very likely for dryland regions (Paeth et al., 2009). In our model, decreasing levels of mean annual precipitation and a higher precipitation variability could both enhance the risk of polarization. Here, we could observe a similar tipping point behavior as before with the ecological conditions, i.e. the transition from no polarization to full polarization into two groups of households with either large herds or herds stuck at L_{crit}. This sensitivity towards climatic conditions has also been found in previous studies. Martin et al. (2014), for instance, showed that income of pastoralists is highly sensitive to decreasing mean annual precipitation, and higher income needs can further shift the limit of tolerable climate change of the households.

Many of these regions are also experiencing demographic transformations, such as the Borana pastoralists in Ethiopia (Homann et al., 2008) or the Kenyan Maasai (Lamprey et al., 2004). Here, population growth challenges traditional pastoral land management and the livelihood of the households. In our model, the number of households present in the system effectively determines the pressure of grazing: if the household population becomes too dense, pastures get used quasi continuously, without ensuring sufficient periods of resting. Such resting periods, however, are important; especially in order to ensure the buildup of reserve biomass which acts as a buffer for future vegetation growth (Quaas et al., 2007).

In order to cope with the effects of change, households need to adopt suitable livelihood strategies. An adequate level of mobility, for instance, is seen as an effective strategy for pastoralists to use pastures and secure their livelihood, especially to compensate the effects of climatic variability (Martin et al., 2014) and grazing pressure on the pastures (Dressler et al., 2012). However, as we have seen in our study, mobility now often comes with a cost (e.g. for buying/renting a truck) that many households struggle to pay. This limits their mobility options and, thus, challenges their livelihood security.

3.5.5 *The potential and limits of agent-based modeling to understand causes for polarization*

Our approach to understand causes for polarization in a pastoralist system was to use an agent-based social-ecological simulation model. Using this technique offers several advantages: the agent perspective enabled us to observe results both on a household level as well as on a population level, which made it possible to not only observe the degree of polarization in the household population, but also which households end in which herd size class. Varying specific parameters allowed us to identify which processes and mechanisms cause polarization, i.e. the variation of household properties versus ecological, climatic and demographic conditions. Specifically, by assuming completely homogeneous households and no mobility costs, we could turn off the impact of spatial processes and initial conditions and thus show the unexpected result that also ecological conditions alone can be a trigger for polarization.

In our current model version, we assumed a couple of simplifications: 1) Annual living costs of households are constant, and we assume that households are always able to pay them, thus creating the possibility for debts. Even though in our model selling livestock represents the only source of income, in reality households try to diversify their income sources in order to avoid a debt situation. Therefore, we implicitly assume that households would cover their living costs from a different income source, or through borrowing money from relatives or neighbors. In the study area in Eastern Morocco, for instance, households draw on private loans for about one fifth of their larger investments (Kreuer, private communication). 2) The sharp threshold for mobility of households is another simplifying assumption that we have already empirically justified in Section 3.5.3.

In a future model version, we could relax some of these assumptions, e.g. we could introduce dynamic living costs that increase with herd size and also limit the amount of debts that a household can make. The mobility threshold which is a binary rule depending on the monetary resources of the household could be transformed into a stochastic rule: households that fall below zero monetary resources have a lower probability to be mobile than households above that threshold. Also, the range of mobility could be flexible instead of only allowing the nearest neighborhood patches.

However, already with a simple model we were able to identify several mechanisms that can lead to polarization between pastoralist households (see Fig. 3.11). On the one hand side differences in economic properties of the households or an increase in population density can lead to socio-economic inequalities. But also changes in ecological conditions or the impact of climate change can enhance the vulnerability of the ecosystem, which increases the pressure on the ecosystem, and thus also creates inequalities that can finally lead to polarization.

4

IMPLICATIONS OF BEHAVIORAL CHANGE ON THE SOCIAL, ECOLOGICAL AND ECONOMIC DIMENSIONS OF PASTORAL SYSTEMS: LESSONS FROM AN ABM

4.1 ABSTRACT

In many dryland regions, traditional pastoral land use strategies are subject to change. Drivers such as demographic change, but also social change (liberalization of markets, new income options) may lead to an adjustment of livelihood strategies of pastoral households. This may come along with a change in the pastoralists' attitudes towards livestock, pasture condition as well as social norms and influences.

In order to provide a better understanding of the social-ecological consequences of such behavioral changes (e.g. giving up a social norm), we have developed a multi-agent simulation model. This model captures feedbacks between pastures, livestock and household livelihood in a common property grazing system. To clarify implications of behavioral changes, we have implemented three stylized household behavioral types which are grounded in social theory and reflect empirical observations. The three behavioral models have been systematically compared regarding their long-term social-ecological consequences. These household types differ in their preferences for livestock, how they value social norms concerning pasture resting and how they are influenced by the behavior of others. By comparatively assessing populations of households which differ in their numbers and composition of household types (behavioral mono-cultures vs. mixtures), we have simulated various scenarios of demographic and behavioral change.

Our simulation results show that, under the traditional household type that abides to a social norm on pasture resting, pasture condition can be maintained provided the overall number of households does not exceed a critical threshold. Contrary, a loss of social norms for resting may lead to pasture degradation and hence to decreasing livestock number in the long-term. However, a change towards a new household type that constrains its herd size aspiration level in the course of diversifying his income sources can lead to improved pasture and livestock conditions even under higher household density. We conclude that changes in household behavior can drastically alter the long-term social-ecological system dynamics and need to be considered to achieve sustainable land use in common property systems.

4.2 INTRODUCTION

About 40% of the world's surface is covered by drylands (UNCCD, 2010) that provide the livelihood for about two billion people. Rainfall in these regions is low on average and highly fluctuating, which in turn limits the growth of vegetation on which pastoralist households rely to feed their animals. In these resource-scarce regions, sustainable and adapted natural resource use has evolved. Pastoralism is a main way of life that allows households to cope with the characteristic environmental variability in dry rangelands (Krätli et al., 2013). Pastoralism is most often the only relevant way of food production in marginal lands (Reid et al., 2014), as it is better adapted to the climate than crop farming or mixed agriculture.

However, to avoid pasture degradation, appropriate grazing strategies are needed. Therefore, most pastoral communities have agreed upon rules for the use of their common land (Reid et al., 2014). Pasture resting is one important component of those rules and in place since centuries. Resting has become a social norm in (formal or informal) regulations, such as the declaration of specific areas as drought reserves in Namibia (Müller et al., 2007b) or pasture access regimes like the Agdal in Morocco (Dominguez et al., 2012). However, in many regions, such traditional norms are at stake as a result of various transition processes ongoing in these regions in the last decades. Liberalization trends since the 1980s have led to an opening of national economies and markets, giving rise to the privatization of land and property (Gertel, 2015), but also to a change in the economic orientation of many pastoral households. The creation of de facto private grazing land can have negative side-effects for the viability of pastoral resource use and livelihood strategies (McCarthy et al., 2004), for instance when land originally reserved as drought reserve is not available to pastoralists anymore. In Morocco, for example, formerly collective land shared by one ethnic lineage (*Walf*) is getting increasingly appropriated as pastoralist households start to claim certain areas as their homeland, effectively converting their right of use into property rights (Kreuer, 2011). Alongside this economic transformation, many countries are undergoing serious demographic transitions that also affect rangeland territories. In Ethiopia, for example, population growth in the Borana region has led to an increase in settlements around deep wells that provide water for animals and households, in a zone traditionally reserved for dry season grazing (Wario et al., 2016). This increase in population density often comes along with an expansion of agricultural land into former grazing areas, resulting in a growing scarcity of pastures for the herds (McPeak et al., 2015). This trend, however, is not restricted to Ethiopia alone and Brottem et al. (2014) even argue that agricultural expansion into former herding areas is the single greatest threat to pastoralism in West Africa. Together, these changes increasingly challenge the livelihood of pastoralists.

Pastoralists' strategies traditionally valued livestock as a symbol of wealth and aimed at large herd sizes. However, in the course of the economic liberalization, customary institutions and regulations are increasingly losing their influence as households adapt their land use and livelihood strategies: on the one hand, they turn towards a higher profit orientation, which comes along with an intensification of livestock production. On the other hand, a diversification of economic activities is used to spread the risk of relying on a single income source. Here, especially labor migration – to bigger cities as well as international – plays an important role to support the households and provide financial resources (Calkins, 2009). This change in household's livelihood strategies, in turn, affects livestock and pasture conditions in an unknown way, since the interdependence of household behavior and its impact on land use sustainability is complex and not well understood.

One way to explore functioning and implications of particularly relevant behavioral strategies is to use a simulation model that captures the dynamics and feedbacks between pastures, livestock and household livelihood in a virtual lab approach (Zurell et al., 2010). In the context of models, especially in land use science, human behavior is often not considered or only in a simplified manner. Crooks et al. (2008) state that the implementation of decision models is often ad hoc and rarely grounded in theory. In a recent quantitative review of 134 agent-based models (ABMs) from land use science, Groeneveld et al. (2017) underpin this statement. They found that the submodels for human decision-making in the majority of models are not explicitly based on a theory. The single most often used theory is Expected Utility Theory.

Thus, agents are assumed to be selfish rational actors (often referred to as *Homo economicus*) who maximize their personal utility based on stable preferences, perfect knowledge and unlimited cognitive abilities that allow them to always determine the optimal decision (Monroe, 2001). This model, however, is often far away from reality as humans rarely act fully rational, they have limited cognitive abilities and often rely on simple heuristics to make decisions (Gigerenzer et al., 1996; Levine et al., 2015). Furthermore, most of these models that are based on the *Homo economicus* completely ignore the social dimension of human decision-making such as social learning, imitation or norms (Levine et al., 2015). This study aims to fill the gap. We develop a multi-agent social-ecological simulation model of a common property rangeland system in which households follow a certain behavioral strategy to choose pastures on which they relocate, feed and breed their herds. We consider three household behavioral types, which are grounded on decision theories, but also reflect important trends that have been observed in different dryland regions (Calkins, 2009; Rachik, 2009; Fernández-Giménez, 2000; Ruttan et al., 1999). The three behavioral types differ in the preferences for livestock, how they value social norms and how they are influenced by the behavior of others. We use the concept of *Descriptive Norms* (Cialdini et al., 1990) to explicitly analyze how household behavior with respect to a norm on pasture resting influences the long-term development of livestock and pasture in a stylized semi-arid common property rangeland system. Using the model, we assess the social-ecological consequences of various scenarios of behavioral and demographic change and address the following research questions:

1. Under which demographic conditions does decision-making matter, i.e. when do the behavioral types lead to the same or to different social-ecological consequences?
2. When can certain behavioral types increase the risk for long-term negative effects such as pasture degradation and livestock loss, and under which conditions might such a collapse be prevailed?
3. What effect does behavioral change have on the long-term social-ecological system dynamics?

To address these questions, we first analyze all three behavioral types separately and then comparatively assess populations of different compositions (behavioral mono-cultures vs. mixtures) of household types to simulate the effect of behavioral change of the pastoral households.

4.3 METHODS

In the following, we describe the multi-agent social-ecological simulation model used in this study in a structured form, based on the ODD+D protocol (Müller et al., 2013). A complete protocol including the description of the submodels can be found in the appendix.

4.3.1 *Model background and purposes*

The aim of the model is to enhance understanding of how human decision-making is influencing the long-term development of livestock numbers, pasture condition and household livelihood in a stylized semi-arid pastoral system. Special interest is in the extent to which a behavioral change in the household's decision-making can drive the system into a degraded state or, respectively, can counteract such a development. We want to gain principle mechanistic understanding in a virtual lab approach rather than analyzing a specific case study. We assume a common property resource use system, i.e. all households have the same access rights to all pastures. Each household raises one herd of livestock. Pastures provide a limited amount of biomass so that households need to move around with their livestock in order to feed them and to let them reproduce. The biophysical dynamics in the model, i.e. rainfall and vegetation growth on the pasture, are kept very simple, as the main focus lies on the household's decision-making and its interplay with the ecological system components. The vegetation model is based on the model of Müller et al. (2007a) and Dressler et al. (2012), a detailed description of the vegetation model can be found in Appendix C.1. The behavioral strategies of the households are based on economic and psychological theories that are described in detail in Section 4.3.4.

4.3.2 *Entities, state variables and scales*

Agents represent pastoralist households H. Each household is characterized by the number of livestock L that it owns, its current location and the behavioral strategy B that it follows. The modeled landscape is represented as a grid of 10 x 10 = 100 pasture patches P. Each patch has a size of 100 ha such that the total landscape has an extent of 10.000 ha. Each pasture patch contains vegetation that is modeled by two functional parts: green biomass G and reserve biomass R. Green biomass G comprises all photosynthetically active parts of the plants and represents the main fodder for the livestock. Reserve biomass R summarizes the storage parts of the plants below and above ground, e.g. roots or woody branches. The most important climatic driver of green biomass growth is precipitation S. We assume a semi-arid climate where rainfall is low on average but highly variable, so that both years of extreme drought as well as above than average rainfall are possible. The model uses discrete time steps. One time step (tick) represents one year. The time horizon T can be set as model parameter, with $T = 100$ years as standard value. A conceptual diagram of the model entities and their relationships is shown in Fig. 4.1.

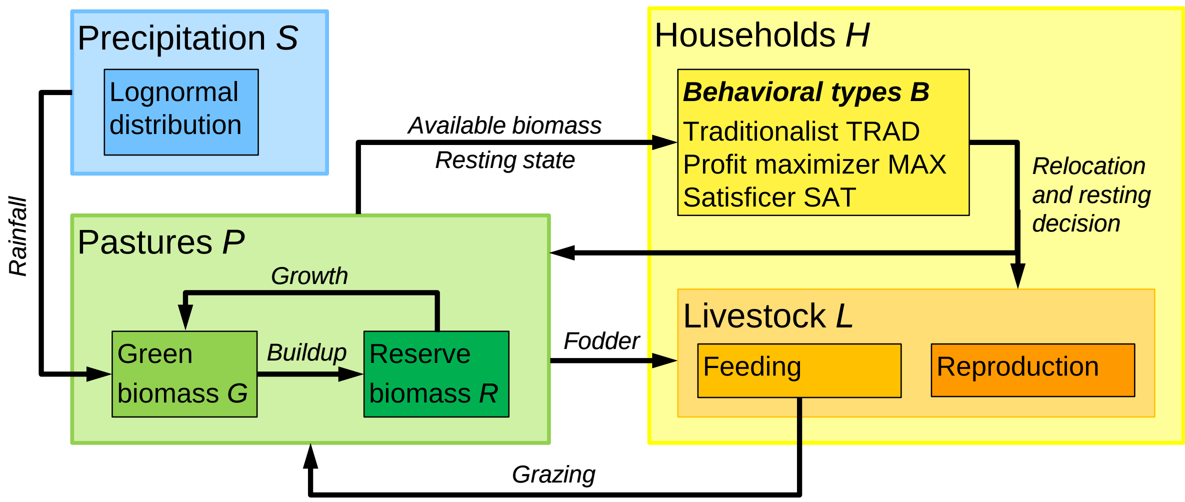


FIGURE 4.1.: Conceptual diagram of the model showing the entities (households H, livestock L, pastures P and precipitation S) and their relationships.

4.3.3 *Process overview and scheduling*

In every year, precipitation and subsequent growth of green biomass on each pasture takes place first. After that, livestock reproduces with a fixed birth rate. A main process carried out in each time step is the pasture selection by the agents. Each agent acts sequentially, whereby the order is determined randomly in each time step. Households try to find a suitable pasture based on their behavioral strategy (described in Section 4.3.4), which considers available biomass and state of the pastures (i.e. rested or not), their current herd size and individual preferences. After a household has selected a suitable pasture, destocking of livestock takes place, if necessary (e.g. due to biomass availability on the selected pasture), and livestock will feed immediately. After that the next household acts. At the end of the year the regeneration of reserve biomass takes place.

4.3.4 *Household behavioral types*

Each household H_i follows a certain behavioral type regarding decision-making B_i that is assigned to it at the beginning of the simulation and does not change in the course of the simulation. We implemented three behavioral types – TRAD, MAX and SAT – that are based on social theories and motivated from empirical observations. To operationalize these theories, we use the MoHuB framework (*Mo*delling *Hu*man *B*ehaviour, Schlüter et al., 2017) that provides a powerful tool to map, describe and compare theories of human decision making and, thus, facilitates their implementation within simulation models. The framework decomposes the decision-making process of an individual actor into several interlinked parts, which are displayed in Fig. 4.2. In the following, we will specify these elements and their implementation in our model.

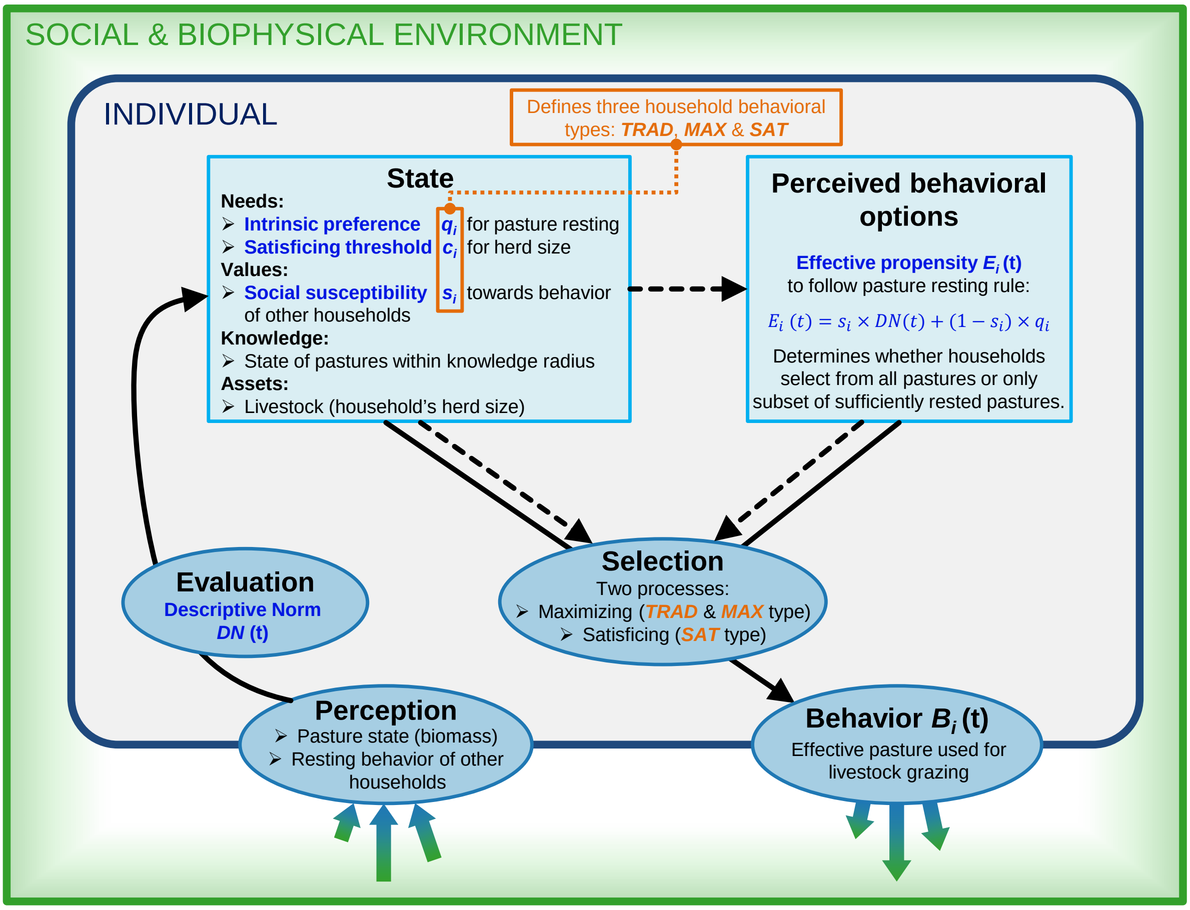


FIGURE 4.2.: Application of the MoHuB framework (Schlüter et al., 2017) for the behavioral types represented in our model. Solid arrows and corresponding ellipses indicate processes, boxes represent structural elements. Dashed arrows represent an influence of one element on another, e.g. the state influencing the set of perceived behavioral options. For more details see main text.

