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Stefano Balbi

Carlo Giupponi

Reviewing agent-based modelling of socio-ecosystems: a methodology for the analysis of climate change adaptation and sustainability

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Reviewing agent-based modelling of socio-ecosystems: a methodology for the analysis of climate change adaptation and sustainability

Stefano Balbi, Carlo Giupponi
Ca' Foscari University of Venice - Department of Economics
Center for Environmental Economics and Management

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Abstract
The integrated - environmental, economic and social - analysis of climate change calls for a paradigm shift as it is fundamentally a problem of complex, bottom-up and multi-agent human behaviour. There is a growing awareness that global environmental change dynamics and the related socio-economic implications involve a degree of complexity that requires an innovative modelling of combined social and ecological systems. Climate change policy can no longer be addressed separately from a broader context of adaptation and sustainability strategies. A vast body of literature on agent-based modelling (ABM) shows its potential to couple social and environmental models, to incorporate the influence of micro-level decision making in the system dynamics and to study the emergence of collective responses to policies. However, there are few publications which concretely apply this methodology to the study of climate change related issues. The analysis of the state of the art reported in this paper supports the idea that today ABM is an appropriate methodology for the bottom-up exploration of climate policies, especially because it can take into account adaptive behaviour and heterogeneity of the system's components.

Keywords
Review, Agent-Based Modelling, Socio-Ecosystems, Climate Change, Adaptation, Complexity.

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Address for correspondence:
Carlo Giupponi
Department of Economics
Ca' Foscari University of Venice
Cannaregio 873, Fondamenta S.Giobbe
30121 Venezia - Italy
Phone: (++39) 041 2349126
Fax: (++39) 041 2349176
cgiupponi@unive.it

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Department of Economics
Ca' Foscari University of Venice
Cannaregio 873, Fondamenta San Giobbe
30121 Venice Italy
Fax: ++39 041 2349210

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1. Introduction

1.1 Global change and complex systems

There is an increasing awareness that global change dynamics and the related socio-economic implications involve a degree of complexity which is not captured by traditional economic approaches that employ equilibrium models. In particular, such a top down analysis of the human-environment system doesn't consider the emergence of social behavioural patterns. This eventually leads to a flawed policy making process which relies on unrealistic assumptions (Moss, Pahl-Wostl, and Downing 2001). Yet, the ultimate source of anthropogenic climate change is the agency of human individuals grouped in social networks and their interaction. At the same time, the responses to climate change, in terms of mitigation of greenhouse gases emissions and in terms of adaptation to climatic variability and slow changes in mean conditions, have to be found in humans behaviour.
In our global system where human activities prevail and endlessly modify the environment, climate change is providing the chance to concretely understand how the environment responds, suggesting a change in human behaviour, both at a local and global level. Climate change can no longer be addressed separately from a broader context of systemic sustainability and adaptation strategies.

The endogenous feedbacks between socio-economic and biophysical processes and the co-evolution of the human-environment system are precisely those kind of dynamics included in the notion of social-ecological systems, or socio-ecosystems (SES). SES are complex and adaptive systems where social (human) and ecological (biophysical) agents are interacting at multiple temporal and spatial scales (Rammel, Stagl, and Wilfing 2007). This definition emphasizes the adoption of a single integrated approach for the analysis of both social and economical agents and the natural components of the ecosystem. It postulates the fact that SES are non decomposable systems, because they emerge from the dynamic interplay between the social and ecological components. SES show specific properties such as: (a) non linear dynamics, alternate regimes and thresholds; (b) adaptive cycles; (c) multiple scales and cross scale effects, (d) adaptive capacity and transformability (Gunderson and Holling 2002).

Given such properties SES have to be considered as complex and adaptive systems (CAS). CAS are dynamic networks of many agents (which may represent cells, species, individuals, firms, nations) acting in parallel, constantly acting and reacting to the behaviour of other agents. The control of a CAS tend to be highly dispersed and decentralized. If there is to be any coherent behaviour in the system, it has to arise from competition and cooperation among the agents themselves. The overall behaviour of the system is the result of a large number of decisions made every moment by many individual agents (Waldrop 1992).
CAS display an ever changing dynamic equilibrium, which fluctuates

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between chaotic and ordered states. On the edge of chaos, these systems are very sensitive to any perturbation from the individual components (Holland 1992). CAS are inherently unpredictable as a whole: “their futures are not determined and their global behaviours emerge from their local interactions in complex, historically contingent and unpredictable ways” (Bradbury 2002).

Since the study of CAS is an attempt to better understand systems which are difficult to grasp analytically, often the best available way to investigate such them is through computer simulations (Gilbert and Troitzsch 1999). As a matter of fact, when dealing with CAS, one has to cope with uncertainty (Perez and Batten 2006). When decision are of major importance and hugely permeated by imperfect knowledge and deep uncertainty, an improved understanding of the use models is needed (Funtowicz and Ravetz 1995). One way is to move towards exploratory modelling, whereby ensembles of scenarios are used to represent possible futures of the system under study and criteria such as resilience and stability are used to compare the robustness of alternative policies (Lempert 2002).

1.2 Introducing agent-based thinking

Past research on computer science (e.g. Wooldridge and Jennings 1995; Ferber 1999; Huhns and Stephens 1999; Weiss 1999) has shown how CAS can be represented by means of multi-agent systems (MAS). MAS is a concept derived from distributed artificial intelligence (DAI), which firstly used it in order to reproduce the knowledge and reasoning of several heterogeneous agents that need to coordinate to jointly solve planning problems. Typically MAS refers to software agents and is implemented in computer simulations.
According to the DAI derived definition of Ferber (1999) a MAS is a system composed with the following elements:

1. an environment (E), often possessing explicit metrics;
2. a set of passive, located objects (O). These objects can be located, created, destroyed or modified by the agents;
3. a set of active agents (A). Agents are particular objects that constitute the active entities of the system;
4. a set of relationships (R) linking objects and/or agents together;
5. a set of operators (Op) allowing the agents to perceive, create, use, manipulate or modify the objects.

Agents are virtual entities that demonstrate: (i) autonomous actions within their environment, (ii) communication with other agents, (iii) limited perception of their environment, (iv) bounded representation of their environment (if any) and (v) decision making process based on satisfying goals and incoming information (Ferber 1999).

Pure MAS, as conceived in DAI, are not fully relevant for modelling SES, which are real systems based on the law of physics and on human social interactions. However, including the fundamental contribution of past

research on artificial life (AL) (e.g. Reynolds 1987; Holland 1992; Langton 1992); individual-based modelling (IBM) (e.g. Huston et al. 1988; Grimm 1999) and social simulations (e.g. Schelling 1978; Axelrod and Hamilton 1981; Epstein and Axtell 1996), we are provided with a very promising framework for the innovative modelling of combined SES and policy-making in the context of sustainable development (Boulanger and Bréchet 2005).
Although this methodology has assumed many names, we adopted the umbrella term agent-based modelling (ABM) which we regard as any systemic and agent oriented modelling approach that employs computer simulations.

