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Modelling forests as social-ecological systems: A systematic comparison of agent-based approaches

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ABSTRACT

The multifunctionality of forest systems calls for appropriately complex modelling approaches to capture social and ecosystem dynamics. Using a social-ecological systems framework, we review the functionality of 31 existing agent-based models applied to managed forests. Several applications include advanced cognitive and emotional decision-making, crucial for understanding complex sustainability challenges. However, far from all demonstrate representation of key elements in a social-ecological system like direct interactions, and dynamic representations of social and ecological processes. We conclude that agent-based approaches are adequately complex for simulating both social and ecological subsystems, but highlight three main avenues for further development: i) robust methodological standards for calibration and validation of agent-based approaches; ii) modelling of agent learning, adaptive governance and feedback loops; iii) coupling to ecological models such as dynamic vegetation models or species distribution models. We round-off by providing a set of questions to support social-ecological systems modelling choices.

1. Introduction

Managed forests are impacted by changes in social and economic systems, while at the same time forest management is a driver of change in the very same systems (Nocentini et al., 2017). The idea of social and economic dimensions as part of forest management is not new, but social, economic and ecological issues have been treated as belonging to essentially different realms (Filotas et al., 2014). While forests are key provisioning ecosystems contributing to human quality of life, large-scale intensive forestry practices risk undermining future provisioning of ecosystem services in the presence of climate change and biodiversity loss (Canadell and Raupach, 2008). In contrast to the traditional view of forestry where forests are primarily managed for wood production, an argument that has been put forward in the last decade is to understand forests as multifunctional systems where social and ecological dimensions are deeply integrated and intertwined (Filotas et al., 2014; Fischer, 2018; Nocentini et al., 2017; Rist and Moen, 2013). This, in turn, calls for a change in perspective and for new approaches (Brockhaus et al., 2021; Leach et al., 2018) that can deal with a heterogeneity of goals and interactions among actors (Fischer, 2018; Gotts et al., 2019).

With the concept of heterogeneous actors, we refer to the many ways in which we as humans relate to and value forests. As has been argued within common property resource management, taking a wide range of objectives into account matter if we are to understand actor decisions and policy impact (Ostrom, 2007). An agent-based model provides the ability to consider heterogeneous actors with a variety of goals, and emerging patterns from interactions among these actors (Heckbert et al., 2010). Earlier research has provided insights into the use of agent-based models in related fields, like agent-based models of land use and land cover change (Matthews et al., 2007; Parker et al., 2003), of coupled human and natural systems (An, 2012), physical and human geography applications (Torrens, 2010), ecosystem management (Bousquet and Le Page, 2004), and agriculture and agri-food supply chains (Huber et al., 2018; Utomo et al., 2018). While we observe increasing use of agent-based models for studying human behavior and forest uses, we are missing an overview clarifying the differences between available models, their framework implementation, features, scopes, and functions. This review aims to fill that gap and is guided by the following questions:

How do existing agent-based models for managed forest systems compare in their ability to simulate a social-ecological system?

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Specifically, how do current applications provide the possibility to simulate:

a) interactions among and between social and ecological subsystems?
b) dynamic representation of processes and behavioral change?
c) flexibility when it comes to the study purpose?

The study contributes to the literature on the use and scope of ABMs in general (Achter et al., 2023; Dai et al., 2020; Filatova et al., 2013; Noszczyk, 2019; Savin et al., 2023), along with modelling social-ecological systems (Schlüter et al., 2019; Wijermans et al., 2023), but with a novel focus on forest systems. The aim is to perform a systematic comparison of agent-based models useful to understanding human-nature interactions in forest systems, conceptualized as social-ecological systems (SES). First, we provide a conceptual background of social-ecological systems, relate it to forest systems and provide an overview of a motivation for using agent-based approaches for studying such systems (Section 2). Next, we describe how the systematic comparison of agent-based modelling applications has been done (Section 3) and show in the results section how reviewed applications compare (Section 4). Lastly, we discuss how the study can guide model choice, and provide insights into current frontiers in agent-based approaches for studying forests as social-ecological systems.

2. Conceptual background

2.1. Social and ecological interactions

The concept of SES refers to social and ecological systems being deeply interlinked and mutually dependent, where the way people and nature interact is understood as constantly changing relations across scales (Berkes, 2017; Berkes and Folke, 1998). The aim from the collaborating group of researchers within common pool resource systems and ecological economics that developed the concept was to provide a structure for analyzing local resource management (Berkes and Folke, 1998).

SES is based on systems theory, which puts focus on exploring relationships and interactions rather than isolated components of a system (Von Bertalanffy, 1972). With that understanding, an SES is more than the sum of its ecological and social parts (Reyers et al., 2018). Several frameworks have been suggested to study social-ecological systems, one prominent being the one developed by Elinor Ostrom (2009). Ostrom's SES framework was developed with the purpose to analyze how multiple forms of governance affect resource systems and resource uses across multiple dimensions and scales (McGinnis and Ostrom, 2014). Ostrom's SES framework builds on collective action theory and focusses on resource user interactions, in contrast to more system-level SES frameworks (Schlüter et al., 2019). In studying forest systems as natural common pool resources, shared and governed by multiple actors, SES has become a common approach to understanding complex dynamics of ownership and responsibility (Schlager and Ostrom, 1992).

The framework is a multi-level framework where the social-ecological system is represented through variables on two levels, the first-tier and second-tier variables. At the first level the framework divides a system into seven categories: resource units, resource system, actors, governance system, social, economic, and political setting, action situations (interactions and outcomes) and related ecosystems. The second-tier variables enable further specification of each subsystem, to for example define resource system size and boundaries, interactions between resource units, location, history of resource use, government organizations, and property-rights systems. Interactions between these elements are what leads to outcomes, and that outcomes from a SES are on multiple scales in space and time (de Mello et al., 2020; McGinnis and Ostrom, 2014; Ostrom, 2007). The complementary social-ecological action situation (SE-AS) framework (Schlüter et al., 2019) highlights social and social-ecological interactions as key components to understand emergent phenomena. While the continued conceptualization builds on the variables in Ostrom's framework, the SE-AS framework emphasizes importantly how action situations are formed, and encourages researchers to "critically reflect on the assumptions made regarding human behavior when analyzing a SES" (Schlüter et al., 2019, p. 5). Decision-making models need to fit the context they aim to represent (Wijermans et al., 2023). We thus see these as important perspectives when considering modelling forests as social-ecological systems.