Each household's *state* is characterized by a set of *needs, values, knowledge* and *assets*. Household's needs are characterized by a certain preference for herd size, as it constitutes its main source of income, but also for the state of the pastures: traditionally, households abide to pasture resting to prevent overgrazing and maintain pasture condition. In our model, we assume a simple resting rule based on a resting threshold θ relative to the maximum possible reserve biomass R_{max}: if $R(t) < \theta \times R_{max}$, the pasture is flagged as "resting needed" and, when pasture conditions have improved, this flag will be removed again, while t indicates the time. We assume that households have an own intrinsic preference $q_i \in [0, 1]$ for pasture resting, but are also influenced by the behavior B_i of all households of the previous time step. We define the household's behavior as $B_i(t-1) = 1$, if it abided to the resting rule and only used pastures that were available for grazing, or $B_i(t-1) = 0$, if it ignored this rule. Based on this, we can express the average behavior of all households, i.e. how they actually behave, by a *Descriptive Norm* $DN(t)$ – in contrast to an Injunctive Norm that states how people should behave (Cialdini et al., 1990). Agents perceive the behavior of the other households as well as the state of the pastures, and evaluate the Descriptive Norm $DN(t)$, which is defined in Equation 4.1 as:

$$DN(t) = \frac{1}{N_H} \sum_{i=1}^{N_H} B_i(t-1) \tag{4.1}$$

where N_H is the number of households. Each agent is weighting the importance of its own preferences q_i and the descriptive norm $DN(t)$ by a weighting factor s_i that defines their susceptibility to the resting behavior of other households. Based on this, agents determine their *perceived behavioral options* by calculating their effective propensity $E_i(t)$ (Equation 4.2) to follow the pasture resting rule:

$$E_i(t) = s_i \times DN(t) + (1 - s_i) \times q_i \tag{4.2}$$

This formulation follows the stylized model of Muldoon et al. (2014) who analyze the formation of standing ovations, based on Descriptive Norms. The *selection* of a behavioral option is carried out by one of two processes, maximizing or satisficing, depending on the behavioral type. We consider that households may have different *preferences* for herd size and that they can differ in their *knowledge* about the state of the pastures and their cognitive capacity. The level of livestock that a household aims for is defined as satisficing threshold c_i for each household H_i. If households are assumed to maximize their livestock, then c_i is quasi infinite. Based on these three parameters – intrinsic preference q_i, social influence s_i and satisficing threshold c_i – we define a three dimensional behavioral space $B(q, s, c)$ (visualized in Fig. 4.3) in which we differentiate three types:

1. The traditional behavioral type (TRAD) has a high preference for herd size and tries to maximize his herd size ($c_i = \infty$, but limited by available green biomass as for all behavioral types). A TRAD strategist also has a high intrinsic preference for pasture resting ($q_i = 0.95$) as he follows traditional resting rules. However, we assume that this type is also susceptible to the behavior of others, depicted in a high social influence value ($s_i = 0.8$). Thus, this type aims to select the pasture with the highest available amount of biomass (he is able to perceive the state of all pastures), taking into account the resting state of the pastures and the behavior of the other households.

2. The short term profit maximizer (MAX) is defined as a fully rational actor that maximizes his personal utility. He only has a preference for herd size and, in order to maximize it ($c_i = \infty$), he always selects the pasture with the highest available amount of biomass. As he is a selfish actor and we assume him to be short term thinking, he is not influenced by

the behavior of others ($s_i = 0$) and ignores all resting rules ($q_i = 0$), as this guarantees him the highest current profit. He has perfect knowledge and therefore perceives the state of all pastures.

3. The bounded rational satisficer (SAT) is conceptualized as a conservatively thinking actor with respect to his herd size. He does not aim to maximize his number of livestock but to reach a satisfactory level of livestock ($c_i \in [c_{min}, c_{max}]$), as he covers part of his income from other sources, thus representing an income diversifier. As we assume this type to be bounded in his vision and cognitive capacity, the satisficer only perceives and evaluates a subset of all pastures within a certain radius around himself. Based on this subset, he follows a simple heuristic and selects the first pasture with sufficient available biomass to sustain his livestock. If he cannot find a suitable pasture, he will select the best pasture of that subset and destock his herd. Likewise, if he finds a pasture that allows him to keep more animals than his satisficing threshold c_i, he will not keep more animals and destock any surplus animals. Similar to the MAX actor, he is not influenced by others in his behavior ($s_i = 0$) and does not abide to resting rules ($q_i = 0$).

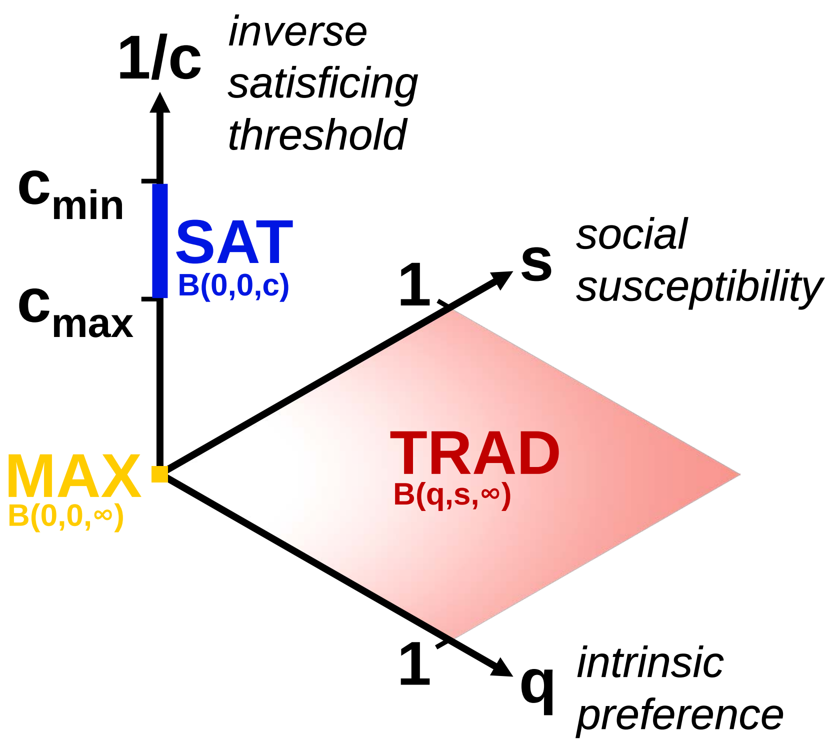


FIGURE 4.3.: Representation of the behavioral strategies along the $(q, s, 1/c)$ axes. The axis of the satisficing threshold c is inverted, so that $c = \infty$ for the MAX and TRAD actor lies in the origin.

4.3.5 *Individual sensing, interaction and heterogeneity*

Households perceive the vegetation state (amount of green and reserve biomass available) of all pastures within a certain radius, depending on their decision behavior (while TRAD and MAX see all patches, SAT is restricted). Because households make their decisions one after the other in a random order, they sense the actions of other households indirectly by perceiving the grazing state of each pasture when they make their decision. The sensing is not erroneous, i.e. households always perceive the true biomass amounts. Interactions between households are indirect via the pasture state. When running scenarios with household populations composed of mixed behavioral types, households differ in their behavior. However, within a single behavioral type, all households behave in the same way.

4.3.6 *Analyzed scenarios and outcome measures*

Our analysis is structured into two parts: In a first step, we consider populations of identical households and analyze how the behavioral types perform with respect to ecological, economic and social output variables. Here, we specifically focus on the influence of demographic change by systematically varying the number of households N_H in the system. In the second step, we simulate populations of households with mixed behavioral types and assess how the mixed populations perform. By varying the composition of the agent population, we can map the conditions of behavioral change. Because we are interested in the long-term sustainability of the system, we run each simulation over a time span of 100 years and then evaluate the final state of the system.

We evaluate the behavioral types across three dimensions of outcomes: As social indicator, we measure the number of households able to stay (i.e. "survive") in the system $N_{H,surviving}$, i.e. households with livestock numbers > 0 at the end of the simulation. The economic indicator is the cumulative herd size over all households L_Σ. Reserve biomass R is the indicator of the ecological state of the system. Here we calculate the average across pastures R_μ.

An overview of the behavioral parameters that we analyze and their values is presented in Table 1. For each parameter combination, we have carried out 100 simulation runs for the analysis of the three individual types and all mixtures based on two behavioral types; 10 simulation runs have been carried out for the mixtures based on all three behavioral types, as here the number of possible behavioral combinations for a given number of households is very large (e.g. 5151 combinations for 100 households).

4.4 RESULTS

In this section, we present the results of the simulation runs. In the first step, we focus on the analysis of single behavioral types, followed by a short comparison of those. As second step, we focus on the mentioned scenarios with different mixtures of behavioral types.

TABLE 4.1.: Overview of the selected behavioral parameters that have been analyzed and their values or ranges. A table of all model parameters can be found in the appendix. R_{max} refers to the maximum reserve biomass per pasture, which is set to 1500 kg/ha.

Parameter	Value / range
Number of timesteps T	100 years
Number of households N_H	$[20, 100]$
Resting threshold θ	$\{0.2, 0.4, 0.6\} \times R_{max}$
Intrinsic preference q_i	0.95
Social influence s_i	0.8
Satisficing threshold c_i	$\{50, 80, \infty\}$ sheep
Share of MAX to TRAD actors δ	$[0, 1]$
Mix of TRAD, MAX and SAT strategies Δ	$\{\%_{TRAD}, \%_{MAX}, \%_{SAT}\}$ with $\%_{TRAD} + \%_{MAX} + \%_{SAT} = 1$

4.4.1 *Analysis of individual household behavioral types*

4.4.1.1 *System dynamics over time*

As first analysis, we present one exemplary simulation run for each behavioral type over 100 years to illustrate the general model dynamics (see Fig. 4.4). The system starts in a completely non-grazed state with 10 animals per household. We see that there is a spin up phase at the beginning of the simulation where livestock accumulates until a maximum is reached after about 5 years, where the carrying capacity of the patches in terms of biomass is reached. MAX and TRAD actors reach a higher livestock peak ($\approx$ 90 animals) than the SAT actor, as they behave as rational optimizers, whereas the SAT actors don't stock more animals than their satisficing threshold $c_i = 80$. After this point, livestock numbers decrease for all three behavioral types as biomass availability is now a limiting factor, apparent from a decline in reserve biomass R_μ. When reserve biomass falls below the resting threshold θ (in this simulation $\theta = 0.4 \times R_{max}$) and pastures are closed off for resting, we can see that some TRAD type households have to leave the system and only 75% of the initial households remain in the system, as they are unable to find a suitable pasture. The MAX type households, on the other hand, do not abide to resting rules, so all households are able to stay in the system. However, not resting the pastures leads to a breakdown of reserve biomass and, consequently, of livestock. The TRAD type households, in contrast, achieve a moderate but stable level of reserve biomass and livestock. The SAT type households do not actively abide to resting rules. However, as they are conservative in their stocking rule and do not put more than 80 animals on a pasture, they indirectly give the pasture the ability to regenerate. Even though reserve biomass and livestock levels drop below the levels of the TRAD household type, they don't collapse as with the MAX household type but level off after 40 years, and even slightly increase afterwards. The number of households that remain in the system declines, too, but not as abrupt as for the TRAD household type, and remains steady at about 80% at the end of the simulation.

4.4.1.2 *The effect of increasing household numbers*

In this section, we investigate all three behavioral strategies separately, depending on the number of households. For this, we assess populations of TRAD $B(0.95, 0.8, \infty)$ – a household type indicating a high preference for resting , MAX $B(0, 0, \infty)$ – a household type which only orients to livestock without abiding to resting rules and the SAT household type, $B(0, 0, \{50, 80\})$, with no preference for resting and which does not aim for a maximum but has a satisfactory level of livestock (see Fig. 4.5). For low initial household densities ($N_H < 45$), we see that for all three household types, all households are able to stay in the system and that the number of total livestock increases, while the level of reserve biomass decreases (considerably for TRAD and MAX, Fig. 4.5C,F; only slightly for SAT, Fig. 4.5I). As household density further increases, pasture condition decreases for all types, and for the TRAD type also depending on the resting threshold θ. The higher this threshold, the sooner pastures need to be rested and the more pastures are not available for grazing at any point in time. This, in turn, results in a constellation where households are not able to find a pasture to feed their animals anymore, such that these households will be forced to exit the system. The higher the resting threshold ($\theta \to 0.6$), the lower is the percentage of households that are able to stay in the system for a given initial household density (see Figure 4A). For the MAX type, $N_{H,surviving}$ is always at 100%. The SAT type, though not abiding to resting rules, shows a different behavior depending on its satisficing threshold: for a threshold of $c_i = 50$ animals, all initially present households are able to survive since small herds do not overuse pastures, whereas for a higher satisficing threshold of $c_i = 80$ animals, the number of surviving households decreases for initial household densities

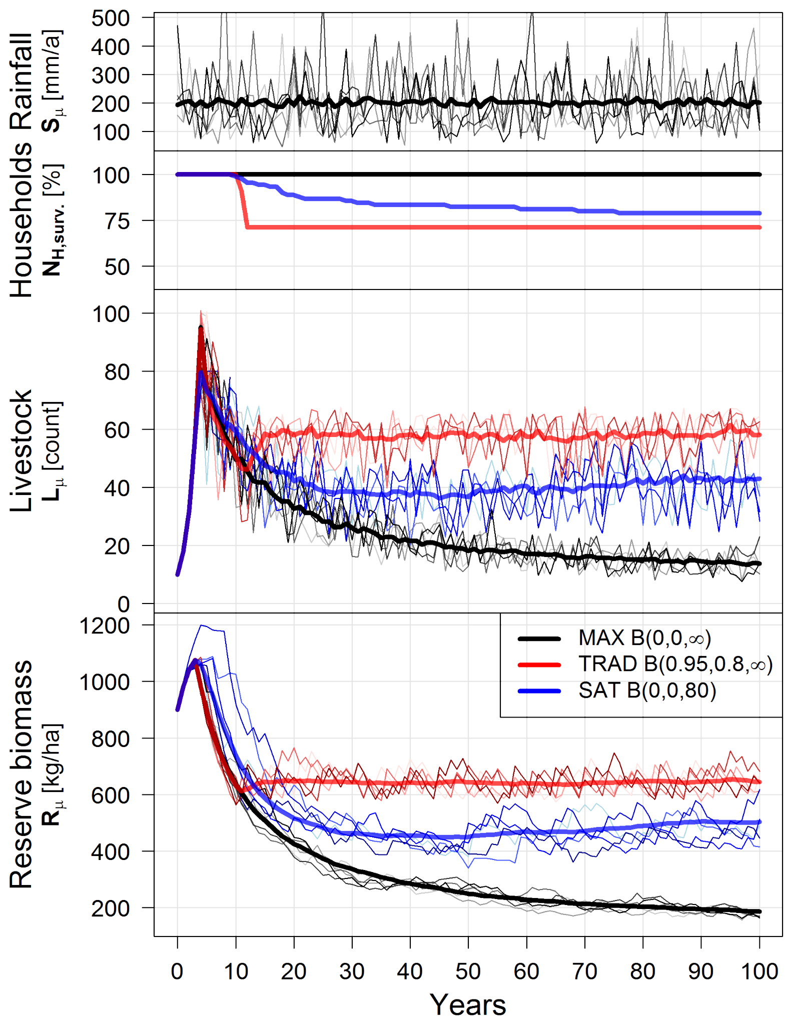


FIGURE 4.4.: Exemplary simulation run over 100 years for all three behavioral types. Panels show rainfall S, the percentage of surviving households $N_{H,surviving}$, herd size L_μ and reserve biomass R_μ. We plot average herd size L_μ here, as we want to highlight the dynamics of single households. For rainfall, reserve biomass and livestock the course of 5 selected patches, respectively households, is plotted (thin lines) with the mean superimposed in bold. The simulation started with 90 initial households, the SAT actor had a satisficing threshold c_i of 80 animals and the TRAD actor an intrinsic preference $q_i = 0.95$ and social need $s_i = 0.8$. The resting threshold θ was set to $0.4 \times R_{max}$.

larger than $N_H = 60$. This is also reflected in the state of the reserve biomass (Fig. 4.5I) which is at a very high level across all initial household densities for $c_i = 50$ animals, whereas for $c_i = 80$ animals it halves (from 1200 kg/ha to 600 kg/ha) for household densities $N_H > 60$.

