# Agent-Based Computational Modelling: An Introduction

Francesco C. Billari[1], Thomas Fent[2], Alexia Prskawetz[3] and Jürgen Scheffran[4]

[1] Istituto di Metodi Quantitativi, Università Bocconi, Milano, Italy
francesco.billari@unibocconi.it
[2] Department Management, Technology, and Economics, ETH Zurich, Switzerland
tfent@ethz.ch
[3] Vienna Institute of Demography, Austrian Academy of Sciences, Austria
alexia.fuernkranz-prskawetz@oeaw.ac.at
[4] ACDIS, University of Illinois at Urbana-Champaign, USA
scheffra@uiuc.edu

**Summary.** Agent-based models (ABMs) are increasingly used in studying complex adaptive systems. Micro-level interactions between heterogeneous agents are at the heart of recent advances in modelling of problems in the social sciences, including economics, political science, sociology, geography and demography, and related disciplines such as ecology and environmental sciences. Scientific journals and societies related to ABMs have flourished. Some of the trends will be discussed, both in terms of the underlying principles and the fields of application, some of which are introduced in the contributions to this book.

## 1 Agent-Based Modelling: An Emerging Field in Complex Adaptive Systems

Since Thomas C. Schelling's pathbreaking early study on the emergence of racial segregation in cities [32], a whole new field of research on socioeconomic systems has emerged, dubbed with a diversity of names, such as social simulation, artificial societies, individual-based modelling in ecology, agent-based computational economics (ACE), agent-based computational demography (ABCD). Accordingly, the literature on agent-based modelling in social sciences has flourished recently, particularly in economics[5], political science[6],

[5] See i.e. the special issue on agent-based computational economics of the Journal of Economic Dynamics and Control [34], especially the introduction by Leigh Tesfatsion, as well as the website maintained by Tesfatsion http://www.econ.iastate.edu/tesfatsi/ace.htm.

[6] See i.e. the review paper by Johnson [23].

and – to a lesser extent – sociology[7]. During the 1990s, this computational approach to the study of human behaviour developed through a vast quantity of literature. These include approaches that range from the so-called evolutionary computation (genetic algorithms and evolution of groups of rules) to the study of the social evolution of adaptive behaviours, of learning, of innovation, or of the possible social interactions connected to the theory of games.

Different to the approach of experimental economics and other fields of behavioural science that aim to understand why specific rules are applied by humans, agent-based computational models pre-suppose rules of behaviour and verify whether these micro-based rules can explain macroscopic regularities. The development in computational agent-based models has been made possible by the progress in information technology (in hardware as well as software agent technology), and by the presence of some problems that are unlikely to be resolved by simply linking behavioural theories and empirical observations through adequate statistical techniques. The crucial idea that is at the heart of these approaches is to use computing as an aid to the development of theories of human behaviour. The main emphasis is placed on the explanation rather than on the prediction of behaviour, and the model is based on individual agents.

As outlined in Axelrod ([1, p.4]), agent-based computational modelling may be compared to the principles of induction and deduction. "Whereas the purpose of induction is to find patterns in data and that of deduction is to find consequences of assumptions, the purpose of agent-based modelling is to aid intuition". As with deduction, agent-based modelling starts with assumptions. However, unlike deduction, it does not prove theorems. The simulated data of agent-based models can be analysed inductively, even though the data are not from the real world as in case of induction.

## 2 From Rational Actors to Agent-Based Models

Established economic theory is based on the rational actor paradigm which assumes that individual actors know their preferences, often measured by a utility function, and the best possible decision, based on complete information about their environment and the supposed consequences. Decision theory deals with the ranking and selection of the options of actors, according to their preferences. Usually a single rational decision-maker maximizes utility (value) under given constraints, where a wide range of methods have been developed to search for and find the optimum. While rational actors may be adequate in environments with a few number of state and control variables, they have limits in complex and uncertain environments and with real human beings of bounded rationality and restrained computational capabilities.

