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Simulating Human Behavior for Understanding and Managing Environmental Resource Use

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Computer simulation allows for the experimental study of dynamic interactions between human behavior and complex environmental systems. Behavioral determinants and processes as identified in social-scientific theory may be formalized in simulated agents to obtain a better understanding of man–environment interactions and of policy measures aimed at managing these interactions. A number of exemplary agent-based simulation studies is discussed to demonstrate how simulations can be used to identify behavioral determinants and processes underlying environmental problems, and to explore the possible effects of policy strategies. Finally, we highlight how agent-based simulation may contribute to our understanding of the dynamics of environmental resources, and how to manage them in a sustainable way.

The often devastating effects of human behavior on natural resources have been observed since ancient times. For example, Plato in his Critias (360 B.C.) already discussed the erosion of Attica due to agriculture. Since a few decades, most notably after Hardin's (1968) paper on the tragedy of the commons, the social sciences took up the challenge of identifying the social and behavioral drivers of environmental resource use, and to develop and test environmental management strategies. Since then, the experimental tradition within the social sciences has yielded an abundance of laboratory studies revealing how various personal and contextual factors influence people's use of an environmental resource. Results

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obtained in studies focusing on, for example, attitudes, interpersonal processes, and social dilemmas, are relevant in understanding how people interact with their natural environment. However, one of the main problems of translating experimental findings to real-world situations is the complex nature of reality. Laboratory studies usually focus on a limited set of variables in a well-controlled environment. In real life, human behavior is determined by a multitude of constantly changing and interacting variables. This is especially true in environmental resource use. On a personal level, factors such as knowledge, attitudes, goals, power, personality, and the like determine the individuals' disposition toward performing certain behaviors. Whereas the effects of single factors are often known, for combinations of such factors the effects are unclear, as the effects may interact in a complex manner, and cannot be simply added or subtracted. At the level of the social system, complexities arise from large populations of heterogeneous people, interacting through networks that are subject to change. The resulting group processes are very complex and often unpredictable, such as public opinion formation, diffusion of new behaviors, and the development of fashions. Complexity of the environment arises from multiple interacting environmental processes (e.g., global warming affects the climate, which affects chances of floods and storms), the different time-scales involved, the large time lags of effects, the unknown regeneration rate of resources, and several feedback and feed-forward mechanisms.

Whereas systematic experimentation is possible by changing a limited number of factors in experimental settings, for instance, the effect of environmental information on the valuation of the fuel efficiency of cars, laboratory experiments are not a suitable tool to study human behavior in complex environmental settings because effects of interventions may depend strongly on the context in which they are implemented. For example, people may respond very differently to (combinations of) policy measures, and they may respond to what other people are doing, causing effects to be sometimes rather unpredictable. Hence, the experimental laboratory approach does not allow for the *a priori* evaluation of policy strategies for the management of complex environmental resources. Case studies offer an alternative tool for studying behavior in complex environments. Whereas these may provide valuable information on the complexities in given domains of consumer behavior, due to the lack of experimental control case studies do not provide the researcher with insights about causal behavioral mechanisms. Rather, a methodology is needed that allows for experimenting with behavioral processes within actors, social processes between actors, and interactions between actors and the environment. Agent-based simulation is a tool that offers a perspective on simulating human behavior in complex environments, and thus may provide a suitable tool to experiment with the management of complex environmental resources.

First, agent-based simulation allows for experimenting with the complexities at individual, social, and environmental levels by formalizing populations of artificial humans, called "agents" in an artificial world. Many factors can be included in these formalizations, and using computer simulations one can conduct thousands of experiments in a short time, thus allowing for exploring the effects of many combinations of factors. Such experiments also reveal to what extent certain combinations of factors result in fairly robust outcomes, or, on the contrary, result in outcomes that are highly susceptible to minor changes in factors.

Second, agent-based simulation allows for the modeling of interactions between individuals. Assuming that social interaction causes information and norms to spread, the accumulation of these interactions can be studied on a population scale. The number of agents to be included in a computer simulation depends only on the power of the computer, but even with an ordinary PC it is possible to simulate populations from 10.000 to 1 million. This allows for showing how population phenomena, for example, opinions on energy issues, may emerge from interactions at the local level.

Finally, agent-based simulation allows for experimenting with policy measures without harming people and the environment. Via simulations the mid-term and long-term effects of policy measures can be studied in scenarios. Different scenarios including different forecasts of economic development and environmental quality could be used to test the effectiveness of policy measures under different conditions. Experiments can be repeated under the same starting conditions with different policy measures (and assumptions on their effect on individuals) as many times as we want. Therefore it is possible to simulate different policy strategies to examine which policy may be optimal in the specific situation at hand.

What Should Be Simulated, and How?