When we look at the total amount of livestock L_Σ (i.e. the cumulative sum of livestock across all households), we see that the TRAD and MAX type households show a maximum at $N_H = 50$. For N_H approaching 100, both livestock L_Σ (Fig. 4.5E) and reserve biomass R_μ tend to zero (Fig. 4.5F) for the MAX type. The TRAD type household, on the other hand, is able to keep livestock at a stable level for increasing household numbers, depending on the resting threshold θ (Fig. 4.5B), on the expanse of decreasing numbers of households. For the third behavioral type, the SAT type household, the livestock sum curve shows a different shape: for low to medium household densities ($N_H \leq 60$), the SAT households are always able to achieve their satisficing threshold, as can be seen from the linearly increasing livestock sum L_Σ. At $N_H = 60$, the $B(0,0,80)$ type household reaches a peak livestock sum of 4800 heads, after

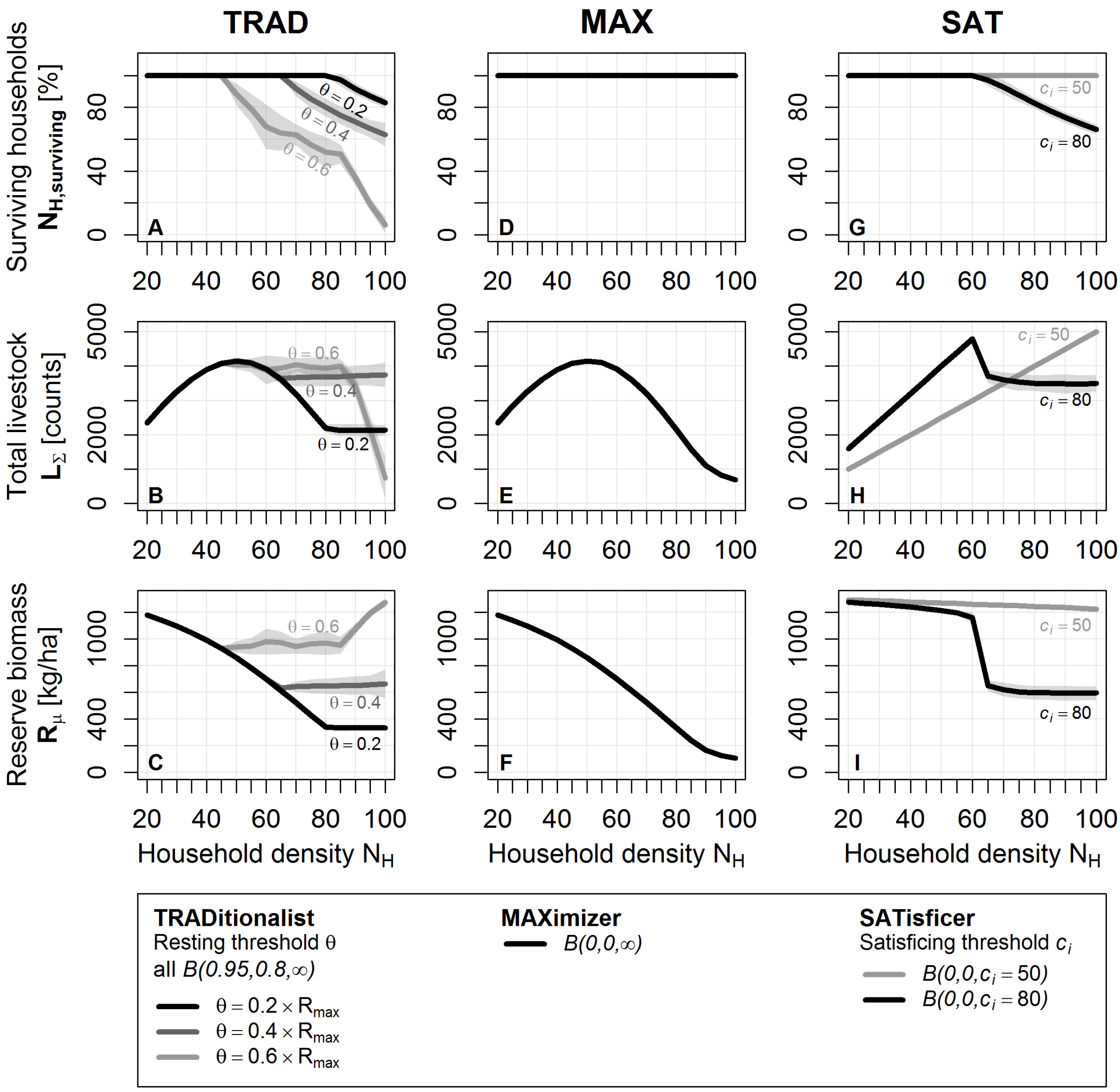


FIGURE 4.5.: Results for TRAD, MAX and SAT type households depending on the initial household density N_H. Lines depict averages across households/patches at the end of the simulation ($t = 200$) and over 100 simulation runs. Shaded area represents two times the standard deviation of the results.

which livestock numbers decrease and then level off. What is striking is that, for the $B(0,0,50)$ type household, cumulative livestock linearly increases up to $N_H = 100$, and beyond an initial household density N_H of 70 households, this strategy reaches a higher cumulative livestock L_Σ than the $B(0,0,80)$ household, and even the highest cumulative livestock compared to all other strategies. This is only possible because of the very conservative stocking approach of this behavioral type, as no household will stock more animals than its satisficing threshold $c_i = 50$.

This analysis has already shown that differences between decision-making become more evident as the number of households increases. Under low to medium numbers of households, especially the TRAD and MAX household types show a similar behavior, as the pasture resources are in a sufficiently good state that the TRAD type is not restricted by its preference for resting, nor does the MAX type overuse pastures in its strive to maximize herd size. For high household densities, all three behavioral types exhibit a very different behavior that is reflected in the different outcomes across the social, economic and ecological analysis dimension.

4.4.2 *Comparison of behavioral mixtures*

4.4.2.1 *Shift from the traditional strategy including pasture resting to pure profit maximization*

We start with populations of N_H households consisting of traditional (TRAD) and short-term profit maximizing (MAX) households. For different initial shares of TRAD and MAX households (where δ describes the share of MAX type households), we have again investigated the economic and ecological output measures at the end of the time span of the analysis (see Fig. 4.6). We have run simulations for two initial household densities, $N_H = 60$ and $N_H = 100$, and the same range of resting thresholds as in the previous analysis (see Fig. 4.6).

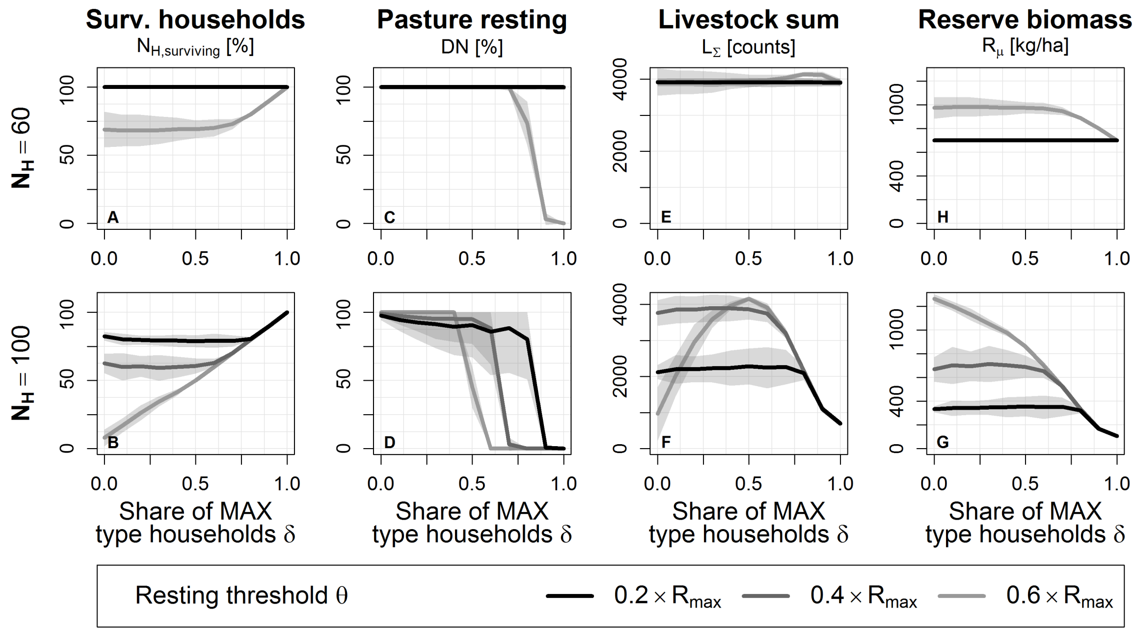


FIGURE 4.6.: Results for a mixed population of TRAD $B(0.95, 0.8, \infty)$ and MAX $B(0, 0, \infty)$ actors for two different initial household densities N_H (top and bottom panel) and three different resting thresholds θ (color-coded lines), depending on the share δ of both strategies. Shaded area represents two times the standard deviation of the results.

We can see that for an increasing share δ of MAX households, the total number of surviving households $N_{H,surviving}$ increases, irrespective of the initial household densities (Fig. 4.6A and B). This is mainly caused by the fact that changing δ from 0 to 1 reflects a shift from a TRAD-dominated to a MAX-dominated population of households: As pastures need to be rested, the TRAD type households that abide to the resting rules have a limited set of pastures available to use, while the MAX type households will use all pastures, thus benefiting from the behavior of the TRAD type households.

For $N_H = 100$ and a high social susceptibility ($s_i = 0.8$), we also see that, once the share δ of MAX households exceeds the threshold of 50%, the presence of resting in the population accounted with the descriptive norm DN drops rapidly from 1 (all households rest the pastures) to 0 (households use all pastures available) (Fig. 4.6D). The increasing share of MAX type households triggers the behavior of the TRAD type households, which either start to follow the majority (because of their high social influence $s_i = 0.8$), or drop out of the system, as they do not find a suitable pasture anymore.

For a medium household density $N_H = 60$, total livestock L_Σ remains at a constant and high level, independent of the share δ of the behavioral types (Fig. 4.6E). Dependent on the resting threshold, the reserve biomass R_μ, is at an intermediate level for $\theta \leq 0.4$. Only for $\theta = 0.6$, R_μ is at a higher level for a share of $\delta \leq 70\%$ MAX type household and decreases afterwards.

For $N_H = 100$, L_Σ is constant for resting thresholds $\theta = 0.2$ and $\theta = 0.4$ at approximately 2000 and 4000 head until a share of $\delta = 0.5$, after which it declines sharply to less than 1000 animals for $\delta = 1.0$ (Fig. 4.6F). Only for a very high resting threshold of $\theta = 0.6$, livestock sum L_Σ is also very low for populations with only TRAD type households. Here, the number of suitable pastures that is available for grazing is so low that it only allows for a very small percentage of the initial 100 households to survive which in turn are not able to accumulate a substantial amount of livestock (even though individually each household has a large herd). Still, the cumulative herd size L_Σ of ≈ 1000 animals for a TRAD type mono-culture population, with about 10% surviving households, is higher than the herd size for a MAX type mono-culture population, where 100% of the households survive, with $L_\Sigma \approx 600$ head (Fig. 4.6F).

4.4.2.2 *Mixture of three household behavioral types: TRAD, MAX and SAT*

In the previous section, we have analyzed how a shift from the traditional household type (TRAD) to a short-term profit oriented maximizer (MAX) would influence the social-ecological behavior of the pastoral system. Now, we extend this analysis by a third dimension by adding the satisficer (SAT) as third behavioral strategy. A household population now consists of a share of households $\Delta = \{\%TRAD, \%MAX, \%SAT\}$ with $\%TRAD + \%MAX + \%SAT = 100\%$. This opens up a large number of possible behavioral combinations for a given number of initial households N_H. Here, we pick the extreme case of a very dense system with 100 initial households. In Fig. 4.7, we present the results for the social, economic and ecological outcome measures in the form of ternary plots, where each axis defines the share of one behavioral type, and each point k of the graph corresponds to one specific share of types Δ_k, e.g. each corner of the triangle corresponds to a pure population of a single behavioral type. We have classified the outcome measures along equally spaced intervals.

As starting point, we choose a population that is close to a TRAD type mono-culture with only a few MAX and SAT type households integrated, which we mark as Δ_A in the plot (the origin of both red arrows). We believe that this mixture reflects the population "how it was" – a stylized case in traditional pastoral communities, i.e. before the onset of change. We can now interpret moving across the space of behavioral mixtures as scenario of behavioral change. We have conducted these simulations for two values of the resting threshold, $\theta = 0.2$ and $\theta = 0.6$ (Fig. 4.7 left and right panel, respectively), for which the plots show qualitatively different pattern.

For a low resting threshold $\theta = 0.2$, we see that no strong qualitative changes occur in a wide area around Δ_A for all three outcome variables. Cumulative livestock L_Σ (Fig. 4.7B1) is at an intermediate level (2000-2500 head) and more than 70% of initial households are able to stay in the system. Reserve biomass R_μ (Fig. 4.7C1), however, remains at a low level as the resting threshold is rather low. Following the trend from Δ_A towards Δ_B reflects the shift from a TRAD type to a MAX type mono-culture population (similar to the results of the previous section). Here, we see that for cumulative livestock L_Σ (Fig. 4.7B1) only an increase of the share $\%_{MAX}$ of MAX type households to more than 75% ($\%_{TRAD} < 20\%$) will lead to a noticeable drop of cumulative livestock below 2000 head. The same decline is apparent for reserve biomass R_μ, with biomass in a very low, quasi degraded, state.

If we now assume an increase in the share $\%_{SAT}$ of SAT type households in the population (i.e. moving towards Δ_C), we see that the state of livestock remains in a range of 2000-2500 head until we reach a share $\%_{SAT}$ of at least 40%. We also see that above $\%_{SAT} \approx 30\%$, the

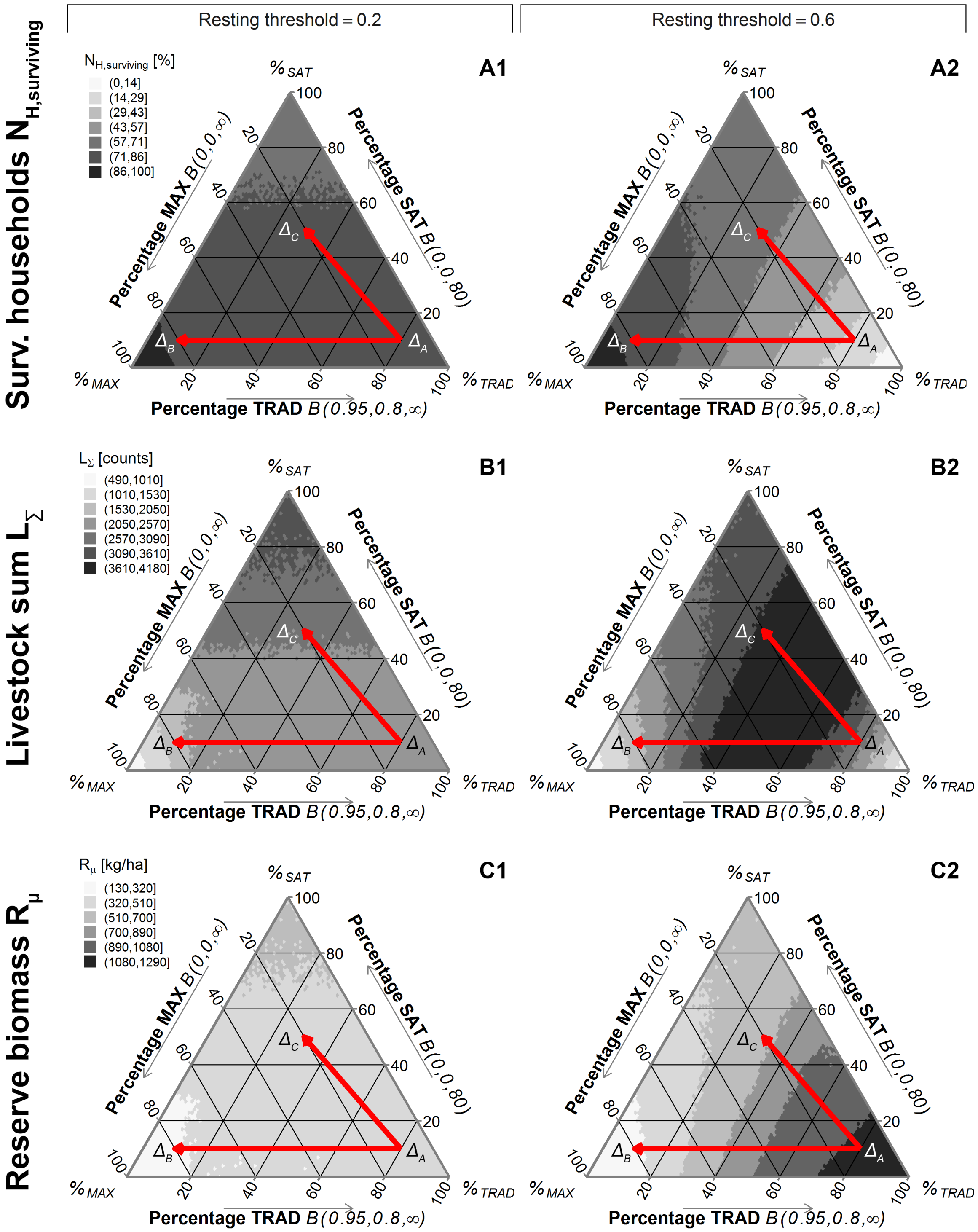


FIGURE 4.7.: Comparison of all three behavioral types TRAD, MAX and SAT. Each axis defines the share of one behavioral type. Results are shown for two values of the resting threshold, $\theta = 0.2$ and $\theta = 0.6$ (left and right panel, respectively). Outcome measures have been classified along equally spaced intervals $\zeta(x)$: for surviving households (A1, A2) $\zeta\left(N_{H,surviving}\right) = 14\%$, for cumulative livestock (B1, B2) $\zeta\left(L_\Sigma\right) = 520$ counts, for reserve biomass (C1, C2) $\zeta\left(R_\mu\right) = 190kg/ha$.

TABLE 4.2.: Comparison of cumulative livestock L_Σ for different shares of TRAD type households, in combination with either only MAX or SAT type households.