2.2. Forests as social-ecological systems

To conceptualize a social-ecological system understanding of a managed forest, let us start by looking at the seven first-tier variables (Fig. 1). The underlying assumption is that social and ecological systems are deeply intertwined, meaning that forest policy, regulations, social relations, and trade flows are all examples of social processes that affect and are affected by forest structure, growth, species diversity and nutrient cycling. The system as a whole is affected by its social, economic and political settings – like economic development, demographic trends, political stability, external governance systems, markets, technology and media organizations (McGinnis and Ostrom, 2014; Ostrom, 2009). Resource units could be plants, understory vegetation and fauna, articulated and defined in different ways: as wood, units of carbon storage or classes of land cover. The second-tier variables like resource unit mobility, growth rate, economic value, number of units and spatial and temporal distribution are used to further specify characteristics of the first-level variables (McGinnis and Ostrom, 2014).

In a managed forest system, important actors are e.g., managers, forest owners, households, firefighters, loggers, indigenous groups, and local communities. The second-tier variables then emphasize actors' socio-economic attributes, their dependence on the resource, their history or past experiences, norms, knowledge, and technologies available.

The governance system includes all organizations and structures that affect the use of the resource. It could entail government and non-government organizations, structures of property-rights, and regulations for monitoring and sanctions. Forests are not closed systems, but are open for inputs to and outputs from other ecosystems in forms of e.g. nutrients, pollution, norms and information (Nocentini et al., 2017). When it comes to interactions and outcomes in managed forests, we could think of important aspects to consider being harvesting patterns, information sharing, conflicts investments, lobbying, networking, equity, and sustainability (McGinnis and Ostrom, 2014).

2.3. Agent-based models

An agent-based model (ABM) is a bottom-up approach to model heterogeneous agents and their actions and interactions, often with an aim to understand patterns that emerge from micro-to macroscale. Specifically worth mentioning for studying a SES, agent-based models have been shown to be useful to combine quantitative and qualitative data (Antosz et al., 2022). The agents in the model are defined by a set of rules that guide their behavior, and could represent an organization, a person, or a household. They act in a world set to represent the physical world such as a landscape with agricultural and forest patches, or be set to a specific scenario, for example a forest policy debate. Depending on the approach, the agents and the landscape may be given dynamic properties that evolve over time. Recent research developments have approached the challenge of dynamic cognitive processes by integrating machine learning to represent agents' learning and memory (Constantino et al., 2021; Sotnik, 2018).

In contrast to traditionally used models within forest management studies, like decision support systems (DSS), top-down equation based or economic models, ABMs give the possibility to model agents that have different objectives, and dynamic interactions between each other and with the environment (Rounsevell et al., 2012). While these properties

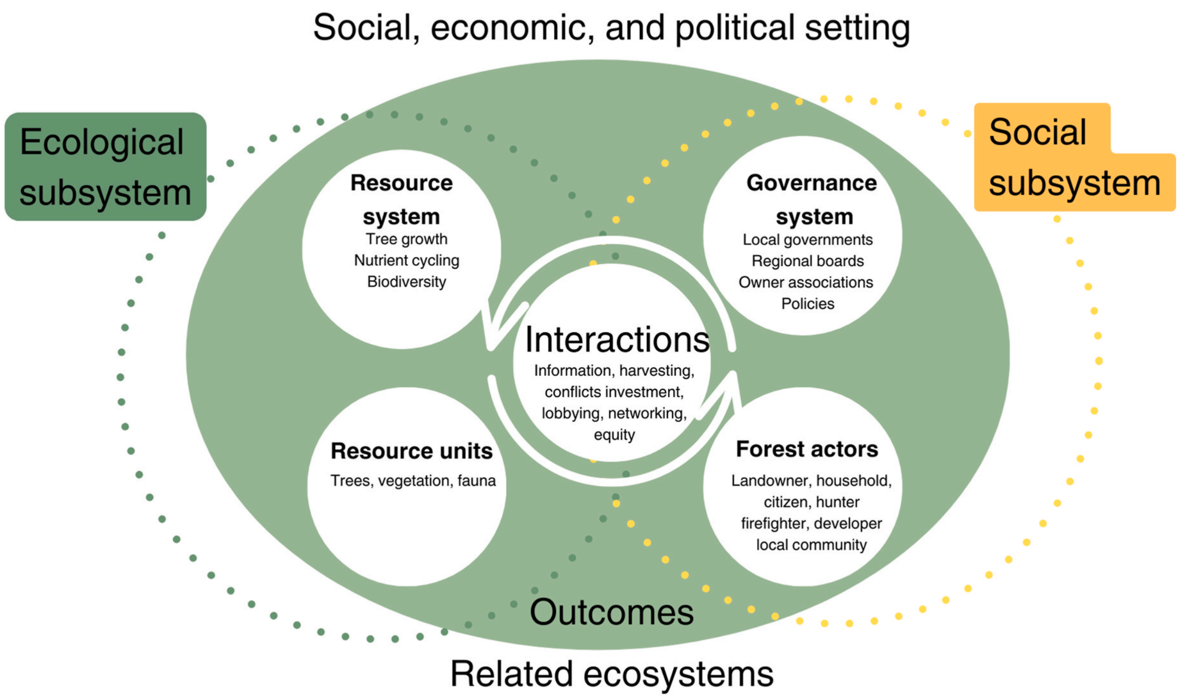

Fig. 1. Conceptualization of forests as a social-ecological system with examples of each group of variables, adopted after Ostrom (2009) and with inspiration from McGinnis and Ostrom (2014).

Table 1
Final search string used for the literature search.

Themes	Logical	Search string
model		"agent-based model*" OR "agent-based" OR "ABM" OR "individual-based model*" OR "IBM" OR "social simulation" OR "multi-agent system*" OR "agent-based simulation*"
forest	AND	forest* OR bioeconomy OR bioenergy NOT "random forest"
management	AND	management OR decision-making OR decisionmaking OR decision OR strategy OR behavior OR behaviour OR approach OR human

make it possible to capture more complexity within forest systems, ABMs have to a large degree been used as a research approach rather than operational decision support tools for forest managers, often argued due to lack of empirical calibration (Matthews et al., 2007; van Vliet et al., 2016). ABM has however advantages that can provide applications beyond theoretical experiments e.g. by being able to integrate stakeholders and participants through participatory modelling (Bommel et al., 2015; d'Aquino et al., 2002). Within integrated environmental assessment models, ABM is considered a good option for purposes of system understanding, social learning and interactions among actors (Groeneveld et al., 2017; Kelly et al., 2013).