For the simulation of interactions between human behavior and environmental systems, the main question is: What kind of behavior should we model, and what determinants and processes should be formalized? People do not behave pro- or anti-environmentally as if environmentally relevant behavior were a special category of behavior (see also Lindenberg & Steg, this issue). Rather, they perform a wide range of behaviors for various reasons, and all these behaviors have a multitude of consequences, including positive or negative[1] environmental consequences. Hence, many theories on general human behavior and its underlying determinants and processes can guide the development of agent rules to simulate man–environment interactions. Jager and Janssen (2003) propose that theories on needs, decision-making processes, and processes of (social) learning comprise key components to be modeled because they describe the motivation to perform behavior, diverse choice processes in selecting behavior, and storage of positive and negative experiences after performing behavior, respectively.

[1] The distinction between positive and negative environmental consequences is a simplification, as these consequences are multidimensional by nature.

Various needs may underlie the many interests and motivations people have to behave in a certain manner (e.g., Maslow, 1954; Max-Neef, 1992). Some behaviors satisfy several needs simultaneously, while other behaviors may satisfy one need at the cost of another. For example, in order to be able to pay their children's education or to buy a car, people may willingly accept to work and live in unhealthy environmental conditions. In simulation models, human needs constitute an important concept for capturing the basic drivers of behavior. The formalization of needs may be of particular importance when (direct) satisfaction of personal needs harms the environment, which in turn may affect need satisfaction in the long run.

Decision processes refer to the way people make choices between various behavioral options, and they determine the storage of (new) information and the formation of attitudes. Relevant processes vary from rather complex weighting strategies to very simple heuristics and habitual behavior (e.g., Gigerenzer & Goldstein, 1996). In conditions of relatively low involvement, people often use simple heuristics to save cognitive effort, which generally results in satisfactory outcomes. However, as a consequence, better or more optimal alternatives may be overlooked. Besides individual decision strategies, people may also employ social decision strategies. Here, people may ask other people for assistance and information, or consider others' behavior as a good example, thus addressing informative as well as normative strategies (see Cialdini & Goldstein, 2004, for an overview).

Social processes play an important role in the diffusion of new behavior and practices (Rogers, 1995). Network effects, describing how norms and information spread through a population, may play a pivotal role here, as the connectivity and structure of a social network have considerable effects on the degree and speed with which social information travels (e.g., Delre, Jager, & Janssen, 2006). Decision strategies are related to learning processes, as previously learned information and behavior will translate into knowledge and attitudes that affect current decision making.

Obviously, the output of an agent-based simulation depends on the input[2]; the formalizations and parameter settings determine the final outcomes of the model. However, the essential point is that the output—in terms of simulated behavior—has often not been hypothesized beforehand. Even in relatively simple situations, for example, where four factors are interacting, we are simply not capable to predict the effect. Computer simulation models, however, may provide us with the exact effects. In more complex situations the researcher may observe that behavioral patterns emerge that have not been programmed in the model, which means that a macrolevel phenomenon grows from the simulation. Such simulations reveal how collective outcomes emerge from behavioral determinants and processes at

[2] Also, in experiments and surveys the output is largely determined by the input, as the experimental conditions restrict the subject's behavioral freedom and the possible answers to a questionnaire.

the microlevel. For example, Delre et al. (2006) were capable of replicating the diffusion curve of Rogers' innovation diffusion theory, including the distinction between the social susceptibilities of innovators, early adopters, majority, and laggards. This is a typical example of the emergence of a macrolevel phenomenon that originates from microlevel dynamics. Hence, whereas the argument that "you get out what you put in" is valid, agent-based simulation can contribute to explaining how collective outputs emerge from individual determinants and processes as formalized in the model.

In the next section, we present a number of studies aimed at exploring behavioral processes underlying environmental problems. These studies illustrate the value of agent-based simulation in revealing how behavioral determinants and processes generate collective outcomes. Following that, some simulations will be presented that more explicitly address the issue of policy making aimed at changing behavior.

Simulating Behavioral Processes in Environmental Management

In this section, we briefly discuss three simulation studies aimed at identifying effects of dynamic behavioral processes, such as the social contagion of environmental over-harvesting. These studies have been selected because they employ agent rules that are grounded in behavioral theory, for example, about social decision making, and they address issues that are relevant in the context of studying behavior–environment interactions, for example, over-harvesting. These studies illustrate: (1) How agent-based simulation contributes to the explanation of well-known empirical phenomena, (2) How agent-based simulation allows for replicating multiple experimental results by allowing for several factors to interact, and (3) How agent-based simulation may be integrated with models of environmental systems.

How Uncertainty Stimulates Over-Harvesting

Introduction. A large number of laboratory experiments has been conducted to explore why people tend to over-harvest from a collective resource under conditions of uncertainty (e.g., Messick, Allison, & Samuelson, 1988; Wit & Wilke, 1998). Explanations for this effect relate to overestimation of the resource size by participants and an outcome-desirability bias tending to overvalue the resource size ratings. Jager, Janssen, and Vlek (2002) hypothesized that over-harvesting due to the desire for higher short-term outcomes would be more socially contagious and would more quickly result in the development of a consumption habit. To test this idea, they conducted a simulation study to explore the dynamics of the way people interact in a common-pool situation, trying to get a deeper understanding of the role social contagion may play in such over-harvesting.

