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Improving the representation of smallholder farmers' adaptive behaviour in agent-based models: Learning-by-doing and social learning

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ABSTRACT

Computational models have been used to investigate farmers' decision outcomes, yet classical economics assumptions prevail, while learning processes and adaptive behaviour are overlooked. This paper advances the conceptualisation, modelling and understanding of learning-by-doing and social learning, two key processes in adaptive (co-)management literature. We expand a pre-existing agent-based model (ABM) of an agricultural social-ecological system, RAGE (Dressler et al., 2018). We endow human agents with learning-by-doing and social learning capabilities, and we study the impact of their learning strategies on economic, ecological and social outcomes. Methodologically, we contribute to an under-explored area of modelling farmers' behaviour. Results show that agents who employ learning better match their decisions to the ecological conditions than those who do not. Imitating the learning type of successful agents further improves outcomes. Different learning processes are suited to different goals. We report on conditions under which learning-by-doing becomes dominant in a population with mixed learning approaches.

1. Introduction

With 500 million small farms globally, smallholders' decisions impact both global food security, and the health of our planet (IFAD, 2003). Environmentally, farmers' decisions, and at a larger scale the development of the agricultural sector, affect outcomes in land-use and land-cover changes, biodiversity loss, soil quality, water availability and climate change, among others (Foley et al., 2005; Tilman et al., 2001). Unpacking the cognitive, economic, and social dimensions of farmer behaviour remains, therefore, relevant to sustainability. To this end, this article advances the modelling and understanding of smallholders' learning and adaptive behaviour, in particular of learning-by-doing and social learning.

Computational models have long been employed to study human-environment interactions in agricultural systems. Most models take a classical economics perspective and represent farmers' decision-making in aggregate ways and as a direct response to market influences (Brown et al., 2017; Huber et al., 2018; Janssen and van Ittersum, 2007). Prevailing are assumptions of rational choice and of access to perfect information on market conditions, strategy options and their associated payoffs. However, knowledge about resource and economic dynamics is usually incomplete, either due to inherent uncertainties about the underlying processes, such as input availability, environmental variability or price fluctuations, or due to social structures and institutions mediating information flows. In addition, empirical studies have shown that individual behaviour is sensitive to cognitive shortcuts, experimentation, peer influences, habits, and cultural norms (Camerer, 1995; Kahneman and Tversky, 2000; Simon, 1955). As such, calls have been made to improve decision-making representation within models by moving beyond rational choice approaches (Huber et al., 2018; Parker et al., 2003; Rounsevell et al., 2014; Schlüter et al., 2012).

Efforts to diversify the range of theories used when modelling human behaviour within social-ecological systems (SESs) are in their early days. Some progress has been made in specifying behavioural approaches alternative to the rational choice theory, as well as in designing and parameterising agent decision models using clear theoretical assumptions or empirical data (Filatova et al., 2013; Groeneveld et al., 2017; Jager, 2000; Janssen, 2016; Schwarz et al., 2019). Within agricultural applications, efforts in this sense have focused on implementing social networks and decision heuristics (e.g., imitation, endorsement) to introduce heterogeneity in farmers' behaviour (Caillaut et al., 2013; Gotts and Pollhill, 2009; Kreft et al., 2023; Malawska and Topping,

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2016; Morgan and Daigneault, 2015; Pacilly et al., 2019; van Duinen et al., 2016; van Oel et al., 2019). Still, the representation of processes of learning about environmental resources under conditions of risk and uncertainty, as well as the effect of social interactions on such learning, rather than merely on outcomes, remain underdeveloped (Bousquet and Le Page, 2004; Brown et al., 2017; Huber et al., 2018; Schlüter et al., 2012; Schulze et al., 2017). Although very advanced and specialized literatures exist on learning processes, for instance reinforcement learning (see a recent review by Neftci and Averbeck (2019), or learning to reduce uncertainty about social interactions or to evolve behavioral strategies in response to other players' moves in game theoretic settings (FeldmanHall and Shenhav, 2019; Leclercq et al., 2023; van den Berg and Wenseleers, 2018), insights from these branches seldomly find their way back into social-ecological and/or agricultural ABMs where the representation of agent decision-making remains rather simple.

Learning is closely linked to adaptation and is often discussed as a normative goal (Armitage et al., 2008; Baird et al., 2014; Fabricius and Cundill, 2014). For farmers, in particular, adaptation is a key aspect of decision-making, understood as a set of "adjustments in agricultural systems in response to actual or expected stimuli" (Robert et al., 2016, p. 2). While concepts of learning and adaptation come in many flavours (Apetrei et al., 2021; Berkes, 2009; Suškevičs et al., 2018; Tosey et al., 2012), here we focus on two processes which are central to natural resource management (Plummer et al., 2012): *learning-by-doing* and *social learning*. The former is used within adaptive management literature to refer to *an iterative cycle of systematically adjusting actions in response to environmental feedbacks* (Allen and Garmestani, 2015; Walters, 1986; Walters and Holling, 1990). The latter is linked to co-management and governance and it involves changes of understanding rooted in participatory processes and social interactions (Reed et al., 2010). We note that the modelling literature makes a distinction between learning and adaptation that is sometimes missed in other fields: learning requires a change in agents' decision rules, i.e., of the associations between sets of states of the world and sets of actions to be undertaken, while adaptation refers to a changed action in response to a change in the environment, without altering the underlying rule (Tesfatsion, 2020). Here, we depart from concepts of learning-by-doing and social learning as they are described in the adaptive (co-)management literatures, and we explore the effects of these processes in a stylised social-ecological system (SES) model.

Against this background, the aims of our paper are twofold: a) to make a methodological contribution to representing *learning-by-doing* and *social learning* in a social-ecological agent-based model; b) to elucidate how these processes and their interactions might affect farmers' decision outcomes. We achieve these by suggesting a conceptual framework to guide the implementation of learning concepts into models, and by applying it to a pre-existing ABM of an agro-pastoral system, RAGE (Dressler et al., 2018). We specify our analysis of the relationship between learning processes and decision outcomes into the following research questions:

1) How are the outcomes of agents' decisions affected by different learning types?
2) How do different ways in which agents learn (learning types) interact and to what effects?

Our study design and assumptions are grounded in three literature streams. First, we take a social-ecological systems perspective, i.e., we regard farmer-environment interactions as "characterised by strong connections and feedbacks within and between social and ecological components that determine their overall dynamics" (Biggs et al., 2021, p. 5). Relational, co-evolutionary and emergence aspects are central to such systems (Preiser et al., 2018; Schlüter et al., 2019a). Second, we understand farming systems as "complex adaptive systems". Time is a key variable, there is path dependence and learning is an ongoing and interactive process influenced by the decision context (Darnhofer et al., 2010). Third, in line with adaptive (co-)management, we posit that farmers' learning about the natural environment to be managed is not limited to individual experimentation, but can also result from interaction and discussions with others (Darnhofer et al., 2010; Munaretto and Huitema, 2012; Plummer et al., 2012).

2. Theoretical background

We begin by situating the core concepts within the literatures from which they emerged and we specify who learns, what is learnt and to what effect (Bennett and Howlett, 1992).

2.1. Learning-by-doing

The concept of learning-by-doing originates from studies of industrial production where it was linked to observed reduction of unit costs over a doubling of output (Wright, 1936). It then entered economics and operations management under the name of "learning curve" (Glock et al., 2019), typically modelled as a power function relating experience to performance (Dosi et al., 2017). In the human-technological systems literature, learning-by-doing is learning due to increased experience which results in declining failure rates (Bointner and Schubert, 2016).

Related concepts are "reinforcement learning", originating in psychology (Brenner, 2006; Skinner, 1938), which is modelled by assigning higher probability to actions that have proven successful (Arifovic and Ledyard, 2004), and "experiential learning", from organizational learning, which describes how generalisations are formed by observation and tested in new situations (see Miettinen, 2000). Appendix A comprises an overview of various learning-by-doing interpretations which can be used as a starting point for various modelling tasks.

In this study, we follow the conceptualisation in the adaptive management literature, where learning-by-doing has been used interchangeably with "experiential learning" to refer to knowledge generation in systems characterised by uncertainty and environmental change (Kato and Ahern, 2008; Lindkvist and Norberg, 2014). As a structured process of adaptation, learning-by-doing encompasses gradual changes in behaviour based on observations of past actions. The emphasis on the process being "structured", i.e., methodical, differentiates learning-by-doing from random trial-and-error (Lee, 1999; Walters, 1997). The subject of learning – who learns – is often left ambiguous, while some authors claim that learning-by-doing can be observed both as a change in individual behaviour, as well as at the community level (Munaretto and Huitema, 2012). The latter situates learning-by-doing close to some views of social learning, as explained in Section 2.2.

For our purposes of developing an agent-based model, we define learning-by-doing as an *individual* process of adjusting decisions based on observations from the environment, and in accordance with an internal, a priori set of decision rules. From the point of view of adaptive management literature, this corresponds to first-order (or single-loop, see Section 2.3) learning because the *rules* by which the behaviour is adjusted are not altered. It also takes place at the level of each individual household, without consideration of external factors or other agents. Lastly, learning-by-doing in this conception does not exclude utility maximisation, nor does it imply optimisation in the sense of classical decision theory, since no expected payoffs are calculated; instead, it is a reactive decision to past observations.

2.2. Social learning

Social learning has also been subjected to diverse and often conflicting interpretations (Apetrei et al., 2021; Rodela, 2011). Miller and Dollard (1941) were the first to propose that individuals observe others and behave according to formed expectations about benefits and rewards (Muro and Jeffrey, 2008). These insights were further developed into Bandura's (1977) social learning theory, who emphasised the observation and imitation of others.

Within economics, imitation has been mostly modelled according to some heuristic as chosen by the modellers, but with few connections to theories of behaviour (Section 2.4). Decision rules could include, for instance, imitating the agents with highest performance or executing an average behaviour (Brenner, 2006).

