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The SOSIEL Platform: Knowledge-based, cognitive, and multi-agent

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ABSTRACT

This article describes the open-source cognitive multi-agent knowledge-based SOSIEL (Self-Organizing Social & Inductive Evolutionary Learning) Platform, designed for building the social components of social-ecological decision support systems, consisting of agents empowered with a cognitive architecture. The platform can simulate the cross-generational progression of one or a large number of agents that can interact among themselves and/or with coupled natural and/or technical systems, learn from their and each other's experience, create new practices, and make decisions about taking and then take (potentially collective) actions. The platform can also be used for conducting hypothetical experiments that are focused on studying the interactions among: (a) cross-generational population dynamics, (b) self-organizing multi-layered social network structures, (c) evolving place-based knowledge, (d) learning, (e) decision-making, (f) collective action and its potential, and (g) social and (when coupled) social-ecological outcomes. The article describes a simple model that was built with the SOSIEL Platform, which simulates the co-evolution of mental models among socially learning agents.

Introduction

Long-term decision-related activities, such as bottom-up and top-down policy development, analysis, and planning, stand to benefit from the creation and application of social-ecological (Folke, 2006; Hummel, 2012; Liu et al., 2007; Ostrom, 2009) decision support systems (DSSs) capable of simulating representative human behavior in social contexts. This is especially the case now as communities, regions, and nations search for strategies aimed at mitigating present and future climate change. Other types of DSSs have already proven to be useful (Power, 2002, 2008), improving both decision-making processes and related outcomes (Holsapple & Sena, 2005; Holsapple & Whinston, 1996; Klein & Methlie, 1995). However, attempts to simulate representative human behavior in social contexts have fallen short of expectations. One explanation is that the agents in the multi-agent models being used to simulate social human behavior lack the levels of knowledge and cognition necessary for them to represent their real-world counterparts (Crooks, Castle, & Batty, 2008; Filatova, Verburg, Parker, & Stannard, 2013; Goldspink, 2000; Parker, Manson, Janssen, Hoffmann, & Deadman, 2003; Sun, 2007).

Knowledge, for example, needs to go beyond local practices and represent more of what is used in the process of local decision-making. This is not only because this kind of local knowledge evolves within the context of interest and, therefore, likely holds valuable insight into the intricacies of the context and the ways to manage it (Berkes, 1999; Berkes, Colding, & Folke, 2000), but also because the success of any policy affecting local populations depends on its compatibility and ability to co-evolve with the peculiarities of local knowledge.

At the same time, cognition needs to reflect all relevant types of behavior (Meyfroidt, 2013), including individual and social, and with relative accuracy produce potential behavior in addition to reproducing past behavior. Furthermore, cognitive bias is integral in human decision-making and needs to be factored in during policy planning and analysis (Gowdy, 2008; Gsottbauer & van der Bergh, 2011). Therefore, for the results of social-ecological DSSs to be useful for practical policy implementation, the simulated behavior needs to first and foremost be humanly possible (as opposed to optimal), suggesting that the behavior needs to be boundedly rational (Gigerenzer & Selten 2001; Gigerenzer, Todd, & The ABC Research Group, 1999; Simon, 1957, 1995; Todd, Gigerenzer, & The ABC Research Group, 2012) and inspired by psychological and sociological processes, as opposed to (optimizing) machine learning.

Cognition also needs to be capable of processing and modifying the knowledge that is relevant for collective action. This is because many, if not most, solutions to policy-related questions require some form of social interaction or collective action (Ostrom, 2007, 2009; Ostrom, Gardner, & Walker, 1994; Rittel & Webber, 1973). Specifically, the represented knowledge needs to reflect the often individual-specific conditions that shape a decision-maker's decision to participate in collective action, as well as the specificities of the collective action, while the represented cognition needs to allow for the modification of any current or newly created knowledge related to collective actions.

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The highest levels of knowledge and cognition in the cognitive and computer sciences are typically represented with *cognitive architectures* (Goertzel, Lian, Arel, de Garis, & Chen, 2010; Kotseruba & Tsotsos, 2018; Langley, 2017; Langley, Laird, & Rogers, 2009), which are computer-based models of the human mind. Therefore, it may be possible to improve our ability to build social-ecological DSSs capable of simulating representative human behavior in social contexts by empowering agents in social-ecological multi-agent models with a cognitive architecture that consists of theoretically-grounded cognitive processes and agent-specific and empirically-grounded knowledge.

This article describes the open-source cognitive multi-agent knowledge-based SOSIEL Platform, designed for building the social components of social-ecological DSSs consisting of agents empowered with a cognitive architecture. The platform can also be used for conducting hypothetical experiments that are focused on studying the interactions among: (a) cross-generational population dynamics, (b) self-organizing multi-layered social network structures, (c) evolving place-based knowledge, (d) learning, (e) decision-making, (f) collective action and its potential, and (g) social and (when coupled) ecological outcomes. Apart from their application in policy development, improving our understanding of such interactions also has the potential of contributing to advancements in related sciences.

The idea of empowering agents in multi-agent systems with a cognitive architecture has been explored since the late nineteen-nineties in the areas of robotics (Agah & Bekey, 1997), organizational structure (Naveh & Sun, 2006; Sun & Naveh, 2004), belief propagation (Jarvis, Jarvis, & Jain, 2006), innovation (Bhattacharyya and Ohlsson, 2010), language learning (Klein, Kamp, Palm, & Doya, 2010), and social learning (Nye, 2014). Despite the variety in applications, research in this area has been sparse and excluding the above and several other examples has mostly been limited to work-in-progress conference papers. In addition to empowering agents with a new cognitive architecture that is rooted in psychology and sociology, the SOSIEL Platform extends this research by introducing a self-organizing multi-layered social network structure, collective action, and cross-generational population dynamics. Collective action is especially relevant in DSSs designed to address common-pool resource management problems (Ostrom, 1990, 2008), while population dynamics are relevant for DSSs designed to support policy development, analysis, and planning across medium- to long-term scales.

The following section briefly introduces the SOSIEL Platform and then describes in detail its knowledge-based, cognitive, and multi-agent characteristics. "Example: Co-evolution of mental models among socially learning agents" describes a simple model that was built with the SOSIEL Platform, which simulates the co-evolution of mental models among socially learning agents. "Discussion" discusses how the SOSIEL Platform contributes to research in the fields of both multi-agent modeling and cognitive architectures and mentions future work. "Conclusion" concludes.

The SOSIEL Platform

The open-source SOSIEL (Self-Organizing Social & Inductive Evolutionary Learning) Platform[1] is a multi-agent system developed in C# for building models that are capable of capturing the spatio-temporal complexity of social contexts in which the heterogeneity of knowledge, the need for learning, and the potential for collective action play a significant role (e.g. Ostrom et al., 1994). Models built with the SOSIEL Platform can simulate the cross-generational progression of one or a large number of boundedly-rational agents, each of which is represented by a general cognitive architecture that consists of theoretically-grounded cognitive processes and agent-specific and empirically-grounded knowledge. The generality of the cognitive architecture implies that the SOSIEL Platform can be used to build models in a large variety of contexts.

A SOSIEL agent can stand for either an individual or an organizational[2] decision-maker. It can interact with other agents and/or with coupled natural and/or technical systems, learn from its own experience and that of others, create new practices, and make decisions about taking and then take (potentially collective) actions. One of the platform's key design objectives was to simulate decision-making that would be neither better nor worse than that of the human counterparts. This objective, which remains to be achieved, is significantly different from the more common pursuit of optimal behavior sought-after in artificial agents. However, it is a necessary objective for policy-focused models that are used as DSSs for exploring humanly-possible scenarios.

The data and metadata required for parametrizing and initializing the SOSIEL Platform are provided as Tables, where: Table 5 describes the individual and social data and metadata required for parametrizing and initializing a population of agents for a specific context, Table 6 describes how the data in Table 5 is used to construct agent profiles, and Table 7 describes the data required for parameterizing and initializing demographic processes. New models are parameterized and initialized by editing CS, JSON, and CSV files, while iteration-based output is modified in CS files and provided in CSV files. Please see *The SOSIEL Platform v1.0 User Guide*[3] for further instructions. The SOSIEL Platform's knowledge-based ("Knowledge-based"), cognitive ("Cognitive"), and multi-agent ("Multi-agent") characteristics are described in detail below.

Knowledge-based

Each SOSIEL agent can be empowered with its own system of knowledge, making the SOSIEL Platform a knowledge-based system (Negnevitsky, 2011; Weiss & Kulikowski, 1984). *Knowledge*, for a SOSIEL agent, is a body of information that reflects how it understands the decision situations within which it makes decisions and is what the agent applies in the process of making a decision within them. A *decision situation* is a time-sensitive decision-specific context within which an agent makes a decision, on their own or in coordination with others, and that is observable to them through a potentially unique set of conditions. This definition of a decision situation is in line with Ostrom and colleagues' definition of an *action situation* (Janssen & Ostrom, 2006; Ostrom, 2005), which plays a central role in Ostrom's Social-Ecological System framework (Ostrom, 2009).