The model. Agents were equipped with a need for subsistence, which could be satisfied by fishing for food, and a need for leisure, which could be satisfied by not-fishing. The trade-off between the subsistence and leisure need prevented agents from simply maximizing one need (e.g. subsistence), which would be fairly unrealistic. Agents' satisfaction was formalized as a weighted sum of the subsistence and leisure needs, which, for matters of model simplicity, were assumed to be equally important. Agents experienced uncertainty: the larger the difference between expected and actual catches of fish, the higher the experienced uncertainty. Expected catch was calculated using data on own previous catch. Agents could use four different strategies in deciding how much to fish, depending on their satisfaction and their uncertainty. These four strategies are a simplified formalization of a more sophisticated classification of decision strategies on the dimensions of cognitive effort and social orientation (see e.g., Jager, 2000; Vlek, 2000). Unsatisfied and certain agents were assumed to deliberate, that is, to consider the consequences of all possible decisions given a fixed time horizon in order to maximize need satisfaction. Unsatisfied and uncertain agents were assumed to engage in social comparison. This implied comparison of own previous behavior with the previous behavior of agents having roughly similar fishing abilities, and selecting the behavior yielding a maximum expected level of need satisfaction. Satisfied and uncertain agents would simply imitate the behavior of other similar agents, thereby avoiding the cognitive effort of determining the maximum outcome as in case of social comparison. Finally, satisfied and certain agents would simply repeat their previous behavior, because this was satisfactory and the environment seems to be stable. When agents engaged in reasoned behavior (deliberation or social comparison), they would update information in their memory to store information on (fishing) abilities, behavioral opportunities, and characteristics (e.g., satisfaction) of other agents. When they engaged in automated behavior (imitation or repetition), they used their memory without updating the information. Thus the outcomes of previous behavior determined the decision-making process the agent engaged in.

Results. The simulation experiments revealed some remarkably simple dynamics that may be largely responsible for the over-harvesting effects observed. In a first simulation experiment (one deterministic run with two agents) it was demonstrated how uncertainty stimulates an imitation effect promoting over-harvesting. Whereas imitation (and other decision rules) was formalized in the model, it was not clear beforehand that this rule would lead to over-harvesting behavior. Over-harvesting appeared to be "socially contagious" in the sense that imitating over-harvesting behavior yielded more often satisfactory outcomes—in the short run—which stimulated repetition and hence often resulted in the formation of a "bad habit." When under-harvesting behavior was imitated, however, the lower outcomes generally caused agents to become dissatisfied, causing them to increase harvesting.

Next, experiments were performed with a stochastic[3] resource-growth function, where the growth of the fish stock varied on every time-step, which had an effect on the expectations of agents. Here, 10 different settings for agents' need satisfaction and 10 settings for uncertainty tolerance were used, thus systematically exploring populations of agents having different tendencies to engage in certain decision strategies—"easily satisfied" and "highly uncertain" conditions resulting in a tendency to imitate. Conducting 10 experiments per condition resulted in a total of 1,000 simulation runs. Again, an "optimism effect" was found, showing that agents could get stuck in an over-harvesting habit. During a negative fluctuation of resource growth—when the renewal of the fish stock was temporarily at a low level—agents decided to harvest less to safeguard future outcomes. Consequently, agents experienced a lower needs satisfaction, causing them to deliberate, thus keeping track of developments in the fish stock. If a positive fluctuation of the resource growth appeared, agents' expectations concerning the future fish stock rose, to which they responded with increased harvesting. As a consequence, their satisfaction increased, and they started to repeat their own behavior. Because during repetition the agents only considered their short-term outcomes, negative fluctuations of the fish stock growth were not observed and thus did not influence their fishing behavior. Hence, the agents habitually continued fishing to the moment that the fish stock was depleted to a level where their satisfaction dropped and the agents switched back to deliberation, only too late to restore the fish stock. Finally, an "adaptation effect" was identified, indicating that the more agents engage in social processing, the less likely it is that a new—preferably resource-protecting—behavior is being discovered.

Implications for understanding behavioral processes. The simulation experiment revealed relatively simple behavioral dynamics that could only become manifest in a more complex setting. The consequences of switching between decision strategies may have a significant impact on resource use, but due to the complexities in the real world such effects are hard to identify using standard laboratory experiments. The difference between the two explanations as suggested by laboratory research—overestimation of resource size and outcome-desirability bias—and the effects found in the simulation experiments is that the latter explains the relation between uncertainty and harvesting in terms of behavioral processes. Rather than identifying fixed factors that often hardly provide points of application for policy strategies because they are less manageable—for example, group size, the simulation identified behavioral processes that—if validated empirically—could provide a starting point for the development of policy measures aimed at changing these processes. For example, the results suggest that at times of "good environmental news" people may be more likely to develop an "environmentally

[3] Here no stochastic variables are incorporated, implying that equal starting settings generate equal results.

bad habit," which would necessitate a precise timing of promotional strategies about "proper behavior." When the basic dynamics of such processes have been identified using simulation studies, empirical follow-up studies could be focused on identifying such effects in the field, and on testing actual policy measures.