One of the conditions that restrains rationality is the social environment itself, in particular the unpredictable behaviour of other agents. Game theory

[7] See i.e. the review paper by Macy and Willer [26], or the review of Halpin [18].

is trying to extend rational decision-making to two and more players, each pursuing their own preferences and utilities in response to the expected or observed decisions of other players. Game theory becomes more difficult to handle when a large number of players interact in a dynamic environment. Dynamic game models describe the interaction between multiple players according to situation-dependent decision rules and reaction functions. In repeated games players can learn and adapt their behaviour to the strategies of other players, possibly leading to the evolution of cooperation. Evolutionary games analyse the selection among competing populations of game strategies according to their fitness in replication.

Recent years saw a transition from rational actor models to agent-based modelling, and from top-down macro decision-making to bottom-up micro-simulation. A common feature of ABMs is that individual agents act according to rules, where utility optimization is just one of many possible rules. Thanks to increasing computational capabilities, it became possible to analyse interactions between multiple agents, forming complex social patterns. Computers turned into laboratories of artificial societies ([12], [13]). Simulations have now the character of experiments in virtual worlds, often with demanding computational requirements.

In cellular automata models, agents behave like insects in virtual landscapes [41]. For a large number of homogenous agents, methods from statistical physics, non-linear dynamics and complexity science are applicable [17], describing self-organization or phase transitions when observed macroscopic properties emerge from the behaviour and interactions of the component agents. Approaches to collective phenomena have been transfered to interdisciplinary fields such as socio-physics and econo-physics, with applications ranging from moving crowds and traffic systems to urban, demographic and environmental planning ([22],[39],[33]).

Key challenges are to find a conceptual framework to structure the diverse field of ABMs, to calibrate the models with data and to integrate ABMs into real-world applications. The selection of strategies and decision rules in computer-based simulation models can be based on observation and include real-world actors and stakeholders, offering a wide field of experimental games for educational and research purposes as well as for decision support and policy advice. Special modelling-simulation environments or toolkits of various kinds are available for performing experiments, which abstract from the details and can be duplicated by other researchers.

## 3 Structure, Behaviour and Interaction of Agents

Agent-based models are usually based on a set of autonomous agents capable to interact with each other as well as with the environment according to rules of behaviour, which can be simple or complex, deterministic or stochastic, fixed or adaptive. An agent can be any organisational entity that is able to

act according to its own set of rules and objectives. All agents can be of the same type (homogenous) or each agent can be different from the other (heterogeneous).

One core question is related to the structure of agents: should agents be simple or should they be complex? Proponents of the simplicity of agents, such as Robert Axelrod [1], support the so-called KISS principle (keep it simple, stupid), and point out that the most interesting analytical results are obtained when simple micro-level dynamics produce complex patterns at the macro level. This approach is analogous to mathematical models where complex dynamics may arise from simple rules. Proponents of the complexity of agents base their views especially in economics, sociology and cognitive psychology, assuming that agents are possibly guided by a set of behavioural rules and objective functions which evolved as a result of interaction and learning in complex environments and shape the individual structure of each agent. Reality tends to be between simplicity and complexity, and agents should be kept as "simple as suitable". Real agents seek to reduce complexity according to their needs and adjust to their social environment, sometimes leading to rather simple collective behaviour, despite the potential for individual complexity.

Agents can include many details matching reality, at different spatial and temporal scales. Depending on the agents' number, their attributes and behavioural rules in their respective environments, ABM's can be of great variety and complexity, making them hard to analyse or predict. Using sensors, agents can perceive their local neighbourhood and receive or send messages ([14]).

Cognitive agents may have cognitive capabilities "to perceive signals, react, act, making decisions, etc. according to a set of rules" ([9]). Their intended actions are shaped by what they think to know about the world (beliefs), based on experience and perception, and what they would like to achieve (desired goals), both represented by an internal model of the external environment. Agents can be autonomous and act independently of any controlling agency, or they can directly interact with or depend on other agents. In their environment agents need information to react and adapt to their observation and to respond to changes in the environment, and they can communicate with other agents via a language. Pursuing goals, agents need to be pro-active, and they can be rational by following a well-defined and logical set of decision rules to achieve these goals.