ABM can explicitly represent the sources of social and biophysical complexity accounting for interdependencies, both in space and time, heterogeneity and nested hierarchies among agents and their environment (Parker et al. 2003).
The main advantages of ABM are found in its abilities to: (a) couple social and environmental systems, linking social and environmental processes; (b) model individual decision-making entities, taking into account the interactions between them and incorporating social processes and non-monetary influences; (c) incorporate the influence of micro-level decision making into the system dynamics, linking these micro-scale decisions to macro-scale phenomena; (d) study the emergence of collective responses to changing environment and policies (Hare and Deadman 2004; Matthews et al. 2007).
Moreover, agent-based models can be constructed and validated in the participatory setting, fostering the process of social learning and, while integrating factual and local knowledge, they can provide assistance for specific decision making (Barreteau, Bousquet, and Attonaty 2001; Guyot and Honiden 2006; Pahl-Wostl 2007).

1.3 Further expansion of ABM

To date, ABM has been used to reformulate some main issues of social and natural science (Bousquet and Le Page 2004). In fact, there exists a consistent body of work on ABM in sociology and social processes (e.g. Conte et al. 2001; Macy and Willer 2002; Gilbert and Troitzsch 1999), economics and finance (e.g. LeBaron 2000; Tesfatsion 2002) and in a set of environmental issues including land use and cover change (e.g. Parker et al. 2003; Veldkamp and Verburg 2004) ecology and natural resource management (e.g. Lansing and Kremer 1993; Bousquet and Le Page 2004), agriculture (e.g. Balmann 1997; Berger 2001), urban planning (e.g. Torrens and O Sullivan 2001; Batty 2005), and archaeology (e.g. Kohler and Gumerman 1999). Altogether these various applications constitute the rich breeding ground for moving towards a new approach to the analysis of climate change issues.

However, there are limited useful publications on ABM in the arena of climate change. Some of them stand a very epistemological level stating the usefulness of the methodology without applying it (e.g. Moss, Pahl-Wostl, and Downing 2001; Patt and Siebenhüner 2005). Few applications explicitly aim at analysing climate change at a theoretical level (e.g. Janssen and de Vries 1998) or at a more empirical level (e.g. Bharwani et al. 2005; Ziervogel et al. 2005; Berman et al. 2004; Werner and McNamara 2007; Barthel et al. 2008; Entwisle et al. 2008). In contrast, there are several ABM applications which generically include climate change elements in their system modelling (e.g. Dean et al. 1999; Barthel et al. 2008; Hasselmann 2008; Filatova 2009; Mandel et al. 2009; Beckenbach and Briegel 2009). Such a few available publications are evidence of an immature area of research. This field of application, only recently, started to rapidly develop, with many research project forthcoming[1], with potential publications in the future.

The justification of this late development can be found in the intrinsic characteristics of the methodology.
Given ABM ability to capture complexity and represent detail, the model has to be built at the right level of description, with just the right amount of detail to serve its purpose. Therefore, the purpose has to be clearly stated in order to try hard to limit the model complexity. The reason is that, as computer models are less constrained technically, their design can still be too complex compared to classical models (Grimm and Railsback 2005). General purpose models aiming at representing a system rather than a problem, which are common in the climate change arena, cannot work.
Moreover, ABM may face challenges of parametrization and validation (Parker et al. 2001). This is particularly evident when one desires to build an empirically grounded model. ABM involves soft factors, difficult to quantify, calibrate and sometimes justify (Bonabeau 2002). Assumptions necessary for statistical verification and validation, such as normality and linearity can be at odds with models designed to accommodate complex behaviours caused by sensitivity to initial conditions, self-organized criticality, path dependency and non linearities (Arthur 1990; Manson 2001; Perez and Batten 2006).
Also the communication phase is more difficult, because the model has to be described in words, other than the universal language of mathematics, and this turns very often to be less efficient (Grimm et al. 2006).
Finally, ABM is not well suited to make quantitative deterministic predictions about how a system will function in the future, or about how to make the system function better in the future, which seems like the issue for the mainstream climate change economics devoted to top-down “hard science”. The outcome of a simulation should be interpreted at a more qualitative level, depending on the degree of accuracy and completeness in the input to the model (Bonabeau 2002).

1 Global Cities Institute of RMIT University and CSIRO in Australia, University of Hohenheim, in Germany, Tyndal Centre in UK, Natural Resources Canada, etc., just to quote some of the institutions with ongoing projects concerning ABM and climate change.

ABM has, to date, had limited impact in policy making, because it has been predominantly used in deterministic rather than exploratory mode, while it should be used in conditions of deep uncertainty, where there is no agreement between stakeholders on correct decisions (Lempert 2002).
Eventually, ABM is object of renewed interested, fuelled by the recent developments on uncertainty analysis applied to climate change (Barker 2008; Weitzman 2009).

The analysis of climate change calls for a paradigm shift (Bousquet and Le Page 2004; Martens 2006; Voinov 2008) as it is fundamentally a problem of complex, bottom-up and multi-agent human behaviour, which involves the entire socio-ecosystem.
This paper aims at integrating the existent know-how on ABM from different scientific communities in order to clarify whether or not this could be an appropriate methodology for modelling the dynamics of SES exposed to climate change and assessing the related policies within the context of adaptation and sustainability.
In the second section we define some core notions of ABM, we clarify the terminology in use, and briefly describe the main scientific domains and research communities applying this methodology. We approach the different domains making reference to the three fundamental dimensions of sustainability identified by the social, the economic and the environmental systems.
We than go deeper into the subject by elucidating how the concepts of agent, environment, emergence, interaction, heterogeneity, space and time, behaviour and validation are treated, including the computing languages, tools and platforms used for the simulations. We reviewed those applications that, in our opinion, better fit the idea of modelling SES and include climate change related elements.
In the fourth section we conclude discussing the main results.

2. ABM and complexity in the three spheres of sustainability

2.1 ABM and the dimensions of complexity

Nowadays ABM constitutes a broad and interdisciplinary movement. Different terms are used to define subtly different approaches to ABM: agent-based simulation modelling (e.g Berman et al. 2004), individual-based modelling (e.g. Grimm and Railsback 2005), multi-agent-based simulation (e.g. Perez and Batten 2006), agent-based social simulation (e.g. Gilbert 2004), multi-agent simulation (e.g. Bousquet and Le Page 2004), multi-actor modelling (e.g. Barthel et al. 2008), etc. According to Hare and Deadman (2004) a key difference, which justifies this terminological diversity, stands in the complexity of the interactions to be modelled. When emphasis is placed on modelling complex interactions, and agents are are simplistic, the AL and ecological roots of ABM prevail. When interactions spawn from the deliberations of the agents and the deliberative social cognition is most important, then the DAI roots are prevalent.

In general there are three types of interaction: direct interaction among agents, which can be physical (grow, push, eat) or by communication, and interactions mediated by the environment (Bousquet and Le Page 2004). By means of interactions, interdependencies exist among agents and their environment, across time and across space.

