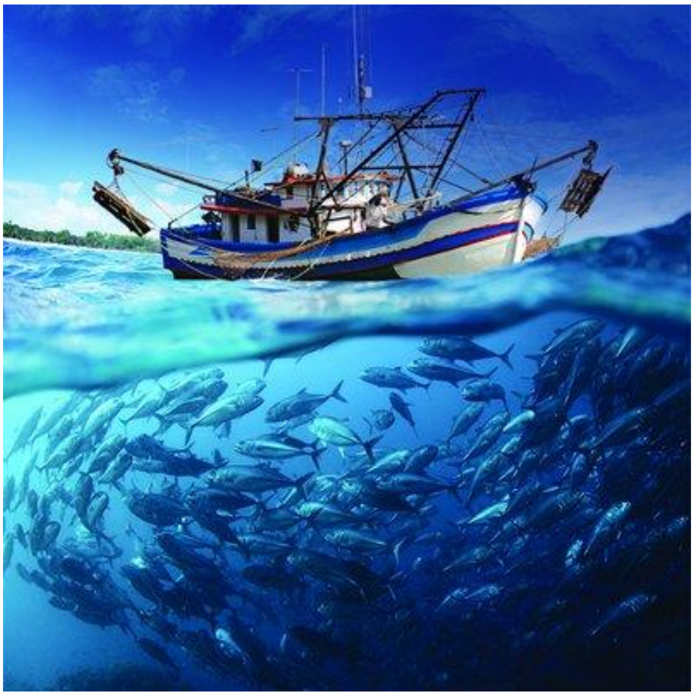

THE EFFECTS OF A COMMUNITY'S INFORMATION SHARING NETWORK ON THE SUSTAINABILITY OF NATURAL RESOURCES: AN AGENT-BASED SIMULATION.

ABSTRACT

As a result of overexploitation, natural resource communities are suffering from declining resource stocks. To avoid the tragedy of the commons, the majority of the actors in a natural resource community need to act cooperatively and extract sustainably. However, collective action is difficult to reach because actors face a social dilemma between extracting a sustainable manner (cooperation) and over extracting (free riding). In this thesis we used the computer simulation method agent-based modeling to demonstrate how changing the number of social ties affects social information and ecological knowledge sharing and thereby natural resource use. Receiving social information about other actors, can affect one's decision in a social dilemma, and actors need ecological knowledge to extract sustainably. We implemented an information sharing structure in a maintenance public good game to construct a simplification of a natural resource community. Our model demonstrated that increasing the social network density increases both types of information sharing. However, it also demonstrates that increasing the density of ties in a community has a contradicting effect on natural resource use. More information sharing impacts the collective ecological knowledge positively but can weaken collective action under certain circumstances. The last chapter of this thesis discusses the limitations and implications of our model results.

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1. Introduction

There is a growing awareness on how human behavior affects the world's natural resources, such as fish, wood, oil, and minerals (Soulé, 2020; Cockburn, 2021). People overexploit natural resources which results in declining resource stocks and eventually overexploitation (Soulé, 2020). A natural resource has been overexploited when people harvest until the resource stock cannot recover anymore (Nuwer, 2020). Overexploitation of a natural resource disturbs the local ecosystem, causes biodiversity loss, and affects the people whose income and wellbeing depend on the condition of the natural resource (Soulé, 2020). Actors in natural resource communities are an example of people who highly depend on their natural resources because they collectively manage the extraction process of local natural resources to generate an income or to provide for food (Fabricius, 2020). However, communities face difficulties sustaining local natural resources because actors who economically benefit from resource extraction impact the sustainability of natural resources, and their financial goal can result in overexploitation of natural resources. Overexploitation of local natural resources would have social and financial consequences for the community because resource extractors would become jobless and lose their source of income. Together with many more, local fishing communities in India suffer from the consequences of a strong decline in fish stocks (Gawade, 2021). Years of unsustainable fishing practices has caused biodiversity loss, which makes it difficult for the current fishermen to generate enough income to live. Because they need to generate income to survive, the local fishermen continue overexploiting the fishery, which will eventually result in the depletion of the natural resource. We need to understand the antecedents of natural resource use to be able to help such communities avoiding overexploitation of local resources and its consequences.

Communities that overexploit their natural resources often struggle to reach collective action, because resource extractors face the social dilemma in which they have to choose between extracting a sustainable manner to support the collective good and over extracting to increase their profits. An extractor receives a higher pay off when he over extract, independent of the actions of other extractors. Over extracting is a form of free riding, which is benefitting from a collective good without contributing to the maintenance of it. Free riding is the rational self-interested choice in a social dilemma because it gives the highest pay-off independent of the actions of other actors. However, the natural resource will be overexploited if no one contributes to the maintenance of it, resulting in the tragedy of the commons where eventually all parties are left in a worse position (Hardin, 1968). Communities need collective action to overcome the free riding problem and to maintain their natural resources, which means that extractors need to start cooperating by extracting sustainable instead of over extracting. Cooperation is a key element for solving collective dilemmas, and there are several mechanisms that can help establishing cooperation. Reputation is an important factor that can promote cooperation (Alexander, 1987), because free riding affects one's reputation negatively after which an actor can get socially punished. Actors can use cooperative behavior as a strategy to invest in their reputation and avoid those punishments (Milinski, 2016). This is referred to as the indirect reciprocity mechanism (Alexander, 1987; Nowak & Sigmund, 2005), where the "reputation threat" might stimulate cooperation and thereby sustainable resource use. However, Schill et al. (2016) demonstrated that besides cooperation, groups also need ecological knowledge to sustain natural resources. Local natural resources have unique characteristics which makes it important to understand how the resource stock responds to extraction behavior (Menzies, 2006). If actors in a community lack knowledge about the local natural resource, it may be difficult to avoid overexploitation.

Both reputational and ecological information can affect natural resource use, and both types of information can be shared through communication. Using a relational approach can be a valid way to study how interactions between resource extractors affect the sustainability of a community's natural resources. Isaac et al. (2007) observed that the diffusion of information in a natural resource community relies on the social relations between resource extractors, meaning that the social network structure could affect the diffusion of social and ecological information and thereby natural resource use (Bodin et al., 2006). Information about one's reputation reaches more actors in a community with more social ties due to social information sharing. In such a community an actor might want to invest in a positive reputation by cooperating, because there is a larger group that learns about his reputation and thus might reciprocate his behavior. Social relations also support the diffusion of ecological knowledge which can positively affect natural resource use, because more actors have access to local ecological knowledge. However, simulation studies demonstrate that communities with a high number of social relationships face the threat of homogenization of knowledge (Bodin & Norberg, 2005), which means that information sharing can promote a consensus about natural resource use, inducing people to behave alike. This impacts natural resource use positively when this consensus is sustainable, but it affects resource use negatively when the normative knowledge is not sustainable.

Even though the diffusion of both social and ecological information affects natural resource use, they have not yet been studied in combination. Changing the social network density could have a contradicting effect on the sustainability of natural resources, because it affects both social and ecological information sharing. We used agent-based modeling to demonstrate how changing the social network density could affect natural resource use under certain assumptions/conditions. Understanding how changes in the social network density affect sustainability can support the development of social network interventions in natural resource communities. We implemented an information sharing structure to analyze how the diffusion of ecological and social information affect natural resource use in the same context. Theorizing about possible contradicting effects can help generate new testable hypothesis and give insights into social network interventions in natural resource communities. This leads to the following research question:

Under what social network density conditions can we expect sustainable behavior in natural resource communities given by the diffusion of ecological and reputational information? In other words, how could changing the density of social ties affect the spread of ecological and reputational information and how could this affect sustainable behavior in natural resource communities?

2. Theoretical background

In this chapter we give the theoretical background of the model by discussing literature regarding important factors in natural resource communities and sustainability. Firstly, we discuss literature regarding cooperation in social dilemmas and give a description of our research model. Next, we give literature regarding two key factors of the model: Reputation and ecological knowledge. We discuss how reputation affects cooperation and thereby natural resource use and the role of ecological knowledge in natural resource communities. Finally, we will discuss the role of social networks in natural resource communities, and how the social network density could affect the diffusion of social and ecological information, and thereby the sustainability of natural resources.

2.1. Cooperation in social dilemmas

Cooperation is needed for natural resource communities to sustain their natural resources and is therefore an important concept in this thesis. Actors in a natural resource community face a social dilemma in which they have to decide between cooperating and free riding. A social dilemma is a situation in which a group would be better off if all actors cooperated, but because individual interests discourage cooperation, it is the rational choice to free ride (van Lange et al., 2013). In natural resource communities, actors have to decide between extracting a sustainable manner and over extracting. Extracting sustainably represents the cooperative option, because an actor would contribute to the maintenance of the collective good, whereas over extracting represents free riding behavior, because an actor does not contribute to the maintenance of the collective good. Table 1 shows a matrix of the simplified scenarios for a resource extractor. Over extracting is the dominant choice, because it gives the highest pay off independent of the actions of other agents. On aggregate this independent decision making results in the tragedy of the commons (Hardin, 1968), because no one contributes to the maintenance of the natural resource.

Table 1

The four scenarios in a social dilemma for natural resource extraction.

	Extractor A cooperates	**Extractor A free rides**
Other actors cooperate	Lower profits + sustaining the natural resource	Higher profits + sustaining the natural resource
Other actors free ride	Lower profits + depletion of the natural resource	Higher profits + depletion of the resource

Cooperation is needed for groups to succeed in their jobs or goals and therefore researchers have been studying why and under which circumstances people act cooperative (Fischbacher et al., 2001; Gächter, 2007; van Lange et al., 2013; Wittek & Bekkers, 2015). Cooperation is a form of prosocial behavior, which is behavior from which others benefit. An explanation for cooperative behavior is that people have social preferences they consider in a social dilemma (Fehr & Fischbacher, 2002; Wittek et al., 2013), because they have inequality aversion (Herreiner & Puppe, 2010), or because they experience positive emotions when they help other actors (Aknin et al., 2013). Reciprocity is another explanation for cooperative behavior (Nowak, 2006), which means that an actor acts cooperatively so his effort may be rewarded in a later encounter. Indirect reciprocity is when an actor cooperates to invest in his reputation (Milinski, 2016), after which a third party who observes/learns about one's behavior might reward the cooperative effort. In this thesis we studied how reputation affects cooperation in natural resource communities.

