Modeling Human Decisions in Coupled Human and Natural Systems: Review of Agent-Based Models

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Abstract

Coupled human and natural systems (CHANS) manifest various complexities such as heterogeneity, nonlinearity, feedback, and emergence. Humans play a critical role in affecting such systems and in giving rise to various environmental consequences, which may in turn affect future human decisions and behaviors. In light of complexity theory and its application in CHANS, this paper reviews various decision models used in agent based simulations of CHANS dynamics, discussing their strengths and weaknesses. This paper concludes by advocating development of more process-based decision models as well as protocols or architectures that facilitate better modeling of human decisions in various CHANS.

Keywords: Agent-based modeling; human decision making; coupled human and natural systems; review.

1. Introduction

Human-nature systems used to be studied in separation, either as human systems constrained by or with input from/output to the natural environment, or as natural environment systems subject to human disturbance. This chasm between ecological and social sciences, along with such unidirectional connections between natural and human systems, has hindered better understanding of complexity (e.g., feedback, nonlinearity and thresholds, heterogeneity, time lags) in coupled human and natural systems (CHANS; Liu et al., 2007). This context has given rise to many empirical research efforts in studying CHANS, emphasizing the aforementioned complexity features.

Synthetic analysis of such research efforts has revealed the multi-scalar and cross-disciplinary nature of much empirical CHANS related research (e.g., Bian, 1997; Phillips, 1999; Walsh et al., 1999; Manson, 2008) as well as many similar complex phenomena shared by many CHANS systems. For instance, the above complexity features were documented at six sites in the world (Liu et al., 2007). Corroborating evidence for these features also comes from empirical work in the Amazon (Malanson et al., 2006a, 2006b), the southern Yucatán (Manson 2005), Wolong Nature Reserve of China (An et al., 2005, 2006), Northern Ecuador (Walsh et al., 2008), and other places around the world. Indeed, such complexity has been the subject of an emerging discipline: complexity theory.

1.1 Complexity Theory

Partially originating from general systems theory (von Bertalanffy, 1968; Warren et al., 1998), complexity theory has been developed with input from fields such as physics, genetic biology, and computer science. Recently receiving considerable attention (Malanson, 1999; O'Sullivan, 2004), this line of research focuses on understanding complex systems (or "complex adaptive systems"). Such systems are presented as intermediate systems between small-number systems (where mathematical approaches such as differential equations are often adequate) and large-number systems (usually represented or described by statistical models such as regressions; Bousquet and Le Page, 2004). Complex systems usually encompass heterogeneous subsystems or autonomous entities, which often feature nonlinear relationships and multiple interactions (e.g., feedback, learning, adaptation) among them (Arthur, 1999; Axelrod and Cohen, 1999; Manson, 2001; Crawford et al., 2005).

Complexity can be manifested in many forms, including path-dependence, criticality, self-organization, emergence of qualities not analytically tractable from system components and their attributes alone, and difficulty of prediction (Solé and Goodwin, 2000; Manson, 2001; Bankes, 2002). Hence researchers have suggested placing more emphasis on understanding and improving the system of interest rather than fully controlling the system or seeking the “orderly and predictable relationship between cause and effect” (Solé and Goodwin, 2000). It is suggested that rather than being treated as a cure-all solution, the complex systems approach be employed as a systematic paradigm to harness (but not ignore or eliminate) complexity and take innovative action to steer the system in beneficial directions.

Even with the above theoretical advancements and technical development (ABM in particular; see below), complexity theory is still considered to be in its infancy, lacking a clear conceptual framework and unique techniques, as well as ontological and “epistemological corollaries of complexity” (Manson, 2001; Parker et al., 2003; Grimm et al., 2005; Manson and O’Sullivan, 2006).

1.2 Agent-based modeling

Like cellular automata (Batty et al., 1994, 1997; Clarke and Gaydos, 1998; Malanson et al., 2006a, 2006b), agent-based modeling (ABM) has become a major bottom-up tool that has been extensively employed to understand the above complexity in many theoretical (e.g., Epstein and Axtell 1996; Axelrod, 1999; Axtell et al., 2002) and empirical (see Section 1.3) studies. What is an agent-based model? In the terms of Farmer and Foley (2009), “An agent-based model is a computerized simulation of a number of decision-makers (agents) and institutions, which interact through prescribed rules." The ABM method has a fundamental philosophy of methodological individualism, which advocates a focus on uniqueness of individuals and interactions among them, and warns that aggregation of individuals may give rise to misleading results (Gimblett, 2002; Bousquet and Le Page, 2004).