There are three approaches to representing knowledge in cognitive architectures (Kotseruba & Tsotsos, 2018) and more generally knowledge-based systems (Negnevitsky, 2011), namely symbolic (cognitivist), emergent (connectionist), and hybrid (which combines the first two). A symbolic approach to representing knowledge was chosen for SOSIEL agents with the aim of making the links among the knowledge acquired from stakeholders, the knowledge parameterized, and the cognitive processing of knowledge during a simulation as interpretable – in terms of transparency, explainability, and analyzability – as possible. This aim is especially important when modeling with stakeholders, which is becoming increasingly common in social-ecological policy analysis (Voinov et al., 2016).

In terms of interpretability, emergent approaches (which typically represent knowledge through an artificial neural network) and hybrid

[1] https://www.sosiel.org/the-sosiel-toolkit/the-sosiel-platform

[2] It is advisable that an agent represents a group only when the group includes no more than one relevant decision-maker. Groups with more than one relevant decision-maker should be represented with an equal number of decision-making agents. This is because the decision-making process of two or more individuals is fundamentally different from the decision-making process of one individual and this difference may have a significant influence on the result of the process.

[3] https://www.sosiel.org/the-sosiel-toolkit/the-sosiel-platform

approaches that include them as components at least partially lack explanatory power and act as a black box (Lipton, 2018; Negnevitsky, 2011). From among the symbolic approaches, the procedural representation of knowledge was selected for SOSIEL agents, mainly due to its fit with the way norms can be represented in the study of common-pool resource management (Crawford & Ostrom, 1995) and the way decision-related heuristics are represented in the study of bounded rationality (Gigerenzer & Selten, 2001; Gigerenzer et al., 1999).

As a result, agent knowledge consists of context-specific variables and related metadata that are organized into situation-specific conditional (IF-THEN) statements and auxiliary information (Tables 5 and 6). Each conditional statement represents a situation-specific decision option and consists of: (a) one or more antecedents, with each antecedent representing the current state of a condition (factor) that the decision option associates with a specific decision; and (b) one consequent, which is a situation-specific conclusion/action that the decision option associates with the current state of the condition(s). The auxiliary information includes: (a) *goals* that decisions are associated with, (b) *context-specific variables* that (directly or indirectly) support decision-making, and (c) *anticipated influences* that the agent expects a decision will have on the goals it is associated with.

Cognitive

The SOSIEL Platform includes one cognitive architecture (Fig. 1), which consists of a memory component, a learning component, and a decision-making component. Each time period, the cognitive architecture is utilized by each agent to organize, update, modify, and utilize its knowledge in the process of learning and decision-making. The use of one cognitive architecture (as opposed to having one for each agent) in the platform's design eliminates unnecessary redundancy and is made possible by the fact that cognitive architectures are typically fixed entities (Langley et al., 2009; Langley, 2017). Each of the components of the cognitive architecture is described below. The memory component is described first because it organizes the knowledge that is updated, modified, and utilized by the learning and decision-making components. The learning and decision-making components are described together due to their interdependent nature.

The memory component

In line with Kelly (1955, 1970) and others (Carley & Palmquist, 1992; Gentner & Stevens, 1983; Johnson-Laird, 2006, 2010; Jones, Ross, Lynam, Perez, & Leitch, 2011; Nersessian, 2007), the memory component of the cognitive architecture organizes a SOSIEL agent's

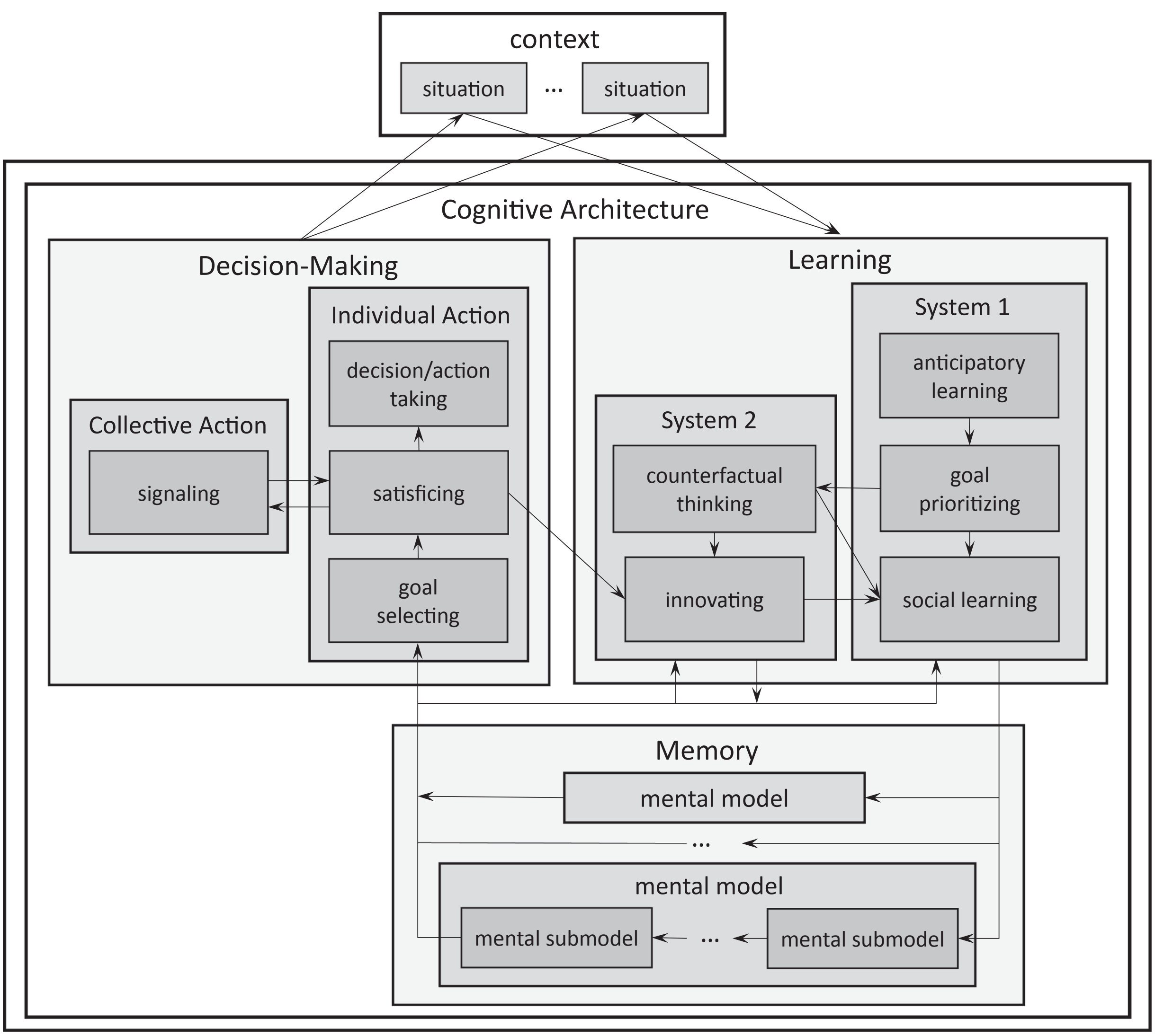

Fig. 1. The figure depicts the cognitive architecture of a SOSIEL agent, information flows within it, and information flows between it and a set of decision situations.

knowledge into mental models and related metadata, which correspond to decision situations in which the agent needs/wants to make a decision. In the case of decision situations that require multiple decisions, the corresponding mental models consist of chains of corresponding mental submodels.

The mental model concept is embedded within Ostrom's Social-Ecological System framework (Ostrom, 2007, 2009) and is increasingly being implemented within the context of environmental cognition (Jones et al., 2011). The maximum number of decisions a specific mental (sub)model can hold is set during initialization. The actual number of decisions a mental (sub)model contains at any point in time during a simulation may fluctuate (at or below the max) as a result of (individual and/or social) learning. In line with Gilhooly and colleagues (1993), the restriction on the possible number of decisions in a mental (sub)model can represent limitations on the agent's memory.