In agricultural contexts, imitation strategies are recognised as effective ways of minimising risks and they often entail copying decision rules rather than specific farming activities (Le et al., 2012). Particularly in situations of risk or where outcomes are highly uncertain, individuals start considering the experiences of others around them, whom they consider successful (Jager, 2000; Nowak et al., 2017). Jager (2000), for instance, elaborate on insights from the psychology literature to suggest a model where heuristics such as imitation and social comparison occur in conditions of high uncertainty, as opposed to deliberation and repetition, which are more frequently employed under low uncertainty. Due to space limitations, a comprehensive discussion of numerous other ABMs that build on Jager's ideas (e.g. Malawska and Topping, 2016; Pacilly et al., 2019; van Duinen et al., 2016; van Oel et al., 2019) is beyond the scope of this paper. Yet all these models integrate evidence that farmers' decisions are influenced by their social *milieu,* i.e., their social networks (Hunecke et al., 2017; Janssen and van Ittersum, 2007). Although personal relationships and trust are important in agricultural decision-making, social mimicry alone might sometimes explain how behaviour spreads (Rebaudo and Dangles, 2011). As innovation diffusion theories suggest, others' behaviours influence decisions when clear benefits of adoption are observed or when there is sufficient adoption of an innovation in a community as to alter perceived norms (Jager et al., 2000; Kreft et al., 2023; Nowak et al., 2017; Weisbuch and Boudjema, 1999).

Lastly, in natural resource management and governance, social learning is strongly linked to participatory processes (Leclercq et al., 2023; Schusler et al., 2003), which may result in changed knowledge, changed actions and/or changed actor relations (Beers et al., 2016). In practice, what exactly changes and who learns is seldom specified. For instance, a much-cited definition of social learning points to changed knowledge, yet situates outcomes at the community, rather than the individual level: "a change in understanding that goes beyond the individual to become situated within wider social units or communities of practice through social interactions between actors within social networks" (Reed et al., 2010, p. 6). Other scholars conceptualize social learning as learning *about* the social milieu, focusing thus on how agents learn to anticipate other people's behaviours (FeldmanHall and Shenhav, 2019; Martinez-Saito and Gorina, 2022; van den Berg and Wenseleers, 2018). To avoid terminology confusion, but also for practical reasons, modelling social learning requires specifying the subjects and objects of learning. To this purpose, a helpful classification is that of Rodela (2011), who identified three perspectives on social learning: an individual-centric perspective, which refers to changes in personal understanding based on social relations, a network-centric perspective emphasizing changes in practices and relationships at group level and a system-centric perspective describing changes in institutional settings and broader policies. Some authors within adaptive (co-)management have employed a network-centric perspective to link social learning with learning-by-doing, by highlighting how joint community experimentation with ecological feedbacks can foster participation and exchange (Munaretto and Huitema, 2012).

In our study, we implement social learning as an *individual-centric process of imitating successful agents* and we compare two alternatives which differ in *what* is being imitated. We then evaluate the effects of social learning not just as individual outcomes, but also at the community level, as a diffusion process over the entire population. Substantially, in our study's conception, social learning differs from learning-by-doing in terms of the learning trigger, namely observations of the natural vs. the social environment, and the explanatory process behind the learning, i.e., cognitive processing of information vs. imitation (see Section 3, Table 1).

2.3. *Effects of learning and process interactions*

Building upon the previous discussion, the concept of a feedback loop is also useful to describe *what* changes as a consequence of learning processes and at which scale. Le et al. (2012) draw on Scholz (2011) to discuss feedback loops and various types of adaptation in the modelling of land-use decisions in an ABM setting. They distinguish between a primary and a secondary feedback loop that determine human behaviour by feeding information from the environment. The primary loop refers to how „human agents perceive the status of the environment and react to it", while the secondary loop requires a „reframing of the agent's behavioural program" (Le et al., 2012, p. 84). This echoes conceptualisations of single-, double- and triple-loop learning. Single-loop learning refers to correcting errors[1] by changing actions based on observed feedback from the environment, double-loop refers to changing existing values and rules that drive actions (Argyris and Schön, 1978; Williams and Brown, 2018), while triple-loop learning is about changing the broader institutional and societal context underpinning the set of possible rules/strategies (Armitage et al., 2008; Pahl-Wostl, 2009). Note, again, that only double-loop learning would qualify as "learning" in a strict modelling / cybernetic sense.

Learning loops clarify what learning can be *about*, but are also not always explicit about *who* is learning. Here, five levels identified by Diduck (2010) may be helpful in specifying learning for model implementation: individual, action group, organization, network, and society. We use these insights about the objects and subjects of learning in Section 3 where we propose and apply a framework for making modelling choices transparent.

2.4. *Linking learning to theories of behaviour*

A final theoretical aspect which is relevant to ABMs and our effort here pertains to the relationship between various learning processes and theories of behaviour. In incorporating agent behaviour, the modeller is confronted with four main tasks: finding theories about decision-making, formalising, implementing and documenting them (Schwarz et al., 2019). However, the place of learning processes within behavioural theories is not always clear. For instance, reinforcement learning and social learning have been listed as theories in their own right, along rational choice and bounded rationality (Schwarz et al., 2019). Our review above suggests that definitions are paramount, as learning processes may be specified in ways that are compatible with multiple theories.

Schlüter et al. (2017) list several theories of behaviour useful for ABMs. Among these, the theory of descriptive norms, which assumes that actors will behave in accordance to what they observe in others, matches our conceptualisation of social learning at the individual level. Similarly, habitual behaviour theory suggests a response to positive experiences as assumed by learning-by-doing and reinforcement learning. However, we note that both theories allow for an operationalisation of learning while taking either a rational choice or a bounded rationality view. The theory of descriptive norms tells us that an agent might imitate the behaviour of others, but it does not specify which criteria are used for selecting whom to imitate: e.g., will the agent maximise utility by imitating the most successful agent they observe, or will they take a satisficing approach imitating the first agent encountered which performs slightly better? In the next section we offer a first modest step towards disentangling such considerations.

[1] In line with the discussion in Section 2.1 these would be errors-of-commission.

Table 1
Conceptual framework for modelling learning-by-doing and social learning. Highlighted rows indicate learning processes that we explicitly analysed in this study.

Model elements	Learning types	Level of learning (who learns)	Level of learning effect	Target of learning (what changes)	Explanatory process description	Learning trigger	Agent's (implicit) goal
Behavioural strategy 1	**Learning-by-doing**	Individual level: agent	Individual level	Agent actions	Cognitive processing of information from the environment	Observation from the environment	Individual profit maximisation
Behavioural strategy 2	**Social learning 1**	Individual level: agent	Individual level	Agent attributes	Imitation of other agents' characteristics / heuristics	Observation of neighbours	Individual profit maximisation
Strategy switching	**Social learning 2**	Individual level: agent	Individual level	Agent learning type (i.e., behavioural strategy)	Imitation of other agents' learning type	Observation of neighbours	Individual profit maximisation
		Individual level: agent	Community level	Distribution of learning types in the simulated world	Diffusion of learning types	NA - Emergent phenomenon	Individual profit maximisation

3. Conceptual framework

3.1. Modelling farmers' learning-by-doing and social learning

In Table 1, we propose a conceptual framework (column headings) for specifying learning processes, and we apply it to learning-by-doing and social learning, as defined in this study. The goal is not to be exhaustive, but rather transparent about our operationalisation decisions.

A first choice was to consider both learning processes as individual learning, i.e., changes situated at the level of one agent, in this case one household unit. *Learning-by-doing* is a change of actions in response to observed feedback from the environment; a cognitive approach to information processing is assumed. We distinguish among two types of social learning. *Social learning 1* is modelled as a change in agent attributes, where the trigger is an observation of other agents' outcomes. *Social learning 2* is a double-loop type of learning, where agents learn by imitation and alter their decision-making *rules* by changing their agent type. The effects of this second-order learning can be observed both at the individual level, as personal performance, as well as at the community level where the initial distribution of learning types in a heterogeneous population changes over time. We decided to focus our analysis of strategy switching on outcomes at the community level, because we thought emergent effects would be more interesting than isolated agent performance.

Second, to keep the model and analysis manageable, we limited the goals of the agents to profit maximisation, i.e., consistent with neoclassical economics. In future models, alternative goals could be used as driving the learning behaviours presented.

3.2. Explicating the role of uncertainty

One important step for modelling learning, which is not elicited by the framework above, is to clarify the role of uncertainty in agent decision-making.

First, different types of learning may be aimed at reducing different types of uncertainty. Four sources of uncertainty in social-ecological systems are discussed in adaptive management: *structural uncertainty, environmental variation, partial control* and *partial observability* (Williams, 2011; Williams and Brown, 2016). *Structural uncertainty* refers to a limited or no understanding of the underlying dynamics that governs how the resource state changes from one time step to the next. *Environmental variation* includes external factors that affect resource dynamics, for instance precipitation patterns. *Partial observability of the resource* may be linked to problems of access, but we also add here distorted or noisy information flows (due to both exogenous or endogenous causes, e.g., selection bias), as well as what other authors call epistemic uncertainty, i.e., limited knowledge of the state of the resource due to improper measurement or insufficient data, among others (Regan et al., 2002). Finally, *partial control* denotes a difference between the intended effects and those that actually occur. This can be due to properties of the agent (attitudes, limited cognitive abilities, errors), but also to other factors affecting the resource state, for instance when multiple users manage the same resource.

In Fig. 1, we elaborate on Williams and Brown's (2016) work to represent how sources of uncertainty in an SES relate to learning-by-doing and social learning. To the typology above we add a *partial observability of the social conditions* (e.g., motives of neighbours' actions, local-world market conditions, governmental regulations, other behavioural drivers). This is particularly relevant for farmers' imitation behaviour, as factors behind others' performance or decisions might not be fully accessible, behaviour might be difficult to copy (Le et al., 2012) or strategies might be difficult to infer from observations (Miller and Page, 2007). Furthermore, the observability of the broader social environment depends on the structure of one's personal network.