3. Methods

We performed a literature review and a systematic comparison of agent-based approaches to modelling forests as social-ecological systems. Models for studying individual actors' behavior can be found under different names – while agent-based modelling or agent-based computational economics are most common in social and economic sciences, individual-based modelling is commonly used in ecological applications (Grimm, 1999; Heckbert et al., 2010). The structure and purpose of the model can be similar, and for this reason we chose to review both agent-based, multi-agent systems and individual-based models, but only to include models that involve interactions between humans and forest systems. The analysis should be understood as comparing models that have the potential to be used for social-ecological systems modeling of forest systems, as we did not require studies to specifically mention the term SES as long as a human-forest relationship was represented in the model.

The literature search was performed in six steps. In the first step, we built a search string around the three main themes: *model, forest* and *management*, see Table 1.

The addition of "NOT random forest" was done to exclude results from the common machine learning algorithm *random forest*. Additions to the search string that were explored but did not add to search results included: "agent-based computational economics", "agent based model", "individual based model", forestry, silviculture and wood.

In the second step, we used the final search string and performed searches in Web of Science and Scopus and explored different alternatives for limiting the scope of the search, see Table 2.

Based on the result of the search we performed the literature search and decided to limit the first part of the search string, the model theme, to include abstract, and the two other parts - forest and management – to title only with the aim to obtain a broad but relevant result. We limited the search to peer reviewed articles and conference papers. The results of the search in the two search engines were exported to Excel and duplicates removed. The search in Web of Science added 6 references that

Table 2
A summary of number of results depending on search criteria, on Web of Science and Scopus respectively.

	Web of Science Core Collection	Scopus	Total
Anywhere	1529	31,290	32,819
Abstract	330	444	774
Title + abstract for method	37	48	85
Duplicates removed			54

were not part of the Scopus search, bringing the total number of results to 54 articles after this step of the process (Fig. 2).

We manually identified papers with model applications of forest management to be used for further analysis. Reviews and applications of purely ecological systems were filtered out. The models being filtered out for being purely ecological showed a pattern of being called individual-based models, which goes in line with earlier studies (Grimm and Railsback, 2006). The term "multi-agent system" was however represented in both purely ecological studies, as well as social-ecological and economic simulations. After this step of the process, 33 articles remained. As we were interested in unique model applications, out of the 33 identified papers, 26 studies presenting unique model applications were kept for further analysis. Finally, through the process of reviewing the search results, an additional 5 models were added because they were referenced in the reviewed articles. Thus 31 articles describing model applications were used for the final analysis (Fig. 2). In continuation, we use the term *model* when referring to a specific application used in a reviewed study, and *platform* when referring to the underlying modelling environment or software.

3.1. Analysis

The reviewed models were analyzed with respect to time step, spatial units, scope (of the model world), validation approach, framework, open-source license, integration to other types of models and complexity of the system. To analyze the complexity of the system, the model was explored in terms of how it represented a) the social system, like characteristics of social actors, government system, ecosystem characteristics, and degree of social agent interaction and b) human-nature interaction. Earlier SES literature has emphasized interactions as a key component to understand how local relationships between people and ecosystems are part in forming emergent patterns affecting the overall system (Aggarwal and Anderies, 2023; Schlüter et al., 2019). We interpret interactions as being either direct or indirect. Studies of ecological communities classify direct and indirect effects, as "direct effects, as the name implies, deals with the direct impact of one individual on another when not mediated or transmitted through a third individual" (Moon et al., 2010, sec. 1; Wootton, 1994). The interactions involved in the model approaches were analyzed as direct when for example a forest owner, represented as an agent in the model, was able to take a management decision with direct effects on land cover, or when a forest manager could be directly influenced by her neighbor's decision. An interaction was interpreted as indirect if the model only represented changes in the managed forest through actions having indirect effects, for example an agricultural subsidy driving forest land use change.

4. Results

The selection resulted in 31 agent-based models applied to forests with social-ecological components. The resulting articles were published

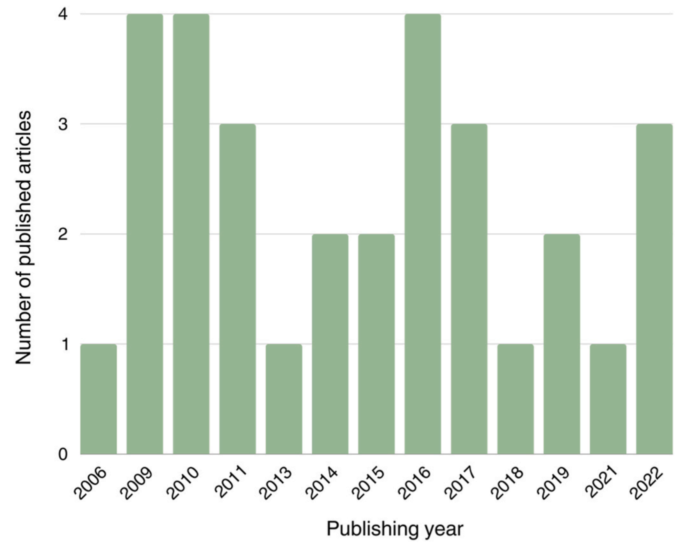

Fig. 3. Publishing year for the reviewed agent-based model applications.

during years 2006–2022 (Fig. 3). The reviewed models were presented in a wide range of journals within environmental, engineering, geosciences, ecology and forestry fields. Forest Policy and Economics (3 papers), Ecology and Society (2 papers), Environmental Modelling and Software (2 papers), and Energy (2 papers) were the journals that had each published more than one reviewed model application.

4.1. Overview of agent-based models

The reviewed models showed a broad range of temporal and spatial scales, scope, validation methods and frameworks employed. We found that models driven on annual timesteps were the most common, often motivated as being the temporal scale at which managers are able to take decisions. We did however see examples of shorter timesteps – daily, like the People and Landscape Model, PALM (Brown et al., 2016) and in seconds, in FFMAS as designed with the aim to develop forest fire management (El Masri et al., 2011). Not all reviewed models were spatially explicit, but in many cases, authors referred to a decision unit on which management decisions are taken. Forest stand or property were common units, but we also detected more detailed examples in meters like the ABM for adaptive forest management, and the NetLogo Mouse foraging model exploring forest management effects on mouse foraging (Gebetsroither et al., 2006; Morán-López et al., 2016; Wilensky, 1999).

Very few of the reviewed agent-based models were applied to scales larger than local. One example was CRAFTY-Sweden, where model outcomes of forest management and land use were shown nationally across Sweden (Blanco et al., 2017). Four of the studies were applied to

Fig. 2. Visual summary of the process of literature search in the two search engines Web of Science and Scopus.

Table 3
Overview of the 31 reviewed agent-based models of human-forest interactions, showing each model's a) purpose, b) time step, c) spatial unit, d) scale, d) platform, e) access to specific code for the application and f) whether the model or platform is provided under open-source license.

