RESEARCH ARTICLE

A new agent-based model provides insight into deep uncertainty faced in simulated forest management

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Abstract

Context Exploratory modeling in forestry uses a variety of approaches to simulate forest management. One important assumption that every approach makes is about the deep uncertainty—the lack of the knowledge required for making an informed decision—that future forest management will face. This assumption can strongly influence simulation results and their interpretation but is rarely studied.

Objectives Our objective was to explore how differences in modeling approaches influence the deep uncertainty faced in simulated forest management.

Methods We used SOSIEL Harvest, a new agent-based extension to a landscape-change model, LANDIS-II, to simulate three approaches to modeling forest management. For each, we used the same forest and management data from Michigan, US, which isolated the differences among approaches as the only variable factor. We then used a new method, also introduced here, to measure and compare the deep uncertainty faced during simulated management. Finally, we used a typology of sources of uncertainty to categorize the sources responsible for this deep uncertainty.

Results The simulated forest management in the three modeling approaches faced substantially different degrees of deep uncertainty, which translated into considerable differences in simulation results. There was an overall negative relationship between deep uncertainty and the ability of the management to respond to forest change and adapt decisions accordingly.

Conclusions While inherent deep uncertainty faced in simulated forest management can be substantial, it is overestimated by exploratory models that underestimate management's ability to respond to forest change. Reducing such model-related uncertainty will allow for more realistic results from exploratory studies of forest management.

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Introduction

Forests provide ecosystem services that are essential for human wellbeing (MEA 2003; Brockerhoff et al. 2017), which makes their sustainable management a global priority (e.g., European Commission 2003; Robertson et al. 2011). However, the complexity in forest dynamics and the unpredictability of human (e.g., development, market shocks, policy) and natural (e.g., wildfires, insect infestations) disturbances substantially challenge the planning of how, how much, and when to best harvest trees (Puettmann et al. 2009; Amacher 2015; Messier et al. 2016). Such complexities create an environment of *deep uncertainty* (Lempert et al. 2003, 2006; Walker et al. 2013; Marchau et al. 2019), which is characterized by insufficient information about a problem, its external drivers, and potential outcomes. Deep uncertainty is different from other forms of uncertainty that can be reduced through further study or estimated with statistics (Walker et al. 2013) and, as such, poses a challenge for forest management.

Deep uncertainty reduces the value of many forecasting models that rely on assigning probabilities to or ranking potential scenarios (Lempert et al. 1996; Walker et al. 2003, 2013; Kwakkel et al. 2010; Workman et al. 2021). As an alternative, researchers and planners often opt for exploratory models, which do not rely on this practice. They use exploratory models to test plans across a broad range of unordered potential scenarios, with the aim of identifying the plan that produces the most robust results across the largest number of scenarios (Bankes 1993; Lempert et al. 1996; Weaver et al. 2013; Maier et al. 2016; Lucash et al. 2017; Lempert 2019; Workman et al. 2021). Exploratory scenarios are often dynamic, further reflecting the deep uncertainty the planners expect to face (Lempert et al. 1996; Walker et al. 2001; Weaver et al. 2013; Lempert 2019), which stems from the unpredictability of how a specific scenario might evolve (possibly in response to the influence of a specific plan) and how well a planner within a scenario might be able to adjust to its evolution.

Exploratory modeling is frequently applied to inform forest management, often with widely varying modeling approaches (Scheller 2020a). For example, some models do not include the capacity for forest management plans to adjust to forest conditions during a simulation (Keeley et al. 2009; Seidl and Lexer 2013; Handler et al. 2014; Albert et al. 2015, 2018; Maxwell et al. 2020), some models base this capacity on predefined probabilities (e.g., Mayer and Rouleau 2013; Wear et al. 2013; Yamada and Yamaura 2017; Rouleau and Zupko 2019; Zupko and Rouleau 2019), and others include the capacity for forest management plans to adjust over time (e.g., Rammer and Seidl 2015; Barros et al. 2017) and at multiple scales (e.g., Bolte et al. 2007).

As a result of the variety in approaches to modeling forest management, the simulated deep uncertainty these models face also varies widely. The simulated deep uncertainty varies in the extent to which it reflects the aforementioned *inherent* deep uncertainty that forest management decisions will face on a specific landscape (stemming from the complex forest dynamics and unpredictable human and natural disturbances) and the extent to which it reflects misrepresentation and mis-estimation of forest management processes and parameters, respectively, which over or underestimate its reflection of this *inherent* deep uncertainty (applying Higgins et al. (2003) to forest management). These differences in deep uncertainty faced during simulated forest management substantially contribute to simulation results (Rinaldi and Jonsson 2020) but are rarely discussed in this context (but see Yousefpour et al. (2012), who review the differences in non-exploratory approaches to modeling forest management under uncertainty).

In this paper, our objective was to explore how differences in modeling approaches influence the deep uncertainty faced in simulated forest management. General limitations in the ability to model human behavior (Meyfroidt 2013; Elsawah et al. 2020; Sotnik 2020) and to measure deep uncertainty (Gomory 1995; Chow and Sarin 2002) prevent identifying any specific approach to modeling forest management as accurate. However, having ways to measure and compare approaches would clarify their differences and stimulate a much-needed discussion about how approaches may be improved. This, in turn, would increase the relevance of exploration studies to real-world forest managers, who often face a gap between information about broad-scale changes in forest conditions (i.e., because of pulse disturbances, such as fire or wind, or press disturbances, such as climate change) and the finer-scale goal-driven management decisions they face (Schmitt et al. 2021).

To this end, we used SOSIEL Harvest, a new agent-based extension to a landscape-change model, LANDIS-II (Scheller et al. 2007), to simulate three approaches to modeling forest management. Agent-based models provide the capacity to simulate the learning and decision-making involved in forest management (Matthews et al. 2007), which helps in the study of how and why management decisions change over time. For each approach, we used the same forest and management data from lands managed by the United States (US) Forest Service in northern lower Michigan to isolate the differences among the approaches as the only variable factor. We then used a new method, also introduced here, to measure and compare the deep uncertainty faced in the simulated forest management. Finally, we used a typology of sources of uncertainty (inherent, model, and parameter; Higgins et al. 2003) to categorize those sources responsible for the deep uncertainty faced in simulated forest management.

Methods and data

Measuring the deep uncertainty faced in simulated forest management

Multiple methods using empirical data and model output to estimate uncertainty (including deep) already exist (Uusitalo et al. 2015; Shaw 2017a). Perhaps the most common among them is the use of the standard deviation of a variable of interest (e.g., Bloom 2009; Baker et al. 2016; Shaw 2017b). However, an increase in the variability of a quantity does not necessarily translate into an increase in its uncertainty (if a trend is still present). On the other hand, the unpredictability of the variable may be a useful proxy (Jurado et al. 2015). Therefore, we used the extent to which simulated forest management actions are unable to achieve a goal as an indicator of the degree of deep uncertainty faced by management during a simulation.

We relied on the assumption that the simulated forest management at least implicitly represents boundedly-rational decision-making (Simon 1957, 1960; Selten 1998; Gigerenzer and Selten 2001; Todd et al. 2012), i.e., making the best decisions possible under existing limitations in cognition and information, which hinder the timely acquisition of required knowledge. This premise assumes that forest management decisions are based on the best information accessible and implies that any significant inability of the simulated management to reasonably set and achieve a goal is due to a substantial lack of required knowledge, i.e., deep uncertainty.

We applied a simple linear regression model to estimate the relationship between the result of simulated management and a management goal. In this case, the result of simulated management was represented by the annual amount of biomass harvested (Tg) through simulated timber harvests (the $HarvestAmount_{t-1}$ variable). We use teragrams (Tg) of biomass as the unit of measurement for readability. The goal was to maintain the percentage of mature forest in the management area at or above its initial age. We first calculated the percentage of mature forests for each tree cohort then aggregated for each forest site and stand to produce the percentage for the entire management area (the $MaturityPercent_t$ variable), which accounts for the differences in the species-specific sexual maturity ages (Table 3). The resulting simple linear regression model takes the following form:

$$MaturityPercent_t = \alpha + \beta * HarvestAmount_{t-1} + \varepsilon_t$$

$HarvestAmount_{t-1}$ (the independent variable) in Tg is what the simulated forest management had direct and complete control over (as long as the quantity of aboveground biomass to be harvested is less than the amount available for harvesting). $Maturity\ Percent_t$ (the dependent variable) is what management only had indirect and incomplete control over via selecting or modifying specific $HarvestAmount_{t-1}$ values.

We selected the simple linear regression model (instead of a more complex model that may have provided a better fit between the two variables) not only for the generality and ease with which it may be applied to different contexts, but also because our aim was to propose a method that assessed boundedly-rational forest management across a wide range of approaches, rather than identifying the best fitting model for a specific context. We then used the model's coefficient of determination (Devore 2012), $r^2 \in [0,1]$, to estimate the deep uncertainty. Specifically, we used $1 - r^2$ to represent the proportion of the variance in the dependent variable ($MaturityPercent_t$) that was unexplainable by the independent variable

(*HarvestAmount$_{t-1}$*) to estimate the degree of deep uncertainty. As a result, the estimate is unit neutral and, therefore, comparable among simulated forest management approaches. It is also spatiotemporal, as it is based on simulated forest management across a spatial landscape and over time.