Because the complexity of the real-life situation makes experimentation very difficult, empirical studies may focus on qualitative descriptions of (longitudinal) cases. Additionally, laboratory experiments may focus on switches in decision strategies so as to experimentally validate the processes as identified by simulation. Such case studies and experiments could provide an empirical basis for the suggestions derived from this simulation study that social influence strategies (e.g., viral marketing targeting specific small groups of connected people), other strategies directed at habitual behavior, and the provision of "good" behavioral examples are important to address the processes behind over-harvesting behavior.

A Simulation of Decision Making for the Sustainable Use of Environmental Resources

Introduction. When people decide how much to use of an environmental resource, their decisions will be influenced by many factors such as own goals, the size of the resource, and the assessment of the way other people will use the resource. These factors interact and influence decisions simultaneously. As already mentioned, many laboratory investigations have been conducted in which these factors were analyzed in an isolated way or included a very limited number of interactions. This is an appropriate first step, but for understanding the real decision processes it is necessary to use a method that takes some of the most relevant factors and processes into account. Therefore, Mosler and Brucks (2003) developed a general dynamic model of resource use by means of computer simulation.

The model. The integrative element of the agent model is a theoretical concept called "social-ecological relevance" which is derived from Festinger's theory of social comparison processes (1954). In this theory Festinger introduces the distinction between social and physical reality. Accordingly, the decision making of an agent can be based upon information from either the physical or the social environment. The hypothesis is that an individual in an environmental resource dilemma simultaneously weights the importance of social factors such as others' behavior, and ecological factors such as the availability of resources. In a next step, the two weightings are merged into one dimension called social-ecological relevance. The latter defines the extent to which social versus ecological factors will affect individual decisions on the use of the resource. Ecological factors in the model include state of the resource and resource uncertainty. Social factors include attributions (who is responsible for the state of the resource?), social values (how do people want to share the resource between themselves and others?), and others' behavior (how are the others behaving?). Together, these factors determine the individual consumption of the environmental resource. Different consumers (viz. agent models) weight these factors differently. For example, a competitive person gives a heavy weight to others' consumption behavior because (s)he does not want to be outperformed. At the same time, resources may be abundant which results in a low weighting of importance of resource size. In such a situation of abundance, a competitive person will attach much more importance to others' behavior than to the state of the resource, and will be likely to over-consume as a consequence of others consuming a lot as well.

Results. The model was tested by seeking to replicate findings of laboratory experiments within the commons dilemma paradigm that used real participants. For these tests, the relevant information on the study's methods (e.g., number of participants, nature of experimental manipulations, personality measurements, number of decisions) was taken from the method section of the original publication. For example, when the real experiment used groups of five participants who made 12 consecutive consumption decisions from a common pool, then the simulation comprised five agents who interacted for 12 runs. To date, tests have shown that the model replicates various experimental findings quite successfully (see Mosler & Brucks, 2003).

Having checked the validity of the agent model by making the aforementioned comparisons, it is now possible to let variables work together whose interaction has not yet been investigated in real experiments. For example, the joint effect of causal attributions, ecological uncertainty, and resource availability has never been studied in the laboratory with real participants. In this case, the simulation revealed that when uncertainty rises, people attributing the state of the resource to ecological factors (e.g., to a natural fluctuation of resources) increase their consumption to a greater degree than people attributing the resource's state to the group's behavior. This is because the latter people attach more importance to others' behavior and less importance to uncertainty about the resource. Consequently, they are less susceptible to the negative influence of resource uncertainty and also consume less. Ideally, these simulation results may serve as basis for hypotheses that can be tested in laboratory experiments in turn.

Implications for understanding behavioral processes. With the simulation model, specific interactions of variables so far examined separately—such as the one reported above—could be demonstrated which means that at least parts of the complex processes for decision making in environmental resource dilemmas could be captured. As a logical next step in research, these interactions have to be replicated with robust empirical methods in the laboratory or in the field. If this succeeds, it implies a big step toward more realistic investigation of the behavior of resource-using individuals. As a consequence, policy measures can be addressed more adequately and will be more effective in changing people's use of an environmental resource toward its sustainability.

Transitions in a Virtual Society

Introduction. Whereas the previous simulation studies used a resource with a very simple growth function, many social—economic–environmental systems are much more complex. Whereas more complex models of environmental systems have been developed, human behavior is usually represented here in simple aggregate functions, not capturing the dynamics of human behavior. In a series of experiments, Jager, Janssen, De Vries, De Greef, and Vlek (2000) explored how psychologically more realistic agents would manage an "artificial world." The basic question was if such formalizations of behavior would result in different human–environment interactions compared to standard economically optimizing agents.