Due to emergence at the level of the coupled SES, additional sources of uncertainty might be relevant (see Schlüter et al. (2019a)), for instance not knowing whether the behavioural strategy observed socially might transfer with similar results to one's context. An acknowledgment of the sources of agent's uncertainty is necessary. Note that this

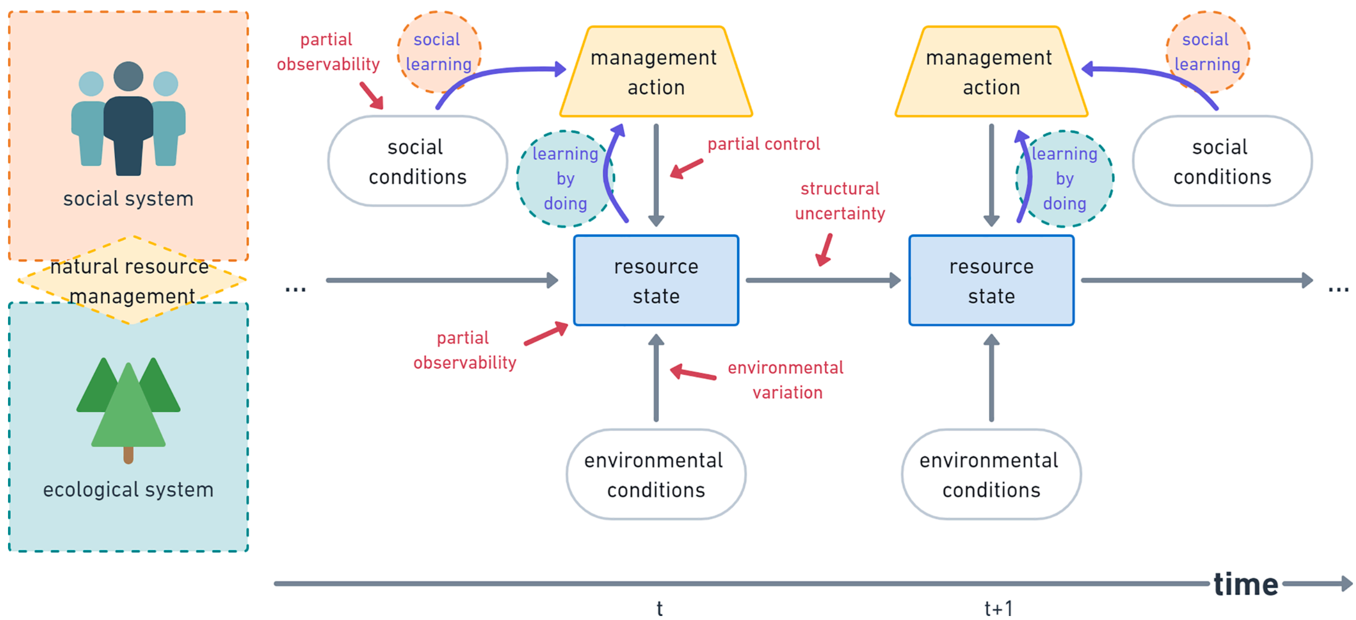

Fig. 1. Sources of uncertainty in social-ecological systems and their relationship to learning. Elaboration based on Williams and Brown (2016).

is different from highlighting model uncertainty sources (stochasticity), as information accessible to the modeller may not be accessible to the agents.

A second consideration is that agents deal with uncertainties in different ways. For instance, pest dynamics models revealed that there are broad differences in how information is diffused, perceived and used (Rebaudo and Dangles, 2011). Huber et al. (2018) emphasise that farmers' heterogeneity in decision-making should capture not only cognitive processes or social interactions, but also the socio-economic and natural context in which they take place, such as opportunity costs for non-agricultural activities and various short-term and long-term calculations. Similarly, Darnhofer et al. (2010) highlight that farmers' choices are constrained by their personal characteristics and external structures, which makes learning a relational understanding of reality rather than an objective cognitive process. Other scholars call for attention to environmental cognitions (Meyfroidt, 2013), the role of risk attitudes in relation to learning (Marra et al., 2003) or to inaccuracies in payback calculations (Muelder and Filatova, 2018). The latter points to our earlier notion of *partial control*.

This theoretical discussion is relevant, insofar as it illustrates the need to account for various sources of uncertainty when representing agent decision-making. In our model we include agent heterogeneity in responding to uncertainty by introducing a stochastic "resistance" parameter to mediate behavioural responses to social and ecological feedbacks (Section 4.2.3).

4. Methods

We implement and study learning processes in a pre-existing rangeland grazing ABM of agro-pastoralist communities, RAGE (Dressler et al., 2018). RAGE is written in NetLogo (Wilensky, 1999) and developed to explore how different theories of human decision-making impact resource management. Although inspired by empirical work, it is a *stylised* social-ecological model.

We decided to build upon this model for several reasons. First, RAGE achieves a good balance between the complexity and simplicity of the social-ecological interactions represented; it falls within the so-called "Medawar zone" (Kuiper, 2016; Loehle, 1990). Studying learning processes requires feedback from the environment to inform decision-making. However, a too complicated model would have made it difficult to tease out the impacts of learning from other confounding variables. Second, the rangeland system is easy to repurpose to represent smallholder livestock farmers. Third, as a spatial model, RAGE allows us to implement social learning based on observation of neighbours – a diffusion process typical for agricultural communities (Beaman and Dillon, 2018; Dowd et al., 2014). Fourth, RAGE was specifically developed to study behavioural strategies beyond rational choice, and it includes a component of collective action and institutional emergence – aspects closely related to social learning. Finally, the sharing and reuse of ABMs is encouraged within the modelling community as a way to enhance verification and transferability of insights (Schulze et al., 2017).

4.1. Original model description

RAGE comprises of a social component, represented by households, and an ecological component, represented by pastures. These interact through various feedbacks. Individual households own livestock and place their herd on pastures to graze. The pasture provides fodder, but grazing pressure affects the amount of available biomass in the future. The regeneration of the pasture is driven by a simple vegetation regrowth model, which includes precipitation. There are two types of vegetation driving the pasture regeneration dynamics: green biomass and reserve biomass. Green biomass consists of plant parts which are easier to consume, such as leaves and small branches; these are grazed first. Reserve biomass represents the stock of stems and roots of the plants which is needed for the regeneration of green biomass. The model runs over several time steps. At each time step, households sense the available biomass on surrounding pastures and make decisions about where, within a pre-specified radius, to place their livestock, in order to achieve their goals, as determined by their typology. Three behavioural types, corresponding to different theories, are implemented in the original model: traditionalist, profit maximiser and satisficer. Every year, livestock numbers increase through reproduction. Livestock heads exceeding the fodder availability on the pasture where they are placed die. When a household reaches a zero-level of owned livestock, it is removed from the model world. Full details about the model components are provided in the original ODD + D protocol (Dressler et al., 2018, 2019). The ODD + D protocol is the current standard in documenting ABMs with agent decision-making (Grimm et al., 2010;

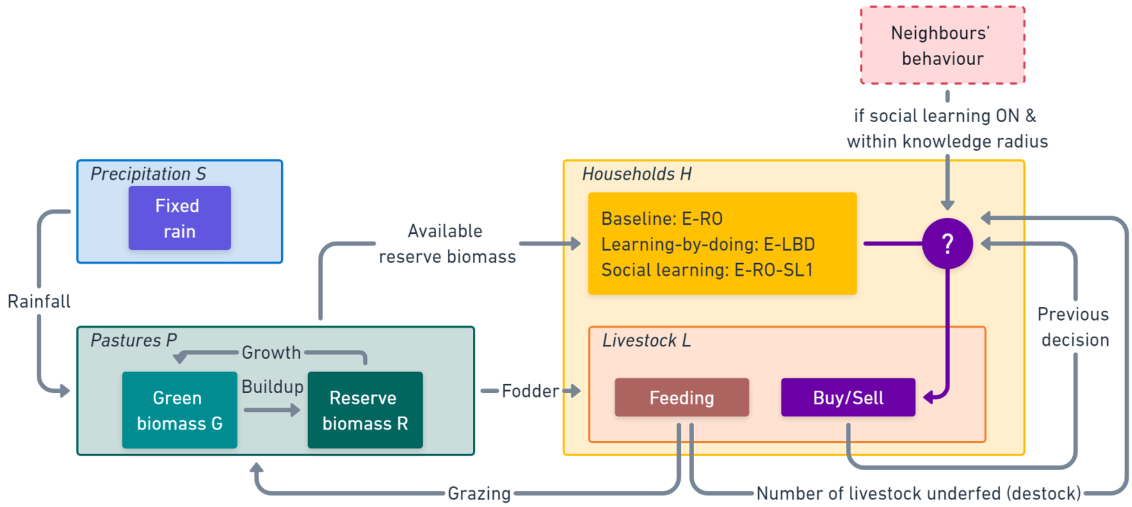

Fig. 2. Schematic representation of the modified RAGE model with the learning extension activated. Adapted from Dressler et al. (2019). E-RO, E-LBD and E-RO-SL1 stand for different types of learning behaviours ("agent behavioural types") – see Section 4.2.4. for details.

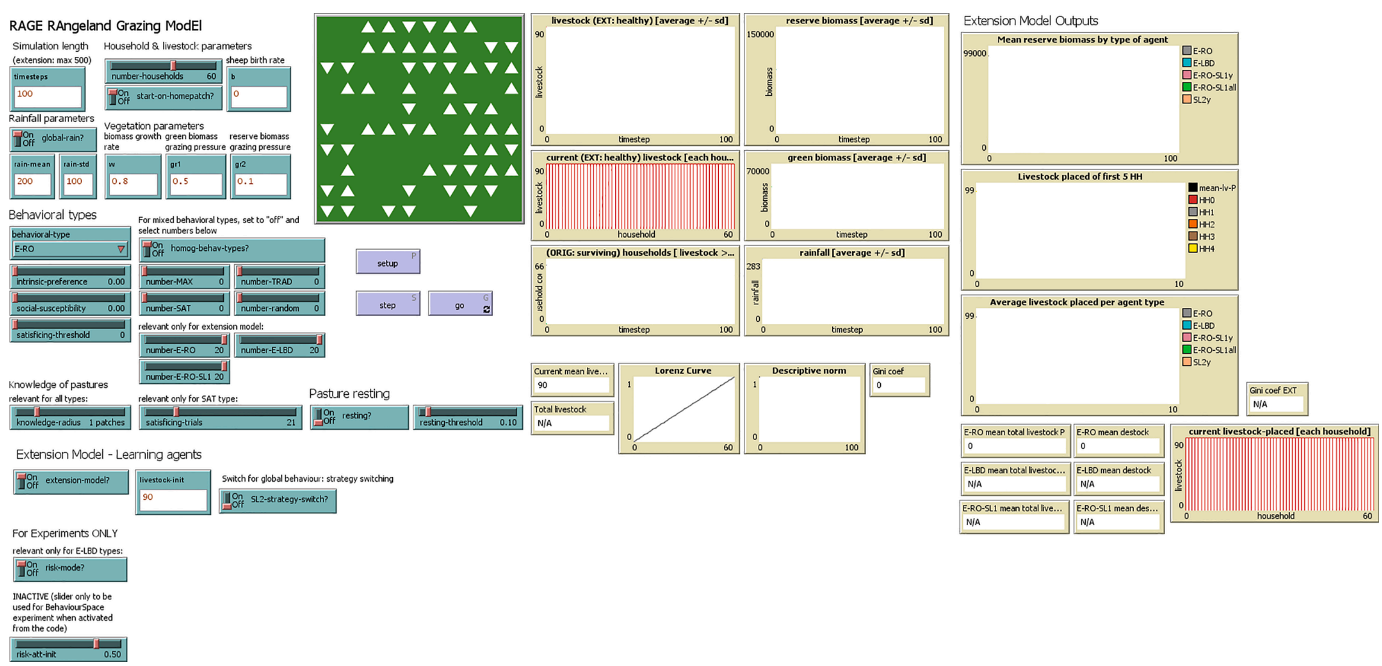

Fig. 3. Screenshot of the extended model interface (NetLogo v.6.1.1. - Wilensky, 1999).