Finally, we used the three sources of uncertainty presented by Higgins et al. (2003) to categorize those sources responsible for the deep uncertainty faced in simulated forest management. The sources include: (a) inherent, which stems from the other (non-management) components of the model; (b) model-related, which is from misrepresentation of forest management processes; and (c) parameter-related, which stems from mis-estimation of forest management parameters. The parameter- and model-related sources of uncertainty add a second layer of boundedness to the bounded rationality of forest management (Sotnik 2020), thereby distorting the inherent deep uncertainty in the model.

A new agent-based model for simulating forest management

We used LANDIS-II (version 7; Scheller et al. 2007), a forest landscape change model that employs a library of dedicated extensions to simulate forest succession, management, and a variety of natural disturbances. Trees are modeled in cohorts, which represent individual trees of a species and age group. Forested vegetation, topographical, and climate conditions are assumed to be homogeneous within forest sites, within which competition, growth, and mortality are simulated. Disturbances and seed dispersal are simulated both within and among sites.

We used LANDIS-II's Biomass Succession extension (version 5.2; Scheller and Mladenoff 2004) to simulate establishment, growth, and competition of tree cohorts; Base Wind extension (version 3.1; Mladenoff and He 1999) to simulate wind events and to induce wind-caused cohort mortality; and a new agent-based forest management extension, SOSIEL Harvest (version 1.1), to simulate boundedly-rational forest management. The Biomass Succession extension uses species-specific parameters, such as shade tolerance and seed-dispersal distances, to simulate aboveground changes in forest biomass based on tree-cohort establishment, growth, and mortality. The Base

Wind extension simulates wind events that cause tree-cohort mortality. Wind event frequency and size are based on a wind rotation period, and tree cohort mortality is determined by a cohort's susceptibility to increasing wind intensity.

The new SOSIEL Harvest extension (SHE) integrates the agent-based SOSIEL (Self-Organizing Social & Inductive Evolutionary Learning) algorithm (version 2.4; Sotnik 2018), which simulates the learning and decision-making of one or more agents, with LANDIS-II's existing Biomass Harvest extension (version 4.3; Gustafson et al. 2000), which provides a rich library of forest management design and implementation options. Together, LANDIS-II with SHE have the potential to simulate adaptive management (Stankey et al. 2005, 2006; Allen and Garmestani 2015) in coevolving coupled human and forest landscapes, which occurs when there is feedback between two or more evolving systems (Janzen 1980; Durham 1991; Nuismer 2017) or when both systems are exposed to the same natural selection pressures.

As a forest simulated by LANDIS-II evolves, it is shaped by internal dynamics as well as climate conditions, forest management, and other disturbances. Forest management, in turn, is shaped by forest conditions and by other personal and social dynamics. This interaction drives structural change in both the forest and its management (Sotnik et al. 2021). Management changes the forest structurally through the addition (planting) and removal (harvesting) of trees. Management itself also changes structurally in response to forest conditions through the addition (innovation) and removal (forgetting) of decision options. Such changes across generations and harvesting seasons produce coevolutionary dynamics.

Each SOSIEL agent makes decisions using a cognitive architecture (Langley et al. 2009; Goertzel et al. 2010; Langley 2017; Kotseruba and Tsotsos 2018) that consists of nine cognitive processes (anticipatory learning, goal prioritizing, counterfactual thinking, innovating, social learning, goal selecting, satisficing, signaling, and action-taking) that enable each agent to interact with other agents, learn from its own experience and that of others, and make decisions about taking, and then take, (potentially collective) actions (Table 1).

Table 1 Descriptions of the SOSIEL algorithm's nine cognitive, behavioral, and social processes

Process name	Description
Anticipatory learning	The process uses change in the states of an agent's goal reference variables to update the anticipated influences of its decision options and its confidence in its ability to attain the corresponding goals
Goal prioritizing	The process applies what an agent learned during anticipatory learning to reevaluate the relative importance of its goals and, if necessary, reprioritize them
Counterfactual thinking	In case an agent loses confidence in its ability to achieve a specific goal, the process checks whether the agent would have behaved differently (i.e., would have chosen an alternative decision option that was readily available) had it earlier known what it just learned during anticipatory learning. If the agent would have behaved differently, then confidence is regained, and the agent moves on to social learning. If the agent would not have behaved differently, (i.e., if it does not find a useful decision option for the current situation), then confidence remains lost, and the agent moves on to innovating
Innovating	The process uses the information learned by an agent during anticipatory learning, the prior period's decision, and the goal of focus to invent a new decision option
Social learning	The process informs an agent of the actions taken in the prior period by its social network neighbors by adding the actions to the agent's corresponding mental models
Goal selecting	The process orders an agent's goals by their updated relative importance levels and chooses the one at the top for each situation the agent is set to take action in
Satisficing	The process uses the updated anticipated influences of decision options to select, for each situation, a decision that best meets an agent's goal within that situation
Signaling	In the case the selected decision option is a collective action, the agent signals its interest in engaging to the other agents. If a sufficient number of others are also interested in engaging in the collective action, they all commit to engaging. Otherwise, they reactivate the process of satisficing to choose another decision option that best meets the goal of focus
Action-taking	The process implements the selected decision

A SOSIEL agent can respond to its external and internal conditions by switching between its decision options, which are conditional (IF/THEN) statements. These statements are parameterizable with forest, personal, and/or social antecedents (the IFs) and a consequent (the THEN). The SOSIEL algorithm organizes decision options into mental models, which are an agent's mental representation of a situation and that are each associated with one or more goals, such as managing a specific species. Decision options in any two mental models are complementary, in that they do not compete with each other for implementation, whereas decision options within a single mental model are substitutes, with only one selected for implementation during the SOSIEL process of satisficing. This design permits agents to take part in a diverse set of situations, with access to a diverse and customized set of decision options, and in pursuit of a diverse and customized set of goals. In addition to switching between decision options, an agent can also respond by reprioritizing the relative importance of its goals. If an agent's confidence in its ability to achieve

a specific goal with its current set of decision options is lost, it is empowered to use its experience to invent new decision options.

Additionally, the SOSIEL algorithm provides the option of regulating the cognitive level of agents in any specific simulation. The cognitive levels bundle the aforementioned cognitive processes in a way that corresponds to existing approaches to modeling agent cognition in general (Sotnik 2018) and forest management in particular (Table 2). Currently, SOSIEL agents can engage in boundedly-rational decision making at the following four cognitive levels:

- Cognitive level 1: An agent chooses a decision option from among those available to it (within a specific mental model) based on the influence it anticipates the decision option will have on a goal. The SOSIEL cognitive processes activated at this level are: goal selecting, satisficing, signaling, and action-taking. Learning is not activated at this level, and therefore the influence the agent anticipates a decision option will have on a goal is not updated during a simulation.

Table 2 The three modeling approaches (A1–3) compared in this study, the corresponding cognitive levels (CL1, CL2, and CL4), their descriptions, and comparable approaches in the field

| Approach	Cognitive level	Description	Comparable approaches
A1	CL1	What and how much is harvested are predetermined before simulation start by a set of predefined decision options. Current forest conditions influence how the stands are ranked, which stands qualify for harvest, which forest sites are selected, and which cohorts are removed. The use of percentages in determining how much of a specific tree cohort is to be removed further aligns harvest intensity with current forest conditions	Albert et al. (2015) Albert et al. (2018) Gustafson et al. (2000)
A2	CL2	What and how much is harvested are determined by an expanded (compared with A1/CL1) set of predefined decision options, management's ability to use its experience to update the anticipated influence of implemented decision options, and its ability to choose the best decision options accordingly. Note: Goal reprioritizing does not activate in our study because management has only one goal	Barros et al. (2017) Mayer and Rouleau (2013) Rammer and Seidl (2015) Wear et al. (2013)
A3	CL4	What and how much is harvested are additionally (compared with A2/CL2) determined by an ability to invent new decision options when the existing decision options are not sufficient in helping achieve a goal	Bolte et al. (2007)

- Cognitive level 2: In addition to what an agent is capable of in cognitive level 1, it also uses feedback from the forest to update the influence it anticipates an implemented decision option will have on a goal, to update its level of confidence in its ability to achieve the goal, and, if necessary, to reprioritize its goals. The additional SOSIEL cognitive processes activated at this level are: anticipatory learning and goal prioritizing.
- Cognitive level 3: In addition to what agents are capable of in cognitive levels 1 and 2, they also learn from each other. The additional SOSIEL cognitive process activated at this level is: social learning.
- Cognitive level 4: In addition to what an agent is capable of in cognitive levels 1, 2, and 3, it also reconsiders its prior period's actions and, if dissatisfied with its ability to achieve its goal(s), invents new decision options. The additional SOSIEL cognitive processes activated at this level are: counterfactual thinking and innovating.

SHE operates in two modes: on its own (Mode 1), which is primarily intended for simulating site-based forest use by mobile agents, and integrated with Biomass Harvest (Mode 2), which is intended for simulating stand-based forest management (Fig. 1). We used Mode 2, in which SHE first calls on the SOSIEL algorithm to analyze forest conditions and choose decision options and then on Biomass Harvest to implement the decision options related to forest management. In this mode, each decision option in the SOSIEL algorithm pairs with a corresponding prescription in Biomass Harvest (Fig. 2). The name of a decision option and the decision option's consequent (the THEN) serve as the link between it and the corresponding prescription.