Agent-based modeling has an intellectual origin from a computer science paradigm called object-oriented programming, which has become popular since the 1980s with the advent of fast computers and rapid advancement in computer science. This paradigm "groups operations and data (or behavior and state) into modular units called objects" (An et al., 2005), and lets the user organize objects into a structured network (Larkin and Wilson, 1999). Each object carries its own attributes (data) and actions (methods) with a separation between interface and implementation (technical details). This separation hides technical details (parts of a clock) inside the system surface (interface of the clock; Figure 1). The "implementation" feature makes the system work, while the user-friendly interface running above the system details "provides simple data input, output, and display functions so that other objects (or users) can call or use them" (An et al., 2005).

[Figure 1 approximately here]

The ABM approach has also benefited abundantly from many other disciplines, which are still fertilizing it. Among these disciplines, research on artificial intelligence (AI) is noteworthy, in which multiple heterogeneous agents are coordinated to solve planning problems (Bousquet and Le Page, 2004). Also contributing to ABM development is artificial life research, which explores "life as it might be rather than life as it is" (Langton, 1988). Many social sciences are also nourishing ABM. For instance, rationalized strategies of agents are developed in cognitive psychology and game theory; sociology is credited with defining modes of and modeling interactions between agents and the environment interactions (Bousquet and Le Page, 2004). In studying social behavior and interactions, ABM usually starts with a set of assumptions derived from the real world (deduction), and produces simulation-based data that can be analyzed (induction). Hence Axelrod (1997) considers ABM as a "third way" in scientific research, which complements the traditional inductive and deductive approaches.

ABM has been used to predict the phenomena of interest (although some scholars may doubt its usefulness in complex systems; e.g., Couclelis 2001), to understand the system under investigation, and to answer many "what if…" questions using the ABM as a "virtual landscape lab for conducting numerical experiments" (Seppelt et al. 2009). ABM also facilitates theorizing based on observations, e.g., comparing ABM outcomes to mathematical models. Despite these strengths, ABMs face limitations such as lack of predictive power at low levels, difficulty in validation and verification (Lempert, 2002; Parker et al., 2003; Matthews et al., 2007), and shortage of effective architectures and protocols (e.g., graphic languages, scale and hierarchy definitions) to represent agents and their interactions need (Bousquet and Le Page, 2004). Particularly, learning processes (part of or precursor of decision making) of many decision makers in the real world are poorly represented in many ABMs (Bousquet and Le Page, 2004).

1.3 Complexity Research in CHANS

The application of complexity theory and its major tool ABM in CHANS is still relatively recent, which can be largely summarized in three threads. The first is the thread of individual-based modeling (IBM) in ecology. This line of research started in the 1970s and advanced in the 1980s, characterized by relatively "pure" ecological studies (thus not CHANS studies in a strict sense) that have contributed to later CHANS related ABM development. Exemplar work includes the bee colony work (Hogeweg and Hesper, 1983), research on *animats* (agents that are located in space and may move or reproduce; Wilson 1987; Ginot et al., 2002), research on "Boids" by Reynolds (1987), and sparrow research by Pulliam et al. (1992). Even though IBM and ABM are considered largely equivalent, some features differentiate one from the other. While IBM focuses more on role of heterogeneity and uniqueness of individuals, ABM, with substantial contribution from computer science and social sciences, gives more attention to decision-making process of agents and their contextual social organizations (Bousquet and Le Page, 2004).

The second thread of ABM use in CHANS is characterized by conceptual or theoretical tests in social science fields (e.g., “thought experiments”). Work under this domain has become popular since the 1970s, including the segregation models of Sakoda (1971) and Schelling (1971), the prisoners’ dilemma for testing cooperative strategies (Axelrod and Dion 1988), and emergence from social simulations (e.g., the SugarScape model; Epstein and Axelrod, 1996). Such efforts, usually made in virtual environments, feature *ad hoc* rules that are used to test ‘what if’ scenarios or explore emergent patterns. Efforts were also invested to answer archaeological questions using ABM, such as how/why certain prehistoric/ ancient people abandoned their settlements or adapted to changing environment (e.g., Axtell et al., 2002; Kohler et al., 2002; Altaweel, 2008; Morrison and Addison, 2008). Such efforts, closely related to explorations in game theory and complex adaptive systems (CAS), are precursors of modeling empirical CHANS below.

