Position Paper

Simulation of socio-ecological transitions with Agent Based Modelling: From real systems to conceptual models

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Abstract

This paper provides an input to the question on how socio-ecological transitions can be empirically simulated. Socio-ecological transitions are characterized by a non-linear development process depending on the interaction between individual behaviour, social structure, and environmental conditions. These transitions can be viewed as emerging phenomena, similar to the process of innovation and imitation, and therefore can be simulated utilizing agent based modelling (ABM). ABM has mostly been applied to simulate socio-ecological transitions on a theoretical level; the empirical applications relate to land use and land use change. One of the major difficulties is to operationalize and quantify the relationship between individual action and social structure. We present an approach relying on Structural Agent Analysis and show how this qualitative method can be used as a basis to develop quantitative rules describing the emergence of social structure phenomena. This workshop has two aims: First, to provide a typology of issues in socio-ecological transitions which have been empirically simulated with ABM. Second, to discuss methodologies for an operationalization and quantification of (i) agent rules; and (ii) interactions among agents on the one hand and between agents and the environment on the other hand, each in the context of socio-ecological transitions.

1. Introduction

Socio-ecological transitions

A transition can be defined as a gradual, continuous process of a system (e.g., firm, society) change where the structural character of the system transforms (Binder, 2005). It is the act of passing from one state to another state. Socio-ecological transitions involve the concomitant change of the human and the social system as well as their interactions. In this case we talk about transitions between socio-ecological regimes, e.g. gather and hunter, agricultural and industrial regime (Fischer-Kowalski & Haberl, 2007; Malaska, 1991) The transition period itself is characterized by a predevelopment, a take off period, an acceleration period, and finally a stabilization period (Figure 1, (Martens & Rotmans, 2002)). A transition is therefore the phase of adaptation in which new socio-ecological patterns emerge and which lies in between two successive and more stable periods of development. It includes a departure point with initial focal variables and an arrival point with terminal variables (Binder, 2005; R.W. Scholz & Wiek, 2002).
Figure 1: Characteristics of transition processes (after Martens and Rotmans (2002))

For planning and managing transition processes, three steps have to be considered: (i) system understanding; (ii) goal formation; and (iii) measure development and planning (Binder, Hofer, Wiek, & Scholz, 2004; R.W. Scholz & Wiek, 2002). In the first step a thorough understanding of the current system and its properties is attained. It includes the definition of the system boundaries, the knowledge of physical characteristics (e.g. material flows) and the investigation of key agents and agent interactions (initial focal variables), and is thus the basis for a successful transition process. A simulation model, based on the key system elements and stakeholders provides additional information for understanding the system and its dynamics within the transition process.

In the second step, the potential future state of the system is determined, that is, goals for the development of the system are set (terminal focal variables). Goal formation is essential in any decision and problem solving process (Brunswik, 1950; Johnson-Laird, 1983; Jungermann, Pfister, & Fischer, 1998; R.W. Scholz, 1987). The goals are usually set either in a consensus building process with the agents or stakeholders identified in step 1 (Susskind, Maurer, Thakkar, Hamilton, & Sherman, 1999) or derived from consensual documents. In the latter case, preliminary goal setting can precede step 1 (Binder, 2005).

The two preceding steps are the foundation for planning strategies, measures and monitoring criteria (step 3). In this step, the different interests of the agents have to be negotiated. An important part of this negotiation is again a consensus building process. A simulation model, based on the key system elements and stakeholders provides additional information for ex-ante simulation of the effect of strategies and measures and furthermore can depict the potential medium-term changes providing additional and valuable information supporting the consensus building process (Cockerill, Tidwell, & Passell, 2004). After the agents have agreed on which strategies and measures to take, monitoring criteria and instruments have to be designed to measure the success of the strategies. This monitoring process should be planned from the beginning, covering the efficiency of the whole process (Heitzer, 2000; Ossadnik, 1996; R.W. Scholz, 2001).

**Simulation of socio-ecological transitions**

Transition processes of socio-ecological systems could substantially be supported by simulation models as these contribute significantly to improving the understanding of the system dynamics, planning of strategies and measures, and may also support the consensus building process by assessing the efficiency and efficacy of measures to achieve the desired transition.