For SHE in Mode 2, each Biomass Harvest prescription consists of two components: one that describes what to manage and how (parameterized through Biomass Harvest's prescriptions table) and another that specifies the percentage of the management area in which the prescription is to be implemented (parameterized through Biomass Harvest's implementation table). In the current version of SHE's Mode 2, the value of a decision option's consequent corresponds to the percentage of the management area to which the paired prescription is to be applied. Also, specifically in Mode 2, manager agents cannot share management areas.

Fig. 1 SHE in the context of LANDIS-II, Biomass Harvest, and additional LANDIS-II extensions. At each timestep, LANDIS-II calls on different extensions to act on the landscape. In this study, two other extensions were included: Biomass Succession and Base Wind, both of which were called on before SHE. In Mode 1, SHE, in turn, calls on the SOSIEL algorithm to analyze landscape conditions and choose decision options and then uses LANDIS-II's harvest management library to implement them. In Mode 2, SHE calls on the SOSIEL algorithm to analyze landscape conditions and choose decision options and calls on Biomass Harvest to implement them
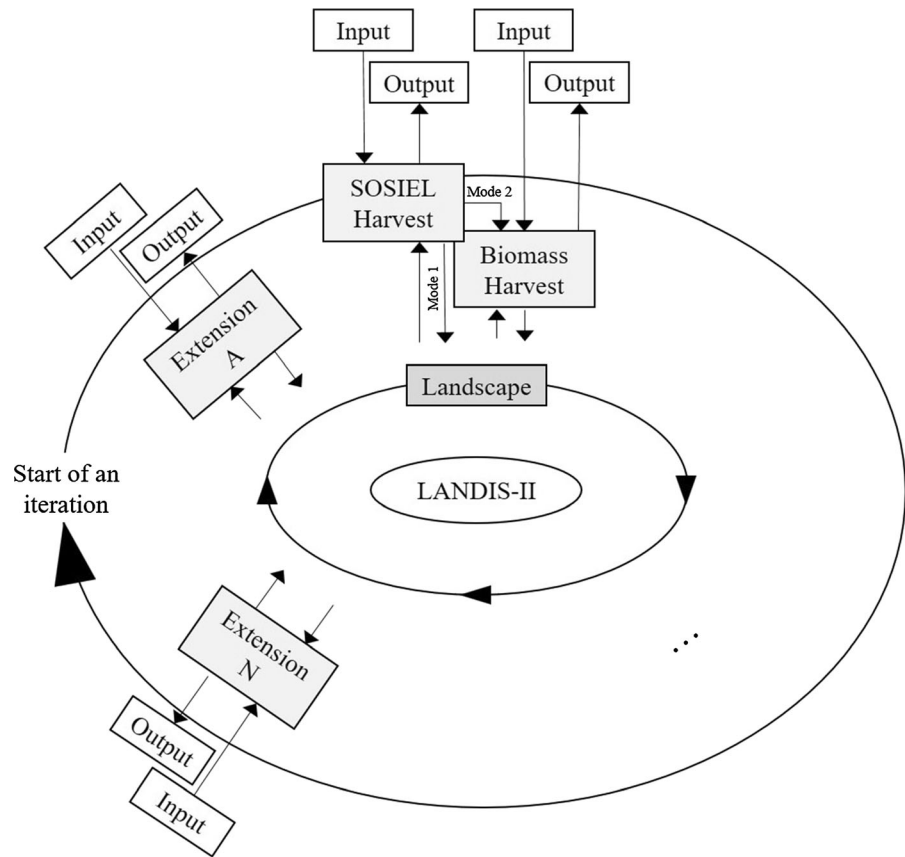
The SOSIEL algorithm can create new decision options in both Modes 1 and 2 (Fig. 3). The process involves using a user-adjustable probability distribution to increase/decrease the consequent value of an existing decision option in the direction that the agent perceives would improve its ability to achieve its most highly prioritized goal. As a result, the only difference between the prior decision option and the new one is the value of its consequent. In Mode 2, SHE additionally creates a new Biomass Harvest prescription where the new decision option's consequent value defines the percentage of the management area in which the prescription is to be implemented. SHE in Mode 2 also adjusts all of the new prescription's biomass removal percentages in the same direction and to the same extent it adjusted the percentage of the management area. As a result, a new prescription differs from the one prior both in the percentage of the management area in which the prescription is to be implemented and the percentage of the biomass to be removed.

Exploration design

We used SHE in Mode 2 to simulate three exploratory approaches to modeling forest management. Mode 2 is well suited to our forest management dataset from Duveneck et al. (2014a, b), which they implemented with Biomass Harvest. We used the SOSIEL algorithm's cognitive levels 1, 2, and 4, respectively (Table 2) to simulate the three approaches, A1 (predefined), A2 (expanded), and A3 (innovation). We skipped cognitive level 3 because in this study we simulated the forest management decisions of only one forest manager per model, thereby precluding the possibility for social learning. As in Duveneck et al. (2014a, b), we simulated each approach for 150 years.

To account for stochasticity in forest dynamics and wind disturbance, we simulated three replicates of each approach. Results were first calculated for each of the three replicates of each of the three approaches (9 replicates in total) and then averaged across each replicate set to derive one set of results for each of the
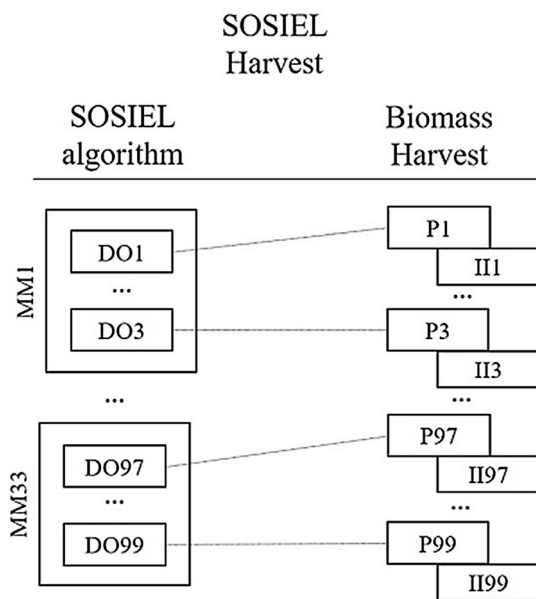
Fig. 2 SHE's Mode 2 pairing of the SOSIEL algorithm's decision options (DOs) with Biomass Harvest's prescriptions (Ps; e.g., clear-cut or selectively harvest certain amounts of select species) and implementation instructions (IIs). The SOSIEL algorithm organizes the decision options that are variants (substitutes) of one another into mental models

three approaches. After observing considerable variation in A3's (innovation) simulation results, we ran five additional replicates of the approach and then recalculated the total (weighted) averages for the entire replicate set.
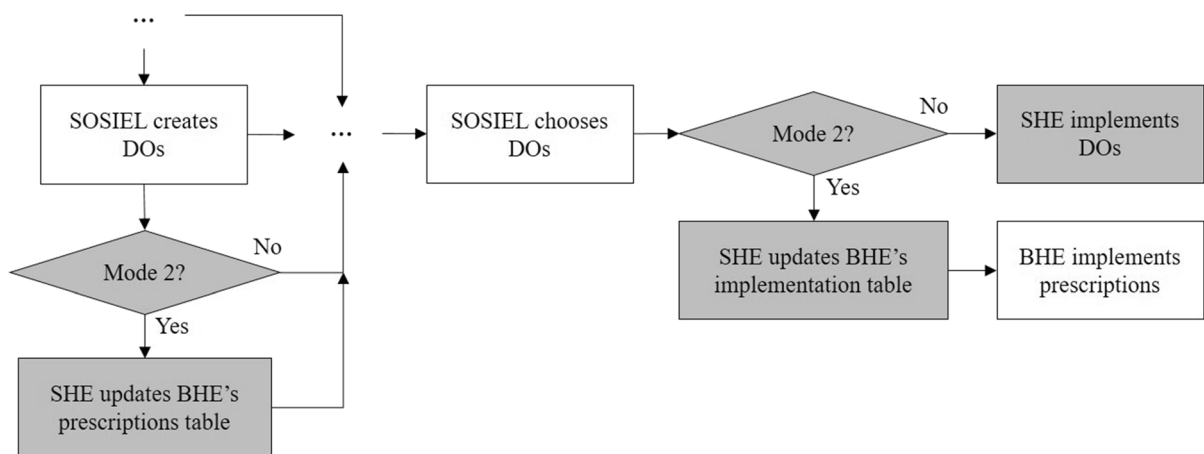
One important difference between A1 (predefined), on one hand, and A2 (expanded) and A3 (innovation) on the other, is how the goal of maintaining the percentage of mature forest in the management area at or above its initial value is incorporated. A1 does not allow for explicit goal pursuit. This is because what, and how much, is harvested in A1 is predetermined before the start of simulation. The goal is also not explicitly specified in Duveneck et al. (2014a, b), which is the source of the prescriptions with which we parameterized SHE. However, the prescriptions in Duveneck et al. (2014a, b) represent a business-as-usual US Forest Service strategy, for which maintaining the percentage of mature forest at or above its initial value is a reasonable goal. Therefore, we assume this goal is implicitly incorporated in the prescriptions.