The third and last thread features applying ABM to realistic CHANS based on empirical data, which is usually coupled with cellular models (e.g., cellular automata) to spatially represent the environment. In tandem with the above theoretical advancements, empirical support, especially data about human systems, is considered essential in advancing our understanding of complex systems (Parker et al., 2003; Veldkamp and Verburg, 2004). Recent years has witnessed considerable work devoted to the advancement of complexity theory and application of ABM in CHANS (e.g., Benenson, 1999; Grimm, 1999; Irwin and Geoghegan, 2001; Gimblett, 2002; Henrickson and McKelvey, 2002; Deadman et al., 2004; Evans and Kelly, 2004; An et al., 2006; Crawford et al., 2005; Fernandez et al., 2005; Goodchild, 2005; Grimm et al., 2005; Messina and Walsh, 2005; Sengupta et al., 2005; Portugali, 2006; Uprichard and Byrne, 2006; Wilson, 2006; Ligmann-Zielinska and Jankowski, 2007; Brown et al., 2008; Yu et al.

2009), including urban systems (Batty 2005). This is further evidenced by multiple complexity theory sessions at the annual conferences of the Association of American Geographers (AAG) in recent years, the NSF-sponsored International Network of Research on Coupled Human and Natural Systems (CHANS-Net), and six CHANS related symposia held at the 2011 AAAS annual meeting in Washington, D.C.

Several major advantages credited to ABM have made it powerful in modeling CHANS systems. First, ABM has a unique power to model individual decision making while incorporating heterogeneity and interaction/feedback (Gimblett, 2002). A range of behavior theories or models, e.g., econometric models and bounded rationality theory (to be reviewed later), can be used to model human decisions and subsequent actions. Second, ABM is able to incorporate social/ecological processes, structure, norms, and institutional factors (e.g., Hare and Deadman 2004). Agents can be created to carry or implement these features, making it possible to "put [putting] people into place (local social and spatial context)" (Entwisle 2007). This complements the current GIS functionality, which focuses on representing form (i.e., "how the world looks") rather than process (i.e., "how it works"; Goodchild, 2004). This advantage makes it technically smooth to couple human and natural systems in an ABM.

CHANS, largely similar to social-ecological systems (SESs) by Ostrom (2007), may have many human and nonhuman processes operating at multiple tiers that are hierarchically nested (Ostrom, 2009). "Without a common framework to organize findings, isolated knowledge does not cumulate" (Ostrom, 2009), preventing effective addressing of the above complexity. ABM is credited with having the flexibility to incorporate multi-scale and multi-disciplinary knowledge, "co-ordinate a range of qualitative and quantitative approaches" (Bithell et al. 2008), and mobilize the simulated world (An et al., 2005; Matthews et al., 2007). Consequently, agent-based modeling is believed to have the potential to facilitate methodologically defensible comparisons across case study sites. For example, ABM was used to synthesize several key studies of frontier land use change around the world (Rindfuss et al., 2007).

1.4 Modeling Human Decision Making in CHANS

In the process of truly coupling the human systems and natural systems within any CHANS, the importance of understanding how human decisions are made and then put into practice can never be exaggerated (Gimblett 2002). Human decisions and subsequent actions would change (at least affect) the structure and function of many natural systems. Such structural and functional changes would in turn exert influence on human decisions and actions. Nonetheless, seeking fundamental insights into human decision or behavior, though of paramount value, is beyond the scope of this paper (even beyond the scope of one discipline). The goal of this paper is to review what and how existing understanding of human decision-making and behavior has been used to model human decisions in CHANS. It is hoped that this review will benefit CHANS researchers by shedding light upon the following perspectives (objectives of this paper):

a. What methods, in what manner, have been used to model human decision-making and behavior?
b. What are the potential strengths and caveats of these methods?
c. What improvements can be made to better model human decisions in CHANS?

Given the previously mentioned characteristics of complex systems, especially those in CHANS, as well as the power of ABM in modeling and understanding human decisions, this paper limits the review to how human decisions are modeled in recent CHANS related ABM work.