Model	Focus	Time step	Spatial unit	Scale	Platform	Code	Open source-license
ABE (Rammer and Seidl, 2015)	Decision-making in forest management	Annual	Forest stand	Local	own	✔	GNU- GPL
AB-GIS (Bone and Dragićević, 2009)	Forest management and land-cover change	Annual	Forest stand	Local	Agent Analyst		
ABM for adaptive (Gebetsroither et al., 2006)	Self-organization processes	Annual	25m2	Local	NetLogo		GNU- GPL
ABM for CPRs (Vallino, 2014)	Common-pool resource governance	NA	Forest stand	Local	NetLogo	✔	CC-BY-NC-SA-4.0
ABM for PES (Sharma et al., 2019)	Auction-based payments for C sequestration	Auction	NA	Auction	NA		
AnyLogic: Bioenergy adap. (Burli et al., 2021)	Bioenergy crop adoption	Annual	Forest stand	Regional	AnyLogic		
AnyLogic: Harvesting opt. (Rukomojnikov et al., 2022)	Managerial decisions using a forest harvester	Hourly	Forest stand	Local	AnyLogic		
BEN ABM (Kempener et al., 2009)	Design and analyze bioenergy networks	Annual	NA	Local	AnyLogic		
ComMod: SCTL (Simon and Etienne, 2010)	Scenarios for community-owned forests	Weekly	1 ha	Local	CORMAS		MIT
CRAFTY- Sweden (Blanco et al., 2017)	Provision of ecosystem services	Annual	1 km2	National	CRAFTY		GNU- GPL
CV-STSM (Yospin et al., 2015)	Climate and LU effects on vegetation change	Monthly	Forest stand	Local	Envision		GNU- GPL
DEED (Robinson and Brown, 2009)	LU development policies	Annual	0.56km2	Local	ArcMap		
Envision: Forest fires (Charnley et al., 2017)	Forest management effects on fire resilience	Annual	3–10 ha	Regional	Envision		GNU- GPL
FABLE (Henderson and Abt, 2016)	Markets and landowner behavior	Annual	Forest stand	Local	NetLogo		GNU- GPL
FFMAS (El Masri et al., 2011)	Communication in forest fire management	Seconds	meters	Local	NA		
FLAME (Leahy et al., 2013)	Landowner goals for timber harvesting	Annual	Forest stand	Local	own		
Forest Actor Interaction ABM (Martínez-Falero et al., 2018)	Participatory forest management	NA	pixels	NA	own		
ForestSim (Zupko and Rouleau, 2019)	Forest policy and bioenergy sustainability	Annual	Forest stand	Regional	MASON	✔	Academic Free Lic. v.3.0
HANIP (Yang et al., 2022)	Tourism and labor migration effects on forests	Annual	8100 m^2	Local	Swarm		GNU- GPL
Heureka + 5 GR (Sotirov et al., 2019)	Provision of ecosystem services	5-year	Forest stand	Local	Heureka		EULA
MASOOR (Edwards and Smith, 2011)	Explore outdoor recreation patterns	Movement	National park	Local	own		
MPB Simulation (Pérez & Dragicevic, n.d.)	Investigate management and insect outbreaks	Annual	Forest stand	Local	Repast S		New BSD
MP ABM (Huang et al., 2016)	Assess bioenergy crop adoption	Annual	Forest stand	Local	NA		
NetLogo Mouse foraging (Morán-López et al., 2016)	Forest management effects on mouse foraging	Movement	1 m	Local	NetLogo	✔	GNU- GPL
PALM (People and Landscape) (Brown et al., 2016)	Assess bioenergy crop adoption	Daily	Catchment	Local	own		
Pyroxene: Forest fire (Maillé and Espinasse, 2011)	Decision support for forest fire management	Multi	Multi	Local	ArcGIS		
Repast Simphony Meta-model (G. Zhang and Li, 2010)	Explore dynamics of forest fire management	NA	NA	Local	Repast S		New BSD
RL-ABM (Bone and Dragićević, 2009)	Multi-stakeholder management	Annual	Forest stand	Local	ArcGIS		
SORTIE + ABM (Bithell and Brasington, 2009)	Forest land-use and hydrology	Annual	20 m	Local	own		
SOSIEL Harvest (Sotnik et al., 2021)	Adaptive forest management	5-year	meters	Local	SOSIEL	✔	LGPL-3.0
Wood fuel market ABM (Kostadinov et al., 2014)	Roundwood and wood fuel markets	Annual	NA	Local	own		

Table 4
Validation methods reported for agent-based models mentioning that validation has been done for the reviewed application.

Model	Validation
ABM for adaptive forest management	Expert interviews, structural validation with experimental data
ComMod: SCTL	Companion modelling process, data and workshops
CRAFTY- Sweden	National Forest Inventory, survey
CV-STSM	Parameterized based on historical land cover
DEED	Survey
Envision: Forest fires	Calibrated based on remote sensing, inventory of vegetation structure, interviews
FLAME	Against observed harvest data
Forest actor interaction ABM	Against observed data - forest and perceptions
HANIP	Ground truth remote sensing data, surveys, Census-data
Heureka + 5 GR	Survey
MASOOR	GPS tracks, surveys
MP ABM	Survey of landowners
NetLogo: Mouse foraging	Validated against 5 data sets of field data
PALM	Survey
Pyroxene: Forest fire	Terrain data
RL-ABM	Mathematical validation
Wood fuel market ABM	Expert workshops, empirical data, visual debugging

regions, involving several different forests or a larger landscape with different land uses. Worth mentioning is that some models focused on markets, networks and decision processes, which gives a different meaning to scope in comparison to the spatially explicit GIS-based model (Table 3).

Validation methods varied and indicated in several cases how the modelling process involved mixed-methods and interdisciplinary approaches including measured data, statistics, surveys, workshops with experts and participants, and geographic information. Table 4 provides an overview for those ABMs where validation methods were reported.

4.2. Interactions

We used degree and types of interactions to compare the ability of the different models to simulate complexity within forest systems. Interactions were divided into indirect vs direct interactions among social actors, compared to indirect vs direct human-nature interactions (see Table 5). In direct social interaction, actors are able to e.g. change their decisions based on neighbors' decisions like in the case with the MP (Mathematical Programming) ABM (Huang et al., 2016) or may have access to a network with contacts and information spreading, like the case with the Wood fuel market ABM where actors took friendship into account (Kostadinov et al., 2014). We also see examples where actors have been given explicit characteristics of empathy and acceptance, in the case of CRAFTY-Sweden and the Forest actor interaction ABM (Blanco et al., 2017; Martínez-Falero et al., 2018) which then influenced their social interactions. Indirect interactions are interpreted when models do not include mechanisms for direct contact between agents, but agents may still be influenced by the outcome of other agents' decisions. An example of an indirect social interaction is the setup of the Agent-based model for Common Pool Resources, ABM for CPRs (Vallino, 2014). The model incorporated mechanisms for agents to change behavior when a certain percentage of forests have been cut in the whole community but did not involve mechanisms for agents to directly communicate with each other. For indirect human-nature interactions,

Table 5
Types of interactions among and between social actors and ecological system. The table reflects the reviewed model applications. Since human-nature interaction was a criterion for included studies, all reviewed model applications involve human-nature interaction either directly or indirectly.