In contrast, A2 and A3 require goal pursuit. The forest management agent in A2 would otherwise be incapable of evaluating its performance or choosing among alternative decision options, and the one in A3 would additionally be incapable of improving its performance through innovation. In A2 and A3, goals are assigned to each mental model (an agent's mental representation of a situation), each of which corresponds to a prescription from Duveneck et al. (2014a, b). This formalization permits the agents in A2 and A3 to use each prescription in pursuit of maintaining the percentage of mature forest at or above its initial value. In designing the three approaches, we developed an overview, design

Fig. 3 SHE's process flow for creating and implementing decision options (DOs) and prescriptions. SHE's decision points and processes are in dark grey, and select SOSIEL algorithm and Biomass Harvest processes are in white. The three dots represent other SOSIEL processes that are not directly related to the process of creating new decision options

concepts, and details (ODD) protocol (Grimm et al. 2006, 2010, 2020; Müller et al. 2013) that describes the differences among the three approaches in greater detail and is available at the following GitHub page: https://github.com/LANDIS-II-Foundation/Project-Michigan-Compare-Harvesting-2021.

Forest and management parameterization in Michigan

In choosing a forest landscape, we aimed to choose one that was neither too predictable nor too unpredictable, as both extremes might make it more difficult to differentiate among approaches. A landscape that is too predictable might lead to all approaches demonstrating an equally low degrees of deep uncertainty. One that is too unpredictable might lead to them demonstrating an equally high degree.

With the above in mind, we chose forests in northern lower Michigan that are managed by the US Forest Service. On one hand, the forests are mixed, composed mainly of the following five forest types: aspen-birch, jack-red-white pine, maple-beech-birch, oak-hickory, and spruce-fir. The richness in species translates into uneven succession and, in turn, maturity dynamics (Table 3). On the other hand, the forests are not exposed to frequent disturbances, such as wildfires or hurricanes, which would make their dynamics unpredictable.

We parameterized LANDIS-II, Biomass Succession, and Base Wind with the simulation parameters used in Duveneck, et al. (2014a, b). Duveneck, et al. (2014a, b) based their initial communities (input to the model as a map of tree cohorts that exist at the beginning of simulation) on the combination of Forest Inventory and Analysis (https://www.fia.fs.fed.us/) plot and forest type data, the Forest Biomass Information System imputation map of stand age, and the Michigan Department of Natural Resources forest classified map from the Integrated Forest Monitoring, Assessment, and Prescription Stage 1 map.

We equipped forest management with business-as-usual prescriptions from Duveneck et al. (2014a, b), which they also implemented on the aforementioned landscape in Michigan (Duveneck, et al. 2014a, b). Duveneck et al. (2014a, b) designed their US Forest Service management prescriptions based on the practices of the Michigan Department of Natural Resources and the Huron-Manistee National Forest.

As a result, simulated forest management in A1 (predefined) and A3 (innovation) was equipped with 33 decision options in the form of harvest prescriptions that varied in their target species and age groups, the type of harvest (e.g., more intensive clear cuts, less intensive selective harvesting), the percentage of management area to manage and biomass to remove, and whether to plant new tree cohorts (Table 4).

Prescription names indicate the category of tree species included (single species [e.g., paper birch], all species in a genus [e.g., oak], or all species in a functional group [e.g., swamp hardwoods]) and the harvest strategy (e.g., patch cutting, clearcut).

For forest management in A2 (expanded), we parameterized SHE with 66 additional prescriptions to allow for dynamic decision making. We created two new prescriptions from each of the 33 original prescriptions in Duveneck et al. (2014a, b) and added them to Biomass Harvest's prescriptions and implementation tables, resulting in 33 combinations of three or 99 prescriptions in total. In addition to the original prescription, each combination contained one prescription in which the values for the percentages of management area to manage and biomass to be removed were increased by 10% from the original and one in which these values were decreased by 10%.

The simulated forest management in A3 (innovation) had the option of expanding on the original 33 decision options by inventing new ones when it was dissatisfied with its ability to achieve its goal. Management in A3 can invent one decision option per mental model per timestep, which translated into no more than 33 per timestep. To imitate forgetfulness and make A3 comparable to A2, we limited the number of decision options a mental model could contain at any point in time to three (i.e., 99 in total).

To generate the consequent values for new decision options, we used the generic values in SOSIEL's general probabilities look-up table. The table establishes a relationship between user-definable probabilities and 10 segments of a dynamic numeric range. In our case, the dynamic range is the set of percentage values between the current percentage of a management area to be harvested and the maximum (100%) or minimum (0%) percentage, depending on whether the process of innovating is increasing or decreasing the percentage of a management area to be harvested, respectively. The generic probability values were created by setting 1% as the probability of the least

Table 3 Simulated species making up more than 1% of initial landscape biomass and their sexual maturity ages

Species name		Sexual maturity age
Common	Scientific	
Balsam fir	*Abies balsamea*	25
Red maple	*Acer rubrum*	10
Sugar maple	*Acer saccharum*	40
Paper birch	*Betula papyrifera*	20
American beech	*Fagus grandifolia*	60
White spruce	*Picea glauca*	25
Black spruce	*Picea mariana*	30
Jack pine	*Pinus banksiana*	10
Red pine	*Pinus resinosa*	15
Eastern white pine	*Pinus strobus*	15
Bigtooth aspen	*Populus grandidentata*	20
Quaking aspen	*Populus tremuloides*	15
Black cherry	*Prunus serotina*	20
White oak	*Quercus alba*	40
Northern pin oak	*Quercus ellipsoidalis*	35
Northern red oak	*Quercus rubra*	25
Black oak	*Quercus velutina*	40
Northern white cedar	*Thuja occidentalis*	30

Table 4 The 33 prescriptions from Duveneck et al. (2014a, b) that were implemented in our study

Aspen clearcut	Oak thinning	Swamp hardwoods clearcut
Aspen clearcut and plant	Paper birch clearcut	Swamp hardwoods patch
Jack pine clearcut	Paper birch seedtree	Swamp hardwoods seedtree
Jack pine clearcut and plant	Paper birch shelterwood	Swamp hardwoods shelterwood
Northern hardwoods patch	Red pine clearcut	Swamp hardwoods thinning
North hardwood shelterwood	Red pine clearcut and plant	White pine clearcut
Oak clearcut	Red pine seedtree	White pine seedtree
Oak clearcut and plant	Red pine shelterwood	White pine shelterwood
Oak patch	Red pine thinning	White pine thinning
Oak seedtree	Red pine patch	Upland spruce fir clearcut
Oak shelterwood	Spruce fir seedtree	White pine patch

likely segment and then calculating the probability of each of the other nine more-likely segments by sequentially multiplying each probability by 1.475. The result is a set of probability values (33.0%, 22.4%, 15.2%, 10.3%, 7.0%, 4.7%, 3.2%, 2.2%, 1.5%, and 1.0%) that together form a power-law-shaped distribution and determine by how much the new consequent value will be higher or lower than the one in the original decision option.

For A2 and A3, we additionally parameterized SHE in line with the SOSIEL algorithm's configuration requirements (Sotnik 2018) and Biomass Harvest's

initial dataset. We introduced a goal: to maintain the percentage of mature trees ($MaturityPercent_t$) in the managed area equal to or above 70% (the approximate percentage at the start of simulation). For the forest management in A3, we set the relationship between each of the decision options (prescriptions) and the goal to negative. This is because increasing the percentage of mature trees requires reducing the percentage of the management area that is harvested.

In summary, the modeled forest management algorithm in A1 had access to the original 33 decision options, in A2 to 99 decision options (33 original plus

66 new), and in A3 to the original 33 plus the ability to invent new decision options (with a limit of 99 at any point in time) (Table 5). The LANDIS-II, Biomass Succession, Base Wind, and SHE input files for each approach are available at the following GitHub page: https://github.com/LANDIS-II-Foundation/Project-Michigan-Compare-Harvesting-2021.

As in Duveneck, et al. (2014a, b), forest succession (tree establishment, growth, competition, age-related mortality), disturbance (wind events and wind-induced mortality), and forest management (harvesting, planting), were implemented at 5-year timesteps with corresponding data output at 5-year intervals.

Results and analysis

Results

Our objective was to explore how differences in modeling approaches influence the deep uncertainty faced in simulated forest management. During year 5, the percentage of mature biomass declined in all simulations from the initial 70% to 59–60% (Table 6). As a result, harvest actions differed substantially among the three approaches starting with year 10. The A1 (predefined) scenario continued implementing the original 33 decision options for the remainder of the

simulation, which resulted in varying harvested amounts from year to year because of changes in available biomass (Table 6).

The A2 (expanded) scenario first used feedback (during year 10) from the forest to update the anticipated influences of the decision options that were implemented in year 5 and then assessed the percentage of mature biomass as unsatisfactory. The updated anticipated influences of the implemented decision options were then compared with those of other decision options and, for each mental model, a different set of decision options were chosen to implement, namely those with 10% lower area harvested and 10% lower harvest amount. Because forest management had only one goal, and because the percentage of mature biomass never reached 70%, these decision options (i.e., those with the lowest available harvest area and amount) continued to be implemented for the remainder of all three simulation replicates.

