M. Isaenko

Exploring the Role of Networks in CPR Governance

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By

M. Isaenko

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Thesis committee:	Dr. H.G. van der Voort,	TU Delft
	Dr. A. Ghorbani,	TU Delft

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Associated code is available at https://github.com/magnwiz/CPR

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Peace,

Matvei Isaenko

Acronyms

ABM	Agent-based model(-ing)
BA	Barabási-Albert
CPR	Common pool resource
CPUE	Catch-per-unit-effort
ERGM	Exponential random graphs model
IAD	Institutional analysis and development
IG	Institutional grammar
OFAT	One-factor-at-a-time
PRIM	Pattern Recognition in Input-Output Mapping
SES	Social-ecological system
SNA	Social network analysis
SSF	Small-scale fishery

Executive summary

Common pool resources (CPR) encompass a diverse range of critical assets, from fisheries and forests to water bodies and grazing lands. What characterizes these resources is their unique blend of properties, specifically two: subtractability and non-excludability. Subtractability implies that individuals' use of the resource diminishes its availability for others, while non-excludability means that it's challenging to exclude individuals from accessing or utilizing the resource. This combination of characteristics creates a complex challenge for the governance of CPR.

These properties pose a significant challenge for CPR governance, as they make these resources vulnerable to the tragedy of the commons, a scenario where individuals, acting in their self-interest, deplete or degrade a shared resource harming everyone within their community of appropriators. This classical illustration of human behavior highlights the potential overuse and depletion of CPR when individuals prioritize their immediate needs over long-term sustainability.

Research has demonstrated that in certain cases, these endogenous institutions prove to be remarkably successful in ensuring the sustainable management of CPR. They often outperform top-down or externally imposed governance approaches. This revelation challenges the conventional wisdom that centralized, regulatory systems are always more effective. Instead, it underscores the capacity of communities to develop their unique, context-specific solutions to the challenges they face.

Understanding the dynamics of how communities establish and maintain these endogenous institutional rules holds significant implications for both policy and further research. It suggests that policymakers should consider incorporating local knowledge and community participation into resource management strategies. It also emphasizes the need for interdisciplinary research that combines insights from economics, sociology, and environmental science to develop more effective governance models for CPR.

Usually CPRs are considered as a part of comprehensive socio-ecological systems (SES) next to agents who appropriate this resource and form a social network. While the relationship between social networks and SES has been explored in various studies, little attention has been directed towards the co-evolution and dynamics of social networks and SES. Notably, there exists a gap in research concerning the interplay between endogenous institutions and evolving social networks within CPR settings. From this research knowledge gap follows central to this study the overarching research question:

How are network topology and dynamics interrelated with the emergence and evolution of institutions for the governance of common pool resources?

Pursuing this question, this research is exploring the interrelation between dynamics of social network structure and the emergence and evolution of CPR governance institutions. Utilizing small-scale fisheries (SSF) as a case study within a SES, I have employed an agent-based model (ABM) that intricately models the emergence of institutional rules. This ABM, purpose-built and adapted for this research, simulates the co-evolution of endogenous institutions and social networks in the context of CPR management. The key elements of this model are a renewable resource, agents with personal strategies, three layers of social networks and institutional rules. Institutional rules in this study are conceptualized using a simplified version of ADICO framework where institution (as well as a personal strategy) is reduced to an action, determining the number of resource units an agent appropriates per time step. Throughout each simulation agents with their personal attributes are initialized and arranged in three layers:

- Kinship network: Modeled with fragmentation, creating strongly tied separate groups. A Barabasi-Albert (BA) network is established within each fragment to represent kinship ties, resulting in scale-free degree distributions.
- Geographical neighbors: Generated as a small-world (Watts-Strogatz) random graph where nodes connect to their k nearest neighbors with rewiring probability.
- Friendship network: Initially established, this directed network evolves with a rewiring rate determined by a probabilistic preferential attachment based on three factors: triadic closure, attribute-driven preferences, and geographical proximity.

During the simulation phase agents extract resource units either by following their personal strategy or an institutional rule, rewire their connections within social network and, if too many agents have their energy levels too low, choose the most common personal appropriation strategy as a new institution. Power asymmetry is also present in the model since only agents with high indegree are eligible to vote for an institution.

Before proceeding with simulation experiments the model was calibrated through OFAT sensitivity analysis conducted with the ema_workbench striving for a balanced behavioral regime where the emergence of institutions oscillates between presence and absence. To achieve this equilibrium, it was crucial to pinpoint the key parameters that significantly impact the number and stability of emergent institutions, measured by the duration of institutional presence, or institutional age. Sensitivity analysis provided a valuable insight into how institutions and social networks co-evolve depending on different rewiring mechanisms. Turns out there are negative feedback mechanisms influencing network-dependent rewiring probabilities and positive feedback mechanisms governing homophily-based probabilities.

With the sensitivity analysis setting the stage, the subsequent focus shifted to scenario discovery, utilizing the PRIM algorithm to further explore the underlying dynamics of institutional emergence and stability within the model.

A series of simulation runs revealed a positive relationship between the degree of initial kins network fragmentation and the probability of a stable institutional regime within CPR extracting communities. However, available empirical data does not support this result.

Finally, policy recommendations were formulated. They suggest (i) identification and connection of fragments within social networks; (ii) analysis of the details of agents resource consumption, (iiI) identification of potential strategy options and (iv) enhancement of the processes that drive creation of gear- (or other attribute-) based connections. Overall, the research has the potential to inform the development of more effective and sustainable approaches to the governance of CPRs.

1 Introduction

Effective governance of common pool resources (CPR) presents a significant challenge due to their unique characteristics. CPRs are natural or man-made resources that (i) are difficult to exclude individuals from using (non-excludability) and (ii) where use by one individual reduces the amount available for others (subtractability). CPRs are characterized by the absence of well-defined property rights and the presence of congestion or rivalry in consumption, which creates a situation where individuals have an incentive to use the resource at a rate that is higher than what is sustainable in the long run. Examples of CPRs include fisheries, forests, water resources, grazing lands, and minerals.

As the global population continues to increase, the demand for resources such as water, land, food, etc, becomes more and more pressing. If a growing number of users will treat resources in a traditional way by maximizing their own short-term profits, the resources will end up being completely depleted. Hardin (1968) in his paper calls it "Tragedy of the Commons" and argues that many different resources are vulnerable to overuse that is likely to happen. Even pollution processes can be considered as ones that lead to the tragedy of commons with the only difference that in this case the resource is not depleted by taking out but reaches some critical amount (Hardin, 1968). Misuse of CPR is continuously being a threat to sustainable development of local communities across the world. The result is a growing concern about how we can ensure that these essential resources are sustainably managed for present and future generations.

But what can possibly prevent CPRs from following the tragedy of the commons? Ostrom (1990) proposes that a finely tuned set of endogenous rules can effectively regulate how actors appropriate resources. This set of rules is often referred to as institutions. Endogeneity of institutions refers to their origin: opposed to exogenous institutions that are set for the system from outside, endogenous institutions originate and evolve from agent interactions within the system.

According to the classification introduced by Ostrom (1990) there are three levels of institutions: constitutional, collective choice and operational. Each of them is interwoven with another one and changes in one of them will occur on deeper levels. However, this factor of set of rules being endogenous to a certain level is more inherent for the operational level responsible for the processes of appropriation, enforcement, provision and monitoring. Changes on other levels are harder to implement and happen less frequently. For the analysis deeper levels should stay exogenous as a fixed set of variables forming a static institutional environment within which actors can operate and make use of different strategies.

To investigate the emergence of institutions that shape the governance of CPRs, scientists often conceptualize this process as a multiplayer evolutionary game. Institutional development is perceived as an evolutionary process that occurs within a social network composed of CPR extractors and appropriators. In this approach, institutions emerge as a result of individuals' interaction, which can be modeled using game-theoretic methods. Moreover, the social network's structure is an important parameter that affects the evolution of institutions (Peña et al. 2016). This interrelationship is observed in both ways: social processes underlying emergence of institutions in turn are able to change social structures (Nishi et al. 2015). Bodin & Crona (2009) suggest that structures can also evolve by altering the nature of the information transmitted through its links, signifying the dynamic nature of this interrelationship.

There are several ways how institutional emergence in governance of CPR can be studied including case studies and laboratory experiments. However, both of them have a significant number of drawbacks that are not inherent for computer simulation (Ghorbani et al. 2017). Particularly agent based modeling is widely and successfully used for institutional design exploration (Ghorbani, 2022). Instead of deriving general patterns from historical data, agent-based models allow to clarify emergence mechanisms of different behavioral patterns (Ale Ebrahim Dehkordi et al. 2021).

By simulating CPR governance under different conditions and within various network topologies, agent-based modeling (ABM) can provide valuable scientific contributions to the field of CPR governance by identifying the conditions that lead to effective and sustainable use of CPRs. This can inform the development of evidence-based policies and governance strategies that promote the conservation and sustainable use of CPRs, improving the well-being of current and future generations.

The following chapters will provide a comprehensive overview of the current state of the art in the field, including a review of relevant approaches and methods, examples of frameworks for institutional analysis and specifically small-scale fisheries. Discussion of the available literature will bring us to the identified knowledge gap. This will be followed by a clear articulation of the research question and sub-questions, which will provide a framework for the subsequent discussion of the research approaches. Further, the model is presented and implemented novelties are explained. Model overview is followed by description of the conducted simulations. Simulation results are presented and thoroughly analyzed, the important connections are highlighted. Finally, by combining the findings and the limitations of the model, practical policy recommendations are formulated and supported by an elaborated discussion.

2 State of the art

The process of conducting a literature review on the sustainable governance of CPRs involved a thorough examination of the existing research on this topic. The starting point for this review was a set of articles provided by the supervisor, which set a foundation for understanding the key issues and challenges associated with CPR governance.

To expand the scope of the literature review, I analyzed the key papers provided by the supervisor to identify the main characteristics of the problems regarding sustainable CPR governance and to identify key papers that described the use of certain methods in this field. To find these works, I utilized several search engines (Google Scholar, Scopus, Semantic Scholar) and selected papers based on the number of citations they received and their overall relevance to the topic. By following the citations from these papers I covered articles that did not emerge during my search based on the key words I utilized. This approach allowed me to build a comprehensive understanding of the literature on sustainable CPR governance and to identify the key studies and findings in this field.

In this chapter, an overview of relevant studies regarding the governance of CPRs will be presented. The chapter will begin by examining the different approaches that have been used to address CPR governance challenges. This will include a discussion of case studies and laboratory experiments and ABM as well as an overview of studies that were focused on the interrelationship between social networks and CPR governance. Second section will explore formalization as one of the main challenges in institutional modeling. This section will present the main frameworks that are currently used for formalizing institutions. In the final section of this chapter the knowledge gap will be highlighted and research questions will be formulated.

2.1 CPR governance: features and regimes

The self-governance of a CPR is successful if the users develop solutions by themselves, aligning extraction rates with resource productivity to achieve a common benefit, and developing resource-specific rules that overcome the problems of free riders and opportunistic behavior (Ostrom, 2005).

A successful community-based management can exclude external users, adapt management rules to local conditions, allow most users to participate in the decision-making process, is recognized by other authorities and have effective monitoring, graduated sanctions, and cheap-easy mechanisms of conflict resolution (Ostrom 1990).

Words “management” and “governance” are often used interchangeably with regards to CPR.. Colin-Castillo & Woodward (2015) define governance as the exercise of policy definition to assure rules to manage the resource. Which means that governance is a broader term that includes management as one of its parts responsible for practical aspects. Throughout this work these terms may be used interchangeably.

Farrell & Knight (2003) highlight three approaches for explaining institutional emergence and evolution. These are power-based bargaining, evolutionary approach and the contract approach. The first one is more focused on developing the rules of how outcomes of collective actions are distributed among participants and the latter two on improved social efficiency. Authors argue that in cases where actors face different sets of alternatives due to power asymmetry, bargaining theory and evolutionary approach provide a better explanation than a contracting one. Knight suggests that a good way to conceptualize bargaining power is to look at the range of alternatives each party has in case the agreement was not reached.

Measure of success in CPR governance is threefold (Frey & Rusch, 2014):
- *social success* is measured as equity or contentedness of agents;
- *economic success* is measured through agents' wealth;
- *ecological success* is measured through productivity or condition of the resource.

A substantial number of research papers are devoted to assessment of local CPR institutions (Okumu & Muchapondwa, 2020). Many scholars have employed various methods such as: socio-anthropological case studies, game theory models, comparative case study analysis with the aim to understand the drivers and conditions behind successful collective action on CPR governance. Some of the obtained results are contradicting and in total introduce too many factors that influence the governance regime to be able to conduct a thorough analysis.

2.2 Social networks in CPR governance

Scientists have been addressing CPR governance with SNA tools for various different purposes. For example, Namibian communes of water users were analyzed to identify the effect several levels of interactions between them have on their institutions related to water usage (Schnegg, 2018). It was found that it is hard to separate the sharing of water from sharing of other resources. Even though there were formal institutions in place including sanctioning, very often agents did not follow them. The author explains it through a concept of institutional multiplexity arguing that in these communities people are dependent on each other in sharing multiple resources and each type has its inherent rules and norms. Hence, actors' behavior cannot be explained by institutions for one type of the resources in isolation from the others.

Depending on the specific goal of analysis networks can be described by a big variety of metrics. Chaudhuri et al. (2021) analyzed several studies on social networks in the agricultural sector and highlighted three key metrics that have a clear implication for farmers' networks (Table 1). In their review, the authors provide a table that reflects the research methods used by other researchers to collect data and conduct their analyses. This list includes regression analysis, semi-structured interviews, group discussion, literature review, qualitative data analysis, spatial autoregressive modeling, nodal analysis for degree centrality, reduced-form regression, econometric analysis, network analysis with UCINET and 3D CoP (community of practice) modeling.

In another research focusing on agricultural communities in Ethiopia, authors analyzed factors that affect adoption of new resource management techniques (Wossen et al., 2013). It was revealed, using probit regression model, that geographical proximity to a peer that has already adopted a new practice, increases the probability of adopting this practice for a household. This is explained by the fact that neighbors are able to observe directly the use of new technologies and learn by watching. Besides, the results have shown the importance of different types of ties a household has within the network. Therefore, on average, adding one tie to the household network would increase the probability of adopting new practices by 6.2%, 4% and 3.6% for kinship, friendship and neighborhood respectively.

In the realm of socio-ecological systems (SES), the impact of social networks comes into play from various angles, as underscored by the comparative research carried out by Olsson et al. (2006). This study delved into five distinct case studies involving different regional systems, revealing essential factors that propel these systems toward more sustainable and adaptable governance models. Particularly interesting is how the study shed light on the dynamic roles of social networks across different stages of system development, especially during the preparatory and navigational phases. Depending on where the system is in its evolution, social networks contribute in different ways. This can range from effectively spreading new ideas to forging new connections and fostering leadership.

This viewpoint aligns with the notion that a successful strategy for managing natural resources involves building interpersonal connections among actors and stakeholders when the system is stable. These connections become valuable assets during times of significant change. Similar suggestions can be found in other works, such as those by Hirschmann (1984) and Gunderson (1999). Thus, the strategic cultivation of social networks emerges as a recurring theme across diverse studies, highlighting its importance in fostering adaptable governance within ever-changing socio-ecological systems.

Table 1. Network metrics and their implications for socio-ecological networks. Adopted from Chaudhuri et al. (2021), García-Amado et al. (2012), Barnes-Mauthe et al. (2015), Bodin et al. (2006), Bodin et al. (2017).

Metrics	Scale	Definition	Implication
Degree centrality	local	Number of direct links of a node	- Better coordination among the agents in network - Ease in decision making - Lack of diversity in solutions - High degree centrality gives power over information transmission
Indegree	local	Number of incoming links of a node	- Number of actors from the network relying on this actor - Reflects hierarchy
Betweenness centrality	local	Number of shortest paths between two nodes in a network	- Productive exchange of relevant knowledge between agents - Development of modularity within

		that lie through this node	a network (partly distinct perspectives than the network as a whole)
Tie strength	local	Intensity of the relationship between two actors	- Strong ties generate trust, facilitate information exchange, provide resources and can enhance productivity - Weak (bridging or linking) ties typically connect dissimilar groups
Density	global	Ratio of the actual number of links to the maximum possible number of links (complete network)	- Stronger relations of trust between agents - Higher participatory action - Easier to establish agreeable network norms and operational methods
Number of components	global	A number of independent networks within the larger network in which all nodes are directly or indirectly in contact with each other.	- Quantifies the degree of fragmentation. - Characterizes reachability within network
Proportion of cutpoints to total points in the network	global	Cutpoints are actors that connect two or more subnetworks. If cutpoints are removed, the network is separated into several fragments.	- Indicates the amount of structural holes and weaknesses in the network

In a similar manner, recent case studies have delved into the concept of adaptive capacity within socio-ecological network structures (Bodin & Chen, 2023). The authors of these studies concluded that further efforts should be directed toward identifying mechanisms and operationalizing adaptive capacity. This emphasis on enhancing our understanding of adaptive capacity highlights the evolving nature of research in this field and the ongoing quest to better harness the potential of social networks in bolstering resilient and responsive governance systems.

2.3 Approaches and methods

The tragedy of the commons has been a topic of great interest among researchers from various backgrounds: from economists to environmentalists. To study this problem, different tools and methods have been used, each with its own strengths and limitations. Some studies have utilized a combination of techniques to provide a comprehensive understanding of the issue, while others have focused on a specific method. In this literature review, we will divide the studies into three main sections based on their main method: laboratory experiment, case study, and computer simulation. Papers discussed in this section are not always explicitly related to the institutional perspective of CPR governance, some of them consider other institutional contexts or a broader theoretical perspective on social processes in multi-agent environments. It was done to demonstrate the fundamental nature of the problem This fact highlights the existing knowledge gap that will be discussed in the following section.

2.3.1 Experiments

Laboratory and field experiments have been widely used in the study of CPR governance to identify the important variables related to institutional mechanisms (Janssen et al. 2008; Ostrom, 2006; Walker et al. 2000). This method allows researchers to manipulate specific variables in a controlled environment and to observe the resulting outcomes, which can provide valuable insights into the causal relationships between institutions, actors, and CPRs.

Ostrom (2006) has shown that laboratory experiments can be also used to study emergence of endogenous institutions. She conducted experiments with varying initial amounts of CPR per actor. The results have shown that by developing a set of rules a group would achieve higher payoffs as a result of their interactions compared to the groups that failed to develop such rules. Walker et al. (2006) have illustrated the emergence of collective choice mechanisms in voting procedures. One of their main findings is that in cases when proposals were adopted they significantly increase efficiency of the process. The results of these researches demonstrate how endogenous institutions emerging from group interactions are able to influence the outcomes of such interactions.

Nishi et al. (2015) conducted a series of experiments where subjects were assigned playing a cooperation game. This study was aimed at exploring the connection between wealth inequality among agents (Gini coefficient) and their ability to cooperate. During the game subjects were given a choice to cooperate or to defect resulting in the amount of wealth they and their neighbors acquire at the end of each round. Results of these experiments demonstrate that visibility of inequality plays an important role since it helps to maintain the initial level of inequality existing in the system. Moreover, experiments have shown that when inequality is made visible, it leads to lower levels of average wealth and cooperation compared to situations where the wealth of neighbors is not visible to participants.

Another important finding of this study (Nishi et al. 2015) emerged from the opportunity of the subjects to break and make ties with each other, based on the knowledge about how cooperative their neighbors were, changing the set of their neighbors. During these experiments it was observed how the network topology dynamics is interrelated with the cooperative behavior. Specifically, they highlighted the role of visibility of wealth inequality among the subjects that affected dynamics of probability of cooperation, average degree and network transitivity (number of triangles).

Nonetheless, there are important limitations that are inherent to laboratory experiments and hinder their ability to provide a comprehensive understanding of CPR governance. One of the main limitations is that laboratory experiments can only study a limited number of scenarios over a short period of time, which makes it difficult to identify sustainable long-term strategies for CPR governance. Additionally, laboratory experiments typically involve a restricted number of parameters, which makes the experimental design relatively simple and limits the extent to which the findings can be generalized to real-world CPR systems (Ghorbani et al. 2017).

2.3.2 Case studies

The study of CPR governance through case studies has been a popular approach in the field of resource governance and governance. Case studies allow researchers to examine the real-world experiences of CPR governance in specific contexts and to understand the complex interactions between institutions, actors, and resources in different CPR systems. Examples of such case studies can be found in the works of Sarker et al. (2008) and Wilson et al. (2016), which provide valuable insights into the challenges and opportunities associated with CPR governance in diverse settings. Their unique feature is the social and biophysical environment that cannot be fully replicated in a lab experiment and especially in a computer simulation but can be very important for understanding agent interactions (Röttgers, 2016).

Sarker et al. (2008) apply CPR logic to water quality governance based on the case of Brisbane River and Moreton Bay in Australia. They argue that water quality itself has characteristics of CPR and suggest to utilize the logic of CPR governance by creating a framework that includes landholders and beneficiaries. This solution is intended to promote cooperation between them and result in improved water quality.

However, the use of case studies as a method for studying CPR governance also has some disadvantages. One of the main limitations is the idiosyncrasy of each case, which makes it difficult to generalize the findings from one case to other CPR systems (Ghorbani et al. 2017). This is due to the unique context and history of each CPR, which may affect the outcomes of CPR governance in different ways. Furthermore, the time horizon for measuring the impacts of CPR governance can also be a challenge, as the resulting effects may not be fully realized for several years or decades, as noted by Beckmann and Padmanabhan (2009).

2.3.3 Institutional modeling

2.3.3.1 ABM for institutional modeling

ABM is increasingly being used as a tool for modeling institutions related to CPR governance. ABM is a computational approach that enables researchers to study the complex interactions between institutions, actors, and resources by simulating the behavior of individual agents and the interactions between them.

This approach allows researchers to examine the impact of different institutional mechanisms and to identify the conditions for effective and sustainable CPR governance.

According to Ghorbani (2022) institutional modeling:

- is a branch of agent-based modeling that focuses on and explicitly models the social aspects of socio-ecological-technical systems;
- supports theory development by enabling modelers to study institutions, and institutional change within, the systems they are embedded in;
- incorporates top-down institutional structures and aims at studying interactions between bottom-up processes and top-down structural patterns.

Institutional modeling has been a valuable tool for studying the mechanisms of the emergence of institutions, particularly in the context of CPR governance (Ale Ebrahim Dekhordi et al. 2021; Ghorbani & Bravo, 2016; Ghorbani et al. 2017).

The authors have developed a simple ABM model that despite its high level of abstraction, showed some insightful findings (Ghorbani & Bravo, 2016). Among these findings, it was discovered that agents did not establish institutions in every case, with one-third of the cases studied showing that agents never formed an institution. This occurred when the CPR was characterized by high abundance and rapid replenishment. These findings highlight the significance of considering the specific characteristics of CPRs, as well as the motivations and behavior of actors in comprehending the emergence of institutions for CPR governance.