Adaptive agents have the capability to learn, i.e. rather than following a fixed stimulus-response pattern, they continuously adapt to changes in their environment according to their expectations and objectives. They evolve in a learning cycle of acting, evaluating the results of the actions dependent on the response of the environment and updating the objective or the actions. By acting an agent employs resources and directs them onto its environment, in order to achieve the objective. Evaluation compares the results of the actions and their impacts with the expectations and objectives. Searching tries to find

better routines for achieving the objective. Adaptive agents can change their objectives and routines.

A general framework for agent-based modelling can be characterized by the following elements (see the contribution by Gebetsroither et al. in this volume):

- Values, targets and objectives
- Resources or production factors
- Observation, expectation and update
- Rules, search routines and actions

These elements occur repeatedly in a cycle of action, evaluation and update. A more comprehensive analysis would consider the complete multi-step process of decision-making, interaction and management, including the following phases [31]:

1. Situational analysis and problem structuring
2. Option identification and scenario modelling
3. Concept development and criteria-based evaluation
4. Decision-making and negotiation
5. Planning and action
6. Monitoring and learning

The different phases are connected by processes such as evaluation, communication, capacity building, information, simulation, validation. Usually ABMs do not apply all phases of this cycle but only selected elements which are of particular relevance for a given problem.

## 4 From Micro to Macro: Modelling Population Processes from the Bottom-Up

Agent-based simulations are increasingly applied in the social sciences. Artificial computational environments serve in fact as small laboratories to simulate social behaviours and interaction among a large number of actors. This includes the study of the complex dynamics evolving from heterogenous populations. Populations are by definition aggregates of individuals, and as such they constitute entities at the aggregate or "macro" level, whereas individual lives contribute to numbers of events, person years and survivors, which are used in the statistical analysis of populations. Demography as such is concerned with the study of populations, and has been traditionally focusing on the macro side of population dynamics, on "macro-demography". However, during the last decades of the Twentieth Century a "micro-demography" emerged with a specific emphasis on the unfolding of individual-level demographic trajectories and on the consequences of individual heterogeneity for the study of population dynamics.

Perhaps surprisingly, other disciplines than the one focusing on population per se have attempted at micro-founding the study of specific types of behaviour using some type of "methodological individualism" approach. In particular, we refer to ecology, sociology, and economics, disciplines that are in particular represented in this book.

In *ecology*, "individual-based modelling" (IBM), e.g. for the study of animal and plant populations, has emerged starting from the mid-1970s as a research program that has led to significant contributions (for a review see [15]). According to Grimm and Railsback [16], individual-based models in ecology fulfill, to a certain degree, four criteria: first, they explicitly consider individual-level development; second, they represent explicitly the dynamics of the resources an individual has access to; third, individuals are treated as discrete entities and models are built using the mathematics of discrete events rather than rates; fourth, they consider variation between individuals of the same age. Individual-based models in ecology are aimed at producing "patterns" that can be compared to patterns observed in reality. The sustainable use and management of natural resources is an important issue but difficult to model because it is characterized by complexity, a high degree of uncertainty, information deficits and asymmetries.

There are not many examples of agent-based models concerning the management of natural resources. A complete agent-based model would have to comprise both social and natural systems and respective agents, which is a challenging task.

In *sociology*, the approach proposed by James Coleman (see [8] Ch. 1) proposes to found social theory ultimately on the micro-level decisions of individuals. Coleman proposes to use a three-part schema for explaining macro-level phenomena, consisting of three types of relations: 1) the "macro-to-micro transition – that is, how the macro-level situation affects individuals; 2) "purposive action of individuals" – that is, how individual choices are affected by micro-level factors; 3) the "micro-to-macro transition" – that is, how macro-level phenomena emerge from micro-level action and interaction.

Colemans conceptual framework is embedded in the notion of "social mechanism" as the key concept to explain behaviour in the social sciences, proposed by Hedström and Swedberg [21], who see the three types of relationships as 1) situational mechanisms, representing the case in which "The individual actor is exposed to a specific social situation, and this situation will affect him or her in a particular way"; 2) action formation mechanisms, representing "a specific combination of individual desires, beliefs, and action opportunities (that) generate a specific action"; 3) transformational mechanisms, specifying "how these individual actions are transformed into some kind of collective outcome, be it intended or unintended". The framework is very similar to the one presented recently by Daniel Courgeau [11] in a review on the macro-micro link.