The A3 (innovation) scenario also responded to the unfavorable feedback during year 10 by updating the anticipated influences of the implemented decision options and by assessing the percentage of mature biomass as unsatisfactory. This assessment led to the invention of 33 additional decision options, each based on one of the previously implemented decision options, increasing its total number of decision options

Table 5 Select configuration details of each approach (A1–A3), including the initial or total number of decision options (DOs), the limit on the number of decision options in a mental model (MM), how the goal (maintain percentage of mature trees equal to or above 70%) is modeled, the relationship between decision options and goals, the corresponding cognitive level (CL), and the cognitive processes activated during simulation

Select configuration details	A1	A2	A3
# of DOs	33 (total)	99 (total)	33 (initially)
Max # of DOs/MM	NA	NA	3
Goal modeled	Implicitly	Explicitly	Explicitly
Relationship between DOs and goal	NA	NA	Negative
Cognitive level	CL1	CL2	CL4
Cognitive processes activated during simulation. Note: Goal prioritizing is not activated in A2 and A3 because management has only one goal	NA	• Anticipatory learning • Goal selecting • Satisficing	• Anticipatory learning • Counterfactual thinking • Innovating • Goal selecting • Satisficing

Table 6 Select results and statistics from the simulations of the three approaches, including the percentage of mature tree cohorts, amount of biomass harvested, the number of decision options used, and calculated deep uncertainty expressed as $1 - r^2$ and the corresponding p-values. Values are averages across the three replicates for each approach, with the corresponding standard deviations in parentheses

Result	A1	A2	A3
Percent mature (%)			
Initial	70	70	70
Year 5	59 (0.00)	60 (0.04)	60 (0.07)
Min	53 (0.00)	54 (0.09)	53 (0.11)
Average	59 (0.02)	61 (0.05)	66 (4.02)
Max	64 (0.71)	65 (0.26)	78 (9.98)
Year 150	58 (0.00)	61 (0.26)	78 (10.40
Harvested (Tg)			
Year 5	4.0 (0.01)	3.5 (0.01)	3.5 (0.00)
Average	6.5 (0.01)	5.9 (0.02)	3.5 (1.62)
Year 150	8.3 (0.16)	7.6 (0.07)	1.0 (1.78)
Total	189.6 (0.17)	171.7 (0.46)	100.0 (47.06)
# of DOs			
Start	33	99	33
End	33	99	99
Regression statistics			
$1 - r^2$	0.76 (0.01)	0.56 (0.03)	0.39 (0.36)
p-value	0.008 (0.00)	0.000 (0.00)	0.006 (0.01)

to 66. This involved using SOSIEL's general probabilities look-up table (see Sect. 2.4) to determine the consequent values (i.e., what percentage of the management area to harvest) of the new decision options, with each value turning out lower than that of its source decision option.

In simulation replicates A3-R1 and A3-R3, this process of assessment and, when necessary, invention of new decision options continued on and off until the goal (maturity above 70%) was reached in year 100, at which point the simulation stopped harvesting (because harvesting on its own was not set as a goal). In replicate A3-R2, the goal was never reached, and the process (of assessment and, when necessary, invention) continued until the end of the simulation. This difference between the results in A3-R1 and A3-R3, on the one hand, and A3-R2 on the other stems from the randomness in the process of generating the consequent values of the new decision options (see

Sect. 2.4). The larger the decrease in the percentage of the management area to harvest each time a new decision option was created, the larger the overall decrease in the percentage to harvest and the effect of the agent's efforts to adapt on its ability to reach the goal.

The A3 scenario resulted in new, invented decision options only when those implemented in the prior period moved management away from achieving the goal and when it could not find any decision options in its corresponding mental models perceived as having the potential to do better. Because there was only one goal—to maintain mature tree cohorts above 70%—harvesting stopped when the goal was met. As a result, on average, 319 decision options were invented during a simulation, with the total number of decision options at any point in time never exceeding 99.

Our results illustrate differences in the degrees of deep uncertainty faced in simulated forest management among the three approaches and in the simulation's ability to approach the goal of at least 70% mature tree cohorts. The degrees of deep uncertainty $(1 - r^2)$ were 0.76, 0.56, and 0.39 for A1 (predefined), A2 (expanded), and A3 (innovation), respectively, with corresponding p-values all below our threshold of 0.05 (Table 6). Figure 4 illustrates the corresponding differences in the scatterplots of the three approaches and, in the case of A3, replicates. The scatterplots illustrate a positive relationship between the percent mature and amount harvested variables in A1 and A2, and both a negative and a positive relationship in A3 (see Sect. 4). Management decisions in A3-R1 and A3-R3 were able to return the percent of mature tree cohorts to above 70%.

We simulated five additional replicates of A3 to further explore the considerable variation in its results, and calculated the average of the eight (3 original and 5 new) replicates in total. The resulting degree of deep uncertainty $(1 - r^2)$ for A3 declined by 0.01 to 0.38 (0.27), while the p-value remained at 0.000 (0.00). In total, management decisions in five (R1, R3, R5, R7, and R8) out of the eight replicates of A3 were able to return maturity to above 70%. The R (version 4.0.5; R Core Team 2021) scripts used for the linear regression analysis and the creation of scatterplots are available on GitHub: https://github.com/LANDIS-II-Foundation/Project-Michigan-Compare-Harvesting-2021.
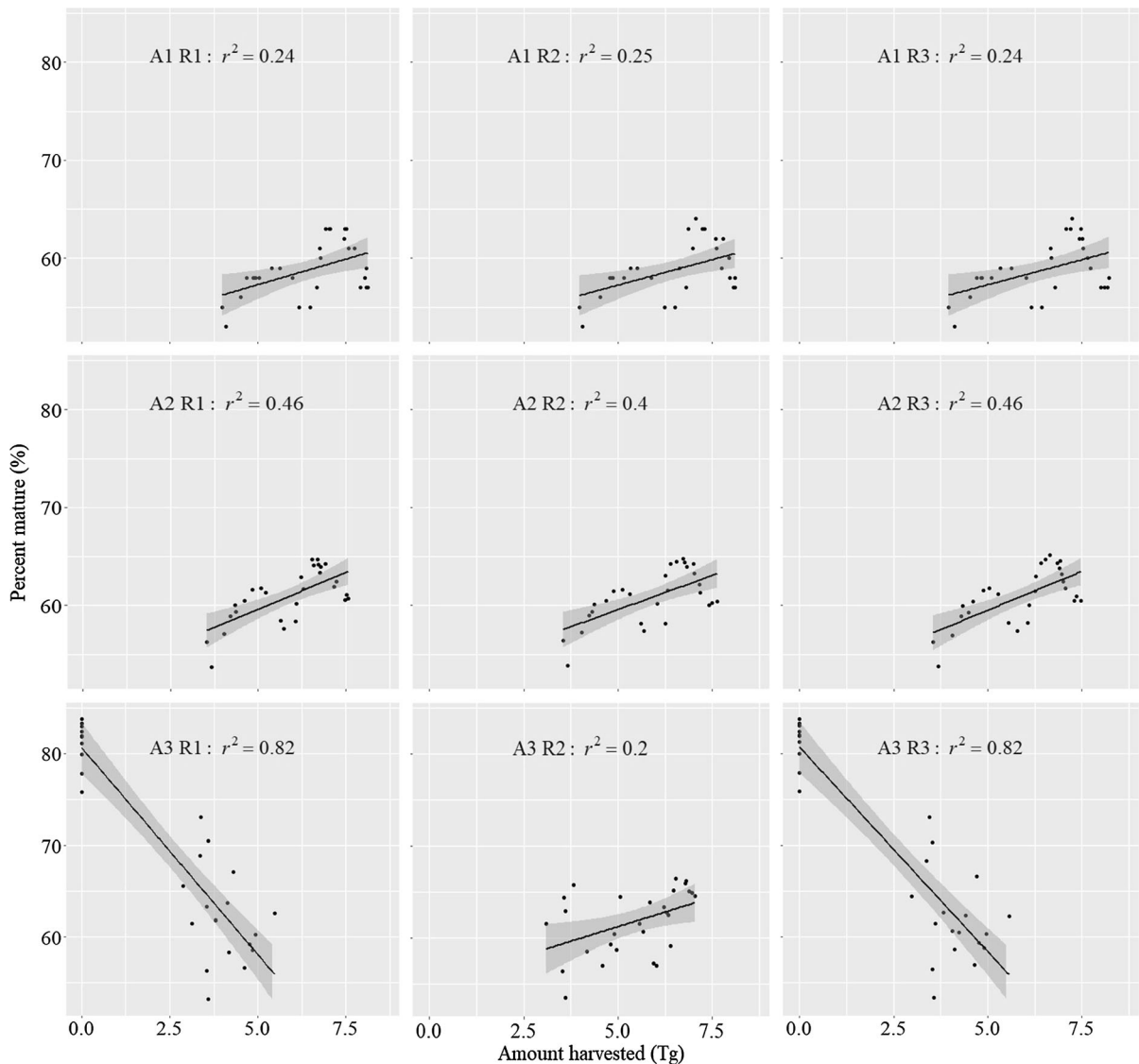
Fig. 4 A comparison of the three simulation replicates (R1–R3) of the three modeling approaches (A1–A3). Dots indicate the percentage of mature trees (%) and biomass harvested (Tg) at corresponding years, solid line indicates the best-fit regression, and the gray area indicates the 95% confidence interval

Analysis

A major factor contributing to the deep uncertainty faced in simulated forest management in all three approaches was the small percentages of management area harvested. The 33 original prescriptions were preset in Duveneck et al. (2014a, b) to harvest 0.01–3.7% of the forest, with 14.21% harvested in total. Such low percentages challenged management of a rapidly growing forest and amplified the deep

uncertainty it faced stemming from forest dynamics. The extent to which the source of this deep uncertainty is inherent or parameter-related depends on the quality of the data used in Duveneck et al. (2014a, b).