For developing simulation models for socio-ecological systems, the ecological as well as the social system have to be included in the model and the interaction between these two subsystems as well as their individual development has to be depicted. One difficulty is that social and environmental changes occur in the short and long-term. This implies that the model has to be able to distinguish between short-term action and consequences (e.g. short term reduction of oil consumption given through economic incentives linked to lower particle emissions) as well as long-term consequences (e.g., changes in traditions leading to a long-term higher degree of utilization of public transport linked to a constant reduction in CO₂ emissions).
Binder et al. (2004) and Binder (2007) propose a heuristic for obtaining a coupled human-environment system model. In their approach, material flow analysis (MFA) is combined with structural agent analysis (SAA). Whereas MFA allows for gaining an overview of the environmentally relevant processes and the related action fields, SAA allows for understanding which individual action is determined by which social structure and how a transition of the social structure might be induced by individual action. SAA is based on the structuration theory of Giddens (1984) and thus bridges between the micro-level (individual behaviour) and macro-level (social structure). The coupling to the MFA-model provides the link to the environmental consequences of the individual action and the structural change.

A simulation model aiming at modelling the transition of the socio-ecological system would require that the information gained in the SAA is used as the basis to develop a quantitative model and linked either - as proposed in the above-mentioned heuristic - to an MFA model, or to another type of environmental process model. For developing a quantitative model of the social system two modelling approaches might be adequate: system dynamics and agent based models.

System dynamics (SD) was introduced by Jay W. Forrester in 1958 to simulate industrial business cycles ((Forrester JW, 1958, 1961)) and has since then been extensively applied for management issues and within environment and social sciences (Bossel H, 2004; Lane DC & MC, 1995; Sterman, 2000). In a SD model, a target system is described with attributes in the form of stock and flow variables representing the state of the target system and its changes, respectively. SD is a top-down approach which claims that evolutionary behaviour of social systems is explainable in terms of feedback loops and state variables (Lane DC, 2000). It operates with aggregate variables and is restricted to the macro level (Gilbert N & Troitzsch KG, 2005). That is, SD does not allow for modelling the interaction between individuals and cannot simulate emergent phenomena.

More recently, agent based modelling (ABM) has been regarded as a promising methodology for quantitative modelling in social science research (Robert Axelrod, 1997; Bousquet & Le Page, 2004; Cedermann, 2005; Epstein & Axtell, 1996; N. Gilbert, 1999; Janssen, 2002; Janssen & Ostrom, 2006; Liljeros, Edling, Amaral, Stanley, & Aberg, 2001; Parker, Manson, Janssen, Hoffmann, & Deadman, 2003). ABM provides a bottom up approach to study social systems as evolving systems of autonomous, individual interacting agents (Janssen & Ostrom, 2006). The majority of applications relate to theoretical issues, showing how simple interaction rules can explain macro-level changes or developments. ABM has been applied in a variety of research fields such as economics (quantitative finance, LeBaron (2001); economic psychology, Janssen and Jager (2001)), social science in general (cooperation, Axelrod (1997); social dilemma research, Gotts et al., (2003)). Even though ABM models exist for simulating environment and resource management (Deadman, 1999), only a few attempts have been made to simulate socio-ecological transitions and if so mostly in the area of land use change.

In contrast to SD, agent based modelling allows for modelling the interaction between individuals and thus to simulate emergent phenomena. It is considered to be most appropriate modelling tool when (i) emergence occurs, which cannot be modelled with other approaches such as system dynamics; (ii) agent interactions affect the system output; (iii) adaptive behaviour of agents and the system is expected; and it is often used (iv) for supporting decision-making in complex situations (Cedermann, 2005; Parker et al., 2003). Thus, ABM seems to be the appropriate tool for modelling socio-ecological transitions.

However, as mentioned above, ABM has mostly been applied for modelling theoretical issues, whereas the application to empirically measurable phenomena is quite rare (Janssen & Ostrom, 2006). Janssen and Ostrom (2006) claim that beside the theory models empirically based ABM models should be elaborated and
validated based on empirical data. They propose four ways of how empirical data can be included into ABM in
dependence of number of subjects and degree of contextualization or generalization. The approaches pro-
posed make a significant contribution for developing empirically-based ABM. Nevertheless, methodologies
have to be further developed and adapted for operationalizing and empirically quantifying agents’ rules, their
interactions, and their relationship with the environment to be able to simulate transitions of socio-ecological
systems.