The learning and decision-making components

In line with Holland, Holyoak, Nisbett, & Thagard (1986) and others (Anderson et al., 2004; Laird, 2012), the cognitive architecture of a SOSIEL agent is symbolic[4] and consists of nine cognitive processes, five of which are related to learning (anticipatory learning, goal prioritizing, counterfactual thinking, innovating, and social learning) and four of which are related to decision-making (goal selecting, satisficing, signaling interest in a collective action, and action-taking). As was the case with representing knowledge, a symbolic approach was chosen over an emergent or a hybrid one with the aim of making the links among the knowledge acquired from stakeholders, the knowledge parameterized, and the cognitive processing of knowledge during a simulation as interpretable as possible. This aim was pursued at the expense of SOSIEL agents being able to reproduce more complex human problem-solving abilities, which architectures that include connectionist components, such as CLARION (Sun, 2002, 2016), have shown to be capable of. Finding a balance between interpretability and problem-solving power remains a challenge in artificial intelligence (Lipton, 2018).

With the aim of being compatible with Ostrom's Social-Ecological System framework (Ostrom, 2009), the selection of which cognitive processes to include among the learning and decision-making processes comprising the cognitive architecture and in which sequence to order them relied on research on:

a. Collective action (Bicchieri, 2006; Blomquist, Schlager, & Tang, 1991; Gilbert, 2006; Goldstone & Janssen, 2005; Ostrom, 1998, 2000; Tuomela & Miller, 1985; Tuomela, 1984; Velleman, 1997),
b. Decision-making (Baron, 2008; Bröder, 2000; Camerer, 2003; Gigerenzer & Goldstein, 1996; Mintzberg, Raisinghani, & Théorêt, 1976; Ostrom, 1998; Rieskamp & Hoffrage, 1999; Simon, 1955, 1956),
c. Goals (Barron & Harackiewicz, 2001; Hoch & Loewenstein, 1989; Kahneman & Tversky, 1979; Miller, Turnbull, & McFarland, 1990; Simon, 1955; Sober and Wilson, 1999),
d. Individual learning (Baron, 2008; Epstude & Roese, 2008; Kahneman & Miller, 1986; Kahneman & Tversky, 1982; Kahneman & Varey, 1990; Lewis, 1973; Mintzberg et al., 1976; Roese & Olson, 1993; Roese, 1997), and
e. Social learning (Bandura, 1977; Festinger, 1942; Hertwig & Hoffrage, 2013; Hilgard, Sait, & Margaret, 1940; Taylor, Lichtman, & Wood, 1984; Wheeler, 1966).

Selection and sequencing were also influenced and guided by the data requirements that arose during the process of knowledge acquisition conducted as part of an ongoing study of human adaptation to climate change in the Ukrainian Carpathian Mountains (Sotnik, 2018).

In line with the dual-process theories of cognition (Duncker, 1945; Evans & Stanovich, 2013; Evans, 2003, 2010; Kahneman & Frederick, 2002; Kahneman, 2011; Sloman, 1996), an agent may activate some or all of the five learning processes during a given time period, depending on how confident they feel within a decision situation. Specifically, three of the learning processes (anticipatory learning, goal prioritizing, and social learning) are always activated, while two of the learning processes (counterfactual thinking and innovating) are activated only when an agent is unconfident in their ability to make a decision within a decision situation.

Because there may be a need to explore different levels of cognition, models built with the SOSIEL Platform can be set to simulate agent behavior at one of four different cognitive levels (CLs), with each subsequent level including more of the cognitive processes (Table 1). CL1 utilizes the most basic level of cognition, which involves the activation of only the decision-making processes. This limits an agent's decision-making process to using current conditions and its *initial* knowledge to choose from its *initial* set of decision options. This level of cognition is typically used in, for example, classic evolutionary game theory (Friedman, 1998; Hofbauer & Sigmund, 2003; Smith, 1982; Weibull, 1995). CL2 extends the set of processes in CL1 to include individual learning processes that use feedback to update an agent's knowledge and allow it to use current conditions and its *updated* knowledge to choose from its *initial* set of decision options. This level of cognition is usually found in models with agents demonstrating basic reinforcement learning, such as, for example, individual evolutionary learning (Arifovic & Ledyard, 2004, 2012; Arifovic, 1994).

CL3 further extends the use of processes by also including social learning, which allows an agent to learn from its social network neighbors and, in turn, to use current conditions and its *updated* knowledge to choose from its set of decision options that was potentially *updated* through social learning. This level of cognition introduces the ability to socially learn (Kiesling, Günther, Stummer, & Wakolbinger, 2012; Macy & Willer, 2002) to agents already demonstrating reinforcement learning and allows for diffusion of information and collective action. Finally, CL4 includes the complete set of learning and decision-making processes, which enable an agent to use current conditions and its *updated* knowledge to choose from its set of decision options that was potentially *updated* through both social learning and innovating. This level of cognition is typically used in multi-agent models of agents that are empowered with a cognitive architecture and that are capable of social interaction (Bhattacharyya and Ohlsson, 2010; Klein et al., 2010; Nye, 2014).

The nine cognitive processes are described below, organized according to the sequence of their activation during a simulation and each time period, which is described in greater detail in “Process activation logic”. Because in the first time period there is no feedback that the learning processes can analyze, only the decision-making processes are activated. During each subsequent time period, feedback from the prior time period permits learning to take place and therefore both learning and decision-making processes are activated. Pseudocode for the cognitive processes may be found in *The SOSIEL Platform 1.0 Pseudocode*.[5]

First time period: only decision-making. This section describes the cognitive processes that each SOSIEL agent engages in during the first time period. As mentioned above, because no feedback has yet been generated for analysis, only the decision-making processes are activated during the first time period. These include: (a) goal selecting, (b) satisficing, (c) signaling interest in a collective action, and (d) action-taking.

[4] A symbolic cognitive architecture, as opposed to an emergent one, relies on symbols such as words in its reasoning, as opposed to an artificial neural network.

[5] https://www.sosiel.org/the-sosiel-toolkit/the-sosiel-platform

Table 1
The four possible cognitive level settings and the corresponding cognitive processes, highlighting in bold those that appear for the first time.

CL1	CL2	CL3	CL4
1. Goal selecting	**1. Anticipatory learning**	1. Anticipatory learning	1. Anticipatory learning
2. Satisficing	**2. Goal prioritizing**	2. Goal prioritizing	2. Goal prioritizing
3. Signaling	3. Goal selecting	**3. Social learning**	**3. Counterfactual thinking**
4. Action-taking	4. Satisficing	4. Goal selecting	**4. Innovating**
	5. Signaling	5. Satisficing	5. Social learning
	6. Action-taking	6. Signaling	6. Goal selecting
		7. Action-taking	7. Satisficing
			8. Signaling
			9. Action-taking

Goal selecting is the first cognitive process activated during the first time period and subsequently the first activated decision-making process in the second and later time periods. In line with Simon (1955), the aim of goal selecting is to generate a list of goals from which goals of focus can be selected during decision-making and in which the goals are ordered by their importance levels (which, during the second and later time periods are updated during anticipatory learning). The reason a list of goals is generated (as opposed to a single goal) is because not all mental (sub)models are associated with all goals. The process of goal selecting consists of the following two subprocesses: (a) generate the *goal importance distribution*, which constructs a distribution of goals that reflects their importance levels; and (b) generate the *goals of focus list*, which applies a uniform distribution to randomly select a list of goals from the goal importance distribution. The result of the goal selecting process is a list of goals, the *goals of focus list*, approximately ordered by their level of importance. The ordering is only approximate because the use of a uniform distribution to select goals implies that, at any point, chance may lead to the selection of a less important goal, thereby introducing a degree of uncertainty.

Satisficing follows: (a) goal selecting and, as will be explained in the next paragraph, (b) collective action. The concept of *satisficing* was coined by Simon (1955, 1956) in reference to a limit humans impose on their search for the best decision option in a decision situation. In line with Simon and others (Baron, 2008; Bröder, 2000; Gigerenzer & Goldstein, 1996; Mintzberg et al., 1976; Rieskamp & Hoffrage, 1999), the aim of the process of satisficing is to select a decision from a set of decision options that best meets the goal of focus in a specific situation. The process of satisficing uses the anticipated influences of decision options that meet current conditions in choosing a decision. It consists of the following two subprocesses: (a) select the decision options from the agent's corresponding mental (sub)model that meet current conditions and, from these, (b) select the best decision option, using the decision options' anticipated influences on the first goal of focus (from the goal of focus list) that is associated with the mental (sub)model. If a mental model consists of a chain of submodels and if the consequents of chosen decision options in the earlier submodels are among the antecedents of the available decision options in the later submodels (in the chain), then only those decision options whose antecedents are satisfied by the consequents are considered for possible selection. If a decision option that meets current conditions does not exist in the respective mental (sub)model, the agent engages in innovating (described in the next section). If innovating does not work, the agent does nothing. Since the process of satisficing limits the selection of a decision to only those available to an agent and not to all possible decision options, agents select what they 'think' is best for them, which may not be the same as what is *ultimately* best for them. The result of satisficing is a decision that is specific to a decision situation.