Another major factor contributing to the deep uncertainty confronted by all of the simulated forest managers was the way the quantity of biomass to be harvested was calculated for each prescription. SHE in Mode 2 (through Biomass Harvest) bases the quantity harvested on the percentage of a tree cohort's biomass.

In A1 (predefined), this translated into the simulated managers being entirely reactive and proportionally fixed to forest dynamics. In A2 (expanded), managers initially proactively adjusted in pursuit of the goal, but then, in the same way as managers in A1, reacted in fixed proportion to the forest dynamics for the remainder of a simulation. This explains the counter-intuitive positive correlation between the percentage of mature tree cohorts and biomass harvested in all but two (A3-R1 and A3-R3) of the simulation replicates depicted in Fig. 4, and the corresponding relatively high degrees of deep uncertainty faced by managers in A1 and A2. An increase in biomass led to both an increase in the percentage of mature trees and the quantity harvested, and vice versa, making the pursuit of a goal such as maintaining maturity equal to or above 70% practically impossible. This way of calculating the quantity of biomass to be harvested for each prescription appears to be a model-related source of deep uncertainty.

Only the forest managers in A3-R1, A3-R3, A3-R5, A3-R7, and A3-R8 (innovation) were able to proactively use new, substantially different decision options to offset this underlying positive relationship between the percentage of mature tree cohorts and biomass harvested and gain control in what were, ultimately, successful attempts to increase the percentage of mature tree cohorts on the landscape. Although such internal struggles between newly learned and habitual behavior are not uncommon with individuals and organizations, its presence here is an artifact of integrating two models (SOSIEL Harvest and Biomass Harvest) with slightly different design principles and, therefore, also likely a model-related source of deep uncertainty. Its influence on simulated results requires further study.

As illustrated by the differences among the scatterplots of the A3 simulation replicates (Fig. 4), accounting for innovation in future forest management introduces additional uncertainty in simulation results, which stems from the inability to predict exactly how simulated forest managers will adjust during a simulation (captured in A3 by the stochasticity in the process of generating new decision options). The forest managers in A3-R1, A3-R3, A3-R5, A3-R7, and A3-R8 adjusted by producing (through a stochastic process) decision options that were sufficiently different from those they were initially equipped with, which enabled them to achieve their goal. The forest

management decisions in A3-R2, A3-R4, and A3-R6 did not produce (through the same stochastic process) decision options that were sufficiently different. However, even the simulated management in A3 likely underestimated this ability of future forest management decision-making to adjust. For example, its innovation only included adjustment of the percentages of management area and biomass harvested, whereas in the real-world, innovation also includes implementing new techniques and technologies (Scheller 2020a). This is also likely a model-related source of deep uncertainty.

The aforementioned differences among and within approaches are reflected in the estimates of the deep uncertainty faced in simulated forest management and suggest that approaches A1 and A2 considerably overestimated deep uncertainty in the Michigan landscape by underestimating the ability of forest management decision-making to respond to forest change. It is intuitive that when management assumptions are frontloaded and not updated during a simulation through feedback, as in A1 and to a lesser extent in A2, there will likely be more deep uncertainty in management throughout a simulation as the forest changes over time. Overestimating the degree of deep uncertainty that future forest management is likely to face underestimates the ability of managers to respond to forest change.

Discussion

We used a new agent-based model to simulate three alternative approaches to modeling management of US Forest Service forests in northern lower Michigan and a new method to estimate the degree of deep uncertainty faced within each approach. We then used a typology of sources of uncertainty to categorize those responsible for the deep uncertainty faced. The estimates of the deep uncertainty varied widely among the approaches, with forest management in A1 (predefined) facing the highest degree, management in A2 (expanded) facing the second highest, and that in A3 (innovation) facing the widest range but, overall, the lowest degree of deep uncertainty. Correspondingly, the final percentages of mature tree cohorts and harvested biomass also differed substantially.

While the simulated forest management decision-making in all three approaches faced deep uncertainty

from *inherent* and potentially *parameter*-related sources, the aforementioned differences stem from *model*-related uncertainty. This is because we designed this exploration study specifically to isolate the modeling approach as the only variable factor among modeling scenarios. The unrealistic constraints on forest management in A1 and A2 that were made apparent by our study suggest that A3 does a better job at estimating the inherent deep uncertainty future forest management by the US Forest Service in Michigan will likely face. This insight is useful for informing future decisions about the best approach to choose for modeling forest management in the region. It also highlights the importance of reducing model-related uncertainty in models of forest management, the second layer of boundedness on the bounded rationality of simulated forest management (Sotnik 2020), which will improve the accuracy of exploratory studies of future forest management.

The method

We illustrated the usefulness of our linear regression modeling method in comparing the deep uncertainty faced in simulated forest management. The method does not, however, need to be limited to its simple form. Expanding the number of independent variables may be useful in cases where more than one variable is available toward pursuit of a goal. In such cases, deep uncertainty would be measured by $1 - R^2$ (Devore 2012). The number of dependent variables (goals) could also be expanded, in which case multivariate multiple regression (Izenman 2008) could be used. However, the method would not be applicable when there is a non-linear relationship between the dependent and independent variable(s).

It is worth noting that a lower degree of deep uncertainty faced in simulated forest management does not on its own imply that the corresponding model is more credible than one in which a higher degree is faced. This is because the higher degree can stem from the latter model capturing more of the inherent deep uncertainty in a simulated landscape or from it incorporating more of the important mechanisms and parameters that introduce corresponding uncertainties (Knutti and Sedláček 2013). Similarly, a lower degree of deep uncertainty faced in simulated forest management does not on its own imply that the corresponding forest-management strategy is better

than one in a model in which the simulated forest management faces a higher degree. Evaluating management strategies would additionally require taking the complexity of the landscape into account. Reducing model-related deep uncertainty while maintaining the same level of important mechanisms would, however, provide a more accurate representation of the inherent deep uncertainty likely faced in future forest management.

In developing the method, we also considered the Akaike Information Criterion (Akaike 1974; Burnham and Anderson 2002b; Burnham et al. 2011; Halsey 2019) and the Bayesian Information Criterion (Schwarz 1978; Burnham and Anderson 2002a, 2004), which are used for comparing the goodness of a model's fit, as candidates for representing the faced degree of deep uncertainty. However, the statistics were not selected in part because they assume that the predicted variable in all of the compared regression models is the same, whereas in our case we were comparing different regression models, in their entirety, and not just different combinations of predictor variables in a single regression model with the same predicted variable. Furthermore, they are not normalized, which makes it unclear how to measure their reverse—the lack of good fit.

The model

This study demonstrates SHE's capacity to simulate three substantially different approaches to modeling forest management. With A3 (innovation), it also demonstrates SHE's capacity to simulate forest management that successfully adjusts in pursuit of a goal, which makes an important contribution to LANDIS-II's ability to model forest management. Although LANDIS-II has been used extensively to simulate forest management and compare scenarios (Lucash et al. 2017; Middendorp et al. 2018; Boulanger et al. 2019; Wu et al. 2019), earlier studies applied predefined prescriptions that, although dependent on changing conditions, did not adjust in pursuit of a goal (A1). The human and natural components of a forested landscape, however, are continuously evolving, requiring forest management to evolve accordingly (Scheller 2020a, b). SHE expands LANDIS-II's capacity to simulate forest management by introducing goal-driven adjustments to prescriptions while

preserving the spatial structure of management across the landscape.

SHE also has the capacity to simulate the pursuit of multiple goals, as well as to use an agent's degree of success in achieving a specific goal to adjust the goal's relative importance through the SOSIEL cognitive process of goal prioritizing (Sotnik 2018). This function has the potential to reflect, in exploratory studies, more of the deep uncertainty faced in real-world forest management, especially when the goals are conflicting (e.g., profit vs. biodiversity). SHE is also capable of simulating more than one agent at a time, which allows for social learning and collective action. These functions introduce processes that real-world forest managers use to overcome uncertainty (e.g., management of common-pool resources; Ostrom 1999). Activating these functions in SHE to study their influence on simulated deep uncertainty and to reflect more of the important processes driving forest management has the potential to further improve forest management modeling across diverse landscapes and increase the relevance of exploratory studies to real-world forest managers.