In the following paragraphs we argue that there are more sources of complexity, which also influence the terminology in use.
Heterogeneity is another major source of complexity. ABM can consider heterogeneous system's components situated in dedicated heterogeneous spaces. Agents' diversity may depend on their experience, values, abilities and resources but also on their spatial position. In fact, heterogeneity may also be present across the environment, space and time (Parker et al. 2003).
Complex interactions and heterogeneity combined typically build up a high degree of spatial and temporal complexity, exemplified in cross-scale interdependencies and nested hierarchies.

Emergence is a central tenet of ABM and the search for emergence is explicitly mentioned in most of the modelling efforts (Parker et al. 2001). An emergent property may be defined as a macroscopic outcome resulting from synergies and interdependencies between lower level system components. Emergence characterizes a complex system, the capacities of whom are greater than the sum of the system. The emergent qualities of a system are not analytically tractable from the attributes of internal components (Baas and Emmeche 1997).
The concept of emergence and the concept of cross-scale hierarchies are related. Identifying emergence, therefore, may require understanding important cross-scale interactions and deliberately building interactions across topological, temporal and structural levels, rather than limiting modelling and analysis to a single scale. Unfortunately this potential to explicitly represent cross-scale interactions and feed backs, both bottom-up and top-down, has been minimally exploited in agent-based models to date (Parker et al. 2001).

Behavioural complexity derives from the agents internal world, their mental model or architecture, which describe their cognition and learning capacity. Often agents are endowed with bounded cognition. They have a limited perception of the environment and derive information from it, which they use to make assumptions about its state. Agents are not meant to be omniscient and fully rational utility maximisers as, for instance, the homo economicus (Gintis 2000). Models of bounded rationality have been used as an alternative in economics (Simon 1955). Furthermore, borrowing concepts from psychology, behavioural economics has included dimensions of economic agents such as emotions, motivations and perceptions (Camerer 2003). In ABM is also possible to incorporate the salient characteristics of actual human decision-making behaviour (Tesfatsion and Judd 2006), including the agents capacity of learning from past experiences.
The combination of behavioural complexity with the complexity related to

interactions and heterogeneity allows the representation of adaptation in agent-based models at both micro and macro scales. The behaviour built into the decision making structure at the individual agent level, which is influenced by the system dynamics, is in turn embedded in the systemic adaptive mechanisms.

2.2 ABM and the triple bottom line of sustainability

In applications of agent-based models to social processes, agents represent people or groups of people and agent relationships represent processes of social interaction (Gilbert and Troitzsch 1999). The fundamental assumption is that people and their social interactions can be credibly modelled at some reasonable level of abstraction, for at least specific and well defined processes (Macal and North 2005).
After Schelling (1978), Epstein and Axtell (1996) extended the notion of modelling human agents to growing artificial societies through agent simulations, with their ground-breaking Sugarscape model. Social science computation is now a consolidated subfield of sociology (Gilbert and Abbott 2005). However, sociological ABM is much more concerned with theoretical development and explanation than with exploratory analysis. These models do not necessarily aim to provide an accurate representation of a particular empirical application (Macy and Willer 2002). Instead, their goal is to enrich the understanding of fundamental processes that might appear in a variety of applications (Axelrod 1997).

In ABM applications to economic systems agents can be both organization and individuals, while the design of interactions aims at performing a natural description of the system, taking into account both the topological and behavioural dimensions of the components' activities (Bonabeau 2002).
Some of the main classical assumption of microeconomics can be relaxed, leading to a more realistic representation of economic systems. Firstly, drawing on behavioural economics, agents are not rational optimizers (Smith 1989). Secondly, agents are not homogeneous. A key observation of complexity science is that agents diversity universally occurs in the real world (Arthur 1999). Thirdly, there can be increasing returns to scale underlying dynamic processes of rapid exponential growth. Such positive feedback loops can create self-sustaining processes that quickly take the system away from its starting point to a faraway state (Arthur 1990). Lastly, the long run equilibrium state of the system might not be the primary information of interest. Transient states may be crucial. Furthermore, not all systems come to an equilibrium (Arthur 2006).
The field of agent based computational economics (ACE) has grown up around the application of ABM to economic systems. ACE is the computational study of economies modelled as evolving systems of autonomous, adaptive and interacting agents (Tesfatsion 2002).

In environmental applications of ABM agents can be both an individual

human or biological organism or, more generically, any biophysical entity, as a reservoir of a natural resource or a part of it.
In biology, ABM has been used to model the possible emergent structures resulting from molecular self-assembly (e.g. Troisi, Wong, and Ratner 2005) and the self-organization of bacterial colonies (e.g. Krawczyk, Dzwinel, and Yuen 2003) but also to model bacterial behaviour and interaction at multiple scales (e.g. Emonet et al. 2005).
However, in the environmental domain, ABM applications were initially developed in ecology at the end of the 1980s following the IBM paradigm (e.g. Huston et al. 1988; Grimm 1999), which introduced the notion of the individual to understand the role of heterogeneity. In ecology an agent is necessarily an individual and scarce emphasis is given to the decision making process of the agents and to the social organization in which these individuals are embedded (Bousquet and Le Page 2004).
In contrast, in ABM applications to ecosystem management an agent can represent any level of organization, while the decision making process and the social organization are crucial. Frequently, these studies examine questions of collective problem solving related to the management of a common natural resource. ABM of ecosystem management is often included in the categories of agent-based land use models (ABLUMs) (Matthews et al. 2007) or as multi-agent systems for land use and cover change (MAS/LUCC) (Parker et al. 2003). In fact, most of the research on ABM and natural resources management overlaps with ABLUMs. This is because many of the environmental applications of ABM have a crucial spatial component and are very often spatially explicit, making use of abstract grids, cellular automata (CA), and, when case specific, maps from geographical information systems (GIS). So the landscape very frequently coincides with the environment where the physical space, the agents and the resources are represented delineating the system's boundaries and its organization.

2.3 Shared streams of research in ABM

The short overview of section 2.2 suggests that the definition of agent cannot be reduced to a specific one, because there are different realms of applications and processes with different agent characteristics, that can be successfully modelled with ABM. As suggested by Goldspink (2000) it's worth defining the minimal agent as “a natural or artificial entity with sufficient behavioural plasticity to persist in its medium by responding to recurrent perturbations within that medium so as to maintain its organization”. The medium is what Ferber (1999) defines as the environment and can be the background environment, in strictu sensu, or the substrate of a social system, and may contain active and/or passive agents. The latter are what Ferber (1999) calls objects. Starting from this any model can add new agent's features.
In the spirit of the interdisciplinary approach we are interested in the points of convergence between different scientific disciplines and a framework to classify them. Building on Macy and Willer (2002), Bonabeau (2002),

Tesfatsion (2003), Bousquet and Le Page (2004) and Janssen (2005) we identified some main streams of research that can be found in each of the three scientific domains constituting the triple bottom line of sustainability.

Within *self-organization and co-evolution of the system* the focus of agent-based models is on the self-organizing capabilities of the system under study, in particular how agents' behavioural rules influence their co-evolution and, ultimately, the system's structure. These models study in evolutionary terms how the decision making at the micro-level affect the macro-structure.