		Human-nature	
		Direct	Indirect
Social	Direct	AnyLogic: Bioenergy adaptation	BEN ABM
		ComMod: SCTL	FFMAS
		CRAFTY-Sweden	Forest actor interaction ABM
		FLAME	
		HANIP	
		MP ABM	
		PALM	
		RePast Simphony Metamodel	
		RL-ABM	
		Wood fuel market ABM	
	Indirect	ABM for PES	ABM for Adaptive Forest Management
		AB-GIS	DEED
		ABE	MASOOR
		ABM for CPRs	
		FABLE	
		ForestSim	
	No	AnyLogic: Harvesting	CV-STSM
		Envision: Forest fires	NetLogo: Mouse foraging
		Mountain Pine Beetle Simulation	Pyroxene
		Heureka+ 5 GR	
		SORTIE + ABM	
		SOSIEL-Harvest	

the model DEED was used to study decision-making in ex-urban development, where the agents' take decisions that have indirect effects on forest cover (Robinson and Brown, 2009). A model that accounts for direct human-nature interaction explicitly models forest owners making decisions on how to manage the forest, such as harvest decisions based on bioenergy demands in ForestSim (Zupko and Rouleau, 2019). When comparing the directness of human-nature interaction and social actor interaction, a third of the models were implementing direct interactions in both aspects, see Table 4. It was more common that models applied a direct human-nature interaction combined with an indirect/no social interaction, than a direct social interaction combined with an indirect/no human-nature interaction, see Table 4. A word of caution is that the results show the reviewed models, which means that the underlying platforms may provide ability to simulate a larger complexity of interactions. That was the case with for example SOSIEL Harvest (Sotnik et al., 2021), which has been described as a platform with advanced developments when it comes to agents' social and cognitive abilities. The reviewed study however simulated one forest manager at a time, meaning that there was no direct contact between agents within a model run.

While types and degree of interactions tell one aspect of how the agent-based models dealt with complexity, in the next section we zoom into degrees of complexity within the social and ecological subsystems respectively (Fig. 4).

4.3. Social subsystem

Agent types considered in the different models vary from no explicit social actors, such as CV-STSM (Yospin et al., 2015) where instead land cover type is used as a proxy for different agents' behavior, to a maximum of nine actor types in the Wood fuel market ABM (Kostadinov et al., 2014). One actor type, like the case of landowners in the FLAME model (Leahy et al., 2013), could still allow for different behavior – when actor characteristics were drawn from a pool of characteristics rather than a set of types. Apart from FLAME, a similar setup was used in the Forest actor interaction ABM (Martínez-Falero et al., 2018), the ABE (Rammer and Seidl, 2015), and the ABM for CPRs (Vallino, 2014).

Models varied in factors affecting actors' behavior. Some used a more traditional approach where actors were dominantly behaving rationally, for example the FABLE model where agent behavior was based on Faustmann/Hartmann equations (Henderson and Abt, 2016). Many models included a range of actor objectives as part of their decision-making, as seen in the five forest owner types of the 5 GR model coupled with the decision support system Heureka (Sotirov et al., 2019). The ability of agents to learn from past experiences adds another dimension to the aspects of complexity, where 7 models included processes of learning agents. One example is the reinforcement learning algorithm included in the RL-ABM (Bone and Dragićević, 2010).

Like the social actors in general, if a government system was present it could vary in how dynamically it was represented– either through policies and legislation implemented as rules for agent behavior in the model, or as separate actors with their own possibility to interact, act and change behavior. Half of the reviewed models represented a government system in at least one of the described ways, and 6 of them included a specific and dynamic government agent, like AB-GIS (Bone and Dragićević, 2009) and ABM for PES (Sharma et al., 2019).

4.4. Ecological subsystem

Most of the reviewed models represent a forest landscape through a land cover map. The land cover map could be static over the modelling period or change in discrete steps as an effect of actor behavior (Burli et al., 2021). A next step reviewed for complexity and dynamic representation of the ecological subsystem was the representation of different tree species or functional types. Here, 18 of the 31 reviewed models included a variety of at least functional types, sometimes down to the