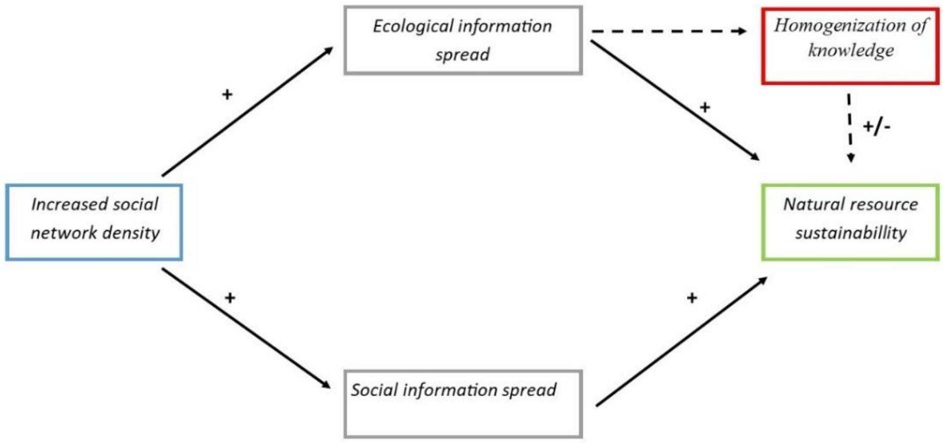

Figure 1: Research model

2.2. The research model

Firstly, we included reputation in our model because studies have shown that reputation affects cooperation, which is needed to sustain natural resources (Alexander, 1987; Nowak & Sigmund, 2005; Ostrom, 2000; Milinski, 2016). Secondly, we included ecological knowledge in this thesis, because actors in natural resource communities need to understand how the natural resource stocks responds to extraction so they can deal with the uniqueness and complexity of natural resources (Menzies, 2006; Schill et al., 2016). We studied how changing the social network density affects the diffusion of both types of information and how that affects natural resource use. People share information with their social relationships (Abrahamson & Rosenkopf, 1997; Isaac et al., 2007), meaning that in communities with more social relationships there is more information sharing. Figure 1 visualizes the research model of this thesis.

2.3. The effect of reputation on natural resource sustainability

Reputation can promote cooperation in several ways and could therefore be an important factor in reaching collective action and maintaining natural resources. Reciprocity and social information sharing are two mechanism that can stimulate cooperation (Milinski, 2016; Nowak, 2006). Direct reciprocity facilitates cooperation when two actors encounter each other multiple times (Nowak, 2006), because a cooperative effort might be rewarded during a future encounter. Indirect reciprocity promotes cooperation when actors do not encounter each other repetitive times. According to indirect reciprocity theory (Alexander, 1987; Nowak & Sigmund, 2005), when one's actions are observable, cooperation can be seen as an investment in a positive reputation. This "reputation threat" might support cooperation by discouraging free riders and rewarding cooperators. When others observe one's behavior in a natural resource community, extracting sustainably could affect his reputation positively, whereas over extracting would affect his reputation negatively. People consider the effects of their actions on their reputation because one's reputation can have implications during future interactions (Milinski, 2016). People with a positive reputation are more likely to receive help than people with a negative one (Nowak, 2006), whereas people with a negative reputation also risk being (socially) punished. An actor might receive a direct higher pay off by over extracting, but he could experience negative consequences of his decision later. The observability of an actor's behavior affects his decision in a social dilemma because the more people learn about his behavior, the more people could reciprocate his free riding behavior. In an environment where one's action are not observable at all, free riding is more profitable, because there are not actors to punish him for it.

Secondly, the reputation of others can also affect an actor's decision in a social dilemma. Kim et al. (2019) showed that people are more likely to cooperate when they believe that their partners will cooperate as well. People who are willing to cooperate when others cooperate as well are conditional cooperators (Rustagi et al., 2010). Conditional cooperators estimate whether their partner will cooperate or defect, which can be based on the reputation of his partner (Gächter, 2007). A conditional cooperator in a natural resource community is most likely to extract sustainably when he estimates that other actors in the community are extracting sustainably as well. He might be triggered to defect if he estimates that other actors are over extracting (de Olivera et al., 2015), because being the only one who extracts sustainably would give him the lowest pay off, while the natural resource gets depleted either way. The more conditional cooperators there are in a community, the more likely a norm of cooperation will be developed (Rustagi et al., 2010). Reputational information is obtained directly through observing one's past behavior, whereas indirect information is gained through information sharing. People can receive social information through gossip (Wu et al., 2016), which occurs when at least two actors evaluate about a third party, without the last mentioned being present (Emler, 1990). Gossip could promote cooperation because cooperation would affect one’s reputation positively, while free riding would spread one’s negative reputation (Giardini & Wittek, 2019).

2.4. Ecological knowledge

Simulations of a behavioral game in which agents extract from an abstract natural resource demonstrated that a group requires ecological knowledge to maintain the natural resource (Schill et al., 2016). Schill et al. modeled ecological knowledge as an estimation of how much they could sustainably extract. Actors could have difficulties with sustaining their natural resources if they do not understand the dynamics between extraction behavior and local resources. Natural resources are unique due to their characteristics, but also because of the ecosystem they are a part of (Menzies, 2006). General knowledge might not be sufficient to sustain natural resources because a fishery at the coast of Denmark might respond differently to certain extraction rates than the fishery somewhere else. Ecological knowledge can be defined as the perceptions that actors have about the local ecosystem, which consists of effective extraction practices, an understanding of how the natural resource functions, and shared norms and rules about resource use (Bettina, 2018). Understanding the dynamics of local natural resources goes paired with understanding the risks of exploitation, which can facilitate natural resource use by raising awareness and knowledge about how to extract sustainably. Actors gain ecological knowledge by observing how their behavior affects the natural resource (Laxman et al., 2004), but due to the complexity of ecosystems, it takes a considerable amount of experience to understand the dynamics between human behavior and a local natural resource. However, actors can also gain ecological knowledge through information sharing. Isaac et al. (2007) identified an ecological information sharing structure in natural resource communities, in which actors regularly shared information regarding the natural resource with the people close to them. Ecological information sharing could give actors access to knowledge that can be valuable for sustaining natural resources. Turner et al. (2014) studied how ecological information sharing in fishing communities affected resource sustainability. He found that communities with ecological information sharing were better able to sustain their fishery than communities without knowledge sharing. Ecological knowledge sharing has two advantages: it can increase awareness of the risk of overexploitation, and actors learn how to extract natural resources sustainably. In this thesis we focused on ecological knowledge sharing in general instead of focusing on a specific natural resource. Natural resources are unique and often ask for specific knowledge, which means that generating knowledge on the local resource through experience or information sharing is relevant for all natural resources.

2.5. Social networks

A social network exists out of actors and ties. Actors are the study objects (resource extractors), and the ties are the (social) relations between the study objects. Social network studies measure a specific type of social relationship between actors to create an overview of how a group is socially structured (Robins, 2015). In groups there is no equal communication between all actors, but people are likely to communicate more regularly with people close to them (Isaac et al., 2007). Social networks are a useful tool to study cooperation problems, because through the implementation of a social network we can create an image of communities by spatially dividing the actors and by analyzing differences between actors in different network positions. With social networks we can link social network positions or social relationships to cooperative behavior. One's social relations can affect cooperative behavior (Sommerfeld et al., 2007) and without a relational approach, we would miss out on important factors that can stimulate cooperation like reciprocity, indirect reciprocity, network embeddedness, and gossip (Alexander, 1987; Giardini & Wittek, 2019; Nowak, 2006; Sommerfeld et al., 2007). We needed to implement a social network structure in our model to study how social and ecological information sharing is affected by the social network density. The amount of information sharing depends on the number of social relations in a group. A measurement of the number of social ties is social density, which is the total number of ties in the network divided by the possible number of ties in the network.

2.5.1. The diffusion of social information

Studies show that groups with a high social network density are more likely to reach collective action (Croson & Bolton, 2012; Fowler & Christakis, 2010), because an increased number of social ties supports the diffusion of social information which can promote cooperation (Abrahamson & Rosenkopf, 1997; Skyrms & Pemantle, 2000). The more social information sharing, the more people will become aware of an actor's past actions, which creates an environment in which free riding strongly affects an actor's reputation. In an environment with much social information sharing, one might try to avoid a poor reputation by cooperating (Gallo & Yan, 2015; Raub & Weesie, 1990; Sommerfeld et al., 2007). Cooperation could be used as an investment in one's reputation, as this might be more profitable than free riding and receiving social punishments. Increased social information sharing can also impact conditional cooperators positively. Actors base their decision on available information about their partners, but this information is often incomplete (Flache, 2020). Social information sharing increases the accuracy of an actor's estimation of who are cooperators and who are free riders, which could lower uncertainty and facilitate cooperation. However, this could also trigger conditional cooperators to free ride (Hartig et al., 2015). If a conditional cooperator receives information about the free riding behavior of other actors, he could get demotivated to cooperate and start to free ride as well (de Olivera et al., 2015). Even if increased network density can make free riding easier to detect, it can also have detrimental effects on cooperation, by inducing more individuals to become free riders.

The effects of social network density on collective action have also been studied in natural resource communities, showing that denser networks do not necessarily prevent overexploitation (Barnes-Mauthe et al., 2013; Bodin & Crona, 2008). A fishing community in Hawaii could not reach collective action because a consensus about fishing regulations could not be reached (Barnes-Mauthe et al., 2013). The community was divided in subgroups based on ethnicity with each their own ideologies about fisheries. Fishermen from different subgroups were prejudiced against each other and there was little space for cooperation. A fishing community in Kenya with a high density of social ties was not able to sustain the local fishery either (Bodin & Crona, 2008), because even if the community implemented fishing limitations to avoid complete depletion of the fishery, the fishermen did not comply with the rules. Researchers observed that fishermen shared much social information with each other, but this did not facilitate sustainable natural resource use. Apparently, the fishermen were not aware of the urgent risks of over extraction and in their opinion reporting rule breaking was more blameworthy behavior than breaking the rules. This is an example in which social cohesiveness fails to sustain collective action. Flache and Macy (1996) constructed a model of social control that demonstrated that strong ties can hinder collective action. The approval of strong interpersonal relationships can cause a second order free rider problem, which is the dilemma for cooperators between taking the cost of punishing a free rider or ignoring the rule breaking. The cohesiveness of the fishery village created an environment in which fishermen did not dare to report rule breaking, because they thought that reporting would be received negatively by other fishermen and thus would affect their reputation negatively. This gave other fishermen the opportunity to continue over extracting without any punishment. In this fishing community the high social network density activated the indirect reciprocity mechanism, which in theory would have supported cooperation and reduced overexploitation, but the data shows that it stimulated a different kind of behavior which was not compatible with natural resource sustainability. These findings show how social mechanisms function depending on the social context (Pawson & Tilley, 1997) and how they generate different outcomes. Communities characterized by a high density of social ties can stimulate the normative behavior, but it depends on the norm whether this is effective in achieving natural resource sustainability.