In this paper we focus on the two aspects of the application of ABM for modelling socio-ecological transitions:

1) Which socio-ecological transitions have been studied with ABM?

2) How can agent rules, their interaction and relationship with the environment be operationalized and
empirically quantified to simulate transitions of socio-ecological systems?

The paper is structured as follows: First we give a short overview on the history and some applications of
ABM in socio-ecological systems. Then we present the different areas in which ABM has been applied for
simulation socio-ecological transitions. We proceed by providing a heuristic for the operationalization and
quantification of ABM for socio-ecological transitions. Finally we describe the contents of the workshop, which
will serve as major input to finalise this position paper.

Even though we study transitions of socio-ecological systems, we depart from the strong assumption that
changes of agents’ behaviour and social structure are the drivers for any type of transition. The effect of these
changes on the environment, and the way the latter influence the decision play therefore a key role within our
modelling approach. Therefore, the focus of the rest of this paper is set on how to model the interaction be-
tween behaviour and social structure in the context of socio-ecological transitions.

2. Agent Based Modelling

2.1 Characteristics of Agent Based Modelling

There are numerous terms for Agent-Based Models or Modelling (ABM) (e.g. Multi-Agent Simulations (MAS),
Individual-Based Models or Simulations, Agent-based Simulations). In this paper we use ABM as a general
synonym including the above-mentioned terms. An ABM is composed of an “agent” and an “environment”.
The agents’ behaviour is defined by simple rules based on interactions among the agents. These rules con-
sist mostly of two-way effects between two or more objects, The environment (in this context environment is
defined as the part of the social, technical or natural environment surrounding the agents has certain auton-
omy, i.e. it has a level of independence from what the agents do, but it can also be influenced by the agents’
behaviour. Both, the interaction among agents and the interaction between agents and their environment is
modelled (Pfeifer, 2001).

In social simulations, agents usually represent parts of the social world (e.g. individuals, groups, organisa-
tions, institutions or societies); They could also represent natural (e.g. cells, organs, plants, animals, popula-
tions or ecosystems) or physical entities (e.g. atoms, molecules, machines, production lines, manufactory
plants or industries). Most applications deal with numerous and heterogeneous agents (R. Axelrod, 1997;
Cedermann, 2005; Epstein & Axtell, 1996; Reynolds, 1987).

The agents’ behaviour is mainly defined through the local interaction with other agents and the environment
and basically independent from central control. The local interaction itself describes the interaction of agents
among their direct neighbour agents and their local environment. Interactive agents allow for the simulation of
adaptive or learning behaviour. Agents do not necessarily have to react in a fixed network or structure, they also can change their networks and/or hierarchical structures (Parker et al., 2003).

Because of the ability of including social, technical and natural agents and environments, ABM allows for modelling a broad variety of socio-ecological transitions based on different individual actions, including changing social and environmental structures.

2.2 History of Agent based modelling

Social science simulation goes back to 1700 starting with differential equations. It started with differential equations, which are the basis for the current system dynamics simulation (Figure 1). Agent based modelling is a relatively “young” tool and can be traced back to the 1940ies. One of the basic ideas behind ABM relates to the self reproduction machine postulated by John von Neumann in 1948. Holistic system properties are generated from single modules whereas the behaviour of the modules is only determined by simple rules and not by the whole context. The shift from the theoretical idea to a practical implementation was first done by John Conway in the late Sixties. With the “Game of Life” he programmed the first cellular automata in which complex patterns emerge from simple rules (Gardner, 1971). Schelling (1978) built a model to show how urban segregation could emerge through unplanned interaction on the micro-level. He was able to show that, even with a very high level of acceptance of other ethnies in the neighbourhood, segregation occurs. Together with the model of flocking birds from Craig Reynolds presented in 1986, Schelling’s segregation model shows the great potential of ABM for the simulation of socio-ecological systems for the first time (Reynolds, 1987).