The stream of research *diffusion processes and networks formation* is interested on how micro-level interactions and transmission of information lead to the emergence of specific structural phenomena such cultural convergence, diffusion processes and endogenous formation of networks. Models often employ learning algorithms like artificial neural networks.

In the stream of research *modelling organizations, cooperation, and collective management* the focus of agent-based models is on how the system's topology and structure influences its behaviour, and in particular which structure stimulate cooperation in the benefit of the collective.

In *parallel experiments* we include those applications that compare computational and empirically observed agents and structures in order to improve the representation of the system under study. This stream has strong linkages with the issue of model validation.

Agent's architecture deals specifically with behavioural complexity. The main issue is how to represent the decision making of the agents and, ultimately, evolution and learning both at a micro- and macro-level.

Programming is necessarily a main cross-cutting issue given the shared computer based approach. OOP techniques (Cox 1986) are often advocated as a crucial mean for constructing an environment in which users can easily tailor models designed to suit their own particular research agendas. In general there remains a certain duality between general purpose languages and more or less specific packages.

While the first three streams define the main research questions of an ABM application and, therefore, tend to be mutually exclusive, the remaining three can be understood as necessary accessories and tools among the ABM movement. We classify some relevant ABM studies belonging to various disciplines in table 1 in order to show that a huge part of the ABM past research can find its proper allocation in this framework.

Table 1 – Classification of ABM according to scientific domain and stream of research

2.3.1 Self-organization and co-evolution of the system

In sociology this stream of research is concerned with the emergent structure in terms of structural differentiation as, for instance, social segregation (e.g. Schelling 1971). Models often investigate spatial clustering using CA. Agents can change location and behaviour in response to selection pressures. Adaptation is based on evolution, which modifies the

frequency distribution of strategies across the population of agents (e.g. Epstein and Axtell 1996).
In economics this stream of research deals with the self-organizing capabilities of specific types of market processes and the co-evolution of firms (Tesfatsion 2002). The most successful studies are those on financial markets (e.g. LeBaron 2000). Evolutionary models can explain important stylized facts such as fat tails, clustered volatility, and long memory, of real financial series (Hommes 2002).
In environmental ABM applications of this stream the focus is on how the behavioural rules of interacting agents lead to the self-organization of the ecosystem's structure and to the state of the common natural resource.

2.3.2 Diffusion processes and networks formation

In sociology these models investigate imitation (e.g. Latane 1996) and diffusion (e.g. Rosenkopf and Abrahamson 1999). Adaptation operates via social influence and is based on learning, which modifies the probability distribution of strategies in each agent's repertoire (Nowak et al. 1998).
In economics these models investigate the dynamics of interaction networks and diffusion processes. Relevant examples of applications focus attention on the endogenous formation of trade networks (e.g Albin and Foley 1992). A further kind of network issue is represented by the transmission of information as occurs with bank panics and stock market crashes (e.g. De Vany and Lee 2001).
In environmental applications of this stream of research both interaction networks and diffusion processes are present. Rouchier et al. (2001) investigated the formation of networks in a field study that focus on seasonal mobility (transhumance) among nomadic cattle herdsmen. Berger (2001) studied the diffusion of agricultural technologies based on the concept of early and late adopters. Deffuant et al. (2002) simulate adoption of organic farming practices as a consequence of governmental policy.

2.3.3 Modelling organizations, cooperation, and collective management

In sociology, studies dealing with emergent order focus attention on the ways in which network structures affect the viability of cooperative behaviour. For example, they can show how egoistic adaptation can lead to successful collective action without either altruism or global (top-down) imposition of control, according to the network properties (Macy and Willer 2002).
In economics, organizations can be seen as CAS (Tesfatsion 2002). One can model the organization's activities by looking at what every actor does. Therefore, it is possible to model the emergent collective behaviour of an organization or of a part of it in a certain context or at a certain level of description (Bonabeau 2002). Studies of firms in the ACE framework have tended to stress the effects of a firm's organizational structure on its own result behaviour (e.g. Prietula et al. 1998). Cooperation and coordination are a prerequisite to achieve an efficient overall performance.

In environmental applications this is a prime issue for the research on management of common pool resources. These models investigate how the system topology and structure influences the collective behaviour towards the common natural resource trying to identify what type of institutional rules may direct individuals to act in the benefit of the collective (Parker et al. 2003). The irrigation system in Bali is an early example of the use of ABM to understand self-governance (Lansing and Kremer 1993).

2.3.4 Parallel experiments

In sociology, organizational life histories generated by simulations are compared with those observed in empirical populations (e.g. Carley 1996; Lomi and Larsen 1998).
In economics, human subject behaviour is used to guide the specification of learning processes of computational agents and computational agent behaviour is used to formulate hypothesis about the root causes of observed human agent behaviour (Tesfatsion 2002).
Both the cited sociological and economic applications adopt an a posteriori approach. In contrast environmental applications tend to adopt an iterative approach by means of participatory techniques, such as role playing games, where human subject experimentation is used to test and ameliorate the computational simulations in an iterative process. In the spirit of adaptive management (Holling 1978) several researchers[2] have developed their agent-based models together with the stakeholders of the problem under concern, improving the acquisition of knowledge, the model construction, the model validation and the model application to decision making (e.g. Bousquet et al. 1999; Barreteau et al. 2001; Guyot and Honiden 2006).

2.3.5 Agents' architecture

In sociology there seems to be a clear distinction between learning and evolution. Learning modifies the probability distribution of strategies in each agent's repertoire. Learning architectures are based on artificial neural networks (Rumelhart and McClelland 1986). Evolution modifies the frequency distribution of strategies across the population of agents. In this case architectures are based on evolutionary algorithms such as genetic algorithm (Holland 1992).
In economics learning is used as a comprehensive term. The learning issue is particularly crucial due to the numerous anomalies discovered in laboratory experiments between actual human-subject behaviours and the behaviours predicted by traditional rational-agent economic theories (Gintis 2000) A broad range of algorithms is used to represent the agents' learning processes including reinforced learning algorithms (e.g. Bell 2001), neural networks (e.g. Luna 2002), genetic algorithms (e.g. Dawid 1996) and classifier systems (Booker, Goldberg, and Holland 1989), genetic

2 We define these researchers as the “French school” of ABM as they are all more or less related to the Centre de coopération internationale en recherche agronomique (CIRAD) of Montpellier and to the Cormas ABM platform.

programming and a variety of other evolutionary algorithms (e.g. Chattoe 1998) that attempt to capture aspects of inductive learning (Tesfatsion 2003). Vriend (2000) put more emphasis on the learning level, which can be individual, meaning on the basis of own experience, or social, in which every agent's experience is considered

In environmental applications various agent's architectures are drawn from computer science in order to represent behavioural complexity (Bousquet and Le Page 2004). Most are based on the evolutionary metaphor, as the genetic algorithm (e.g. Manson 2005). Others are defined architectures for competitive tasks, whereby choices are made by agents when they receive several stimuli which activates different tasks (e.g. Drogoul and Ferber 1994). Neural networks are employed in order to place emphasis on the agent's learning capacity: the perception-action relation is modelled by a network whose connections evolve (e.g. Grand and Cliff 1998). Agent's decisions may also be expressed in terms of parametrized functions by means of vector calculation describing the addition of physical forces (e.g. Reynolds 1987), linear programming describing processes of optimization more or less bounded (e.g. Balmann 1997), multi-criteria analysis (e.g. Deffuant et al. 2000), etc. One last way to model cognitive agents is the belief-desire-intention (BDI) architecture (e.g. Wooldridge and Jennings 1995) where agents memorize the space and the resources in a sort of mental map but also other agents' reputation when it comes to the moment of interaction.