2.5.2. The diffusion of ecological information

Model simulation demonstrated with the implementation of information sharing networks that increasing the network density supports the diffusion of ecological information (Abrahamson & Rosenkopf, 1997; Bodin & Norberg, 2005). In communities with a high social network density, more people have access to ecological knowledge, as people share ecological experiences and knowledge with their social relations (Isaac et al., 2007). However, high density networks pose the risk of increasing homogeneity of knowledge (Abrahamson & Rosenkopf, 1997; Bodin & Norberg, 2005; Little & McDonald, 2007). When there is regular interaction regarding natural resource use, people tend to adapt to the normative behavior in the group, after which communities can reach a consensus on natural resource use. This consensus can support natural resource use, but in cases of incorrect knowledge, the homogenization of knowledge could be problematic. Bodin and Norberg (2005) modeled ecological knowledge as an understanding of how extraction rates affected the natural resource, which could develop through experience and by receiving information from others. The model demonstrates that actors will also form their ideas about natural resource use when they did not receive ecological information from others. This means that in a network with a low density of ties, there is more variation in ideas of resource use. Heterogeneity of knowledge supports dealing with problems in a creative and innovative way but could also mean that a part of the community is not extracting sustainably because they lack the relevant knowledge. In contrast, communities with a high-density of social ties have less variation in ideas about resource use because there is more ecological information sharing (Abrahamson & Rosenkopf, 1997). The ecological information sharing model demonstrated that once high-density networks are in an unsustainable state, they have difficulties to recover from this (Bodin & Norberg, 2005). Turner et al. (2014) studied fishing communities in the United Kingdom and found that information sharing is beneficial for natural resource use, but that there was indeed little variation of knowledge in high-density networks. Inaction in the fishing community in Kenya was also partly caused by a consensus about a fishery that was not sustainable (Bodin & Crona, 2008). Finding a balance between connectivity that provides people with ecological knowledge and the risk of complete homogenization is a challenge that is important to address (Bodin et al., 2006; Turner et al., 2014). It is necessary to study the combined effects of social and ecological information sharing on the sustainability of natural resources. We used a combination of agent-based modeling and behavioral experiments to study under what social network conditions we can expect sustainable behavior in natural resource communities given by the diffusion of ecological and reputational information. In other words, how could changing the density of social ties affect the spread of ecological and reputational information, and how could this affect sustainable behavior in natural resource communities?

3. How sustainability in complex systems can be studied

Natural resource communities are complex social systems because the ideologies of actors about natural resource use can change over time due to social interactions. The behavior of actors in a social dilemma can be affected by interaction (Gächter, 2007), and actors can gain ecological knowledge through communication (Isaac et al., 2007). To understand such complex systems, we need to capture stochasticity so we can analyze how behavior and characteristics develop over time. Behavioral experiments and agent-based modeling are two methodologies that capture stochasticity and are often used to study complex social systems (Bodin & Norberg, 2005; Gallo & Yan, 2015; Kim et al., 2019). We combined those two methods to study social dilemmas and the diffusion of ecological knowledge in natural resource communities. Before we go into the description of the model, we explain how behavioral experiments and agent-based modeling can be used to study complex systems.

3.1. Behavioral experiments

Social dilemmas are often studied with behavioral experiments (Gallo & Yan, 2015; Kim et al., 2019), in which participants interact in a structured way. Like AgentEx (Schill et al., 2016), our simulation model represents a behavioral experiment where agents face a social dilemma: To cooperate or to free ride for multiple rounds. Behavioral games represent stylized interactions, and therefore they lack the contextual richness of field studies, but at the same time they make it possible to study single decisions performed by self-interested players. Different types of public good games have been studied in sociology to understand how certain incentives can stimulate cooperative behavior (Ostrom, 2000; Sonnemans et al., 1996; Tomassini & Antonioni, 2020; van Dijk et al., 2002). In a basic public good game, the participants have a number of tokens. They have to decide whether they put their tokens in the public pot (cooperating) or keep it for themselves (free riding). After everyone made their decision, the tokens that have been put in the public pot will be doubled and divided over all players. If everyone would cooperate, the public pot will have the maximum number of tokens, resulting in the best possible collective pay off. However, keeping your tokens and profiting from the public good gives the higher individual profit independent of what the others decide. On aggregate, this independent decision-making results in the lowest pay off for the group. Our experimental simulation differs from the classic public good game because it is an abstract representation of a natural resource community, meaning that the agents do not provide the public good, but instead must maintain it. Gächter et al. (2017) showed that maintaining a public good is often more difficult than providing a public good, because not contributing to the public good is often perceived more blameworthy than overexploiting something (Cubbit et al., 2011). Not contributing might have a bigger impact on an actor's reputation, which increases the threshold to free ride.

There are, however, incentives like sanctioning, face-to-face communication, and reciprocity that stimulate participants to show cooperative behavior (Nowak, 2006; Ostrom, 2000; Yamagishi, 1986). Researchers implement different incentives in public good games to understand under which circumstances cooperative behavior appears. A possible extension of the public good game is the implementation of social ties among participants (Tomassini & Antonioni, 2020). After participants interacted with others, they form social ties (van Dijk et al., 2002). The nature of this social relationship can affect an actor's decision-making in a social dilemma when he meets this person again. A social tie with a positive memory can stimulate cooperative behavior, while a negative memory can stimulate free riding

3.2. Agent-based modeling

To study how changing the social network density of a community affects natural resource use, we used agent-based modeling to construct and simulate a maintenance public good game. Agent-based modeling is a computer simulation method, which is used as a stylized and highly abstract representation of the real world (Squazzoni, 2012). Agent-based models usually contain a group of agents, i.e., entities representing individuals, animals, organizations, but in this study, they represent people playing a maintenance public good game. During the simulation, agents interact with other agents, and make decisions based on set behavioral rules. Agents are autonomous entities designed to behave according to certain rules implemented in the model. Agents can have different characteristics and are able to learn during the simulation. Agent-based models are useful because they are stochastic, and heterogeneity in groups of agents can be modeled. Agent-based modeling is used in sociology to study complex social systems (Squazzoni, 2012) in which the aggregated behavior at the macro-level, which is the main focus of the discipline (de Graaf & Wiertz, 2019), cannot be analytically disentangled because the link from micro to macro level is more complex due to interdependence between study objects (Ornstein & Hammond, 2021). Macy & Flache (2009) showed that if study objects are not independent, linear regression of individual characteristics on behavioral outcomes could suggest misleading explanations, because the role of mutual social influence between interdependent individuals is neglected. With agent-based modeling we explored how certain mechanisms affect human behavior over time. For this thesis, agent-based modeling was needed to theorize about the complexity of natural resource communities. Whether a community is able to sustain their natural resources is not simply an aggregation of the behavior of its individuals. Indeed, it is a complex social system due to interdependence between resource extractors and heterogeneity in characteristics.

The theory and the model in this thesis have been inspired by AgentEx (Schill et al., 2016). In this study Schill et al. analyzed behavior experiments, based their agent-based model on those experiments, and simulated different scenarios based on the results. The original AgentEx was developed to explain the behavioral patterns shown by participants in behavioral experiments. More specifically, an explanation was developed and tested elaborating the conditions under which cooperative groups can over or underexploit the shared resource. Each time step in the model reflects an experimental round in which agents may communicate and form an agreement about extraction, extract the resource, and be confronted with the actual level of the new resource. Within the model agents could learn to extract sustainably by reflecting on the dynamics between extraction behavior and a renewable resource. The conditions of initial knowledge about the resource dynamics (ecological knowledge) differed per scenario to demonstrate the importance of initial ecological knowledge in sustaining natural resources.

The interdependency between study objects in natural resource communities makes studying the social mechanisms complex, which means that we need a simplification to understand how social and ecological information sharing affect natural resource use. With agent-based modeling, we created a simplified abstract world, where we focus on the two information sharing mechanisms. This gave us the opportunity to theorize about the effects of social network density on the behavior of resource extractors. Gaining a better understanding of those mechanisms can help us shape social network interventions to avoid depletion of natural resources. For this study, the program Netlogo has been used to construct a simulation of resource extractors playing a maintenance public good game. Netlogo is a multi-agent programmable modeling environment which is used by many researchers (https://ccl.northwestern.edu/netlogo/). Netlogo is used to simulate natural and social phenomena. It is particularly well suited for modeling complex systems which develop over time (Wilensky, 2021).

4. Model description

We used the ODD protocol to give a clear description of the model. The ODD protocol is often used for agent-based model descriptions and divides it in three sections: overview, design principles, and details (Grimm et al., 2006). The overview and detail section can be found in this chapter, and the design principles section can be found in the appendix.

4.1. Overview

4.1.1. Purpose

The goal of this agent-based model was to study how changes in the social network density in natural resource communities could affect the spread of social and ecological information, and thereby natural resource use. We designed a group of agents that played a maintenance public good game and analyzed how the agents behaved on different network densities. We aimed to improve our understanding of the role of a community's social network density in natural resource use by implementing both information sharing mechanisms in one model.

4.1.2. Entities, state, and variables and scales

The model consists of a group of 80 agents that play a maintenance public good game in which they collectively have to manage an abstract natural resource. Agents have attributes that affect their decision-making, also presented in table 2. Firstly, agents are characterized by a binary attribute that determines whether an agent is a conditional cooperator or a free rider. We chose to use those two types of agents because behavioral experiments showed that not all actors are completely self-interested (Fehr & Gintis, 2007; Gächter, 2007). They observed that beside the self-interested actors, some participants also showed cooperative behavior if they estimated that their partners would cooperate as well. Even though we generalized the types of actors, the difference between actors is expected to be more nuanced in reality. However, we decided to implement two types of agents in the model to avoid that the complexity of different types of actors would distract from the purposes of the model. Secondly, agents have a reputational memory of the behavior of other agents, which can develop over time due to social interactions. A conditional cooperator calculates the sum of the reputational information about his partners, and he does not cooperate if this memory is negative. Positive reputational information about a partner is counted as plus one, negative reputational information is counted as minus one, and no reputational information is neutral. The conditional cooperators will cooperate when the sum of the information about its partners is above 0 (e.g., the sum of two cooperators and one free rider would be one, which means that a conditional cooperator would cooperate). We choose a relatively forgiving conditional cooperating rule to reflect some degree of leniency in cooperation strategies. Kollock (1993) demonstrated with his behavioral game model that more lenient strategies outperform restrictive strategies, because if a conditional cooperator uses a restrictive strategy, he will choose defection when observing the slightest disturbance. More flexible strategies are needed to sustain cooperation, because they leave room for errors and external factors. Finally, agents have individual ecological knowledge that is used to form a sustainable extraction. This variable can develop over time, as agents are able to update their individual ecological knowledge by reflecting on the natural resource stock after extraction, and by receiving ecological information from other agents.

Each round agents are placed in groups of four. They combine their individual knowledge with the individual knowledge of their group members to form a collective group knowledge. Agents extract from the natural resource stock based on the group knowledge. The natural resource stock regrows after the extraction process with a logistic growth function, meaning that the sustainability of the natural resource stock depends on how much the agents extract. If the natural resource stock is at 0, it cannot regrow anymore, which means that the natural resource has been depleted. The agents have social ties that connect them to other agents, and they use those social ties to share social and ecological information with other agents.