References

Akaike H (1974) A new look at the statistical model identification. IEEE Trans Autom Control 19(6):716–723

Albert M, Hansen J, Nagel J, Schmidt M, Spellmann H (2015) Assessing risks and uncertainties in forest dynamics under different management scenarios and climate change. For Ecosyst 2(1):14

Albert M, Nagel R-V, Sutmöller J, Schmidt M (2018) Quantifying the effect of persistent dryer climates on forest productivity and implications for forest planning: a case study in northern Germany. Forest Ecosyst 5(1):33

Allen CR, Garmestani AS (eds) (2015) Adaptive management of social-ecological systems. Springer Netherlands. https:// doi.org/10.1007/978-94-017-9682-8

Amacher GS (2015) The forest harvesting problem: Have we reached the limit of our understanding? In: Halvorsen R, Layton DF (eds) Handbook on the economics of natural resources. Edward Elgar Publishing Limited, Cheltenham, pp 206–248

Baker SR, Bloom N, Davis SJ (2016) Measuring economic policy uncertainty. Q J Econ 131(4):1593–1636

Bankes S (1993) Exploratory modeling for policy analysis. Oper Res 41(3):435–449

Barros AMG, Ager AA, Day MA, Preisler HK, Spies TA, White E, Pabst RJ, Olsen KA, Platt E, Bailey JD, Bolte JP (2017) Spatiotemporal dynamics of simulated wildfire, forest management, and forest succession in central Oregon, USA. Ecol Soc 22(1):art24

Bloom N (2009) The impact of uncertainty shocks. Econometrica 77(3):623–685

Bolte JP, Hulse DW, Gregory SV, Smith C (2007) Modeling biocomplexity—actors, landscapes and alternative futures. Environ Model Softw 22(5):570–579

Boulanger Y, Arseneault D, Boucher Y, Gauthier S, Cyr D, Taylor AR, Price DT, Dupuis S (2019) Climate change will affect the ability of forest management to reduce gaps between current and presettlement forest composition in southeastern Canada. Landsc Ecol 34(1):159–174

Brockerhoff EG, Barbaro L, Castagneyrol B, Forrester DI, Gardiner B, González-Olabarria JR, Lyver PO, Meurisse N, Oxbrough A, Taki H, Thompson ID, van der Plas F, Jactel H (2017) Forest biodiversity, ecosystem functioning and the provision of ecosystem services. Biodivers Conserv 26(13):3005–3035

Burnham KP, Anderson DR (2002a) Advanced issues and deeper insights. In: Model selection and multimodel inference: a practical information-theoretic approach, 2nd ed. Springer, pp 267–351

Burnham KP, Anderson DR (2002b) Information and likelihood theory: a basis for model selection and inference. In: Model selection and multimodel inference: a practical information-theoretic approach, 2nd ed. Springer, pp 49–97

Burnham KP, Anderson DR (2004) Multimodel inference: understanding AIC and BIC in model selection. Sociol Methods Res 33(2):261–304

Burnham KP, Anderson DR, Huyvaert KP (2011) AIC model selection and multimodel inference in behavioral ecology: some background, observations, and comparisons. Behav Ecol Sociobiol 65(1):23–35

Chow CC, Sarin RK (2002) Known, unknown, and unknowable uncertainties. Theor Decis 52:127–138

Devore, J. L. (2012). Simple Linear Regression and Correlation. In *Probability & Statistics for Engineering and the Sciences* (8th ed., pp. 468–522). Brooks/Cole.

Durham WA (1991) Coevolution: genes, culture, and human diversity. Stanford University Press, Stanford

Duveneck MJ, Scheller RM, White MA (2014a) Effects of alternative forest management on biomass and species diversity in the face of climate change in the northern Great Lakes region (USA). Can J for Res 44(7):700–710

Duveneck MJ, Scheller RM, White MA, Handler SD, Ravenscroft C (2014b) Climate change effects on northern Great

Lake (USA) forests: a case for preserving diversity. Ecosphere 5(2):art23

Elsawah S, Filatova T, Jakeman AJ, Kettner AJ, Zellner ML, Athanasiadis IN, Hamilton SH, Axtell RL, Brown DG, Gilligan JM, Janssen MA, Robinson DT, Rozenberg J, Ullah IIT, Lade SJ (2020) Eight grand challenges in socio-environmental systems modeling. Socio-Environ Syst Modell 2:16226

European Commission (Ed) (2003) Sustainable forestry and the European Union: initiatives of the European *Commission*. Office for Official Publications of the European Communities.

Gigerenzer G, Selten R (eds) (2001) Bounded rationality: the adaptive toolbox. MIT Press, Cambridge

Goertzel B, Lian R, Arel I, de Garis H, Chen S (2010) A world survey of artificial brain projects, Part II: biologically inspired cognitive architectures. Neurocomputing 74(1–3):30–49

Gomory RE (1995) The known, the unknown and the unknowable. Sci Am 272(6):120–120

Grimm V, Berger U, Bastiansen F, Eliassen S, Ginot V, Giske J, Goss-Custard J, Grand T, Heinz SK, Huse G, Huth A, Jepsen JU, Jørgensen C, Mooij WM, Müller B, Peer G, Piou C, Railsback SF, Robbins AM, Robbins, MM, Rossmanith E, Rüger N, Strand E, Souissi S, Stillman RA, Vabø R, Visser U, DeAngelis DL (2006) A standard protocol for describing individual-based and agent-based models. Ecol Modell 198(1–2):115–126

Grimm V, Berger U, DeAngelis DL, Polhill JG, Giske J, Railsback SF (2010) The ODD protocol: a review and first update. Ecol Model 221(23):2760–2768

Grimm V, Railsback SF, Vincenot CE, Berger U, Gallagher C, DeAngelis DL, Edmonds B, Ge J, Giske J, Groeneveld J, Johnston ASA, Milles A, Nabe-Nielsen J, Polhill JG, Radchuk V, Rohwäder M-S, Stillman RA, Thiele JC, Ayllón D (2020) The ODD protocol for describing agent-based and other simulation models: a second update to improve clarity, replication, and structural realism. J Artif Soc Soc Simul 23(2):7

Gustafson EJ, Shifley SR, Mladenoff DJ, Nimerfro KK, He HS (2000) Spatial simulation of forest succession and timber harvesting using LANDIS. Can J for Res 30(1):32–43

Halsey LG (2019) The reign of the p-value is over: What alternative analyses could we employ to fill the power vacuum? Biol Lett 15(5):20190174

Handler S, Duveneck MJ, Iverson L, Peters E, Scheller RM, Wythers KR, Brandt L, Butler P, Janowiak M, Shannon PD, Swanston C, Eagle AC, Cohen JG, Corner R, Reich PB, Baker T, Chhin S, Clark E, Fehringer D, Fosgitt J, Gries J, Hall C, Hall KR, Heyd R, Hoving CL, Ibáñez I, Kuhr D, Matthews S, Muladore J, Nadelhoffer K, Neumann D, Peters M, Prasad A, Sands M, Swaty R, Wonch L, Daley J, Davenport M, Emery MR, Johnson G, Johnson L, Neitzel D, Rissman A, Rittenhouse C, Ziel R (2014) Michigan forest ecosystem vulnerability assessment and synthesis: a report from the Northwoods Climate Change Response Framework project (NRS-GTR-129; p. NRS-GTR-129). U.S. Department of Agriculture, Forest Service, Northern Research Station. https://doi.org/10.2737/NRS-GTR-129

Higgins SI, Clark JS, Nathan R, Hovestadt T, Schurr F, Fragoso JMV, Aguiar MR, Ribbens E, Lavorel S (2003) Forecasting plant migration rates: managing uncertainty for risk assessment. J Ecol 91(3):341–347

Izenman AJ (2008) Modern multivariate statistical techniques. Springer, New York. https://doi.org/10.1007/978-0-387-78189-1

Janzen DH (1980) When is it coevolution? Evolution 34(3):611

Jurado K, Ludvigson SC, Ng S (2015) Measuring uncertainty. Am Econ Rev 105(3):1177–1216

Keeley JE, Aplet GH, Christensen NL, Conard SG, Johnson EA, Omi PN, Peterson DL, Swetnam TW (2009) Ecological foundations for fire management in North American forest and shrubland ecosystems (PNW-GTR-779; p. PNW-GTR-779). U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station. https://doi.org/10.2737/PNW-GTR-779

Knutti R, Sedláček J (2013) Robustness and uncertainties in the new CMIP5 climate model projections. Nat Clim Chang 3(4):369–373

Kotseruba I, Tsotsos JK (2018) 40 years of cognitive architectures: core cognitive abilities and practical applications. Artif Intell Rev. https://doi.org/10.1007/s10462-018-9646-y

Kwakkel JH, Walker WE, Marchau VAWJ (2010) Classifying and communicating uncertainties in model-based policy analysis. Int J Technol Policy Manag 10(4):299

Langley P (2017) Progress and challenges in research on cognitive architectures. In: Proceedings of the thirty-first AAAI conference on artificial intelligence (AAAI-17), 7

Langley P, Laird JE, Rogers S (2009) Cognitive architectures: research issues and challenges. Cogn Syst Res 10(2):141–160

Lempert RJ (2019) Robust decision making (RDM). In: Marchau VAWJ, Walker WE, Bloemen PJTM, Popper SW (eds) Decision making under deep uncertainty: from theory to practice. Springer, New York, pp 23–51. https://doi.org/10.1007/978-3-030-05252-2