Figure 1: History of the social simulation (After Gilbert and Troitsch (1999)

ABM and many other computer aided applications would not have developed so far without the efforts in artificial intelligence and artificial life. The term “artificial life” became generally known after a workshop organised by Christopher G. Langton 1987 with the same name. In Langton’s workshop, scientists from different research fields concluded that many phenomena of living systems could not be modelled linearly. Based on these conclusions, Langton stated a paradigm change in modelling of living systems:
“……bottom-up rather than top-down modelling, local rather than global control, simple rather than complex specifications, emergent rather than pre-specified behaviour and population rather than individual simulation (Langton, 1987).”

A further major contribution in the field was the book “Growing Artificial Societies” from Epstein and Axtell (1996). In the “Sugarscape” model they retrace fundamental collective behaviours such as group formation, cultural transmission, combat, and trade emerge from the interaction of individual agents following a few simple rules.

2.3 ABM for the simulation of socio-ecological transitions

As mentioned above, a transition is a phase of adaptation in which new socio-ecological patterns emerge, and which lies in-between two successive and more stable periods of development. The ABM applications for simulating socio-ecological transitions can be differentiated in “general” transitions (more on a theoretical level), and “case specific” (empirical) transitions. According to general modelling theory the generalized models have a higher validity and the specialised models a better accuracy (Stachowiak, 1973).

The general models (mostly theoretical issues) focus on modelling specific individual behaviour (e.g. adaptation, learning, cognition) and on simulating widely observed phenomena like the common-pool resource problem. The major advantage of ABM for the theoretical simulation of socio-ecological transitions is that it allows for implementing reactive and goal-directed behaviour of agents. Furthermore, by including psychological concepts like emotion, motivation, perception, and trust (Janssen, 2002), it accounts for the fact that most agents are not fully rational in their behaviour. ABM of common-pool resources permits testing of theories of individual action and group behaviour through computer simulation. Thus, it is possible to explore the interaction between resource management institutions and natural resources over time in order to develop and assess scenarios and strategies for socio-ecological systems (Deadman, 1999; Janssen, 2002). Typically, this type of ABM models would deal with issues such as common pool management. For the example regarding the tragedy of the commons Deadman (1999) states:

“Agent-based modelling provides an interesting new opportunity for the study of common-pool resource problems because it permits theories of individual action and group behaviour to be tested through computer simulations (Deadman, 1999).”

Most of the case specific (empirical) models of socio-ecological transitions refer to land use and land cover change (Berger, 2001; Berger, Schreinemachers, & Woelcke, 2006; Bousquet & Le Page, 2004; Lambin, Geist, & Lepers, 2003; Manson, 2005; Matthews, Gilbert, Roach, Polhill, & Gotts, 2007; Parker et al., 2003; Veldkamp & Verburg, 2004). In these cases, it has been shown that emergent phenomena such as landscape patterns can only be modelled with computational tools like ABM. For example Parker et al. (2003) state:

“An emergent phenomenon such as landscape pattern may be practically modelled only with computational tools, such as MAS (Multi-agent simulation) models (Parker et al., 2003).”

If decision-making is also simulated utilizing these models additional advantages of ABM arise as stated by Matthews et al. (2007). “Specific advantages of agent-based models include their ability to model individual decision-making entities and their interactions, to incorporate social processes and non-monetary influences on decision-making, and to dynamically link social and environmental processes (Matthews et al., 2007).”

Recently, ABM has also been applied as a tool to improving water management (Pahl-Wostl, 2002). In this case, social learning and adaptive management was analyzed. Schlüter and Pahl-Wostl (2007) propose ABM
to explore characteristics and mechanisms of resilience in complex resource management systems. Pahl-Wostl states: “Agent-based models prove to be a very promising approach for including the human dimension into Integrated Assessment modelling in a more realistic fashion (Pahl-Wostl, 2002).”

As a conclusion, theoretical socio-ecological phenomena and empirical case studies have been simulated with ABM. The applicability of ABM for simulating socio-ecological transitions is given as these transitions include the interaction of the social system and the ecological system, which can be modelled as agents – environment interaction.