Table 2

State variables and scales

Variables	Variables	Description	Range
Agent attributes	Individual knowledge	Agents have initial knowledge about the natural resource dynamics. A value of five is the lower bound and represents the strongest over extraction. 34 is the upper bound and represent the strongest under extraction. The number represents an estimation of a sustainable stock after the group extraction. A value of 5 means that the agent estimates that his group should extract until a partial resource stock of five units to gain the maximum sustainable profit.	*5 - 34*
	Prosocial preferences	Agents with prosocial preferences are conditional cooperators, agents without prosocial preferences are free riders.	*Prosocial preferences (1) no prosocial preferences (0)*

	Reputational memory	Agents memorize past interactions with other agents. There are three possible memories: no memory (0), a negative memory (-1), and a positive memory (1). This memory affects the decision-making process of agents. Conditional cooperators calculate the sum of their reputational memory about their group members. If the sum is above 0, they cooperate, if the sum is below 0, they defect (e.g., one negative + one positive + one positive = 1, which means that the conditional cooperator cooperates).	*-1, 0, 1*
	Social ties	Agents can have social ties that connect them to other agents. Agents can share social and ecological information through ties with other agents.	*Tie (1), no tie (0)*
Collective variables	Density	The density represents the total number of social ties divided by the total of possible social ties in the group. In this model we ran simulations on six density levels.	*0, 0.025, 0.05, 0.1, 0.2, 0.4*
	Natural resource stock	Agents collectively extract from the natural resource stock. When the natural resource stock is 0, the agents overexploited the natural resource.	*0 - 680*
	Partial resource stock	Each round the natural resource stock will be equally divided over the 20 groups. Agents extract from the partial stock that belongs to their group. At the end of the round the sum of all partial stocks forms the natural resource stock.	*0 - 34*
	Group knowledge	The group knowledge is the average of agent's individual knowledge within the group.	*5-34*

4.1.3. Process overview and scheduling

Figure 2 visualizes the ten steps of the simulation cycle. Firstly, the agents will be divided in groups of four. Each group gets an equal share of the current natural resource stock and with this partial stock each group plays the maintenance public good game. When a new cycle starts, agents will be placed in new randomized groups. Secondly, the agents form a collective group knowledge, which is the average individual knowledge in the group. The group extraction is the partial natural resource stock minus the group knowledge and the agreed-on extraction is the group extraction divided by four. Agents also create an individual extraction, which is the group extraction divided by three. In step four, agents decide between the group extraction (cooperation) and their individual extraction (free riding). Agents base this decision on their prosocial preferences and the social information they have about their group members. The decision making process has been visualized in figure 3. In step five agents extract from the partial resource stock that belongs to their group, and in step six they observe the behavior of their group members. Agents create a negative memory of a group member that defected and a positive memory of group members that cooperated. In step seven agents share those observations with other agents through their social ties, after which the receiving

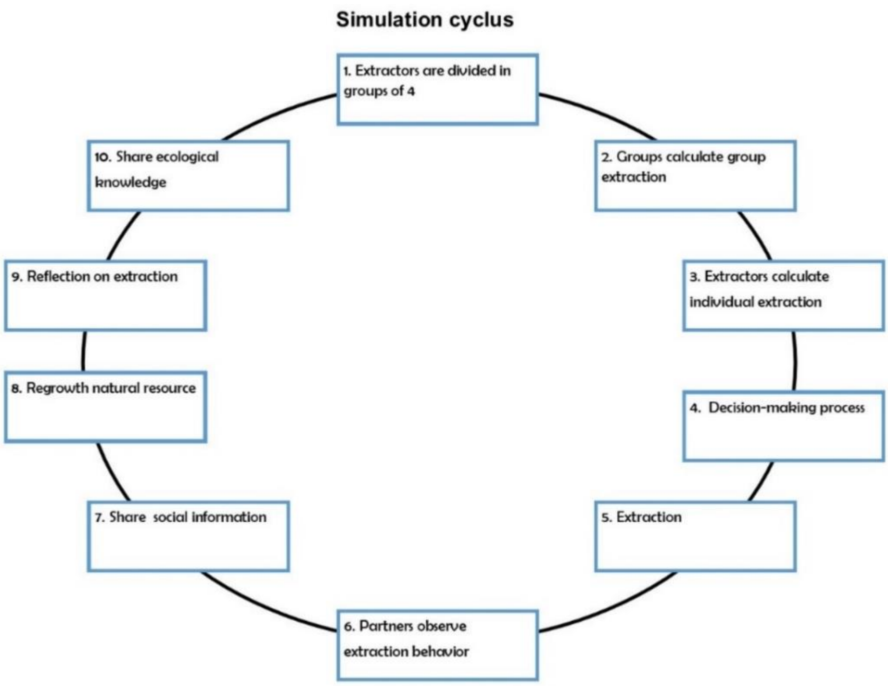

Figure 2: Simulation Cycle

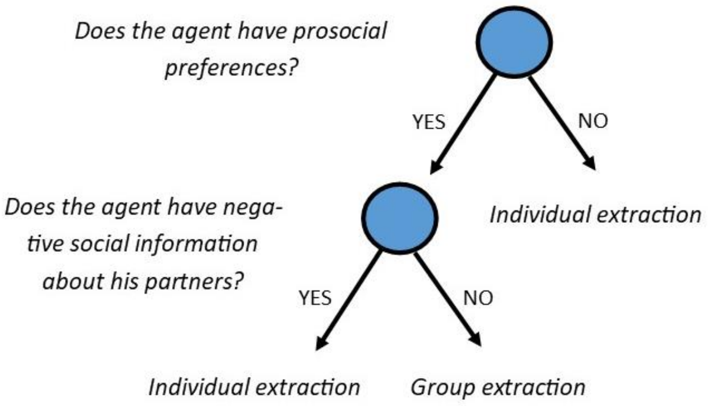

Figure 3: Decision-making process

agents adopt this information by creating a similar memory about the observed agent. In step eight all partial resource stocks regrow with a logistic growth function. Agents reflect on their group performance based on the regrowth of the partial resource stock. A high regrowth function means that the group extracted sustainably. A low regrowth function means that the group either over or under extracted. The higher the regrowth function, the more likely that the agents change their individual knowledge to the group knowledge. When the regrowth function is perfect, agents adapt fully to the group knowledge, whereafter they gain ecological knowledge. This also means that when an agent has sustainable knowledge without knowing it, he affects the group knowledge in the sustainable direction, but then adapts to a less sustainable group knowledge. Agents need a confirmation of a sustainable regrowth to gain confidence in their knowledge. This reflects some bounded rationality in the ecological reasoning of actors (Filatova et al., 2013). It can be unclear whether an actor's estimation is sustainable because multiple actors extract from the same natural resource. Actors have to learn about the resource dynamics based on collective extractions and outcomes. Agents that gained sustainable knowledge will share their knowledge with their social ties. Agents without sustainable knowledge that receive this information adjust their individual knowledge to the incoming knowledge. Once an agent gained sustainable ecological knowledge, he trusts his own knowledge, and he will not adapt to the group knowledge. Table 3 gives a more detailed description of the model's algorithm.

Table 3

Elaboration of the model steps

Step in the simulation	Description of the function
1. Extractors are divided in groups of four	The agents are randomly divided in groups of four extractors. The natural resource stock will be equally divided over the groups. Every group plays a maintenance public good game with their group members and the partial resource stock. All partial stocks will be pooled together at the end of the round. Each round, the agents will be divided in new randomized groups. What is left of the natural resource stock will again be equally divided over the new groups.
2. Groups calculate group extraction	Agents have individual knowledge. This is an estimation of which (partial) resource stock is sustainable after the group extraction. A group knowledge of 25 would mean that the agents estimate that extraction until a resource stock of 25 would be the most sustainable option. Individual knowledge ranges from 5 until 34. The group knowledge is the average of the individual knowledge of the agents in the group. To calculate the group extraction the group knowledge will be extracted from the partial resource stock. The group extraction will be equally divided over the four agents that are part of the group. This is the agreed-on extraction per agent. This group forming process is inspired by AgentEx (Schill et al., 2016), and has been applied on a bigger scale.
3. Agents calculate individual extraction	Agents create an individual extraction which represents free riding. The individual extraction is the group extraction divided by three instead of by four. The individual extraction has a minimum of 2.5, meaning that if the group extraction is lower than 10, agents will set their individual extraction on 2.5. We ran simulations with different parametrizations and noticed that if we put the minimum individual extraction higher, unsustainable extraction

	resulted quickly in resource depletion. We chose a relatively mild form of free riding to reflect long term effects of over extracting behavior. Natural resources can be quite resilient, and actors need to continue over extracting for a longer period of time before the resource is completely depleted.
4. Decision-making process	Agents follow the steps shown in figure 3 to decide between cooperating (group extraction) and free riding (individual extraction). Agents without prosocial preferences choose the individual extraction. Agents with prosocial preferences only choose the individual extraction if they have a negative memory about the other agents in the group. If the agent does not have a negative memory about the other agents in the group, he chooses the group extraction. The agent (with prosocial preferences) can have no information (+0), positive information (+1), or negative information (-1) about a group member. The agent calculates the sum of the social information about his group members. When the sum is 0 or higher, the agent will cooperate, when the sum is below 0, the agent will defect.
5. Extraction	The agents extract from the partial natural resource stock that belongs to their group.
6. Partners observe extraction behavior	Agents create a directed memory link to the other agents in the group. If an agent extracted the group extraction, the other agents create a positive memory link to him (1). If an agent extracted the individual extraction, the other agents in the group create a negative memory link to him (-1). Those directed memory links only change when an agent (in)directly observes that this specific agent behaves differently.
7. Share social information	Agents share those observations with their social relations. Agents who received this social information will create a similar memory link towards this specific agent. However, agents only share social information when they went for the group extraction in that round. An agent that indirectly received social information keeps this memory, and only adjusts this information when he in(directly) observes that this specific agent behaves differently.
8. Regrowth natural resource	After the extractions, the partial natural resource stocks regrow with a logistic function. Ideally, every group extract until a partial stock between 25 and 29. This gives a regrowth function of 9. A partial stock lower than 25 or higher than 29 will give a lower a regrowth function. At the end of every round all partial stocks will be pooled together. In the beginning of the next round, the natural resource stock will again be divided over the 20 groups. If partial stock >= 50 [set regrowth 0] If partial stock => 45 AND <= 49 [set regrowth 1] If partial stock => 40 AND <= 44 [set regrowth 3] If partial stock => 35 AND <= 39 [set regrowth 5] If partial stock => 30 AND <= 34 [set regrowth 7] If partial stock => 25 AND <= 29 [set regrowth 9] If partial stock => 20 AND <= 24 [set regrowth 7] If partial stock => 15 AND <= 19 [set regrowth 5] If partial stock => 10 AND <= 14 [set regrowth 3] If partial stock => 5 AND <= 9 [set regrowth 1] If partial stock <= 4 [set regrowth 0]

9. Reflect on extraction behavior	Agents observe how their group performed. Agents are more likely to change their individual knowledge to the group knowledge when the regrowth of the partial resource stock is high. If regrowth = 9 [set individual knowledge group knowledge] If regrowth = 7 [set individual knowledge (group knowledge + individual knowledge) / 2 If regrowth = 5 [set individual knowledge (group knowledge + individual knowledge * 2) / 3 If regrowth = 3 [set individual knowledge individual knowledge] If regrowth = 1 [set individual knowledge individual knowledge] If regrowth = 0 [set individual knowledge individual knowledge] When the regrowth is 9 (highest), agents learn what the sustainable knowledge is and fully adopt the group knowledge.
10. Share ecological knowledge	Agents that gained the sustainable ecological knowledge share this with other agents through their social ties. Agents on the receiving end will only adopt the knowledge when they have not yet gained ecological knowledge.