The process of *signaling interest in a collective action* follows satisficing when the selected decision during satisficing is a collective action and interest in it has not yet been signaled to members of associated social networks. The concept of signaling was coined by Spence (1973) and in this context is an expression of interest in and a proposal of joint commitment to a collective action (Bicchieri, 2006; Blomquist et al., 1991; Gilbert, 2006; Ostrom, 1998, 2000; Tuomela & Miller, 1985; Tuomela, 1984; Velleman, 1997). The result of signaling interest in a collective action is an updated list of agents committed to the collective action. After all agents interested in collective action had a chance to express their interest, the process of satisficing is reactivated. If a sufficient number of agents have signaled interest in a collective action, then during satisficing the collective action becomes their selected decision. If, however, the number of agents signaling interest is not sufficient, then the collective action is deactivated as a potential decision option during the current period and the agents reengage in satisficing.

The process of *action-taking* may involve doing nothing or engaging in an individual or a collective action. To facilitate both sequential and simultaneous decision-making (Camerer, 2003), action-taking is activated sequentially by agent type (which is described in the introduction to "Multi-agent" and Table 5). Additionally, whether agents of the same type take action sequentially or simultaneously can be set during initialization for all decision situations. The result of action-taking is the effect of decisions on corresponding variables.

Second and later time periods: learning and decision-making. A SOSIEL agent engages in both learning and decision-making processes during the second and later time periods. Because decision-making processes were described in the previous subsection, they are only referenced in this subsection, which focuses on the learning processes that include: (a) anticipatory learning, (b) goal prioritizing, (c) counterfactual thinking, (d) innovating, and (e) social learning.

Anticipatory learning is the first out of the learning and decision-making processes that is activated in the second and later time periods. In line with Kahneman and Miller (1986) and others (Hoch & Loewenstein, 1989; Miller et al., 1990; Mintzberg et al., 1976), the aim of the process is to use the change in the states of goal variables to update the anticipated influences of decision options, assess the success of decision options, and gauge confidence in attaining goals. The process of anticipatory learning consists of the following three subprocesses: (a) update the anticipated influence(s) on goal(s) of the decision option(s) that was/were implemented in the prior period; (b) assess the success of this/these decision option(s) in contributing to the attainment of goal(s); and (c) establish whether, by consequence, the agent is confident or unconfident in attaining the goal(s). The results of anticipatory learning are updated goal-specific anticipated influences and confidence states.

Goal prioritizing always follows anticipatory learning. In line with Kahneman and Tversky (1979) and others (Barron & Harackiewicz, 2001; Sober and Wilson, 1999), the aim of goal prioritizing is to use what was learned during anticipatory learning to reevaluate the importance levels of goals and, if necessary, reprioritize them. The process of goal prioritizing has a stabilizing effect on agent behavior and has the option of being turned off as a mechanism if its stabilizing effect contradicts reference behavior. The process of goal prioritizing consists of the following two subprocesses: (a) determine the relative difference between goal value and focal goal value and (b) adjust the proportional importance levels of goals respectively. The result of goal prioritizing is a reevaluated and, if appropriate, a reprioritized set of proportional importance levels.

Counterfactual thinking follows goal prioritizing only in the case that a mental (sub)model is modifiable[6], there is a lack of confidence in relation to a goal, and the number of decision options matching conditions in the prior period was equal to or greater than two. A loss of

[6] A mental (sub)model is modifiable if the consequents of the decision options that comprise it are numeric.

confidence, which may occur during the process of anticipatory learning, triggers counterfactual thinking as an effort to explain the discrepancy between the anticipated and actual results of a decision. In line with Lewis (1973) and others (Baron, 2008; Epstude & Roese, 2008; Kahneman & Miller, 1986; Kahneman & Varey, 1990; Roese & Olson, 1993; Roese, 1997), the aim of counterfactual thinking is to check whether or not the agent would have behaved differently (i.e., if an available alternate decision had been selected) had it known in the prior period (which is represented by a prior set of conditions) what it knows in the current (which is represented by updated anticipations). If an alternative satisfactory decision is identified, then confidence is regained and the agent moves on to the process of social learning. If, however, an alternative decision is not identified, then the agent remains unconfident and continues with individual learning by engaging in innovating, before moving on to social learning. The process of counterfactual thinking consists of the following two subprocesses: (a) search for a better decision option and (b) assess the success of the search. The result of counterfactual thinking is knowledge of whether a potentially better decision option is present in the corresponding mental (sub)model and whether there is a potential change to the state of uncertainty.

Innovating follows: (a) counterfactual thinking, when counterfactual thinking is unsuccessful in reinstating confidence by finding a potentially better decision option from the existing set of options; and (b) satisficing, when satisficing is unsuccessful in finding a decision option that matches current conditions. In line with Kahneman and Tversky's (1982) work into how new hypothetical options can be created during the process of counterfactual thinking, this process of innovating involves an agent using the information learned during anticipatory learning and the prior period's decision to create a new decision option that includes the same antecedent(s), a new experience-based consequent, and a consequent-aligned set of new anticipated influences. A new experience-based consequent is generated using a generalized probability table that displays a power-law distribution. Once a new decision option is created, it is introduced into the respective mental (sub)model and made available for decision-making. The result of innovating is a new decision option.

Social learning follows: (a) goal prioritizing, when an agent after anticipatory learning is confident; (b) counterfactual thinking, if an agent's confidence is regained during counterfactual thinking; and (c) innovating, when an agent remained unconfident after counterfactual thinking. In line with Bandura (1977) and others (Festinger, 1942; Hertwig & Hoffrage, 2013; Hilgard et al., 1940; Taylor et al., 1984; Wheeler, 1966), the aim of social learning is to learn from social network neighbors, be they successful or unsuccessful. The process is activated regardless of whether the agent is confident or not. This is because both passive and active social learning are captured in the process. The process consists of the following two subprocesses: (a) review the decision options chosen by social network neighbors in the prior period and (b) incorporate into the corresponding mental (sub) model those options that had been unknown. The result of social learning is one or more new decision options.

The above-described process of social learning is followed by the decision-making processes, which are activated in the same sequence they were described in "First time period: only decision-making". Action-taking is always the last process of any iteration.

Summary. In summary, agents in models designed with the SOSIEL Platform can engage in five learning and four decision-making processes, which may result in some or all agents engaging in individual and/or collective actions. Initially, new information about a decision situation within which a SOSIEL agent needs/wants to make a decision is processed by anticipatory learning, which updates in the agent's respective mental (sub)model the anticipated influences on goals of the prior period's decision and through a comparison to prior period's anticipated influences updates the agent's state of confidence. Goal prioritizing, in turn, assesses the relative success with which the agent is achieving its goals and if necessary reprioritizes the agent's goals accordingly. If, as a result of the new information, the agent is not confident in its decision-making within a decision situation, it engages in counterfactual thinking, which checks whether knowing what is known now would have led in the prior period to the selection of a better decision option. If a better option was available, then the agent becomes confident and moves on to social learning. If one was not available, then the agent engages in innovating, which involves using the prior period's decision and new information to generate a new decision option and adding it to the respective mental (sub)model. After innovating, if confidence was lost and not regained after counterfactual thinking, or otherwise after goal prioritizing, the agent moves on to social learning, which involves learning unknown decision options from the neighbors of the social networks in which the agent is a member.

The process after social learning is goal selecting, which, with a degree of probability, uses (potentially re-prioritized) goal importance levels to generate a ranked list of goals to select a goal to focus on. Once the list of goals has been identified, from which goals can be selected for specific situations, an agent engages in satisficing by using the anticipated influences of decision options and information about the goal of focus to choose what it perceives as its best decision option. If a decision option that meets current context conditions does not exist in the respective mental (sub)model, the agent (re)engages in innovating. If one or more decision options that meet current context conditions exist, then the one or the best one is chosen randomly. If the decision option *is* a collective action, then the agent signals to other agents its interest in the collective action and waits to see if a sufficient number of agents are also interested. If a sufficient number are interested, the agent selects the collective action as its decision. If a sufficient number are not interested, the agent excludes the collective action as an option during the current time period and engages again in satisficing. As a result, the behavior of a SOSIEL agent may change from one period to another due to any one or a combination of the following six reasons:

1. The social, personal, and/or other (e.g. ecological) conditions have changed;
2. Anticipated influences of the prior period's decisions have changed;
3. Relative importance levels of goals have changed;
4. A newly-created decision option is preferred and selected over the previous;
5. A socially-learned decision option is preferred and selected over the previous; and/or
6. Due to size limitations on mental (sub)models, the addition of a newly-created or socially-learned decision into a mental (sub)model pushes out a previously-preferred and -selected decision.