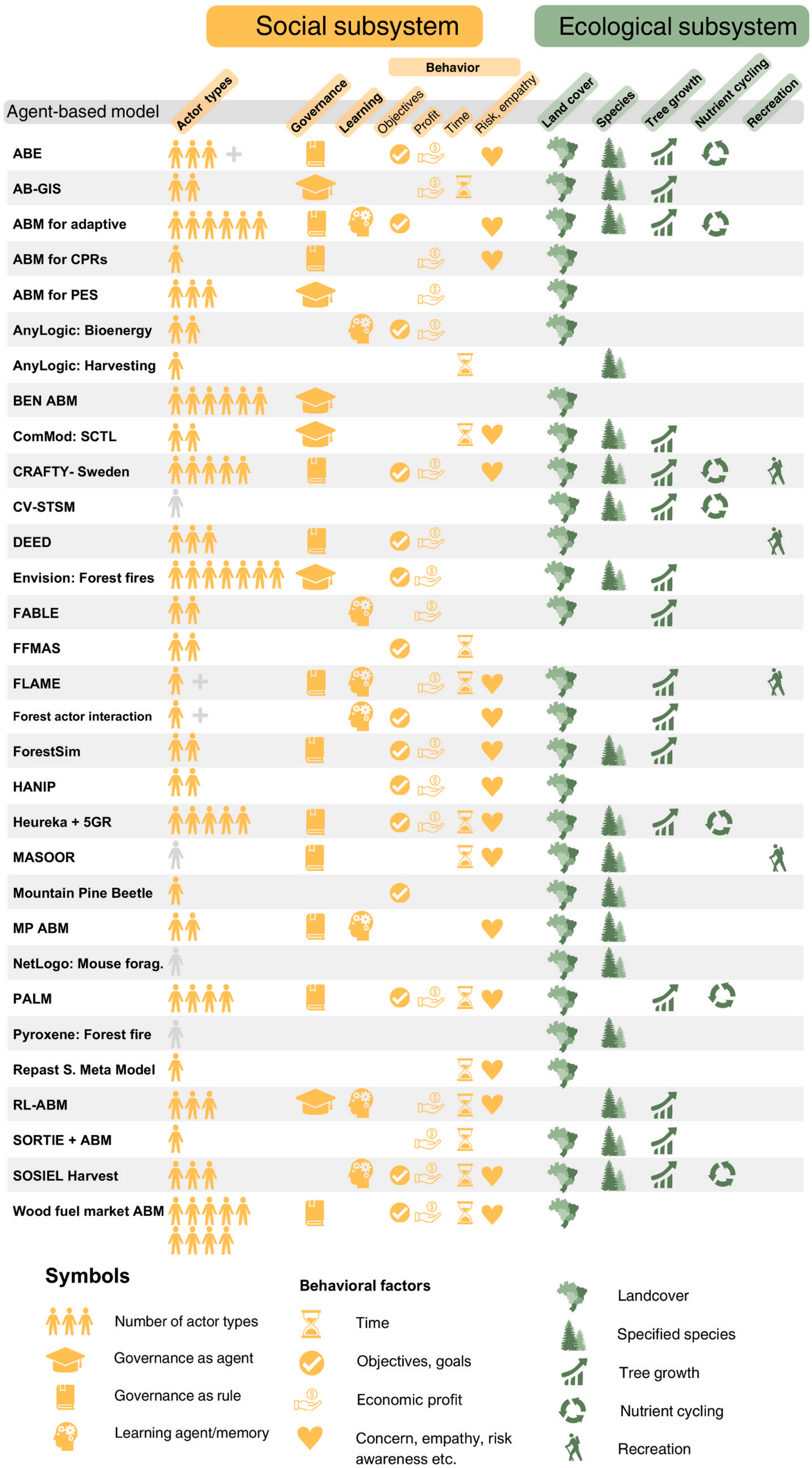

Fig. 4. Agent-based models applied to human-forest interactions with respect to characteristics of the social and ecological system represented in each model. From left to right, the figure describes: Social subsystem a) number of actor types, b) government system representation as agent or legislation, c) learning agents and d) types of factors determining agent's behavior and for the ecological subsystem e) land cover, f) functional types/species, g) tree growth, h) nutrient cycling and i) recreational features explicitly modelled in the landscape. Greyed actor symbols indicate that actors are indirectly represented, through e.g., a forest management decision. A grey + indicates that actor types are not pre-defined, but resulting from a pool of actor characteristics.

level of individual species. Of those not representing tree species diversity, it could either be motivated by the focus of the model being more general, like forest fire coordination in the case of the Repast Simphony Meta-model (G. Zhang and Li, 2010) or reflect the state of the empirical case as a monoculture forest.

Tree growth and nutrient cycling are two other factors to describe the representation of ecological complexity and feedback within the models. Several of the reviewed agent-based models were coupled with dynamic vegetation models to deal with these feedback mechanisms. Examples of that are the individual-tree based JABOWA III, used in the ABM for adaptive forest management (Gebetsroither et al., 2006), the ecosystem model LPJ-GUESS in CRAFTY-Sweden (Blanco et al., 2017), SORTIE coupled with an ABM (Bithell and Brasington, 2009), and the forest landscape model LANDIS-II used in the SOSIEL Harvest application (Sotnik et al., 2021) and Pyroxene: Forest fire (Maillé and Espinasse, 2011).

Recreational features in the landscape were represented in 4 of the 31 reviewed models. The ways in which recreation was included varied but could for example be a number representing recreational value of an element in the forest that the agents took into account in their decision-making. The most explicit example was the Multi-Agent Simulation of Outdoor Recreation, MASOOR (Edwards and Smith, 2011) which explicitly modelled visitor routes within a recreational area.

5. Discussion

We find that existing agent-based models are used with a broad range of aims, from those building on traditional decision support systems for forest management, to applications with a wider range of actor types and decision alternatives to model more complex social patterns. To model forests as social-ecological systems, the results show that existing models focusing on managed forests provide a range of opportunities. There is a range of platforms that can be used as a basis for adapting a model for a specific study, and specific forest models can be used as inspiration when setting up an ABM for a specific purpose. In the following section we discuss the implications of the results for modelling SES and conclude each sub-section with a question to guide model choice.

5.1. Purposes

The review shows a broad range of model purposes, from models focusing on private and community forest management to landscape level spatial planning, supply of timber and non-timber products, recreational activities, and risk management. While some models are built on their own platform limited to a specific purpose, others are more flexible and could be adapted to other purposes than currently, largely depending on the flexibility of the software platform they are programmed in. As examples, the platforms CRAFTY and SOSIEL are designed for providing a basis for exploring land use issues, whereas ForestSim and HEUREKA+ 5 GR are developed for forest systems specifically (Murray-Rust et al., 2014; Sotirov et al., 2019; Sotnik, 2018; Zupko and Rouleau, 2019).

By the varied use of data and methods to parameterize and validate models, we observed a large tendency of involving interdisciplinary perspectives in the agent-based approaches, which is in line with what Savin et al. (2023) discuss in relation to climate policy: Agent-based models can work as a framework to integrate multiple perspectives which taken together lead to more coherent policy support. Psychology, sociology, economics and political science can support in explaining resistance to policy measures, for example by integrating bounded rationality or other behavioral models, role of information, norms, human needs and opinion polarization (Gotts et al., 2019; Savin et al., 2023).

Modelling forests following an SES framework would allow for seeing forest management in a system context, and an agent-based approach shows promise for involving dimensions of both institutional and individual behavior. Understanding human behavior as part of complex adaptive systems, of which SES is an example, has been argued to lay ground for policy "to create contexts that enable and support a diversity of solutions to emerge from local initiatives" (Schill et al., 2019, p. 1080). In this systematic comparison we have seen examples of forest actors being equipped with characteristics that go beyond the commonly used toolbox in environmental policy and modelling: empathy, environmental concern, beauty appraisal and recreational preferences. For these dimensions to be of use to support policy making, there is a need for model development especially when it comes to model validation, and applications beyond single case studies. For selection of an appropriate model, we would suggest asking: *What purpose and research question shall the model answer and what corresponding functionalities are required?*

5.2. Dynamic social-ecological representations

Of the reviewed model applications, we see wide variation in the complex dynamics included where some models are more developed in terms of the social subsystem and others in the ecological subsystem. As mentioned earlier, this is a common critique of SES studies – being too narrowly focused on one of the subsystems (Cote and Nightingale, 2012; Vogt et al., 2015). If sustainability is the purpose of an analysis, the separation between subsystems becomes a problem: "Addressing only the social dimension of resource management without an understanding of resource and ecosystem dynamics will not be sufficient to guide society toward sustainable outcomes" (Folke et al., 2005, p. 443). We would like to discuss two aspects of dynamic representations in the reviewed models: within the forest resource system and the governance system.