4.2. Details

4.2.1. Initialization

In this section we explained why we elected the initialization of the variables for the simulation scenarios. Figure 4 shows the interface of the model in Netlogo to give an impression of the model. The buttons, choosers, and slider are located at the left side of the interface (blue circle), the visualization of the social network and the natural resource are located in the middle (red circle), and the plots and monitors are at the right side of the

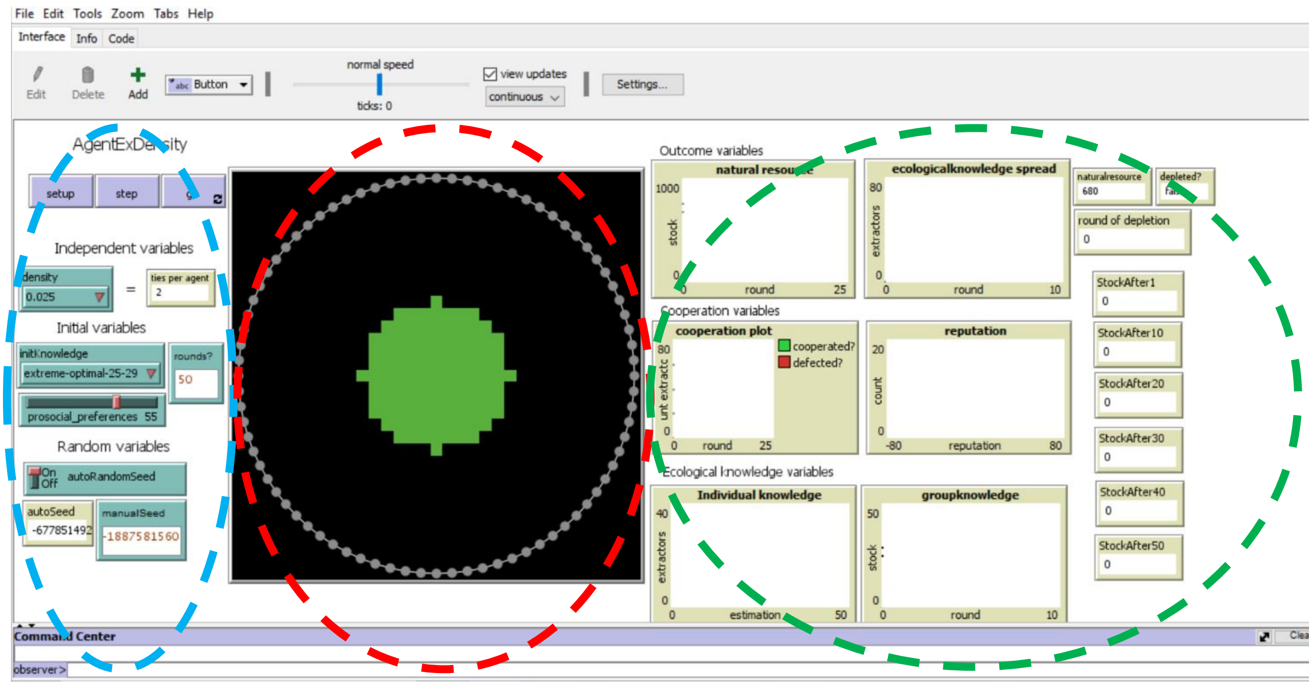

Figure 4: Model interface at tick 0 (scenario 2).

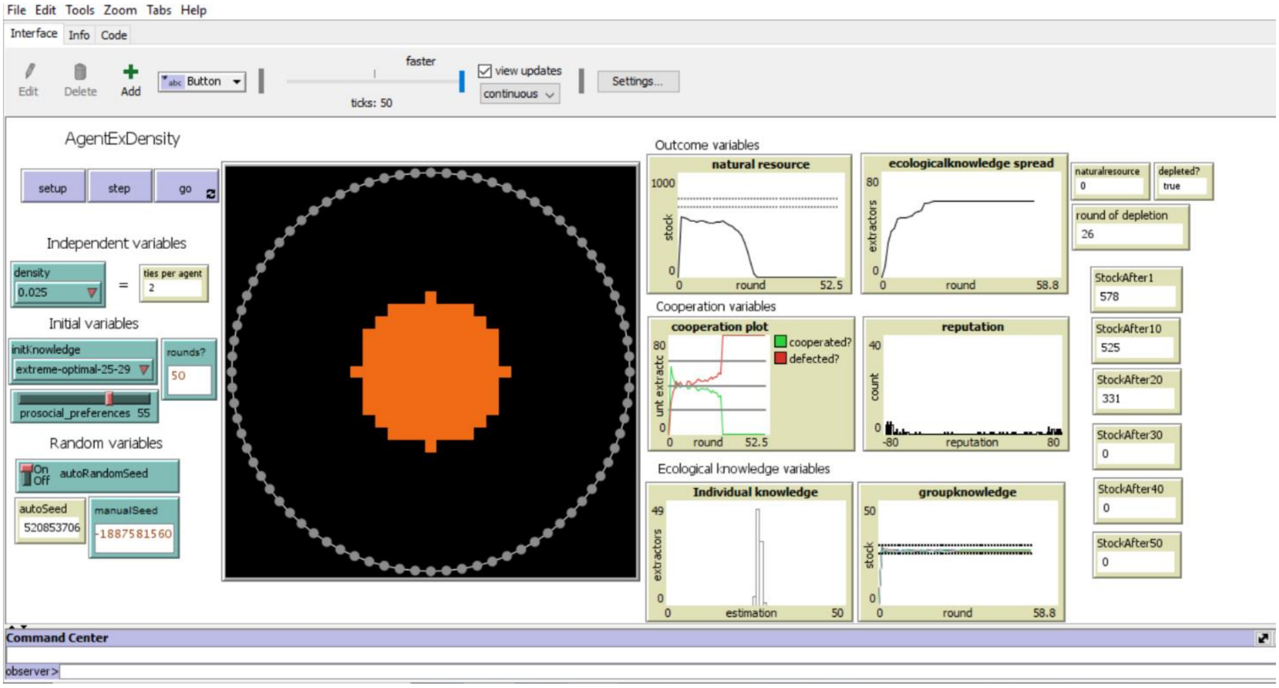

Figure 5:Model interface after 50 ticks (scenario 2).

interface (green circle). The buttons are used to run the simulation, and the choosers and sliders are used to set the initializations of the variables. Figure 5 shows the interface of the second scenario at the end of a simulation run (50 ticks) with the measurements given by the plots and monitors.

Group size

We chose to model a group of 80 agents, because it can be evenly divided in 20 groups of four. The groups of four are inspired by AgentEx (Schill et al., 2016), where they used this group size in the execution of their behavioral experiments. We chose a group of 80 agents so we could implement a social network structure to study the effects of the diffusion of social and ecological information on natural resource sustainability. If the group size was too small, we would not be able to implement different relevant network structures, because information would reach all agents too fast. With 80 agents we can model different network densities to compare its effects on resource sustainability.

The social network

The 80 agents are set up in a circle and can have social ties to other agents. Figure 6 is a screenshot of the interface of our simulation in Netlogo and shows how the social network has been structured. The 80 agents are positioned in a circle and form ties to the agents spatially closest to them. There is homogeneity in the network positions of agents, meaning that changing the density of ties affects all agents equally. If the social network density is zero, agents have no social ties to any agents. In simulations with a density of 0.025, agents have social ties to two agents who are spatially closest to them. That means that agents have a social tie to their closest left and right neighbor. With a density of 0.05 they have social ties to the four closest neighbors, etc. We ran repetitions on six social network densities (0, 0.025, 0.05, 0.1, 0.2, 0.4). Social ties are undirected which means that the social relations are reciprocal. This type of tie was elected because the social network represents an ecological and social information sharing network, in which information goes both ways.

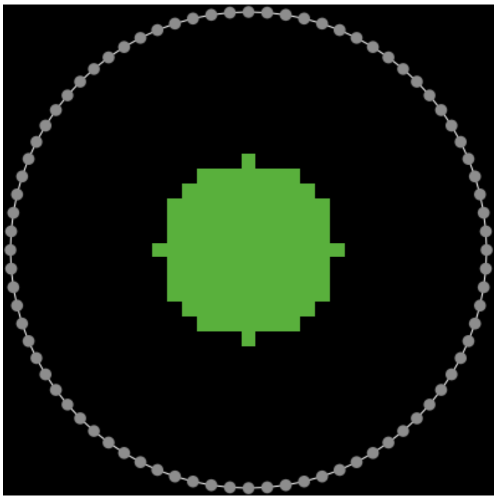

Figure 6: Netlogo interface on a social network density of 0.025 (two ties per agent). The grey dots represent the agents, and the lines between them represent the social ties. The green object in the middle represents the natural resource and its color displays its state (green = high stock, yellow = medium stock, orange = low stock, red = depleted).

The natural resource

In AgentEx, the sustainable natural resource stock after extraction was set between 25 and 29. If the agent extracted until a value between 25 and 29, the natural resource stock would regrow by nine (Schill et al., 2016). This model was inspired by AgentEx, and we implemented a similar extraction process. We started with a natural resource stock of 680, because in our model there are 80 agents extracting from the natural resource stock. At the start, each group is responsible for a partial natural resource stock of 34 (680 / 20). Just like in AgentEx, extracting until a partial natural resource stock between 25 and 29 would result in a regrowth function of nine. The growth function is smaller in case of over or under extraction.