As we noticed before, the micro level is the natural point of departure in *economics*, also when pointing to the macro level as the important out-

come. While the first generation of economic simulation models was rather focused on stylized empirical phenomena, the emergence of agent-based modelling during the last 10 years has shifted the emphasis from macro simplicity to micro complexity of the socio-economic reality. As noted by van den Bergh and Gowdy [36, p. 65] "During the last quarter century, the microfoundations approach to macroeconomic theory has become dominant". Mainstream economics, also known as "neoclassical" economics traditionally considers a "representative agent" who maximizes a potentially complex utility function subject to potentially complex budget constraints. This and other hypotheses lead to mathematically tractable models of macro-level outcomes. The new economics approach that applies the toolkit of neoclassical economics to demographic choices has been a key success of the work of Gary Becker (see e.g. [6]). This approach has now reached a level of maturity that can be attested from the literature on population economics (see e.g. [42]). That we ought to start from the micro level is also clearly stated by an economist who is particularly interested in population matters, Jere Behrman, who states that "For both good conditional predictions and good policy formation regarding most dimensions of population change and economic development, a perspective firmly grounded in understanding the micro determinants - at the level of individuals, households, farms, firms, and public sector providers of goods and services of population changes and of the interactions between population and development is essential" [7].

The attention on the policy relevance of research on population (including policy implications of results) is undoubtedly the main characteristic that comes to the surface when looking at research on population economics. Micro-based theories of behaviour are thus used to cast "conditional prediction" of reactions to a given policy, with these reactions affecting macro-level outcomes. Within economics, several scholars have objected to the neoclassical paradigm from various perspectives (see e.g. [7] for objections to critiques concerning population-development relationships). Of particular interest are the critiques on mainstream economics that concern the assumption that agents are homogeneous and the lack of explicit interaction between agents (see e.g. Kirman [24]). Kirman's point is that even if individuals are all utility maximizers (an idea that has also been challenged by several scholars), the assumption that the behaviour of a group of heterogeneous and interacting agents can be mimicked by that of a single representative individual whose choices coincide with the aggregate choices of the group is unjustified and leads to misleading and often wrong conclusions.

To overcome this micro-macro "aggregation" problem, that is the transformational mechanism in Coleman's scheme, some economists have proposed to build models that resemble that of IBM in ecology. Models in agent-based computational economics (ACE) explicitly allow the interaction between heterogeneous agents (see e.g. the review by Tesfatsion [34]).

## 5 Population Dynamics from the Bottom-Up: ABCD

We now document the emergence of the agent-based modelling approach in demography as a specific case-study.

Without the strong paradigm of the "representative agent" that underlies mainstream economics, demography has to solve aggregation problems taking into account that demographic choices are made by heterogeneous and interacting individuals, and that sometimes demographic choices are made by more than one individual (a couple, a household). For these reasons, and for the natural links to current micro-demography, computer simulation provides a way to transform micro into macro without having to impose unnecessary assumptions on the micro level (among those homogeneity, lack of interaction).

Agent-based computational demography (ABCD) has been shaped by a set of tools that models population processes, including their macro level dynamics, from the bottom up, that is by starting from assumptions at the micro level [4]. Agent-based computational demography includes also microsimulation that has been used to derive macro-level outcomes from empirical models of micro-level demographic processes (i.e. event history models), but also formal models of demographic behaviour that describe micro-level decisions with macro-level outcomes.

It is interesting to notice that demography has for a long time been using simulation techniques, and microsimulation has become one of the principal techniques in this discipline, being a widely discussed and applied instrument in the study of family and kinship networks and family life cycle ( [19]; [38]; [30]; [20]; [35]). Microsimulation has also been widely used in the study of human reproduction and fecundability ([29]; [27]), migratory movements [10] or whole populations [25], and its role has been discussed in the general context of longitudinal data analysis [40]. Evert van Imhoff and Wendy Post [37] provide a general overview of the topic. Microsimulation has been used to study and predict the evolution of a population using a model for individuals.