The model. An artificial world called Lakeland was constructed based on a simple integrated model comprising two natural resources: a fish stock in a lake and a nearby gold mine. Mining would pollute the lake and have a negative effect on the fish stock. The model also included an economical submodel, allowing the agents to sell fish and gold, and to buy food and status-enhancing products. The 16 agents were equipped with four needs: (1) subsistence, to be satisfied with fish or gold, (2) identity, expressed as the relative amount of money an agent owns in comparison to a subset of agents having about similar abilities, (3) leisure, referring to the share of the time spent on leisure, and (4) freedom, associated with the total amount of money owned. The decision strategies the agents could employ were deliberation, social comparison, imitation, and repetition, formalized in the same manner as discussed in the section on how uncertainty stimulates overharvesting. Allowing the agents to shift between these four strategies due to changes in satisfaction and uncertainty resulted in formalization of the behaviorally rich "homo psychologicus," whereas limiting its decision strategy purely to (utility-maximizing) deliberation formalized the "homo economicus" (see Jager et al., 2000).

Results. For both the homo psychologicus and the homo economicus conditions, 100 simulation runs were performed. Remarkable differences were found concerning the behavioral dynamics of the homo economicus versus the homo psychologicus. The transition from a fishing to a mining society was more complete for the psychologically realistic agents. Due to processes of imitation and social comparison, many more agents started working in the mine than was optimal from an economical point of view. This instigated extra pollution of the lake, which led to a decreasing fish stock. As a consequence, the relative harvest from the mine was larger, thereby propagating the completion of the transition. These results confirmed the idea that macrolevel indicators of sustainability, such as pollution and fish harvest, are strongly and predictably affected by behavioral processes at the microlevel.

Implications for understanding behavioral processes. The simulation experiment described in this section demonstrated that the incorporation of a microlevel perspective on human behavior within integrated models of the environment yields a better understanding of the processes involved in environmental degradation. In particular, the large-scale transition toward mining was explained by processes of imitation and social comparison. Future studies should establish whether the same processes are functioning in real-life transitions. One suggestion is that these processes have also played a role in the twentieth century transition toward a car-based transportation system. Whereas policy strategies were not tested in this model, this simulation model revealed the relevance of behavioral processes as a driver of a large-scale transition. Policy makers wishing to support an envisaged transition—for example, the hydrogen transition—could benefit from using such processes, i.e., by enhancing the social visibility of the desired behavior, and/or by creating uncertainty concerning the (future) availability of undesired behavioral options, to mention just two examples.

Exploring the Effects of Environmental Policy Strategies for Sustainable Management of Environmental Resources

A challenging application of simulation models lies in the experimental evaluation of policy measures. Because simulation models allow for capturing a part of real-world complexity, it is possible to experiment with policy making in a dynamic context. This implies that the nonlinear effects of policy measures can also be studied, thus providing a perspective on the robustness versus volatility of policy effects. This is important, because the effects of policies may be less clear in a dynamical context, which would require a close monitoring of effects and adequate policy responses to unforeseen (negative) developments. In using simulation models to explore the effects of policy measures, a clear link between the empirical context and the simulation contributes to the applicability of simulation results in practical policy settings. In this section, we discuss three studies in which effects of policy measures are examined using agent-based simulation tools.

Determining Policy Effectiveness of a Car-Speeding Campaign

Introduction. Car use is one of the most detrimental activities for environmental sustainability. One possible policy measure could aim at reducing driving speeds, which decreases noise and pollution, and increases traffic safety. In the area of car use and driving behavior, reliable and effective behavior-change measures can hardly be found (see also Gärling & Schuitema, this issue). Policy measures sometimes have effects on behavioral change and sometimes not and we do not know why. If we would understand how these measures work at the individual level, we could develop more reliable, more specific, and more effective measures.

In a campaign promoting slower driving speeds that took place in Münsingen, a Swiss municipality, Mosler, Gutscher, and Artho (2001) designed measures that confronted people with inner (cognitive) contradictions, which resulted in a remarkable reduction of average driving speeds. The campaign was evaluated and used to test the validity of a simulation model.

The model. A multi-agent simulation model was developed (Mosler, 2002), based on the theory of cognitive dissonance (Festinger, 1957). This theory specifies different ways in which people deal with inner inconsistency, for example, between their behavior and their attitudes. In the model, these processes occurring in the agent are described as follows. If agents experience a discrepancy, or dissonance, between attitude and behavior, they will attempt to reduce dissonance by either changing attitude or changing behavior. Agents will change the factor showing the least resistance to change, which is determined by a comparison of people's attitudes and behavior with the values they hold. Personal values make up a person's general, basic orientation. The smaller the difference between values and attitude or behavior, the greater the resistance to change. The extent of attitude or behavioral change is determined by the difference between attitude and behavior, or in other words, by the magnitude of the actual dissonance. This change in attitude or behavior is then weighted in terms of self-responsibility, in such a way that if a person has no feeling of self-responsibility for the behavior (e.g., (s)he is forced to show the behavior) there will be no change, as no dissonance exists.