Prosocial preferences

The number of agents with prosocial preferences in the simulation affects the sustainability of the natural resource considerably. The initialization of this variable determines how many conditional cooperators there are in the simulation, and it needs to be chosen carefully. The

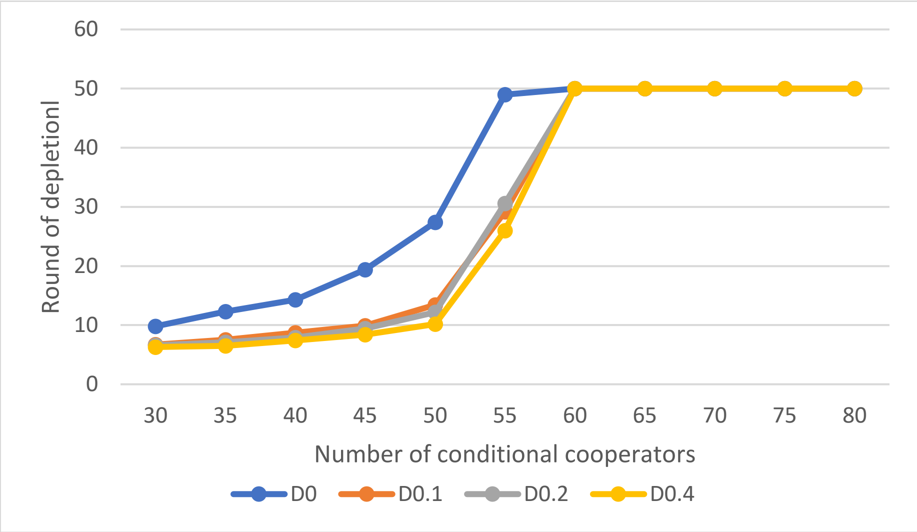

Figure 7:The effect of prosocial preferences on natural resource sustainability. The social network density is given by the color of the dot (blue = density of 0, red = density of 0.1, grey = density of 0.2, orange = density of 0.4). Each dot represents the average of 10 simulation runs on a social network density level combined with a number of conditional cooperators.

behavioral rule for conditional cooperators is that they start with a cooperative strategy when they have no information about their partners, and they free ride when they know that the majority of the group are free riders. The implementation of this behavioral rule assumes initial friendliness of conditional cooperators, which we used to reflect their prosocial preferences (Fehr & Fischbacher, 2002). Starting with a cooperative strategy is a friendly but effective strategy to sustain cooperation, because according to their own rule (cooperation under the condition that one's partner cooperates) (Rustagi et al., 2010), starting with cooperating gives the highest chance of creating a sustainable cooperative relation. We need to carefully choose the initialization of the prosocial preferences variable, because we do not want that the number of conditional cooperators completely determines the outcome of the simulation. If there are too many conditional cooperators, cooperation would be reached independent of the social network density, and with too little cooperators, the agents would not reach cooperation independent of the social network density. We ran 440 simulations with different numbers of conditional cooperators on different social network densities to observe what a relevant initialization of the prosocial preferences variable would be. We measured in which round the agents depleted the natural resource and visualized the results in figure 7. The agents are able to sustain the natural resource longer when more agents have prosocial preferences. Simulations that have less than 50 agents with prosocial preferences are not able to sustain the natural resource longer than 30 rounds. Simulations that have more than 60 agents with prosocial preferences are able to sustain the natural resource independent of the social network density. In our simulation we used 55 conditional cooperators, as on this initialization there is variation of natural resource sustainability between simulation with different social network densities.

Length of the simulation and measurements

One simulation run consists of 50 ticks. If the natural resource is depleted before the end of the simulation, the game ends. We set a maximum of 50 rounds, because within 50 rounds we noticed differentiation in resource sustainability between network densities, meaning that a maximum of 50 rounds gave us enough rounds to analyze how change in the social network density affects natural resource use. We ran ten simulation runs for each scenario. In each run we measured the natural resource stock at seven moments in the simulation: at the start, after one round, after 10 rounds, after 20 rounds, after 30 rounds, after 40 rounds, and at the end of the simulation. We calculate the average development of the natural resource stock on the six social network density levels.

4.2.2. Scenarios

Table 4 presents an overview of the different simulation scenarios, illustrating the parameters used for each simulation.

Table 4

Simulation scenarios

	Range of individual knowledge 5-34	**Range of individual knowledge 25-29**
No agents have prosocial preferences	Baseline model (1)	-
55 agents have prosocial preferences	Both ecological and social information spreading scenario (4)	Social information spreading scenario (2)
All agents have prosocial preferences	Ecological information spreading scenario (3)	-

Scenario 1

The baseline model was used to analyze whether the model works and to compare it to the other scenarios. There are no agents with prosocial preferences, and no agents start with ecological knowledge. We ran ten simulations on each of the six social network densities. We expected that the natural resource will be depleted in one of the first rounds. There are no conditional cooperators in the simulation, which means that all agents choose the individual extraction, which leads to depletion of the natural resource.

Scenario 2

In this scenario, we analyzed how the social network density affects natural resource sustainability through the spread of social information. All agents had initial individual knowledge between 25 and 29. Agents started with sustainable knowledge to ensure this variable would not take the focus of the social information spreading mechanism. The simulation consisted of 55 conditional cooperators. We ran ten simulations on each of the six social network densities and measured the average stock of the natural resource stock at seven points in a simulation run (at the start, after 1 tick, 10 ticks, 20 ticks, 30 ticks, 40 ticks, 50 ticks). We expected that a higher social network density affects collective action negatively. Agents with prosocial preferences receive more social information about their partners, which could trigger them to free ride.

Scenario 3

In this scenario, we focused on the spread of ecological knowledge and its effect on natural resource sustainability. All agents in the simulation were conditional cooperators, so the sustainability of the natural resource depended on the spread of ecological knowledge. All agents had an initial individual knowledge between 5 and 34. We ran ten simulations on each of the six social network densities, and we measured the average natural resource stock at the seven points in each simulation run. We expected that if the social network density increased, the agents would be better able to sustain the natural resource. Agents could form a sustainable group knowledge at a faster pace, because more agents had access to ecological knowledge. A fast spread of ecological knowledge could support sustainability of natural resources.

Scenario 4

In this scenario, we activated both the social information sharing and the ecological knowledge sharing mechanism. Agents had initial individual knowledge between 5 and 34 and there were 55 conditional cooperators in the simulation. We ran ten simulations on each of the six social network densities, and we measured the average stock of the natural resource stock at the seven time points. We expected that increasing the social network density would have contradicting effects on natural resource use. There is little ecological information sharing in low density networks, which complicates reaching collective ecological knowledge. In high density networks it is more likely that the agents reach collective ecological knowledge, but due to (negative) social information sharing conditional cooperators could be triggered to start defecting as well.

5. Results

5.1. The baseline model (S1)

This chapter describes the results of the four simulation scenarios. The simulations showed that increasing the social network density affected the sustainability of the natural resource. The baseline model had no agents with prosocial preferences, and no agents with initial sustainable knowledge. As expected, the natural resource was on average depleted after four rounds. The social network density did not affect the outcomes of the baseline model, because there were no conditional cooperators active in the simulation. Agents would choose the individual extraction always over the group extraction. A community with only defectors is unlikely to sustain their natural resources.

5.2. The effect of social information sharing on collective action (S2)

Increasing the social network density affects natural resource sustainability negatively in the social information sharing scenario. Figure 8 shows that the natural resource stock decreases at a faster pace in simulations with a higher social network density. A conditional cooperator only defects when he has negative social information about his partners. In a simulation with a higher social network density, there is more social information sharing, which triggered conditional cooperators to defect in an environment with defectors.

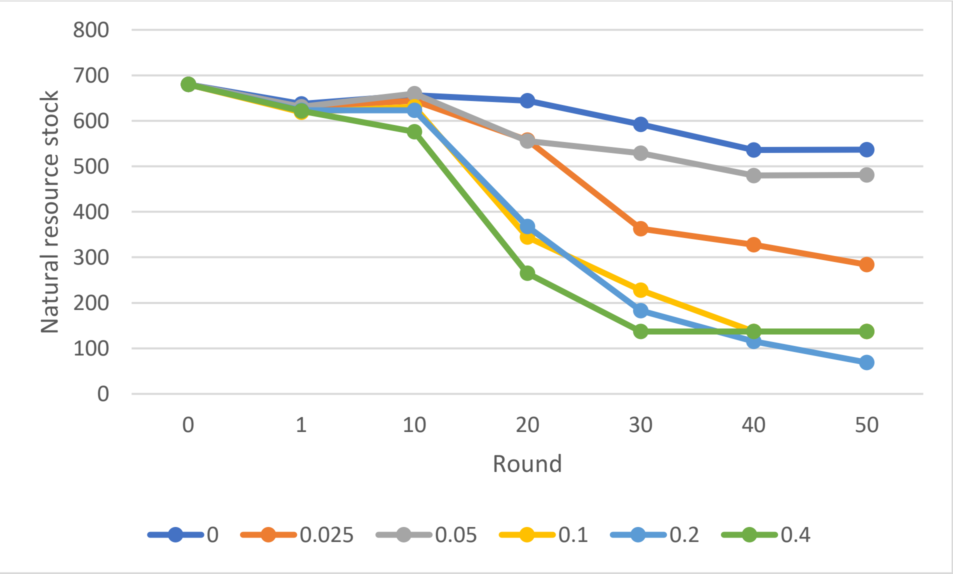

Figure 8: Development of the natural resource stock in scenario 2. The colors show the density in the simulations (blue = 0, orange = 0.025, grey = 0.05, yellow = 0.1, blue = 0.2, green = 0.4). Each dot represents the average natural resource stock of 10 simulation runs on the relevant time point.

If an agent free rides in a simulation with a social network density of 0, only the agents in his group create a negative memory link towards him. But when the social network density is higher, more agents learn about his behavior. Increasing the social network density increases the visibility of agents' choices. Figure 9 and figure 10 are graphs from the Netlogo model interface and show the cooperation plot and the reputation of the agents after one round. Both simulations have a similar cooperation plot, but the reputation histograms are different. In the simulation with a social network density of 0.4, agents that cooperated have a high reputation value, and agents that defected have a low reputation value. Agents without prosocial preferences are not triggered to cooperate, because in this simplified model there is no incentive for them to care about their reputation. However, agents without prosocial preferences are triggered to defect when they learn that other agents are not contributing to the maintenance of the public good. As expected, the increased visibility of actors' behavior does not support sustainability of the natural resource.

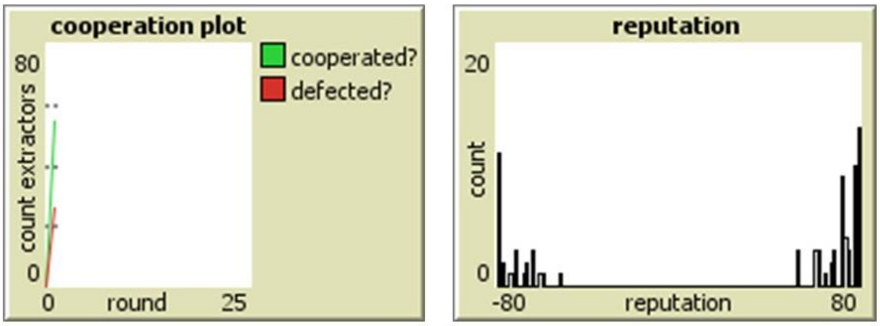

Figure 9a: Cooperation plot of the agents after the first round. Figure 9b: Distribution of agents' reputation after 1 round on a social network density of 0.4 (55 agents with prosocial preferences).

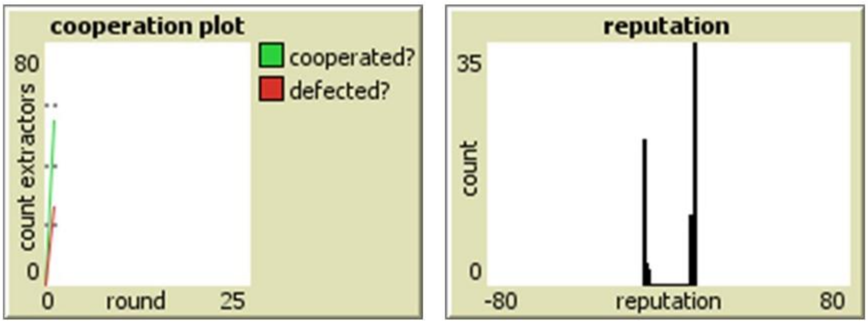

Figure 10a: Cooperation plot of the agents after the first round. Figure 10b: Distribution of agents' reputation after 1 round on a social network density of 0.025 (55 agents with prosocial preferences).