What does ABCD add to demographic microsimulation in helping to bridge the gap between micro-demography and macro-demography? The emphasis of demographic microsimulation has been on the macro-level impact of a certain set of parameters estimated at the micro-level from actual empirical data. There has been no particular emphasis on the theoretical side. Agent-based models do not necessarily include only parameters estimated from actual empirical data, but it may include parameters that are relevant for a specific theoretical meaning. In fact, microsimulation is to the event history analysis what macrosimulation (i.e. population projection based on aggregate-level quantities like in the cohort-component model) is to traditional, macro-level, formal demography. On the other hand, agent-based computational demography is the micro-based functional equivalent of mathematical demography.

Some of the reasons why ABCD helps bridging the macro-micro gap in demography are mentioned in this context (see [5] for a full discussion).

First, it is relatively easy to include feedback mechanisms and to integrate micro-based demographic behavioural theories (and results from individual-level statistical models of demographic behaviour such as event history models) with aggregate-level demographic outcomes. This ability to include feedback is possibly the most important gain of ABCD models. In such models, space and networks can be formalised as additional entities through which the agents will interact.

Second, compared to mathematical modelling, it is relatively easy to introduce heterogeneous agents that are not fully rational. Hence, the paradigm of the representative, fully rational agent that has and often still penetrates many economic and sociological applications can easily be relaxed in agent-based modelling.

Third, when building agent-based computational models, it is indispensable to adopt simple formulations of theoretical statements. Although agent-based modelling employs simulation, it does not aim to provide an accurate representation of a particular empirical application. Instead, the goal of agent-based modelling should be to enrich our understanding of fundamental processes that may appear in a variety of applications. This requires adhering to the KISS principle.

Fourth, using agent-based approaches, it is possible to construct models for which explicit analytical solutions do not exist, for example social interaction and generally non-linear models. Agent-based models are used to understand the functioning of the model and the precision of theories need not be limited to mathematical tractability. Simplifying assumptions can then be relaxed in the framework of an agent-based computational model. But as Axtell [2] notes, even when models could be solved analytically or numerically, agent-based modelling techniques may be applied since their output is mostly visual and therefore easier to communicate to people outside academia. In general, we can see formal modelling of population dynamics using differential equations and agent-based computational models as two ends of a continuum along the macro-micro dimension [28].

Finally, it is possible to conceive artificial societies that need not necessarily resemble present societies; such artificial societies can be seen as computational laboratories or may allow to reproduce past macro-events from the bottom-up.

## 6 Contributions of ABMs to Economic, Demographic and Ecological Analysis

The present book describes the methodology to set up agent-based models and to study emerging patterns in complex adaptive systems resulting from multi-agent interaction. It presents and combines different approaches, with applications in demography, socio-economic and environmental sciences.

### 6.1 Socio-Economics

*Andreas Pyka* and *Thomas Grebel* provide a basic instruction on how to model qualitative change using an agent-based modelling procedure. The reasons to focus on qualitative change are discussed, agent-based modelling is explained and finally an evolutionary economics model of entrepreneurial behaviour is given as an example. The conceptual framework for the analysis of entrepreneurial behaviour is composed of several building blocks (actors, actions, endowments, interaction, evaluation and decision processes), which are not separate and unrelated entities but represent the conceptual view on the issue, as a result of a systematization process. Actors are not modelled by a representative agent but by a population of heterogeneous agents. For any of two subpopulations (agents and firms) rules and routines are derived which govern the particular actions of the agents, the interaction and interrelation of the agents within and among the sub-populations. The nature of the actors and their heterogeneity is shaped by the endowment with resources and their individual routines, which are related to the satisficing behaviour and bounded rationality of the actors. Routinized behaviour causes some inertia and stability of the system. Some actors join networks with other actors and found a firm, others disentangle their networks or even go bankrupt. The basic conceptual building blocks are implemented in the actual model of entrepreneurial behaviour.