Share of TRAD households $\%_{TRAD}$	Cumulative livestock L_Σ MAX households only ($\%_{SAT} = 0\%$)	SAT households only ($\%_{MAX} = 0\%$)
30%	3221	3743 (+16%)
25%	2758	3532 (+28%)
20%	2169	3435 (+58%)

class breaks run parallel to the isolines of $\%_{SAT}$. This indicates that above a certain share of SAT type households, the explicit shares of MAX and TRAD type households have no effect on the level of livestock. Thus, both types are equivalent in their effect, although they behave differently. In other words, a decrease of the share of TRAD type households, even below $\%_{TRAD} = 20\%$, does not lead to a breakdown of livestock. This means that the share of SAT households prevents the system from a collapse. An increase of the share of SAT type households even leads to a noticeable improvement of livestock levels, with L_Σ increasing to over 2500 head for $\%_{SAT} > 40\%$ and to over 3000 head for $\%_{SAT} > 70\%$. This pattern also holds for reserve biomass R_μ (Fig. 4.7C1), however, noticeable improvements are only visible for $\%_{SAT} > 70\%$. Only for the percentage of surviving households $N_{H,surviving}$ (Fig. 4.7A1), a shift towards a SAT type mono-culture leads to a decrease of $N_{H,surviving}$ for $\%_{SAT} > 60\%$.

When we turn to the results for a high resting threshold $\theta = 0.6$, we see that the qualitative pattern changes: In a large range of mixing ratios of behavioral types (all shares with $\%_{TRAD} > 30\%$), the borders between classes of the outcome measures now run parallel to isolines of the share $\%_{TRAD}$ of TRAD type households. Starting again at Δ_A, we see that a TRAD type mono-culture population that abides to the resting rules results in a very good ecological state of the system, with reserve biomass R_μ around 1100 kg/ha (Fig. 4.7C2). However, such a high level of reserve biomass can only be achieved at the expense of livestock and surviving households, which are both at a very low level. Here, we see that a very high resting threshold has a strong effect on the system dynamics: already a slight decrease in the share of TRAD type households to about $\%_{TRAD} \approx 65\%$ leads to a sharp increase of cumulative livestock, as well as an increase in the percentage of surviving households. This, of course, leads to a decrease of reserve biomass, as households that do not abide to resting rules (MAX or SAT types) use pastures not accessed by traditionalist households. What is striking now is that there is a large region of combinations of all three behavioral types that achieve an economic optimum in terms of the highest cumulative livestock L_Σ. For shares of TRAD type households between 70% and 35%, the results are also independent of the shares of MAX and SAT type households in the population. However, as $\%_{TRAD}$ decreases further, we see that breaks between classes do not run in parallel to isolines of $\%_{TRAD}$ anymore but are shifted. In Table 4.2, we compare the level of cumulative livestock for different shares $\%_{TRAD}$ of TRAD type households in combination with a) only MAX and b) only SAT type populations.

We can see that the lower the share of TRAD type households, the higher is the difference between MAX and SAT populations. Thus, an increase in the share of SAT over MAX type households can effectively increase the herd size, when TRAD type households disappear in the system. Though the same pattern holds for reserve biomass as well, levels do not improve as strongly as for cumulative livestock, for the same shift in strategy composition. Only the number of surviving households is not improved for a shift towards SAT type mono-cultures.

4.5 DISCUSSION

4.5.1 *The value of traditional strategies in a changing world*

SHORT SUMMARY With this study, we investigated the influence of the details of the representation of human behavior on the ecological, economic and social dimension of a semi-arid pastoralist system. We implemented three behavioral types that reflect – in a simplified representation – livelihood strategies of pastoralist households as they were in the past (TRAD) and the direction in which they are evolving nowadays (MAX, SAT). We have seen that as long as the household density is moderate and resting is rather weak, the details of the households' behavior do not make a difference for the system's dynamics. With increasing household density and resting intensity, however, the differences in the households' behavior resulted in increasingly different qualitative and quantitative ecological, economic and social outcomes. While the traditional, norm-abiding type (TRAD) ensures the ecological state of the system in regions where population is not too dense, its strategy might fail when household density increases, and households willing to abide to resting rules are not able to find suitable pastures anymore and, thus, are unable to ensure their economic livelihood. Households that shift their strategy towards a short term maximization of profits (MAX), while abandoning traditional resting rules, might be able to ensure their livelihood in the short term. However, insufficient pasture resting is likely to render this strategy as unsustainable over the long term, as pastures degrade and subsequently herd sizes collapse as well. A more conservative stocking approach, as applied by the bounded rational satisficer (SAT), can tolerate larger household densities. A lower stocking level, though, is only realizable if households have some other source of income to satisfy their needs and secure their livelihood. Although these model results are quite bold, there is empirical evidence for them from several regions around the world. In the following, we will therefore underpin our simulation results by linking them to empirical observations.

PEOPLE CHANGE THEIR VALUES Traditionally, pastoralists have always valued livestock, as it constitutes the main asset to secure their livelihood and also represents a status symbol. The use of common property pastures, however, has never been a question of open access. Instead, the management of common property is most often determined on a communal level, and access to pastures has been subject to some sort of coordination (Ruttan et al., 1999). The opening of dry season pastures, for example, is often determined consensually and enforced by community sanctions (Galaty, 1994). However, traditional pastoral strategies are disappearing in many regions, as people change or are forced to change their values. For centuries, pastoralists on the High Plateau in Eastern Morocco have pursued a form of extensive pastoralism that included the relocation of their herds and tents in response to the current climatic conditions. However, this strategy is in decline since the mid of the 20th century (Rachik, 2000). Factors that led to this change include an aggravation of the climatic situation (prolonged droughts) as well as an economic and technical transition, which resulted in the abandonment of the camel in favor of motorized transport and an increased monetarization of the society (Kreuer, 2011). Rachik (2009) documented that the increasing importance of money in the life of pastoralists is changing their attitude: monetary considerations now come before cooperation and charity, as money facilitates anonymous relationships and contributes to the breakdown of community relations based on permanent cooperation (Rachik, 2009). In our model, we have analyzed a strategy that besides aiming at a large herd size traditionally has a high intrinsic preference for pasture resting in order to preserve its state. However, as the strategy also includes a value of social susceptibility, it reflects that herders most often do not act solely on their own choice, but rather in consensus with all other herders that belong to their community. Furthermore, herders often follow grazing decisions of successful individuals in their community (McCabe, 1997). When people gradually change their values, for example adjusting preferences for resting in favor of increasing their own wealth, other pastoralists might follow suit, leading to a) a marginalization of those who still try to stick to the rules and b) a long-term breakdown of the system, as piece by piece resources are overexploited. We could observe this behavior in our model when we simulated household populations with a gradually increasing share of MAX strategists in relation to the TRAD household type: already a small percentage of MAX households that do not abide to the resting rule could lead to TRAD households either changing their behavior (not resting anymore) or losing their herd and exiting the system, as they were unable to find suitably rested pasture. In most communities, such exploiting behavior would be subject to sanctions, which we have not included in the current model version. On the other hand, we could also observe ranges of behavioral mixtures, especially in the analysis of all three behavioral types, in which no substantial changes in the system dynamics took place (provided that the change in behavioral composition does not exceed certain limits/thresholds). Thus, the system also exhibits a certain robustness towards changes in household behavior.

NEW PEOPLE ENTER THE SYSTEM Due to globalization and demographic change, many regions are facing both a growing population as well as the influx of land users from other regions or countries. This leads to a higher competition for the scarce resources provided by the pastures and puts traditional strategies under twofold pressure: as we have seen with our model, a pasture use strategy that works well under low household densities (TRAD) might not be adequate under high household densities, as the aim to preserve the state of the pastures comes into conflict with the aim to secure the household's livelihood. This is for example reflected in Eastern Tibet's Yushu Region, where a more than doubled population since the 1950s has led to an increase in the total livestock number of the region, and more and more pastoralists are left without pasture and will fail to subsist from their shrinking number of livestock (Gruschke, 2011). In our model, population growth – represented by the increase in the number of households – already challenges the TRAD household type. Even though households were still apt to follow the resting rule, they were just incapable of finding a suitable pasture and forded to leave the system. The remaining household population, on the other hand, was able to achieve rather large herd sizes. This effect, however, is rather artificial, as in our model households that were forced to leave the system are not able to come back, whereas in reality the spot of one household would most likely be filled by another household. In addition to population growth, people that newly enter the system can also challenge traditional strategies. A survey amongst herders in two districts in west-central Mongolia revealed that both poor herders and those who became herders only after the privatization of the herding collectives in the 1990s were more likely to violate rights of pasture access and trespass upon other herder's campsites (Fernández-Giménez, 2000). Likewise, herders with less secure rights to pastures – which applies to both poor and new herders – were more likely to graze reserve pastures out of the season. A significant challenge also stems from agricultural expansion into former pastoral grazing grounds that has been observed in many regions (McPeak et al., 2015; Brottem et al., 2014; Ruttan et al., 1999). This may lead to pastoralists being forced to use grazing reserves in times of the year when they should be rested and community elders being unable to enforce traditional sanctions (Ruttan et al., 1999).

With respect to implications for governmental interventions: They should be designed in such a way that they strengthen traditional institutions rather than undermining them. Not without reason, it has been argued that environmental regulations based on traditional custom and sanctioned by community institutions are more likely to be respected than those imposed by external authorities (Ruttan et al., 1999).

A PATH AHEAD – LESSONS FOR PASTORALISM? So far, we have reflected on factors that might challenge the traditional values and livelihood strategies of pastoralists. However, there also exist strategies that can avoid negative effects, as the satisficer household type (SAT) has shown in our model. The main idea behind the SAT household type is that households might reduce the level of livestock that they need to keep by diversifying their income sources. Households with a (reasonably) low satisficing threshold in terms of herd size ensure that pastures are rested, as they reduce the pressure on the pasture. Our simulation results have shown that this strategy can be long-term sustainable, even though households do not directly abide to resting rules. Moreover, from the viewpoint of the whole population of households, the SAT household strategy could tolerate the highest total number of livestock in the system: sacrificing some of the individual household's needs resulted in a collective benefit for all households. There exist several options for pastoralist households to spread their risk of relying on livestock production as single income source, which can be roughly summarized under income diversification. In Tibet, for example, many pastoralists have specialized themselves on the collection of caterpillar fungus, which is very profitable (Gruschke, 2011). However, this also bears the danger of overspecialization and creating a new lock-in, as some households now generate the majority of their income from the collection of the caterpillar fungus. Taking up wage labor outside of pastoralism represents another option of income diversification. Especially labor migration to bigger cities or even abroad has become an important strategy. Calkins (2009), for example, reports in empirical narratives of the Rashâyda pastoralists in Sudan, that especially international labor migration plays an important role to support the families' livelihood at home ("Nomadic pastoral mobility was replaced by international labour migration to the Gulf.", Calkins, 2009, p. 54), and that earnings from labor migration could even facilitate a further diversification.

4.5.2 *The mode of human decision-making matters*

Humans and their behavior represent a key uncertainty for sustainable management; still, most often they have been neglected in the study of natural resources and its management (Fulton et al., 2011). The rising popularity of agent-based modeling that allows the flexible integration of individual decision-making has produced quite a number of studies which represent human decision-making explicitly (Groeneveld et al., 2017, for the field of land use ABMs). However, many implementations of the decision making process are based rather on independent ad-hoc assumptions, and only seldom on behavioral theories that exist in economics, psychology or sociology (Crooks et al., 2008; Groeneveld et al., 2017). In recent years, a rethinking has taken place that argues for an explicit integration of more sophisticated models of human decision-making into formal models of natural resource use, and agent-based models in particular (Schlüter et al., 2017; Crooks et al., 2008; Parker et al., 2003). Especially under the influences of processes such as demographic and social change, assuming the behavior of land users to be fully rational falls short of a realistic representation of human behavior. In this study, we have explicitly posed the question under which demographic conditions decision-making matters for the dynamics of a pastoralist grazing system, and have presented the first social-ecological simulation model (to the author's knowledge) that addresses this question. To adequately represent the decision-making of pastoralist households, we have considered the role of social norms, which are known to be a key element that influence human decision-making. Social norms have been widely studied in the social sciences (e.g. Berkowitz, 1972; Bandura, 1977; Kallgren et al., 2000; Borsari et al., 2003; Goldstein et al., 2008). Descriptive norms (that describe how people behave) have been studied, in particular, for environmentally related problems, e.g., by Schultz et al. (2007) in the context of energy saving behavior, or by Cialdini (2003) on pro-environmental behavior. However, in the context of social-ecological systems, descriptive norms have only rarely been considered (one example being the work of Feola et al., 2010). One reason for this can be attributed to the difficulty of implementing a social science theory such as Descriptive Norms within a dynamic modeling context. Theories often face ambiguities when they are translated into formal equations and model code, and modelers need to make assumptions in order to achieve a functional implementation (Schlüter et al., 2017). Here, frameworks such as MoHuB framework (*MO*delling *HU*man *B*ehavior, Schlüter et al., 2017) aim to facilitate the process of theory selection and operationalization. We have successfully used MoHuB to conceptualize the behavioral types (TRAD, MAX and SAT) in the model. One step in which the framework has been especially useful, was to uncover missing elements within a theory that need to be specified or filled with elements from another theory. Descriptive Norms, for instance, does not specify how the selection process takes place, therefore we integrated two processes, maximizing and satisficing, to fill this gap. However, we have also seen that implementing a behavioral theory is not a straightforward task but rather an iterative process, even for such rather simple behavioral theories. Implementing more complex models of human decision-making therefore requires the stronger involvement of social scientists into the modeling process.

In the end, taking up the methodological challenge of implementing human decision making has proven to be worthwhile, as we could indeed show that the mode of human decision making matters: when population size (expressed in the number of households) increases, the three behavioral types have led to both qualitatively and quantitatively different outcomes on all three dimensions of analysis. Especially the comparative analysis of populations with mixed behavioral types revealed that the negative ecological and economic consequence of a displacement of the traditional household type (TRAD) by a short-term profit maximizer (MAX) can be prevented by the satisficer household type (SAT). With a simplified representation of household decision making we would not have been able to obtain this result.

4.5.3 *Conclusion*

To conclude, we have shown with our study that the way human decision making is represented in ABMs matters. In a very stylized model of a common property grazing system, three different behavioral types have shown very different results, depending on the impact of demographic change. Therefore, simply assuming household's decision making to be homogeneous and rational (i.e. assuming a *Homo economicus*, as many social-ecological models still do), will leave out important details. Thus, we need more social science research in conjunction with ecological research (Ruttan et al., 1999). When researchers try to address social-ecological problems, they should at least think about whether human decision making is relevant for the problem or not. With regard to pastoral systems, we have shown that households might increasingly get under pressure when social and demographic change renders their traditional livelihood strategies as not viable anymore. As households adjust their strategies, policies that aim at enhancing their livelihood should consider the inherent variability of dryland areas that makes some strategies less likely to be successful (e.g. intensification of production). One option that can help to secure household's livelihood lies in income diversification as it gives households the chance to spread their income risk and can reduce the pressure on the ecosystem, because households do not need to rely completely on livestock raising and can lower their stocking rates.

5

DISCUSSION

5.1 SUMMARY: THREE STUDIES ON RESOURCE USE DECISIONS

In this thesis, we have analyzed three studies on resource use under global change within two different contexts: dryland pastoralism and disaster risk management. Though all three studies addressed different research questions, the overarching aim of all three studies was to analyze under which conditions human resource use decisions are sustainable and enable to cope with the effects of global change processes. In this first section, we will give a short summary on all three studies and highlight the innovative contributions of them.

STUDY 1: DISASTER MANAGEMENT PERFORMANCE UNDER DEMOGRAPHIC CHANGE
Disaster management organizations are a key element to ensure flood protection of communities. In the case study region, the Free State of Saxony, Germany, many cities were repeatedly hit by strong floods in the last years, while at the same time undergoing a phase of demographic change and institutional restructuring. These changes affect the performance of disaster management organizations. Although modeling studies in the context of disaster management exist, these models are often very complex and developed for prediction purposes. In contrast, our model was developed as an exploratory tool that enabled us to obtain a better understanding of the driving factors that determine disaster management performance in the long run. The focus of the analysis was on the impact of a) changes in organizational settings that affect the available resources of disaster management organizations, b) differences in flood characteristics, e.g. increases in flood intensity that translate into a higher demand posed onto the organizations and c) different geographical settings. We applied a simple rule to measure the performance of disaster management: only when coping time – the effective response time to put all protection measures into place – is below a given threshold, protection can be guaranteed. By measuring and evaluating coping time across a number of different scenarios (based on points a)-c) above), we were able to reveal that demographic change, causing a loss in manpower, had the most profound impact on the performance of disaster management organizations. However, we also found that deficiencies in manpower can partly be substituted by other resources, namely technological advances such as better information availability or increased transportation capacity, but only if they are appropriately set in action. Based on these results, we could derive, for instance, that performance might be at risk particular in rural, upstream regions with very short lead times.

STUDY 2: POLARIZATION OF HOUSEHOLDS IN THE EASTERN MOROCCAN HIGH PLATEAU Polarization – a division of a population into opposing factions – has been observed in recent years in the Eastern Moroccan High Plateau. Here, especially an economic polarization has been observed: one the one hand, into a group of wealthy pastoralists that is able to raise large herds and buy trucks to relocate their animals, and on the other hand a group of impoverished households that experience decreasing herd sizes and become increasingly immobile. Evidence for this polarization has been gathered in several empirical studies, e.g. using household surveys or interviews, and researchers have argued about its driving forces. However, reasons for polarization are not completely understood. We presented here a first study using modeling (to the author's knowledge) that explicitly strives to identify the mechanisms and driving forces of polarization in a common property natural resource system. We have specifically analyzed economic, ecological, climatic and demographic factors and how they affect the risk of polarization. We could show that heterogeneities in household assets (namely livestock and monetary resources) are only one reason for polarization. More strikingly, changes in ecological conditions and the impact of climate and demographic change can also cause polarization, even if households are completely homogeneous in their characteristics. To obtain this result, the representation of the social-ecological feedbacks between the household's resource decision, their herds and the pastures in the model was essential. Altered ecological conditions (e.g. due to a change in species composition) may result in a higher pressure on the pastures, as households still use the pastures in the same way. This increases the risk of pasture degradation, which can then also lead to a polarization between the households. Similar results could be obtained from the analysis of demographic and climate change.