5.3. The diffusion of ecological knowledge (S3)

Increasing the social network density impacts sustainability of the natural resource positively in the ecological knowledge sharing scenario. Figure 11 shows that agents were more often able to reach the desired state of the natural resource in simulation runs with a higher social network density. It can take several rounds before agents find the desired state. In simulations with no ecological knowledge sharing, it takes a considerable amount of time before all agents reach this desired state. In simulation runs with a higher social network density, agents share their ecological knowledge once they find the desired state. However, simulations on all density levels sustained the natural resource because a group of conditional cooperators will never fully overexploit the natural resource. They might over or under extract based on the incorrect individual knowledge, but their individual knowledge cannot reach below 0.

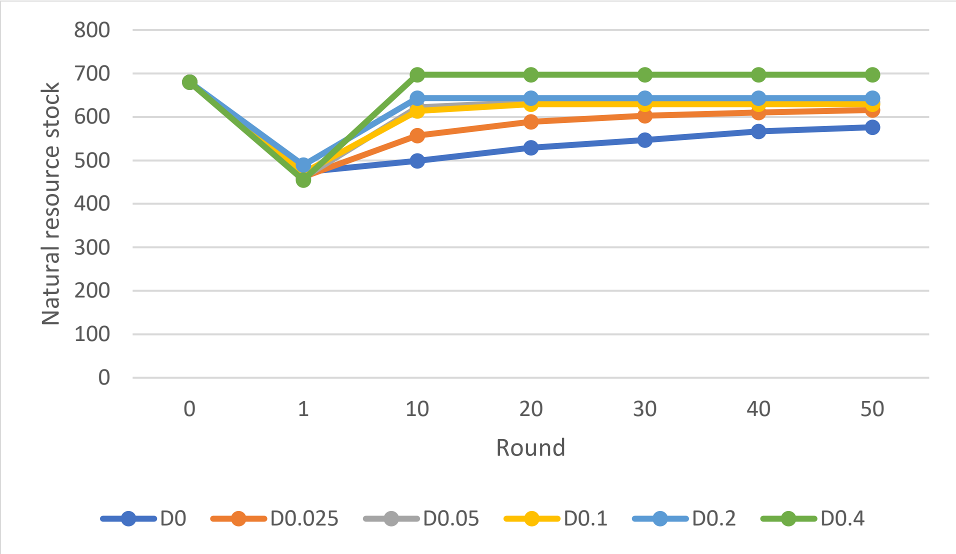

Figure 11: Development of the natural resource in scenario 3. The colors show the density in the simulations (blue = 0, orange = 0.025, grey = 0.05, yellow = 0.1, blue = 0.2, green = 0.4). Each dot represents the average natural resource stock of 10 simulation runs on the relevant time point.

5.4. The complete model (S4)

In the last scenario, we implemented both information spreading mechanisms. We expected that increasing the social network density would have contradicting effects through social and ecological information sharing, meaning that it would not necessarily improve natural resource use. We ran the simulation with 55 conditional cooperators and the results have been visualized in figure 12. We observed that the agents were not able to sustain the natural resource on any social network density. In the simulations with a low social network density, agents were not able to collectively learn how to extract sustainably. This in combination with a group of defectors led to depletion of the natural resource. When we increased the social network density, more agents had access to ecological knowledge, but due to social information sharing conditional cooperators were triggered to defect which also led to depletion of the natural resource. Figure 13 shows the group knowledge in simulations with a

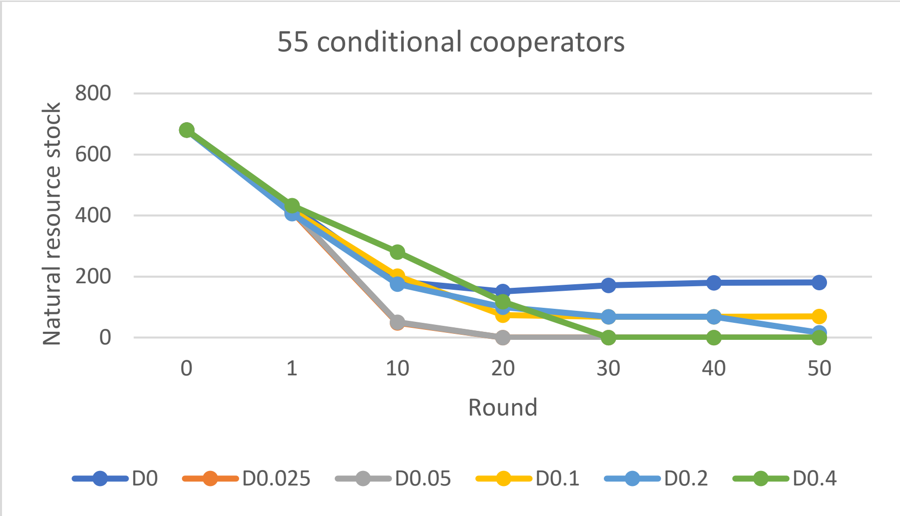

Figure 12: The development of the natural resource stock on different social network density levels in scenario 4. The colors show the density in the simulations (blue = 0, orange = 0.025, grey = 0.05, yellow = 0.1, blue = 0.2, green = 0.4). Each dot represents the average natural resource stock of 10 simulation runs on the relevant time point.

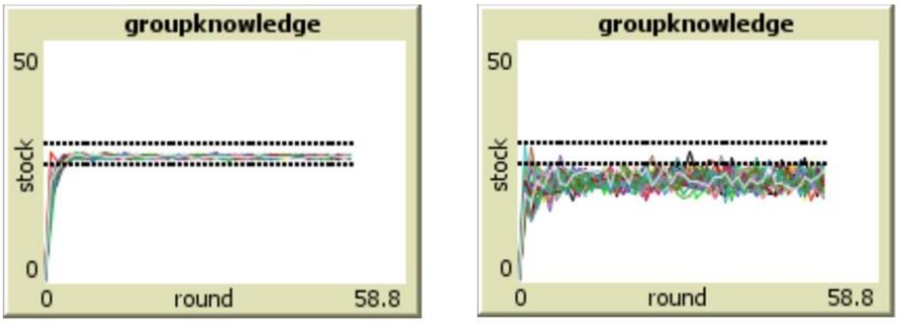

Figure 13a: Group knowledge of the groups in a simulation with a social network density of 0.4. Figure 13b: Group knowledge of the groups in a simulation with a social network density of 0.025. Each colored line is the formed combined knowledge of one group over time (agents are not stuck to one group but change each round). The area between dotted lines is the sustainable group knowledge.

social network density of 0.4 (a) and 0.025 (b). More groups are able to form a sustainable group knowledge in the simulation with a social network density of 0.4 than in the simulation with a social network density of 0.025. In this scenario the planned group extraction does not equal the actual extraction, because the agents without prosocial preferences do not choose the group extraction. This disturbs the reflection process because agents are not always able to see whether their group extraction was accurate. Without ecological knowledge sharing, agents are not able to collectively gain ecological knowledge and manage the natural resource. As expected, the simulation results demonstrate that changing the social network density affects the sustainability of natural resources in contradicting ways. This demonstrates the complexity of natural resource communities and how interfering with them can have unintended consequences.

The simulation demonstrates that social information spreading affects collective action, because conditional cooperators receive negative information about other agents. This suggests that there might be a tipping point in the number of initial conditional cooperators within the simulation beyond which more social ties may become beneficial for collective action. We ran an additional simulation with 56 and 57 conditional cooperators and represented the results in figure 14. The results demonstrate that high density networks perform better with more conditional cooperators. There is a tipping point at 56 conditional cooperators after which there is mostly positive social information sharing. In this case, a high social network density is beneficial for the sustainability of natural resources because ecological knowledge is more accessible, and an increased spread of positive reputational information promotes cooperation by conditional cooperators.

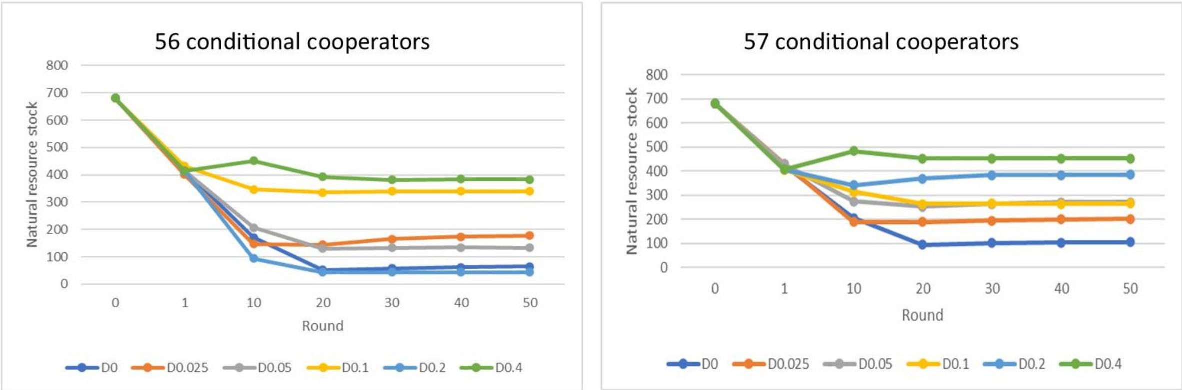

Figure 14: The development of the natural resource stock on different social network density levels with 56 (left graph) and 57 (right graph) conditional cooperators. The colors show the density in the simulations (blue = 0, orange = 0.025, grey = 0.05, yellow = 0.1, blue = 0.2, green = 0.4). Each dot represents the average natural resource stock of 10 simulation runs on the relevant time point.

6. Discussion and conclusion

For this thesis we developed an agent-based model to demonstrate how the social network density could affect social and ecological information sharing and thereby natural resource use. There is a growing body of literature on how the social network density affects cooperation through social information sharing (Alexander, 1987; Bodin & Crona, 2008; de Olivera et al., 2015), and how the social network density affects ecological information sharing and thereby natural resource use (Bodin & Norberg, 2005; Turner et al., 2014; Schill et al., 2016). However, both information sharing structures have to our knowledge not yet been studied in the same context. We implemented an information sharing structure in a simulation of a maintenance public good game, to analyze how the diffusion of ecological and social information would affect natural resource use. In this chapter, we start off by giving a summary of the model results, and we discuss the limitations of the results and its implications.