Results. In the actual campaign that took place, a number of different interventions were applied, designed to encourage drivers in Münsingen to slow down (see Mosler et al., 2001). Three types of these measures are pertinent to cognitive dissonance theory. First, personal commitment in writing to drive slowly was designed to engender dissonance, in that an inner inconsistency would arise between the behavior people pledged to perform and their previous behaviors and attitudes. Second, prompts were designed to make existing inner inconsistency salient, thereby setting off the dissonance process within the person. As prompts, 120 colored flags showing the campaign logo and the "Voluntary Slow-Down in Münsingen: 30 km/h" slogan were hung throughout the town, and key chains and bumper stickers showing the campaign logo were distributed to serve as daily reminders. Third, feedback measures to make inner inconsistency salient were also used. During the entire campaign, three mobile units measuring driving speeds were moved from place to place within the municipality. Clocked speeds posted on the electronic boards gave drivers feedback on their actual speeds and served to remind them about the campaign.

To assess the effects of the actual campaign, a questionnaire survey was conducted before and after the campaign using the same sample. The questionnaire was used to determine the values of the relevant variables for each respondent and to discover people's reactions to the measures implemented. The campaign ran for 25 weeks.

Using assumptions about the way the policy measures would work and the collected data, it was possible to successfully model the dissonance processes occurring in people through the course of the campaign. To run the model, the data of the before-survey were used as starting values and they were processed for 25 runs. In order to test how adequately the model reflected the actual processes in the real persons, the measured values from the after-survey and the simulated values for attitude and behavior after 25 runs were compared to find out if they matched. Several parameters of the simulation first had to be determined. Therefore a number of simulations with different parameter constellations was run until an optimal prediction of the end values of attitude and behavior was reached for one-half of the sample (total N = 134). The same parameter values were then used to validate the simulation with the other half of the sample. For the first half of the sample (with the optimized end values) the attitude change of 87% and the behavior change of 65% of the cases could be predicted (afterward) correctly. For the second half of the sample the attitude change of 84% and the behavior change of 61% of the cases could be predicted correctly.

Conclusions about environmental policy making. The results reveal that with the simulation it was possible to replicate the outcomes of the dissonance reduction processes triggered by policy measures, in many different people over a reasonable period of time. The simulation improves our understanding of the intra-individual processes that take place in a campaign designed to produce attitude and behavior changes through addressing inner contradictions. It is possible to use simulation with the already determined parameters, into which precampaign data have been fed, as a support tool for determining in advance which measures would lead to optimal changes in attitudes and behavior in a given population. For future campaigns, therefore, it should be possible on the basis of preliminary surveys to determine in advance the policy measures that would be most effective.

Environmental Technologies for Households: Shared Solar Power Plants

Introduction. Two billion people in the world are living without electricity and it will be a big challenge to provide them with energy in an environmentally sustainable way. Shared solar power systems could provide a clean, sustainable, and autonomous form of energy. But so far, experience has shown that solar electrification can lead to technical problems (due to wrong sizing of the system, for example) as well as social conflicts (due to power limitations).

The model. To study the dynamics of these two sources of trouble, a model has been developed that consists of a technical submodel (corresponding to a shared solar power plant) and a social submodel (corresponding to the user community; see Brucks & Mosler, 2002). The submodel of the shared solar power system consists of all components usually found in a real solar power system. The photovoltaic modules produce electric current according to information about the meteorological situation at a given place at a given time. According to actual electrical current from the modules, actual voltage of the batteries, and the complete load of the user community, the charge controller determines the input and output of the batteries which in turn feed back the actual state of charge to any single household of the community.

The core of the community model consists of agents that represent single households. Any number of agents can be implemented, and all functions according to a model of human resource use (see the subsection on decision making above, see also Mosler & Brucks, 2003). Agents get two crucial pieces of information that influence their decision making: the actual state of charge of the batteries (the resource size) and the average use of other agents (use of others). They weight and process this information according to individual attributes (the social values of the household) and their perception of the situation (attribution: what to blame for the actual state of charge, the technical system or the users). Based on the decision process, agents decide how to change their behavior, that is, increase or decrease their electricity consumption to a certain degree.

Results. A case study was conducted in Santa Maria de Loreto, a rural community of 50 households on Cuba. Since a couple of years, this remote village is equipped with a shared solar power system that usually runs very well and provides all households with enough energy for lighting, radio and TV, and other small appliances.

With a simulation run of the complete energy demand of all houses (i.e., 50 "household" agents) during a period of 6 days (Jan. 29–Feb. 03, 2002) as measured by manually reading hourly each house's energy meter, it could be shown that the simulation reproduced the behavior of the whole system for 144 hours (=6 days) quite well. Knowing that the simulation model was able to sufficiently reproduce the actual behavior of the villagers, it was then adapted to the following real-life scenario.