Lempert RJ, Schlesinger ME, Bankes SC (1996) When we don't know the costs or the benefits: adaptive strategies for abating climate change. Clim Change 33(2):235–274

Lempert RJ, Popper SW, Banks SC (2003) The challenge of long-term policy analysis. In: Shaping the next one hundred years: new methods for quantitative, long-term policy analysis, 1st ed. RAND Corporation, pp 1–9

Lempert RJ, Groves DG, Popper SW, Bankes SC (2006) A general, analytic method for generating robust strategies and narrative scenarios. Manag Sci 52(4):514–528

Lucash MS, Scheller RM, Gustafson JE, Sturtevant RB (2017) Spatial resilience of forested landscapes under climate change and management. Landsc Ecol 32(5):953–969

Maier HR, Guillaume JHA, van Delden H, Riddell GA, Haasnoot M, Kwakkel JH (2016) An uncertain future, deep uncertainty, scenarios, robustness and adaptation: How do they fit together? Environ Model Softw 81:154–164

Marchau VAWJ, Walker WE, Bloemen PJTM, Popper, SW (eds) (2019) Decision making under deep uncertainty: from theory to practice. Springer. https://doi.org/10.1007/978-3-030-05252-2

Matthews RB, Gilbert NG, Roach A, Polhill JG, Gotts NM (2007) Agent-based land-use models: a review of applications. Landsc Ecol 22(10):1447–1459

Maxwell CJ, Serra-Diaz JM, Scheller RM, Thompson JR (2020) Co-designed management scenarios shape the responses of seasonally dry forests to changing climate and fire regimes. J Appl Ecol 57(7):1328–1340

Mayer AL, Rouleau MD (2013) ForestSim model of impacts of smallholder dynamics: forested landscapes of the upper Peninsula of Michigan. Int J for Res 2013:1–13

MEA (2003) Ecosystems and human well-being: a framework for assessment. Island Press, Washington

Messier C, Puettmann K, Filotas E, Coates D (2016) Dealing with non-linearity and uncertainty in forest management. Curr for Rep 2(2):150–161

Meyfroidt P (2013) Environmental cognitions, land change, and social–ecological feedbacks: an overview. J Land Use Sci 8(3):341–367

Middendorp RS, Vanacker V, Lambin EF (2018) Impacts of shaded agroforestry management on carbon sequestration, biodiversity and farmers income in cocoa production landscapes. Landsc Ecol 33(11):1953–1974

Mladenoff DJ, He HS (1999) Design, behavior and application of LANDIS, an object-oriented model of forest landscape disturbance and succession. In: Spatial modeling of forest landscape change: approaches and applications. Cambridge University Press, pp 125–162

Müller B, Bohn F, Dreßler G, Groeneveld J, Klassert C, Martin R, Schlüter M, Schulze J, Weise H, Schwarz N (2013) Describing human decisions in agent-based models – ODD + D, an extension of the ODD protocol. Environ Model Softw 48:37–48

Nuismer SL (2017) Introduction to coevolutionary theory. W. H Freeman and Company, New York

Ostrom E (1999) Self-governance and forest resources [Occasional Paper No. 20]. Center for International Forestry Research, p 19

Puettmann KJ, Coates KD, Messier C (2009) A critique of silviculture: managing for complexity. Island Press, Washington

R Core Team (2021) R: a language and environment for statistical computing (4.0.5) [R]. R Foundation for Statistical Computing. http://www.R-project.org/

Rammer W, Seidl R (2015) Coupling human and natural systems: simulating adaptive management agents in dynamically changing forest landscapes. Glob Environ Chang 35:475–485

Rinaldi F, Jonsson R (2020) Accounting for uncertainty in forest management models. For Ecol Manag 468:118186

Robertson G, Gaulke P, McWilliams R, LaPlante S, Guldin R (2011). National report on sustainable forests—2010 (FS-979; p. 212). USDA Forest Service

Rouleau M, Zupko R (2019) Agent-based modeling for bioenergy sustainability assessment. Landsc Urban Plan 188:54–63

Scheller RM (2020a) Technologies for innovating forward. In: Managing landscapes for change, vol 27. Springer, pp 89–100. https://doi.org/10.1007/978-3-030-62041-7

Scheller RM (2020b) What is a landscape? In: Managing landscapes for change, vol 27. Springer, pp 9–18. https://doi.org/10.1007/978-3-030-62041-7

Scheller RM, Mladenoff DJ (2004) A forest growth and biomass module for a landscape simulation model, LANDIS: design, validation, and application. Ecol Model 180(1):211–229

Scheller RM, Domingo JB, Sturtevant BR, Williams JS, Rudy A, Gustafson EJ, Mladenoff DJ (2007) Design, development, and application of LANDIS-II, a spatial landscape simulation model with flexible temporal and spatial resolution. Ecol Model 201(3–4):409–419

Schmitt KM, Ontl TA, Handler SD, Janowiak MK, Brandt LA, Butler-Leopold PR, Shannon PD, Peterson CL, Swanston CW (2021) Beyond planning tools: experiential learning in climate adaptation planning and practices. Climate 9(5):76

Schwarz G (1978) Estimating the dimension of a model. Ann Stat 6(2):461–464

Seidl R, Lexer MJ (2013) Forest management under climatic and social uncertainty: trade-offs between reducing climate change impacts and fostering adaptive capacity. J Environ Manag 114:461–469

Selten R (1998) Features of experimentally observed bounded rationality. Eur Econ Rev 42(3–5):413–436

Shaw BD (2017a) Uncertainty analysis of experimental data with R. CRC Press/Taylor & Francis Group

Shaw BD (2017b) Uncertainty of a measured quantity. In: Uncertainty analysis of experimental data with R. CRC Press/Taylor & Francis Group, pp 75–90

Simon HA (1957) Models of man, social and rational: Mathematical essays on rational human behavior in a social setting. Wiley, New York

Simon HA (1960) The new science of management decision. Harper, New York

Sotnik G (2018) The SOSIEL platform: knowledge-based, cognitive, and multi-agent. Biol Inspir Cognit Arch 26:103–117

Sotnik G (2020) The doubly-bounded rationality of an artificial agent and its ability to represent the bounded rationality of a human decision-maker in policy-relevant situations. J Exp Theor Artif Intell 32(5):727–749

Sotnik G, Fischer AP, Ibáñez I, Cousins SJM (2021) A transdisciplinary typology of change identifies new categories of adaptations and forms of co-adaptation in coupled human and natural systems. Sustain Sci. https://doi.org/10.1007/s11625-021-00979-y

Stankey GH, Clark RN, Bormann BT (2005) Adaptive management of natural resources: theory, concepts, and management institutions (PNW-GTR-654; p. PNW-GTR-654). U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station. https://doi.org/10.2737/PNW-GTR-654

Stankey GH, Clark RN, Bormann BT (2006) Learning to manage a complex ecosystem: Adaptive management and the Northwest Forest Plan (PNW-RP-567; p. PNW-RP-567). U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station. https://doi.org/10.2737/PNW-RP-567

Todd PM, Gigerenzer G, ABC Research Group (2012) Ecological rationality: Intelligence in the world. Oxford University Press, Oxford

Uusitalo L, Lehikoinen A, Helle I, Myrberg K (2015) An overview of methods to evaluate uncertainty of

deterministic models in decision support. Environ Model Softw 63:24–31

Walker WE, Rahman SA, Cave J (2001) Adaptive policies, policy analysis, and policy-making. Eur J Oper Res 128(2):282–289

Walker WE, Harremoës P, Rotmans J, van der Sluijs JP, van Asselt MBA, Janssen P, Krayer von Krauss MP (2003) Defining uncertainty: a conceptual basis for uncertainty management in model-based decision support. Integr Assess 4(1):5–17

Walker WE, Lempert RJ, Kwakkel JH (2013) Deep uncertainty. In Encyclopedia of operations research and management science. Springer https://doi.org/10.1007/978-1-4419-1153-7_1140

Wear DN, Huggett R, Li R, Perryman B, Liu S (2013) Forecasts of forest conditions in U.S. regions under future scenarios: a technical document supporting the Forest Service 2010 RPA Assessment. USDA

Weaver CP, Lempert RJ, Brown C, Hall JA, Revell D, Sarewitz D (2013) Improving the contribution of climate model information to decision making: the value and demands of robust decision frameworks: the value and demands of robust decision frameworks. Wiley Interdiscip Rev 4(1):39–60

Workman M, Darch G, Dooley K, Lomax G, Maltby J, Pollitt H (2021) Climate policy decision making in contexts of deep uncertainty—from optimisation to robustness. Environ Sci Policy 120:127–137

Wu Z, Dai E, Wu Z, Lin M (2019) Future forest dynamics under climate change, land use change, and harvest in subtropical forests in Southern China. Landsc Ecol 34(4):843–863

Yamada Y, Yamaura Y (2017) Decision support system for adaptive regional-scale forest management by multiple decision-makers. Forests 8(11):453

Yousefpour R, Jacobsen JB, Thorsen BJ, Meilby H, Hanewinkel M, Oehler K (2012) A review of decision-making approaches to handle uncertainty and risk in adaptive forest management under climate change. Ann for Sci 69(1):1–15

Zupko R, Rouleau M (2019) ForestSim: spatially explicit agent-based modeling of non-industrial forest owner policies. SoftwareX 9:117–125