The results indicate that the most advanced representations of forest system dynamics are seen in ABM approaches integrated with forest models or dynamic vegetation models. These model integrations enables depth in the analysis of the ecological processes, which may counteract the tendency of SES studies to underrepresent and often rely on secondary data for ecological variables (Nagel and Partelow, 2022). Through an overview of forest models in *Encyclopedia of Theoretical Ecology*, Dietze and Latimer (2019) explain the degree to which models involve dynamic representations of forest ecosystem dynamics, and which processes that are involved by dividing these into two larger model types: community ecology models and ecosystem ecology models (Dietze and Latimer, 2019). Community ecology models have often been developed to simulate forest gap dynamics and light competition as it is a limiting resource in many forest ecosystems. Developed to capture dynamics on small spatial scales, from individual trees (SORTIE), to patch (JABOWA III) and landscape level (LANDIS-II) (Botkin, 1993; Canham et al., 1999; Scheller et al., 2007), models with a base in community ecology are in the forefront when it comes to modelling density interactions in tree growth, seed dispersal with its effects on tree composition, and tree crown distribution (Nuttle and Haefner, 2005). Ecosystem ecology models on the other hand, have been developed to simulate carbon fluxes and water and nutrient cycles. Interaction between individual species or trees is limited, but soil and rooting dynamics are often better captured (Dietze and Latimer, 2019).

Earlier studies have emphasized that modeling forest dynamics is much determined by how tree growth and mortality is represented, for example if growth is process-based on relations between photosynthesis and ecosystem Net Primary Production (NPP) or empirically based on correlation with environmental variables (Medlyn et al., 2011; Porté and Bartelink, 2002). Other aspects are for example how models treat small scale interactions and stochasticity of tree mortality (Keane et al., 2001) and if space is represented based on points, as in JABOWA-III and LPJ-GUESS (Botkin, 1993; Smith et al., 2014) or area, as in SORTIE and LANDIS-II (Canham et al., 1999; Dietze and Latimer, 2019; Scheller et al., 2007). These aspects impact how key dynamic forest processes like disturbance from wind, fire and drought are simulated (Seidl et al., 2011).

While coupling an ABM with a forest model or dynamic vegetation model comes with advantages in the ability to represent complexity of ecological forest processes, it adds additional modelling challenges like matching between ecological processes on different spatial and temporal scales (Dietze and Latimer, 2019; Medlyn et al., 2011). A wider discussion on the implications of coupling an ABM to specific forest model types is outside the scope of this study, but as a key take away for future research, a guiding question for model choice when it comes to ecological dynamics is: *What type of ecological processes are driving and limiting factors for the study's purpose and research question?*

Agent-based approaches are pointed out as being promising for incorporating governance systems but earlier studies have shown that in practice, many ABMs incorporate governance as an exogenous variable (e.g., a fixed rule) rather than active agents that can change the rules or incentives faced by forest manager agents (Rounsevell et al., 2012). We see a similar pattern in the reviewed forest ABMs where a governance system is present in almost half of the model applications, but more commonly through rules for the agents to follow rather than as an autonomous governance agent making governing decisions. This follows earlier research looking at how institutional behavior is represented across different land-based sectors (Brown et al., 2017). While the presence of governance as rules allows for the researcher to change and explore governance dynamics, judging from the applied setups, we assume this approach leads to a more static representation of governance in the social-ecological system. In contrast, governance as an agent as in the case of CORMAS, Envision: Forest fires and RL-ABM (Bone and Dragićević, 2010; Charnley et al., 2017; Simon and Etienne, 2010), allows for a higher degree of flexibility and dynamic representation of governance, as the governance agent can have its own emerging behavior across the simulated time frame and in turn interact with the resource system and resource users. This would allow for incorporating theories on adaptive governance and institution development into simulations, which responds to previous calls from for example common-pool-resource scholars on strengthening governance and collective structures' aspects both in SES applications and in ABM modelling overall (Bourceret et al., 2021; Epstein et al., 2020; Folke et al., 2005; Janssen and Ostrom, 2006a; Kremmydas et al., 2018). As a guiding question for model choice, we suggest researchers to ask: *Are governance rules static or do they need to be modelled as adaptive governance decisions?*

5.3. Social-ecological interactions

Interactions between social actors and the ecological system are key to understanding an SES (Kline et al., 2017). In a review of agent-based models used for agricultural policy evaluation, the authors pointed out direct actor interactions (rather than indirectly through, e.g., markets, as usual in economic models) as a crucial aspect for future research (Kremmydas et al., 2018). Through this review we have found ten forest ABM applications that include direct interactions among and between parts of the social and ecological subsystem. Allowing simulated forest actors to be influenced by each other's decisions, as one example of a direct social interaction, opens up for including important social dynamics within managed forests like power (Boonstra, 2016), loyalty (Beland Lindahl et al., 2013), and trust (Hujala and Tikkanen, 2008). If there is a need to develop approaches for empirically based decision support, dynamics like social organization and loyalty have shown to play an important role in forest management decisions (Beland Lindahl et al., 2013; Curtis et al., 2023).

The representation of social dynamics in the simulation approaches can be further enhanced in the applications that include learning agents. Desire to learn has been used as a dimension for separating decision-making modes across non-industrial private forest owners (Hujala et al., 2007), showing the importance for decision-making not only of interactions between forest actors but also from actors' own learning processes of earlier experiences and from decision support functions like advisory services (Curtis et al., 2023).

From a modelling point of view, there is a tradeoff between complexity considered and interpretability of the outcome, to avoid a risk of 'over parameterization'. A challenge that might make direct interactions and feedbacks difficult to include are mismatches between scales, where spatial and temporal scales of management do not match scales of ecological processes (Cumming et al., 2006). The question of complexity and interactions must thus take temporal and spatial scales into account, but also in reference to the degree of dynamics contained in the simulation setup. Based on this, we recommend two key questions to ask when choosing a model: 1) *Should actors and their behavior be influenced by other agent's decisions?* 2) *How important are ecological feedbacks and social interactions for understanding the research problem?*

5.4. Frontiers

Finally, we discuss common features and insights that the study has gleaned into frontiers in development of forest ABMs.

To begin with, methods for calibration and validation of the reviewed forest agent-based models are varied including workshops, surveys, expert interviews, remote sensing and field measurements, indicating that ABMs have a strong potential of combining theory with empirical data (Janssen and Ostrom, 2006b). But 14 of the reviewed applications do not mention validation at all. Despite efforts such as the ODD, a protocol to document agent-based models, and the recently developed OsDD to take sustainability aspects into account (Grimm et al., 2006, 2020; Secchi et al., 2023), our overview suggests that current reporting of and standardized methods for model validation in forest ABMs are largely missing.