The cognitive processes comprising the learning and decision-making of SOSIEL agents together produce reinforcement learning (Aarts & Dijksterhuis, 2000; Anderson, 1983; Butz, 2002; Kaelbling, Littman, & Moore, 1996; Newell & Rosenbloom, 1981; Stolzmann, 2000; Sutton & Barto, 1998), which is one of the most successful and widely-used techniques for representing learning and decision-making by artificial agents. From an evolutionary learning perspective, the decision-option-creating process of innovating is variety producing, while the homogenizing process of social learning and the (adjustable during initialization) size of a mental (sub)model are variety reducing. The interactions among the variety-producing and -reducing processes, as well as the influences from context-specific variables and other processes, exert natural-selection pressures on decision options for which mental (sub) models serve as niches within an ecosystem of agents.

Multi-agent

The SOSIEL Platform is a multi-agent system (Bonabeau, 2002; Jennings, 2000; Wooldridge, 1997) that can consist of one or a large number of SOSIEL agents, which may be organized into one or more agent types. Agents organized into a type share the same mental (sub) models and thereby goals, but not necessarily the same goal importance levels, decision options, or anticipations (Table 5). Three processes involving multi-agent interaction were described in the previous section, namely social learning, signaling interest in a collective action, and collective action-taking. These processes occur through a self-organizing and potentially multi-layered social network structure (Padgett & Powell, 2012).

The structure of a social network has been found to play a significant role in the willingness of social network members to act collectively (Carlsson & Sandström, 2008; Folke, Hahn, Olsson, & Norberg, 2005; Newig, Günther, & Pahl-Wostl, 2010; Olsson, Folke, & Berkes, 2004; Schneider, Scholz, Lubell, Mindruta, & Edwardsen, 2003) and both social network structure and collective action have been found to have significant influence on environmental decision-making and in turn environmental outcomes (Bodin & Prell, 2011). Which agents are participating in a collective action may change over time. A collective action will continue to persist as long as there is a sufficient number of interested participants and will cease if it has a term limit that expires and/or the conditions for one or more participants change and the collective action stops being the preferred choice of action for a sufficient number of agents (Gilbert, 2006; Ostrom, 2009).

Additionally, the SOSIEL Platform can be set to introduce demographic processes that, as a result of potentially adding, pairing, and/or removing agents (as in Pablo-Martí, Santos, & Kaszowska, 2015), also modify their potentially multi-layered social network structure. During initialization, the SOSIEL Platform takes as an input an (un)structured population of agents and can either introduce structure into it or develop the existing structure by applying to it a set of specific demographic processes (births, pairing, deaths), the pseudocode for which is provided in *The SOSIEL Platform 1.0 Pseudocode*.[7] The output is a population of agents with a self-organized social structure that is the emergent property resulting from the interactions among the specific characteristics of the agents, potentially any pre-existing social structure, and demographic processes. Parameterizing and initializing the demographic processes requires a set of population-level statistics (Table 7) and for the agents to possess the following attributes: (a) age, (b) sex, (c) household status, (d) pairing status, and, potentially (e) a set of social networks.

Fig. 2 depicts the relationship between a population of agents and its social structure and demographic processes, which change the population and its social structure during a time period by adding, pairing, and/or removing agents.

The demographic processes may be set to be activated during: (a) the initialization stage of a specific simulation and/or (b) a specific simulation in the following ways.

- During the initialization stage of a simulation, the demographic processes can be set to simulate for a preset number of iterations with the aim of generating a population-specific social network structure. The number of iterations required to produce a social network structure that reflects a population and its population dynamics processes depends primarily on the size of the population.
- During a specific simulation, the demographic processes can be used each time period to update the social location and status of agents.

In summary, agents in models built with the SOSIEL Platform can engage in social learning and, potentially, signaling interest in a collective action and collective action-taking. These processes occur through a self-organizing and potentially multi-layered social network structure. Additionally, the models can be set to introduce demographic processes that, as a result of adding, pairing, and/or removing agents, also modify their social network.

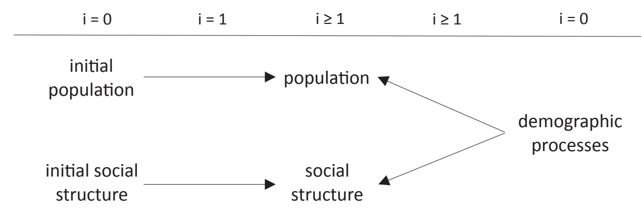

Fig. 2. The dynamic relationship between a population of agents and its social structure and demographic processes; "i" stands for iteration.

Process activation logic

During every time period of a simulation, the SOSIEL Platform updates the agents (and related variables) by activating a set of demographic and cognitive processes. The demographic processes are activated at the population level, affecting those agents that meet specific criteria, while the learning and decision-making processes are activated separately for each agent, starting with agents belonging to agent type one and progressing through agent types in an ascending order.

The platform activates the above-mentioned set of processes in subsets (Fig. 3), based on the need of some processes to have all agents of a specific type updated before the process can be activated. Each subset of cognitive processes is applied to one agent at a time, which is randomly selected (without replacement) from among the agents of the same type. In total, the population of agents is updated five times before agents take (simultaneous or subsequent) actions. Every activation of a subset of processes can be seen as an update to the population in preparation for subsequent subsets, with the last/final process being action-taking.

Below are descriptions of what occurs during each round of updating and, when applicable, an explanation for its place in the sequence:

- Activation of demographic processes, which have the potential to remove agents and are therefore activated before the cognitive processes in order to avoid unnecessary computation;
- Activation of individual learning processes are activated before the process of social learning in order to update the knowledge of agents before it is shared;
- Activation of the social learning process;
- Activation of the decision-making processes, which occurs after agents had the opportunity to engage in individual and social learning; and
- Reactivation of satisficing, in the case a collective-action-based decision option was chosen during step four and after agents had a chance to assess interest from others in the collective action.

The fourth and fifth rounds may need to simulate more than once whenever a collective action is selected but not pursued and the next best decision option is also a collective action. Also, the second round may reactivate if the process of satisficing during the fourth round is unable to find an option that meets conditions.

Example: co-evolution of mental models among socially learning agents

The aim of this section is to provide a simple example of a model built with the SOSIEL Platform and, in doing so, demonstrate the functioning of some of the platform's essential processes. With this aim in mind, the model selected was one that displays the co-evolution of mental models among socially learning agents. Specifically, the model demonstrates two of the SOSIEL Platform's essential processes, namely social learning and collective action. The model was initially built as

[7] https://www.sosiel.org/the-sosiel-toolkit/the-sosiel-platform

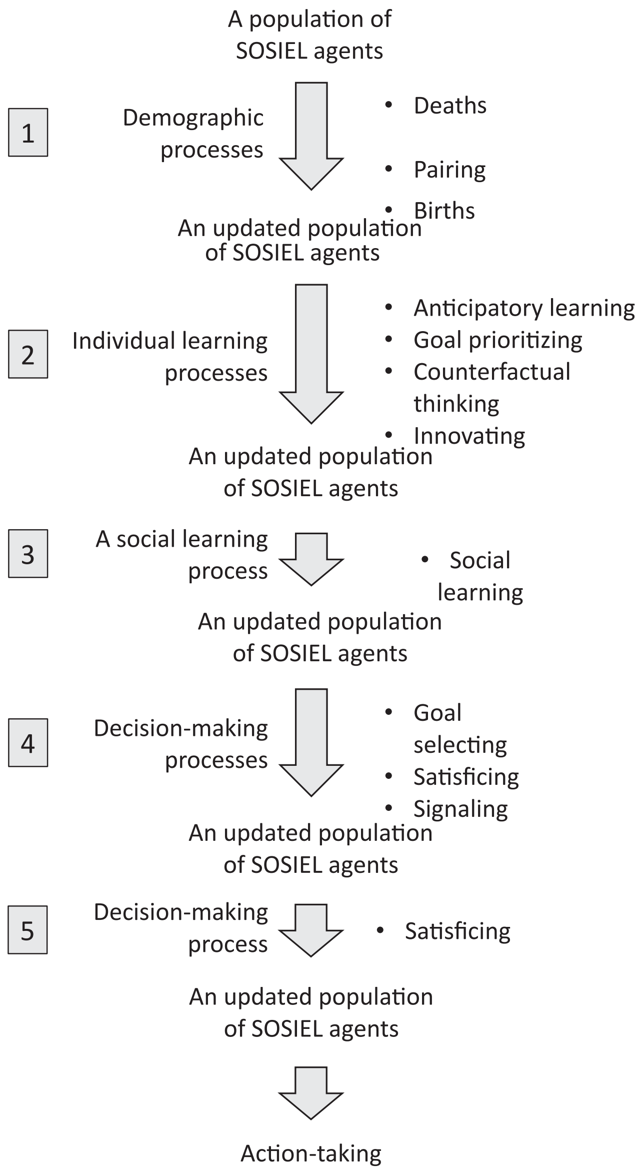

Fig. 3. The figure depicts how the SOSIEL Platform activates processes in subsets, updating the entire population in between rounds. In total, the population is updated five times per time period.

part of an ongoing study into human adaptation to climate change in a heavily forested valley in the Ukrainian Carpathian Mountains, called Bohdanska Dolyna (Sotnik, 2018). The study focuses on developing a decision support system that would simulate local co-evolutionary human-forest interactions and that could be used by local- and national-level decision-makers in planning sustainable development.