In further research the model was validated on historical data and used to study how different parameters affect institutional characteristics (Ghorbani et al. 2017). This research demonstrated effects that resource parameters and the level of cheating among the agents have respectively on stability and age of an emerging institution,

Other studies utilizing the same approach (Ale Ebrahim Dekhordi et al. 2021) have shown the dependence of characteristics of emerging institutions on initial heterogeneity of actors. According to Reeves et al. (2022) heterogeneity of actors can be observed on different stages of simulation: initialization and runtime. In this case heterogeneity was characterized by the amount of resource each agent possessed at the beginning of simulation, thus, belonging to the initialization stage. Findings of this research suggest the importance of considering the role of sanctioning mechanisms and frequent institutional adjustments in the long-term governance of CPRs.

2.3.3.2 Network perspective on institutional modeling

Social network analysis (SNA) has been used to study the effects that structural parameters of networks have on processes that happen within them. In combination with ABM it allows researchers to investigate interconnections between network topologies and evolution, social or biological processes arising from behavior of individuals. This chapter presents an overview of studies that have utilized the network perspective to model the emergence, evolution, and impact of institutions. This chapter is intended to demonstrate the importance of incorporating network analysis into institutional modeling for a comprehensive understanding of the dynamics of CPR governance.

May (2006) provides an overview of the types of networks used for modeling social systems. These include Erdős-Renýi random graphs, 'small world' networks, and 'scale-free' networks, each characterized by different degree distributions, as well as metrics such as clustering coefficient and diameter. These network types can affect the spread of ideas and information among agents on vertices, as demonstrated by Peña et al. (2016). They found that some graphs, such as stars and scale-free networks, were more favorable for spreading ideas, while others hindered the process.

Reeves et al. (2022) demonstrate the importance of agent heterogeneity and social network structure in the spread of infectious diseases such as COVID-19. Using ABM, the authors examine how network updates force agents to change their social contacts and how this affects the spread of the disease. Specifically, they investigate how individual differences, such as risk tolerance, interact with the network structure to influence the spread of COVID-19. While not explicitly focused on the emergence of institutions within social networks, this study highlights the critical role of network dynamics and individual heterogeneity in shaping social processes and their outcomes.

Social networks in reality are dynamic structures and this factor should be taken into account when studying social interactions. Moreover, the key element is the link between intermediate outcome of these interactions and structure formation. Previous studies (Boero et al. 2010), where agents were playing an investment game, showed that variation in a fixed network structure has no significant effect on the outcomes of the game. In this particular research simulations that were carried out on a complete graph, small-world and scale-free networks have led to very similar results. At the same time two out of four models with dynamic networks have shown higher investments and return rates than those of static ones. Authors claim that the ability of making and breaking ties based on agents' states has led to isolation of free-riders and better cooperation levels.

2.3.3.3 Agent-oriented and ties-oriented models for network analysis

Usage of SNA can be found across many different fields of science where it supports scientists in their research regarding a wide variety of topics. Although, in general there are two possible reasons why scientists decide to use SNA together with ABM (Will et al. 2020):

- To study diffusion: i.e. how ideas, goods or diseases spread through links of a network. In case of CPR governance the most relevant examples of diffusion are spread of strategies of extraction and appropriation of the resource and spread of the resource itself. The latter is only possible if there is a mechanism established that allows agents to exchange resources through links among them.
- To study network integration: i.e. how agents' position in a network affects the outcomes of interactions. In other words how connections between agents relate with institutional settings emerging from their interactions..

There is a class of stochastic actor-oriented network models that allows one to utilize a combination of ABM and SNA methods to study the aspects of the development of social networks. These models have the purpose to represent network dynamics on the basis of observed longitudinal data, and evaluate these according to the paradigm of statistical inference (Snijders et al., 2010). Network dynamics in these models is driven by mechanisms identified earlier through theoretical or empirical research. Some examples of such drivers are reciprocity, transitivity, homophily, and assortative matching. An illustrative instance is the examination of friendship dynamics within a Dutch school class (Snijders et al., 2010)..

Similarly, actor-oriented models find application in domains beyond social interactions.In another research an actor-oriented model was applied to study interfirm networks in the genomic industry (Van De Bunt & Groenewegen, 2007). The research showed that firms have a preference for (i) high-stats partners and (ii) partners with whom they share organizational group affiliations.

Another class of models utilized for cross-sectional modeling – the exponential random graph models ('ERGM'), or p∗ models. Herzog & Ingold (2019) utilized inferential SNA and exponential random graphs models (ERGMs) to explore the relationship between actors involved in cooperation on water quality management for the Rhine river in the Basel region and demonstrated that agents are more likely to share a tie if they (i) have similar perception regarding the problems related to water quality (ii) co-participate in ecological forums.

ERGM are tie based unlike ABM, they suit best for systems where there is a dynamic equilibrium, that means that all the changes in the outcome can be understood as fluctuations without a very clear, systematic trend (Snijders et al., 2010). ABMs are more general and do not necessarily require an equilibrium and, thus, are able to provide insights into how individual behaviors collectively shape the network's evolution. Besides, ERGMs specialize in analyzing cross-sectional data that unlike longitudinal data are a reflection of a phenomenon in a particular moment in time.

ERGM and stochastic-oriented actor-based models are relatively new and the available literature is quite limited. No papers addressing usage of such models for collective action and institutional emergence were found.

2.3.4 Frameworks for institutional analysis

Frameworks discussed in this section provide an opportunity to scholars and policy makers to perform a systematic and comparative institutional assessment (Ostrom, 2011). Through making use of such frameworks it is possible to combine elements of various theories such as economics, behavioral science, social network theory, game theory, etc. into a model and to produce a certain outcome. The latter can be used further to better understand the real structure or process the simplified model is describing.

2.3.4.1 Institutional analysis and development

In order to model a system where agents interact within a certain environment, one should first formalize the system by outlining its boundaries and defining how different elements are arranged and the way they interact with each other. Following the classification (Ostrom, 1990), institutions can be described in three interacting levels: constitutional, collective choice and operational. The latter influences how appropriation, enforcement, provision and monitoring processes are organized in the system and, therefore, is a dynamic part of the environment when it comes to institutional modeling of CPR. On other levels changes happen during larger time spans compared to the usual time horizon of studies and, thus, can be included in the model as a set of static parameters.

But not only institutions define the actor environment. As it is shown on figure 1, biophysical conditions and structure of the community also affect agent behavior (Ostrom, 2005). Figure 1 clearly demonstrates several feedback loops that this concept implies. Such a structure allows to capture co-evolution of agents and their environment when modeling socio-ecological systems.

Each block from the diagram (FIg.1) depicts a set of variables as well as fixed values. For example, figure 2 reveals the inner structure of action situations with actors' positions being one of the key variables (Ostrom, 2005; 2011). Whether a variable is sensitive to feedback mechanisms or is represented as a fixed value depends on the scope of the model and on the research question.

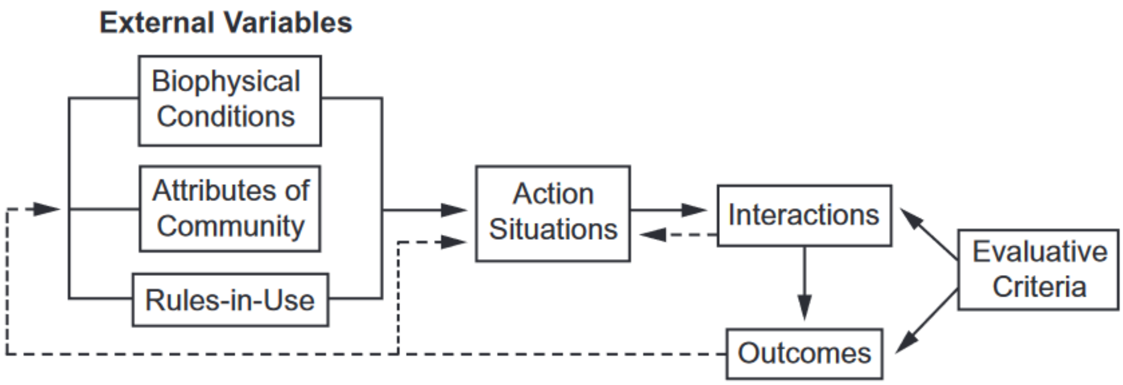


Figure 1. The IAD framework (Ostrom, 2005)

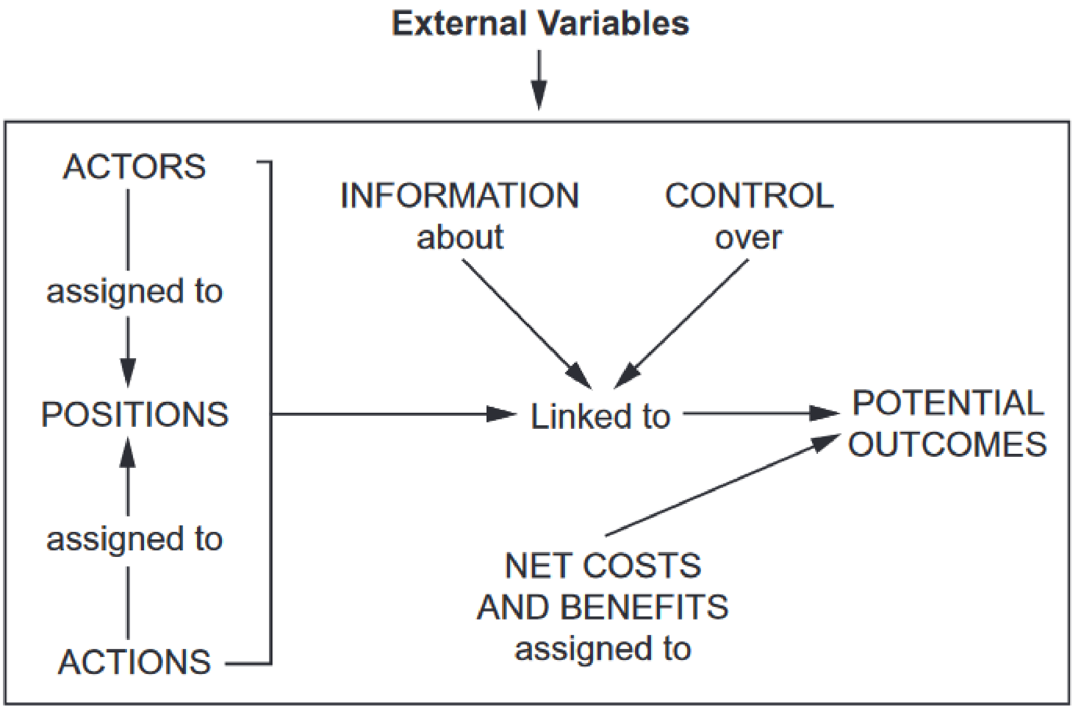


Figure 2. The internal structure of an action situation (Ostrom, 2005).

3 Knowledge gap and research question

The tragedy of the commons in the context of CPR governance has attracted the attention of scholars from various disciplines. However, despite considerable research efforts, the mutual influence of network structure and the institutions that emerge for regulating CPR usage remains underexplored. Previous studies have demonstrated that network characteristics can impact the outcomes of multi-actor games within social networks. Bodin & Crona (2009) highlight the importance of a thoughtful analysis of the relation between network structure and social processes in order to obtain a deeper understanding of resource governance.

Yet, the role of network characteristics in the emergence and evolution of institutions for CPR governance has not been thoroughly investigated. Since evolution of network and emergence of institutions can happen in parallel, the same holds for the opposite type of relation. The main challenge of this research is theoretical exploration of causal relations between the networks and institutions. Therefore, this study seeks to address this knowledge gap by exploring the interrelation between dynamics of social network structure and the emergence and evolution of CPR governance institutions.

The main research question is then:

How are network structure and dynamics interrelated with the emergence and evolution of institutions for the governance of common pool resources?

The main research question serves as the guiding theme for this study. To delve into this complex inquiry and provide a structured framework for analysis, several subquestions have been formulated:

1. How does the initial network structure impact the emergence of institutions for CPR governance?
2. How do institutions and networks co-evolve depending on different rewiring mechanisms?
3. How can the connection between network parameters and institutional settings for CPR governance be utilized to provide effective policy recommendations?

These subquestions collectively facilitate a comprehensive exploration of the central research question, offering a nuanced understanding of the intricate relationship between network structures, institutional dynamics, and their implications for the governance of common pool resources.

The literature discussed above underscores the notion that despite the challenges inherent in governing SSF, they contain the essential characteristics of SES where the evolution of social networks significantly influences the formation of institutional structures. Thus, SSFs serve as an apt case study for probing the interwoven relationship between network dynamics and the emergence of institutions. This research aims to explore this complex interaction, investigating how these dynamics work together to shape the ways SSFs are governed.

4 Research approach

In this chapter, the research design choices for studying the emergence of institutions are highlighted. First, the advantages of ABM and computer simulations are discussed. Then the chapter proceeds with outlining the boundaries of the research by focusing on institutions in fisheries and provides the reasons for that as well as more details on specific features of these institutions. Finally, it presents the ADICO framework that is derived to conceptualize these institutions in order to incorporate them into the model.

4.1 Why ABM

There are also other modeling formalisms such as discrete event modeling, system dynamics or methods based on ERGM that are used in scientific research. The literature research provides strong arguments for using ABM with its obvious advantages for studying the emergence of institutions compared to other methods:

- Flexibility: ABM and simulation is able to cover a wide range of scenarios and test the impact of different variables on the emergence of institutions. This provides a more nuanced understanding of the mechanisms driving institutional emergence and change.
- Complexity: The outcome of agents' interactions in a network is influenced by both their strategies and the network structure. Game theory and network analysis provide a useful framework for understanding these interactions. However, as Nowak (2006) suggests, the arising number of variations requires the use of a computer simulation. And ABM is a suiting tool to capture this complexity.
- Capturing dynamics: ABM excels in capturing dynamic processes over time. In contrast, some methods, like Exponential Random Graph Models (ERGM), are better suited for cross-sectional data analysis and may struggle to effectively capture the evolving nature of network dynamics.

4.2 Refining research scope: focusing on fisheries

4.2.1 Data-based strategic choice

The model developed for this study as well as prior and already validated models that served as inspiration are described in detail in chapter 5. However, here I am going to discuss some aspects of the decision-making process underlying the model's development as they have guided the research and are important for understanding the reasons behind choices regarding research design.

The development of any model is not complete without its validation. Empirical data can be used to validate model on different stages of its development: (i) existing theoretical and empirical knowledge is usually utilized to define specific features of model components that translate a theoretical system into ABM and (ii) empirical data can be compared to the outcomes of simulations in order to make conclusions whether those modeling choices were able to replicate the mechanisms that are present in real-life systems (Squazzoni, 2005).

Data that were used for the first type of validation is mostly present in section 2 and will be additionally highlighted in the next section. Second type of validation is more complicated as it assumes the existence and availability of data that would cover more or less the same mechanisms and variables as are involved in the scope of this specific study.

.

Fortunately, the data set, that has already been used in an array of studies on CPR, was also made available for me thanks to Ulrich Frey. This data set was compiled by the Workshop in Political Theory and Policy Analysis at Indiana University headed by Elinor Ostrom (Poteete et al., 2010). This compilation encompasses diverse CPR contexts, including 66 irrigation cases, 56 fishery cases, along with instances from forestry and other sectors and consists of almost 600 variables. Each case in the dataset corresponds to a specific user group obtaining a particular resource unit from a resource system by following a set of rules. If different groups accessed the same resource or if the rule set was modified, it would create a distinct case in the dataset (Frey & Rusch, 2014).

It is assumed that SESs that describe appropriation of CPRs often demonstrate similar behavior and many theoretical concepts or empirical results targeting one domain are generalizable to others. At the same time it is easier to build a model around the data from a specific domain since it reduces a degree of uncertainty by limiting the number of options for features and components. Based on available empirical data two different domains were considered: fishery and irrigation system. Because of (i) the way the resource was conceptualized in previous models and (ii) the significant role of spatial distribution of agents in the case of irrigation, fishery was chosen as the central concept to build the model around.

4.2.2 Institutions in small-scale fisheries

According to the estimates of Nielsen et al. (2008) small-scale fisheries (SSF) employ over 10 million fishers contributing around 31 million metric tons of catch which is roughly one third of the total global catch. While fisheries play a critical role in global food security, the governance of small-scale fisheries presents unique challenges compared to larger fisheries. The challenges in governing small-scale fisheries are multifaceted. Unlike larger fisheries, small-scale fisheries often lack centralized management structures, making it challenging to implement uniform regulations. The diverse nature of SSF, operating in varying ecological and social contexts, further complicates governance efforts. Variability in resource availability, economic conditions, and community dynamics requires adaptable and context-specific management strategies.

Numerous studies are devoted to analyzing the role of different institutions in governing SSF. Extensive research has highlighted the significant influence of fishing gear type on the ecological impact of these fisheries. Studies conducted by Shester and Micheli (2011) quantified the ecological impact using factors such as bycatch and habitat disturbance. They found that different fishing gear types have varying effects on these ecological indicators. Another study by Castello et al. (2013) examined fishing data from various sites in the floodplains of the Amazon river. Their findings revealed that the distribution of total catch per gear type varied not only between sites but also across different seasons. A list of gear is presented in table 3. This variation is attributed to the diverse requirements and behavior of different species, which are influenced by location and seasonal factors. Consequently, there is a degree of heterogeneity in the gear used at different fishing locations. Community-based regulations in the lower Amazon region, as analyzed by Almeida et al. (2009), often include limitations on fishing gear, locations, targeted species, or a combination thereof. Notably, the study found that gillnets were banned in a majority of the analyzed agreements, lasting for a duration of 4 to 6 months. Nielsen et al. (2008) identified various gear types utilized in small-scale fisheries across different countries, including handlines, longlines, dive gear, traps, nets, gill nets, push nets, and small trawlers. The diversification of gear and the species composition of catches have been shown to contribute to the economic stability of households (Castello et al., 2013). These findings collectively highlight the importance of understanding institutional arrangements in SSF for effective resource management and sustainable practices.

Table 2. Drivers of social tie formation (Alexander et al., 2018).

Drivers	Definition	Evidence in SSF	Contextually relevant drivers
Structurally driven	Creation and termination of ties are driven by existing connections	● Triadic closure is one way to capture bonding ties (Ramirez-Sanchez and Pinkerton 2009; Alexander et al. 2015)	● Triadic closure
Attribute driven	Creation and termination of ties are driven by similarities in actors' attributes	● Gear based homophily (Crona and Bodin 2006; Cox et al. 2016) ● Kinship based homophily (Ramirez-Sanchez 2011) ● Ethnic based homophily (e.g. Barnes-Mauthe et al. 2013) ● Leaders as individuals being sought after (e.g. Alexander et al. 2015)	● Gear based homophily ● Leaders
Exogenous contextual factors	Geographical environment drives the creation and termination of ties	Involvement in other types of social networks ● Co-op membership Geographic Proximity ● Fishing grounds (e.g. Maya-Jariego et al. 2016) ● Landing sites (no empirical work to date)	● Geographic proximity

In addition to the aforementioned aspects of SSF, community cohesion and the formation of social ties are critical factors in understanding institutional arrangements. According to Alexander et al. (2018), the literature identifies three major types of processes that drive the building of new ties within fishing communities. The first type is structurally driven, characterized by the phenomenon of triadic closure, where individuals tend to form connections with others who already share a mutual connection. This process contributes to the formation of cohesive social networks within the community. The second type is attribute driven, which emphasizes factors such as leadership and similarity in fishing gear used.

Fishers with similar gear types may be more inclined to establish connections based on shared practices and experiences. Lastly, exogenous contextual factors, particularly geographical proximity, play a role in tie formation. Fishers who are located in close proximity to one another are more likely to establish social connections due to the convenience and frequency of interaction. Understanding these drivers of tie formation and community cohesion is crucial for comprehending the emergence and dynamics of institutional arrangements in SSF.

Table 3. Description of the most common fishing gear in SSF of Amazon basin (Castello et al., 2013).

Name	Description
Harpoon	Wooden pole with sharp metalic head used for catching large species
Fence trap	Wooden fences built on the ground directing fish into traps
Fishing rod	Rod, line, and hook used for medium-sized species
Longline	Line with several hooks used to catch large river species
Arrow	Light-weight rod with sharp metallic head used for medium sized species
Handline	Line and hook used for various species
Gillnet	Multi- or single-filament nets used for various species
Castnet	Funnel-shaped net used for small pelagic species
Trident	Wooden pole with metalic trident used for medium-sized species in shallow water

Furthermore, it is worth noting that decision-making processes within fishing communities can be influenced by power dynamics and social exclusion. García-Amado et al. (2012) highlight the presence of certain groups within the community who are excluded from the decision-making processes. This exclusion can have implications for the governance and institutional arrangements within small-scale fisheries. The study suggests that the inclusiveness of individuals in decision-making is associated with the number of incoming links they have in the social network. It argues that individuals tend to seek out and establish connections with others to enhance their involvement in decision-making processes. This finding emphasizes the significance of social connections and network structures in shaping the participation and influence of individuals within fishing communities.

In biological as well as economical studies related to fisheries there is a standard indicator used to assess fish stocks and efficiency of fishing activity — Catch Per Unit of Effort (CPUE) (Yudawan et al., 2022; Maunder & Punt, 2004). Each type of fishing gear represents a certain productivity rate that is defined as catches with a unit weight per catching effort. CPUE is a good proxy for an aggregated personal strategy of a fisher since it accounts for both the frequency of fishing activity and the gear type in use.

4.3 Institutional grammar

The Institutional Grammar (IG), also known as ADICO or ABDICO, is a framework developed by Crawford and Ostrom (1995) and extended by Siddiki et al. (2011) to conceptualize institutions. The framework views institutions as a set of institutional statements, where each statement consists of a maximum of six components. These components are (ADICO):

- **Attributes**
  - Attributes describe the participants in the situation to whom the institutional statement applies
- **Deontic type**
  - Deontic operators are obligated, permitted and forbidden.
- **aIm**
  - The aim component describes the action or outcome to which the institutional statement applies
- **Condition**
  - Conditions are the set of parameters that define when and where an ADICO statement applies. If there is no condition stated, it implies that the statement holds at all times.
- **Or else**
  - 'Or else' is the consequence of non-compliance to an assigned institutional statement.

This formalization of institutional settings allows for the use of ABM to study the dynamics of institutional arrangements over time. It is a widely used tool among researchers to analyze the emergence of institutions and the evolution of institutional arrangements in response to changes in the system (Ale Ebrahim Dekhordi et al. 2021; Ghorbani & Bravo, 2016; Ghorbani et al. 2017).

5 Model

This chapter focuses on the development of the ABM that was used further for simulations. This process and its result I consider to be the central part and the most significant scientific contribution of the whole thesis. To my knowledge, this is the first ABM that (i) was developed with the aim to support CPR management, (ii) was developed using Python libraries and (iii) is capable of capturing both: emergence of institutions and evolution of social networks. The chapter is divided into several parts: first part describes the existing ABM models that were created for studying emergence of CPR-related institutions, and their main elements, the second part is devoted directly to the model developed within this study.