2. **Methods**

To achieve the above goal and the specific objectives, a collection of articles was assembled through two approaches. The first approach is a search on Web of Science using the following combination of key words: Topic=((Agent based modeling) or (multi-agent modeling) or (agent based simulation) or (multi-agent simulation)) AND Topic=((land use) or (land cover) or geography or habitat or geographical or ecology or ecological) AND Topic=((human decision making) or (environment or environmental)).

The first topic defines the tool of interest: only work using agent-based modeling for the reason discussed above. Given that different authors use slightly different phrasing, this paper incorporated the most-commonly used alternative terms such as multi-agent simulation. The term "individual based modeling" was not used as one of the key words because as a term predominantly used by ecologists, it involves work largely in the "purely" ecological domain and rarely contains research directly related to human decisions in CHANS. The second topic restricts the search to be within areas of land use and land cover change, geography, and ecology[1]. This decision is based on our interest in work in these areas that characterize research related to CHANS systems.

The third topic reflects the major interest of this paper, which relates to human decisions that give rise to environmental consequences. We also include papers on all human-related agents, e.g., individual persons, households, or groups. This paper did not use "AND" to connect the two parts because this is too restrictive and many relevant papers (including several renowned ones of which the author is aware) are filtered out.

The second approach is complementary to the first, which assembles articles through the author's personal archive that has been established since 2002. This archive also includes relevant books or book chapters that are not in the database on Web of Science, but the author knows (in regard to using ABM in CHANS). These papers, books, or book chapters assembled in the past nine years are also used to evaluate the completeness of the above online search.

[1] Keywords like "anthropology" or "archaeology" are not used simply because doing so increases the number of papers found and most of them are not relevant to the topic of this paper. Without using such keywords some papers have still been found that are related to using ABM to study anthropologic phenomena such prehistoric settlement (see Section 1.3).

3. Results

According to the above online search, 155 articles[2] were found to be published on the topics of interest from 1994 to 2010. Out of these 155 articles, 69 were beyond our planned scope (e.g., in pure ecology or cell biology), i.e., they do not fit the above criteria (expressed by the above keywords). From the second approach, a total of 28 publications (i.e., papers, book chapters, or books) were found. Therefore a total number of 114 publications were included in this review, which comprises the reference list.

Under these search criteria, it appears that ecologists and geographers take the lion's share in CHANS related ABM work. The top six journals were Ecological Modelling (11), Environmental Modelling & Software (11), Environment and Planning B (6), Geoforum (6), Agriculture, Ecosystems & Environment (5), and Journal of Environmental Management (5). The publications in this domain have increased linearly from 1994 to 2010 (Figure 2). This article did not include the counts in 2011 (2 till the submission of this paper in February) because many are still incoming and thus unable to be included.

[Figure 2 approximately here]

Before getting to the major findings, it is important to introduce how data related to human decisions are collected as well as how agents are characterized. Data collection for agent-based models, especially for modeling real CHANS, is usually very time-consuming and sometimes considered as a drawback of this approach (Gimblett 2002). Various means, such as direct observations (e.g., Miller et al. 2010), surveys or interviews (e.g., Saqalli et al. 2010), government archives (e.g., An et al. 2005), remote sensing and GIS (e.g., Brown et al. 2007), and/or statistical census or surveys were used to acquire data

[2] If "individual based modeling" is added as part of the search key words, 308 papers are found and vast majority of these added 153 papers have nothing to do with human decision making and are thus considered irrelevant.

that facilitate modeling human decisions. When data are readily collected, agents in related CHANS models were usually assigned with real data collected at the same level (e.g., An et al., 2005) or data sampled from aggregate (statistical) distributions or histograms (usually available from a higher level such as population; Miller et al. 2010). In modeling land use decisions, data are often only available at the latter (aggregate) level (Parker et al. 2008).

Overuse of aggregate distributional or histogram data may risk losing the strength of ABM because such data may lead to average "agents". Heterogeneity of agents plays a critical role in deciding how agents interact, feedback, react, and adapt (Matthews et al., 2007). Also such overuse may lead to hidden or implicit conflicts between those characteristics assigned to agents, e.g., a newly established household assigned to be located at a high elevation (near the maximum in the survey data) may be also "given" a large amount of cropland, which is not very likely to happen in the panda reserve of An et al.'s (2005) model. To some degree, attention to correlation among variables can avoid this problem (Zvoleff in preparation).