Müller et al., 2013).

4.2. Model extension and design choices

We implemented learning processes within RAGE as a module that can be switched on/off from the visual interface in NetLogo. Enabling the module alters the original model into the structure illustrated in Fig. 2 (see Fig. 1 in Dressler et al., 2019 for comparison). Details on the extension module are described in a separate ODD + D protocol (Supplementary Information A).

4.2.1. Model overview

We transformed the model from a common pool resource – rangeland – to an agricultural system with private property, where individual households are able to experiment over time with their owned patch of land. The decision of agents hence changes from *where* to place their livestock, to *how many heads of livestock* to place on their own pasture. Each household exploits the pasture (patch) on which it is situated. Up to 100 households are randomly distributed across a 10 × 10 world at the beginning of the simulation (Fig. 3). They are all endowed with the same number of initial livestock.

As in the original model, all pastures are initialised with identical ecological states and dynamics (initial biomass quantities, vegetation parameters, vegetation regeneration equations etc. – see ODD + D protocols). This permits comparisons among agents' ecological performance as a result of their decisions and learning. To retain comparability, we deactivated stochasticity associated with precipitation. This can be easily reversed in future work, but it was beyond the scope of our study to explore learning effects under *environmental variability*.

Livestock placed on the pasture feed as before: first they consume green biomass, then, when this is depleted, they may consume up to a percentage *gr2* (the grazing pressure, here set at 10 %) of the total

Table 2
Variable classification for three main experiments and the corresponding refined research questions. "Homogeneous agent types" refers to the model world being initialised with all agents of the same type, while "Heterogeneous agent types" refers to a world with a mixed population of all three agent types.

	Independent variables	Control	Dependent variables
Experiment 1. (RQ1) Homogeneous agent types	Type of learning (E-RO vs. E-LBD vs. E-RO-SL1)	Population size Initial herd size For SL: knowledge radius Model seed r-parameter Repetitions Time steps	Economic outcomes: mean total livestock healthy Ecological outcomes: mean reserve biomass Social outcomes: inequality (Gini-index)
Experiment 2. (RQ2a) Heterogeneous agent types	Interaction of learning types (strategy switching, i.e., SL2 vs. no strategy switching)	Initial distribution of learning types (counts)	Economic outcomes: mean total livestock healthy Ecological outcomes: mean reserve biomass Social outcomes: inequality (Gini-index)
Experiment 3. (RQ2b) Heterogeneous agent types	Initial distribution of learning types (counts)	Population size	Final distribution of learning types (agent type counts)

Research Questions
(RQ1): How are the outcomes of agents' decisions affected by different learning types?
(RQ2): How do different types of learning interact and to what effects?
a) How does second-order learning affect learning agents' decision outcomes?
b) How do first-order learning strategies diffuse in a population of mixed agents?

reserve biomass. For input parameters to the vegetation and livestock feeding sub-models we used the default fixed values from the original model (Supplementary Information E4). If in a certain round more fodder is needed than the sum of available green biomass and 10 % of the remaining reserve biomass, the exceeding amount is used to calculate how many livestock were hungry/underfed (we call this "*destock*"). This variable is considered by households in their subsequent decisions.

We assume that households have full control over the size of their herd and they will buy and sell as much livestock as they need to achieve the desired number of livestock to be placed on the pasture. Livestock reproduction is therefore no longer relevant and the birth rate is set to 0. Household decisions on herd size are also not constrained economically, assuming unlimited budget and demand/supply on some external, exogenous market. Agents' economic objective is to maximise their herd size.

Household decisions depend on their learning type, observations from the SES, past experiences and properties of their neighbourhood (see ODD + D protocol). Our extension adds four main elements: agent memory, agent heterogeneity in dealing with uncertainty (the *r-parameter*), new agent behavioural types, and global strategy switching.

The model runs for a pre-set number of time steps. In the original model, a time step corresponds to one year, due to the existing of livestock reproduction. In our extension, a time step can be interpreted more loosely, depending on the question for which the model is used, but at a minimum it corresponds to a period of time over which a meaningful observation of the change in pasture state can be made (e.g. a season).

4.2.2. *Agent memory*

Agents who employ learning strategies rely on information from current and past observations, as well as their own past decisions. Thus, each agent is equipped with a memory of relevant information: the number of livestock underfed/hungry at the end of the last time step (*destock*), the number of livestock placed last time (previous decision) and the observed amount of reserve biomass at the beginning of the last timestep.

4.2.3. *Agent heterogeneity in dealing with uncertainty: the r-parameter*

To capture variability in how agents respond to the information acquired from their social-ecological environment we introduce an "***r**-parameter*" (***r*** from "*resistance*") which is initialised with a different value for each agent. From a theoretical standpoint, ***r*** represents the propensity of the agent to change their default behaviour based on various factors, for instance: the uncertainty in the sensing (*partial observability of the resource system*), noise in the information received, or an inherent characteristic of the agent, such as their risk attitude. In a generic ABM of social learning, Nowak et al. (2017) have used a similar variable to mediate between observed outcomes and behaviour and to incorporate "beliefs, norms, self-efficacy, and intention, as well as other external factors" (p.5). This was called the "propensity to engage in a particular behaviour".

In our model, the ***r**-parameter* can take any value between −0.95 and +0.95 in increments of 0.05 and it is randomly drawn from a discrete uniform distribution and fixed for each agent at the beginning of the simulation. Due to model stochasticity, the distribution of the r-parameter values in the agent population at the beginning of any given model run is random, but in the limit, over many repetitions and a large number of agents the distribution of the r-parameter of all agents will approximate the discrete uniform distribution. The effect of different *de facto* r-parameter distributions can be studied by calculating the mean-r value at the beginning of each simulation (see Supplementary Information F8 and F9). An agent's ***r*** value represents the percentage by which they will deviate from a "rationalised" or "default" decision of how much livestock to place on the pasture. The "default" decision is a calculation that follows directly from the agent's decision algorithm

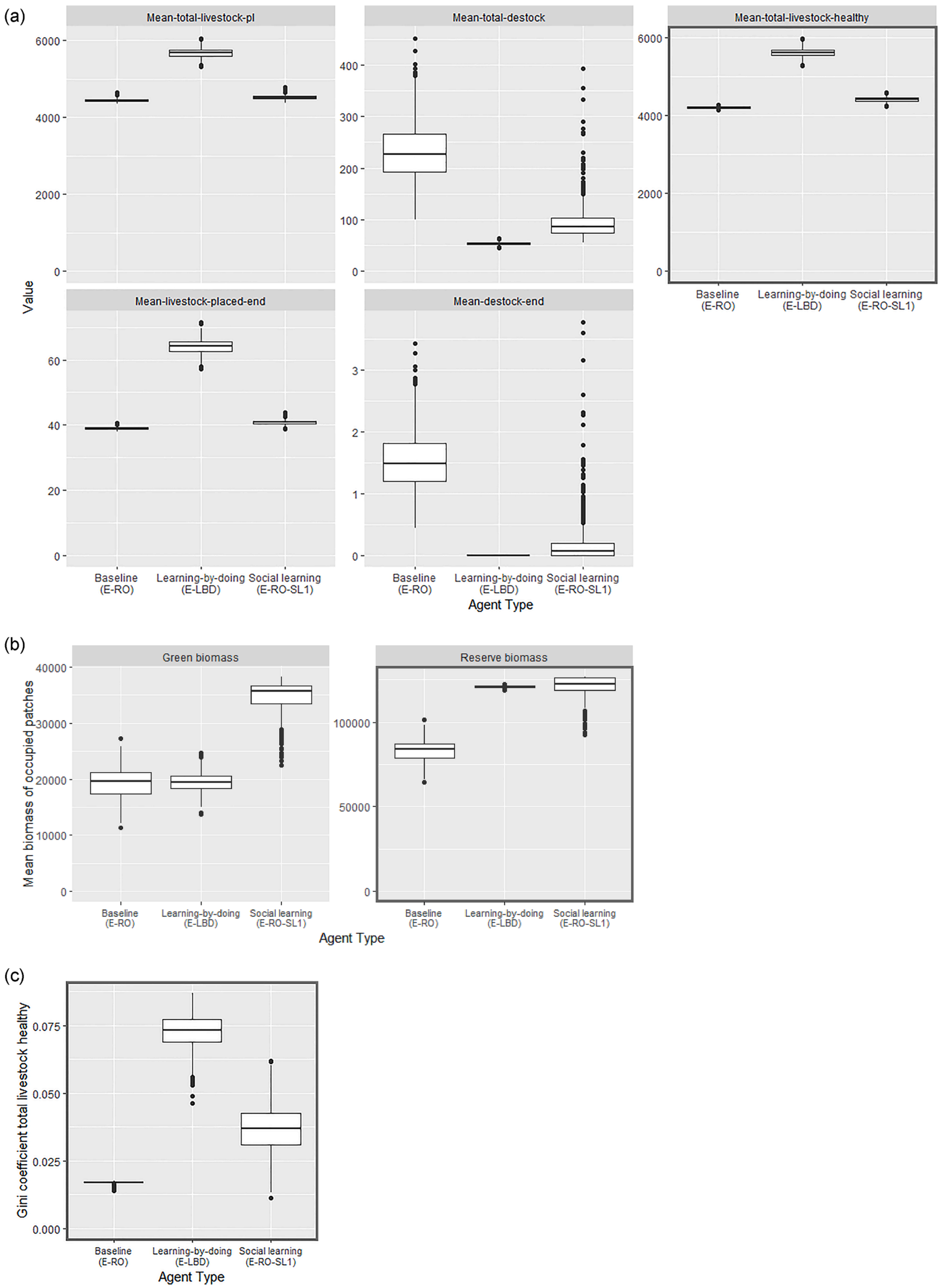

Fig. 4. Outcomes for three homogeneous populations (Experiment 1): (a) Economic; (b) Ecological; (c) Social. Main dependent variables are highlighted with border. Data points are averaged values over the entire population. The model was run 1000 times, for 100 timesteps each, with representative input parameters (number of households: 50, number of initial livestock: 90) – see Table E.1 in the Supplementary Information. *Mean-total-livestock-pl* is the average number of livestock placed on the pasture over the entire simulation and all agents. It is the sum of *Mean-total-livestock-healthy* and *Mean-total-destock*. *Mean-livestock-placed-end* is the average number of livestock placed on the pasture in the last round of the simulation, calculated over the entire agent set. "E-RO" is the reference group, i.e., non-learning agents.