2.3.6 Programming

In sociology, applications are more oriented towards ad-hoc platforms. Gilbert and Bankes (2002), provide a comprehensive enumeration of available languages and tools without identifying the best options. According to Tobias and Hofmann (2004), who evaluated four freely available and JAVA based programming libraries, Repast is the most suitable simulation framework for the applied modelling of social interventions based on theories and data. In contrast, Terna (1998) focuses on Swarm, which is the ground breaking and most dated tool of this type.

In economics, there remains a considerable gap between powerful general purpose languages and packages easy learned (Tesfatsion 2002). On the one hand, significant programming skills are needed in order to master general purposes languages such as C++ and Java, where applications are built from scratch. On the other hand there is a proliferation of ad-hoc packages, often not powerful enough for many economic applications, which can't communicate with each other and don't facilitate an easy sharing and comparison of modelling features. Economic applications often opt for a programming language or a generic but powerful software as NetLogo or Swarm (e.g. Luna and Stefansson 2000).

Also environmental applications are more oriented towards ad-hoc packages. Bousquet and Le Page (2004) survey some platforms developed with OOP distinguishing between generic softwares (e.g. Swarm and NetLogo), those dedicated to social and ecological simulation (e.g. Ecosim,

Repast and Cormas), and specific platforms for ad- hoc applications (e.g. Manta, Arborscapes). According to Railsback et al. (2006) NetLogo is highly recommended, compared to Mason, Repast and Swarm, even for prototyping complex models. Cormas is a well tested software for ecosystem management which supports participatory processes (Le Page et al. 2000). Repast is well considered for its flexibility but requires higher programming skills.
Many of the packages which have not been cited in this section can be found in the appendices of Tobias and Hofmann (2004) and in Schut (2007).

3. ABM of socio-ecosystems and climate change

In the past 10 years there have been few studies that modelled socio-ecosystems and included climate change elements related to mitigation or adaptation issues. In this section we review those papers that, in our opinion, are suitable to this purpose and are already published or close to publication. However, we suggest to look at the following comparative analysis as a first attempt to envision, in a comprehensive manner, the issue of climate change through the lenses of ABM. Several research projects, which are currently developing new relevant studies for this same issue, are expected in the near future.

Janssen and de Vries (1998) are specifically concerned with the behavioural aspects of ABM applied to climate change adaptation. Agents are groups of decision makers who operate at the international level and have different world-views and management styles towards climate change.
Dean et al. (1999), Werner and McNamara (2007), Entwisle et al. (2008) and Filatova (2009) deal with ABM and land use. Dean et al. (1999) is an early example of ABM of a local socio-ecosystems, which include climate change elements in order to simulate human responses and the outcome of adaptation. The model represents the behaviour of culturally relevant agents on a defined landscape in order to test hypothesis of past agricultural development and settlement patterns. Werner and McNamara (2007) investigate how the economic, social and cultural factors surrounding the human response to river floods, hurricanes and wetlands degradation affect a city landscape. Entwisle et al. (2008) focus on the responses to floods and drought at a regional level in terms of agricultural land use and migration, explicitly taking into account social networks. Filatova (2009) incorporated climate change related risks in an agent-based land market for coastal cities, which simulates the emergence of urban land patterns and land prices as a result of micro scale interactions between buyers and sellers.
Berman et al. (2004), Bharwani et al. (2005) and Ziervogel et al. (2005) are the only published empirical field studies, which explicitly aim at exploring local adaptation in the context of climate change and sustainable development by means of ABM. As Bharwani et al. (2005) and Ziervogel et al. (2005) refer to the same research project, we chose to review Bharwani et al. (2005) for its more comprehensive model description. Grothmann and Patt (2005) is a useful socio-cognitive model that can be used in ABM of

this kind where is important to capture the most significant behavioural determinants of adaptation. It has been tested in similar studies but not applied in the reviewed paper and therefore it is not present in table 2. Berman et al. (2004) assess how scenarios associated with economic and climate change might affect a local economy, resource harvest and the well-being of an existing community. Bharwani et al. (2005) investigate whether individuals, who adapt gradually to annual climate variability, are better equipped to respond to longer-term climate variability and change in a sustainable manner.

Barthel et al. (2008) developed an ABM framework for water demand and supply future scenarios where the socio-ecosystem is enabled to react and to adapt to climate change.

Hasselmann (2008), Beckenbach and Briegel (2009) and Mandel et al. (2009) concern macroeconomic models which employ, more or less explicitly, an agent-oriented framework in dealing with growth and climate change at a regional to global level. Hasselmann (2008) introduces few representative actors in a macroeconomic model of coupled climate-socio-economic system conceptualized following a system dynamics approach. The focus is on the evolution of this coupled system according to behaviour of the agents pursuing different goals while jointly striving to limit global warming to an acceptable level. Mandel et al. (2009) developed an agent-based model of a growing economy where growth is triggered by the increase of labour productivity proportionally to investments. Beckenbach and Briegel (2009) investigate the relationship between innovations, economic growth and carbon emissions.

Building on Parker et al. (2001) and Grimm et al. (2006) we review the cited papers according to the following categories:

1. in *stream of research* we show how is possible to associate any of them to one of the streams in table 1;
2. in *system under study* and *climate issue* we describe the object of the model, it's physical boundaries and the climatic problem at stake;
3. in *agents* and *environment* we define how the respective concept are applied in practice;
4. in *emergence* we identify which system-level phenomena truly emerge from individual traits;
5. in *interactions* we depict how the complexity of interactions is treated;
6. in *heterogeneity* we show how the diversity of the system elements is captured;
7. in *space and time* we describe the spatial and temporal dimensions, the process scheduling and the model initialization;
8. in *behaviour* we focus on how the model deals with behavioural complexity;
9. in *verification and validation* we look at the strategies used to understand the model performance and the ability to represent the system under study;
10. finally, in *technical aspects* we identify the implemented

programming languages and tools and other technical issues.

The main results of this classification effort are reported in table 2.

Table 2 – Comparative analysis of agent-based models of SES with climate change elements

3.1 Stream of research

This classification shows that the framework regarding the streams of research proposed in table 1 remains valid in the climate change arena. However, at this early stage there seems to prevail one distinct research question. More than half of the studies we analysed are concerned about the self-organization and co-evolution of the system. Not surprisingly, this is the stream that paved the way to the application of ABM to social processes, meaning that the first examples of ABM dealing with climate change are following the most consolidated path of development.