5.1 Influences from prior models

The research will use a combination of ABM and approaches from SNA to answer the main research question. The ABM model is based on previous works (Ale Ebrahim Dehkordi et al. 2021; Ale Ebrahim Dehkordi et al. n.d.; Ghorbani et al. 2017; Ghorbani & Bravo, 2016). The model, originally developed in Netlogo (Ghorbani & Bravo, 2016), was transferred to Python (Mesa) (Ale Ebrahim Dehkordi et al. n.d.) and throughout its versions was used to study how emergence of institutions affects resource and agents' wealth, the relation between wealth inequality and cooperation, the effects social and environmental shocks have on institutional stability and so on. Moreover, this model has been validated on an empirical dataset using 122 cases of irrigation systems and fisheries (Ghorbani et al. 2017).

Even though the versions of the model being adapted for specific research questions have certain differences, the main components and mechanisms of their interactions have been preserved throughout the iterations:

- Resource: There is a single shared and renewable resource. At every time step the resource grow is defined as $\Delta R = rR(1 - \frac{R}{K})$, where R – the amount of resource at previous time step, K – the carrying capacity and r – the reproduction rate. At the beginning of every simulation the resource is set at carrying capacity $R(t = 0) = K$.
- Agents: Every agent has a current strategy, a set of neighbors, yield level (wealth) and a set of personal parameters: social influence, individual cheating propension, conservative value.
- Individual strategies: Strategies are conceptualized using ADICO framework. Every strategy has two components: action (aIm according to IG), that stands for how many units of resource an agent can yield at a time, and condition, that defines under which circumstances the action can be performed.
- Simple learning: Agents in the model employ a "best strategy" approach, retaining the strategy that yields the highest consumed resource as they learn from experience throughout the simulation (Ale Ebrahim Dehkordi, n.d.).
- Strategy change occurs when an agent's wealth falls below a predefined threshold. This change can happen through three procedures: 1) copying the strategy of the most successful neighbor with the highest wealth, 2) randomly selecting a new

strategy resembling innovation, or 3) choosing the best strategy the agent has experienced thus far based on learning (Ale Ebrahim Dehkordi, n.d.).

- Institutional rules: Institutions have the same components as individual strategies plus the frequency of monitoring and the amount of wealth (resource) the cheaters must pay.
  - *Voting:* if institutional threshold is met, the most frequent individual strategy becomes institution.
  - *Cheating:* depending on the agents' cheating propensity they might follow their individual strategy instead of the institution.

5.2 Extended model

This subchapter describes the model that was created and utilized within this study. The description mainly follows the ODD+D protocol for ABM suggested by Müller et al. (2013). This framework is widely adopted in the scientific community to ensure thorough documentation and reproducibility of ABM. It's important to mention that this model's description draws upon and extends the work initiated by Ale Ebrahim Dehkordi et al. (n.d.). This collaborative foundation serves to maintain continuity while also incorporating refinements to address new research inquiries and enhance its mechanics. Structural elements of the ODD+D protocol that were considered to be rather formal and not paramount for understanding of the model were moved to the Appendix A.

5.2.1 Purpose

This ABM is designed to simulate the co-evolution of endogenous institutions and social networks in the context of CPR management. The primary objective of this model is to explore the interplay between emerging institutions and the evolving structure of social networks. By examining how these two factors influence each other over time, the model aims to provide insights into the dynamics of self-organized governance systems for CPRs. Through a series of simulations, the model seeks to shed light on the reciprocal relationship between institutions and social networks, uncovering how changes in one factor can lead to adaptations in the other. By capturing the feedback loops and co-evolutionary dynamics, this ABM contributes to a deeper understanding of the mechanisms underlying sustainable CPR management strategies.

The model is designed for researchers and policymakers interested in understanding the interplay between endogenous institutions and social networks in the context of CPR management. Specifically, this model targets those who seek to explore the mutual influence and co-evolution of these dynamic elements and how they collectively shape the governance of CPRs. Additionally, individuals and organizations focusing on resilience and SES might find the model useful and interesting to explore.

5.2.2 Process overview and scheduling

Each run of the model consists of two main phases: initialization and simulation of the appropriation process. During the initialization phase, the model is created using the provided input parameters. These parameters define the initial state of the following components of the model:

- Resource: $R(t = 0) = K_0$ – the initial carrying capacity and r – the reproduction rate.
- Agents: Initialize 100 agents. Each agent has its own set of "personal values" (cheating propensity, social influence, etc.), initial energy level and initial personal strategy that consists of action that defines how many units of resource an agent appropriates each time step.
- Social networks (figure 3):
    a. Kinship network (undirected, fixed) is modeled as several components representing fragmentation. Pseudocode that describes this algorithm is available on the listing 1.
        i. The whole population is separated into fragments of a certain size, corresponding to the strongly tied groups.
        ii. Within each fragment, a Barabasi-Albert (BA) network is created to represent kinship ties. The "m" parameter represents the number of edges that are added to the network at each step during the network's growth process in a Barabasi-Albert network and is kept constant at the value of 3.
        iii. The BA model is used to generate a network with a scale-free degree distribution, so every component independent of its size has similar degree distribution.

Listing 1. Pseudocode with the algorithm for creating a kins network.

```
Initialize an empty list called "fragments"
Set an "upper_limit" to the total number of agents

If the desired number of fragments (n_fragments) is greater than 1:
    Repeat the following for each fragment until there is only one fragment left:
        Calculate a "delta" value to ensure a minimum fragment size
        Generate a random "fragment" size within a specified range
        Append the "fragment" size to the "fragments" list
        Update the "upper_limit" by subtracting the current fragment size

    Create the last fragment with the remaining agents and add it to "fragments"
Else:
    Create a single fragment containing all the agents and set it as "fragments"

For each "fragment" in the "fragments" list:
    Generate a Barabasi-Albert graph with "fragment" nodes and "ba_m" edges per node
    Adjust node numbering to ensure consistency across fragments
    Combine the fragment graph with the overall network
    Update the node numbering offset
```

    b. Geographical neighbors (undirected, fixed). This network is generated as a small-world (Watts-Strogatz) random graph where each node is connected to its k nearest neighbors and with a probability p that an edge in an initial regular structure is rewired. Parameters k and p were kept constant at values of 2 and 0.4 respectively.

c. Friendship (directed, flexible). Friends network once established (initialization process is described on listing 2) keeps changing with a frequency defined by rewiring rate. A directional friendship tie is established with a probability that consists of 3 weighted summands that are calculated according to the algorithm on listing 3:
    i. Triadic closure: Determines the probability of a directed edge from node i to node j based on the presence of common neighbors in their kinship network. Nodes that share many common neighbors are more likely to form a friendship connection. For the initialization phase this probability is calculated by considering the ratio of common adjacent nodes between nodes i and j from two other layers of networks (kins and geographical neighbors). This summand takes values in a range [0, 1].
    ii. Attribute-driven: Determines the probability of a directed edge from node i to node j based on adherence to the same strategy. Nodes with similar gear types are more likely to form a friendship connection. This probability is calculated based on the similarity of both institution parameters. This summand is binary and takes only values 0 or 1.
    iii. Exogenous contextual factors (geographical proximity): Determines the probability of a directed edge from node i to node j based on their geographical proximity. Nodes that are geographical neighbors are more likely to form a friendship connection. This probability is based on the spatial proximity between the nodes. This summand is binary and takes only values 0 or 1.

Listing 2. Pseudocode with the algorithm for creating a friends network.

```
Create an empty directed graph called self.friends_net
Add nodes to self.friends_net for each agent, with IDs from 0 to (self.num_agents - 1)

For each node in self.friends_net:
    Get agent1 as self.schedule.agents[node]

    For each another_node in self.friends_net:
        If node is not equal to another_node:
            Get agent2 as self.schedule.agents[another_node]
            Calculate prob as agent1.init_friendship_probability(agent2)
            Generate rand_num as a random number between 0 and 1
            If rand_num < prob:
                  Add a directed edge from node to another_node in self.friends_net with
weight=prob
                Add agent2's unique ID to agent1's friends_out
                Add agent1's unique ID to agent2's friends_in
```

- Institution: at the beginning of simulation there is no institution agents should comply with.

The full list and descriptions of input parameters for each component can be found in Appendix A.

Listing 3. Pseudocode that demonstrates an algorithm that calculates rewiring probability and its difference with the mechanisms that calculates initialization probabilities for connections of the friends network .

```
# Initialization: Calculate triadic closure probability
p1 = common_kin_and_neighbors_count / total_kin_and_neighbors_count if
common_kin_and_friend_count else 0

# Rewiring: Calculate triadic closure probability
p1 = common_kin_and_friend_count / total_kin_and_friend_count if
common_kin_and_friend_count else 0

# Calculate binary probability related to attribute-driven or gear homophily
p2 = 1 if self.action == another_agent.action else 0

# Calculate binary probability related to geographical proximity
p3 = 1 if another_agent.unique_id in self.geo_neighbors else 0
self.model.probabilities['geographical'].append(p3)

# Calculate the total rewiring probability
p = (triaidc_weight * p1) + (attribute_weight * p2) + (geographical_weight * p3)

Return p
```

During the simulation phase the model performs the same procedures at each time step (figure 4):

1. Agents act
    a. Reduce their own energy by consuming a certain amount
    b. If energy is low, it means that it's time to change a strategy:
        i. If agent is innovative, they choose:
            1. Either the best performing strategy from their experience
            2. Or their confidence level is low and they pick a random strategy
        ii. Else: it chooses strategy from the most successful adjacent agent
        iii. If there is an institution in place:
            1. If agents personal strategy yields more: agent might cheat and use personal strategy
            2. Else: extracts resource by following institution
        iv. Else: there is no institution yet, agent extracts resource by following its personal strategy
2. If it's institutional emergence time:
    a. If many agents have low energy levels, voting takes place and the most frequent personal strategy is considered to be an institution,
3. Monitoring: a certain percentage of agents is checked and fined if cheated
4. If based on rewiring rate it's time to rewire, the friends network is getting updated based on the new agents' properties (listing 4)
5. Renewable resource grows according to its rate.

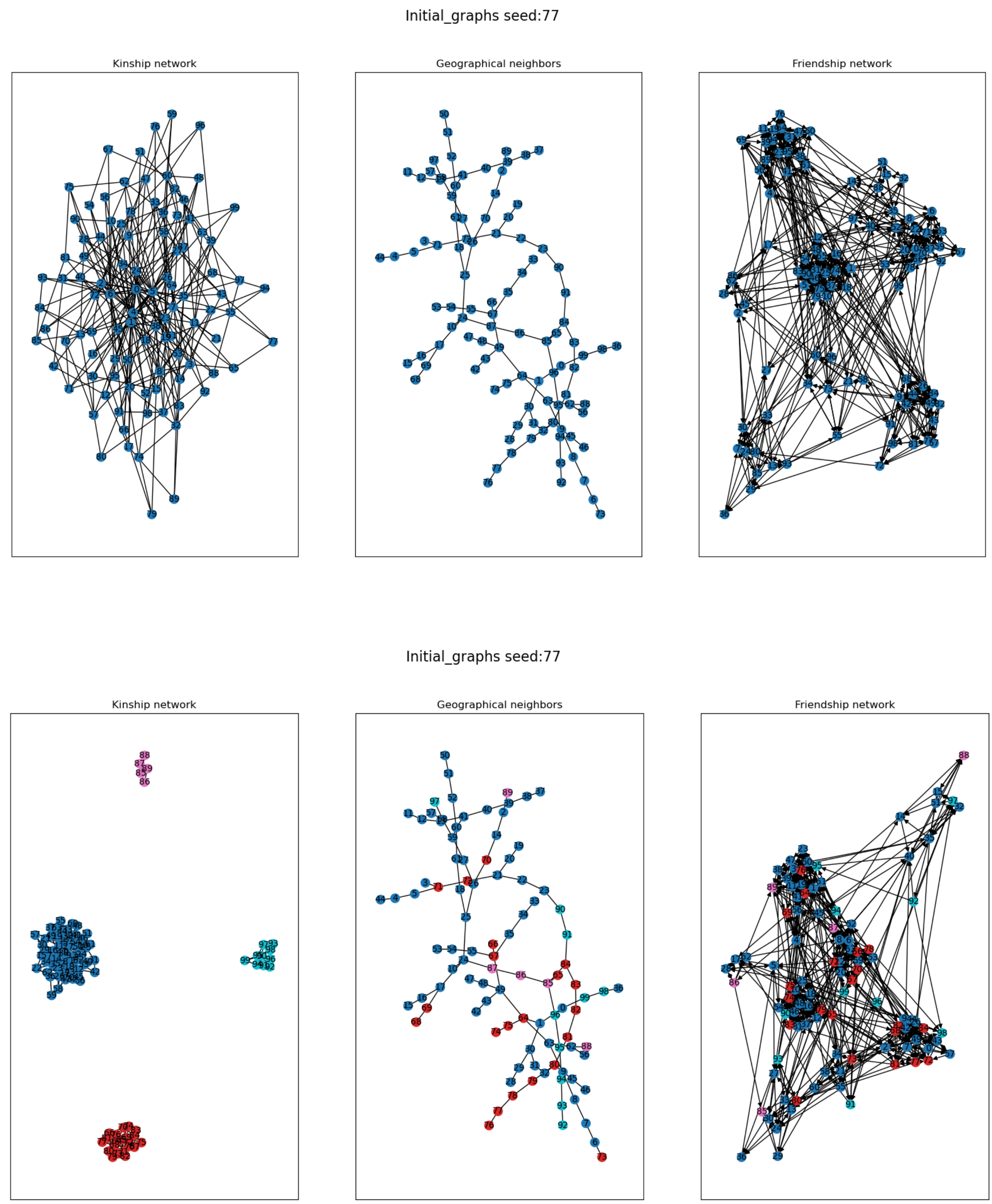


Figure 3. Examples of initial graphs that represent 3 layers of social network with different numbers of fragments: 1 (upper) and 4 (lower).

Listing 4. Pseudocode that demonstrates an algorithm of friends network rewiring process

```
Function update_friends_net(self):
    # Adjust friendship ties
    Current friends network as backup_net
    num_rewired = 0

    # Check for broken links
    num_edges1 = Count edges in backup_net
    Initialize an empty set called broken_links_temp

    For each node in backup_net:
        Get agent1 as the agent associated with the current node
        For each another_node in backup_net.nodes():
            Get agent2 as the agent associated with another_node

            If node is not equal to another_node:
                If edge (node, another_node) exists in backup_net:
                    Get edge_weight from the backup_net's edge data

                    If Random number is less than (1 - edge_weight):
                        Remove edge (node, another_node) from self.friends_net
                        Add (node, another_node) to broken_links_temp
                        Increment num_rewired

    # Create new links
    Initialize an empty set called new_links_temp
    num_edges2 = Count edges in self.friends_net

    While num_rewired is greater than 0:
        Create a list called nodes containing node IDs from 0 to (self.num_agents - 1)
        Create a shuffled list called edges_shuffled containing all possible node pairs
        Shuffle edges_shuffled

        For each node, another_node pair in edges_shuffled:
            If edge (node, another_node) doesn't exist in self.friends_net:
                Get agent1 as the agent associated with node
                Get agent2 as the agent associated with another_node
                Calculate prob as agent1.rewiring_probability(agent2, backup_net)

                If Random number is less than prob and num_rewired is greater than 0:
                    Add edge (node, another_node) to self.friends_net with weight=prob
                    Add (node, another_node) to new_links_temp
                    Decrement num_rewired

    # Calculate new and broken links
    Calculate new_links as new_links_temp difference (intersection of new_links_temp and 
broken_links_temp)
    Calculate broken_links as broken_links_temp difference (intersection of 
new_links_temp and broken_links_temp)
    # Record results
    Store new_links in self.links_emerged at self.stepcounter
    Store broken_links in self.links_broke at self.stepcounter
    Store self.friends_net in self.friends_evolution at self.stepcounter
    Calculate self.clustering_friends as clustering coefficient of self.friends_net
    num_edges3 = Count edges in self.friends_net
```

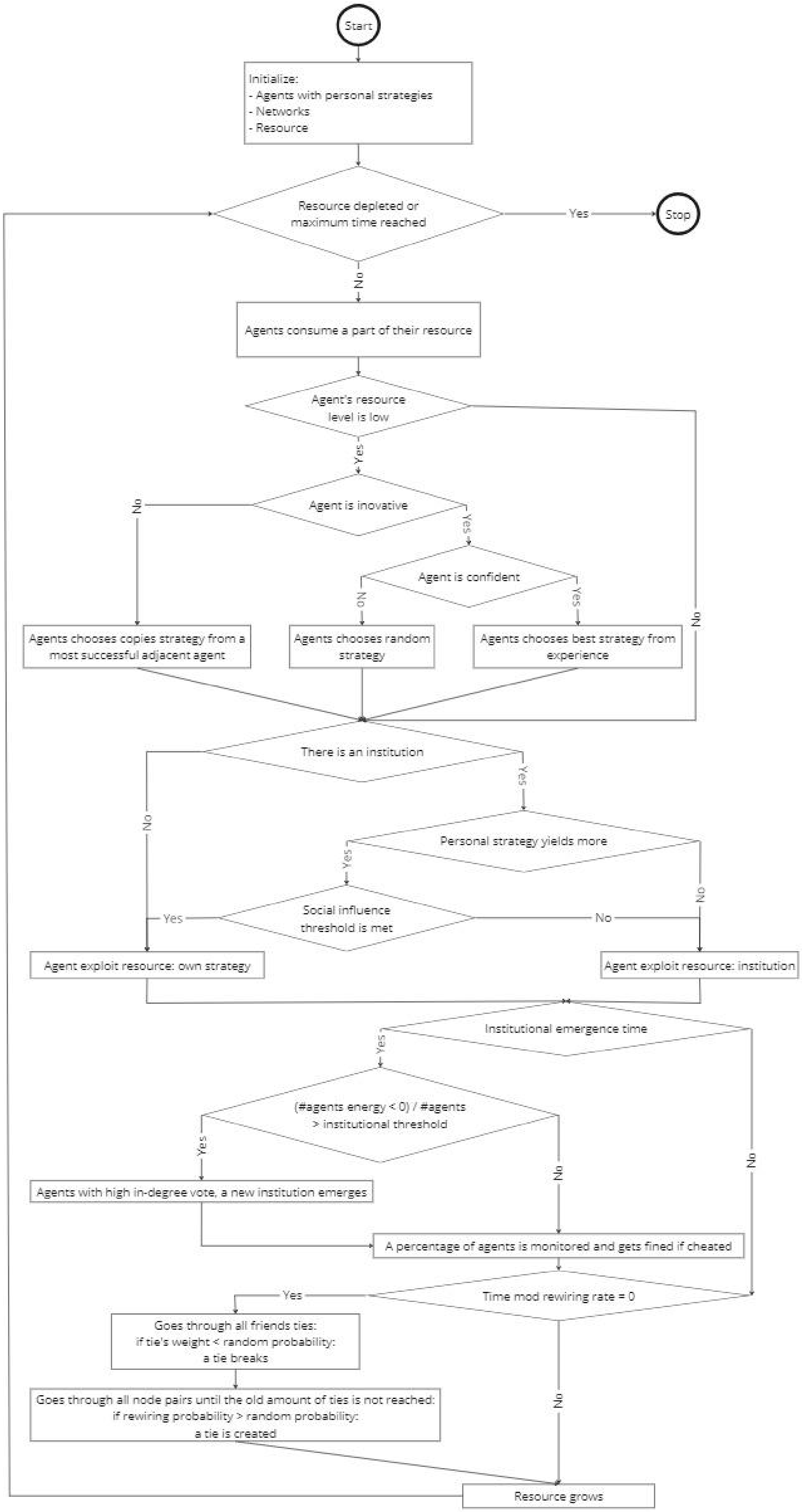


Figure 4. Flow chart of a simulation run

5.2.3 Theoretical and empirical background

This section provides principles that composed the basis of the modeling choices and respective sources. A more elaborated reflection upon these choices can be found in chapter 9.1.2. Since the prior versions of the model have been already validated, there was only a need to build new components and features in accordance with the theory and empirical data that was available in the literature.

- Network parameters:
  - Fragmentation: Ethnic fragmentation as an example of the presence of tightly connected fragments that have weaker connections among each other (Barnes-Mauthe et al., 2013; Barnes-Mauthe et al., 2015)
  - Characteristics: There are several properties that are inherent to the structure of social communities. Small-world property and power-law degree distributions are in the spotlight of different studies. However, Girvan & Newman (2002) highlight another property that is observed across many different networks: groups of tightly connected nodes that are connected with each other through weaker links. The three network layers in this model are derived to capture these properties.
  - Tie strength diversity: Different ties strength based on tie intimacy: (family > friend > professional acquaintance) (Barnes-Mauthe et al., 2015; Ramírez-Sánchez & Pinkerton, 2009; Wossen et al., 2013)
  - Number of nodes: Empirical data examples suggest varying numbers of families and households, ranging from 35 to 150 families (Castello et al., 2013) and 18 to 156 households with a median of 67 (Almeida et al., 2009). Additionally, studies have used a sample size of 159 fishers in Hawaii (Barnes-Mauthe et al., 2013). Previous iterations of the model have also used the same number of nodes, as reported in Ale Ebrahim Dehkordi et al. (2021), Ale Ebrahim Dehkordi et al. (n.d.), Ghorbani et al. (2017), and Ghorbani & Bravo (2016).
- Rewiring mechanisms: For the friendship network, the strength or probability of a link is assigned as a weight to each connection. At each time step corresponding to the rewiring rate, the network undergoes dynamic changes where existing links have the potential to break, and new links may emerge based on the same three parameters: triadic closure, attribute-driven factor, and geographical proximity (exogenous contextual factor). These parameters influence the likelihood of tie formation and dissolution within the friendship network. The weight assigned to each link represents the total probability of its existence, taking into account the combined effects of these parameters. This dynamic nature of the friendship network allows for the continuous evolution of social connections, reflecting the changing dynamics of social interactions and relationships within the fishing community.
  - Drivers of cohesion: what affects the probability of social ties creation (triadic closure, geographical proximity and gear-based homophily). An overview can be found in table 2. (Alexander et al., 2018; Bodin et al., 2014; Alexander et al., 2020; Snijders et al., 2010).
- Power relations: It was assumed that not all agents are entitled to vote as they are excluded from the decision making process.

  - The role of indegree in power relations: More powerful agents that participate in decision-making have higher in-degree centrality based on their friendship and kinship ties, because other agents in the network value these connections (García-Amado et al., 2012; Barnes-Mauthe et al., 2015)
- Institutional structure: It is assumed that agents perform fishing activities every day. Because of that, the conditional part of institutions (and personal strategies) has been removed from the model since it represented frequency of resource extracting activities.

6 Model calibration and sensitivity analysis

This model has features of both: law- and data-driven models. This is the reason why it does on one hand rely on data but on the other hand is overparameterized which results in many parameters that are not supported by the data available (Saltelli, 2008). Hence, calibration of these parameters is a necessary step to define the range (or constant values) of input parameters that will result in a desired behavior regime. This is to ensure that the resource will not be depleted too early and there will be a balanced mix between outcomes when institutional emergence happens.