STUDY 3: IMPLICATIONS OF BEHAVIORAL CHANGE ON PASTORAL SYSTEMS The third study addressed explicitly trends of behavioral change in pastoral communities that affect the way in which households use common property pastures. In many dryland regions, drivers such as demographic or social change cause an adjustment of livelihood strategies of pastoralist households. This behavioral change has been empirically observed in different regions. However, the long-term consequences of this change were not clear and have been examined for the first time (to the author's knowledge) in this thesis with the help of a multi-agent social-ecological simulation model. We have implemented three different household behavioral types that are based on economic and psychological theories, namely the *Homo Economicus*, *Bounded Rationality* and *Descriptive Norms*. By assessing household populations which differ in density and composition of household types, we have simulated various scenarios of demographic and behavioral change. Here, behavioral types differed in their preferences for livestock, how they value social norms concerning pasture resting and how they are influenced by the behavior of others. We found that changes in household behavior can drastically alter the long-term social-ecological system dynamics: a traditional household type that abides to resting norms is able to maintain pasture integrity, but only if household density does not exceed a critical threshold. An increasing household density in connection with a shift towards a more profit oriented household behavioral type that does not abide to traditional resting rules leads to livestock loss and pasture degradation. A change towards an income diversifying new household type can lead to improved pasture and livestock conditions, as this type constrains its herd size aspiration level and relies on other income (re-)sources. With the help of our model, we could affirm the statement that the mode of human decision-making matters and needs to be taken into account more explicitly, especially when we aim to achieve sustainable resource management.

Based on this short summary of the three individual studies, we will now use the following two sections to synthesize the results and draw conclusions on a general level.

5.2 THE RELEVANCE OF MULTI-SCALE EFFECTS FOR DECISION MAKING

The three studies presented in this thesis addressed quite different resource use contexts – disaster management versus pastoralism. However, we can still draw several parallels between common elements that all three studies share. In the following, we will point out six conceptual links (I.-VI.) and discuss them with regard to all three studies.

The three studies are all centered on one central topic: resource use decisions of individual actors in social-ecological systems. Therefore, we consider at first the impact of decisions on resources (LINK I.), and the feedback that these decisions can have on other resources as well as on future decisions or decisions of other actors (LINK II.). Conversely, we also consider the impact that resources can have on decisions, namely their role as constraint for decisions that enable a certain scope of action (LINK III.). Here, we can identify key resources in all three studies that were of high significance for the system dynamics. These three links mainly relate to the individual actors, but when we look at the decisions of all actors in the system, we can observe the combined impact of the individual decisions on the state of the social-ecological system (LINK IV.). This link explicitly addresses one of the research aims formulated at the beginning of the thesis (*aim b)* investigating the social-ecological feedbacks and their drivers). Corresponding to another research aim (*aim c)* analyzing the effect of global change), we examine the role of global change as driver of the system conditions and the scope of action (LINK V.). Especially under the influence of global change we have found that access to certain resources gains in importance, as resources can act as buffer mechanisms (LINK VI.) to mitigate the adverse effects of global change. We have visualized these conceptual links in Fig. 5.1 and will now discuss them in detail.

We begin our reflections at the micro-level where resource use decisions are at the core of the system dynamics. First of all, *agents make decisions on resources* (LINK I.): pastoralist households decide how much livestock to keep on a pasture, and therefore how much fodder is consumed by the animals. Disaster management organizations decide how many sandbags to load and transport to a disaster site. With this they change the number of sandbags available at the sandbag reserve (supply) as well as the number still needed at the disaster site (demand). Here, individual decisions impact on resources and change resource stocks. However, changing one resource stock can have consequences for other resources as well, as there can be a *feedback of one resource use decision on other resources* (LINK II.A.): As livestock grazing, i.e. biomass consumption, influences the regeneration capacity of the pastures, each household decision where and how much to graze influences the future state of the pasture. Here, a second feedback comes into effect: the state of the pasture, specifically the amount of biomass available for consumption, determines how much livestock can be kept on that pasture. Therefore, a current household decision on the number of livestock that is kept on the pasture directly affects the same decision in the future (LINK II.B.). As we have seen in Chapter 4, a household strategy that only aims at profit maximization, i.e. a maximum number of livestock, is not sustainable on the long-term. A satisficer, however, who stocks less livestock than the pasture would allow and therefore indirectly rests the pasture, can ensure the state of both livestock and pastures. *Pasture biomass*, therefore, represents a *key resource*, and its state is vital for the long-term sustainability of the pastoral system. Of course, this feedback does not just affect decisions of the same household, it can also affect decisions of other households.

Decisions can not only have an impact on resources, conversely resources can have an impact on decisions: they can act as *constraints for decisions* that either enable or disable a certain action (LINK III.). With this, resources become part of the boundary conditions of the decision. Access to a certain resource may be necessary to enable, or enhance, a decision. As we have seen in Chapter 2, *information* is a key resource that influences the performance of disaster

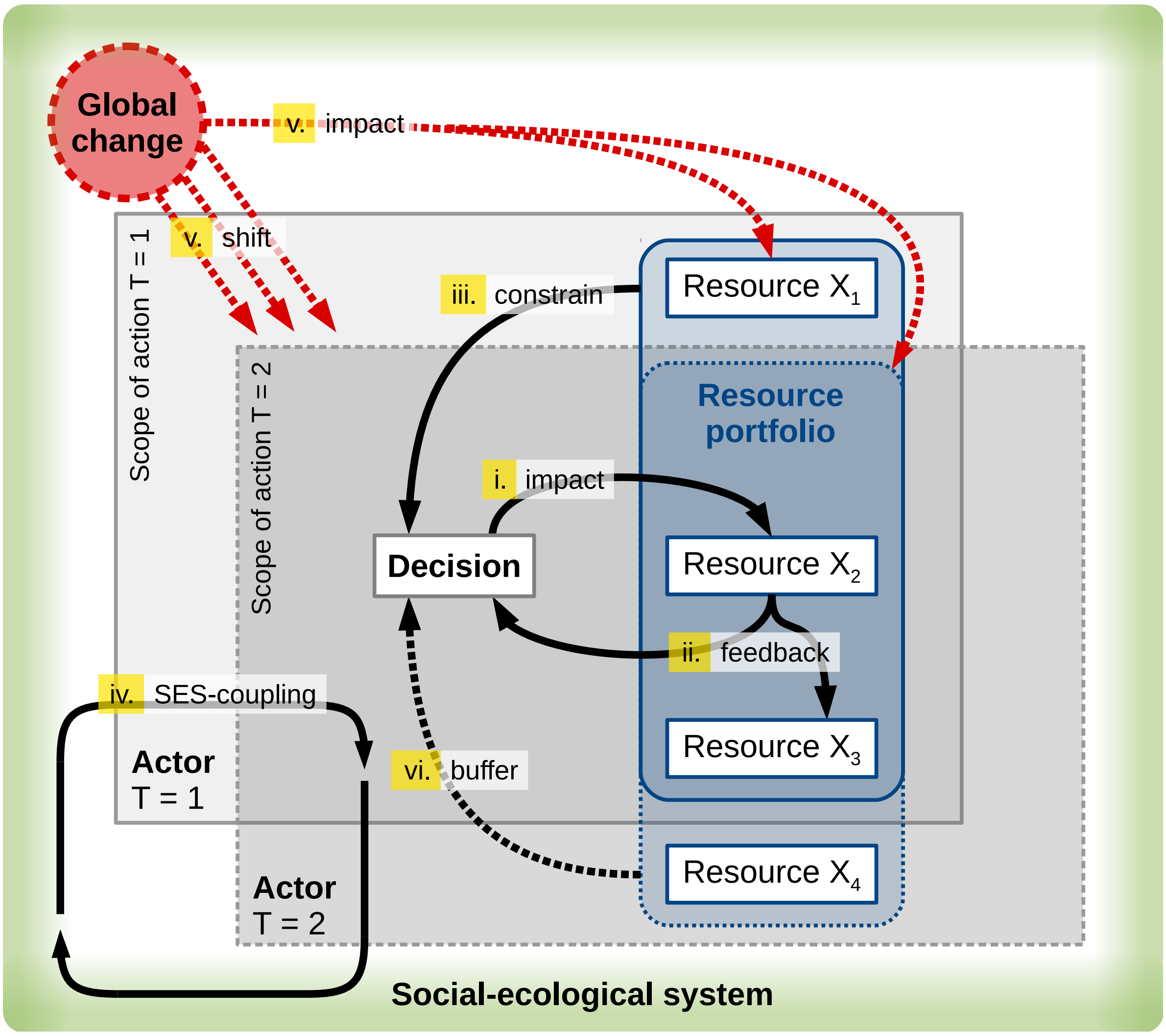


FIGURE 5.1.: Conceptual link between individual decisions, resources and global change. Resources X_1,...,X_4 are part of a resource portfolio of an actor and stand exemplarily for the set of resources that an actor might decide upon. The impact of global change (indicated by dashed boxes and dashed arrows) might shift the scope of action or the composition of resource portfolio over time, as signified by T = 1 and T = 2. Conceptual links are indicated by the yellow labels i.-vi.

management: when disaster management organizations only had partial information access, unnecessary trips to disaster sites with no demand could occur, which elongated the coping time. In reality, such unnecessary trips can put protection at risk. Having full and immediate knowledge about the state of all disaster sites removes a source of uncertainty for the decision-making of the organizations and thus eliminates unnecessary extra trips. The analyses in Chapter 4 have shown that the compliance, respectively non-compliance, with *social norms on pasture resting* regulates the access to pastures and determines whether pastures are getting rested or not. Here, the norm on pasture resting represents a social-institutionalized resource (cf. Gertel, 2007, Table 1.1 in Chapter 1). The way in which households "use = follow" this norm, enables, respectively prevents, households to access another resource (pasture biomass). This, in turn, has consequences for the long-term development of the pastures (insufficient resting), as we have stated before.

When we switch our viewpoint to the macro-level, we can observe first that the *combination of all agent decisions shapes the state of the social-ecological system* in which they are embedded (LINK IV.). While each pastoralist household only uses one pasture, the emerging dynamics that result from the combination of the resource use decisions of all households determine whether pastures are in a long-term viable state or face the danger of degradation. Conversely, also the dynamics of the ecological system can shape outcomes of the social system, as we have seen in Chapter 3. Here, ecological conditions (biomass growth rate and grazing harshness) were found to be strongly influential for the likelihood of the occurrence of polarization between pastoralist households, i.e. a social phenomenon. This emphasizes the strong link between the social and biophysical components within the considered common pool resource system.

A second observation at the macro-level relates to the impact of the *global change processes that drive system conditions and shape the possible scope of action in which the decisions of agents take place* (LINK V.). This has consequences for the resource portfolio of the agent, as change can increase or decrease the amount of a specific resource, or it can eliminate access to a certain resource while a new resource comes into play. Especially the combined effects that result from the interplay of different dimensions of change are difficult to predict and have therefore been emphasized in particular in the analysis. One driver that has been important throughout all three studies has been demographic change, even though its impact differed between both resource contexts. In the context of pastoralism, population growth induced a shortage of resources, as more households competed over the same scarce resource, namely pasture biomass. In Chapter 3 the impact of demographic change was even intensified by climate change: lower mean precipitation or higher rainfall variability limit the pastures ability to grow and regenerate, and thus further increased the risk of polarization between households.

In the study on disaster management (Chapter 2), demographic change had the most profound effect on the performance of disaster management organizations: the decreasing availability of helpers limits the operational readiness of disaster management organizations, to a larger degree than technical limitations (e.g. reduced transportation capacity of trucks). If under climate change the frequency and intensity of flood events increases, the demand posed onto the organizations and the protection performance they are able to supply will drift further apart. Under these conditions, the access to information gains in importance: as we have stated before, full information access enhances disaster management performance as it eliminates unnecessary trips to disaster sites. However, if manpower, the main driver of disaster management performance, is sufficiently available, information access is of secondary importance. Only when the number of available helpers decreases and manpower becomes a limiting factor, having full knowledge can – to some degree – compensate this loss and avoid an increase in coping time. Here, access to information acts as a *buffer mechanism* (LINK VI.) that becomes important when other resources are not available in sufficient manner anymore.

Therefore, the importance of buffer mechanisms is dependent on the pressure that the system is exposed to, which is influenced by global change. Also, in the context of pastoralism buffer mechanisms are important. Here, ensuring a sufficient resting of the pastures provides a buffer that allows the pastures to regenerate. Traditional strategies that pay attention to pasture resting (by abiding to social norms on resting, Chapter 4) might not be viable anymore under demographic change, if the competition over scarce resources challenges the livelihood of households. This requires a behavioral change, for example adjusting the household's preferences for livestock, in terms of herd size. However, to successfully realize such a behavioral change, households need to find ways to meet their needs besides raising livestock, for example through a diversification of income sources. Such a diversification would then be a buffer strategy on the household level.

Given the importance of resting as buffer mechanism in pastoral systems even allows us to draw an implicit conclusion for and analogy to the disaster management context: Here, the importance of setting up new retention areas or restoring natural retention areas such as floodplain forests has been widely discussed in recent years. Such areas could act as a buffer for rivers carrying high water. Especially in regions where disaster management performance is under pressure due to the impacts of global change, such retention areas could contribute to a reduction of the pressure that lies on the organizations.

5.3 METHODOLOGICAL REFLECTIONS

5.3.1 *The potential of agent-based modeling*

For all three studies, we decided to develop and apply agent-based simulation models to address the research questions of the studies. This choice of methodology was a deliberate one, as agent-based models allow us to represent individual decisions of actors and their interactions, and observe the outcome of these decisions on a higher system level (Bonabeau, 2002; Holland, 1992).

One main advantage of using an ABM is the possibility to represent and model the effects of various forms of heterogeneity (Kelley et al., 2011; Jager et al., 2000), in particular heterogeneity in agent characteristics and their decision-making. This allowed us to define a household population where individual households followed different decision-making strategies (defined as "behavioral types" in Chapter 4), and to vary the share of these strategies within the population. In doing so, we could show that different mixes of behavioral types lead to qualitatively different social-ecological outcomes, if the share of a certain behavioral types exceeds a certain threshold. These outcomes can range between long-term stability and system break down, in terms of pasture and livestock condition. Such results could not have been obtained solely from the analysis of single behavioral strategies (which has also been done in Chapter 4).

Heterogeneous agent populations were also a crucial aspect for the study on the emergence of polarization (Chapter 3). Although households followed the same decision rules, differences in their properties (mobility costs) and assets (initial herd sizes and monetary resources) were important here. By using the multi-agent model, we could determine qualitatively a) which initial household conditions led to polarization between households, and b) when such a polarization occurred. Here, the analysis showed that polarization always occurred within the first years of the simulation and that reaching a viable herd size in order to pay annual living costs was the crucial mechanism behind. We could verify this threshold herd size using an analytical calculation, independent of the agent-based model.

A second advantage of ABMs is that it allows both to observe joint dynamics of all agents at the system level, but also to track individual agents and their fate. In particular, we could not only determine the overall degree of polarization between households, but also which households end up in which herd size class. This enabled us to trace back the cause of polarization to either individual household characteristics, spatial settings, or to system-level properties by determining whether households systematically fell into one herd size class, or by chance.

Besides these explicit advantages of agent-based models that justify our choice of method, our decision to develop rather stylized models is equally well-founded: stylized models enable to rapidly generate hypotheses and test them in the model (Turner, 2003), and to explore new strategies (Schlüter et al., 2013). For example, the stylized vegetation model used in both studies on pastoralism (Chapters 3 & 4) is simple enough to gain a mechanistic understanding of its dynamics (e.g. analyzing the impact of grazing harshness), but also complex enough to represent effects such as the feedback between grazing and biomass growth. A further advantage of stylized models is that they are not dependent on large amounts of quantitative data which are often difficult to obtain. Instead, qualitative system knowledge and the possibility to conduct sensitivity analysis for a wide parameter range can sufficiently contribute to an adequate model implementation.

5.3.2 *Implementing human decision-making in ABM: potential and challenges*

One major focus of this thesis was on the implementation of decision-making strategies of actors in order to realistically represent resource use decisions in our models. We used different approaches to achieve this goal: using rather simple heuristics ("if-then"-rules of disaster management, Chapter 2), economic calculations (cost-benefit analysis for the relocation of herds, Chapter 3) as well as specific decision theories (*Maximizer* (Homo Economicus), *Satisficer* (Bounded Rationality) and *Descriptive Norm Follower*, Chapter 4). In particular the implementation of social and psychological theories on human decision-making in social-ecological models offers a large potential, but also challenges.

Humans rarely act fully rational, especially under conditions of information uncertainty (e.g. state of pastures that depends on variable rainfall, Chapter 3 & 4), limited cognitive abilities (e.g. time constraint for disaster management organizations to make decisions, Chapter 2) or personal preferences (e.g. preference of households for pasture resting, Chapter 4). Many of these points are addressed in human decision-making theories, however, modelers face a couple of fundamental challenges when they want use such theories: a) selecting a suitable theory from the vast amount of available theories, b) specifying causal relationships, which many theories do not provide, and making assumptions on elements that are not described by a theory, and c) formalizing a theory in model code (Schlüter et al., 2017). We faced these challenges particularly in Chapter 4. First of all, selecting an adequate theory that represents the decision-making of pastoralist households required the consideration of several theories. Some of those theories were rejected in the end, as we realized that they either do not fully fit the type of decision (e.g. Theory of Planned Behavior that describes how intentional decisions are formed, whereas pastoralist decisions are rather habitual) or because they did not fit to the model in its current form (e.g. Prospect Theory that addresses decision making between options with probabilistic outcomes, whereas the outcomes of household decisions in the model are deterministic). Also, after we selected a set of suitable theories, arriving at an adequate implementation was an iterative process that also involved trial and error. Here, it is important to note that we only name it an adequate implementation, not the right implementation, as one theory can have several right implementations. Still, through operationalization of three behavioral theories in model rules, and the systematic analysis of the social-ecological consequences of behavioral and demographic change, we made contributions to bring forward the adequate incorporation of human decision-making in social-ecological systems research.

In contrast to concrete theories on human behavior, the use of simple heuristics, i.e. "rules-of-thumb" that are most often based on empirical observations, provide another way to incorporate decision-making into ABMs. Even though they lack a theoretical foundation, they can be included and adjusted quite easily in the model and therefore the impact of a changed decision rule is quickly observable. We have used such rules in the study on disaster management (Chapter 2), as the approach relates well to the workflow of disaster management organizations in reality: they do not have a specific theory that they follow in their operations, but rather a set of tried and tested rules and procedures that are based on their experiences with past events.