Conversely, in Berman et al. (2004) the model purpose is to project how local institutions shape human adaptation to hypothetical futures. In Bharwani et al. (2005) the focus is on the emergence of strategies over time as a part of a cultural process. In Barthel et al. (2008) the focal point is on the implications for water management, given the system specific structure. These are all examples of the stream of research on modelling organizations, cooperation, and collective management.

Two very different studies are concerned about diffusion processes and networks formation. Entwisle et al. (2008) considers social influence at a local scale and at an empirical level , while Beckenbach and Briegel (2009) is about the diffusion of innovation at a global scale and in abstract terms.

Janssen and de Vries (1998) and Beckenbach and Briegel (2009) are models where the agent's architecture is a research question per se. Grothmann and Patt (2005) could be added to this subset even though it is not exactly an ABM model.

The programming phase is generally made to be case specific. Only in one case (Mandel et al. 2009) a generic software is produced, which can be applied to case studies other than the German economy.

Parallel experiments are not diffused but in three cases they are utilized to substantially improve the credibility of the model. In Dean et al. (1999) and Mandel et al. (2009) this is achieved a posteriori through statistical means. In Bharwani et al. (2005) this is an iterative process based on the participation of the stakeholders.

3.2 System under study and climate issue

ABM shows abilities to model local, regional and global systems both at a very abstract or more realistic level. We can distinguish between two typologies of ABM dealing with climate change: (a) the majority, that focus on adaptation, analysing regional and local systems and (b) few global models, that are concerned about mitigation (Janssen and de Vries 1998; Hasselmann 2008; Mandel et al. 2009; Beckenbach and Briegel 2009). In the first case the level of detail is at the community (or network of communities) level. In the second case there is much more aggregation even if a certain degree of heterogeneity is introduced by means of the agent-based thinking. Notwithstanding the novelty of the methodology this dichotomy appears quite conservative with respect to the climate change literature. In no case adaptation and mitigation are treated together.

3.3 Agents and Environment

Agents can represent various human actors at different decisional levels. Very surprisingly households emerge as the main category of agents in the climate change arena, as if it was the basic unit of reference, independently from the scope.

In general the number of agent's types is limited, in order to control complexity. Most of the model employ 1 to 3 agent's classes. Werner and McNamara (2007) is an exception with seven types of agents, which exponentially increase the level of details and the heterogeneity complexity of the model.

The notion of environment is treated in a variety of ways. Very often these models rely on equations or indicators, which can be defined as sub-models describing theoretical spaces of interaction. Most of the models employ economic sub-models. In models dealing with land use and in Barthel et al. (2008) there is a significant correspondence between the landscape of the system under study and the environment of the ABM, however they also employ non-spatial sub models. The best example is Filatova (2009) in which the environment is constituted by the land market model where the price negotiation process and transactions take place and the by the cellular grid where the urban dynamics are represented.

3.4 Emergence

Emergence remains a central tenet of ABM dealing with climate change. Most of the models identify the economic outcome as an emergent property of the system. Other emergent properties are linked to demographic aspects and, where the spatial dimension is explicit, to land use patterns, which can be visualized on the grid. Those models that are concerned about mitigation look at carbon emissions as emerging from the system behaviour. The studies belonging to the stream on modelling organizations, cooperation, and collective management see these outcomes as a consequence of emerging behaviours.

3.5 Interactions

In the climate change arena, ABM is consistently employed in order to capture the complexity of interactions. With the exceptions of Janssen and de Vries (1998), Bharwani et al. (2005), Barthel et al. (2008) and Hasselmann (2008) models investigate interactions both among agents and between the agents and their environment. Most of the studies show interdependencies across spatial and temporal scales. In Berman et al.

(2004), Hasselmann (2008) and Mandel et al. (2009) interdependencies are particularly complex and can manifest with time lags and in form of feedback loops. In Entwisle et al. (2008) and Beckenbach and Briegel (2009) social influence is particularly crucial, given their main research question.

3.6 Heterogeneity

In contrast with the mainstream literature on climate change economics, with ABM the representative agent is avoided, even in those ground-breaking macroeconomic applications (Hasselmann 2008; Mandel et al. 2009). Agents can vary for demographic characteristics, location, own endowment, individual abilities, perception of the world, attitudes and behaviour. Clearly, the level of diversity is linked to the level of detail of the model and therefore this ABM ability can be more effectively employed in the local dimension. However, some degree of aggregation is always necessary. Heterogeneity can also concern the spatial attributes in those cases in which the model is spatially explicit, as in Dean et al. (1999), Werner and McNamara (2007), Barthel et al. (2008), Entwisle et al. (2008) and Filatova (2009).

3.7 Space and time

Notwithstanding the suitability of the methodology, in the climate change arena the spatial representation of the environment is not the prevailing option. More than half of the model considered are not spatially explicit. Not only those models which are dealing with the global system are aspatial but also some dealing with local adaptation (Berman et al. 2004; Bharwani et al. 2005). Instead, Dean et al. (1999), Werner and McNamara (2007), Barthel et al. (2008), Entwisle et al. (2008) and Filatova (2009) are spatially explicit and make use of cellular grids. However, in Filatova (2009) the space represented by the grid remains abstract, while in the rest of these spatially explicit models the space is based on a GIS capturing the real geography of the system under analysis. Dean et al. (1999) and Filatova (2009) implement CA, given the emphasis on neighbouring effects, as by definition of MAS/LUCC.
Most of the models are run for a time period of approximately 100 years, where every year is a time step. This is in average a time period of significance in order to capture climate change effects both in adaptation and mitigation terms. However, there can be exceptions in both directions. Dean et al. (1999) consider a 1000 years time period, given the archaeological value of their study. On the contrary Mandel et al. (2009) investigate a period of 40 years. In Beckenbach and Briegel (2009) time steps don't correspond to the years under consideration: a period of 30 years is simulated in 120 steps, in order to capture more details about the evolution of the system in the short to medium term. In Filatova (2009) time is abstract and follows market cycles.
Process scheduling can be programmed in a quite simple way, by executing

the full repertoire of activities for all the agents each year (e.g. Dean et al. 1999), or in a more complex manner. For instance, in Berman et al. (2004) the sequence of decisions to be taken by agents follows different time clocks for different activities. Demographic change, household formation, seasonal wage employment, and migration follow a five-year cycle. On the other hand, the model recomputes hunting activities dynamically five times per year.
Given the fact that the methodology shows a certain path dependency, initialization is a prime object of testing. Initialization is strictly linked to the model purpose. For example, in Filatova (2009) all land is assumed to be under agricultural use and the city centre is exogenously set. Conversely, Dean et al. (1999) is initialized with the available archaeological data while Berman et al. (2004) with parameters obtained from field work and local experts.