In their contribution, *Markus Franke, Andreas Geyer-Schulz* and *Bettina Hoser* analyse asymmetric directed communication structures in electronic election markets. They introduce a new general method of transforming asymmetric directed communication structures represented as complex adjacency matrices into Hermitian adjacency matrices which are linear self-adjoint operators in a Hilbert space. With this method no information is lost, no arbitrary decision on metrics is involved, and all eigenvalues are real and easily interpretable. The analysis of the resulting eigensystem helps in the detection of substructures and general patterns. The formal method is applied in the context of analysing market structure and behaviour based on market transaction data from the eigensystem. As an example, the results of a political stock exchange for the 2002 federal elections in Germany are analysed. Market efficiency is of special interest for detecting locally inefficient submarkets in energy markets.

### 6.2 Population and Demography

*Mike Murphy* discusses the role of assortative mating on population growth in contemporary developed societies. Assortative mating is a widespread feature of human behaviour, with a number of suggested benefits. The question of whether it contributes to population growth in contemporary societies is considered using the micro simulation program SOCSIM. Ways of parameterising heterogeneous fertility and nuptiality, and the relationship of such parameters

to those of both fathers and mothers are considered. One conclusion is that the effect of assortative mating in which the fertility backgrounds of spouses are positively correlated leads to higher population growth. A population with a higher long term rate of growth, no matter how small the advantage, will come to dominate numerically any population with a lower one and the overall population eventually becomes effectively homogeneous and consists only of the higher growth population. Further progress will require developments in theory, data, modelling and technology, but assortative mating remains one of the most persistent and enduring features of humans and other species.

*Belinda Aparicio Diaz* and *Thomas Fent* analyse an agent-based model designed to understand the dynamics of the intergenerational transmission of age-at-marriage norms. A norm in this context is an acceptable age interval to get married. It is assumed that this age-interval is defined at the individual level and the individuals' age-at-marriage norms are transmitted from parents to their children. The authors compare four different transmission mechanisms to investigate the long term persistence or disappearance of norms under different regimes of transmission. They investigate whether results also hold in a complex setup that takes into account heterogeneity with respect to age and sex as well as the timing of union formation and fertility. To create a more realistic model of evolving age norms, the characteristics of the agents are extended, and the age-at-marriage norms are split into two sex-specific age-at-marriage norms. The results provide information about how additional characteristics and new parameters can influence the evolution of age-at-marriage norms.

To explain the differences in obesity rates among women in the United States by education, *Mary A. Burke* and *Frank Heiland* model a social process in which body weight norms are determined endogenously in relation to the empirical weight distribution of the peer group. The dramatic growth in obesity rates in the United States since the early 1980's to close to 30% in 2000 has been widely publicised and raised attention to the problem of obesity. Obesity significantly elevates the risks of diabetes, heart disease, hypertension, and a number of cancers, and remains a prominent public health priority. The agent-based model embeds a biologically accurate representation of variation of metabolism which enables to describe a distribution of weights. Individuals are compared to others with the same level of educational attainment. The agents are biologically complex, boundedly rational individuals that interact within a social group. Using heterogeneous metabolism and differences in average energy expenditure, an entire population distribution of body weights is generated. Weight norms are defined as a function of aggregate behaviour, and deviation from the norm is costly. Consistent with the observed distribution of body weights among women in the U.S. population, the model predicts lower average weights and less dispersion of weight among more educated women. While previous models have made qualitative predictions of differential obesity rates across social groups, they have not captured the differences in the overall weight distributions that this model is able to reproduce. The model is

also used to investigate competing hypotheses based on behavioural or genetic differences across education groups.

### 6.3 Ecology and Environment

*Volker Grimm* and *Steven F. Railsback* specify agent-based models in ecology by discussing two modelling strategies that have proven particularly useful: pattern-oriented modelling (POM), and a theory for the adaptive behaviour of individuals. These two strategies are demonstrated with example models of schooling behaviour in fish, spatiotemporal dynamics in forests, and dispersal of brown bears. Schooling-like behaviour is based on simple assumptions on individual behaviour: individuals try to match the velocity of neighbouring individuals, and to stay close to neighbours which leads to the emergence of school-like aggregations. This demonstrates how simple behavioural rules and local interactions give rise to a collection of individuals which are more or less regularly spaced and move as one coherent entity. The question is discussed how to learn about how real fish behave by combining observed patterns, data, and an IBM. Specific properties of real fish schools are quantified, such as nearest neighbour distance and polarisation, i.e. the average angle of deviation between the mean direction of the entire school and the swimming direction of each fish.