5.3.3 *Methodological advancements: operationalization of the resource portfolio concept*

The resource portfolio is a concept from social geography (Gertel, 2007) that fits well to the scope of our studies. We have especially used and operationalized this concept in the three studies as it has a very wide notion of what is a resource (in contrast to the rather narrow understanding of "natural resources", for instance) and it emphasizes the convertibility of resources. So far, the resource portfolio has been used most often in empirical studies, e.g. household surveys (Breuer, 2007; Kreuer, 2011) or interviews (Freier et al., 2012). In these studies, the resource portfolio is used more as a static concept, where the focus lies on one or a few points in time. Of course, this is mainly owed to the fact that such empirical studies are very time consuming and cannot be repeated in such regular intervals, as a simulation model is able to produce data points. Our modeling approach is able to fill this gap, as we can seamlessly monitor the development of a household's resource portfolio over time.

Empirical studies usually also have a central focus on households, their resources and the conversion of those resources, whereas the link to resources of the ecosystem is not as strong. The dynamic coupling of social and ecological components in our models allows us to shed a light on the relationship between, for instance, household livelihood assets (such as livestock, or monetary resources) and allocative resources provided by the ecosystem (pasture biomass). From the viewpoint of the resource portfolio, the social-ecological feedback link between biomass and livestock corresponds to a resource conversion within the households' resource portfolios. However, whereas livestock represents a purely allocative resource that belongs to one particular household, pasture biomass is furthermore also a social-institutionalized resource, as it a) represents a resource that is shared among all households and b) access to that resource can be governed by rules, such as social norms on pasture resting (see Chapter 4). With the help of our modeling approach, we can also analyze the differences between the short-term and long-term perspective of resource conversions: a strategy that maximizes current herd size, and therefore increases the conversion of biomass to livestock in the short-term, is likely to face livestock loss over the long-term, when no biomass is available anymore to be converted into livestock.

5.4 FINAL CONCLUSION

Mankind increasingly shapes their environment: as of 2002, more than 75% of the global land surface has been directly influenced by human activity (Ellis et al., 2008; Sanderson et al., 2002). If we want to achieve a sustainable use of resources, especially of natural resources, we need to consider human decision-making as an integral part of all approaches that aim at sustainable development.

In this thesis, we have contributed to broaden our understanding of human decision-making in the context of social-ecological systems. We have developed three multi-agent simulation models within two different resource use contexts. In each study, we have taken the perspective of resources, how they influence the decision-making of individual actors and how they impact on the social, ecological and economic dimensions of the system. Here, the operationalization of a social-geographic concept – the resource portfolio – has provided a theoretical foundation for our analysis. The impact of global change has shown that certain resources, such as access to information, become especially important when the pressure on the system increases, as they can act as buffer mechanisms. Although further research in the field of human decision-making and its influence on resource use in social-ecological systems is needed, we could already depict with very simple, but theoretically well-founded models, in which way different types of human behavior drive social-ecological system dynamics.

6

FURTHER CONTRIBUTIONS TO PEER-REVIEWED ARTICLES

Besides the three studies presented in this thesis, further contributions have been made to the following peer-reviewed publications during the course of this dissertation project:

STANDARDISED AND TRANSPARENT MODEL DESCRIPTIONS FOR AGENT-BASED MODELS: CURRENT STATUS AND PROSPECTS Müller, B., Balbi, S., Buchmann, C.M., de Sousa, L., Dressler, G., Groeneveld, J., Klassert, C., Le, Q.B., Millington, J.D., Nolzen, H., Parker, D.C., Polhill, J.G., Schlüter, M., Schulze, J., Schwarz, N., Sun, Z., Taillandier, P., and Weise, H. (2014). In: *Environmental Modelling & Software* 55, pp. 156–163. DOI: `http://dx.doi.org/10.1016/j.envsoft.2014.01.029`

Agent-based models are helpful to investigate complex dynamics in coupled human–natural systems. However, model assessment, model comparison and replication are hampered to a large extent by a lack of transparency and comprehensibility in model descriptions. In this article we address the question of whether an ideal standard for describing models exists. We first suggest a classification for structuring types of model descriptions. Secondly, we differentiate purposes for which model descriptions are important. Thirdly, we review the types of model descriptions and evaluate each on their utility for the purposes. Our evaluation finds that the choice of the appropriate model description type is purpose-dependent and that no single description type alone can fulfil all requirements simultaneously. However, we suggest a minimum standard of model description for good modelling practice, namely the provision of source code and an accessible natural language description, and argue for the development of a common standard.

THEORETICAL FOUNDATIONS OF HUMAN DECISION-MAKING IN AGENT-BASED LAND USE MODELS – A REVIEW Groeneveld, J., Müller, B., Buchmann, C.M., Dressler, G., Guo, C., Hase, N., Hoffmann, F., John, F., Klassert, C., Lauf, T., Liebelt, V., Nolzen, H., Pannicke, N., Schulze, J., Weise, H., and Schwarz, N. (2017). In: *Environmental Modelling & Software* 87, pp. 39–48. DOI: `http://dx.doi.org/10.1016/j.envsoft.2016.10.008`

Recent reviews stated that the complex and context-dependent nature of human decision-making resulted in ad-hoc representations of human decision in agent-based land use change models (LUCC ABMs) and that these representations are often not explicitly grounded in theory. However, a systematic survey on the characteristics (e.g. uncertainty, adaptation, learning, interactions and heterogeneities of agents) of representing human decision-making in LUCC ABMs is missing. Therefore, the aim of this study is to inform this debate by reviewing 134 LUCC ABM papers. We show that most human decision sub-models are not explicitly based on a specific theory and if so they are mostly based on economic theories, such as the rational actor, and mainly ignoring other relevant disciplines. Consolidating and enlarging the theoretical basis for modelling human decision-making may be achieved by using a structural framework for modellers, re-using published decision models, learning from other disciplines and fostering collaboration with social scientists.

A FRAMEWORK FOR MAPPING AND COMPARING BEHAVIOURAL THEORIES IN MODELS OF SOCIAL-ECOLOGICAL SYSTEMS Schlüter, M., Baeza, A., Dressler, G., Frank, K., Groeneveld, J., Jager, W., Janssen, M.A., McAllister, R.R.J., Müller, B., Orach, K., Schwarz, N., and Wijermans, N. (2017). In: *Ecological Economics* 131, pp. 21–35. DOI: `http://dx.doi.org/10.1016/j.ecolecon.2016.08.008`

Formal models are commonly used in natural resource management (NRM) to study human-environment interactions and inform policy making. In the majority of applications, human behaviour is represented by the rational actor model despite growing empirical evidence of its shortcomings in NRM contexts. While the importance of accounting for the complexity of human behaviour is increasingly recognized, its integration into formal models remains a major challenge. The challenges are multiple: i) there exist many theories scattered across the social sciences, ii) most theories cover only a certain aspect of decision-making, iii) they vary in their degree of formalization, iv) causal mechanisms are often not specified. We provide a framework- MoHuB (Modelling Human Behavior) - to facilitate a broader inclusion of theories on human decision-making in formal NRM models. It serves as a tool and common language to describe, compare and communicate alternative theories. In doing so, we not only enhance understanding of commonalities and differences between theories, but take a first step towards tackling the challenges mentioned above. This approach may enable modellers to find and formalize relevant theories, and be more explicit and inclusive about theories of human decision making in the analysis of social-ecological systems.

A

APPENDIX TO CHAPTER 2

This is the appendix to Chapter 2 "Towards thresholds of disaster management performance under demographic change: exploring functional relationships using agent-based modeling".

A.1 ODD+D protocol

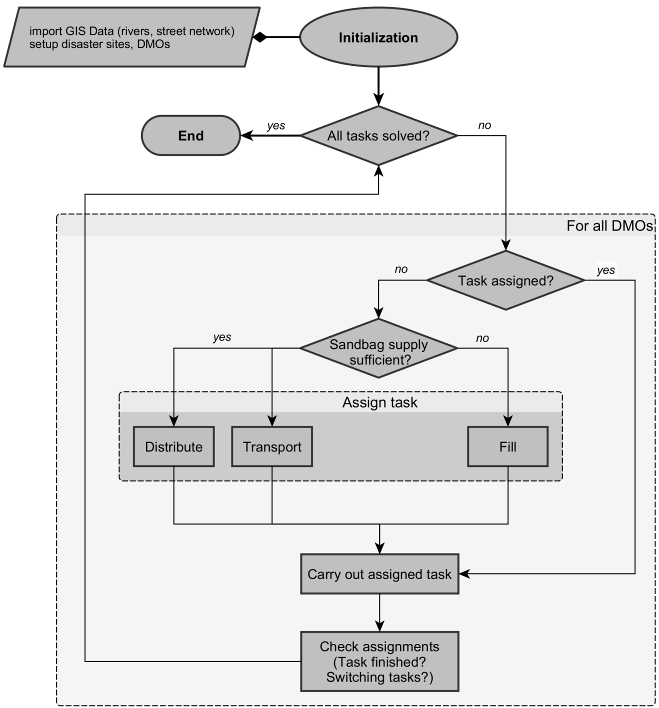
Table A.1.: ODD+D Protocol.

Outline		**Guiding questions**	**Description**
I) Overview	I.i Purpose	I.i.a What is the purpose of the study?	The purpose of the model is to analyze the performance of disaster management and understand how it is affected by change (e.g. demographic, climatic, or technological). There are three main questions: (1) Which dimension of change has the most profound influence on the performance of disaster management? (2) Can we identify bottlenecks or critical thresholds for the capacities of disaster management to ensure protection? (3) How do these thresholds depend on the regional geographic and demographic setting?
		I.ii.b For whom is the model designed?	The model is designed for both scientists and stakeholders, as an exploratory tool to understand the functioning of disaster management under change and as a discussion tool to illustrate these results to experts, address possible shortcomings and highlight options for improvement.
	I.ii Entities, state variables, and scales	I.ii.a What kinds of entities are in the model?	- There is a single type of agents (DMOs), each representing a unit or group of helpers of a disaster management organization. - The physical environment of the model is characterized by a map that includes a transportation network (streets), rivers, flood prone areas and certain target sites as entities.

ODD+D Protocol.

Outline		Guiding questions	Description
		I.ii.b By what attributes (i.e. state variables and parameters) are these entities characterized?	DMOs: - team-size: number of helpers associated to the group - sandbags-capacity: transportation capacity, i.e. number of sandbags that can be transported by this group in one turn (corresponding to vehicle size) - moving-speed / speed-min / speed-limit: current moving speed as well as minimum and maximum speed of the DMO vehicle - assigned-task: one of 'fill sandbags', 'transport sandbags', 'distribute sandbags' - information-access: partial knowledge / full knowledge Disaster sites: - location: location of the site on the map and connection to the transportation network - sandbags-needed / sandbags-present / sandbags-distributed: respective number of sandbags needed in total to fulfil the task, currently present, and already distributed at the site - fixed?: true/false, indicating whether all tasks at the site are fulfilled or not Sandbag reserves: - location: location of the site on the map and connection to the transportation network - number-sandbags-filled: current number of sandbags filled and present at the site Transportation network: - street-type: one of 'primary', 'secondary', 'tertiary' or 'motorway' defining the type of the street - max-speed: speed limit, depending on street type Rivers and flood prone areas: - location: location on the map
		I.ii.c What are the exogenous factors / drivers of the model?	Different processes of change (e.g. demographic change, climate change) influence the system and thus the model dynamics. These effects are included via certain parameters that are systematically varied, such as the number of DMO agents N_{DMO} that can decrease as a consequence of demographic change.
		I.ii.d If applicable, how is space included in the model?	The model is spatially explicit and uses GIS data as input for the location of rivers, flood prone areas as well as the transportation network.
		I.ii.e What are the temporal and spatial resolutions and extents of the model?	- Time: One time step (tick) represents one minute. There is no fixed time horizon as the model runs until all tasks are finished. - Space: The spatial extent corresponds to a defined region, e.g. a city, one grid cell has a resolution of 40 m x 40 m

ODD+D Protocol.

Outline	**Guiding questions**	**Description**
I.iii Process overview and scheduling	I.iii.a What entity does what, and in what order?	In each time step, the model checks first, whether all tasks are solved or not. If yes, the simulation stops, otherwise it steps into the main routine that is executed for each DMO agent: - At the beginning of the simulation each DMO gets assigned an initial task. In each subsequent time step, the model checks if the DMO has an assigned task, if yes, it carries out that task, otherwise a new task will be assigned. - Depending on the assigned task, the DMO agent will either: a) Fill sandbags, with a given rate, depending on the team-size of the DMO b) Transport sandbags, which involves loading sandbags onto the vehicle, moving along the transportation network, and unloading sandbags c) Distributing sandbags at the disaster site, with a given rate, depending on the team-size of the DMO - At specified intervals, DMO agents will also check whether they should switch to another task, e.g. if more capacity is needed to fill sandbags or to transport sandbags The main routine of the model is also depicted in the following figure: 

ODD+D Protocol.

Outline		**Guiding questions**	**Description**
II) Design concepts	II.i Theoretical and Empirical Background	II.i.a Which general concepts, theories or hypotheses are underlying the model's design at the system level or at the level(s) of the submodel(s) (apart from the decision model)? What is the link to complexity and the purpose of the model?	- The model has been developed in order to depict the case of flood protection and disaster management in Saxony, however its generality should facility the transferability to other settings, too. - The model components are kept rather simple, as the model's purpose is to serve as a virtual lab, rather than as a prediction tool. - Complexity arises from the decision making of the agents and interaction between the agents and the model environment.
		II.i.b On what assumptions is/are the agents' decision model(s) based?	DMO decision making is based on simple heuristics, e.g. "if-then" rules.
		II.i.c Why is a/are certain decision model(s) chosen?	Under disaster conditions, DMOs rarely have the time to derive an optimal decision and have to rely rather on certain routines, past experiences or ad-hoc decisions. Therefore we employ simple "if-then" rules rather than more complicated optimization algorithms.
		II.i.d If the model / a submodel (e.g. the decision model) is based on empirical data, where does the data come from?	- The spatial setting of the model (rivers, flood prone areas, street network) is based on freely available GIS data. - Some decision making rules and their parameters are based on basic rules / guides used by disaster management organizations for flood protection.
		II.i.e At which level of aggregation were the data available?	GIS data were available at a local (e.g. city) level.
	II.ii Individual Decision Making	II.ii.a What are the subjects and objects of decision-making? On which level of aggregation is decision-making modeled? Are multiple levels of decision making included?	- DMO units are the subject of decision making. - The object of decision making is the execution of tasks (filling, transporting, distributing sandbags) at certain target sites. - There is only one level of decision making.

ODD+D Protocol.

Outline		Guiding questions	Description
		II.ii.b What is the basic rationality behind agents' decision-making in the model? Do agents pursue an explicit objective or have other success criteria?	- Agents follow certain heuristics when making decisions, based on the level of information available to them. - Their objective is to fulfill all tasks at all target sites in a preferably short amount of time.
		II.ii.c How do agents make their decisions?	See II.ii.b or III.iv.a for details.
		II.ii.d Do the agents adapt their behavior to changing endogenous and exogenous state variables? And if yes, how?	Yes. Agents can switch between tasks, when the need arises, e.g. when tasks at a specific disaster site are fulfilled, DMOs can switch to a different site or when sandbag supply at the filling site is running low, agents can switch from transporting/distributing sandbags to sandbag filling.
		II.ii.e Do social norms or cultural values play a role in the decision-making process?	No.
		II.ii.f Do spatial aspects play a role in the decision process?	Yes. The current location of the DMO agents and the distance to target sites is incorporated into their decision.
		II.ii.g Do temporal aspects play a role in the decision process?	DMO agents make decisions based only on the current state of the system.
		II.ii.h To which extent and how is uncertainty included in the agents' decision rules?	Uncertainty is not included in the decision making.
	II.iii Learning	II.iii.a Is individual learning included in the decision process? How do individuals change their decision rules over time as consequence of their experience?	No, learning is not included.
		II.iii.b Is collective learning implemented in the model?	No.

ODD+D Protocol.

Outline		Guiding questions	Description
	II.iv Individual Sensing	II.iv.a What endogenous and exogenous state variables are individuals assumed to sense and consider in their decisions? Is the sensing process erroneous?	- DMO agents have full knowledge about the spatial settings of the model (transportation network, location of all target sites). - Each DMO agent has a certain level of information access about the state of each site: a) Full knowledge: complete knowledge about the state of all disaster sites at all times. b) Partial knowledge: knowledge can only be acquired through direct contact, i.e. when they are at a site, and will be remembered from then onwards. - The sensing is not erroneous.
		II.iv.b What state variables of which other individuals can an individual perceive? Is the sensing process erroneous?	DMO agents are not able to sense the state variables of other agents.
		II.iv.c What is the spatial scale of sensing?	DMO agents have full spatial knowledge.
		II.iv.d Are the mechanisms by which agents obtain information modeled explicitly, or are individuals simply assumed to know these variables?	Agents are assumed to know the values of the sensed variables.
		II.iv.e Are costs for cognition and costs for gathering information included in the model?	No.
	II.v Individual Prediction	II.vi.a Are interactions among agents and entities assumed as direct or indirect?	Interaction between DMO agents is indirect as they perceive the status of the target sites (disaster sites/sandbag reserve) and can adapt their behavior based on the actions of other agents at these sites.
		II.vi.b On what do the interactions depend?	Interaction does not depend on any parameters/conditions.
		II.vi.c If the interactions involve communication, how are such communications represented?	Not applicable.

ODD+D Protocol.

Outline		Guiding questions	Description
		II.vi.d If a coordination network exists, how does it affect the agent behavior? Is the structure of the network imposed or emergent?	In the current model version, DMO agents act independently to solve their tasks. A coordination between of tasks between agents is planned.
	II.vii Collectives	II.vii.a Do the individuals form or belong to aggregations that affect, and are affected by, the individuals? Are these aggregations imposed by the modeler or do they emerge during the simulation?	Agents do not form collectives in the current model version.
		II.vii.b How are collectives represented?	Not applicable.
	II.viii Heterogeneity	II.viii.a Are the agents heterogeneous? If yes, which state variables and/or processes differ between the agents?	Currently, within any single simulation all DMO agents are homogeneous in their properties.
		II.viii.b Are the agents heterogeneous in their decision-making? If yes, which decision models or decision objects differ between the agents?	No.
	II.ix Stochasticity	II.ix.a What processes (including initialization) are modeled by assuming they are random or partly random?	- Disaster sites are randomly distributed at the beginning of each simulation. - The order in which DMO agents act in each time step is determined randomly by the Netlogo ‘ask’ command.

ODD+D Protocol.