Validation of agent-based models has been a topic of debate for a long time, especially for demonstrating the usefulness of agent-based approaches for solving real-world problems in policy processes (Brown et al., 2017; Elsawah et al., 2020; Heppenstall et al., 2021; Leombruni and Richiardi, 2005; Moss and Edmonds, 2005; Polhill and Salt, 2017; Troost et al., 2023). Scholars have for example encouraged the Enhancing Realism of Simulation, EROS, principle, focusing on including psychological theories when designing agent behavior (Jager, 2017). At the same time, constructivist scholars studying policy processes have highlighted the role of values, norms, and actors' different perspectives as important aspects in shaping how policies are developed and implemented (for an interesting discussion related to modelling, see Malbon and Parkhurst, 2023).

As we have seen, forest agent-based models are designed to focus on different parts of a forest SES. Validation can support in determining whether to have confidence in a model for its intended purpose (Forrester and Senge, 1979; Troost et al., 2023) as well as clarifying which assumptions, values and norms that are represented in the model. This could be done either through empirical, or structural validation. To be more concrete, Troost et al. (2023) have suggested the KIA protocol for validation of agent-based models. The protocol takes a holistic approach to model validation, in being a process that goes in parallel with model development choices. Having the protocol alongside an SES framework could be mutually beneficial – supporting for example in clarifying which parts of the system we are interested in – the output of the SES, or the inner structures, relationships, and processes? The SES framework can in turn support in defining the context and purpose that we aim the model to be valid within. Coming back to the question of model choice, a pragmatic question to help guiding in this regard in addition to the KIA protocol, is: *What type of data is available for calibration and validation?*

A second aspect for further development is an agent's cognitive ability when it comes to memory and learning. In various research areas, the dynamic aspect of knowledge is highlighted. Knowledge is exchanged and adjusted through social interaction, adapted by actors to local policy contexts, and an object of cognitive bias in policy making and implementation (Dressel et al., 2020; Ostrom, 2007; Rodríguez

Valencia et al., 2019).

By incorporating the dynamic processes of memory and learning into modelling, we would be better able to capture how behavior is adapted as actors communicate and learn in complex adaptive systems like an SES (Schlüter et al., 2019). In this review, a few forerunning model applications such as the one based on the SOSIEL platform (Sotnik, 2018; Sotnik et al., 2021) have incorporated the potentials of machine learning into agent behavior, but learning is still a frontier of development in ABMs in particular and SES modelling in general (Lippe et al., 2019).

From the reviewed studies, we found those agent-based models commonly being in the forefront of memory and learning are engaging with literature on knowledge representation, for example the bodies of work on cognitive architectures (Kotseruba and Tsotsos, 2020), goal reasoning (Addison, 2024), social networks (Li et al., 2023; Manzo and Matthews, 2014), and practice diffusion and adoption (H. Zhang and Vorobeychik, 2019). An example of a cognitive architecture that we could point readers to, specifically for agent-based model application, is the Behaviour with Emotions and Norms, BEN (Bourgais et al., 2020).

Forest agent-based models coupled to ecological models such as dynamic vegetation models or species distribution models showed the greatest abilities of representing ecological processes dynamically. This meant simulating land cover and land use changing over time rather than agents interacting with a static landscape based on initial land cover data. This so-called hybrid approach allows for feedback loops between ecological and social processes, a key aspect in SES theory (Martin and Schlüter, 2015; Miller and Frid, 2022) but is so far only implemented in a few forerunner models. A useful discussion on challenges and steps in setting up a hybrid approach and a suggested procedure can be found in Martin and Schlüter (2015).

5.5. Limitations

The review is based on published models, and as flexibility is one of the strengths with agent-based approaches, it is possible that despite a reviewed study not representing a certain feature, one could develop within a specific agent-based platform additional actor types, landscape processes, ecological interactions, and cognitive abilities.

6. Conclusions

This study has provided a review and comparison of agent-based approaches to modelling forests as complex social-ecological systems. The rich set of reviewed models demonstrates the ability of agent-based models to be used for interdisciplinary forest research.

The reviewed model applications target a broad range of research questions, which means that they focus on representing different aspects of a managed forest system. Despite all models including human-forest interactions, only a few show the ability to represent key elements of a social-ecological system like relations, through direct interactions, and dynamic representation of social and ecological processes to incorporate feedback mechanisms. For more socially evolving models we noticed a need for developing the representation of adaptive governance, in order to capture institutional dynamics of the overall SES. Dynamic ecological processes are already being captured in more advanced ways in the applications coupled with separate vegetation models. We can thus observe that agent-based modelling of social-ecological systems is very much a field under development. Taken together, the review shows that ABMs have the ability to be adequately complex for modelling dynamic processes in both social and ecological subsystems.

When it comes to flexibility, we see that the models based on existing agent-based frameworks have advantages with it being relatively easy to adjust the approach to other purposes beyond the reviewed application. Overall, the results show that existing models focusing on managed forests provide a range of opportunities, either to be used as platforms where the model could be adapted for the requirements of a particular study or as inspiration for when setting up an ABM for a specific purpose.

Our comparison points to three key areas for further development of agent-based approaches to modelling managed forests: i) addressing calibration and validation of models; ii) modelling of agent learning and the dynamics of such feedback loops including adaptive governance agents; iii) coupling to ecological models such as dynamic vegetation models or species distribution models.

Whether the research project uses a social-ecological systems framework or a similar approach for studying human-nature interactions, the following set of questions for reflection aims at supporting an informed selection of a relevant agent-based model approach in relation to the research purpose at hand:

- *Purpose*: What purpose and research question shall the model answer and what are the corresponding functionalities that are required?
- *Ecological processes:* What type of ecological processes are driving and limiting factors for the study's purpose and research question?
- *Social processes:* Are the governance rules static or need to be modelled as adaptive governance decisions? Should actors and their behavior be influenced by other agent's decisions?
- *Complexity:* How important are social-ecological feedbacks and interactions for understanding the research problem?
- *Pragmatism:* What type of data is available for calibration and validation?

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Software availability

NA.

CRediT authorship contribution statement

Hanna Ekström: Writing – review & editing, Writing – original draft, Visualization, Project administration, Formal analysis, Data curation, Conceptualization. **Nils Droste:** Writing – review & editing, Supervision, Conceptualization. **Mark Brady:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

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

Data availability

All data (reviewed articles) are shared within the manuscript

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