3. Operationalisation and quantification of ABM models for socio-ecological transitions

3.1 Conceptual framework

In this paper we refer to Giddens’ structuration theory, which has been conceptualized for socio-ecological systems by Binder (2007) as follows (Figure 2): “The conceptual framework includes social structures (divided into rules and resources), the agent and his or her action, and the environment or material flow system sketched here in an aggregated box. Agents make decisions and act within existing social structural conditions (external factors) as well as their personal motivations and individual environmental awareness (internal factors) (see also Scholz and Binder, (2003)). The action of agents has two effects. First, it affects the environment. Here we distinguish according to Scholz and Binder (2003), a short and long-term effect1. The change in the environment, in turn, can affect agents and structures as follows: It might affect the environmental awareness of agents directly (e.g. health problems related to air pollution). Or it might affect the environmental awareness of the society (e.g., effects of climate change), leading to changes in social structures (e.g. laws, feebates for reducing CO2 emissions).

Second, as mentioned above, agents’ action affects the social structure by either reproducing or changing it2. Whereas the impact of social structure on human action is immediate, the potential effect of action on structure can be understood as a long-term feedback loop (Barley & Tolbert, 1997). Thus, the way social structure affects current human action, i.e. by restricting or enabling certain patterns of human agency, is synchronic; that is, the effect of structure on decision-making occurs in the moment of decision-making (Figure 1). The feedback of actions on structure, however, is diachronic; that is, structure is not changed simultaneously as action occurs. “

![Figure 2: Interaction between social structure, individuals & environment (After Binder, (2007) and Giddens, (1984))](image)

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1 A short-term effect is an immediate effect, for example the CO2 emissions from a car leading to an increase of ozone in the summer months. A long-term effect is the delayed effect, for example, climate change due to the sum of CO2 emissions.
For the operationalization of the interaction between individual behaviour and social structure, we base ourselves on the steps 1, 2, 3, 5 and 7 in the SAA heuristic as defined by Binder (Table 1; Binder, 2007). Here we provide only a summary of the most important aspects of each step. Please see Binder (2007) for details and examples.

Table 1: Seven steps for operationalizing the agents, their interaction, and the social structure (Binder, 2007)

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<tr>
<th>Main agents and the structural factors affecting their decisions (steps 1-4)</th>
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<td>Step 1</td>
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<th>Agents’ options, restrictions, facilitators and their interferences (steps 5-6)</th>
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<th>Feedback of action on structure (step 7)</th>
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3.2 Selection of agents and social structure affecting their decisions

Step 1: Identify the relevant agents

The goal of this step is to identify all the relevant agents directly or indirectly affecting the ecological system and its relevant variables determined before (Binder, 2007; Hirsch Hadorn, Wölfing Kast, & Maier, 2002; Maier Bergé & Hirsch Hadorn, 2002). The agents having a direct impact on the main variables can be readily determined if an agent related system analysis was performed in advance (Binder et al., 2004). The agents indirectly affecting the system can be determined either by analyzing their interaction with the system along the production-consumption chain (Maier Bergé & Hirsch Hadorn, 2002), their functional relationship (Hermanns et al., 2004) or by studying which agents interact with each other through, for example, information flows (Hirsch Hadorn et al., 2002). We consider it important to define groups of relatively homogenous agents with similar behavioral characteristics.

3.3 Interactions among agents, structure and environment

Step 2: Analyze for each agent the relevant social structures affecting his/her actions

The goal of this step is to identify which aspects of the social structure affect agents’ decisions impacting the socio-ecological system. For doing so we define first structural elements, as the four main elements (i.e., elements, signification, legitimation, allocative, and authoritative resources) constituting the social structure of the system (Binder, (2007); based on Giddens, (1984)). These structural elements remain the same in any of

2 One typical example is language. We reproduce the grammar and the language each day, but slowly change part of the vocabulary over time.
the systems studied. Then, each of the four structural elements has to be explicitly operationalized by one or several structural factors. The operationalization process should be carried out in a combination of literature review, and expert interviews (Mieg, 2000), aiming at obtaining a clear definition and possibly also a perception of the dynamics of each factor. The factors and their definitions should be validated in interviews with some of the involved agents (Binder, 2007).

Second, the structural factors have to be related to the agent groups determined in step one. Herefore either a semi-quantitative survey with a representative sample of each agent group or guided expert interviews can be performed. Agents should be asked which factors affect their decision-making with respect to the main variables affecting the socio-ecological system.