(Supplementary Information B) and corresponds to $r = 0$. Most agents will have an $r \neq 0$, which means that they will decide to place more ($r > 0$) or less livestock ($r < 0$), deviating by up to ±95 %.

4.2.4. Agent behavioural types

We define three new types of agent behaviours building upon the "herd size maximising" agent type (MAX) from the original model (see also Supplementary Information B).

The **baseline agent** type takes decisions without any learning (extension-*r*-only, **E-RO**). It follows the MAX behaviour by removing all livestock that was underfed in the previous round (captured by the *destock* variable) .[2] The main difference is the addition of the *r-parameter* as an agent attribute. Consequently, E-RO agents are heterogeneous in their decisions as they adjust their herd size by deviating from *destock* by a percentage *r*. This behaviour type is necessary to enable comparability of outcomes with the learning-by-doing and social learning agents.

Learning-by-doing agents (E-LBD) employ more sophisticated rules for deciding how much livestock to place on the pasture. They observe the changes in the amount of reserve biomass available on the pasture compared to previous rounds and respond with a proportional change in their herd size. For instance, an estimated decline in the amount of observed reserve biomass of 6 % will indicate that a reduction of 6 % in the herd size is also necessary, with certain adjustments to also account for the previously observed underfed livestock (*destock*). An observation of increasing reserve biomass leads to a proportional increase in the herd size. This is the "rationalised" decision corresponding to $r = 0$. If $r \neq 0$, the final decision will deviate from this value by *r*.

Social learning agents (E-RO-SL1) are an implementation of *social learning 1*, as shown in Table 1. These agents compare their own economic performance to the performance of their neighbours (from the neighbourhood delimited by a knowledge radius *k,* where $k = 1$ corresponds to the agent's Moore neighbourhood, i.e., the 8 direct neighbours around the agent). Economic performance is evaluated as number of healthy livestock (i.e., not underfed, sustained by the pasture) in the current round. If there are neighbours who are performing better, then the agents will copy the *r-parameter* of the most successful neighbour, i. e., the one with the highest number of healthy livestock. Decisions on how to adjust the herd size are further taken following the baseline behaviour E-RO, i.e., the learning is just the copying of the *r-parameter* and then the herd size is determined just like in the baseline agents' case.

Our implementation of social learning focuses on the *dispositions* underlying the agent's decision rather than on the choice itself. In other words, agents copy their neighbours' *r-parameter* rather than their previous decision (*the number of livestock placed*). This is because it is the *r-parameter* which drives differences in success. Imitating others' decision of how much livestock to place on the pasture would have led to different results depending on the pasture state at the time of imitation, so a learning effect could not be evaluated. In addition, social learning processes and adoption of new practices assume information exchange about the underlying mechanism of the decision (Liu et al., 2018). This is in line with the observation that farmers more easily copy decision rules rather than specific activities (Le et al., 2012).

4.2.5. Strategy switching

To address our second research question, we also implemented a global behaviour where all agents may, at each time step, change their decision strategies, i.e., their agent behavioural types. This is done by imitating the agent type of the most successful neighbours, where success is evaluated as highest number of healthy livestock, like in the case of E-RO-SL1 agents. An agent can change their behavioural type once every round, and for as many rounds as they observe a more successful neighbour (see also the ODD + D protocol in Supplementary Information A / III.iv.a). This introduces temporal dynamics of learning strategies and enables us to study *second-loop* social learning (*social learning 2* in Table 1).

4.3. Experiments and model settings

We explored our model following design-of-experiments (DOE) principles (Lorscheid et al., 2012). DOE is a systematic process for planning and conducting model runs so that reliable conclusions can be drawn about the relationships between input parameters, model outputs and the processes behind. First, we refined our research questions and classified the variable of interest corresponding to three experimental objectives (Table 2). Then, we conducted one-factor-at-a-time sensitivity analyses for the control variables in order to determine potential tipping points in how they affect the response variables (Broeke et al., 2016). In turn, these informed our sampling of parameters for global sensitivity analyses, as well as the input values for the experiments described below (see also Supplementary Information F):

- **RQ1 Outcomes – Experiment 1.** *Comparing social-ecological outcomes of different learning types.* We compared model results under three different settings of initial homogeneous populations: baseline (no learning, i.e., E-RO), learning-by-doing (E-LBD); and social learning (E-RO-SL1) agents, respectively.
- **RQ2a Interactions – Experiment 2.** *Assessing the effect of second-order social learning (SL2) on social-ecological outcomes of a heterogeneous population of agents.* We evaluated the effects of strategy switching in a heterogeneous population with initially equal proportions of agents of three types (E-RO, E-LBD and E-RO-SL1).
- **RQ2b Interactions – Experiment 3.** *Learning type diffusion in a heterogeneous population with strategy switching.* We conducted three sub-experiments to explore learning diffusion in a heterogeneous population with three agent types. In the first sub-experiment we investigated the diffusion of learning-by-doing behaviour when this type of behaviour starts as a very small minority. The second sub-experiment assessed the diffusion of social learning behaviour when starting off as a small minority. The third sub-experiment was a "battle" (Janssen and de Vries, 1998) of learning types, aiming to identify which type becomes dominant over time in a world initialised with equal proportions of agent behavioural types (1/3 each).

Independent variables. For experiment 1, the independent variable is the *type of learning*, with three factorial levels: E-RO, E-LBD, E-RO-SL1. In experiment 2, *strategy switching* (SL2) takes two factorial levels: active/inactive. Experiment 3 assesses how the *initial numbers of agents* of each behavioural type in a mixed population with strategy switching changes over time, i.e., which type becomes dominant.

Dependent variables. In experiments 1 and 2 we measure economic, ecological and social outcomes, operationalised with three key variables: the *mean total livestock healthy* over the entire period of simulation, the *mean reserve biomass* at the end of the simulation and the *Gini-index of total livestock healthy* over the entire population. The *Gini-index* is a standard measure of inequality that takes values between 0 and 1, where 1 corresponds to the highest inequality. Here, it measures how the total livestock healthy at the end of the simulation is distributed across the entire population of agents. For model verification, we also include results on other variables.

For experiment 3, the dependent variable is the *number of agents* of each behavioural type at the end of the simulation.

Control variables. These were used for sensitivity analyses to ensure robustness of our model input parameters.

Further details on the dependent and control variables are provided in the Supplementary Information D.

[2] In the original model, it was considered that all livestock exceeding the available amount of fodder (captured by the *destock* variable) would die.