3.8 Behaviour

The prevailing options for modelling behaviour are: (1) goal oriented heuristic rules drawn from field work expressed in form of statements and (2) utility functions based on economic theory expressed in form of equations. The first are preferred in the most empirical studies such as Berman et al. (2004) and Bharwani et al. (2005) but there can be exceptions mixing different options (e.g. Hasselmann 2008). The two studies that are more concerned about the agent's architecture, Janssen and de Vries (1998) and Beckenbach and Briegel (2009), employ respectively a genetic algorithm (Holland 1992) and a satisficing rule (Simon 2000). Janssen and de Vries (1998) simulated a learning process where agents may change their mind when they are surprised by observations, and make adjustments in their decisions according to their new perception of the problem. In Beckenbach and Briegel (2009) the multiple-self nature of the economic actor feeds different forces each of which is directed in favour of a possible mode of action.
Other models insert elements of learning (e.g. Bharwani et al. 2005; Barthel et al. 2008) and genetic evolution (e.g. Mandel et al. 2009). In Bharwani et al. (2005) agents are endowed with the capacity of learning from previous experience so that they can modify their decision trees. In Barthel et al. (2008) each agent dispose of an history tracing successful and failed plan execution of previous time steps providing them with learning capabilities. In Mandel et al. (2009) agents update their belief according to information from the previous time step. On the long term, technologies and prices evolve genetically according to the profitability of firms. A genetic algorithm regulates any economic sector entry and exit, imitation and mutation.
On the behavioural side, it is worth noting that Berman et al. (2004) and Bharwani et al. (2005) also admit forms of collective adaptation in order to respond to harvest shortfalls.

3.9 Verification and Validation

ABM confirms it's main pitfall in validation and verification even in the climate change arena. Almost half of the literature that we considered simply don't treat the argument. This is mainly justified by the models' level of abstraction, which impose a serious limitation to achieve any form of model testing. In contrast, those models that employed parallel experiments (see section 3.1) definitely overcame this problem. In Dean et al. (1999) verification and validation are extensively treated. Many iterations involving altered initial conditions, parameters, and random number generators have been performed in order to assess the model's robustness. Graphical output of the model includes a map for each year of simulated household residence and field locations, which runs simultaneously with a map of the corresponding archaeological and environmental data. These paired maps facilitate comparison of historical and simulated population dynamics and residence locations in statistical terms. In Mandel et al. (2009) input-output tables are used for validation, comparing real data and simulations results. In Bharwani et al. (2005) the model is driven by data collected from the field in a bottom-up process. Verification and validation, in accordance with the "French school", are achieved through the feedbacks deriving from the iterative inclusion of stakeholders by means of interviews, questionnaires and role games.

The remaining models are not fully satisfying from this point of view even if some have produced significant efforts. In Barthel et al. (2008) the means of verification and validation that have been applied are indirect and not of numerical type, including expert knowledge and consumer experiences. Filatova (2009) compare the model outcomes to the results deriving from other theories. In particular the land market model has been able to replicate qualitative properties of the standard equilibrium-based monocentric urban market model. Berman et al. (2004) achieve statistical verification by means of Monte Carlo simulations.

3.10 Technical aspects

Almost half of the models that we considered make use of an ABM platform. Three of them used Repast, one Netlogo and one Vensim, which is more appropriate for system dynamics but includes some agent-based features. Four models are programmed from scratch making use of a all set of different languages including Object Pascal, Visual Basic, UML and JAVA. As expected OOP turns out to be a real mainstream with regards to the implementation of ABM.

Quite surprisingly, Janssen and de Vries (1998) and Werner and McNamara (2007) only rely on mathematical equations. This proves the ability of ABM to be expressed in mathematical terms even if maths is not the ABM natural environment.

4. Conclusions

This paper reviewed the state of the art in ABM. We were interested in understanding how consolidated is this approach in dealing with the complexity of the coupled human-environment systems. More specifically, we wanted to investigate whether if ABM could be an innovative but sound methodology to model the dynamics of SES exposed to climate change and assess the related policies.

Our analysis suggests that ABM is today a quite consolidated interdisciplinary approach. In particular we showed that, at the theoretical level, the research questions are the same across social, economic and environmental applications. We were able to identify six main research purposes that we called the streams of research of ABM, as reported in section 2. The resulting framework can be used to categorize any ABM effort belonging to any sustainability dimension. This may support Boulanger and Bréchet (2005) who concluded that ABM is the most promising modelling approach for sustainability science. The intrinsic trans-disciplinarity of the methodology certainly justifies its application to the modelling of SES, where the human and the environmental systems co-evolve and a significant integration of the knowledge belonging to different domains is needed.

Past research often regarded ABM as bottom-up methodology alternative to top-down equilibrium-based models but, to our knowledge, few publications have some relevancy in the climate change arena. Therefore, we reviewed those agent-based models of SES which included some kind of climate change related issue in order to clarify how the main ABM elements are applied, according to the systems under analysis. Our analysis, in section 3, described how the notions of agent, environment, emergence, interaction, heterogeneity, space and time, behaviour and validation are treated in each study, including the computing languages, tools and platforms used for the simulations. The results support the idea that ABM is an appropriate bottom-up methodology for the exploration of climate policies.
ABM seems particularly well suited to the analysis of adaptation to climate change of local systems. Applications of this type spawn across all the streams of research of ABM composing the main body of work on agent-based models dealing with climate change. Households are the most crucial agents while the environment is the natural and economic landscape that can be expressed in spatially explicit terms and/or in form of sub-models describing theoretical spaces of interaction.
Surprisingly ABM also shows the possibility to be employed in more top-down orientations where the main issue is mitigation at a global level. Few ground-breaking studies are showing the way to insert agent-based thinking into macroeconomic models overcoming some unrealistic aggregative simplifications of traditional equilibrium models. One possible direction for further development of ABM research on climate change is the joint analysis of mitigation and adaptation.

In addition to the expected qualities of the methodology, i.e. the emergence of outcomes at the macro-level from micro-interactions, some specific

strengths of ABM are particularly meaningful when dealing with climate change. The main advantages of ABM applied to climate change related issues are the abilities to take into account adaptive behaviour at the individual or system level and to introduce a higher degree of heterogeneity resulting into a more natural representation of the system, compared to equilibrium-based models.
In the climate change arena adaptive behaviour means the possibility to enable the SES to react, which is crucial in order to avoid unrealistic or meaningless results. At this early stage, behavioural architectures are mainly based on heuristic rules and on utility theory. More specific architectures exist but are not often employed.
Heterogeneity is another particularly relevant aspect, because people have different perceptions of the risk, environmental sensitivities, capacity to cope with change and so forth. Neglecting this diversity may lead to missing some crucial driver of change. ABM effectively shows the ability to overcome this problem.

The main disadvantage of ABM, as in other domains of application, stays in the challenges of testing the model which is not always very clear and often neglected. Where feasible participatory approaches seem the most suitable solution. For this reasons local applications may appear more robust. Further research is needed to consolidate ABM applications to the global system.