Third, the interaction between the structural factors has to be analyzed. This provides an understanding of how the structural factors are related to each other and what their mutual influence is. For analyzing the interactions qualitatively, the cross impact analysis is an appropriate tool (e.g. Godet, 1986; Götte, 1991; Mißler-Behr, 1993; Roland W. Scholz & Tietje, 2002; Vester, 2002; von Reibnitz, 1992). The unidirectional direct impacts of one factor on the others are assessed in a cross-impact matrix using an ordinal scale from 0 to 2 (0 means no influence, and 2 strong influence; see Lang et al. (2006) for an example of such a cross impact analysis). It has been shown that the interactions between the structural factors are also likely to differ for each stakeholder group and should therefore be analyzed for each group separately (Binder, 2007; Knoeri, 2007).

**Step 3: Weigh the impact of the structural factors on agents’ actions.**

The goal of this step is to understand the weighted relevance of the structural factors on agents’ decisions. This step is essential for the quantification of the effect of different structural factors on behaviour. The results of the cross impact analysis in step 2 give already a first insight into the type of interrelatedness among the structural factors in general. These results also have to be ranked for comparison of the factor relevance among the stakeholder groups (Binder, 2007).

There is extensive literature on weighting procedures (Jia, Fischer, & Dyer, 1998). In our case, the method has to fulfill two conditions: first, since we expect weighting of the impact of structural factors to be highly uncertain, the method should relatively robust to response uncertainty. Second, since we aim at obtaining a quantitative model, the method should provide information on the relative distance between the ranking positions of the different structural factors. Jia et al. (1998) showed, utilizing a simulation approach, that ratio weights or rank order weights performed better than other procedures if uncertainty was large. Ratio weights may be obtained using the swing weight method or inferred by the direct estimate of the impact of structure on decision-making (Keeney & Raiffa, 1976). Rank order weights (Barron & Barrett, 1996) require that agents can prioritize the different structural factors (SF) and assess whether the difference in impact from the SF1 (Structural Factor 1) to SF2 is as large as that from SF2 to SF3 (Jia et al., 1998). Note that the weighting for the different structural factors differs among stakeholders, as does their interrelatedness.

Alternatively the analytical hierarchy process (AHP) can be applied in the quantification step. AHP is a decision making approach structuring alternatives into a weighted multiple choice criteria hierarchy (Saty, 1980). A first attempt for applying AHP to estimate the probability of choices was made by Knöri (2007).
Relationship between environment and behaviour

The effect of environmental change on behaviour can be seen similarly as the effect of social structure on behaviour. Environmental characteristics and the perception thereof impact on agents' behaviour. According to Scholz and Binder (2003), three levels of environmental awareness of agents can be defined, which affect the degree in which environmental concern are integrated into the decision-making process of these agents. The transition from one level of awareness to another can be simulated with ABM and is affected by the severity of environmental change or “damage” and its direct relationship to the agents’ action. That is, it would take more and longer processes to become aware that own behaviour is related to long-term and regionally distant environmental changes. The variables defining the environmental awareness have to be defined as the structural factors and their weights determined as described above.

As shown in Figure 2, environmental change is directly linked to behavioural change. If the agents were selected based on an MFA model (Binder et al., 2004) then the change in behaviour can be directly linked back to a change in the material flow system. Otherwise in the set up of the model, the type of interaction between behaviour and environmental process model has to be defined. It has to be considered that also in the environmental process model, emergence might occur, which would make the simulation more complex. That is, instead of a quasi-stationary or dynamic material flow model another agent based model depicting the dynamics and non-linear development of the environmental system would have to be designed.

3.3 Modelling transitions: the need of knowing the potential changes in the behavioural patterns and their effect of structure

In order to be able to model potential transition pathways it is necessary to determine what potential options or changes in behaviour the agents might envision, which relates to step 5 of the SAA heuristic.

Step 5: Identify agents' options, constraints, and facilitators for successful transitions.