Outline		Guiding questions	Description
	II.x Observation	II.x.a What data are collected from the ABM for testing, understanding, and analyzing it, and how and when are they collected?	- For each simulation, the time needed to fulfill all tasks – the coping time – is measured as the main indicator of performance. - When the model is run interactively (using the graphical interface), several variables can be monitored during a simulation run, e.g. a) The current distribution of tasks onto the DMO agents. b) The degree to which tasks are fulfilled. c) The location and movement of the agents, as well their movement speed.
		II.x.b What key results, outputs or characteristics of the model are emerging from the individuals? (Emergence)	As the agents act independently, we can observe if changes in their properties or their available resources lead to an increase or decrease in the resulting coping time at the end of the simulation.
III) Details	III.i Implementation Details	III.i.a How has the model been implemented?	The model has been implemented in NetLogo 5.2.0.
		III.i.b Is the model accessible and if so where?	The model will be made accessible at openABM.org
	III.ii Initialization	III.ii.a What is the initial state of the model world, i.e. at time t=0 of a simulation run?	At the beginning of the simulation, the spatial layout of the model is set up. A given number of disaster sites is distributed at random locations along rivers and flood prone areas. A given number of DMO agents is placed along certain fixed initial positions of the transportation network.
		III.ii.b Is initialization always the same, or is it allowed to vary among simulations?	Initialization between simulations varies only in the location of disaster sites which is determined randomly and the location of DMO agents (which are fixed points on the transportation network, but the distribution of agents among these points can differ).
		III.ii.c Are the initial values chosen arbitrarily or based on data?	Initial values are partly based on empirical data (e.g. spatial layout) and partly derived from sensitivity analysis that have been carried out with the model.

ODD+D Protocol.

<table>
<tr><th colspan="2">Outline</th><th>Guiding questions</th><th>Description</th></tr>
<tr><td></td><td>III.iii Input Data</td><td>III.iii.a Does the model use input from external sources such as data files or other models to represent processes that change over time?</td><td>Yes, for the spatial layout of the model the following data was used:
<table>
<tr><td>Element</td><td>Data soure</td><td>available at</td></tr>
<tr><td>Street network</td><td rowspan="2">OpenStreetMap</td><td rowspan="2"><code>http://download.geofabrik.de/europe/germany/sachsen.htm</code></td></tr>
<tr><td>Rivers</td></tr>
<tr><td>Flood prone areas</td><td>Saxonian State Office for Environment, Agriculture and Geology (Landesamt für Umwelt, Landwirtschaft und Geologie)</td><td><code>http://www.umwelt.sachsen.de/umwelt/wasser/8841.htm</code></td></tr>
</table>
Data has been preprocessed in ArcGIS for simplification.</td></tr>
<tr><td></td><td>III.iv Submodels</td><td>III.iv.a What, in detail, are the submodels that represent the processes listed in ‘Process overview and scheduling’?</td><td>setup:
- Imports all map data and sets up the world, i.e. creates DMO agents, disaster sites and sandbag-reserves and puts them on the map.
- The spatial layout (i.e. rivers, flood-prone areas and street network) is the same in every simulation. The location of sandbag reserve(s) can be fixed or determined randomly. The location of disaster sites and DMO agents will be determined randomly in each simulation, albeit with some constraints, e.g. disaster sites can only be placed within flood probe areas.

go:
- Main routine of the model that is carried out in each time step (tick).
- Checks if there are still open tasks and loops through set of DMO agents and calls their tasks.</td></tr>
</table>

ODD+D Protocol.

Outline		Guiding questions	Description
			check-assignments: - Carried out by each DMO agent when a) its current task is finished or b) after a specified amount of time (e.g. 30 min) to check whether it needs to switch to a different task. - Routine will check the current need for sandbag transportation / sandbag filling / sandbag distribution and if e.g. demand for sandbags at the sandbag reserve is higher than the current total filling rate, the DMO agent will switch to “fill sandbags” (if his previous task was “transport sandbags”). fill-sandbags: - Routine carried out by DMOs assigned to filling sandbags. If the DMO agent is not presently at a sandbag reserve, it will move to the nearest sandbag reserve. At a sandbag reserve, the agent will fill sandbags with a fixed rate (r-DMOs-filling) per tick that depends on the team-size of the agent. distribute-sandbags: - Routine carried out by DMOs at disaster sites when they are assigned to filling sandbags. The agent will distribute sandbags with a fixed rate (r-DMOs-distributing) per tick that depends on the team-size of the agent.

ODD+D Protocol.

Outline	Guiding questions	Description
		transport-sandbags: - Routine carried out by DMOs assigned to transporting sandbags. - Consists of several subroutines that are carried out depending on the current location of the DMO agent, which can be either a sandbag-reserve, a disaster site, or some location on the street network. - Routine in pseudocode:

```
if (sandbags-loading?) {
  // loaded sandbags < transportation
      capacity
  if (at-sandbag-reserve?) {
    load-sandbags
  }
  else {
    set sandbags-loading? = false
    move-to-sandbag-reserve
  }
}
else {
  // enough sandbags loaded
  if (arrived at assigned disaster site?) {
    if (tasks at site finished?) {
      // task has already been finished, so
      // a new target site will be assigned
      assign new disaster site*
      calculate-disaster-path
      move-to-disaster
    }
    else {
      if (# sandbags loaded > 0) {
        unload-sandbags
      }
      else {
        set sandbags-loading? = true
      }
    }
  }
  else {
    move-to-disaster
  }
}
```

ODD+D Protocol.

Outline		Guiding questions	Description
			load-sandbags: - the agent loads sandbags at a sandbag reserve (with rate r-DMOs-loading) until the transportation capacity of the DMO agent is reached. unload-sandbags: - the agent unloads sandbags at a disaster site (with rate r-DMOs-unloading) until the number of loaded sandbags is zero. move-to-disaster / move-to-sandbag-reserve: - Subroutine that lets DMO agents move along the transportation network towards a given target site. Depends on a precalculated path, given by the calculate-[...]-path functions. - Agents move forward on the transportation network towards the next node in their path. The distance that they move forward depends on their current moving-speed and the speed limit of the street. Once they reach the next node this node will be deleted from their path until they reach their final node = target site. - DMO agents can accelerate and decelerate in the range of [speed-min, speed-limit] and the speed-limit of the street. They will accelerate to the maximum speed when the “road is free”, i.e. when they don’t encounter any other DMO agent in front of them and they move along the street. They have to decelerate at intersections (i.e. nodes in their path) and when they encounter other agents within a given distance in front of them. calculate-disaster-path / calculate-sandbag-reserve-path: - These routines are called to calculate that path through the transportation network to a) a specific target site or b) the nearest (i.e. shortest distance) target site. The path is calculated using the A*-search algorithm (Hart et al., 1968; Goldberg and Werneck, 2005; subroutine A*-path) Plotting, output and some helper functions are not described here to maintain the conciseness of the description.

ODD+D Protocol.

Outline	Guiding questions	Description
	III.iv.b What are the model parameters, their dimensions and reference values?	

Parameter	Description	Standard value
Global		
number-DMOs	number of DMO agents N_{DMO}	20
number-disasters	number of disaster sites $N_{Disasters}$	40
number-sandbag-reserves	number of sandbag reserves $N_{Reserves}$	1
case-site	which case site	Leipzig / Neisse
DMO specific		
DMOs-information-access	level of information access (partial knowledge / full knowledge, see II.iv.a)	partial knowledge
DMOs-sandbag-capacity	transportation capacity of DMO agent	500
r-DMO-filling*	rate for filling sandbags	0.6
r-DMO-loading*	rate for loading sandbags	1.5
r-DMO-unloading*	rate for unloading sandbags	1.5
r-DMO-distributing*	rate for distributing sandbags	1.3
team-size	number of helpers belonging to this DMO agent	10
speed-min / speed-limit	minimum and maximum moving speed of DMO agent	5 / 50 [km/h]
disasters specific		
sandbags-needed	number of sandbags needed at a specific site	depends on sandbags-needed-total and sandbags-needed-distribution
sandbags-needed-total	number of sandbags needed in total (across all sites)	50000
sandbags-needed-distribution	distribution of sandbag demand across sites (homogeneous: same demand at all sites, heterogeneous: different demand at each site)	homogeneous
sandbag-reserve specific		
initial-sandbags	number of filled sandbags already present at begin of simulation	0

* see Table in Supplement B for details

ODD+D Protocol.

Outline		Guiding questions	Description
		III.iv.c How were submodels designed or chosen, and how were they parameterized and then tested?	The submodels were designed with the same "virtual lab" approach in mind as the whole model. The robustness of the submodels has been tested using global sensitivity analysis over an extensive parameter range to determine sensible sets of parameter combinations.

A.2 MODEL ASSUMPTIONS

Table A.2 gives an overview on model assumptions made for certain tasks of the DMO agents, the data source that the assumptions are based on and how they have been translated into model parameters.

TABLE A.2.: Model assumptions.

<table>
<tr><th>Model task</th><th>Assumption</th><th>Source</th><th>Model parameter</th></tr>
<tr><td rowspan="2">Sandbag filling</td><td>Filling rate for sandbags:
- Average: 40-60 sandbags per helper per hour
- Trained helpers: 80 sandbags per helper per hour</td><td>[1] Taschenkarte Deichverteidigung, THW Ortsverband Emden, as of 12/2007, obtainable from www.deichverteidigung.de</td><td rowspan="2">$r_{filling}$
$= [0.6,1.2]\ S \times H \times \min^{-1}$
$= [36,72]\ S \times H \times h^{-1}$

S – Sandbags
H – Helper</td></tr>
<tr><td>Filling via funnel and tying sandbags:
- 180 sandbags per hour in a group of 5-6 helpers ≈ 30-36 sandbags per hour per helper</td><td>[2] Umgang mit Sandsäcken und deren Verwendung, Udo Wawerek THW Ortsverband Dinslaken</td></tr>
<tr><td rowspan="2">Sandbag loading / unloading</td><td>Loading / unloading from truck (by hand):
- If distance to truck < 10 m: 80 sandbags per helper per hour</td><td>[2]</td><td rowspan="2">$r_{loading}$ / $r_{unloading}$
$= [1.0,2.0]\ S \times H \times \min^{-1}$
$= [60,120]\ S \times H \times h^{-1}$</td></tr>
<tr><td>Loading / unloading (palettes):
- If filled sandbags are directly stored on palettes (~ 50-70 Sandbags per palette), they can be loaded much faster</td><td>[1], estimated value</td></tr>
<tr><td>Sandbag distribution</td><td>Distribution at target site (i.e. dike):
- 80 sandbags per helper per hour</td><td>[1]</td><td>$r_{distributing}$
$= [1.0,1.3]\ S \times H \times \min^{-1}$
$= [60, 78]\ S \times H \times h^{-1}$</td></tr>
<tr><td rowspan="2">Transportation</td><td>Transportation capacities:
- calculated from average sandbag weight of 15-20 kg [1]
<table>
<tr><th>Type</th><th colspan="2">Loading capacity</th></tr>
<tr><th></th><th>Weight [t]</th><th>Sandbags</th></tr>
<tr><td>Transporter</td><td>1 – 2</td><td>50 – 120</td></tr>
<tr><td>Small truck (e.g. „Unimog”)</td><td>3 – 7</td><td>200 – 400</td></tr>
<tr><td>Large truck</td><td>10 – 15</td><td>500 – 1000</td></tr>
<tr><td>Lowloader</td><td>20 – 40</td><td>1000 – 2500</td></tr>
</table></td><td>Various technical specifications:
- [3] THW Hamburg Nord http://www.thw-hamburg-nord.de/kfz/fgr-hang1.htm
- [4] PrimoCargo http://www.primocargo.de/deutsch/medien/info-pool/lkw-auflieger
- [5] Der Unimog 300/U400/U500. Technik. Fakten. Daten. DaimlerChrysler AG, http://www.mercedes-benz.com/unimog</td><td>$DMO_{Capacity} \in \{250, 500, 1000, 2000\}$ sandbags per DMO unit</td></tr>
<tr><td>Vehicle speed / speed limits:
<table>
<tr><th>Type</th><th>Motorway</th><th>Outside built-up areas</th><th>Inside built-up areas</th></tr>
<tr><td>Car / transporter [< 3.5 t]</td><td>130 km/h[1]</td><td>100 km/h</td><td>50 km/h</td></tr>
<tr><td>Truck [3.5 – 7.5 t]</td><td>80 km/h</td><td>80 km/h</td><td>50 km/h</td></tr>
<tr><td>Truck / lowloader [> 7.5 t]</td><td>80 km/h</td><td>60 km/h</td><td>50 km/h</td></tr>
</table>
[1] recommend maximum speed</td><td>[6] Straßenverkehrs-Ordnung (StVO): § 3 Geschwindigkeit, § 18 Autobahnen und Kraftfahrstraßen, http://www.gesetze-im-internet.de/bundesrecht/stvo_2013/gesamt.pdf</td><td>Speed limits per street type
<table>
<tr><th>Type</th><th>Speed limit</th></tr>
<tr><td>motorway</td><td>80 km/h
60 km/h</td></tr>
<tr><td>primary</td><td>50 km/h</td></tr>
<tr><td>secondary</td><td>50 km/h</td></tr>
<tr><td>tertiary[2]</td><td>30 km/h</td></tr>
</table>
[2] assumed as residential areas with 30 km/h zones</td></tr>
</table>

B

APPENDIX TO CHAPTER 3

THIS IS THE APPENDIX TO CHAPTER 3 "POLARIZATION IN (POST-)NOMADIC RESOURCE USE IN EASTERN MOROCCO: INSIGHTS USING A MULTI-AGENT SIMULATION MODEL".

B.1 MODEL FLOWCHART

Fig. B.1 shows the temporal sequence of model processes carried out in one time step. The flowchart has been adapted from Hoffmann (2014) & Dressler et al. (2012).

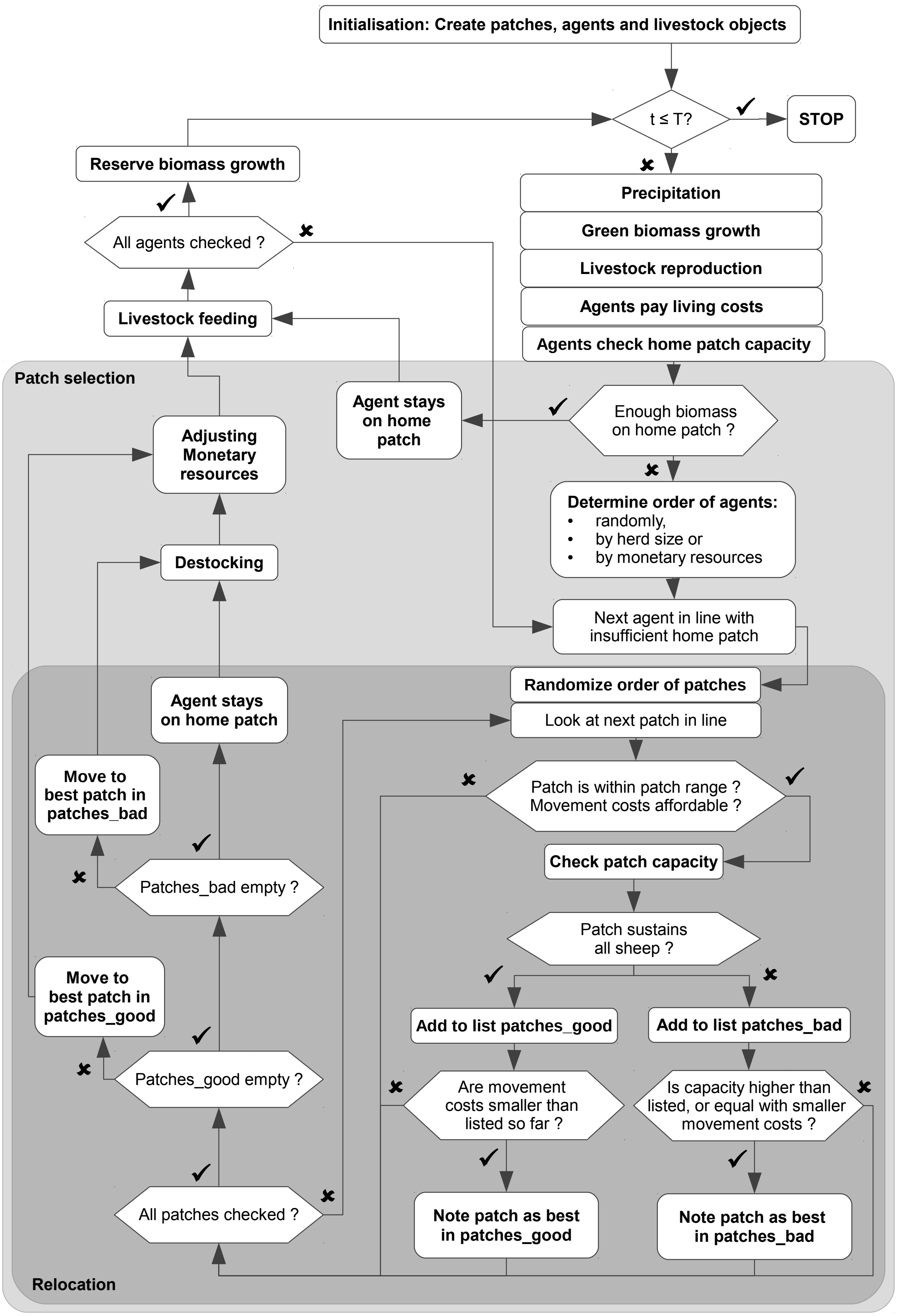


FIGURE B.1.: Flowchart of the main model processes. Round-cornered rectangles indicate processes, rhombuses indicate conditionals.

C

APPENDIX TO CHAPTER 4

THIS IS THE APPENDIX TO CHAPTER 4 "IMPLICATIONS OF BEHAVIORAL CHANGE ON THE SOCIAL, ECOLOGICAL AND ECONOMIC DIMENSIONS OF PASTORAL SYSTEMS: LESSONS FROM AN ABM".

C.1 ODD+D PROTOCOL

TABLE C.1.: ODD+D Protocol.

Outline		Guiding questions	Description
I) Overview	I.i Purpose	I.i.a What is the purpose of the study?	The main purpose of the study is to asses how human decision making influences the long-term livestock and pasture conditions in a stylized semi-arid grazing system. There are two main questions that we try to answer: 1) Under which demographic conditions (number of households) do different behavioral types lead to long-term negative consequences such as pasture degradation and livestock loss, and under which conditions such a collapse might be prevailed. 2) Can a change in decision making lead from an unsustainable resource use (i.e. overusing pastures and long-term degradation) to sustainable resource use? The model implements different human decision models to test for appropriate land use strategies. The models range from standard rational economic approaches to more bounded rationality decision models. The purpose is to systematically compare the decision models that are implemented at the individual level assessing how they influence the outcomes of the three questions from above.
		I.ii.b For whom is the model designed?	- Scientists: understanding the underlying mechanisms behind impacts of human decision making on resource use. - Students: teaching model, to understand how human decision making can be represented in a model.
	I.ii Entities, state variables, and scales	I.ii.a What kinds of entities are in the model?	- There is a single type of agents (households), each representing a pastoralist household. Each household acts independently from each other, following a certain set of decision rules. - The spatial environment is represented as a grid (patches) with each grid cell representing a pasture that provides biomass for livestock grazing.