Sensitivity analysis is the quantification of variability in ABM outcomes from model parameters. There are contradicting guidelines available in the literature regarding the better type of sensitivity analysis. Some authors state that global sensitivity analysis using Sobol' indices is more comprehensive and leads to more accurate results since it is able to capture interactions between the uncertain input parameters (Saltelli et al. 2008; Ligmann-Zielinska et al. 2014). However, in their comparative study Ten Broeke et al. (2016) argue that one-factor-at-a-time (OFAT) suits better as a starting point of any sensitivity analysis of an ABM because of the presence of multiple levels, nonlinear interactions and feedbacks, and emergent properties. Taking into account large computational costs of global sensitivity analysis, and the arguments above I decided to proceed with the OFAT method.

Scenario discovery is a complementary technique to sensitivity analysis. It focuses on identifying specific scenarios or conditions that lead to desired or undesired outcomes (Bryant & Lempert, 2010). Scenario discovery has almost similar mechanics as sensitivity analysis but is done with another purpose. If sensitivity analysis is derived to quantify the effect of each parameter on the outcomes, scenario discovery helps to uncover specific regions in uncertainty space that are responsible for desired outcomes. In this work scenario discovery is done using PRIM (Pattern Recognition in Input-Output Mapping) algorithm.

The ultimate goal of calibration of the model's parameters is to define the range of the variables that will be varied during experiments in a way that all scenarios of interest are covered. This will ensure that the dependencies between social networks and institutions that are in the spotlight of this research are captured throughout these experiments and described.

6.1 Sensitivity analysis: OFAT

The OFAT sensitivity analysis using the ema_workbench aimed to calibrate the agent-based model to achieve a balanced regime of behavior where institutional emergence alternates between presence and absence. In order to achieve this desired balance, the key parameters should be identified. In this case the importance of a parameter for model calibration is determined by the degree to which it affects the number of emergent institutions and their stability that can be reflected by how long an institution is in place or so called institutional age.

6.1.1 Fixed seed

This series of experiments involved three parameters: "max_action," "n_actions," and "num_ticks," each explored individually within specified ranges while keeping other parameters constant. The analysis was conducted to identify parameter values that would result in this desired regime. The outcomes, including "agents_avg_consumption," "mean_comb_degree," "num_institutions," and "n_actions," were used to assess the model's behavior under varying parameter settings. The fixed seed value ensured consistency in the results and allowed for a comprehensive understanding of the model's reaction to parameter variations. For each parameter 100 scenarios were explored with each scenario being a point in uncertainty space.

Table 4. Parameters of the first series of experiments.

Parameter	Description	Variable type	Constant value	Uncertainty boundaries
max_action	The largest amount of resource extraction an actor is able to choose as a strategy	int	20	(0, 50)
n_actions	Number of actions items in the actions list.	int	8	(5, 12)
num_ticks	Number of time steps to run simulation for	int	2000	(1000, 5000)

Table 5. Outcomes of the first series of experiments.

Outcome	Description	Variable type
agents_avg_consumption	The average amount of resource extracted by an agent during the whole run	int
mean_comb_degree	Degree centrality of a combined network (kins + friends + geographical neighbors)	real
num_institutions	Number of times an institution has emerged (num_institutions = 1 ⇔ no institution)	int
n_actions	Number of actions items in the actions list.	int

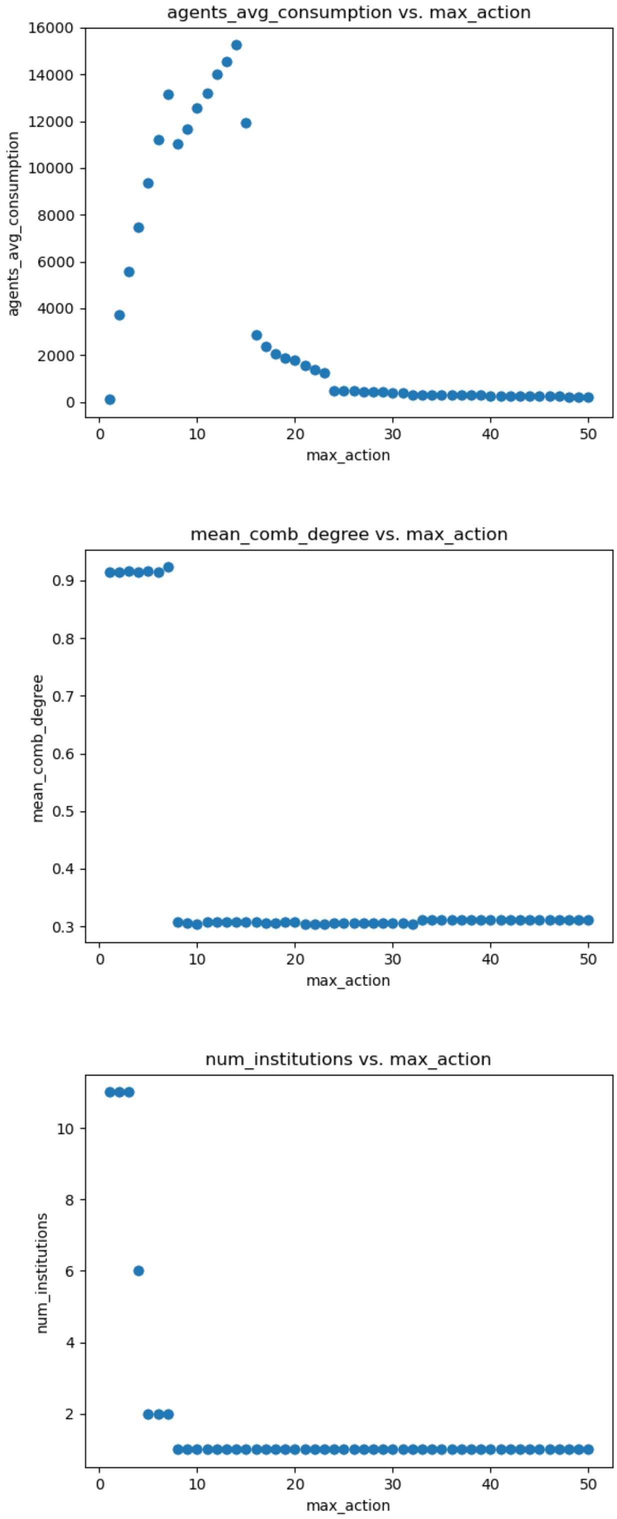


Figure 5. Results of OFAT sensitivity analysis with the varying parameter being max_action and results being agents_avg_consumption (upper), mean_comb_degree (middle) and num_institutions (lower).

Scatter plots on figure 5 demonstrate the dependencies of three outcomes of interest from the variable max_action that defines the maximum amount of resource that an agent is able to extract by following their own strategy or an institution.. Notably, all three outcomes exhibit distinct thresholds where the behavior of the system undergoes significant changes. These thresholds suggest critical points where altering the value of max_action prompts substantial shifts in the model's behavior, as reflected by the corresponding outcomes. All three plots have peaks at the value of the parameter max_action = 8. Since the default number of actions is 8, in this case the list of available strategies looks like [1, 2, 3, 4, 5, 6, 7, 8]. It is clear that with a further decrease in the parameter, there will be more and more duplicate values in the list (because num_actions = 8 and all elements must be integers), which will lead the system to a faster consensus regarding institution. In addition, with a decrease in max_action, the energy level of an increasing number of agents will decrease to critical levels, which also has a positive effect on the establishment of the institute. These results underscore the significance of the largest extraction amount available to the agents for emergence and evolution of institutions.

Simulation runs with n_actions and num_ticks as varying parameters did not result in any changes of institutional regimes. All runs resulted in the absence of any institutions at the end.

6.1.2 Variable seed

The second set of calibration runs consisted of the larger number of uncertainties and outcomes. Results of the first set of OFAT runs were utilized to adapt the boundaries of the exploration space. Besides, in this set the seed parameter was random for each run of the set. For each parameter 20 scenarios were explored with each scenario being a point in uncertainty space.

Table 6. Parameters of the first series of experiments.

Parameter	Description	Variable type	Constant value	Uncertainty boundaries
max_action	The largest amount of resource extraction an actor is able to choose as a strategy	int	20	(10, 20)
n_actions	Number of actions items in the actions list.	int	8	(2, 10)
n_fragments	Number of tightly connected fragments	int	2	(1, 4)
rewiring_rate	Represents the number of ticks after which the friends' network is updated.	int	10	(1, 100)

num_voting_agents	Number of agents eligible to vote for instittuion	int	50	(1, 100)
emergence_time	The number of ticks after which agents decide upon institution	int	200	(100, 500)
innovation_rate	Shows how innovative an agent is. It is a probability of an agent to switch to a new strategy without relying on neighbors.	real	0.5	(0, 1)
max_social_influence	The upper limit for agents social_influence that affected cheating probability	real	0.5	(0,1)
energy_consumption	The amount of energy agents loose every time step	int	5	(2, 20)
k_0	Initial resource level	int	30000	(15000, 40000)

Table 7. Outcomes of the second series of experiments.

Outcome	**Description**	**Variable type**
agents_avg_consumption	The average amount of resource extracted by an agent during the whole run	int
mean_comb_degree	Mean value of degree centrality of a combined network (kins + friends + geographical neighbors)	real
variance_comb_degree	Variance of degree centrality of a combined network (kins + friends + geographical neighbors)	real
num_institutions	Number of times an institution has emerged (num_institutions = 1 ⇔ no institution)	int
mean_inst_age	Mean value of periods when institution was active	int

variance_inst_age	Variance of periods when institution was active	int
n_actions	Number of actions items in the actions list.	int

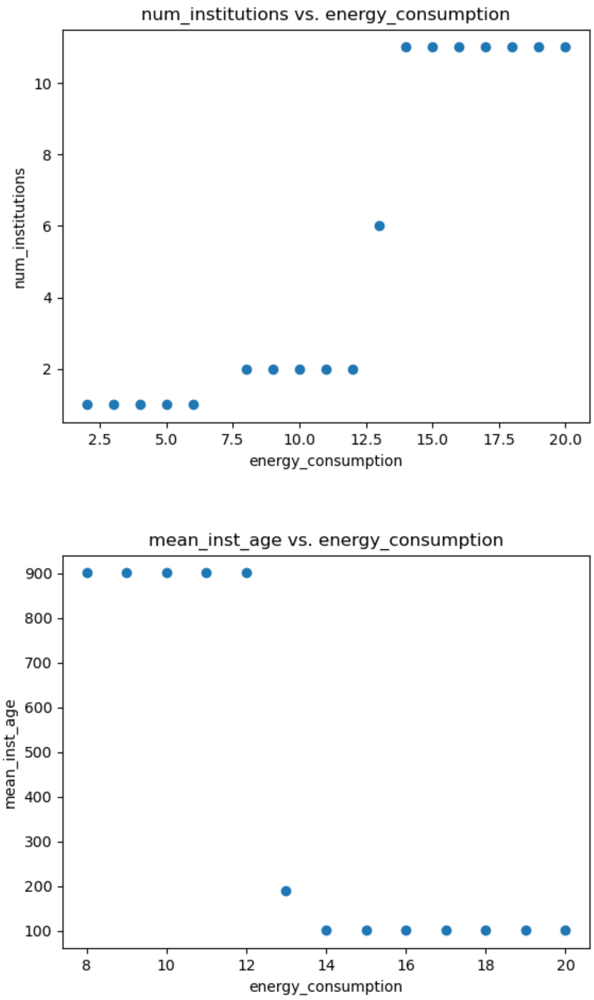
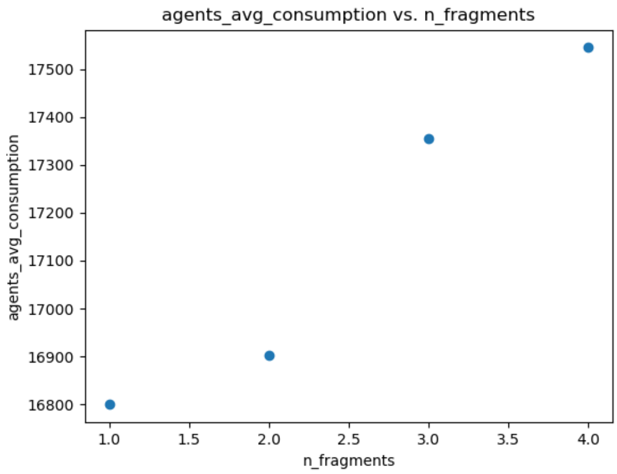


Figure 6. Results of OFAT sensitivity analysis with the varying parameter being energy_consumption and results being num_institutions (upper), mean_inst_age (lower).

The graphs on Figure 6 demonstrate institutional characteristics being plotted against the energy_consumption parameter. Upper graph shows all 3 types of institutional regimes: with the parameter less than 6, the extracted resource is enough for agents to ensure that energy falls below the critical level only from the number of agents insufficient to surpass threshold of institutional change; between 6 and 12 there is a segment with a stable institution, but with parameter values greater than 12, the number of institutions jumps up and reaches its saturation when the value equals 11. This number stands for the case when at every time of institutional emergence a new institution has been established. Lower graph holds similar principles with the only difference being that cases with no institutions are not present there since when there is no institution, there is also no age recorded. allow us to say that the energy_consumption parameter, along with max_action (as shown earlier), plays a key role in establishing a balanced mode of operation of the model.



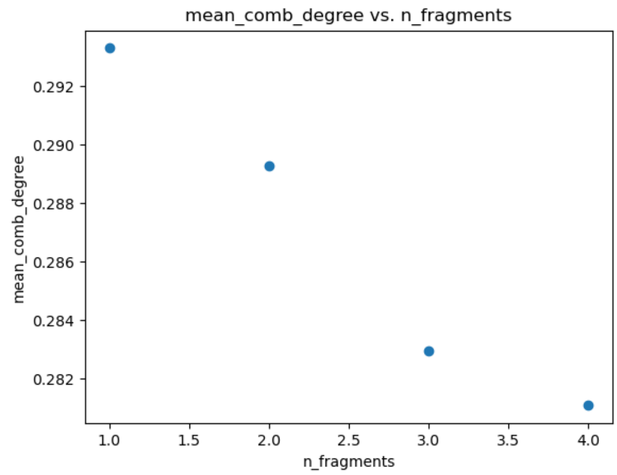


Figure 7. Results of OFAT sensitivity analysis with the varying parameter being n_fragments and results being agents_avg_consumption (upper) and mean_comb_degree (lower).

In figure 7, you can observe graphs of the dependence of agents_avg_consumption and mean_comb_degree on the number of closely related fragments from which a social network of relatives is formed. The fact that the mean_comb_degree decreases with the growth of the number of fragments is understandable. As more closely related clusters are integrated into the kins network, the network's structure becomes more fragmented, with agents forming smaller subgroups based on their original fragments. This fragmentation could lead to a decrease in the overall mean degree centrality. Agents within these smaller subgroups might use their strong connections, contributing to higher internal cohesion but potentially fewer external connections, resulting in a lower mean degree centrality.

There are absolutely clear trends on both charts. As the number of fragments increases, the average amount of resource extracted increases but the mean degree centrality decreases. These results look contradicting at first since lower degree centrality is usually associated with worse coordination among the agents in the network and the latter is supposed to lead to agents using not optimal strategies and extracting less than they could. However, It actually means that optimal strategies developed in conditions of high degree centrality do not equal higher extraction rates. This outcome does not provide clear insights on the influence of n_fragments on institutional regimes, as all runs where this parameter was changed resulted in the absence of institutions. However, these graphs do show its effect on average extracted levels of the resource and this link theoretically is able to influence institutional emergence, because the condition of common action to be taken is binded with the energy levels of agents through institutional threshold. Therefore the fact that there was no dependency observed on the number of emerging institutions may be the drawback of OFAT method that is sensitive to the constant values of other variables that compose the baseline scenario.

6.1.3 Rewiring weights

In this section sensitivity analysis focused on the rewiring weights within the friends network of the model is presented. The process of rewiring involves the adjustment of connections between agents, thereby shaping the dynamics of their social interactions. By systematically varying the weights associated with rewiring, I was aiming at shedding some light on the interplay between network topology, agents' behaviors, and the emergent institutions. This investigation enables a deeper understanding of how different rewiring scenarios influence the model's outcomes, shedding light on the underlying mechanisms that contribute to the dynamics of resource governance within the system.

These simulations were executed with the same model outcomes as in the previous section plus the ones from table 8. The weights were changed within the limits of (0, 0.99). For each weight a set of experiments over 100 scenarios was carried out. To fulfill the natural constraint that all 3 weights should sum up to 1 (as they represent , when one weight (for example, weight_triadic) was sampled within the range of (0, 0.99), the rest were calculated as (1 - weight_triadic) / 2. Thus, this is not purely OFAT analysis which might put some limitations on the interpretability of the results.

Table 8. Outcomes of a series of experiments devoted to rewiring weights.

Outcome	Description	Variable type
p_total_mean	Mean value of all calculated rewiring probabilities (total sum)	real
p_total_variance	Variance of all calculated rewiring probabilities (total_sum)	real
p_attribute_mean	Mean value of all calculated rewiring probabilities (attribute homophily summand)	real
p_attribute_variance	Variance of all calculated rewiring probabilities (attribute homophily summand)	real

p_triadic_mean	Mean value of all calculated rewiring probabilities (triadic summand)	real
p_triadic_variance	Variance of all calculated rewiring probabilities (triadic summand)	real
p_geo_mean	Mean value of all calculated rewiring probabilities (geographical proximity summand)	real
p_geol_variance	Variance of all calculated rewiring probabilities (geographical proximity summand)	real

In this section figures present the results of sensitivity analysis for different weights of each of the 3 components of rewiring probability. several curious patterns were found at once. First, I propose to compare the behavior of the total probability in all three cases (figure 8). It is easy to notice that from case to case the nature of this dependence changes to almost the opposite. In cases where the probability depends on network characteristics (geographic proximity, triadic closure), with the growth of the corresponding weight, the probability value converges to 0. In the case of attribute homophily, the probability on the contrary increases and finally reaches saturation. Such a cardinal difference in behavior may be due to the presence of a negative feedback mechanism for probabilities associated with network characteristics and a positive one for homophily-based probability. Similar conclusions can be drawn from the analysis of the figure 9 that demonstrates the dependencies between mean_comb_degree and the 3 rewiring weights. The insight of these results is especially bright when considering the symmetric nature of the total rewiring probability (p_total) that is coded in the following way (formula 1):

$$p_{total} = p_{triadic} \times w_{triadic} + p_{attribute} \times w_{attribute} + p_{geo} \times w_{geo} \qquad (1)$$

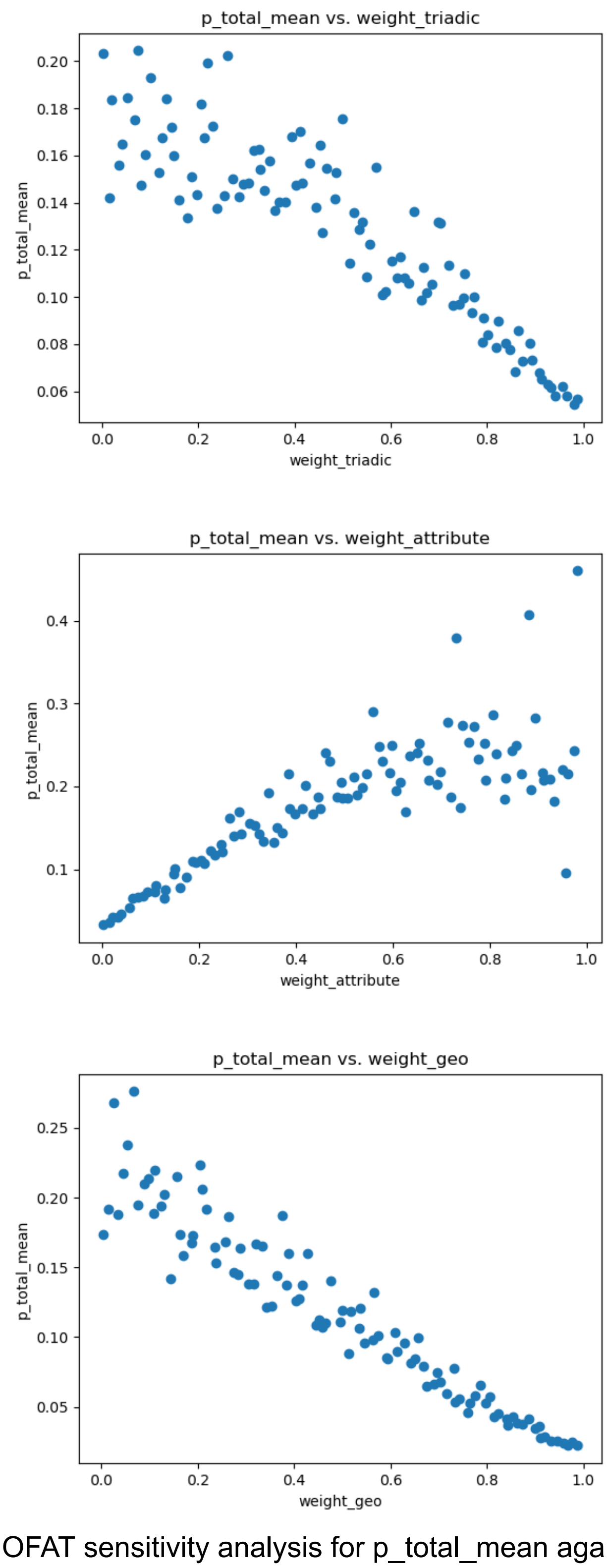


Figure 8. Results of OFAT sensitivity analysis for p_total_mean against weight_triadic (upper), weight_attribute (middle) and weight_geo (lower)..