The goal of this step is to determine the potential array of options an agent might have in the future. In SAA, options are defined as sustainable ways of acting (Hirsch Hadorn et al., 2002). Here we enlarge the term to consider all possible ways of acting, sustainable or non-sustainable. The options affect the socio-ecological system as defined in the system analysis, Step 1, and Step 2. That is, for each agent, several options for action affecting – either directly or indirectly (through another agent) – the socio-ecological system can be determined.

The structural factors determined in the Step 2,3 and 4 might both constrain or facilitate implementation of the described options (Table 5). Constraints are defined as structural factors that might prevent agents from choosing a certain option (Binder, 2007; Hirsch Hadorn et al., 2002). Constraints, for example, can be (i) traditions; (ii) laws prohibiting a specific management type; or (iii) material price structure creating a negative price incentive (e.g., oil). On contrary, facilitators are structures that support sustainable action. Facilitators, for example, can be subsidies for a specific action (e.g., subsidies for solar energy in buildings).

The definition of options has to be done for each agent group separately. It can be performed by the researcher, in expert interviews, or can be based on literature analysis.
Step 7: Estimate potential effects of agents’ actions on structure.

The goal of this step is to estimate the potential effect of agents’ actions on structure. As shown above (Figure 1), the impact/influence of structure on action is synchronous, while that of action on structure is diachronous. That is, there is a long-term feedback of action on structure. It is extremely difficult to estimate or anticipate to what extent changes in action might modify the structural factors and elements (Barley & Tolbert, 1997; Yuthas, Dillard, & Rogers, 2004).

Here having defined the agent rules to be modelled with an ABM, we should be able to understand emergence of structure, based on the changes of individual behaviour. That is, the effect of strategies on behaviour and social structure and on the environmental system can be simulated.

4. Conclusion

This paper discussed the potential of ABM for simulating socio-ecological transitions. We showed that for theoretical issues such as management of common property resources, ABM has proven to be a powerful tool. In the area of operationalization and empirical case studies, however, only first attempts have been made and a few examples exist showing the utility of ABM for simulating socio-ecological transitions. These empirical examples relate mostly to land use change and have a spatially explicit character simulating the change of a landscape in dependence of the changes of individual parcels. Janssen and Ostrom (2006) furthermore show how empirical data could be used to validate or set up an ABM.

Still, to the knowledge of the authors, a typology of issues in socio-ecological transitions, the appropriateness of ABM for modelling them, and the necessary methodologies for obtaining an empirically based ABM model is still missing. With the current paper we provide first ideas on how such an operationalization and quantification process based on the structural agent analysis (Binder, 2007) could be made. We expect that with the experience of the workshop participants, we will be able to fill the gaps and provide a valuable input to the ABM modelling community.

5. Goals of the workshop

The workshop will consist of three parts: A general introduction framing the issue, a presentation of case studies related to transitions of socio-ecological systems by the workshop participants, and a discussion of the below-mentioned questions.

5.1 Applications of ABM in the context of socio-ecological transitions

The main question to be addressed is:

- Which socio-ecological transitions have been studied with ABM?

Related questions are:

- For which types of socio-ecological transitions?
- What were the advantages and drawbacks?

5.2 Operationalisation and quantification of socio-ecological transitions in the context of ABM

In this part of the workshop we refer to the modelling cycle by Page (1991). Page described the modelling procedure as an iterative cycle with four phases, model design, implementation, simulation and interpretation
(Figure 2). In the model design phase a conceptual model is built from the real system, the conceptual model is implemented as a computer model in the implementation phase. The computer model generates in simulation runs simulation data, which are analysed and interpreted by comparing them with real system data. In this workshop we focus on step 1: model design.

Figure 2: Modelling cycle (after Page, 1991)

The main question to be addressed is:

- How can agent rules, their interaction and relationship with the environment be operationalized and empirically quantified to simulate transitions of socio-ecological systems?

Related questions are:

- Which agents and social structures should be considered?
- How can the interactions among agents, social structure and the environment be operationalised?
- How can the interactions among agents, social structure and the environment be quantified, i.e. which methods and concepts from which disciplines can be used for doing so?
- Do specific application fields require specific operationalisation and quantification procedures?
- To which extent can the operationalisation and quantification procedures be generalised?

As it is intended to work with a wiki-platform, participants are kindly invited to bring along their laptops.
6. References