Interviews with local community leaders suggested that an important part of adapting to climate change in the area could be transitioning to new and more sustainable employment/income opportunities, such as engaging in green business. Related interviews with local community members further showed that: (a) not all households know how to engage in a green business, (b) most households only occasionally get to interact with other households engaging in a green business, and (c) engaging in a green business often requires the participation of more than one household member. To represent these context-specific characteristics, agent cognition in the model was set to include: (a) social learning, (b) satisficing, (c) signaling interest in a collective action, and (d) action-taking.

The other cognitive processes that are part of the SOSIEL cognitive architecture were excluded from agent cognition. The process of anticipatory learning was not activated because the income from the income sources was assumed to remain constant from period to period and therefore having the agents update their anticipated influences of the income sources was unnecessary. The processes of goal (re-)prioritizing and selecting were not activated because agents in the model are pursuing only one goal – increasing income – which makes the two processes unnecessary. And, lastly, the processes of counterfactual thinking and innovating were not activated because the aim of the model at the stage it was being designed and is being presented here was to simulate the process of starting a green business, as opposed to inventing a new income opportunity.

The model was designed to run for ten iterations (years) and simulates seven household members from two households making decisions about their income sources. The decision situation within which the agents make their decisions is defined by a set of income options (Table 2), while the agents are defined by a set of attributes (Table 3). Agent attributes also include: (a) their goal, which in this model is to increase income; and (b) for each income option in their mental model, its anticipated influence on the goal. However, these two attributes are left out of Table 3 because in this decision situation agents share the same goal and the anticipated influence on the goal equals the corresponding income (since income from income sources was assumed to remain constant).

In each iteration, every agent first engages in social learning, which involves incorporating into its mental model (of the decision situation) the prior period's decision options of its social network neighbors that were previously unknown to them. After social learning, an agent engages in satisficing, which first involves identifying in their mental model those income options that meet their current conditions (e.g. age, required savings) and then choosing the one that has the highest anticipated income. If the chosen income option *is not* a collective action (i.e. not requiring more than one participant), they decide to pursue it. If, however, the chosen option *is* a collective action, the agent signals interest in engaging in it to its household members and then waits until they have an opportunity to also signal interest. If a sufficient number of household members signal interest, they engage in a green business. Otherwise, they return to satisficing and explore their other income options. The only collective action in this model is engaging in a green business, which requires commitment from at least two household members.

As a result, agents adapt their behavior according to changes in their

Table 2
Income options and their attributes.

Income source	Annual income ($)	Age range	Gender	Disability status	Required savings ($)	Min. # of participants
1. Chores at home	0	age > 0	any	any	0	1
2. Forestry	39,600	18 ≤ age ≤ 60	male	no	0	1
3. Work abroad	192,000	18 ≤ age ≤ 60	male	no	0	1
4. Pension	21,600	age > 60	any	any	0	1
5. Disability comp.	21,600	18 ≤ age ≤ 60	any	yes	0	1
6. Green business	384,000	18 ≤ age ≤ 60	any	no	1,200,000	2
7. Picking mushrooms	6,000	8 ≤ age < 18	any	no	0	1

Table 3
Household members and their attributes. The “Initial decision options” column lists for each agent the decision options they have stored in their mental model at the beginning of the simulation. The listed numbers correspond to the numbering of decision options in Table 2. The “Other social relations” column lists for each agent the name of a social network that they are a member of (in addition being a member of their household).

HH	HH member	Age	Gender	Disability status	Initial decision options	Other social relations
H1	H1 M1	35	male	no	1, 2, 4, 5, 6, 7	none
	H1 M2	30	female	no	1, 2, 4, 5, 6, 7	church
	H1 M3	75	female	no	1, 2, 4, 5, 6, 7	none
H2	H2 M1	40	male	no	1, 2, 3, 4, 5, 7	none
	H2 M2	35	female	no	1, 2, 3, 4, 5, 7	church
	H2 M3	14	male	no	1, 7	none
	H2 M4	50	male	yes	1, 2, 3, 4, 5, 7	none

age, their knowledge, and the level of their household’s savings. As shown in Table 4, in Y2 (year two), H2 M2 (member 2 from household 2) learns (at church) from H1 M2 about green business as a potential income opportunity. However, since H2 does not have the savings necessary for starting a green business (the savings of H2 in Y2 is \$315,600 < \$1,200,000), its members cannot open a green business and therefore H2 M2 does not share the idea with its household members. In the meantime, H2 M3 learns from H2 M1 and H2 M2 about two new income opportunities, but does not choose them because his age does not meet the age required.

In Y5, H2 M3 becomes 18 years old and joins H2 M1 in working abroad. The new influx of higher income (from \$6000 to \$192,000) speeds up H2’s ability to reach the minimum for starting a green business. In Y6, H2 M2 notices that its household’s savings are now above the minimum for starting a family-owned green business (\$1,284,000 > \$1,200,000) and decides to both share the idea with its household members and signal interest in engaging in it. H2 M1 and H2 M3 notice the benefit in engaging in a green business and also express interest. After each sees that the idea has support from more than one household member, they agree to and subsequently start a green business collectively.

The model demonstrates the co-evolution of mental models through a complex relationship among factors influencing decision-making, which include access to knowledge and personal- and household-level constraints. Recognizing and analyzing these complex micro-level relationships has the potential of improving our understanding of context-specific social change and, in turn, our ability to design effective policies. The model served as a starting point for representing decision-making of local community members in the decision support system being built for Bohdanska Dolyna and was used with community leaders in the process of verifying some of the initial knowledge acquired from community members.

Discussion

The SOSIEL Platform contributes to research in the areas of multi-agent modeling and cognitive architectures. This section puts these contributions into context and briefly mentions future work.

Multi-agent modelers of artificial societies traditionally follow the KISS (Keep It Simple, Stupid) principle in designing models, which is partially a result of the multi-agent approach to modeling having its roots in cellular automatons (Greenberg & Hastings, 1978; Wolfram, 2002) and partially due to the challenges in analyzing model results that often include large sets of data (Axelrod, 1997). As a result, the knowledge and cognition of agents in multi-agent models have typically been relatively simple. For example, in Environmental Modelling &

Table 4
Variable states during each of the ten iterations, with the states that are discussed in the text in bold. The “# of dec. opts.” row lists the number of decision options in the agent’s mental model at the end of each iteration. The “Chosen dec. opt.” row lists the decision option the agent chose for action-taking during the corresponding iteration.

		Variables	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8	Y9	Y10
H1	H1 M1	Age	35	36	37	38	39	40	41	42	43	44
		# of dec. opts.	6	6	6	6	6	6	6	6	6	6
		Chosen dec. opt.	DO6	DO6	DO6	DO6	DO6	DO6	DO6	DO6	DO6	DO6
		Income	384,000	384,000	384,000	384,000	384,000	384,000	384,000	384,000	384,000	384,000
	H1 M2	Age	30	31	32	33	34	35	36	37	38	39
		# of dec. opts.	6	6	6	6	6	6	6	6	6	6
		Chosen dec. opt.	DO6	DO6	DO6	DO6	DO6	DO6	DO6	DO6	DO6	DO6
		Income	384,000	384,000	384,000	384,000	384,000	384,000	384,000	384,000	384,000	384,000
	H1 M3	Age	75	76	77	78	79	80	81	82	83	84
		# of dec. opts.	6	6	6	6	6	6	6	6	6	6
		Chosen dec. opt.	DO4	DO4	DO4	DO4	DO4	DO4	DO4	DO4	DO4	DO4
		Income	21,600	21,600	21,600	21,600	21,600	21,600	21,600	21,600	21,600	1,800
	H1 savings		1,200,000	1,965,600	2,731,200	3,496,800	4,262,400	5,028,000	5,793,600	6,559,200	7,324,800	8,090,400
H2	H2 M1	Age	40	41	42	43	44	45	46	47	48	49
		# of dec. opts.	6	6	6	6	6	**7**	7	7	7	7
		Chosen dec. opt.	DO3	DO3	DO3	DO3	DO3	**DO6**	DO6	DO6	DO6	DO6
		Income	192,000	192,000	192,000	192,000	192,000	**384,000**	384,000	384,000	384,000	384,000
	H2 M2	Age	35	36	37	38	39	40	41	42	43	44
		# of dec. opts.	6	**7**	7	7	7	7	7	7	7	7
		Chosen dec. opt.	DO1	DO1	DO1	DO1	DO1	**DO6**	DO6	DO6	DO6	DO6
		Income	0	0	0	0	0	**384,000**	384,000	384,000	384,000	384,000
	H2 M3	Age	14	15	16	17	18	19	20	21	22	23
		# of dec. opts.	2	**4**	4	4	4	**5**	5	5	5	5
		Chosen dec. opt.	DO7	DO7	DO7	DO7	**DO3**	**DO6**	DO6	DO6	DO6	DO6
		Income	6,000	6,000	6,000	6,000	**192,000**	**384,000**	384,000	384,000	384,000	384,000
	H2 M4	Age	50	51	52	53	54	55	56	57	58	59
		# of dec. opts.	6	6	6	6	6	**7**	7	7	7	7
		Chosen dec. opt.	DO5	DO5	DO5	DO5	DO5	DO5	DO5	DO5	DO5	DO5
		Income	21,600	21,600	21,600	21,600	21,600	21,600	21,600	21,600	21,600	21,600
	H2 savings		120,000	315,600	511,200	706,800	902,400	**1,284,000**	2,433,600	3,583,200	4,732,800	5,882,400