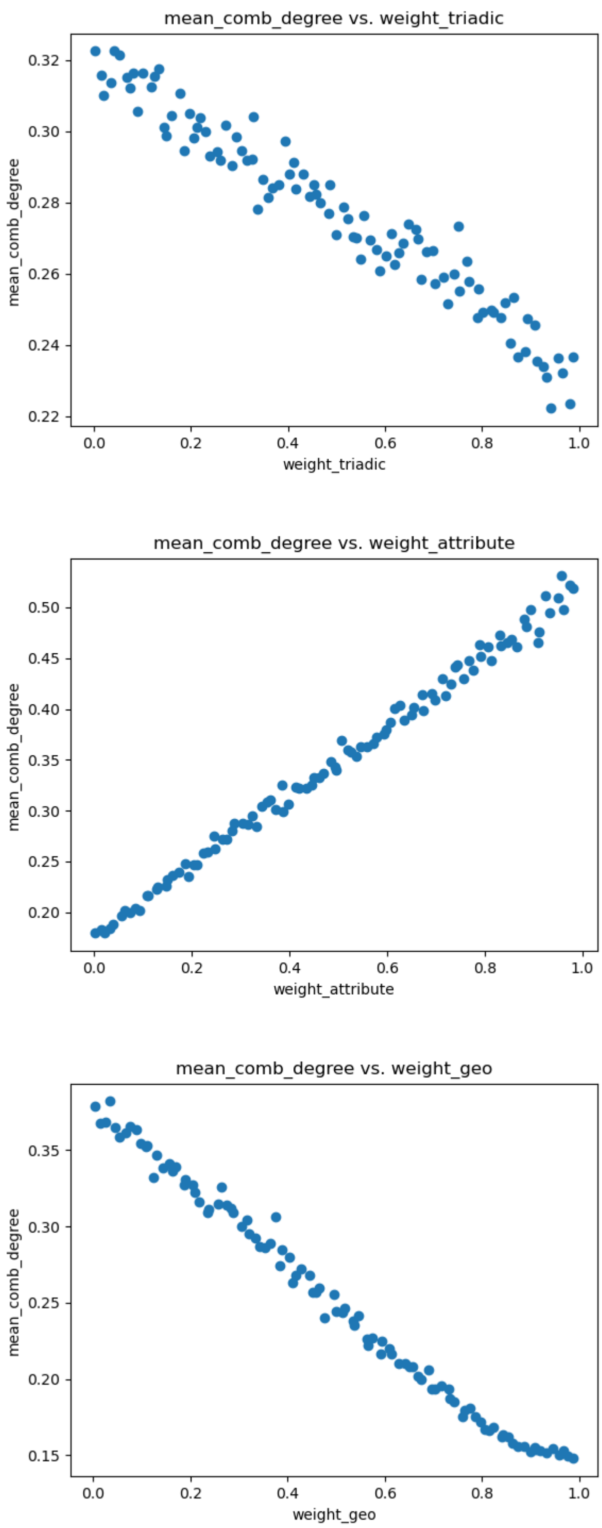


Figure 9. Results of OFAT sensitivity analysis for mean_comb_degree against weight_triadic (upper), weight_attribute (middle) and weight_geo (lower).

6.2 Scenario discovery: PRIM

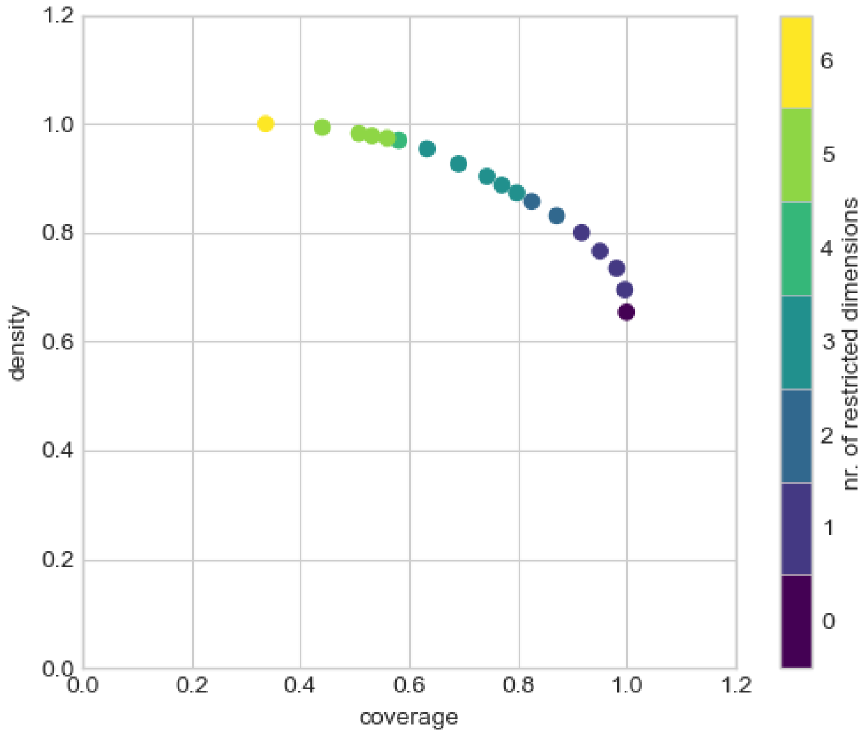
Results of sensitivity analysis provided information on parameters that affect the institutional regime. However, only few parameters (num_actions and energy_consumption) exhibit influence on institutional regime, while the simulation runs where other uncertain parameters were changing resulted in the absence of any institution. This might be because this parameter does not affect the process of emergence or because the constant values of other parameters did not allow for other regimes. The main goal of simulations in this chapter is to perform scenario discovery using the PRIM algorithm.

The PRIM is a data analysis technique designed to identify patterns in high-dimensional data, often used in the context of model output or simulations. It operates by iteratively defining boxes in the input space, effectively "peeling" away layers of data. These boxes represent subsets of the input space where the output exhibits distinctive behavior. The main logic of PRIM involves refining these boxes to reveal specific rules or conditions that explain the variations in the output. By focusing on localized regions of the input space, PRIM uncovers simple rules that capture how different input conditions lead to various outcomes. This method is valuable for gaining insights into complex interactions within a model's inputs and for discerning the conditions that drive specific outcomes.

Scenario discovery is aimed at connecting ranges of uncertainties with the desired set of simulation outcomes and is used here complementary to the sensitivity analysis. Particularly in this case I was interested in finding out what combinations of ranges of uncertainties are corresponding to the outcomes to different institutional regimes such as (i) the absence of institutions, (ii) emerged stable institution or (iii) various unstable emerged institutions.

The upper graph on figure 10 shows the peeling trajectory as a result of the PRIM steps. Each point represents a box in uncertainty space and its color corresponds to the amount of dimensions of this box or in other words the number of parameters that are limited on this step. This figure shows the trade-off between coverage and density, where coverage represents the ratio of the outcomes of interest within the box to the total number of outcomes of interest and density represents the ratio of outcomes of interest within the box to the number of outcomes inside it. Since the goal of this analysis was to define ranges of uncertain parameters that lead to different institutional regimes, the condition that there was at least one institution emerged during this run has defined the outcomes of interest.

There are several interesting details this graph can tell us about the connection between uncertain parameters and the regime with an institution being present. First, the lower point on this graph, that represents the whole uncertainty space, already starts very high, showing that nearly 65% of 500 scenarios that were tested have led to at least one institution. A detailed look at the data (Fig. 11) shows that there were 173 with no institutions, 170 with only one and 157 with more than one. This is already quite a satisfactory result since it shows the seeked balance between institutional regimes.



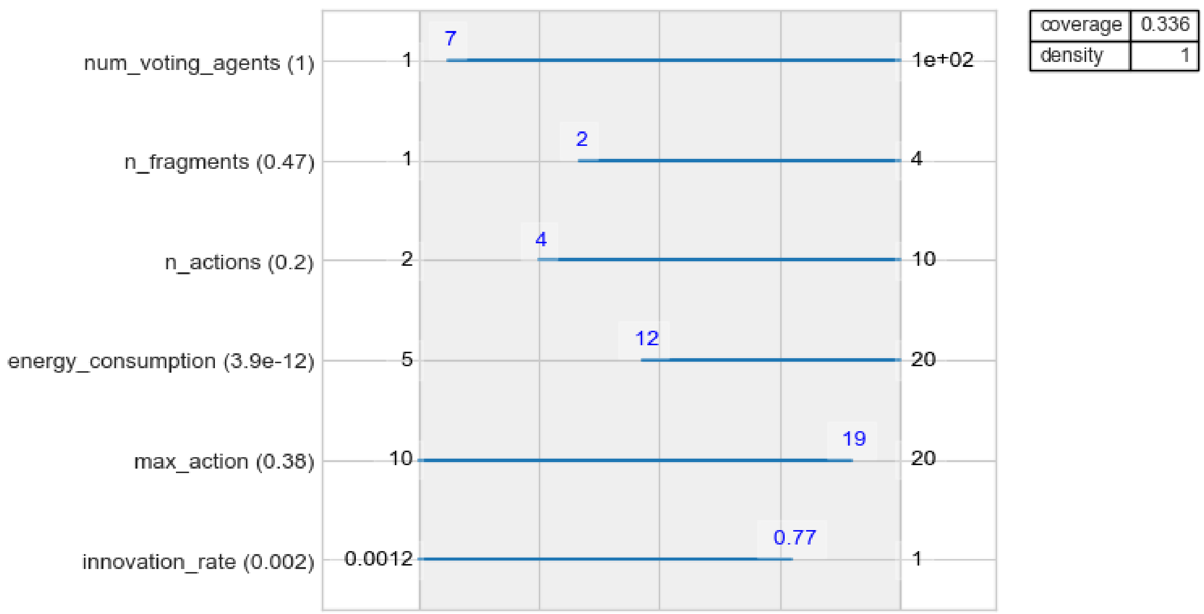


Figure 10. PRIM peeling trajectory analysis plot: steps of peeling trajectory (upper) and box parameters (lower).

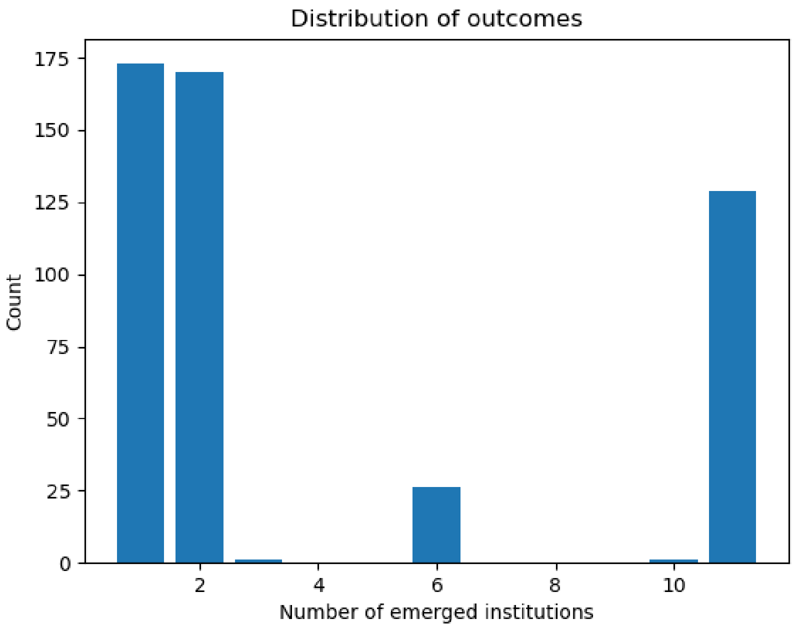


Figure 11. Distribution of outcomes regarding the number of emerged institutions.

7 Simulation experiments

This section presents the results of simulations after model calibration. The uncertain parameters were set to be random within the ranges defined throughout the calibration process, described in the section above, and a 1000 simulations were performed with different seeds in order to obtain enough samples from the uncertainty space and corresponding outcomes. These results are supposed to derive the answers to the research questions formulated earlier. Specifically to the first subquestion: “How does the initial network structure impact the emergence of institutions for CPR governance?”.

Results are grouped by the number of tightly connected fragments in kins network and presented in figure 11 in the form of graphs where each point is a simulation outcome. Before we proceed with the discussion I want to remind my reader that due to an artifact of the model all outcomes are shifted due to the fact that in the outcome data even if there were no institutions established, the value of num_institution will be 1. The half-violin plots and box plots show the distribution of the outcomes.

Both graphs demonstrate a two-peaked distribution that is a marker of the 3 institutional regimes that are present in each series of outcomes. In the case of the upper graph that demonstrates distribution of the variable “mean_inst_age” the upper peak is related to the outcomes with the value of 900. This value corresponds to the stable institution that has emerged at the first emergence time (200) and lasted for the rest 1800 time steps. The lower peak is in-between the values that are responsible for the absence of institutions (0) and unstable institutional regimes (100). For the lower graph the upper peak represents the unstable regime and the lower is in between the absence of any institutions and the stable one. There is also a noticeable group of outcomes that I have not mentioned yet. It consists of outcomes with 6 institutions and an average institutional age of 190. This group of outcomes represents a very interesting case where at first there was an unstable institutional regime that has converged to a stable one after 4 unsuccessful attempts.

Outliers that do not belong to any of the groups discussed above represent cases where either a resource was depleted and simulation runs ended before reaching 2000 time steps or another number of institutions has emerged. This group of outcomes is better seen on the upper graph since age is more sensitive to the early termination of simulation than the number of institutions. Figure 13 demonstrates the same graph but without the cases when a resource has been depleted. In comparison with figure 12 it reveals valuable insights. First, on figure 12 the median of cases on the graph with institutional age was lower for the number of fragments exceeding 2 and after the outliers were removed, this trend is no longer present on figure 13. Second, the box plots on figure 13 for the number of institutions demonstrate that as the number of fragments increases, the outcomes are becoming more clustered as the interquartile range becomes smaller. **This trend can be explained by assuming that as the number of tightly connected fragments within networks increase, the likelihood of an unstable institutional regime decreases.** Indeed, the bar plot on figure 14 shows that explicitly. This suggests that communities with more fragmented social networks tend to exhibit greater stability in their institutional arrangements.

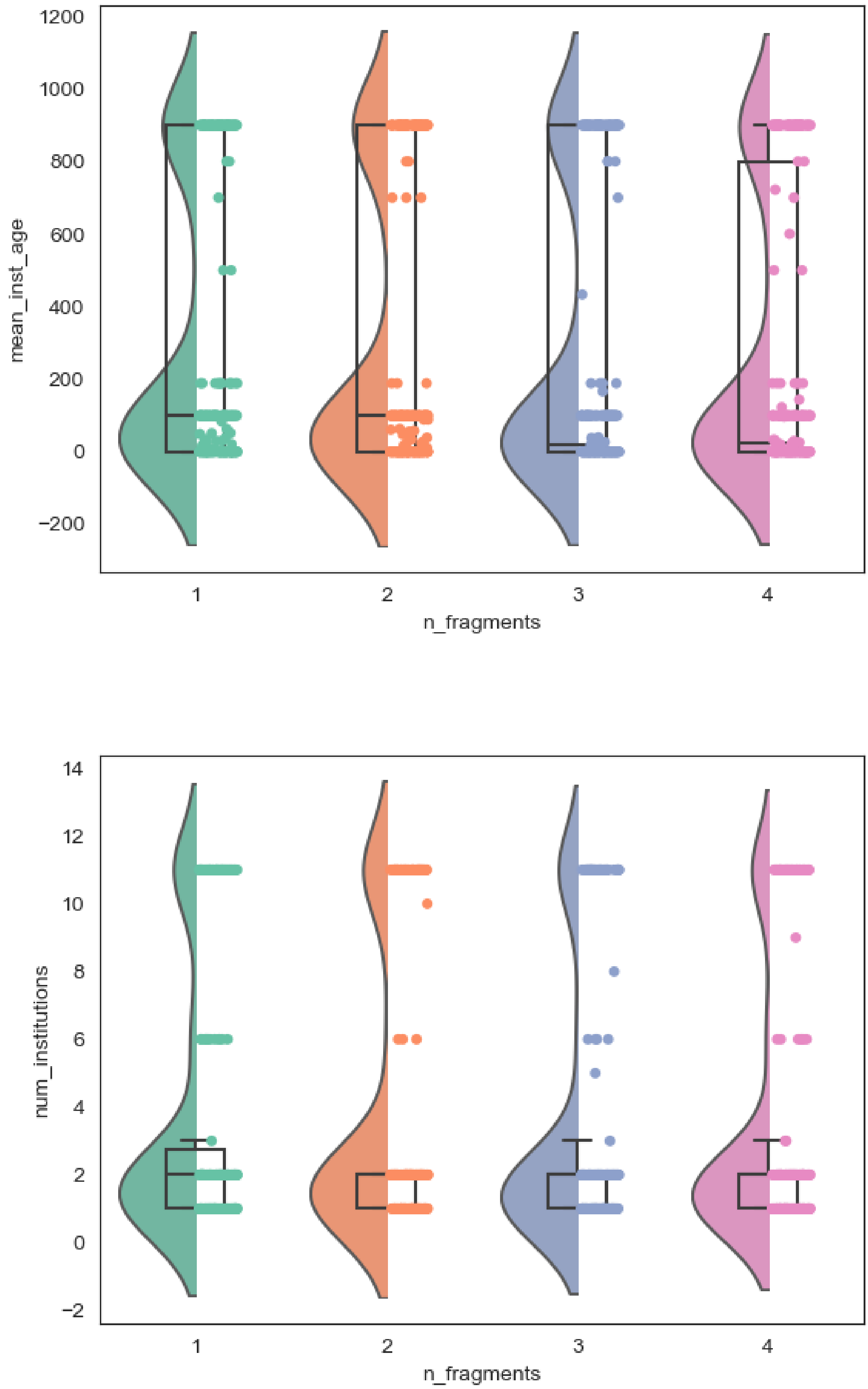


Figure 12. Half violin plots and box plots that demonstrate the distribution of mean_inst_age (upper) and num_institutions (lower) for the outcomes based on the n_fragments.

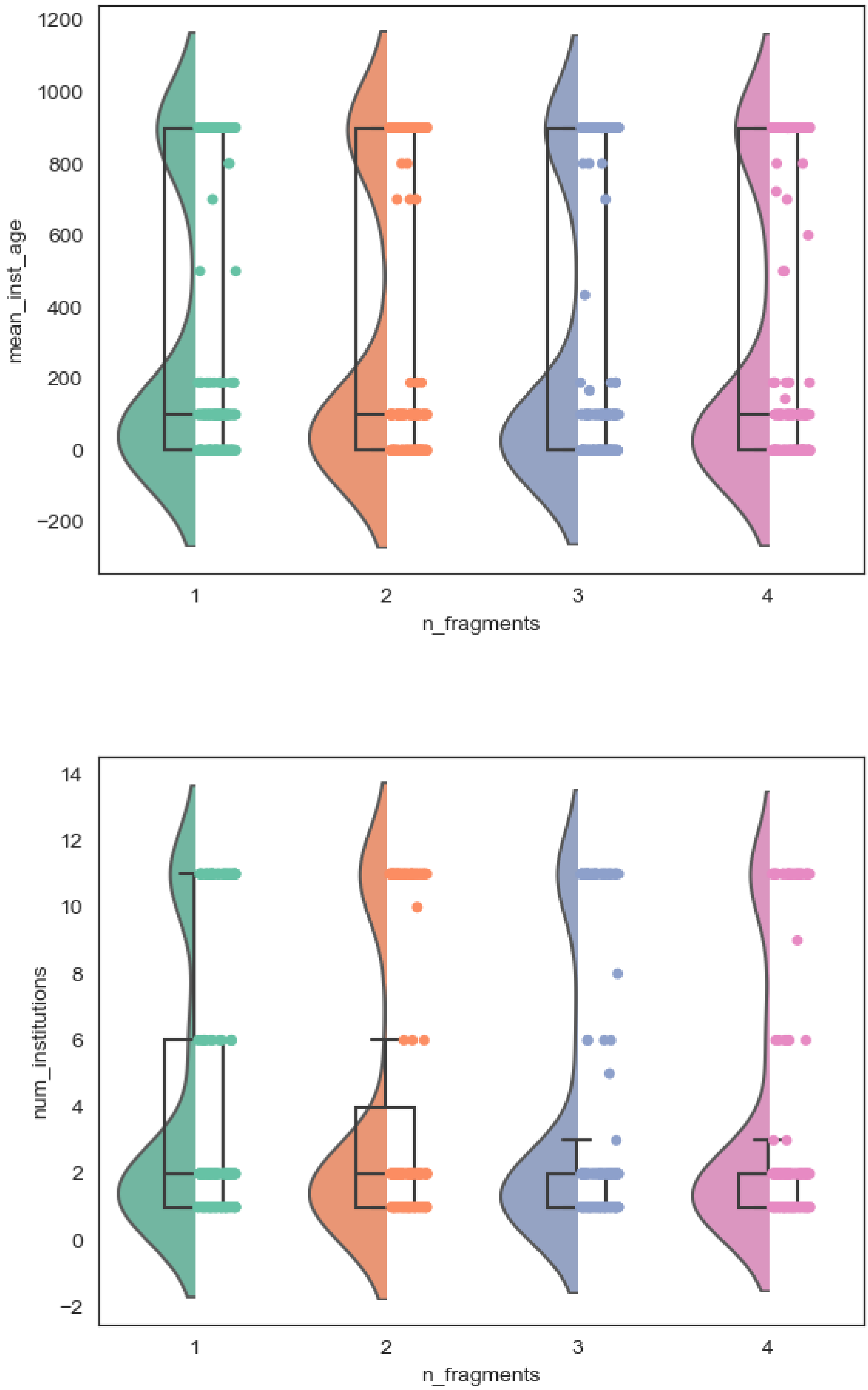


Figure 13. Half violin plots and box plots that demonstrate the distribution of mean_inst_age (upper) and num_institutions (lower) for the outcomes based on the n_fragments after removal of cases when resource has been depleted.

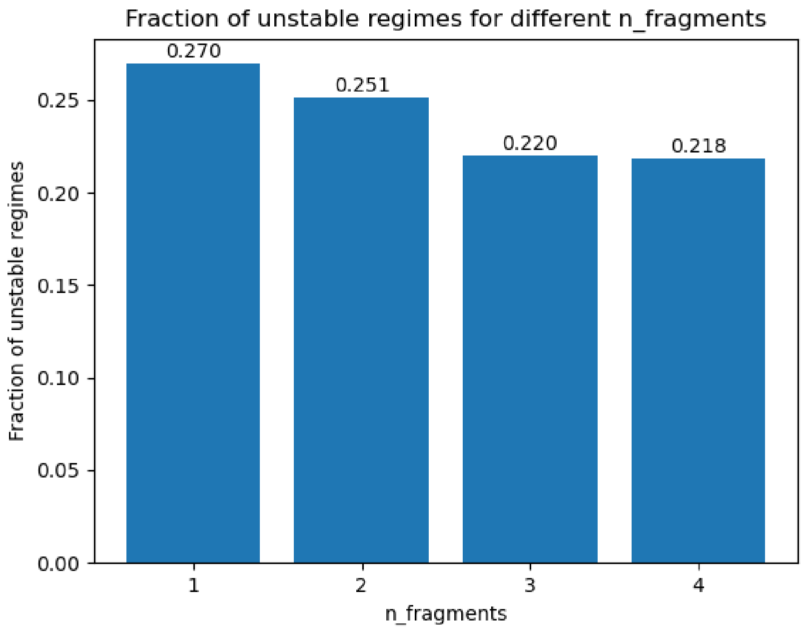


Figure 14. Bar plots that demonstrate the fraction of cases with unstable institutional regimes for the outcomes based on the n_fragments after removal of cases when resource has been depleted.

8 Empirical data

The dataset discussed in Section 4.2.1 was employed for model testing. This dataset encompasses a wide array of variables, reflecting both the fragmentation of the surveyed communities and the stability of their institutional frameworks. The initial step involved a comprehensive examination of the complete variable list, consisting of nearly 600 variables. From this extensive list, 45 variables were identified as potentially relevant to the research objectives. These selected variables encompassed aspects such as the composition of appropriator subgroups, interrelations between these subgroups, requirements for resource access (e.g., clan or ethnic group membership, licensing), and three variables specifically addressing the stability of the operational rules under consideration.