Recently, one component of the solar power system in Santa Maria de Loreto was damaged and caused a loss of power of about 50%. The reaction of the mayor was to divide the village into two halves who took turns using the remaining energy. In other words, a household was allowed to switch on appliances only any other day. In a cooperative community like Santa Maria de Loreto, probably a solution could be found that would be more convenient for the people than repeatedly restricting the use of each household to zero for a whole day. Through simulating the entire village again, we tried to predict how people would behave in a power shortage if they knew about the state of the batteries and the consumption behavior of their neighbors, which is actually not the case. The "household" agents were then reacting on the feedback about the state of charge and interacting with each other via a social network. Once again, a simulation run over 144 hours (=6 days) with 50 household agents was conducted where the simulated photovoltaic system had only half of its usual power output, but no rules were enforced and the people had complete feedback about the state of charge and the behavior of others. In terms of the system's performance (e.g., batteries' state of charge), the simulation showed that the village performed the same or better when no consumption rules were enforced. Note that in this case people could use energy every day and voluntarily committed themselves to reducing consumption.

Conclusions about environmental policy making. Besides the application shown in the previous sections that was concerned with the management of an existing solar power system, the simulation tool serves as a help for planning solar power systems in nonelectrified remote villages. Once enough data have been collected about a candidate village, the size and design of the solar power system can be planned and tested on the computer. At the same time a social arrangement can be found on the way the system should be managed by the community. In simulation trials, the size or design of the solar power plant can be modified and social measures applied. The goal is to simulate optimal management of the plant by a given community and, from that, to derive important considerations for the installation and operation of shared solar power plants in such communities. In general, the example demonstrates that with the help of the simulation method it will be possible to advise politicians for designing and building environmental–technical systems which can be used in a sustainable way by the people.

Diffusion of Green Products

Introduction. In promoting the diffusion of green products, one strategy is taxing the nongreen products. Imposing a tax on nongreen products can be done abruptly, thus causing a "tax-shock" in the system, or it can be done gradually. Janssen and Jager (2002) presented a model-based analysis of the introduction of green products having low environmental impacts, testing how different tax regimes would affect the speed and the degree to which green products would gain market share. Because markets may differ concerning the speed of new product development, two prototypical markets were compared, a stable market and a market with continuous product development. Because they wanted to explore how the effects of tax regimes are related to assumptions on behavioral processes, they compared the ways in which the tax affected economically maximizing agents versus "behaviorally rich" agents.

The model. Both consumers and firms were simulated as populations of agents who differ in their behavioral characteristics. For the formalization of the consumers the methodology as described in the section on how uncertainty stimulates overharvesting. Agents had two needs, namely a social and a personal need. Personal need expressed the personal preferences or taste of an agent for certain products. The more a product matched the personal preference position (on an abstract preference dimension ranging from 0 to 1), the higher the personal need satisfaction. Social need was formalized as agents having a preference for consuming the same products as their neighbors. The more neighbors consumed the same product, the higher the satisfaction of the social need. Prices influenced the relative satisfaction rate of using a product, causing a higher price to have a negative effect on need satisfaction. Overall need satisfaction was thus a weighted function of both the personal and social need, taking into account the price of a product.

The decision strategies agents could employ were deliberation, social comparison, imitation, and repetition, formalized in the same manner as discussed earlier. Two experimental conditions were being used, the "homo psychologicus (HP)" condition where the agents were allowed to shift between these four strategies, and the "homo economicus (HE)" condition where agents engaged exclusively in deliberation.

Concerning the producers, also two conditions were created. First, a stable market was formalized as offering a fixed number of products, namely, five "green" and five "nongreen" ones. A continuous product-development market was formalized by allowing producers to replace at any moment an existing product with a new product (green or nongreen). If an existing product dropped below a market share of 10%, producers could launch a new product. Initially, all firms produced nongreen products, allowing for studying how green products might penetrate such a market. Taxing was formalized either as "fast," introducing a full tax at $t = 50$, or as "slow," implicating a gradual increase starting at $t = 25$ and reaching a maximum level at $t = 75$.

Results. Simulation experiments illustrated the influence of different behavioral characteristics on the success of switching to green consumption. It was found that in a stable market the tax regime makes the largest difference. Although the HP responded a bit slower than the HE on a tax increase, the major finding was that a slow increase in tax resulted in a slow increase in market shares of green products, whereas a fast tax resulted in a fast increase of market share. In the continuous product development condition, however, it was not the tax regime but the behavioral characteristics that made the main difference. Here, it was found that the HE responds much slower to a change in tax regime than the HP. This counterintuitive result can be explained as follows. Due to the optimizing behavior of the HE, the producers were stimulated to develop products matching the personal preference of agents. In the HP condition, however, agents could develop habitual behavior, and thus were more likely to continue consuming an existing product, at the neglect of more attractive products. In the HE condition, product development thus was more effective in satisfying the personal needs of agents. Imposing a tax regime consequently had a smaller effect on the HE, as they consumed products fitting their personal need more than in the HP condition. Because the HP derived a lower level of need satisfaction from their existing product consumption, they were more susceptible to change toward green products when the tax regime changed.

Here, it hardly mattered whether the introduction of the tax was fast or slow.