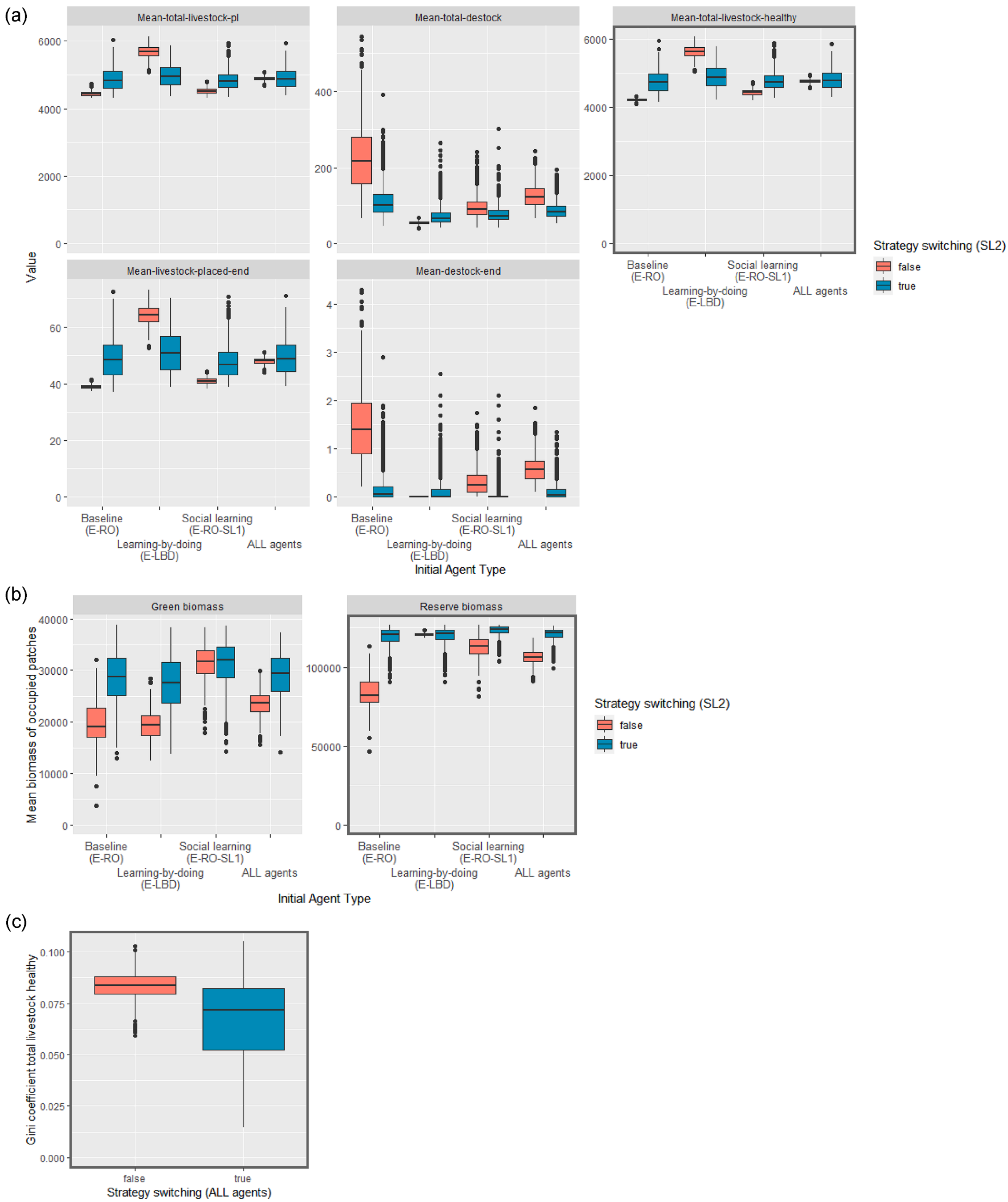

Fig. 5. Outcomes of strategy switching in a mixed population of agents (Experiment 2): (a) Economic; (b) Ecological; (c) Social. Main dependent variables are highlighted with border. Data points are averaged values over the entire population. The model was run 1000 times, for 100 timesteps each, with representative input parameters (number of households: 60, number of initial livestock: 90) – see also Table E.2 in the Supplementary Information. Results labelled with "ALL" are averaged over the entire population of mixed agents (setup: 20 E-RO, 20 E-LBD, 20 E-RO-SL1). Disaggregated results are also shown in (a) and (b) relatively to the agents' initial behavioural types.

Table 3

Statistical table for strategy switching effects. Results for independent-samples *t*-tests by variable of interest and groups of agent types at the beginning of the simulation. Highlighted rows indicate the main dependent variables used to operationalize economic, ecological and social outcomes (see Section 4.3). For each variable, the differences between the two treatments (Group 1, without strategy switching vs. Group 2, with strategy switching) have been evaluated based on 1000 model runs in each treatment (N1/N2). E-RO = baseline; E-LBD = learning-by-doing; E-RO-SL1 = social learning; ALL = all agents.

Variable	Agent type (initial)	Strategy switching		Statistic	df	p	p adj	p adj significance
		Group 1 (N1 = 1000)	Group 2 (N2 = 1000)					
Mean-destock-end	ALL	false	true	47.02	1763.53	0.00	0	****
Mean-destock-end	E-LBD	false	true	−14.96	999.00	0.00	0	****
Mean-destock-end	E-RO	false	true	51.49	1365.79	0.00	0	****
Mean-destock-end	E-RO-SL1	false	true	26.38	1682.04	0.00	0.00	****
Mean-livestock-placed-end	ALL	false	true	−5.93	1072.17	0.00	0	****
Mean-livestock-placed-end	E-LBD	false	true	52.62	1424.44	0.00	0	****
Mean-livestock-placed-end	E-RO	false	true	−45.85	1018.08	0.00	0	****
Mean-livestock-placed-end	E-RO-SL1	false	true	−36.86	1071.38	0.00	0.00	****
Mean-total-destock	ALL	false	true	31.81	1748.56	0.00	0	****
Mean-total-destock	E-LBD	false	true	−22.15	1053.60	0.00	0	****
Mean-total-destock	E-RO	false	true	37.79	1455.98	0.00	0	****
Mean-total-destock	E-RO-SL1	false	true	15.42	1910.09	0.00	0.00	****
Mean-total-livestock-healthy	ALL	false	true	−5.14	1087.50	0.00	0	****
Mean-total-livestock-healthy	E-LBD	false	true	61.22	1468.90	0.00	0	****
Mean-total-livestock-healthy	E-RO	false	true	−53.91	1018.96	0.00	0	****
Mean-total-livestock-healthy	E-RO-SL1	false	true	−37.15	1210.00	0.00	0.00	****
Mean-total-livestock-pl	ALL	false	true	−1.02	1111.42	0.31	1	ns
Mean-total-livestock-pl	E-LBD	false	true	59.66	1496.08	0.00	0	****
Mean-total-livestock-pl	E-RO	false	true	−41.57	1108.92	0.00	0	****
Mean-total-livestock-pl	E-RO-SL1	false	true	−35.34	1188.86	0.00	0.00	****
Green biomass	ALL	false	true	−37.69	1518.62	0.00	0.00	****
Green biomass	E-LBD	false	true	−45.39	1489.11	0.00	0.00	****
Green biomass	E-RO	false	true	−43.57	1954.15	0.00	0.00	****
Green biomass	E-RO-SL1	false	true	1.01	1886.08	0.31	1.00	ns
Reserve biomass	ALL	false	true	−77.38	1928.77	0.00	0.00	****
Reserve biomass	E-LBD	false	true	5.48	1051.26	0.00	0.00	****
Reserve biomass	E-RO	false	true	−96.18	1653.81	0.00	0.00	****
Reserve biomass	E-RO-SL1	false	true	−34.67	1363.05	0.00	0.00	****
Gini-index livestock healthy	ALL	false	true	25.92	1204.60	0.00	0.00	****

5. Results

5.1. Experiment 1 – decision outcomes: learning-by-doing vs. social learning

Economically, our findings suggest that learning-by-doing agents are more successful than other agent types at maintaining high numbers of livestock on their pastures without overshooting too often the carrying capacity (Fig. 4a). The immediate response to observed pasture conditions translates into an adjustment of livestock numbers while the reserve biomass is still high, permitting a quick regeneration of the pasture condition and minimum economic losses (total number of livestock that are under-fed).

Social learning behaviour also leads to higher numbers of healthy livestock than the baseline behaviour, but much lower than learning-by-doing. Compared to baseline (E-RO), social learning agents make herd size decisions that are closer to the carrying capacity of the pasture, as indicated by a much lower number of underfed livestock (*destock*). That social learning has a relatively low economic success as a strategy is consistent with Le et al. (2012) who also find that imitation does not improve incomes very much. The reason could be linked to the different conditions in which the successful farmers who are imitated are operating vs. those of the imitator. In the case of our model, by the time that a social learning agent starts imitating the attributes of a neighbour with more livestock, their pasture is already in a different condition, so they can no longer make up for lost economic opportunities if the final results are measured with a cumulative variable such as the ***total*** healthy livestock, i.e., over the entire simulation. However, the alternative indicators on the second row of Fig. 4a, which measure livestock numbers at the end of the simulation, show that social learning agents stabilise their herd size decision at a higher level than no learning agents (high *livestock-placed-end*), which is also better matching the pasture condition (*low destock-end*). A complementary explanation is that certain values of the *r-parameter* lead to higher livestock numbers, so they are selected more often by social learners (see Section 6).

Ecologically, social learning agents maintain a slightly higher level of reserve biomass than learning-by-doing agents (Fig. 4b). This is to be expected, given the economic outcomes discussed above, as smaller herd sizes translate into a lower grazing pressure on the pasture. More interesting is that the pastures occupied by non-learning agents have lower reserve biomass at the end of the simulation than those occupied by learning-by-doing or social learning agents. Although they do not place large herd sizes on their pastures, non-learning agents degrade the pastures the most and they also have the highest numbers of underfed livestock. This shows that there is a mismatch between their herd size decisions and the carrying capacity of the pasture. In contrast, learning agents' decisions appear to better approximate ecological limits and maintain the pastures. This is aligned with the theoretical expectations that learning processes contribute to reducing structural uncertainty about the "optimal" level of resource use.

Finally, from a **social outcomes** perspective, learning-by-doing results in the highest economic inequality at the end of the simulation, with some agents having stabilised their herd size at low values and others at much higher values (Fig. 4c). A world of social learning agents also results in higher economic inequality than a world of non-learners, but still lower than that of learning-by-doing population. An explanation for this is linked to the economic and ecological outcomes discussed above. Non-learners deplete their resource and are all similar in their poor economic performance. Because social learners mimic each other, they select for *r*-values with high economic success, and their final