ODD+D Protocol.

Outline		Guiding questions	Description
		I.ii.b By what attributes (i.e. state variables and parameters) are these entities characterized?	Households: - homepatch: household's home pasture, e.g. where they have a permanent tent - livestock: the number of animals that the household currently owns - destock: the number of animals that the household had to destock in the current time step - strategy-choice: the behavioral strategy that the household follows (each strategy is characterized by a set of variables, see II.ii.b) - household-knowledge-radius: the radius in which households perceive pasture conditions around their current location Patches: - green-biomass, reserve-biomass: the current amount of green and reserve biomass available on the patch (at the beginning of each time step) - green-biomass-over, reserve-biomass-over: the amount of green and reserve biomass left over after feeding took place (at the end of each time step) - rain: the amount of rainfall that has fallen in the current time step and that contributes to biomass growth - is-available-for-grazing?: indicators whether the patch is available for grazing in the current time step and whether it is being grazed in the current time step - is-rested?: indicator whether the patch is rested, and henceforth in certain decision models not available for grazing in the current time step
		I.ii.c What are the exogenous factors / drivers of the model?	- The vegetation growth is driven by stochastic rainfall. - Certain policies can influence the system, e.g. resting can determine when pastures are accessible and when not.
		I.ii.d If applicable, how is space included in the model?	The model is spatially explicit. Space is represented as a grid of pasture patches. We use a torus, i.e. the grid wraps in both horizontal and vertical direction.
		I.ii.e What are the temporal and spatial resolutions and extents of the model?	- The model uses discrete time steps. One time step (tick) represents one year. The time horizon can be set as model parameter, with timesteps = 150 years as standard value. - Each grid cell (patch) represents a 100 ha pasture. The model landscape is 10 x 10 = 100 patches.

ODD+D Protocol.

Outline		Guiding questions	Description

	I.iii Process overview and scheduling	I.iii.a What entity does what, and in what order?	- Initialization: set up of households (initial livestock, location) and patches (initial biomass)
			- In each tick:
			  - On all patches: rainfall occurs and green biomass grows accordingly
			  - All households (sequentially):
			    - Livestock reproduces and each household relocates with their herd, according to their behavioral strategy (e.g. optimizing, satisficing, random, etc.)
			    - Livestock feeds on the pasture biomass, and if necessary animals will be destocked, if not enough fodder is provided
			  - On all patches: reserve biomass grows, depending on the green biomass and the feeding intensity of the households

II) Design concepts	II.i Theoretical and Empirical Background	II.i.a Which general concepts, theories or hypotheses are underlying the model's design at the system level or at the level(s) of the submodel(s) (apart from the decision model)? What is the link to complexity and the purpose of the model?	- We assume a common property resource use system, i.e. every pastures are in principle accessible to every household. - The model components are kept very simple, as the main focus of the model is to gain a mechanistic understanding of interplay of household decision making and the ecological and economic outcomes on the system level. - Complexity arises out of the feedback between the ecological and economic component of the model: The decision where to graze and how much livestock to keep directly impacts the vegetation on the pastures. The amount of biomass available, in turn, limits the number of livestock that can be kept on a pasture. The long-term viability of the system therefore depends on the individual decisions of each household.
		II.i.b On what assumptions is/are the agents' decision model(s) based?	Different decision models are implemented for the households that are based in part on theories (homo economicus, bounded rationality, descriptive norms), as well as observations from case studies.
		II.i.c Why is a/are certain decision model(s) chosen?	One aim of the model is to compare different types of land use strategies by testing how different behavioral models of the agent influence the long-term development of the system, i.e. how livestock numbers and vegetation conditions change in the long run. Therefore we implemented decision models that follow standard rational approaches (optimization), as well as bounded rational decision models that are either motivated by psychological theories (e.g. Descriptive Norms) or more empirical observations of how households decide (e.g. Satisficing).

ODD+D Protocol.

Outline		**Guiding questions**	**Description**
		II.i.d If the model / a submodel (e.g. the decision model) is based on empirical data, where does the data come from?	The model is not based on empirical data. However, parts of the model (e.g. the vegetation growth) are parameterized to resemble the High Plateau in Morocco.
		II.i.e At which level of aggregation were the data available?	Not applicable.
	II.ii Individual Decision Making	II.ii.a What are the subjects and objects of decision-making? On which level of aggregation is decision-making modeled? Are multiple levels of decision making included?	- Households are the subject of decision making. The relocation of the herds between pastures is the object. - There is one level of decision making, the household level.
		II.ii.b What is the basic rationality behind agents' decision-making in the model? Do agents pursue an explicit objective or have other success criteria?	- We have implemented three behavioral types that are based on economic and psychological theories, namely *Homo economicus*, *Bounded rationality* and *Descriptive Norms*. - Each household's objective is to maintain a certain level of livestock, and in order to achieve it they relocate their herd in each time step (year).
		II.ii.c How do agents make their decisions?	Agents decision rules are implemented mainly as if-then rules.
		II.ii.d Do the agents adapt their behavior to changing endogenous and exogenous state variables? And if yes, how?	Yes. Households move their herd onto different pastures according to currently available forage. Depending on the behavioral strategy that each household follows, the subset of pastures that is available to them can be adapted (see the following section II.ii.e for details).
		II.ii.e Do social norms or cultural values play a role in the decision-making process?	Yes.
		II.ii.f Do spatial aspects play a role in the decision process?	Yes. The household-knowledge-radius determines the area (i.e. the of patches) that a household perceives for relcocation in the next step around themselves.

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Outline		Guiding questions	Description
		II.ii.g Do temporal aspects play a role in the decision process?	Households make decisions based only on the current state of the system.
		II.ii.h To which extent and how is uncertainty included in the agents' decision rules?	Uncertainty is not included in the decision making.
	II.iii Learning	II.iii.a Is individual learning included in the decision process? How do individuals change their decision rules over time as consequence of their experience?	No, learning is not included.
		II.iii.b Is collective learning implemented in the model?	No.
	II.iv Individual Sensing	II.iv.a What endogenous and exogenous state variables are individuals assumed to sense and consider in their decisions? Is the sensing process erroneous?	- Households sense the vegetation state of the pastures (amount of green and reserve biomass available.) within their knowledge radius. Because agent decision making is sequentially, households sense the actions of other households indirectly by perceiving the grazing state of each pasture when they make their decision. - Households sense the behavior of other households via a descriptive norm that summarizes whether households rest pastures or not. - The sensing is not erroneous, i.e. households always perceive the true biomass amounts.
		II.iv.b What state variables of which other individuals can an individual perceive? Is the sensing process erroneous?	Households are not able to sense the state variables of other agents.
		II.iv.c What is the spatial scale of sensing?	The scale depends on the value of the household-knowledge-radius. The scale can be set from purely local (radius = 0 patches) to global (radius = 5 patches).

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Outline		Guiding questions	Description
		II.iv.d Are the mechanisms by which agents obtain information modeled explicitly, or are individuals simply assumed to know these variables?	Agents are assumed to know the values of the sensed variables.
		II.iv.e Are costs for cognition and costs for gathering information included in the model?	No.
	II.v Individual Prediction	II.v.a Which data uses the agent to predict future conditions?	Households do not predict future conditions.
		II.v.b What internal models are agents assumed to use to estimate future conditions or consequences of their decisions?	Not applicable.
		II.v.c Might agents be erroneous in the prediction process, and how is it implemented?	Not applicable.
	II.vi Interaction	II.vi.a Are interactions among agents and entities assumed as direct or indirect?	Interactions between households are indirect. Households perceive the state of the pastures and therefore the relocation of herds of other households and can take these into account when deciding where to move.
		II.vi.b On what do the interactions depend?	Interaction does not depend on any parameters/conditions.
		II.vi.c If the interactions involve communication, how are such communications represented?	Not applicable.

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Outline		Guiding questions	Description
		II.vi.d If a coordination network exists, how does it affect the agent behavior? Is the structure of the network imposed or emergent?	Not applicable.
	II.vii Collectives	II.vii.a Do the individuals form or belong to aggregations that affect, and are affected by, the individuals? Are these aggregations imposed by the modeler or do they emerge during the simulation?	Households do not form collectives in the current model version.
		II.vii.b How are collectives represented?	Not applicable.
	II.viii Heterogeneity	II.viii.a Are the agents heterogeneous? If yes, which state variables and/or processes differ between the agents?	Household's state variables are homogeneous.
		II.viii.b Are the agents heterogeneous in their decision-making? If yes, which decision models or decision objects differ between the agents?	Households take the same decision: where to relocate their herd and how many animals to stock. However, households can be heterogeneous in their decision strategy (see II.ii.b or III.iv.a).
	II.ix Stochasticity	II.ix.a What processes (including initialization) are modeled by assuming they are random or partly random?	- Rainfall is modeled by a lognormal distribution with given mean and standard deviation. This influences the biomass growth on each patch. - Agents are initialized with random location. - The order in which agents act is determined randomly in each time step. - Depending on the chosen behavioral model, household decisions can be random, or might consider only a random subset of patches.

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Outline		Guiding questions	Description
	II.x Observation	II.x.a What data are collected from the ABM for testing, understanding, and analyzing it, and how and when are they collected?	In the graphical user interface, we plot the values of the following variables for each time step: - Livestock distribution: mean and standard deviation across all households, current livestock for each household, Gini coefficient and Lorenz curve of livestock distribution (a measure for inequality) - Number of surviving households, i.e. households with livestock > 0 - Rainfall: mean and standard deviation across all patches - Vegetation: mean and standard deviation of green biomass and reserve biomass across all patches For parameter variations conducted with the NetLogo Behavior Space, we collect for every simulation the final states of: - Livestock distribution: average herd size and standard deviation across households, as well as total sum of livestock, gini coefficient of livestock distribution (a measure for inequality) - Household count: total number of surviving households, i.e. households with livestock > 0 - Vegetation: average and standard deviation of green biomass,and reserve biomass across all patches
		II.x.b What key results, outputs or characteristics of the model are emerging from the individuals?	As we assume a common property regime, and households make decisions independently, we can observe whether decision making leads to sustainable resource use or pasture degradation, and therefore also livestock loss, over the long term. Which situation occurs depends on the chosen behavioral model, as well as the parameters that are chosen.
III) Details	III.i Implementation Details	III.i.a How has the model been implemented?	The model has been implemented in NetLogo 5.2.0.
		III.i.b Is the model accessible and if so where?	The model will be made accessible at openABM.org
	III.ii Initialization	III.ii.a What is the initial state of the model world, i.e. at time t=0 of a simulation run?	At the beginning of each simulation, pastures are initialized with the same amount of fodder and households are randomly distributed across the landscape, with each patch holding one household maximum. All households start with the same amount of livestock.
		III.ii.b Is initialization always the same, or is it allowed to vary among simulations?	Initialization between simulations varies only in initial household location which is determined randomly.
		III.ii.c Are the initial values chosen arbitrarily or based on data?	Initial values are arbitrarily chosen.

ODD+D Protocol.

Outline		Guiding questions	Description
	III.iii Input Data	III.iii.a Does the model use input from external sources such as data files or other models to represent processes that change over time?	No external data is used.
	III.iv Submodels	III.iv.a What, in detail, are the submodels that represent the processes listed in 'Process overview and scheduling'?	<u>Rainfall</u>: - Annual rainfall is modeled using a lognormal distribution with a given mean and standard deviation. Values are either drawn for each pasture (individual rainfall) or globally, producing the same rainfall for all pastures (global rainfall). - $\text{rain}(t) \sim \text{LogNorm}(\text{rain-mean}, \text{rain-std})$ <u>Vegetation growth:</u>: - Vegetation is modeled as a single representative perennial plant type that consists of two functional parts: green biomass G and reserve biomass R. Green biomass comprises all photosynthetic active parts of the plants and serves as the main fodder for the livestock. Reserve biomass summarizes the storage parts of the plant below and above ground (e.g., base stalk and roots). - Green biomass growth is determined by precipitation and by the amount of reserve biomass on the pasture. Reserve biomass buildup depends strongly on green biomass: Grazing reduces the amount of green biomass that can fully contribute to the growth of reserve biomass, measured by the grazing pressure of the livestock (only ungrazed green biomass can fully contribute to reserve biomass growth). Additionally, parts of the reserve biomass, termed Redible, can be consumed (destroyed) by the livestock if green biomass is not sufficient. - Every patch represents one pasture, for which green biomass and reserve biomass growth is modeled individually. - Biomass growth is modeled using two differential equations: - $$\begin{aligned} G[t] =& G[t-1] + rain[t] \times rue \times R[t-1] \\ & with\ G[t] \leq \lambda \times R[t] \\ R[t+1] =& R[t] + w \times \{gr1 \times (G_{init}[t] - G[t]) + G[t]\} \\ & \times \{1 - d \times R[t]\} \\ & - \{m_r \times R[t] + (gr_2 \times R[t] - R_{edible}[t])\} \end{aligned}$$ where $R_{edible} \in [0, gr2 \times R[t]]$ quantifies the portion of consumed reserve biomass in the current tick.

ODD+D Protocol.

Outline	Guiding questions	Description
		Livestock reproduction: - Livestock reproduce with a constant reproduction rate b at the beginning of each time step: - $L[t] = (1 + b) \times L[t-1]$ Household relocation: - In each tick households select a pasture, according to a relocation-strategy, which will be discussed below. - Households move sequentially in a random order (determined by command "ask"). - Distances between pastures are considered via the knowledge-radius parameter: The value sets the number of (extended) Moore neighborhood radii around the current focal pasture of the household, that will be taken into account when they select a new pasture, e.g. knowledge-radius = 1 specifies the 8-cell nearest neighbors, knowledge-radius = 2 the 8-cell + 16-cell = 24 nearest neighbor cells and so on. - Strategy "TRAD": The TRAD type represents a traditional household type that tries to maximize his herd size ($c_i = \infty$)). A TRAD strategist also has a high intrinsic preference for pasture resting ($q_i = 0.95$) as he follows traditional resting rules. However, this type is also susceptible to the behavior of others, depicted in a high social susceptibility ($s_i = 0.8$). Thus, this type aims to select the pasture with the highest available amount of biomass (he is able to perceive the state of all pastures), taking into account the resting state of the pastures and the behavior of the other households. - Strategy "MAX": The MAX type represents a short term profit maximizer, and will choose the pasture with the highest available biomass within its knowledge-radius, in order to maximize herd size ($c_i = \infty$). The type does not abide to resting rules ($q_i = 0$) and is not susceptible to the behavior of other households ($s_i = 0$). - Strategy "SAT": The SAT type does not aim to maximize his number of livestock but to reach a satisfactory level of livestock ($c_i \in [c_{min}, c_{max}]$). This type is bounded in his vision and cognitive capacity, and therefore only perceives and evaluates a subset of all pastures within a certain radius around himself. Based on this subset, the type follows a simple heuristic and selects the first pasture with sufficient available biomass to sustain his livestock. If it cannot find a suitable pasture, it will select the best pasture of that subset and destock its herd. Likewise, if it finds a pasture that allows it to keep more animals than its satisficing threshold c_i, it will not keep more animals than that and destock any surplus animals. Similar to the MAX type, it is not influenced by others in its behavior ($s_i = 0$) and does not abide to resting rules ($q_i = 0$).

ODD+D Protocol.

Outline		Guiding questions	Description

			Livestock feeding and destocking:
			- Livestock has a constant amount of fodder uptake of 640 kg per animal per year. After moving, the agent will determine if he needs to destock livestock and if so, how much.
			`fodder-needed[t] = intake x L[t]`
			`fodder-available[t] = G[t] + gr2 x R[t]`
			
			`if ( fodder-needed[t] > fodder-available[t] )`
			`then {`
			`L[t] = L[t] - (fodder-needed[t] - fodder-available[t]) / intake`
			`}`
			- Livestock will then feed immediately, so that the next household will make his decision based on the updated biomass values

ODD+D Protocol.

Outline	Guiding questions	Description
	III.iv.b What are the model parameters, their dimensions and reference values?	(see parameter table below)

Parameter	Description	Standard value / range
number-households	number of households in the system N_H	80
timesteps	number of ticks T that the model runs [years]	40
w	biomass growth rate	0.8
rue	rain use efficiency $[kgG \times (kgR \times mm)^{-1}]$	0.002
lambda	growth limit of green biomass G, relative to reserve biomass R	0.5
R_{max}	growth limit of reserve biomass [kg / 100 ha]	150000
d	density dependence of reserve biomass, $d = \frac{1}{Rmax}$	1/150000
m_r	reserve biomass mortality rate	0.1
gr_1	green biomass grazing harshness, *quantifies the reduced contribution of grazed green biomass to reserve biomass growth*	0.5
gr_2	reserve biomass grazing harshness, *quantifies the share of edible reserve biomass*	0.1
b	livestock birth rate	0.8
intake	fodder intake of livestock [kg / a]	640
rain-mean	mean annual rainfall [mm / a]	200
rain-std	standard deviation of annual rainfall [mm / a]	100
relocation-strategy	behavioral strategy of the household for livestock relocation	one of: TRAD, MAX, SAT
knowledge-radius	radius of perception of pastures	5
intrinsic preference q_i	household's intrinsic preference for pasture resting	0-1
social susceptibility s_i	strength of susceptibility to the resting behavior of other households	0-1
satisficing threshold c_i	herd size aspiration level [sheep]	50, 80, ∞
resting threshold θ	threshold for pasture resting, relative to R_{max}	0-0.6

ODD+D Protocol.

Outline		Guiding questions	Description
		III.iv.c How were submodels designed or chosen, and how were they parameterized and then tested?	The different decision submodels were chosen to build a "virtual lab" to test how decision making influences resource use and if different behavioral models lead to different outcomes. The ecological submodels are based on already tested and published models of (Mueller et al., 2007) and (Martin et al., 2014) and parameterized in the same way. The decision models have been tested using global sensitivity analysis over an extensive parameter range to determine sensible sets of parameter combinations.

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