Conclusions about environmental policy making. The results from this simulation experiment indicate that assumptions concerning the decision making of agents and related market dynamics are critical in understanding the effectiveness of policy measures. Moreover, this experiment provided a perspective on the way policy measures, in this case tax policy, can be tested in a multi-agent simulation. Obviously the efficacy of policy measures depends on many more factors than can be captured in a relatively simple multi-agent simulation as discussed here. However, these experiments reveal some of the dynamics that may determine the effectiveness of policy measures in the real world, and thus may contribute both to the understanding of the success of real-world policy measures, and to the development of more effective policy measures.

Implications for Research and Policy Making on Environmental Problems

The studies presented illustrate how behavioral determinants and processes in environmental problem situations may be formalized in agent-simulation rules, and demonstrate how the operation of these rules leads to aggregate effects. Agent-based simulation thus offers a tool to explain the behavioral determinants and processes responsible for environmental events that happened in the past. Moreover, this article illustrated how multi-agent simulation can be used to test environmental polices in a context determined by complexities at the individual, social, and environmental level. This is an important advantage of multi-agent simulation, as most environmental policy making takes place within complex and dynamic environments, where many different (groups of) stakeholders are interacting. Moreover, policy measures generate outcomes on the personal, social, and environmental level, which are being valued differently by different (groups of) people. Due to such complexities, the effects of policy measures are often difficult to forecast, since they become manifest only after a long time.

Obviously, in solving environmental resource dilemmas, policy measures have to address human behavior. However, the course of developments in social systems is often capricious, and many autonomous developments may take place beyond the—limited—control of policy makers. Simulations may contribute to understanding the behavioral dynamics underlying these developments. Rather than forecasting developments and effects of policies, simulations contribute to the understanding of the dynamics, and the identification of possible scenarios, while indicating possible ways to encourage or steer certain developments. Forecasting turbulences in a certain behavioral domain may reveal the necessity of dynamic policy making, involving a close social monitoring of, and fast policy response to behavioral changes. For example, simulations may indicate that the effect of, for example, a promotional campaign in a given context, is unstable due to strong autonomous social processes in the field, but that in case of an emerging failure a timely support, for example, by public figures endorsing the campaign, may prevent such failure. In practice, this would mean that such campaigns are started with a supportive strategy standing by, the latter being launched as soon as field monitoring indicates a potential failure of the campaign.

Simulations may address relatively limited areas of policy making, of which the car speeding campaign is a nice example. A major challenge, however, is to apply simulations in exploring the dynamics of large-scale societal transitions. One example is the forecasted hydrogen revolution (e.g., Dunn, 2002), which would imply a major transition of society. In modeling such a complex and large-scale development, one is confronted with many conflicting perspectives from various stakeholders, such as policy makers, industry, consumers, NGOs, and scientists. Here, the development of the simulation itself would require intensive discussions with stakeholders, serving the debate on the crucial issues in understanding the process. This development process is also called the "agenda-setting function" of simulations, as during this stage decisions are being made concerning what factors and processes are relevant for the issue to be simulated. Next, a simulation could serve as a training tool for various stakeholders in trying to explore policy strategies that would be effective and acceptable at the same time.

Difficulties with agent-based simulation relate to formalization and validation. Concerning formalization the challenge resides in simplifying the often complex theories of social science and the complex reality into simple sets of rules. Acknowledging the sensitivity of models for small changes in this formalization, this implies that for practical applications it is important to explore how different formalizations—and parameterizations—affect the results obtained with the model. The more robust the outcomes are, the greater the confidence one may have that the simulation model captures relevant behavioral dynamics. For example, the social contagion of over-harvesting was a result found over a range of different parameter settings, which indicates the robustness of this effect.

Concerning validation the difficulty resides in the comparison of simulation results to empirical data. If we are dealing with complex behavioral domains, we have to realize that the current situation is just a single manifestation of the wide collection of possible outcomes. Obviously, if developments had taken another course, the empirical data describing the current situation could have been rather different. This implies that calibration of a computer simulation model against an empirical data set describing a single event at the macrolevel is a risky business, unless the macroeffect can be observed in many conditions and represents a kind of stylized fact. The latter would imply that data are available on a larger set of comparable macroevents, and that all these data show a (qualitatively) comparable trajectory of developments.

In sum, agent-based simulation offers a rich methodology that is expected to contribute significantly to the study of behavior–environment interactions, and to provide a valuable tool for exploring the effectiveness of policy measures in complex environments. To apply such models effectively in the context of environmental management, it is crucial that agent rules are grounded in behavioral theory relevant for the issue at stake. This allows for an empirically valid simulation of the dominant behavioral dynamics, and it provides points of application for policy measures addressing these processes. Simulation model runs have to be capable of replicating empirically observed phenomena, and hence it is important to collect a large number of cases as reference scenarios, showing a range of possible developments and behavioral dynamics in real-world systems. Policy applications of agent-based simulations will both allow for and benefit from aligning behavioral theory and empirical case studies in modeling exercises.

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