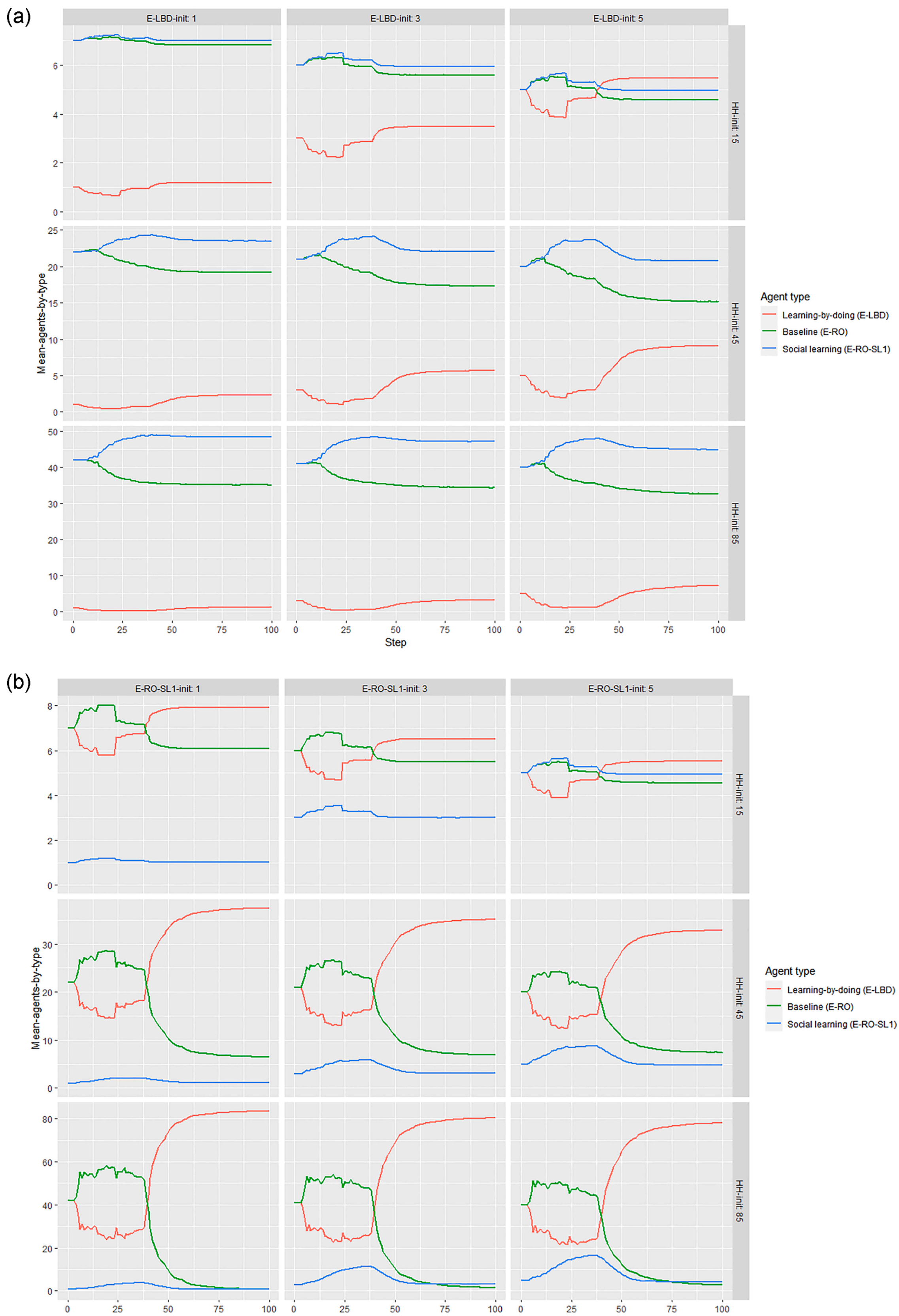

Fig. 6. Diffusion of learning behaviours - evolution of agent counts over time, by agent type (Experiment 3): (a) Few initial learning-by-doing agents; (b) Few initial social learning agents; (c) Equal initial proportions of agent types. Results are shown as averages over 1000 repetitions, with representative input parameters (number of initial livestock: 90) and for various values of the initial number of households (HH-init) – see also Table E.3 in the Supplementary Information. E-LBD-init = number of initial learning-by-doing agents; E-RO-SL1-init = number of initial social learning agents; HH-init = number of initial households.

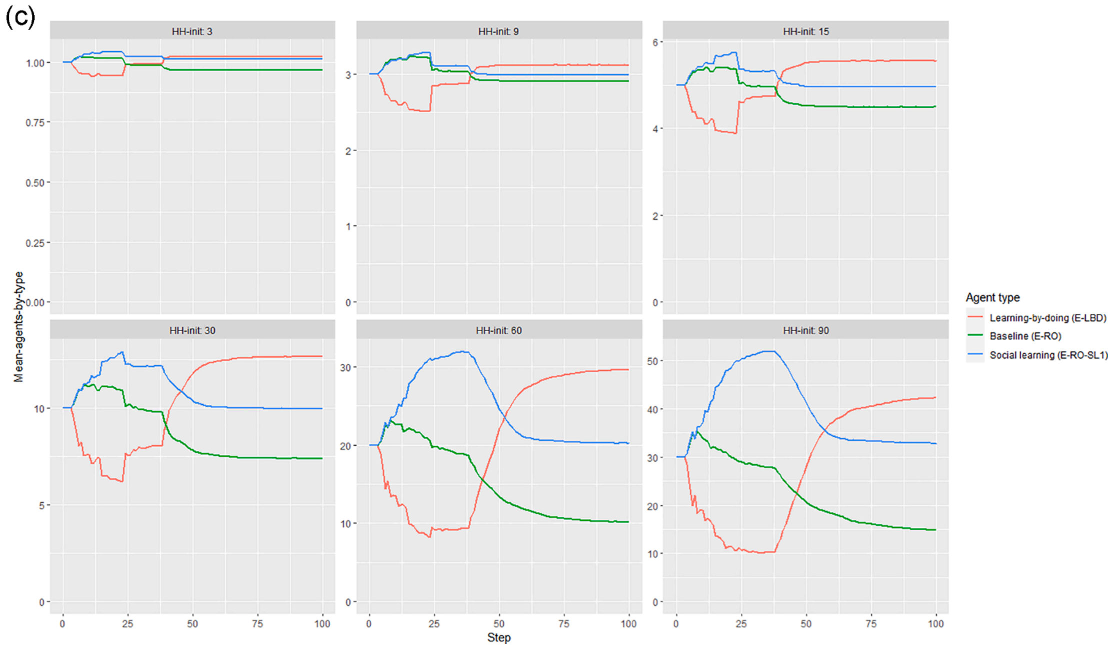

Fig. 6. (*continued*).

outcomes are also quite similar. However, learning-by-doing agents' results are more diverse, as they are directly influenced by the original *r*-value. While no generalisations can be made from our model, it is interesting to speculate about the cultural role that imitation might have in both increasing knowledge (and reducing uncertainty) and evening out differences in performance.

5.2. *Experiment 2 – learning interactions: strategy switching effects*

We evaluated the economic, ecological and social outcomes of second-loop social learning (SL2), i.e., strategy switching, in a mixed population of 20 E-RO, 20 E-LBD and 20 E-RO-SL1 agents (Fig. 5a-c).

Overall, the average performance of an agent was higher on all outcome variables of interest when strategy switching was enabled compared to when it was not (boxplots labelled as "ALL", see also Table 3). Wealth distribution was also more equal (lower Gini-index) in the treatment where the population was engaged in SL2. When breaking down these results by agent behavioural types, economic results (mean total numbers of healthy livestock) improved for baseline and social learning agents, and regressed for learning-by-doing agents. Ecologically, all agent categories performed better when strategy switching was active.

These results indicate that social learning 2 has a moderating effect on the number of livestock that learning-by-doing agents choose to place on the pasture, but without significant improvements on the pasture state compared to the other agent types. Arguably, the observed reduction in the average healthy herd size of learning-by-doing agents could be the direct result of the adoption of a different behavioural type. However, we obtained similar results when grouping agents based on their behavioural types at the end of the simulation, instead of their initial ones. Thus, once more, social learning through imitation appears to equalise outcomes (see also Bala and Goyal, 1998).

5.3. *Experiment 3 – learning interactions: diffusion of learning behaviour*

The results of our third experiment suggest that, while social learning behaviour spreads more easily in the beginning of the simulation, learning-by-doing behaviour tends to become dominant in the long-term. However, learning-by-doing behaviour will not be able to spread in the population if the initial numbers are very low relatively to the two other types of agents (sub-experiment 1). Similarly, social learning behaviour cannot spread significantly if the initial numbers are very low (sub-experiment 2). When the world is initialised with equal numbers of agents of each type (sub-experiment 3), learning-by-doing behaviour spreads the most, followed by social learning behaviour, regardless of the population density (Fig. 6). The successful spread of social learning strategies in the beginning may be related to inherent properties of the decision-making algorithms, but in the long-term, the ability of learning-by-doing behaviour to better match the pasture conditions will pay off economically. Our results also hint at the possible existence of a tipping point in the percentage of learning-by-doing agents needed for this behaviour to become dominant in the population. Studies of critical mass have demonstrated tipping points in social conventions occurring when as little as 10 % of the population engages committedly in a specific behaviour (see e.g., Centola et al., 2018). It appears that around 20–30 % of the agents need to be engaged in learning-by-doing for this behaviour to become dominant, but we have not done ample investigations to determine the presence and exact value of such a threshold.

6. Discussion

The theoretical gap in conceptualising learning-by-doing and social learning for modelling means that we still had to make assumptions and choices which could be debated. To address this, we proposed a conceptual framework for modelling learning which helps to make decisions transparent. Where suitable, we also suggested alternatives that could be tested in future studies. For instance, although we tried to step away from classical rational choice models and to introduce behavioural heterogeneity in how agents respond to the same information from the environment (*r-parameter*), depending on various sources of uncertainty (see Section 3.2), agents' goals were still limited to economic utility maximisation. A theoretical advancement would be for multiple learning processes to be mapped onto meta-theories of human behaviour that match their ontological and epistemological assumptions (see Section 2.4). This would ensure that modelling decisions are consistently aligned with a pre-selected theory (Groeneveld et al., 2017; Schwarz et al., 2019).

Our model results have shown that learning-by-doing most improved economic performance, while social learning 1 most improved environmental performance. Adding a second-order learning process (social learning 2) as strategy switching further improved social-ecological outcomes on all indicators. In diffusion experiments, learning-by-doing behaviour became dominant at the end of the simulation. However, diffusion appeared to depend not solely on the number of households adopting the behaviour, but also on the time of adoption, which indicates an underlying relationship with the state of the ecosystem. Social learning behaviour is initially more frequently adopted, but once the regenerative capacity of the ecosystem is being depleted (low reserve biomass), the benefits of an incremental, learning-by-doing, management approach become more evident and this behaviour wins over other strategies.

An explanation for this transition in dominant strategies is likely related to how individual performance differs for each learning type as a function of the *r-parameter* (see Supplementary Information F8/F9). Learning-by-doing agents perform better economically (total number of healthy livestock) for negative than for positive values of the *r-parameter*. Negative values can be interpreted as less cautious responses to the noise and uncertainties signalled in the environment. However, baseline and social learning agents' performance depends on the interplay between *r-parameter* values and environmental pressure (initial number of livestock). At low levels of livestock, social learners will select for positive values of *r*, as those yield the highest economic returns. When environmental pressure is high, a higher value of *r* (too much cautiousness) means that the adaptation speed is low, which leads to poorer performance than for negative *r* values. These effects may also be linked to the numerical constraints embedded in the vegetation regeneration function and different equations for vegetation models could be tried out in the future. Yet, such underlying dynamics have real world relevance, as they are indicative of the co-dependence and co-evolution of human response and ecological thresholds (Brede and de Vries, 2010; Lindkvist and Norberg, 2014) and highlight again the importance of modelling coupled SESs (Schlüter et al., 2019b).

The stylised nature of our ABM limits the generalisability of our findings in applied settings. Several limitations of the model call for further work and model tweaking in order to validate our findings in empirical contexts with smallholders (Malek and Verburg, 2020).