Software's (2013) Thematic Issue on Spatial Agent-Based Models for Socio-Ecological Systems, agent cognition either did not include learning (Smajgl & Bohensky, 2013; Sun & Müller, 2013) or was limited to imitation (Caillault et al., 2013).

More recently, the number of multi-agent models incorporating psychological features has been increasing (Jager, 2017), as has been interest among psychologists in applying multi-agent modeling (Conte & Giardini, 2016; Jackson, 2017; Jager & Ernst, 2017). The models with the highest degrees of cognitive sophistication among multi-agent models are what Jager (2017) referred to as integrative models. For example, Brousmiche, Kant, Sabouret, & Prenot-Guinard (2016) integrative model includes agents empowered with a rational and an emotional component and can simulate attitude formation, while Schröder and Wolf's (2017) model includes agents empowered with an artificial neural network and can simulate attitudinal diffusion and change.

The SOSIEL Platform contributes to the field of multi-agent modeling by empowering agents with a general theoretically-grounded cognitive architecture that consists of five learning processes, a memory structure, and four decision-making processes. The platform can simulate individual learning (including innovating), social learning, collective action, and decision-making, and thereby allows for more nuanced behavior results. It also allows for the study of the relationships between these cognitive processes and (a) cross-generational population dynamics, (b) self-organizing multi-layered social network structures, (c) evolving place-based knowledge, (d) decision-making, (e) collective action and its potential, and (f) social and (when coupled) ecological outcomes. The SOSIEL Platform also serves as a framework for those interested in integrating other cognitive architectures into multi-agent systems that allow for similar or other cognitive capabilities.

On the other hand, developers of cognitive architectures traditionally follow the KIDS (Keep It Descriptive, Stupid) principle in their design, which stems from their interest in the details of how the mind works. With the focus on internal cognitive processes, models with cognitive architectures are typically one-agent systems (Goertzel et al., 2010; Kotseruba & Tsotsos, 2018; Langley et al., 2009; Langley, 2017). There are, of course, exceptions to this rule, which include isolated applications of CLARION (Naveh & Sun, 2006; Sun & Naveh, 2004) and other cognitive architectures (Bhattacharyya and Ohlsson, 2010; Jarvis et al., 2006; Klein et al., 2010; Nye, 2014) in multi-agent contexts. The SOSIEL Platform contributes to the field of cognitive architectures by embedding agents with a cognitive architecture into social contexts that can include one or many other agents, one or more self-organizing layers of social network structure, exposure to demographic processes, and the possibility of collective action. The platform also serves as a framework for those interested in integrating a cognitive architecture into other multi-agent systems that allow for similar or other social properties.

Proponents of the KISS approach may argue that empowering agents in multi-agent models with a cognitive architecture increases the degrees of freedom in the model that make it more difficult to observe the essential drivers of a phenomenon of interest. However, research over the past several decades that now forms the foundations of behavioral economics (Camerer, 2003; Gintis, 2009) has shown unequivocally that the perfectly- or near-perfectly-rational agents in simple models often fail to represent human behavior. How sophisticated an artificial agent's knowledge and cognition needs to be in order to represent human behavior in relevant contexts is still poorly understood. However, improving our understanding requires delving into the complex relationship among human knowledge, cognition, and social interaction.

As pointed out by Castelfranchi (1998), one cannot understand what holds a group together without first understanding why each member is in the group. As demonstrated by Castelfranchi and other cognitive scientists (Conte & Castelfranchi, 1995; Jager, 2017; Sun, 2007), it is difficult if not impossible to understand some social behavior without understanding the involved cognitive processes of its members first. For social scientists, integrating higher levels of cognition into multi-agent models allows for the exploration of what occurs in the social context when cognitive parameters are varied (Hélie & Sun, 2015). Similarly, cognitive scientists can explore what changes on the cognitive level when social parameters are altered.

While the design of the SOSIEL Platform is based on the integration of prominent research from the behavioral (Anderson, 1983, 1993; Baron, 2008; Evans & Stanovich, 2013; Holland et al., 1986; Johnson-Laird, 2010; Kahneman & Miller, 1986; Kahneman & Tversky 1982; Laird, 2012), computer (Jennings, 2000; Negnevitsky, 2011; Wooldridge, 1997), and social (Bicchieri, 2006; Camerer, 2003; Gilbert, 2006; Hertwig & Hoffrage, 2013; Ostrom, 1998, 2000, 2009; Padgett & Powell, 2012; Spence, 1973) sciences, and models that were built with it have been verified in a number of social and social-ecological contexts (Sotnik, 2018), its success in producing models that can simulate representative human behavior in social contexts still needs further testing. Insight from such testing can then be used to further improve the SOSIEL Platform, the modular design of which permits for removal, modification, and/or addition of a process without significantly affecting the integrity of other processes. For example, the platform's process of innovating is currently designed to work in situations in which the consequents of decisions are numeric and involves finding a (higher or lower) number that better fits the current context. While there are many situations in which this form of innovating is effective (e.g. choosing the rate of resource use or the size of a group), future work will involve extending the process of innovating to other situation types.

Additionally, as described in the introduction to "Cognitive", the cognitive architecture utilized by SOSIEL agents remains fixed during a simulation, while the knowledge varies. However, it is likely the case that cognitive architectures can vary among individuals potentially as much as, if not more than, the decision situations they find themselves in. Furthermore, it is possible, if not likely, that architecture and knowledge coevolve through aging and exposure to intellectually encouraging and/or stiffening events. For example, as with knowledge, existing cognitive processes may also be modified and new ones may be learned or even created. Cognitive plasticity may be essential for the type of learning required by social-ecological DSSs. Therefore, future work will involve exploring ways in which the cognitive architecture utilized by SOSIEL agents can co-evolve with agent experience.

Conclusion

This article described the SOSIEL Platform and its knowledge-based, cognitive, and multi-agent characteristics. In terms of the platform's knowledge-based character, each SOSIEL agent can be empowered with its own system of knowledge, which consists of context specific variables and related metadata that are organized into conditional statements (which represent decision options) and auxiliary information. The approach to representing knowledge fits with the way norms can be represented in the study of common-pool resource management and the way decision-related heuristics are represented in the study of bounded rationality.

In terms of its cognitive character, the SOSIEL Platform includes one cognitive architecture, which consists of a memory component, a learning component, and a decision-making component. Each time period, the cognitive architecture is utilized by each agent to organize, update, modify, and utilize its knowledge in the process of learning and decision-making. The cognitive architecture's memory component organizes an agent's knowledge into mental models and related metadata, which correspond to decision situations in which the agent needs/wants to make a decision. The mental model concept is embedded within Ostrom's Social-Ecological System framework and is increasingly being implemented within the context of environmental cognition. The cognitive architecture's learning component consists of five

Table 5
It describes the context-specific and/or hypothetical knowledge and metadata required for parametrizing and initializing the SOSIEL Platform.