*Ernst Gebetsroither, Alexander Kaufmann, Ute Gigler* and *Andreas Resetarits* present a preliminary version of an agent-based model of self-organisation processes to support adaptive forest management. The modular approach consists of two separate, but interlinked submodels. While the forest submodel includes a very large number of comparatively simple agents, the socioeconomic submodel comprises only a few complex agents defined by a fixed set of an objective and several routines, technologies and resources. The use of forest resources is determined by the interrelations between specific forest management methods and the specific demand for timber of industries producing wood-based goods. The timber market includes two types of agents which belong to the sectors "forestry" offering timber with a long-term planning horizon and "industry" producing wood-based goods with a short-time perspective. Their relation is characterised by imperfect competition, imperfect information, strategic behaviour and learning. Other potentially important agents are either not included in this model (e.g. tourists, hunters) or considered as exogenous forces (e.g. state authorities, communities, demand for wood-based products, competing sources of timber supply). The main question is how self-organisation processes on the timber market (demand for the forest resource "timber") as well as in forest succession (available stock of timber) influence each other and which effects of adaptive management methods can be expected on the overall system's behaviour. Running simulations with an empirically calibrated model (using forestry data and interviews of experts) allows to test specific forest management routines under controlled conditions and restrictions.

*Rosaria Conte, Mario Paolucci* and *Gennaro Di Tosto* use an evolutionary variant of the Micro-Macro Link (MML) theory in biological evolution to understand the emergence of altruism, applied to food sharing among vampire bats. Behaviour at the individual level generates higher level structures (bottom-up) which feed back to the lower level (top-down). Starting from ethological data a multi-agent model is used to analyse the key features of altruistic behaviour. Every agent in the simulation is designed to reproduce hunting and social activity of the common vampire bats. During night, the simulated animals hunt, during day they perform social activities (grooming and food-sharing). A high number of small groups (roosts) provide social barriers preventing altruists from being invaded by non-altruists (simple loop). When the ecological conditions vary (e.g., the number of individuals per group increases), altruism is at risk, and other properties at the individual level evolve in order to keep non-altruists from dominating, and to protect the whole group (complex loop). The two loops are illustrated by simulation experimenting on individual properties, allowing altruists to survive and neutralise non-altruists even under unfavourable demographic conditions.

### 6.4 General Aspects

To establish the potential importance of the interplay between social and physical spaces, *Bruce Edmonds* exhibits a couple of agent-based simulations which involve both physical and social spaces. The first of these is a more abstract model whose purpose is simply to show how the topology of the social space can have a direct influence upon spatial self-organisation, and the second is a more descriptive model which aims to show how a suitable agent-based model may inform observation of social phenomena by suggesting questions and issues that need to be investigated. Taking the physical and social embeddedness of actors seriously, their interactions in both of these "dimensions" need to be modeled. In his view, agent-based simulation seems to be the only tool presently available that can adequately model and explore the consequences of the interaction of social and physical space. It provides the "cognitive glue" inside the agents that connects physical and social spaces.

To build an agent-based computational model of a specific socio- environmental system, *Jim Doran* discusses designs to create the software agents. The currently available range of agent designs is considered, along with their limitations and inter-relationships. How to choose a design to meet the requirements of a particular modelling task is illustrated by reference to designing an informative agent-based model of a segmented, polycentric and integrated network (SPIN) organization. As an example, a social movement in the context of environmental activism is discussed, representing a segmentary, polycentric and integrated network composed of many diverse groups, which grow and die, divide and fuse, proliferate and contract. The adaptive structure of SPINs prevents effective suppression by authorities and opponents, an aspect that

is relevant for the stability and disruption of networks, in particular terrorist networks.

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