For example, one limitation is the discrete choice between learning-by-doing and social learning for agents, rather than allowing simultaneous adoption of both learning strategies. While this choice was intentional, given our goals to understand and compare the independent effects of each learning process, we acknowledge that in real-world scenarios, farmers often employ a combination of both individual and social learning mechanisms. Incorporating concurrent learning-by-doing and social learning would demand a more intricate decision-making process for the agents. This would entail merging feedback from the environment with observations of neighbours' behaviour. While Jager (2000) reviewed the literature to elucidate the switch between cognitive decision-making processes and simpler heuristics, such as imitation, depending on uncertainty and risk levels, there remains limited understanding of how these cognitive calculations and social behaviours might synergistically influence a single decision.

Another model limitation is that the *r-parameter* serves as a surrogate for the nuances in decision-making arising from both environmental factors (encountering "noise" or misinformation in agents' environment, such as receiving conflicting advice or misinterpreting certain signs from the environment, which can influence their decision-making) and individual characteristics (unique risk attitudes, beliefs, and norms that shape agents' decisions – while some farmers might be more risk-averse, others might be willing to experiment with new practices). Farmers, through prolonged interactions and observations, can discern these deviations in their neighbours. For instance, by gauging the biomass of a neighbouring pasture, a farmer can estimate the "rational" livestock capacity. If they consistently observe a neighbour exceeding this capacity yet thriving economically, they might interpret this as a successful, albeit riskier, strategy and adapt accordingly. While our model simplifies these real-world nuances into the single *r-parameter*, it is an abstraction that captures the multifaceted nature of farming decision-making under uncertainty. The choice to model it this way allows us to systematically study the effects of deviations from rational behaviour, providing insights into how farmers might adapt when faced with varying levels of information, risk, and social influence.

Equally important, the number of animals and green or reserve biomass need to be interpreted within the broader context of farming. While these serve as valuable indicators in our model, they are simplifications of the intricate interplay between ecological and economic outcomes in farming. Similarly, the model's timesteps imply a period over which a meaningful observation of the change in pasture condition can be made. In real-world applications, a more detailed analysis would need to consider what a realistic temporal correspondent of a timestep might be, but also a variety of other factors, including monetary measures and land value, to provide a comprehensive view of a farm's sustainability and profitability.

Finally, we implemented learning-by-doing as a reactive rather than proactive process (Robert et al., 2016). Such a passive adaptive management approach has been previously found effective in highly noisy systems (Lindkvist et al., 2017) – and that is also the case for our model. Depending on the policy question at hand, an implementation of learning-by-doing as proactive adaptation to expected future effects, or as a diversification of options beyond adjusting herd sizes (Choquette-Levy, 2019) might be appropriate. Similarly, while we operationalised social learning with an attention to its *outcomes*, a common emphasis in the literature is *on the deliberative process* of groups of actors (Cundill and Rodela, 2012), so validation may require further improving the institutional layer in the model and linking it to the learning processes extension.

Despite these limitations, our model falls in the Medawar zone (Loehle, 1990; Sun et al., 2016), and, as such, our results are useful for elucidating core dynamics and for advancing the research agenda of representing learning processes in agent-based models.

7. Conclusion

Efforts are still needed to better link ABMs to theories and concepts (O'Sullivan et al., 2016), and to integrate learning. Our study is, to our knowledge, a first attempt to operationalise in a smallholder farmers' ABM context two learning processes which are central to adaptive (co-)management. In particular, our discussion of double-loop social learning as a process where agents change their learning type responds to a need for better representing transformational adaptation at farm level (Huet et al., 2018), i.e., the processes determining farmers to switch from incremental adaptation to farm structural changes (Reidsma et al., 2018).

In line with theory, both learning-by-doing and social learning contributed to reducing structural uncertainty about the "optimal" level of resource use, and learning agents were better able to match their decisions to the pasture state than baseline ones. The two learning processes differed, however, in the indicators for which they performed best. It appears that different objectives call for different types of learning. In addition, agents' propensity for responding more or less cautiously to noise and uncertainty interacts with resource system thresholds and states (Brede and de Vries, 2010), reiterating the need for integrative modelling approaches that explicitly consider multiple feedbacks between the social and ecological subsystems and their emergent outcomes (Feola and Binder, 2010; Schlüter et al., 2019b).

Future research could consider implementing alternative, but comparable, operationalisations of learning-by-doing and social learning to see if our results can be reproduced. In particular, it would be interesting to account for the fact that, in our model, learning-by-doing is occurring slightly faster than social learning, by systematically studying the effects of both processes on different time scales. In addition, developing generic ABM modules with a broader repertoire of learning processes would be useful for empirical applications. In an empirical model, the *r* parameter would need to be defined in a much narrower sense to refer to one specific measurable agent or environment characteristic that can distort the objective information received (e.g., risk attitude or noise in communication). Further, while in our evaluation of learning outcomes we used multiple indicators for different areas of impact (economic, ecological and social), future studies might try to combine indicators into standardised units, so as to allow for multi-criteria optimisation towards specific outcomes. This would open the avenue for using such models as policy tools to assess which learning strategies could be supported by a social planner towards specific objectives. Last, but not least, our model could, with minimum additional work, be used to study institutional emergence / norm formation and collective action within SESs, an area which is also currently under-explored in models, but upcoming (Cumming et al., 2020).

Software availability

The model has been implemented in NetLogo 6.1.1 (available Open Source, see Wilensky, 1999). The extended model is published at ComSES: Learning Extension - RAGE RAngeland Grazing Model (version 1.0.0) https://www.comses.net/codebases/e103feef-2785–41e6-affb-8306c979e83c/releases/1.0.0/.

Details on system requirements for running NetLogo: https://ccl.northwestern.edu/netlogo/6.1.1/docs/requirements.html#32-bit-or-64-bit.

CRediT authorship contribution statement

Cristina I. Apetrei: Conceptualization, Methodology, Software, Validation, Formal analysis, Writing – original draft, Writing – review & editing. **Nikita Strelkovskii:** Conceptualization, Methodology, Writing – review & editing, Supervision. **Nikolay Khabarov:** Conceptualization, Methodology, Writing – review & editing, Supervision. **Valeria Javalera Rincón:** Conceptualization, Methodology, Writing – review & editing, Supervision.

Declaration of competing interest

Cristina I. Apetrei reports financial support and administrative support were provided by the International Institute for Applied Systems Analysis [IIASA Funds – Barry Callebout Fellowship]. The first author had previously met and collaborated with authors of the original model RAGE. Nikita Strelkovskii, Nikolay Khabarov and Valeria Javalera Rincón declare no known competing financial interests nor personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Model outputs used for the analyses in this paper are available on Figshare, at: http://doi.org/10.6084/m9.figshare.24917670.

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Supplementary materials

Supplementary material associated with this article can be found in the online version, at: doi:10.1016/j.ecolmodel.2023.110609.

Appendix A

Learning-by-doing – cross-field evolution of a concept

The concept of learning-by-doing has been used in various fields, and understanding its evolution is important when attempting to model it.

Learning-by-doing originates from studies of aircraft and ship production in the 1930s, when Wright (1936) observed a 20 % reduction of unit costs over a period of time where the output had doubled (Dosi et al., 2017). Such relationships between unit costs and improvements in production were subsequently observed in other industries, and became known in economics and operations management under the names of: "progress curves", "learning curves", "startup curves" or "improvement curves" (Glock et al., 2019). The differences in terminology depend on the explanations attributed to the cost reduction. For instance, a "learning curve" assumes that cumulative experience leads to a reduction of the time necessary to produce one unit of output (Miketa and Schrattenholzer, 2004), while a "progress curve", *sensu* Wright, allows for other drivers, such as research and design (R&D), product changes, or capital investment (Thompson, 2011).

Learning curves have been typically expressed in models as power functions relating experience to performance (Dosi et al., 2017). Some applications employ two-factor learning curves, distinguishing between cumulative experience, "learning by doing", and accumulated knowledge, i.e., "learning by searching" (Miketa and Schrattenholzer, 2004). For example, in energy transition modelling, "learning-by-doing" pertains to the declining cost of renewable energy substitutes as a function of production capacity (Jouvet and Schumacher, 2012), while "learning-by-searching" refers to incorporating the R&D costs of energy innovation (Berglund and Söderholm, 2006).

Within the literature on human-technological systems, learning-by-doing is related to humans' ability to learn from their mistakes (Bointner and Schubert, 2016). The focus is on how experience leads to declining failure rates over time. Because mistakes can occur due to other factors than lack of learning, e.g., forgetting, scholars emphasise the need to distinguish between "errors of commission" and "errors of omission" (Bointner and Schubert, 2016).

From psychology, the notion of reinforcement learning is relevant. Its roots go back to Skinner's (1938) operational conditioning which states that negative outcomes will lead to avoiding a specific action in the future, while positive outcomes will make the action reoccur. In its original understanding, reinforcement learning involves no conscious reflection (Brenner, 2006). However, in economic applications, considerations of an automatic response to stimuli have been mostly left aside, and "routine-based learning models" emerged, where cognition is assumed (Brenner, 2006, p. 908). There is a broad literature on algorithms for reinforcement learning which can inform methodological choices in ABMs. For instance, a typical way to model reinforcement learning is by assigning a higher probability in the future to actions that have proven successful in the past (Arifovic and Ledyard, 2004).

At the beginning of the twentieth century, learning-by-doing had also gained popularity as an educational method (Thompson, 2011), following ideas developed by Dewey (1988). Closely related, "experiential learning" was coined by Kolb (1984), the founder of organizational learning, to describe how abstract concepts and generalisations are formed by observation and tested in new situations (see Miettinen, 2000). Here, "experience" and "reflection" are central.

Finally, within adaptive management, learning-by-doing has borrowed traits from the various fields above. The term has been used interchangeably with "experiential learning" to describe a structured process of adaptation in environments characterised by uncertainty and change (Kato and Ahern, 2008; Lindkvist and Norberg, 2014 Walters, 1997; Lee, 1999). Learning-by-doing can take place both at the level of individual behaviour, and at the community level (Munaretto and Huitema, 2012). It is this conceptualisation that is used in this paper, as detailed in Section 2.1.

All these perspectives provide pointers to how learning-by-doing could be implemented in a model, but modellers' choices will depend on the research goals and the theoretical angles taken.

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