Subsequently, a thorough evaluation of this subset aimed to pinpoint variables that met two key criteria: (i) a degree of similarity to those utilized in the simulation runs throughout the study and (ii) the availability of comprehensive and well-documented data. During this evaluation, a preference was given to variables characterized by quantitative values and those previously employed by researchers in related studies. Consequently, a variable denoted as "opl_NUMSUBGP" was selected due to its resemblance to the "num_fragments" variable employed in this study.

Notably, Indicator that reflects Institutional stability has been previously defined by Ghorbani et al. (2017) through recoding three variables into a new one. The mentioned variables that were used are presented in table 9.

Table 9. Variables that were utilized for testing

Name	Question
opl_NUMSUBGP	How many subgroup forms are being completed in relation to this operational level form?
opl_BEGDATE	Where relatively precise information exists about the beginning and ending of the operational level coded on this form, post it below:
opl_ENDDATE	Where relatively precise information exists about the beginning and ending of the operational level coded on this form, post it below:
opr_RULEDUR	Approximately how long has the general framework of the rules-in-use described above governed the activities of this subgroup?

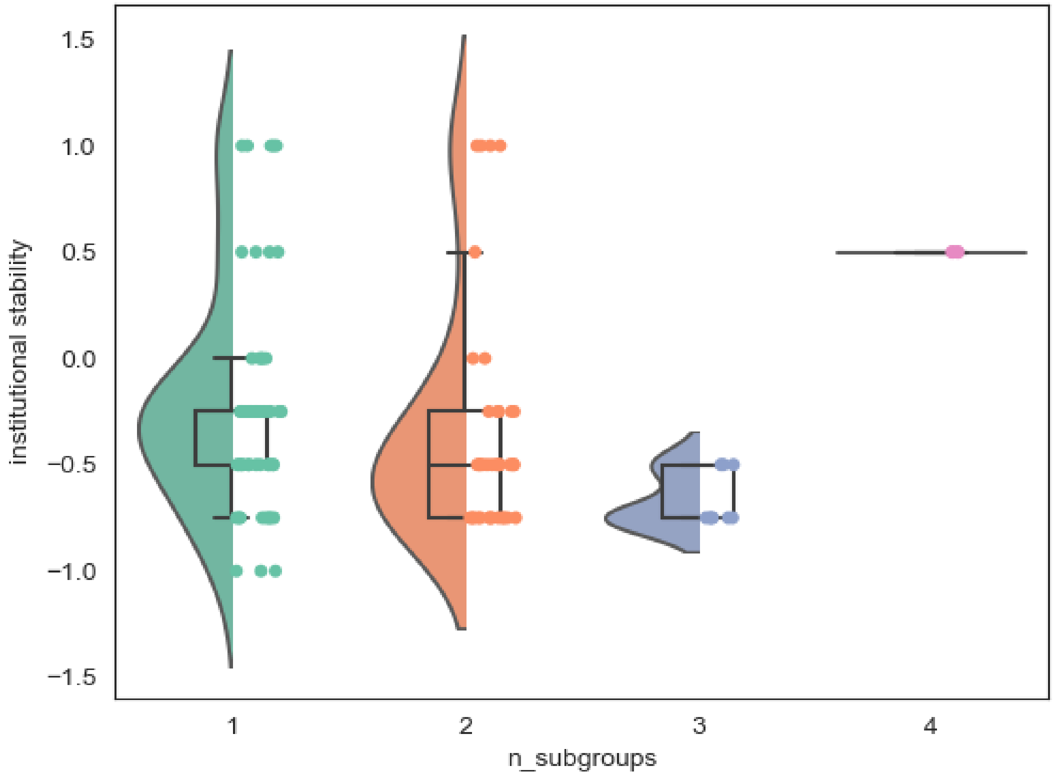


Figure 15. Half violin plots and box plots that demonstrate the distribution of the composite indicator of institutional stability depending on the number of subgroups among users.

Figure 15 demonstrates the distribution of institutional stability for different numbers of subgroups. These distributions are plotted based on 122 irrigation (66) and fishery (56) cases that are present in the dataset. Regrettably, due to data accessibility constraints, it was not possible to segregate and exclusively utilize the fishery-related data.

The figure by itself shows that stable institutions mostly prevail in cases with one or two subgroups. The first two distributions have an already familiar two-peaked form, where there is a bigger one below zero that represents institutions that did not last very long and minor peaks on top that stand for more stable arrangements. Cases describing institutions within communities with three and four subgroups are represented quite poorly, which makes it difficult to compare them with the first two subgraphs. However, cases representing institutions within communities featuring three or four subgroups are less prevalent, making their comparison with the first two subgraphs more challenging. From this figure alone, it remains somewhat ambiguous whether a noticeable trend of median reduction exists or if this is primarily attributable to data limitations.

Even though effort was made to pick relevant variables and to combine suitable indicators, comparison of these distributions with the ones obtained from experiments appears to be problematic. It is because of the way this empirical data was collected. Here each case corresponds to a specific user group obtaining a particular resource unit from a resource system by following a set of rules. If different groups accessed the same resource or if the rule set was modified, it would create a distinct case in the dataset. While data collected through simulation experiments contained runs with unstable institutional regimes where during one run there were several consecutive institutions. Because of this reason data collection was organized in an aggregated manner translating information about a whole run with certain initial parameters rather than focusing on each individual institution. Therefore points on figures 13 and 15 represent different events and direct comparison of these two figures would be inappropriate. This mismatch demonstrates that the validation process requires a separate preparation of the model beforehand in order to organize data collection in a way that will be suitable for the further comparison and analysis.

Considering the arguments above, it is still possible to compare the meanings of the insights from analyses of experimental and empirical data. Although experimental results suggest a positive relationship between the degree of fragmentation in social networks and the stability of institutional arrangements within communities, empirical evidence does not align with this hypothesis.

9 Conclusion

9.1 Discussion

In this chapter I would like to return to the research questions that were directing this study and reflect upon decisions that were made throughout this research as well as on the insights it has produced. The research process can be seen as composed of the following parts: (i) literature search and data collection, (ii) model conceptualization, (iii) software implementation, (iv) running simulation experiments, (v) analyzing simulation results and (vi) deriving policy recommendations and discussion. Further in this section I will discuss each step in detail.

9.1.1 Literature search and data collection

This discussion starts with the reflection upon the searching process of the relevant literature. Literature research lies at the foundation of every research and might be perceived as a formal step that is supposed to provide the context for the following 'meaningful' sections. However, in my case literature search has played a crucial role not only as a context setting tool but as a supportive instrument for every following step. With this regard it is fair to say that it was more of an iterative process rather than just an initial part of the research.

In general the topic of CPR has many dimensions and thus many researchers from various disciplines touch upon it in their studies. Such interdisciplinary nature of the topic imposes a number of difficulties related to diversity of approaches and theoretical frameworks that can be applied in these studies. This diversity translates into a variety of potential key words one would utilize for a comprehensive search in the topic. This limitation forced me to follow a combined approach where key-words-based search was supplemented with a citation based approach. Key words were used to find an initial set of paper for each subtopic and then I mostly followed citations to expand my bibliography. The described methodology has its own drawbacks since it might cover only a certain cluster of papers with more independent authors being left out. Of course, the iterative manner of the process has helped to partially bridge this gap as throughout the later steps I still often encountered relevant and valuable papers for the previous subtopics.

As I have already mentioned, the aim of the literature search was not only to provide relevant context for this study but to frame it as well as to find data to support modeling choices. The later goal was the most challenging one to achieve and will be described in further sections.

Besides data used for modeling choices I also needed data for validation of my model. These data was kindly provided by Ulrich Frey and is described in section 4.2.1. Here I would like to point out that even though this data set is quite extensive, it was challenging to find relevant variables that are both present in the data set and can be calculated and recorded as a result of simulation experiments. There are also drawbacks of this data set such as a possible bias towards regions with scarce data available.

9.1.2 Model conceptualization and software implementation

In this section I want to reflect on the model and how the mechanisms that are responsible for interrelationships between institutions and social networks were implemented. A detailed description of the reference and the developed models is provided in chapter 5. This section contains discussion on the choices that were made within this study. For more details regarding the reference models and their conceptualization process address respective articles.

9.1.2.1 Networks

First and foremost there were three layers of networks implemented based on the theoretical and empirical data, where each network layer corresponded to (a) certain network properties(y). All three layers are generated at the beginning of every simulation run but networks of kins and geographical neighbors are fixed and the network that represents friendship ties changes throughout the simulation. For the first two it was necessary to choose random graph models suitable for their initialization that would accurately reflect their properties, while for the third one both: initialization and consecutive rewiring needed to be conceptualized.

Kins network appeared to be specifically challenging to model as it is supposed to reflect the fragmentation within the community. I want to point out again that kinship is not unique in this regard and fragmentation in CPR sharing communities may be based on ethnic, religious, cultural or other types of diversity that implies strong ties within each fragment (subgraph) and weaker ties with an outside network (other subgraphs). After studying available literature no single random model was found that had explicit control over fragmentation or clustering parameters. There were two alternative options considered: either to use the existing random models during the network initialization process at the beginning of each simulation to generate a number of random networks until the generated network satisfies the desired parameters; or to split nodes into subgraphs and to model each subgraph as a random network. The research proceeded with the latter option as it requires less computational capacities and gives more control over the generation process. The algorithm is described in pseudocode on listing 1.

The layer of network related to geographical neighbors was modeled simpler as a random Watts-Strogatz graph. There were instances of this random network that were disconnected graphs and they were kept as they represent isolated exclaves that might be present especially if a community is spread over a territory separated by water e.g. over islands.

Friends network has imposed two main challenges: processes of initialization and rewiring.
Rewiring process has been conceptualized first as it has a clear theoretical background described in 5.3.3. Its first challenge was the combination of probabilities related to triadic closure, geographical proximity and gear-based homophily into one rewiring probability. Several commonly used methods of such combination were considered: weighted sum, product and maximum. Maximum has been excluded from consideration, because, taking into account the binary nature of the two drivers, contribution of triadic closure would be undervalued. Between the product and weighted sum, the latter has been chosen. Even though these parameters were proven to be among drivers of social cohesion, relative

significance of each of them is uncertain. Weights in this case allow for a finer calibration of this process (formula 1).

The initialization process appears to be less important at first since it provides only the initial state that will be changed throughout the process of rewiring considering that it happens relatively often (more often than institutional change). However it cannot be generated using the same mechanism that is further used for breaking and making ties since triadic closure, one of its parts, is based on the ratio of common friends and kins the two actors have and, thus, cannot be calculated before the friends network is even established. Hence, another initializing mechanism is required. I considered two options: a random network model or a modified rewiring mechanism. First one is easier and faster but might cause a significant change in the network at the beginning of the simulation throughout the first rewiring procedures. It is because rewiring has in its logic attribute-based preferential attachment. Among classical random graph models, only the BA network model is able to offer preferential attachment, and even there, it is typically degree-based. This means that when a network is created in such models, nodes with higher degree centrality tend to acquire more connections. This limitation could be avoided by giving the model additional time at the beginning of the simulation to achieve a state of dynamic equilibrium, at which in each rewiring iteration, approximately the same number of connections are being rewired.

Nevertheless I decided to avoid this limitation and utilized the modified rewiring algorithm where for the part of triadic closure instead of the ratio of common kins and friends that is used for rewiring probabilities, the ratio of common kins and geographical neighbors was calculated. By going through each node pair throughout initialization directed ties occurred based on the probabilities. The number of links in a network then has been the same throughout each specific simulation run since, as it was shown on listing 4, broken ties were always compensated by the same number of emerged ties. At the same time between simulation runs the total number of friendship ties may differ as it depends on heterogeneity and on other initial parameters that define the initial state of the friends network.

The alternatives and the arguments provided in this section describe the decision making process behind the network conceptualization. Each layer was derived to represent certain social network properties found in literature. As it can be seen, for example in the rewiring mechanism these layers meet and affect each other, reflecting the multiplexity of social interactions that is often highlighted in studies on social theory. However, it is still an open question, to what extent this layered representation is accurate and to what extent the combined network inherits the properties of its layers.

9.1.2.2 Linking institutions and network structure

The model was specifically tailored for this research to address the unique research questions concerning the intricate interplay between social networks and the institutional dynamics governing Common-Pool Resources (CPR). To achieve this goal, several mechanisms were employed to establish links between institutional parameters and network structures. These mechanisms encompassed:

1. **Rewiring probability**: The model incorporated mechanisms related to triadic closure and attribute-driven factors within the rewiring probability calculation. These

mechanisms reflected the social processes by which individuals form and maintain connections based on shared attributes and common connections.

2. **Indegree and voting eligibility**: Another mechanism established a link between indegree (the number of incoming connections) and an agent's eligibility to vote within the institutional framework. This mechanism aimed to capture the influence of an agent's network centrality on their institutional role and decision-making power.
3. **Priority in strategy copying**: The model introduced a priority mechanism for strategy copying, where an agent prioritized copying the strategy of certain types of neighboring agents. This mechanism considered factors such as kinship, friendship, and geographical proximity, reflecting the diverse nature of social relationships and their impact on decision-making.
4. **Social parameters and cheating**: Surrounding agents, defined through an agent's outgoing connections, influenced an agent's decision regarding cheating. This mechanism accounted for the social context in which an agent operates and how the behavior of their immediate network associates can influence their own actions.

However, it's essential to acknowledge that these mechanisms come with specific limitations:

1. **Limitations of rewiring probabilities**: The first mechanism's limitations were discussed in detail in the previous section, highlighting the challenges associated with capturing complex network dynamics solely through triadic closure.
2. **Representation of Indegree**: The second mechanism's applicability is constrained by the representation of layers within the directional graph. While indegree can be calculated for the directed friends network, this calculation doesn't encompass connections within kins and neighbors networks. These connections were assumed to be bidirectional, and their contribution to indegree and outdegree calculations was considered.
3. **Rare conditions in strategy copying**: The third mechanism, based on priority in strategy copying, may encounter limitations due to the infrequent occurrence of several agents having similar energy levels, which are randomly assigned within a specific range. Additionally, the prevalence of friendship ties in the model often led to agents predominantly copying their friends' strategies.

Despite these limitations, the combination of these mechanisms provides a comprehensive framework to capture the intricate interplay between institutional and network parameters. While individual mechanisms may have constraints, their collective integration allows for a nuanced understanding of how social networks and institutional dynamics interact and shape outcomes within the context of Common-Pool Resource management.

9.1.3 Research questions examination and policy recommendations

In this section, I undertake an examination of the research subquestions that have guided this study. These subquestions form the backbone of the investigation into the interplay between network structures, institutional dynamics, and the co-evolution of these elements within the context of CPR governance. As an overarching conclusion, contributions of the results to the main research question are discussed.

1. *How does the initial network structure impact the emergence of institutions for CPR governance?*

It was already pointed out that according to the CPR theory the interrelationship between social network and institutional parameters is assumed to be bidirectional. Various limitations of the format of the master thesis did not allow me to conduct a comprehensive analysis of this relationship in both directions. This subquestion was chosen as a basis for simulation experiments with the aim to validate the results through comparison with available empirical data. The results of these simulations are demonstrated and discussed in chapter 7.

Experimental results clearly illustrate a noteworthy trend: as the number of network fragments increases, outcomes tend to become more clustered, as evidenced by the decreasing interquartile range. This trend finds a plausible explanation when considering that a higher number of tightly connected fragments within networks is associated with a reduced fraction of unstable institutions. Indeed, this correlation is prominently displayed in the bar plot presented in figure 14. It implies that communities characterized by more fragmented social networks tend to exhibit enhanced stability in their institutional arrangements. In other words, there appears to be a positive relationship between the degree of initial network fragmentation and the probability of a stable institutional regime within these communities.

However, it is important to note that empirical data does not align with this observed trend. The empirical evidence does not conclusively support an opposite trend either, mainly due to limitations in interpretability and data availability.

2. *How do institutions and networks co-evolve depending on different rewiring mechanisms?*

Simulation experiments that were carried out through this study do not provide specific insights on this matter. However, another part of this research, which is sensitivity analysis, is able to shed light on the principles of coevolution of social networks and institutions.

Different rewiring mechanisms were tested through varied weights that were used for calculation of rewiring probability. It was demonstrated that the behavior of the total rewiring probability (p_total) altered significantly based on the type of rewiring mechanism. When considering network-characteristic-dependent probabilities, such as those associated with geographic proximity and triadic closure, an increase in the corresponding weight led to a decrease in probability values. Conversely, in the case of attribute homophily reflecting the similarity of individual strategies, increasing the weight resulted in a continuous rise and eventual saturation of the probability. This divergence in behavior can be attributed to the presence of negative feedback mechanisms influencing network-dependent probabilities and positive feedback mechanisms governing homophily-based probabilities.

Figure 9, depicting the relationship between mean degree centrality of a combined social network (“mean_comb_degree") and the three rewiring weights, echoed these findings. It illuminated how the nature of the rewiring mechanisms influenced the average combined degree of agents in the network. The observed sensitivity of network behaviors to different rewiring mechanisms suggests that communities may need to carefully consider how they foster social cohesion and cooperation among their members.

3. *How can the connection between network parameters and institutional settings for CPR governance be utilized to provide effective policy recommendations?*

Policy recommendations stem from the conclusions drawn from answering the previous subquestions. These recommendations are targeting local community leaders, organizations or individuals that aim at establishing and maintaining a participatory system that supports community-based decision making regarding institutions regulating CPR. The ultimate purpose of this system should be a development of an environment that (i) stimulates development of stable institutions, (ii) ensures principles of adaptive governance and (iii) provides social and economic success for agents and ecological success for the resource. In my study a SSF was taken as an example and the abovementioned policy recommendations will be formulated specifically for this case.

Taking into account the conducted research of the literature and my findings highlighted in this paper, my recommendations will mostly relate to the preparatory phase of development of the system. It relates to the period of preparation for a possible emergent institution, unlike the navigation phase that covers the period when an institution has already emerged.

- It is important to Identify or stimulate creation of tightly connected groups within a community. In my model these fragments of social networks were associated with kinship relationships but in fact they can also be based on ethnic, religious, cultural or other types of homophily. Simulation results show that presence of these groups increase probability of achieving a stable institutional regime.

- Analysis of the needs of the actors will give a better understanding of the resource consumption. What part of the extracted resource can be translated into profit? What part of the resource is consumed by the actor themself? Are there other processes that can be viewed as in- or outflows of something that can be translated into energy/wealth consumption levels? Sensitivity analysis conducted throughout this study proved that by answering these questions one could better understand the steps that need to be taken in order to bring the system to the point where institutional emergence is more probable.

- Regardless of the phase and position of the decision-maker in the system, it is necessary to conduct analysis of what types of resources do agents share and how their extraction, distribution and usage are interwoven with each other. The described model shows that the size of an array of available strategy options plays a crucial role and thus needs to be assessed before any policy interventions. This will dictate a suitable scope for development of a balanced policy. Policies developed in isolation can lead to resource(s) depletion or shortage.

- In conclusion, elevating the significance of gear-(attribute-)based homophily emerges as a potent instrument. The research indicates that as the preference for attribute-based connections grows, social networks can consist of more enduring and resilient bonds. This achievement can be realized through various means:

- Fishing Cooperatives: Encourage the formation of fishing cooperatives where fishers with similar gear preferences collaborate to collectively manage resources. These cooperatives can facilitate knowledge sharing, gear maintenance, and coordinated resource extraction.
- Gear Maintenance Workshops: Organize workshops specifically focused on gear maintenance and repair. This would not only enhance homophily but also ensure that fishers with similar gear types can effectively collaborate in maintaining their equipment.
- Online Gear Communities: Develop online platforms or social media groups dedicated to specific gear types. Fishers can join these communities to interact, ask questions, and share experiences.

How are network structure and dynamics interrelated with the emergence and evolution of institutions for the governance of common pool resources?

Answering the main research question from the very beginning appeared to be an ambiguous goal. Even though this thesis has always followed the track this question has set, it obviously has not encompassed analysis that is broad enough to answer this question. As a result, the focus of this study has shifted towards less comprehensive yet clear and precise subquestions. In my opinion it is still important that this question was raised as it highlights the spacious knowledge gap available for future research. Besides, it provided an understanding of design principles for the constructed model that in my opinion is suitable for further more comprehensive research based on this research question. And, finally, it provides understanding regarding the empirical data that is needed to validate the model.

The sensitivity analysis shows that such institutional parameters as the maximum number of resource units that are available as an option for a personal extraction strategy ("max_action") has a significant influence on characteristics of social networks. This is a notable insight and exploring this reverse dynamic promises to shed light on how institutions, in their varied forms, shape the contours of social networks in the context of CPR governance.

9.2 Model limitations

Limitations of the applied methods and approaches were discussed in corresponding sections. Here I want to focus on the limitations that are inherent to the designed model:

- <u>Limited resource awareness</u>: Agents are not aware of the state of the resource. Usually agents are aware of specific characteristics of their particular resource and of its current state.
- <u>Single resource, single institution</u>: There is only one type of resource while often agents share different types of resources that are interdependent (i.e. water-food-energy) (Chaudhuri et al., 2021). And there is only one institution regulating it. The model does not take into account institutional multiplexity. Often agents share different resources at the same time and cannot separate sharing one type of resource with sharing another, which makes emerging institutions much more

complex (Schnegg, 2018). Even in the case of a fishing community, usually multiple species of fish are being shared and regulated (Ruddle, 1998; Castello et al., 2013).

- SIngle interaction arena: It is assumed that there is only one arena where agents interact to establish an institution. In fact the real cases often include multiple arenas with varying compositions of agents involved (Herzog & Ingold, 2019).
- Agent Memory Limitation: Agents have a simple memory, only their "best" past action ist recorded. It is not coherent with the rational choice concept of cooperation developed by Ostrom (1998) that highlights the role of agents' past actions in fostering cooperation.
- Constant network size: Network size did not change throughout the experiments. In reality CPRs are open to new participants. Although, sometimes institutions that govern CPR aim at excluding people from outside (Castello et al., 2013; Etiegni et al., 2017).
- Limited generalizability: Cases of small-scale fisheries demonstrate a striking variety of conditions. For example, there is a significant difference between operations of small-scale fisheries in H-HDI and ML-HDI countries (Nielsen et al., 2008). There are 5 times more small-scale fisheries per area in ML-HDI countries while a single fishery from an ML-HDI country will catch on average 5 times more fish per year.
- Assumption of full information: It is assumed formally that actors have full information about the network and the other actors. In practice, actors' information about the network is usually limited.
- Limited institutional structure: institution (as well as personal strategy) was only limited to an action item. This was done to reduce complexity of the analysis and was based on the assumption that agents go fish every day. In fact, fishing is usually a seasonal activity and condition items in institutional structure could be accounting for the period of time during the year when fishing is prohibited.