Two open issues should finally be highlighted and are related to programming and documenting agent-based models.
While there already exist various ABM packages and tools that can be employed in this field (e.g. Repast and NetLogo), it makes sense to think about a dedicated platform, for the future, which could simplify the modelling options into local and global systems and posses a library of household type agents and of specific socio-cognitive models of adaptation. This would certainly improve the accessibility of the methodology to those who cannot spend too much time in learning a programming language.
Finally, a communication barrier remains evident. While our specification effort in table 2 may be more appropriate to explain the models to a public not trained on ABM, we also felt the need to find a common communication standard of the models we were analysing. We therefore recommend to the modellers to take into account a protocol such as in Parker et al. (2001) and/or Grimm et al. (2006) for their future publications.

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Table 1 – Classification of references according to scientific domain and stream of research

ABM Streams \ Domains		Social	Economic	Environmental
ABM Main Research Questions	**Self-organization and co-evolution of the system (SOCES)**	Schelling (1971) Epstein & Axtell (1996)	Marks (1992) Arthur et al. (1996) Bower & Bunn (2001) Hommes (2002)	Bousquet et al. (1993) Deadman & Gimblett (1994) Kohler & Carr (1996) Balmann (1997) Torrens (2001) Parker & Meretsky (2004)
	Diffusion processes and networks formation (DPNF)	Latane (1996) Nowak & Vallacher (1998) Rosenkopf & Abrahamson (1999)	Albin & Foley (1992) De Vany & Lee (2001) Tesfatsion (2001) Janssen & Jager (2002)	Rouchier et al. (2001) Berger (2001) Deffuant et al. (2002)
	Modelling organizations, cooperation and collective management (MOCCM)	Axelrod & Hamilton (1981) Cohen et al. (2001) Takahashi (2000) Cecconi & Parisi (1998)	Prietula et al. (1998)	Lansing & Kremer (1993) Barreteau & Bousquet (2000) Becu et al. (2003) Feuillette et al. (2003) Mathevet et al. (2003)
ABM Accessories and Tools	**Parallel experiments (PE)**	Lomi & Larsen (1998) Carley (1996)	Arthur (1993) Chan et al. (1999)	Bousquet et al. (1999) Barreteau et al. (2001) Guyot & Honiden (2006)
	Agent's architecture (AA)	Rumelhart & McClelland (1986) Holland (1992)	Booker et al. (1989) Dawid (1996) Chattoe-Brown (1998) Gintis (2000) Vriend (2000) Bell (2001) Luna (2002)	Reynolds (1987) Drogoul & Ferber (1994) Wooldridge & Jennings (1995) Grand & Cliff (1998) Deffuant et al. (2000) Manson (2005)
	Programming (P)	Terna (1998) Gilbert & Bankes (2002) Tobias & Hofmann (2004)	Luna & Stefansson (2000)	Savage & Askenazi (1998) Le Page et al. (2000) North et al. (2006) Railsback et al. (2006)

Table 2 – Comparative analysis of agent-based models of SES with climate change elements

Reference	Stream of research	System under study[1]	Climate issue[2]	Agents[3]	Environment[4]	Emergence[5]	Interactions[6]	Heterogeneity[7]	Space / Time[8]	Behaviour[9]	Verification and Validation	Technical aspects
Janssen & de Vries (1998)	SOCES & AA	GL	CE	DM	Economy-energy-climate model	EO, CE	A-E	Agent's cultural perspectives	Aspatial; 100 years	GA	Absent	Mathematical equations
Dean et al. (1999)	SOCES & PE	LL Arizona (US)	R	HH	SCG and production model	PLUC	A-E, A-A	Agent's age, location and grain stocks; SA	CA, GIS based; 1000 years	HR	Statistical	Programmed in Object Pascal
Berman et al. (2004)	MOCCM	LL Canada	T, SP	I, HH	Environmental, economic and social indicators	EO and demographic change	A-E, A-A	Agent's age, HH type, education, wage-work and hunting-time capabilities	Aspatial; 40 years; complex scheduling	HR; CR	Statistical verification	Programmed in Visual Basic
Bharwani et al. (2005)	MOCCM & PE	LL South Africa	F, D	Farming HH	Planting fields and market place model	Crop yields and food security	A-E	Agent's wealth, crop type, location and timing	Aspatial; 100 years	Decision tree rules; LA; CR	Participatory	Repast
Werner & McNamara (2007)	SOCES	LL Georgia (US)	F, H	7 sets of economic agents	Economic model and landscape model	PLUC	A-E, A-A	Agent's types, prediction models and utility functions; SA	GIS re-sampled on a 100 x 100 grid; ~200 years	U functions	Absent	Matlab
Barthel et al. (2008)	MOCCM	CRL Germany	T, R	HH, C, F	SCG	Water supply and consumption	A-E	Agents' type, location, level, behaviour, preferences and plans; SA	1x1 km cells, GIS based; 100 years	U based decision rules and LA	Partial Participatory	DeepActor programmed in UML 2.0
Entwisle et al. (2008)	DPNF	CRL Thailand	R, F, D	I, HH, C	SCG and social networks	Migration, social connections and PLUC	A-E, A-A	Agent's demography, wealth, social ties; SA	GIS based grid; time not specified	Probability rules	Under development	Repast
Hasselmann (2008)	SOCES	GL	T, CE	F, HH, Banks, DM	Three levels macroeconomic model	EO, CE	A-E	Environment levels, agent's objectives, physical units	Aspatial; 100 years	HR	Absent	Vensim
Beckenbach & Briegel (2009)	DPNF & AA	GL economy	CE	F	Sectoral demand model and inter-sectoral input/output tables	EO, CE	A-E, A-A	Agents' prevailing force among innovation imitation routine	Aspatial; 120 time steps equal to 30 years	Satisficing rules balancing different goals	Absent	Repast
Filatova (2009)	SOCES	LL Holland	F	HH, land owners	SCG and Land market model	Land prices and PLUC	A-E, A-A	Agents' location preferences , individual budget, risk perception; SA	CA, 35 x 63 cells; abstracts space and time	U maximization	Structural	NetLogo
Mandel et al. (2009)	SOCES & PE & P	CRL German economy	CE	HH, F, DM, Financial system	Economic process as schedule of events	EO, unemployment, wages.	A-E, A-A	Agents' type, economic activities, time steps	Aspatial; 40 years	HR, GA	Statistical	Lagom generiC programmed in Java

Notes to table 2:

[1] Global Level (GL), Country or Regional Level (CRL), Local Level (LL). [2] Carbon Emissions (CE), Temperature (T), Rainfall (R), Snow Precipitations (SP), Floods (F), Droughts (D), Hurricanes (H). [3] Households (HH), Individuals (I), Decision Makers (DM), Communities (C), Firms (F). [4] Spatial Cellular Grid (SPG). [5] Economic Output (EO), Patterns of Land Use and Cover (PLUC). [6] Agent-Environment (A-E), Agent-Agent (A-A). [7] Spatial Attributes (SA). [8] Cellular Automata (CA), Geographical Information Systems (GIS). [9] Heuristic Rules (HR), Utility (U), Learning Algorithm (LA), Genetic Algorithm (GA), Collective Response (CR).