Name	Metadata	Definition	Description
Agent type(s)	Definition: A category for agents that share the same mental models and thereby goals, but not necessarily the same goal importance levels, decision options, or anticipations		
	Description: A word or a combination of words and/or numbers separated by "_"		
	Associated mental model(s)	The mental models that are associated with the agent type	A set of mental models
Social network(s)	Definition: A category for agents that interact with each other.		
	Description: A word or a combination of words and/or numbers separated by "_"		
Variable(s)	Definition: An attribute of an agent or a situation that is either individually known (e.g. income) or commonly known (e.g. market price)		
	Description: A word or a combination of words and/or numbers separated by "_"		
	Current state	Indicates the attribute's initial/current state	A real number
	Is cumulative	Indicates whether the attribute is cumulative	A binary (trues/false) setting
	Relationship with another variable	Indicates whether the attribute correlates positively or negatively with another attribute. This is relevant in the cases when one attribute is a consequent of a decision option and another is a goal	A binary (+/−) setting
	Probability table(s)	Establishes a relationship between potential states of a variable and corresponding probabilities	A table consists of two columns, one of potential states of a variable, while the other of corresponding probabilities. Probabilities are represented to the thousandth decimal point, (i.e., 0.001)
Goal(s)	Definition: A variable that represents an agent's desired state for a specific attribute		
	Description: A word or a combination of words and/or numbers separated by "_"		
	Reference variable	The variable that the goal is related to	A word or a combination of words and/or numbers separated by "_"
	Type	Indicates whether a goal is to: (a) maximize or (b) minimize a reference variable, manage it (c) above, (d) below, or (e) at a focal value, or (f) within an interval	A categorical setting
	Focal value(s)	The value(s) of the reference variable corresponding to goal type	A real number
Mental (sub)model(s)	Definition: A category for decision options that represent a decision situation.		
	Description: A word or a combination of words and/or numbers separated by "_"		
	Associated goals	Indicates which goals are associated with the decision situation	A set of goals
	Modifiable	Indicates whether the decision in the mental (sub)model can undergo innovation	A binary (yes/no) setting
	Max number of decisions	Indicates how many decisions the mental (sub)model can store	A whole number
Decision option(s)	Definition. A relationship between a set of conditions that is associated with a decision situation and a conclusion or action.		
	Description: A conditional (IF/THEN) statement		
	Mental model	The mental model a decision option is assigned to	The name of the mental model
	Antecedent(s)	A required condition for the decision to be considered as a potential option	An equation consisting of a variable and a specific state of that variable, separated by a mathematical operator
	Consequent	A conclusion or action	An equation consisting of the name of a variable and a specific state of that variable, separated by an equal sign
	Required number of participants	In the case the decision option is a collective action, indicates how many other agents from indicated social networks must also signal interest in the decision option for it to be actionable	A whole number
Action-taking	Definition: The process of action-taking by agents can be implemented simultaneously or sequentially		
	Description: A binary (simultaneously/sequentially) setting		

processes (anticipatory learning, goal prioritizing, counterfactual thinking, innovating, and social learning), while its decision-making component consists of four processes (goal selecting, satisficing, signaling interest in a collective action, and action-taking). In line with the dual-process theories of cognition, an agent may activate some or all of the five learning processes during a given time period, depending on how confident they feel within a decision situation.

Because there may be a need to explore different levels of cognition, models built with the SOSIEL Platform can be set to simulate agent behavior at one of four different cognitive levels, with each subsequent level including more of the cognitive processes. The cognitive processes comprising the learning and decision-making of SOSIEL agents together produce reinforcement learning, which is one of the most successful and widely-used techniques for representing learning and decision-making by artificial agents. The interactions among the variety-producing and -reducing processes, as well as the influences from context-specific variables and other processes, exert natural-selection pressures on decision options for which mental (sub)models serve as niches within an ecosystem of agents.

In terms of its multi-agent character, agents in models built with the SOSIEL Platform can engage in social learning and, potentially, signaling interest in a collective action and collective action-taking. These processes occur through a self-organizing and potentially multi-layered social network structure. Additionally, the models can be set to introduce demographic processes that, as a result of adding, pairing, and/or removing agents, also modify the social network.

As a result, models built with the SOSIEL Platform can simulate the cross-generational progression of one or a large number of boundedly-rational agents, which can interact among themselves and/or with coupled natural and/or technical systems, learn from their and each other's experience, create new practices, and make decisions about taking and then take (potentially collective) actions. The platform can also be used for conducting hypothetical experiments that are focused on studying the interactions among: (a) cross-generational population dynamics, (b) self-organizing multi-layered social network structures, (c) evolving place-based knowledge, (d) learning, (e) decision-making,

Table 6
It describes the information comprising an agent profile.

Name	Metadata	Definition	Description
ID	Definition: A way to differentiate an agent from others Description: A letter or a combination of letters and/or numbers, potentially separated by "_"		
Type ID	Definition: A way to differentiate agents of the same type from those of other types Description: A letter or a combination of letters and/or numbers, potentially separated by "_"		
Subtype ID	Definition: It is possible to initially define more than one agent with one agent profile. In such a case, this agent profile becomes an agent subtype Description: Either nothing or a letter or a combination of letters and/or numbers, potentially separated by "_"		
	Number of agents	The number of agents belonging to an agent subtype	A whole number
Social network(s)	Definition: The social network(s) that an agent is a member of Description: A set of social network names		
Variable(s)	Definition: An attribute of an agent or a situation that is individually known (e.g. income) Description: A word or a combination of words and/or numbers separated by "_"		
	Current state	Indicates the attribute's initial/current state	A real number
Goal(s)	Definition: Each agent has their own set of goals Description: A set of goals		
Importance level(s)	Definition: Each one of an agent's goals is assigned a relative agent-specific importance level Description: A constant from interval [0, 1], with the sum of all the importance levels of an agent's goals adding up to 1		
Mental model(s)	Definition: A component of the general cognitive architecture that relates to a situation Description: A set of mental model names		
Decision option(s)	Definition: The potential venues of action to be taken within a decision situation Description: A set of decision options		
	Anticipated influence on goal(s)	Indicates the influence the agent anticipates the decision will have on each of the goals it is associated with	A real number
Agent status	Definition: Determines whether an agent should be processed during a time period Description: A binary (active/inactive) state		

(f) collective action and its potential, and (g) social and (when coupled) ecological outcomes.

The SOSIEL Platform contributes to research in the areas of multi-agent modeling and cognitive architectures. For social scientists, integrating higher levels of cognition into multi-agent models allows for the exploration of what occurs in the social context when cognitive parameters are varied. Similarly, cognitive scientists can explore what takes place on the cognitive level when social parameters are altered. To date, the SOSIEL Platform was used to build models requiring different cognitive level settings, including as part of an ongoing study into human adaptation to climate change in the Ukrainian Carpathian Mountains (Sotnik, 2018).

While the design of the SOSIEL Platform is based on the integration of prominent research from the behavioral, computer, and social sciences, and models that were built with it have been verified in a number of social and social-ecological contexts, its success in producing models that can simulate representative human behavior in social contexts still needs further testing. Insight from such testing can then be used to further improve the platform, the modular design of which permits for removal, modification, and/or addition of a process without significantly affecting the integrity of other processes.

Table 7
It describes the context-specific and/or hypothetical population-level statistics that are required for parameterizing and initializing the three demographic processes modules.

Name	Definition	Description
Maximum age	Represents an agent's maximum possible age	A positive integer
Death probability	Represents an agent's age-varying probability of dying	A table consisting of two columns, one listing the potential states of the age variable and the other the corresponding probabilities of dying
Birth probability	Represents the age-varying probability of a pair of heterosexual agents having a baby	A table consisting of two columns, one listing the potential states of the average age variable and the other the corresponding probabilities of the pair having a baby
Adoption probability	Represents the age-varying probability of a pair of homosexual agents adopting	A table consisting of two columns, one listing the potential states of the average age variable and the other the corresponding probabilities of the pair adopting
Pairing probability	Represents the probability of two agents pairing	A constant from interval: [0, 1]
Sexual orientation rate	Represents the probability that a pair will be homosexual (female-female or male-male)	A constant from interval: [0, 1]
Homosexual type rate	Represents the probability that a homosexual pair will consist of two female agents	A constant from interval: [0, 1]
Pairing age interval	Represents the age within which agents can pair	Two constants, a min and a max, from interval: [0, max age]
Minimum age for household head	Represents the minimum age at which an agent can become the head of their household	A constant from interval: [0, max age]
Average number of years between births	Represents the average number of years that pass in between births	A constant from interval: [0, max age]

Software availability

- Name of software: The SOSIEL Platform
- Version: 1.0
- Developer: Garry Sotnik (1604 SW 10th Ave., Portland, OR 97201, 503.725.4975, gsotnik@pdx.edu)
- Year first available: 2018
- Software required: Windows OS, .Net Framework v4 or higher
- Availability: open-source (https://www.sosiel.org/the-sosiel-toolkit/the-sosiel-platform)
- Program language: C#
- Program size: 15.2 MB

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Appendix A. Supplementary data

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