9.3 Further research opportunities

Section 9.1.3 touches upon the possibilities of complementary research. In this section I would like to mention model limitations that are important or would be interesting to tackle:

- Given the theoretical nature of this work, it was complicated to make modeling choices based on empirical data. It holds even more for specific parameters that require a numerical value attached to them. Of course absolute values are usually not relevant in models that demonstrate validity at a qualitative level, but indices that operate on a relative scale can help to translate empirical data into sound modeling choices. One of these indices is catch-per-unit-effort (CPUE) (Almeida et al., 2009). It can help to translate combinations of fishing gear, vessel types and resource abundance levels into numerical parameters that correspond with the effort of fishers needed to extract a certain amount of resource. It is an interesting direction since it gives an opportunity to inform agents about the state of the resource.
- Monitoring can be performed by the leaders who are also entitled to vote. This feature will bring a whole new dimension to the model. It can possibly shed light on bribery issues, for example.
- The study has highlighted the significance of refining initialization algorithms that afford greater control over the initial parameters of the system. While this research provided valuable insights under the constraints of its existing initialization methods, it became evident that a more nuanced and sophisticated approach to setting initial

conditions can lead to deeper and more precise examinations. This increased control will facilitate more targeted investigations into the dynamic relationship between network configurations and the emergence of institutions.

There will always be a big overarching challenge for the future researcher that I have also experienced during my studies – data. While the research made substantial steps within the constraints of available data, it became evident that comprehensive data collection is essential to unravel the complexities of CPR governance fully. Future researchers should prioritize the collection of extensive and detailed data, encompassing a wide array of network characteristics, institutional dynamics, and individual strategies. This comprehensive dataset will serve as a robust foundation for investigations into the coevolution of networks and institutions. Without this foundation and a thorough validation simulation results and the produced policy recommendations should be treated very carefully.

9.4 Summary

In my thesis I was studying the interrelation between network topology and dynamics and the emergence and evolution of institutions for the governance of CPR. This research was intended to shed some light on what is the role of networks in formation of endogenous institutions and the possible insights for policy makers and users of CPR. To answer my research question, I utilized the agent-based institutional model and enhanced it by adding three dimensions of social networks and connecting them through various mechanisms to other parts of the model trying to capture the complexity of SESs.

Therefore, through the combination of ABM and approaches from SNA I conducted a series of simulations that were imitating co-evolution of endogenous institutions and network topology. Through variation of input and output parameters the patterns were derived from the model and thoroughly analyzed. Notably, they suggest a positive relationship between the degree of network fragmentation and the stability of institutional structures within these communities. This implies that more fragmented social networks tend to exhibit greater stability in their institutional arrangements. Furthermore, the research reveals the presence of negative feedback mechanisms influencing network-dependent probabilities and positive feedback mechanisms governing homophily-based probabilities. These findings underscore the complexity of CPR governance, where network structures, institutional dynamics, and personal strategies interact in intricate ways.

The results of this analysis were utilized to provide policy recommendations for regulation of CPRs. Mainly these recommendations evolve around: (i) identification and connection of fragments within social networks; (ii) analysis of the details of agents resource consumption, (iiI) identification of potential strategy options and (iv) enhancement of the processes that drive creation of gear- (or other attribute-) based connections. Overall, the research has the potential to inform the development of more effective and sustainable approaches to the governance of CPRs.

References

Ale Ebrahim Dehkordi, M. (n.d.). *How wealth inequality influences cooperation in common-pool resource management: An agent-based model to compare theoretical hypotheses*.

Ale Ebrahim Dehkordi, M., Ghorbani, A., Bravo, G., Farjam, M., van Weeren, R., Forsman, A., & De Moor, T. (2021). Long-Term Dynamics of Institutions: Using ABM as a Complementary Tool to Support Theory Development in Historical Studies. *Journal of Artificial Societies and Social Simulation*, *24*(4), 7. https://doi.org/10.18564/jasss.4706

Alexander, S. M., Armitage, D., & Charles, A. (2015). Social networks and transitions to co-management in Jamaican marine reserves and small-scale fisheries. *Global Environmental Change*, *35*, 213–225. https://doi.org/10.1016/j.gloenvcha.2015.09.001

Alexander, S. M., Bodin, Ö., & Barnes, M. L. (2018). Untangling the drivers of community cohesion in small-scale fisheries. *International Journal of the Commons*, *12*(1), 519–547. https://doi.org/10.18352/ijc.843

Almeida, O. T., Lorenzen, K., & McGRATH, D. G. (2009). Fishing agreements in the lower Amazon: For gain and restraint. *Fisheries Management and Ecology*, *16*(1), 61–67. https://doi.org/10.1111/j.1365-2400.2008.00647.x

Barnes-Mauthe, M., Arita, S., Allen, S., Gray, S., & Leung, P. (2013). The Influence of Ethnic Diversity on Social Network Structure in a Common-Pool Resource System: Implications for Collaborative Management. *Ecology and Society*, *18*(1). https://doi.org/10.5751/ES-05295-180123

Barnes-Mauthe, M., Gray, S. A., Arita, S., Lynham, J., & Leung, P. (2015). What Determines Social Capital in a Social–Ecological System? Insights from a Network Perspective. *Environmental Management*, *55*(2), 392–410. https://doi.org/10.1007/s00267-014-0395-7

Beckmann, V., & Padmanabhan, M. (2009). Analysing Institutions: What Method to Apply? In V. Beckmann & M. Padmanabhan (Eds.), *Institutions and Sustainability: Political Economy of Agriculture and the Environment—Essays in Honour of Konrad Hagedorn* (pp. 341–371). Springer Netherlands. https://doi.org/10.1007/978-1-4020-9690-7_16

Bodin, Ö., & Chen, H. (2023). A network perspective of human–nature interactions in dynamic and fast-changing landscapes. *National Science Review*, nwad019. https://doi.org/10.1093/nsr/nwad019

Bodin, Ö., Crona, B., & Ernstson, H. (2006). Social Networks in Natural Resource Management: What Is There to Learn from a Structural Perspective? *Ecology and Society*, *11*(2), resp2. https://doi.org/10.5751/ES-01808-1102r02

Bodin, Ö., Crona, B., & Ernstson, H. (2017). Social Networks in Natural Resource Management: What Is There to Learn from a Structural Perspective? *Redes. Revista Hispana Para El Análisis de Redes Sociales*, *28*(1), 1. https://doi.org/10.5565/rev/redes.684

Bodin, Ö., & Crona, B. I. (2009). The role of social networks in natural resource governance: What relational patterns make a difference? *Global Environmental Change*, *19*(3), 366–374. https://doi.org/10.1016/j.gloenvcha.2009.05.002

Boero, R., Bravo, G., & Squazzoni, F. (2010). *Trust and Partner Selection in Social Networks: An Experimentally Grounded Model* (arXiv:1008.4705). arXiv. http://arxiv.org/abs/1008.4705

Castello, L., McGrath, D. G., Arantes, C. C., & Almeida, O. T. (2013). Accounting for heterogeneity in small-scale fisheries management: The Amazon case. *Marine Policy*, *38*, 557–565. https://doi.org/10.1016/j.marpol.2012.09.001

Chaudhuri, S., Roy, M., McDonald, L. M., & Emendack, Y. (2021). Reflections on farmers' social networks: A means for sustainable agricultural development? *Environment, Development and Sustainability*, *23*(3), 2973–3008. https://doi.org/10.1007/s10668-020-00762-6

Colin-Castillo, S., & Woodward, R. T. (2015). Measuring the potential for self-governance: An approach for the management of the common-pool resources. *International Journal of the Commons*, *9*(1), 281. https://doi.org/10.18352/ijc.490

Crawford, S. E. S., & Ostrom, E. (1995). A Grammar of Institutions. *American Political Science Review*, *89*(3), 582–600. https://doi.org/10.2307/2082975

Etiegni, C. A., Irvine, K., & Kooy, M. (2017). Playing by whose rules? Community norms and fisheries rules in selected beaches within Lake Victoria (Kenya) co-management. *Environment, Development and Sustainability*, *19*(4), 1557–1575. https://doi.org/10.1007/s10668-016-9799-2

Farrell, H., & Knight, J. (2003). Trust, Institutions, and Institutional Change: Industrial Districts and the Social Capital Hypothesis. *Politics & Society*, *31*(4), 537–566. https://doi.org/10.1177/0032329203256954

Frey, U. J., & Rusch, H. (2014). Modeling Ecological Success of Common Pool Resource Systems Using Large Datasets. *World Development*, *59*, 93–103. https://doi.org/10.1016/j.worlddev.2014.01.034

García-Amado, L. R., Pérez, M. R., Iniesta-Arandia, I., Dahringer, G., Reyes, F., & Barrasa, S. (2012). Building ties: Social capital network analysis of a forest community in a biosphere reserve in Chiapas, Mexico. *Ecology and Society*, *17*(3). https://www.jstor.org/stable/26269061

Ghorbani, A. (2022). Institutional modelling: Adding social backbone to agent-based models. *MethodsX*, *9*, 101801. https://doi.org/10.1016/j.mex.2022.101801

Ghorbani, A., & Bravo, G. (2016). Managing the commons: A simple model of the emergence of institutions through collective action. *International Journal of the Commons*, *10*(1), Article 1. https://doi.org/10.18352/ijc.606

Ghorbani, A., Bravo, G., Frey, U., & Theesfeld, I. (2017). Self-organization in the commons: An empirically-tested model. *Environmental Modelling & Software*, *96*, 30–45. https://doi.org/10.1016/j.envsoft.2017.06.039

Girvan, M., & Newman, M. E. J. (2002). Community structure in social and biological networks. *Proceedings of the National Academy of Sciences*, *99*(12), 7821–7826. https://doi.org/10.1073/pnas.122653799

Gunderson, L. (1999). Resilience, Flexibility and Adaptive Management—- Antidotes for Spurious Certitude? *Conservation Ecology*, *3*(1). https://doi.org/10.5751/ES-00089-030107

Hardin, G. (1968). The Tragedy of the Commons. *Science*, *162*(3859), 1243–1248. https://doi.org/10.1126/science.162.3859.1243

Herzog, L. M., & Ingold, K. (2019). Threats to Common-Pool Resources and the Importance of Forums: On the Emergence of Cooperation in CPR Problem Settings. *Policy Studies Journal*, *47*(1), 77–113. https://doi.org/10.1111/psj.12308

Hirschmann, D., & Vaughan, M. (1984). *Women farmers of Malawi: Food production in the Zomba District*. https://www.semanticscholar.org/paper/Women-farmers-of-Malawi-%3A-food-production-in-the-Hirschmann-Vaughan/f1c8b37a4b79f92fb6ef5d6cb41796dbc8480bc4

Janssen, M. A., Goldstone, R. L., Menczer, F., & Ostrom, E. (2008). Effect of rule choice in dynamic interactive spatial commons. *International Journal of the Commons*, *2*(2), 288. https://doi.org/10.18352/ijc.67

Ligmann-Zielinska, A., & Sun, L. (2010). Applying time-dependent variance-based global sensitivity analysis to represent the dynamics of an agent-based model of land use change. *International Journal of Geographical Information Science*, *24*(12), 1829–1850. https://doi.org/10.1080/13658816.2010.490533

Maunder, M. N., & Punt, A. E. (2004). Standardizing catch and effort data: A review of recent approaches. *Fisheries Research*, *70*(2–3), 141–159. https://doi.org/10.1016/j.fishres.2004.08.002

May, R. M. (2006). Network structure and the biology of populations. *Trends in Ecology & Evolution*, *21*(7), 394–399. https://doi.org/10.1016/j.tree.2006.03.013

Maya-Jariego, I., Holgado Ramos, D., & Florido Del Corral, D. (2016). Relations between professional groups in the Atlantic and Mediterranean fishing enclaves of Andalusia (Spain): A personal networks approach with clustered graphs. *Marine Policy*, *72*, 48–58. https://doi.org/10.1016/j.marpol.2016.06.013

Müller, B., Bohn, F., Dreßler, G., Groeneveld, J., Klassert, C., Martin, R., Schlüter, M., Schulze, J., Weise, H., & Schwarz, N. (2013). Describing human decisions in agent-based models – ODD + D, an extension of the ODD protocol. *Environmental Modelling & Software*, *48*, 37–48. https://doi.org/10.1016/j.envsoft.2013.06.003

Nielsen, J., Dodson, J., & Friedland, K. (2008). *Small is Beautiful ? A Database Approach for Global Assessment of Small-Scale Fisheries : Preliminary Results and Hypotheses*. https://www.semanticscholar.org/paper/Small-is-Beautiful-A-Database-Approach-for-Global-%3A-Nielsen-Dodson/730c388facc81a97379268e37cf9310c748efca8

Nishi, A., Shirado, H., Rand, D. G., & Christakis, N. A. (2015). Inequality and visibility of wealth in experimental social networks. *Nature*, *526*(7573), Article 7573. https://doi.org/10.1038/nature15392

Okumu, B., & Muchapondwa, E. (2020). Determinants of successful collective management of forest resources: Evidence from Kenyan Community Forest Associations. *Forest Policy and Economics*, *113*, 102122. https://doi.org/10.1016/j.forpol.2020.102122

Olsson, P., Gunderson, L. H., Carpenter, S. R., Ryan, P., Lebel, L., Folke, C., & Holling, C. S. (2006). Shooting the Rapids: Navigating Transitions to Adaptive Governance of Social-Ecological Systems. *Ecology and Society*, *11*(1). https://www.jstor.org/stable/26267806

Ostrom, E. (1990). *Governing the commons: The evolution of institutions for collective action*. Cambridge University Press.

Ostrom, E. (1998). A Behavioral Approach to the Rational Choice Theory of Collective Action: Presidential Address, American Political Science Association, 1997. *American Political Science Review*, *92*(1), 1–22. https://doi.org/10.2307/2585925

Ostrom, E., (2005). Understanding Institutional Diversity. Princeton, NJ: Princeton University Press.

Ostrom, E. (2006). The value-added of laboratory experiments for the study of institutions and common-pool resources. *Journal of Economic Behavior & Organization*, *61*(2), 149–163. https://doi.org/10.1016/j.jebo.2005.02.008

Ostrom, E. (2011). Background on the Institutional Analysis and Development Framework. *Policy Studies Journal*, *39*(1), 7–27. https://doi.org/10.1111/j.1541-0072.2010.00394.x

Peña, J., Wu, B., Arranz, J., & Traulsen, A. (2016). Evolutionary Games of Multiplayer Cooperation on Graphs. *PLOS Computational Biology*, *12*(8), e1005059. https://doi.org/10.1371/journal.pcbi.1005059

Ramirez-Sanchez, S. (2011). *The role of individual attributes in the practice of information sharing among fishers from Loreto, BCS, Mexico* (Ö. Bodin & C. Prell, Eds.; 1st ed., pp. 234–254). Cambridge University Press. https://doi.org/10.1017/CBO9780511894985.011

Ramirez-Sanchez, S., & Pinkerton, E. (2009). The Impact of Resource Scarcity on Bonding and Bridging Social Capital: The Case of Fishers’ Information-Sharing Networks in Loreto, BCS, Mexico. *Ecology and Society*, *14*(1), art22. https://doi.org/10.5751/ES-02841-140122

Reeves, D. C., Willems, N., Shastry, V., & Rai, V. (2022). Structural Effects of Agent Heterogeneity in Agent-Based Models: Lessons from the Social Spread of COVID-19. *Journal of Artificial Societies and Social Simulation*, *25*(3), 3.

Röttgers, D. (2016). Conditional cooperation, context and why strong rules work—A Namibian common-pool resource experiment. *Ecological Economics*, *129*, 21–31. https://doi.org/10.1016/j.ecolecon.2016.03.013

Ruddle, K. (1998). The context of policy design for existing community-based fisheries management systems in the Pacific Islands. *Ocean & Coastal Management*, *40*(2), 105–126. https://doi.org/10.1016/S0964-5691(98)00040-4

Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., Saisana, M., & Tarantola, S. (2008). *Global Sensitivity Analysis: The Primer*. John Wiley & Sons.

Sarker, A., Ross, H., & Shrestha, K. K. (2008). A common-pool resource approach for water quality management: An Australian case study. *Ecological Economics*, *68*(1), 461–471. https://doi.org/10.1016/j.ecolecon.2008.05.001

Schnegg, M. (2018). Institutional multiplexity: Social networks and community-based natural resource management. *Sustainability Science*, *13*(4), 1017–1030. https://doi.org/10.1007/s11625-018-0549-2

Shester, G. G., & Micheli, F. (2011). Conservation challenges for small-scale fisheries: Bycatch and habitat impacts of traps and gillnets. *Biological Conservation*, *144*(5), 1673–1681. https://doi.org/10.1016/j.biocon.2011.02.023

Siddiki, S., Weible, C. M., Basurto, X., & Calanni, J. (2011). Dissecting Policy Designs: An Application of the Institutional Grammar Tool. *Policy Studies Journal*, *39*(1), 79–103. https://doi.org/10.1111/j.1541-0072.2010.00397.x

Snijders, T. A. B., van de Bunt, G. G., & Steglich, C. E. G. (2010). Introduction to stochastic actor-based models for network dynamics. *Social Networks*, *32*(1), 44–60. https://doi.org/10.1016/j.socnet.2009.02.004

Ten Broeke, G., Van Voorn, G., & Ligtenberg, A. (2016). Which Sensitivity Analysis Method Should I Use for My Agent-Based Model? *Journal of Artificial Societies and Social Simulation*, *19*(1), 5. https://doi.org/10.18564/jasss.2857

Van De Bunt, G. G., & Groenewegen, P. (2007). An Actor-Oriented Dynamic Network Approach: The Case of Interorganizational Network Evolution. *Organizational Research Methods*, *10*(3), 463–482. https://doi.org/10.1177/1094428107300203

Walker, J. M., Gardner, R., Herr, A., & Ostrom, E. (2000). Collective Choice in the Commons: Experimental Results on Proposed Allocation Rules and Votes. *The Economic Journal*, *110*(460), 212–234. https://doi.org/10.1111/1468-0297.00497

Will, M., Groeneveld, J., Frank, K., & Muller, B. (2020). Combining social network analysis and agent-based modelling to explore dynamics of human interaction: A review. *Socio-Environmental Systems Modelling*, *2*, 16325–16325. https://doi.org/10.18174/sesmo.2020a16325

Wossen, T., Berger, T., Mequaninte, T., & Alamirew, B. (2013). Social network effects on the adoption of sustainable natural resource management practices in Ethiopia. *International Journal of Sustainable Development & World Ecology*, *20*(6), 477–483. https://doi.org/10.1080/13504509.2013.856048

Yudawan, G. A., Khayrruraja, A., Islamiati, A., & Rizal, A. (2022). Fisheries as Common-Pool Resources, Its Management and Impact on Fishing Ecosystem in Indonesia: A Mini-Review. *Asian Journal of Fisheries and Aquatic Research*, 30–36. https://doi.org/10.9734/ajfar/2022/v18i130430

Appendix

Appendix A: Model overview

A.1 Entities, state variables and scales

There is a single type of resource that represents fish and there are agents that extract and appropriate this resource that represent anglers from a small-scale fishery. The agents form three layers of social network: kins', geographical neighbors and friends, which direct their interactions. When extracting the resource agents follow either a personal strategy or an institution that emerged from their interactions. Both strategies and institutions have an identical structure: the amount of the resource that agents extract each time step.

Table A1. Agents

Attribute	Description
energy	Captures the amount of energy that an agent currently has. It decreases every tick based on consumption needs, and increases based on appropriation activities. Each time an institution is established, wealth is returned to the initial value.
initial_energy	Energy at the beginning of simulation
current_action	How many resource units an agent is appropriating every time step
cheated	A Boolean variable that shows whether the agent cheated in the previous tick
cheating_propensity	The probability of cheating
innovation_rate	Shows how innovative an agent is. It is a probability of an agent to switch to a new strategy without relying on neighbors.
confidence	A Boolean variable. If True, an agent will change their strategy based on the best strategy they had before.
fragment	Shows the index and the size of the fragment in kinship network an agent belongs to
consumed_resource	Shows the amount of the resource an agent has extracted up to this point of simulation. Is updated every time step.

best_action	Action that has yielded to the highest energy level. Imitates a simple learning process from experience.
best_energy	Highest energy level that an agent has had through simulation.
voting	A Boolean variable that shows whether an agent is entitled to vote for an institution.
own_idea_fine	Variable that represent an agent's perception of how big is the fine for cheating.
own_idea_monitoring	Variable (percentage) that represents an agent’s perception on how often they will be monitored to check whether they have cheated or not.
friends_in	IDs representing agents who consider this agent as a friend (inward relationship)
friends_out	Set of unique IDs representing agents whom this agent considers as friends (outward relationship).
kins	Set of unique IDs representing agents who are considered kin by this agent, based on the kin network.
geo_neighbors	Set of unique IDs representing agents who are geographic neighbors of this agent in the geographical network.
in_degree	The number of relationships this agent has where other agents consider this agent as a friend (inward relationships), kins or geographical neighbors.
out_degree	The number of relationships this agent has where this agent considers other agents as friends (outward relationships), kins or geographical neighbors.

Table A2. Resource

Attribute	Description
r	Resource growth coefficient. In each round of the simulation, the amount of resource is increased based on this value given a particular growth function.

K_0	Amount of the resource at the beginning of simulation (initial).
resource type	Fishery.

Table A3. Social networks

Kins' network

Network consists of several fragments of different sizes. Each of them is modeled as a Barabási-Albert network

Attribute	Description
type	Undirected, fixed
fragments_list	A list containing the number of agents in each fragment within the kins network. The sum of agents across fragments equals the total number of agents in the model.
n_fragments	The number of tightly connected fragments
ba_m	The average number of edges that each new node creates during the Barabási-Albert network generation process. It influences the preferential attachment mechanism.

Geographical network

Network of geographical neighbors. Modeled as a Watts-Strogatz graph

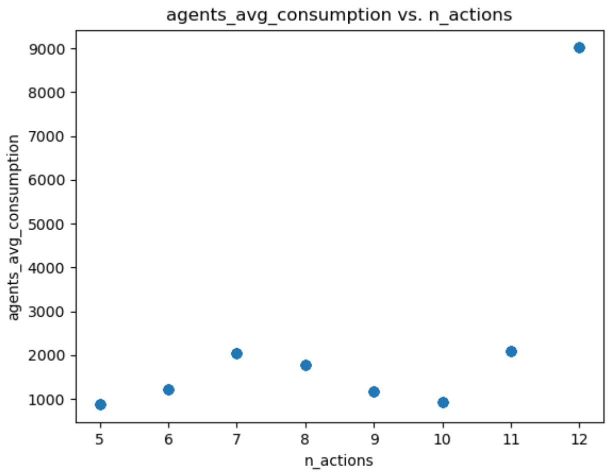
Attribute	Description
type	Undirected, fixed
ws_k	The number of nearest neighbors each node is connected to in the Watts-Strogatz graph. It influences the local clustering of the geographical network.
ws_p	The probability of rewiring each edge in the Watts-Strogatz graph. It determines the level of randomness and long-range connections in the geographical network.