6.1. Summary of the findings

Firstly, our simulation results demonstrated that increasing the social network density can negatively affect collective action. In simulations with a higher social network density there is more social information sharing, which gives agents a clearer idea of who are cooperators and who are free riders. In an environment with defectors, social information sharing triggered conditional cooperators to stop cooperating and start defecting. More social information sharing did not activate the indirect reciprocity mechanism (Alexander, 1987), because agents without prosocial preferences did not care about their reputation. This model reduced complexity of natural resource communities, which led to the exclusion of social control or punishment. This simplification suggests that without those factors, social information sharing could affect collective action negatively. Secondly, our simulation demonstrated that increasing the social network density can affect the diffusion of ecological knowledge positively. In simulations with a low social network density, agents took more time to find the desired state of the natural resource. Increasing the social network density supported ecological knowledge sharing and the agents were able to find the desired state of the natural resource at a faster pace. Lastly, the simulations with both information sharing mechanisms demonstrated that increasing the social network density does not necessarily impact natural resource use positively. Even though, increasing the social network density made ecological knowledge more accessible, it also triggered conditional cooperators to free ride. Interfering with the number of social ties had negative implications for the sustainability of the natural resource, because more information spread has a contradicting effect on the sustainability of natural resources. However, our simulations with more conditional cooperators demonstrated that there is a tipping point in the number of initial conditional cooperators after which a high social network density is also beneficial for collective action. If actors mainly share positive evaluations about others, conditional cooperators continue cooperating.

6.2. Limitations

The simulation results have limitations that need to be addressed. Firstly, because the model is a simplification of the real world, possible influential factors have been left out. In our model agents without prosocial preferences are not directly affected by their reputation. Even though in reality people can get socially punished for having a poor reputation. Because there was no punishment for having a low reputation value, agents without prosocial preferences were not affected by their reputation and were not avoiding a low reputation value. Examples of social mechanisms that promote cooperation via reputation are meritocratic matching and partner selection. Heinrich et al. (2015) implemented a meritocratic matching system in a contribution model to see how fuzziness about the behavior of others would affect cooperation. Meritocratic matching is group matching based on an actor's contributions to the public good. The model demonstrated that less fuzziness led to more cooperation, because they could more accurately match cooperators with each other. With this type of matching cooperators can survive because free riders are excluded from their groups. Partner selection is another mechanism that can promote cooperation via reputation. Vilone et al. (2016) demonstrated with their model that cooperation can survive if actors are able to select their own partners. When actors preferably partner up with actors with a good reputation, free riders will be excluded by cooperators. The partner selection mechanism promotes to act cooperative because people do not want to be excluded. Model simulations demonstrated that, with the implementation of a social network in combination with a partner selection algorithm, sharing evaluations about actors' behavior can affect cooperation positively (Giardini & Vilone, 2016). Based on social information, actors can select with whom they want to partner up. The more information an actor has, the more accurately he can select cooperators as his partner and reject free riders. Social information sharing lowers the chance that actors can free ride without social consequences, which makes cooperation the more electable option. Other model simulations of a public good game tested different reactive strategies on free riding behavior and demonstrated that punishing free riders by rejecting them as a partner is more efficient for reaching cooperation than defecting (Giardini et al., 2013). The implementation of only one reactive strategy on free riders (defection) might not be a perfect representation of how actors could deal with free riders, and it would be interesting to implement different reactive strategies in future extension of the model. However, it is important to consider the possibility that more social information sharing will not always stimulate cooperation. To activate the indirect reciprocity mechanism (Milinski, 2016), there needs to be consequences for free riders. Without this, increased social information sharing could indeed demotivate conditional cooperators (de Olivera et al., 2015).

Secondly, agents only shared sustainable ecological information. The correct information might not be so clear in reality and unsustainable information might also be shared. In our simulation, the homogenization of knowledge was not a problem, because agents only shared sustainable information. However, much ecological information sharing can also affect the sustainability of natural resources negatively. When agents have incorrect knowledge, the homogenization of knowledge could be problematic (Bodin & Norberg, 2005).

Thirdly, agents without ecological knowledge always adopted ecological knowledge from their social relations, but whether people adopt new information might depend on their source of information and their own adoption threshold. Some people might adopt new information at a fast pace, while others will only be convinced by new information when most people around them also accepted this information (Rogers, 1958; Diederen et al., 2003). If people will only adopt new information if 33% of their social environment did as well, network embeddedness could slow down the diffusion of new information (Centola, 2007). If an actor has many social relations, more people in his social environment need to adopt the new information to reach the threshold of 33%.

Fourthly, we assumed that agents could perfectly observe the behavior of their partners in the public good game. However, in reality the behavior of other actors might not be so observable. In natural resource communities, actors might not be able to perfectly observe the behavior of other extractors, or they might only be able to reflect on the resource stock over time. The aim of this model was to theorize about how sharing of social and ecological information could work in the same context. We could have implemented different observation mechanisms like imperfect observations, or that the agents generalized the behavior of their partners based on (partial) natural resource outcome, but we chose to implement a perfect observation system to stress the effect of social information sharing on natural resource sustainability. However, adding fuzziness to observations could create a more realistic representation of the real world and it would be interesting to implement this in future extension of the model.

Lastly, the relational approach could have been used in several ways. We focused on the density of ties and chose to model homogeneity in network positions of the agents to decrease randomness in the model. However, we could have considered different network structures (brokerages, structural holes), strength of ties, or contagion processes. Implementing additional social network features could help us to study the role of social networks in natural resource sustainability.

6.3. Implications

The insights of this thesis have implications for further research on sustainability of natural resources. The simulation demonstrated that under certain circumstances changing the social network density can have contradicting effects on natural resource use. To simplify natural resource communities, we left out possible relevant factors like social punishments and the diffusion of incorrect knowledge. We should continue to study these factors, because they can moderate the effect of the social network density on the sustainability of natural resources. We suggest a possible extension of the model in which a form of social punishments and the possibility of incorrect knowledge sharing will be implemented. The next step is to test this theory in the real world by studying natural resource communities. The social network study in Kenya is a perfect example of how the complexity of natural resource communities can be studied (Bodin & Crona, 2008). They combined social network analysis with interviews about perception of resource use. The interviews could explain the effect of the social network density on natural resource use. Combining empirical social network analysis with qualitative questionnaires can help us understand how norms and perspectives moderate the effect of the social network density on natural resource use. We need to keep developing our understanding of complex social-ecological systems like natural resource communities before we can interfere with them. Social network interventions can be used to make communities more efficient or prevent people from free riding by changing the social network structure (e.g., increasing connectivity with the goal to stimulate social cohesion (Valente, 2012)). However, the simulations results demonstrated that changing the social network density can lead to unintended consequences for natural resource use. We suggest that policy makers do extensive research before they interfere with the social network structure of a natural resource community. Natural resource communities are unique groups of people with their own qualities and weaknesses. Applying a general intervention on multiple natural resource communities could affect the sustainability of some of the communities negatively. For example, increasing the social network density could have negative consequences on cooperation if actors are not aware of the risks of overexploitation (Bodin & Crona, 2008). Understanding a community's rules, norms and values regarding natural resource use is necessary to be able to effectively help them with sustaining their natural resources.

6.4. Conclusion

This thesis studied the effect of changing the social network density of communities on natural resource use. We combined the effects of social information and ecological knowledge sharing on natural resource use to analyze how both mechanisms together affect natural resource use. The concept of studying socio-ecological systems like natural resource communities by modeling a behavioral experiment was inspired by AgentEx (Schill et al., 2016). AgentEx demonstrated with their model that ecological knowledge is needed to extract sustainably. We followed up on this finding by implementing a social network structure to study how the social network density affects natural resource use. We demonstrated that increasing the social network density gives more actors access to ecological knowledge. Without ecological knowledge sharing it can take a considerable amount of time before actors understand natural resource dynamics, which can be problematic for sustaining natural resources. We combined the ecological knowledge sharing with social information sharing because many studies showed the importance of reputation in social dilemmas (Giardini & Wittek, 2019; Milinski, 2016; Nowak, 2006). We modeled a group of agents playing a maintenance public good game with a social and ecological information sharing structure. Our model demonstrated that changing the social network density has contradicting effects on the sustainability of natural resources. Increasing the social network density gives more actors access to ecological knowledge but can also trigger conditional cooperators to defect when there are no social punishments for free riding. The insights of our model demonstrate the complexity of natural resource communities. There is no simple answer to our research question, because the effects of changing the social network density on natural resource use depend on multiple factors like norms, perceptions, available knowledge, etc. To be able to help natural resource communities in sustaining their natural resources, we must continue to study how these factors can moderate the effect of the social network density on natural resource use.

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Appendix

Design concepts

Table 5 gives a description of the design concepts of the model.

Table 5

Design concepts

Theoretical background behind the model	We based the simulation rules on theories from the field of public good games, rational choice theory, social networks, and natural resource management. Agents share social and ecological information with other agents through their social ties. Studies found that people share ecological and social information with people close to them (Abrahamson & Rosenkopf, 1997; Isaac, Erickson, Quashie-Sam, & Timmer, 2007), and that people most likely adopt new information from people close to them (Centola, 2007). The agent attribute prosocial preferences is based on extended rational choice theory. In behavioral experiments participants cooperated even though free riding would give them a higher pay off (Fehr & Fischbacher, 2002), which could be explained by that people have in some extent aversion to inequality (Herreiner & Puppe, 2010). An agent's decision to cooperate or to free ride is affected by the social information he has about their partners. We modeled this, because experiments showed that conditional cooperators are more likely to cooperate when they believe that their partners cooperate as well (Rustagi, Engel, & Kosfeld, 2010). This also means that conditional cooperators can get triggered to stop cooperating when they receive negative social information about their partners (de Olivera, Croson, & Eckel, 2015; Hartig, Irlenbusch, & Kölle, 2015).
Learning	Agents can update their individual knowledge after interaction with other agents or by reflecting on how the natural resource stock responded on their extraction. Agents also receive social information that affects their

	decision-making. However, the decision rules are fixed, and the agents are not able to learn in this area.
Sensing	Agents sense the (partial) natural resource stock size. Agents sense that if their partial natural resource stock regrows with 9 units, they reached a sustainable state. They sense this because with a regrowth function of 9, the partial natural resource stock regrows to the starting partial stock of the resource (34 or higher).
Predicting	An agent makes a prediction of the behavior of his group members based on the social information he has about the other agents.
Interaction	Agents interact with other agents in three different ways. The first interaction is during the maintenance public good game, where agents combine their individual knowledge to form a group knowledge. The second and third interaction are the social and ecological information sharing, which depends on the social ties between agents.
Collectives	The natural resource stock is the collective good. The agents fail to sustain the natural resource when the stock is 0. The partial natural resource stock is temporarily the collective good for a group and agents extract collectively with their group members from it. Every group forms a group knowledge, which is the collective knowledge that determines whether they are able to estimate a sustainable group extraction or not.
Heterogeneity	Agents are heterogenous in their prosocial preferences, individual knowledge, and reputation.
Stochasticity	Agents start with a neutral reputation and initial individual knowledge, but those variables can develop over time when they interact with other agents. The group formations and the natural resource stock also develop over time. Those stochastic factor are needed to study how agents affect each other's behavior over time.
Observation	We observed the state of the natural resource stock at seven time points in a simulation run: at the start, after 1 round, after 10, after 20, after 30, after 40, and after 50. We compared how the natural resource stock develops on different social network densities.

	To demonstrate how the diffusion of reputation and ecological knowledge affect the sustainability of natural resources we measured the behavior of agents (cooperation plot), and their reputation. With those measurements we analyzed how the social network density affects cooperation through social information sharing. We also measured the diffusion of ecological knowledge and the formed group extractions to analyze how the social network density affects the spread of ecological information.