Friends' network Network that represents ties of friendship. A tie between two agents can be broken or established according to the rewiring probability.	
Attribute	Description
type	Directed, dynamic
rewiring_probability	Existing probability of a link between two agents that is calculated as a sum of 3 parameter-based probabilities. Parameters: common neighbors, action (gear) homophily and geographical neighborhood.
weights	A dictionary that assigns a weight to each summand probability.
rewiring_rate	Represents the number of ticks after which the friends' network is updated.

Table A4. Institution

Attribute	Description
list_actions	List of possible actions. At the beginning each agent randomly chooses an action item from the list. The action that has to be executed by every agent in the simulation.
max_action	The largest action item in the list.
n_actions	Number of actions items in the actions list.
emergence_time	The number of ticks after which agents decide upon institution
threshold_institutional_change	The threshold needed to establish an institution. If the ratio of agents with negative energy is less than this threshold, then it is not enough for institution to emerge.
max_fine	Sets the upper limit for the amount of penalty paid by agents in case they are monitored when cheated.
max_monitoring	Sets the upper limit for the percentage of agents who will be monitored for cheating.

Appendix B: OFAT



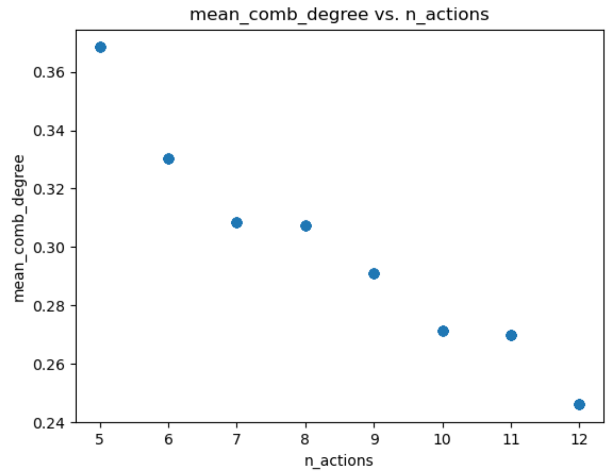


Figure B1. Results of OFAT sensitivity analysis with the varying parameter being n_actions and results being agents_avg_consumption (upper), mean_comb_degree (middle) and num_institutions (lower).

Notably, in the upper plot on Figure B1, as the value of n_actions increases, there is a corresponding upward trend in agents_avg_consumption. Conversely, the lower plot demonstrates a declining trend in the number of institutions (num_institutions) as the value of n_actions grows. This behavior could mean that with the increased number of strategies available, action (gear) heterogeneity increases what affects the probability of emergence of new links.

Figure B2 demonstrates that with the growth of the innovation_rate parameter, agents manage to get more resources. This is consistent with the notion that it is easier for more innovative agents to find a successful strategy. Figure B3 demonstrates the absence of any influence of the initial resource state on agent_avg_consumption. It was expected since the model does not support any mechanism of feedback between agents and the resource they are extracting.

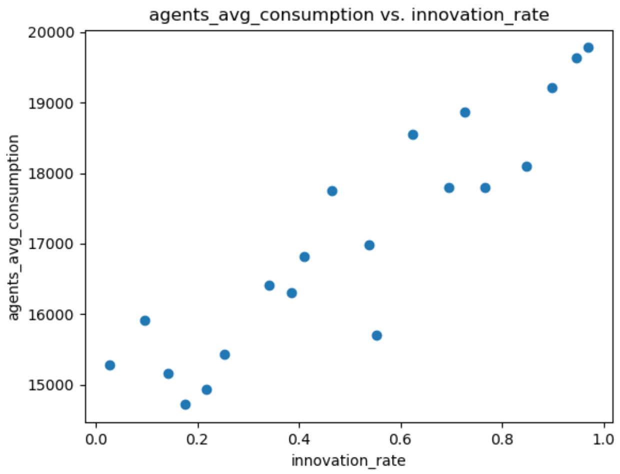


Figure B2. Results of OFAT sensitivity analysis with the varying parameter being innovation_rate and results being agents_avg_consumption.

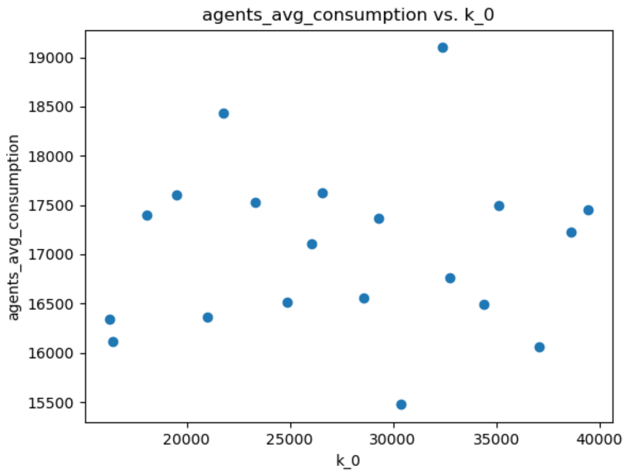
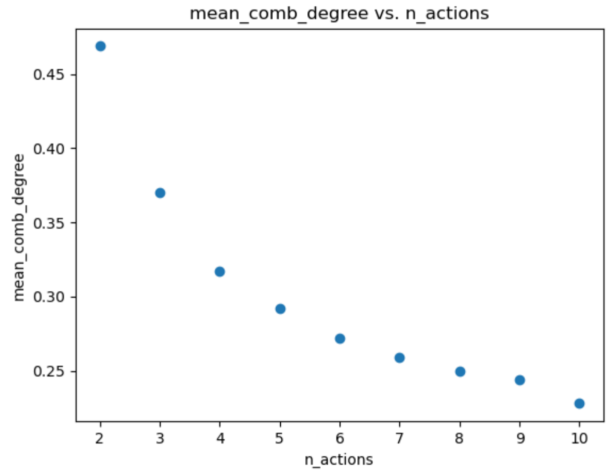


Figure B3. Results of OFAT sensitivity analysis with the varying parameter being k_0 and results being agents_avg_consumption.

Results on Figure 9 support the ones on Figure 5. Averaged over several seeds, this figure shows a clear non-linear relationship between the parameter and the outcome.



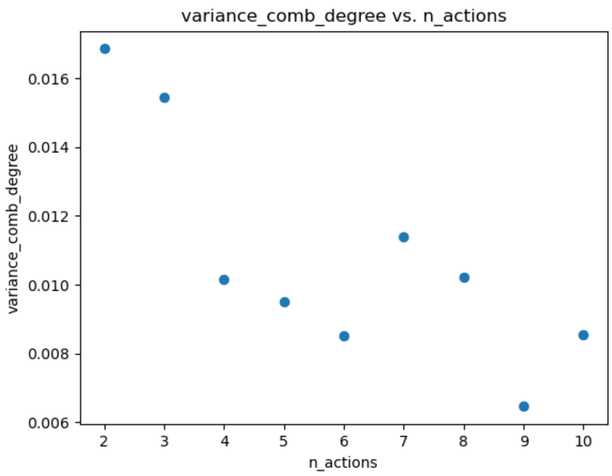


Figure B4. Results of OFAT sensitivity analysis with the varying parameter being n_actions and results being mean_comb_degree (upper) and variance_comb_degree (lower).

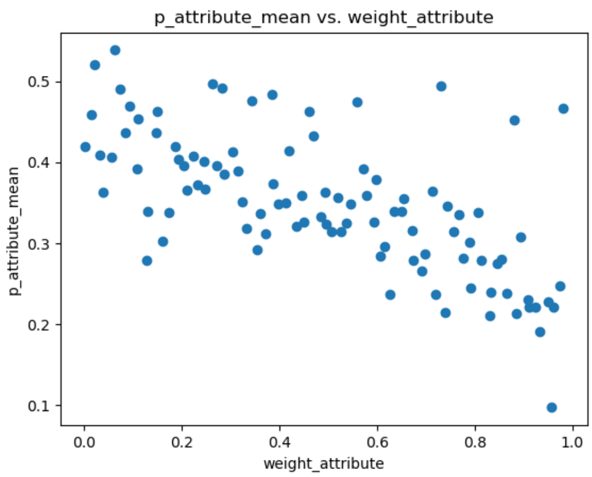


Figure B5. Results of OFAT sensitivity analysis with the varying parameter being weight_attribute and results being p_attribute_mean.

Appendix C: Other results of experiments

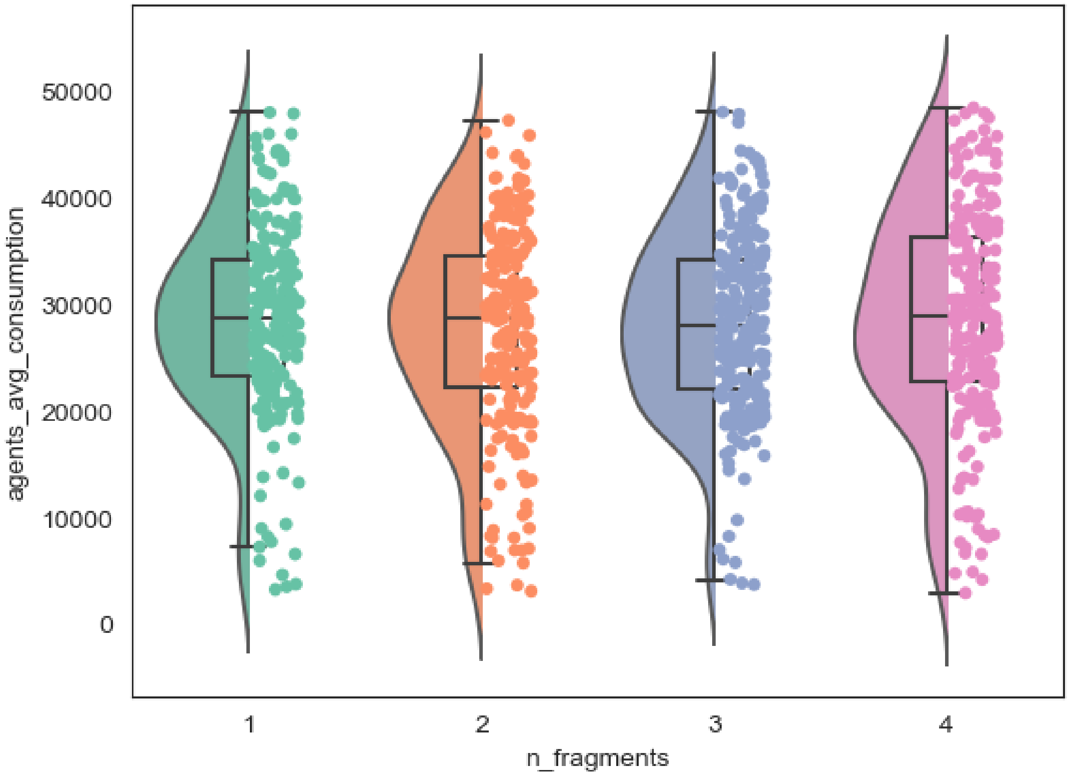


Figure C1. Half violin plots and box plots that demonstrate the distribution of agents_avg_consumption for the outcomes based on the n_fragments.

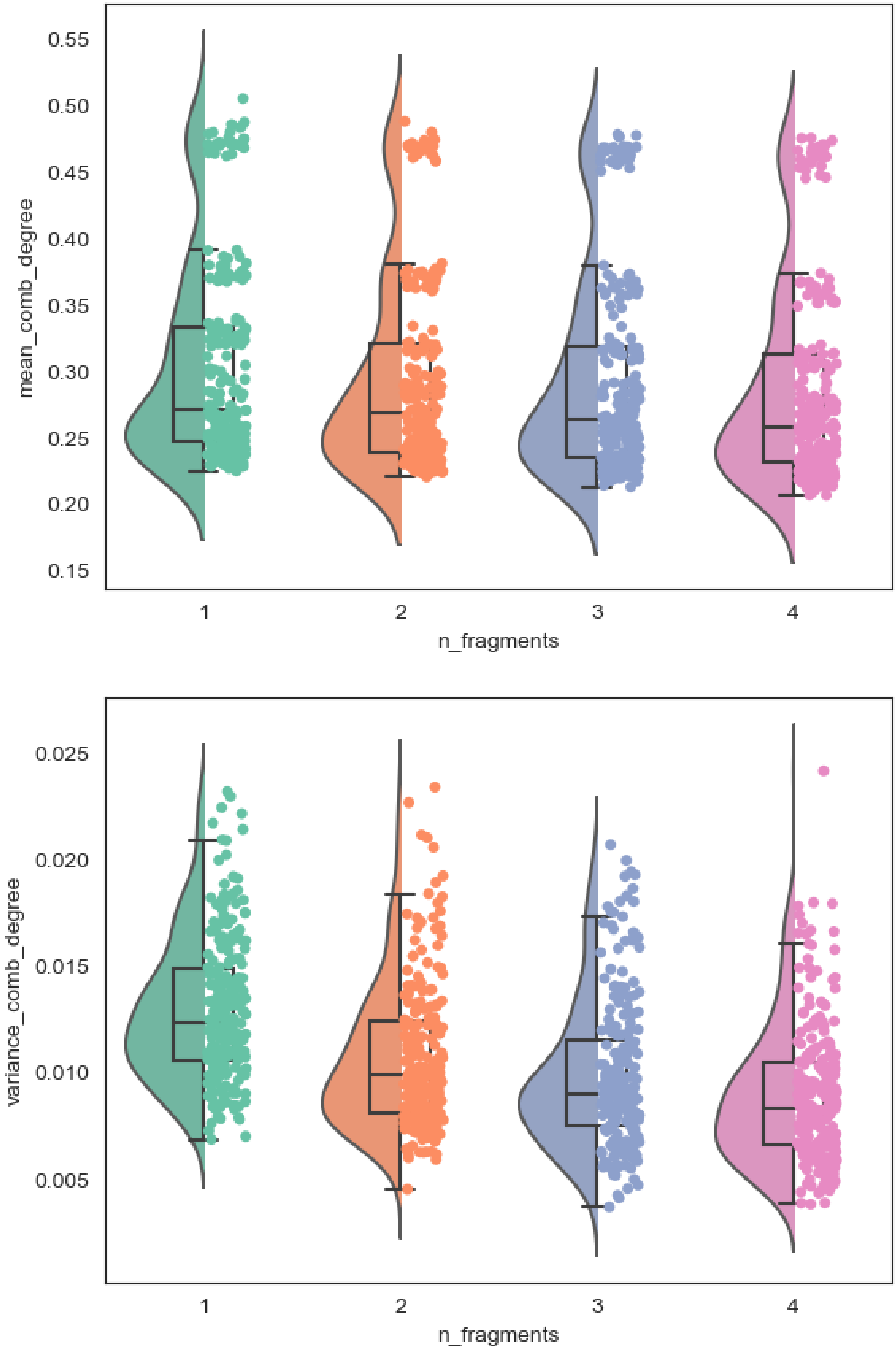


Figure C2. Half violin plots and box plots that demonstrate the distribution of mean_comb_degree (upper) and variance_comb_degree (lower) for the outcomes based on the n_fragments.

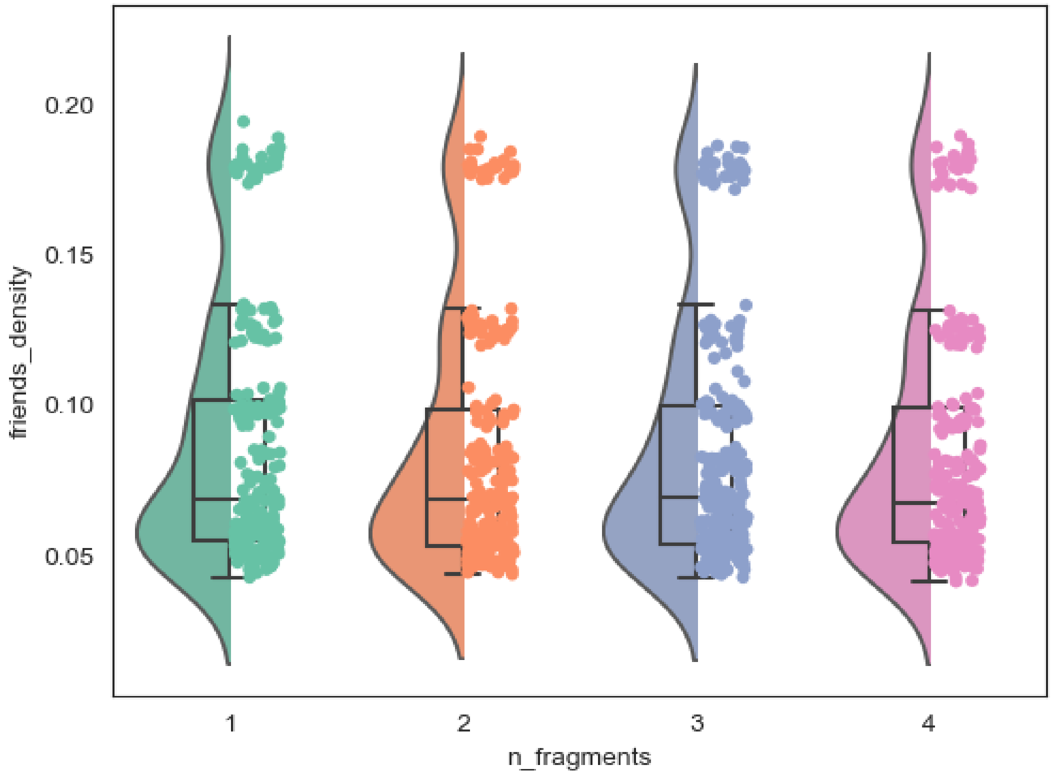


Figure C3. Half violin plots and box plots that demonstrate the distribution of friends_density for the outcomes based on the n_fragments.

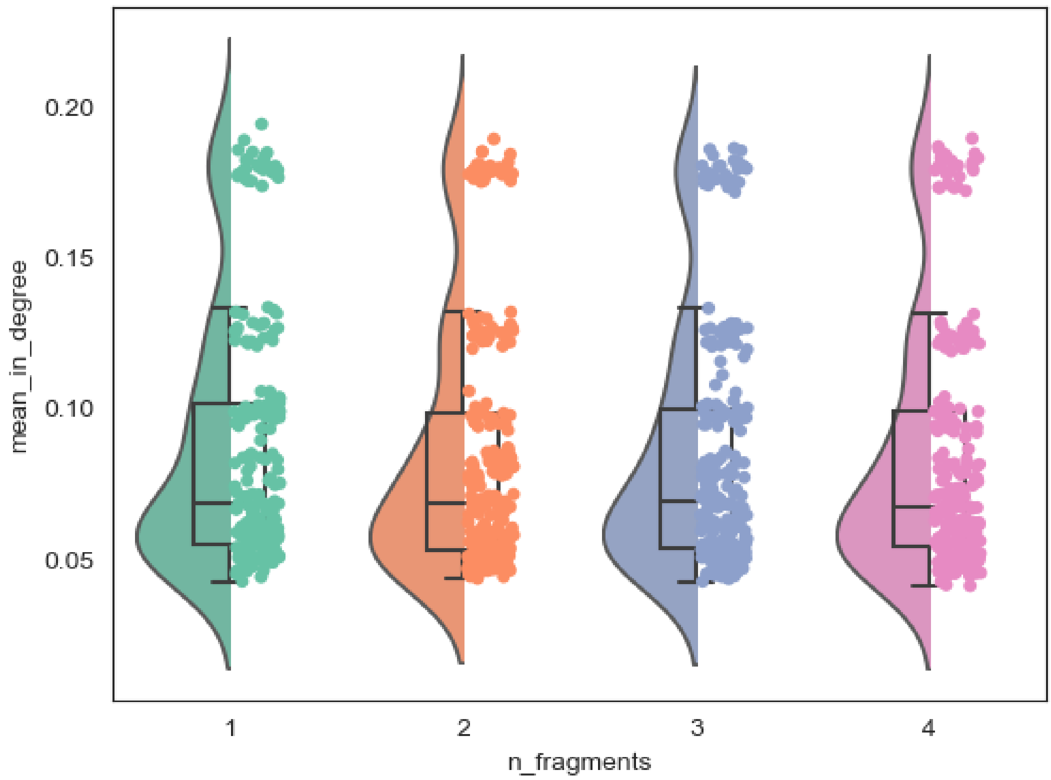


Figure C4. Half violin plots and box plots that demonstrate the distribution of mean_in_degree for the outcomes based on the n_fragments.

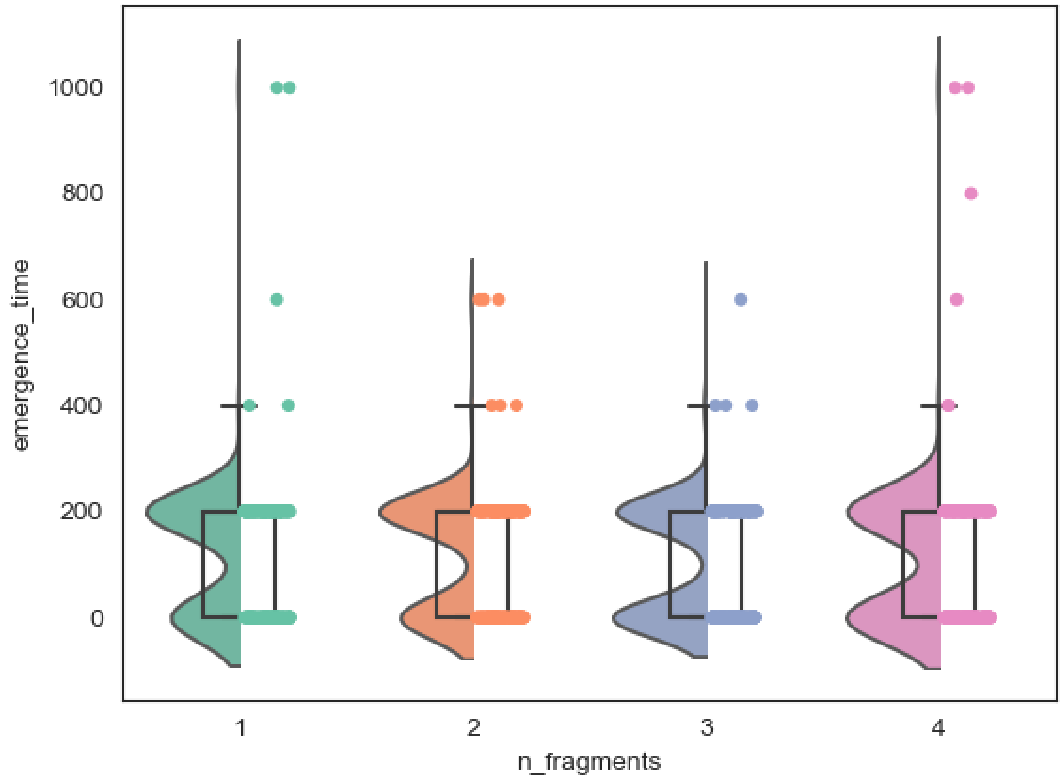


Figure C5. Half violin plots and box plots that demonstrate the distribution of emergecnce_time for the outcomes based on the n_fragments.