Below a total of nine types of decision models (each type as one subsection) are summarized and presented based on my review of the set of articles in relation to modeling human decision in CHANS. A certain paper may use multiple decision models, and this review does not intend to identify and recognize all of them. Instead, this article aims to extract generic decision models that are typically used in CHANS related ABMs. Also worthy of mention is that decision models and decision rules are used interchangeably. Although actions, behaviors, and decisions are not exactly equivalent (e.g., an action may come out as a result of a decision), these terms are used also interchangeably in the context of the above goal and objectives (Section 1.4).

3.1 Microeconomic models

Here the microeconomic models (or rules) refer to the ones that are usually used for resource related decisions. Agents make decisions to maximize certain profit, revenue, or rate of profit (e.g., Plummer et al., 1999) associated with various optional activities such as transactions, renting, and inheritance of a certain product or resources (e.g., Parker and Meretsky, 2004; Purnomo et al. 2005; Evans et al., 2006; Fowler, 2007; Acevedo et al. 2008; Evans and Kelley, 2008; Li and Liu, 2008; Milington et al., 2008; Filatova et al. 2009; Gibon et al., 2010; Miller et al., 2010). In many instances, certain more abstract utility (e.g., Cobb–Douglas utility function; see Chiang, 1984), consumption, or aspiration (e.g., Simon 1955; Gotts et al., 2003) functions are used in place of monetary income. These functions often take an additive or exponential form of a weighted linear combination of many criteria under consideration (e.g., Jager et al., 2000; Brown et al., 2004, 2006; Bennett and Tang, 2006; Liu et al., 2006; Zellner et al., 2008; Chu et al., 2009; Le et al. 2008, 2010). With such utility definition, it is possible to calculate the probability of an agent's choosing one option (e.g., one site or one opportunity) as the probability that the utility of that option is more than or equal to that of any other option based on the McFadden's theorem (McFadden 1972).

Whatever is in use, the agents are assumed to make rational choices. It is believed that in real world, such choices or decisions are usually affected, constrained, or bounded by imperfect resources (including knowledge and information) or limited ability to make use of such resources (Bell et al., 1988; Simon, 1997). This line of bounded rationality can also be seen from the literature of behavioral decision theory, which posits that agents should be limited in their environmental knowledge, and their decisions should be made relatively simply. Furthermore, agents tend to seek satisfactory rather than optimal utility when making relevant decisions (Kulik and Baker, 2008).

Numerous empirical studies fall into this category of microeconomic models. Examples include the land use agents who choose sites for various land use purposes (Brown and Robinson, 2006; Brown et al., 2008; Revees and Zellner, 2010), the farmers who choose sites and routes to collect fuelwood (An et al., 2005), and land buyers in a coastal township who search for the location that maximizes their utility function constrained by their budget (Filatova et al., 2011). Variants include calculation of a preference function for a particular land use at a location (Ligtenberg et al., 2010; Chu et al., 2009). All these examples are characterized by one common feature: computing a certain utility (could also be named Potential Attractiveness; Fontaine and Rounsevell 2009) value for available options and then choosing the one with the best (maximum or minimum) value.

3.2 Space theory based models

Geographic theories treat distance differently. Absolute distance between locations is often considered when individuals make decisions, giving rise to theories of absolute space. Christaller's central place theory (Christaller 1933) and von Thünen's circles of production (von Thünen 1826) belong to this set of theories. When household agents evaluate candidate sites for their residential location in the HI-LIFE model (Household Interactions through LIFE cycle stages; Fontaine and Rounsevell 2009), the Euclidean distances to the closest physical and social features (e.g., the main road network, train stations, key service areas, large cities) are incorporated in calculating each site's Potential Attractiveness (PA). Distances to the-like physical and social features (e.g., peace and order situation) are also considered in the agent-based models of Loibl and Toetzer (2003), Brown et al. (2004), Huigen et al. (2006), and Li and Liu (2008).

The characteristics of a certain location in space (e.g., slope) as well as its location relative to other locations also affect the "attractiveness" (Loibl and Toetzer, 2003) of a certain site, thus affecting individual agents' choice of location for a certain purpose. This accounts for the theories of relative space. For instance, the environmental amenities (e.g., closeness or availability of coastlines, water bodies, and green areas such as national parks) belong to the relative space consideration (Brown et al., 2004; 2008; Yin and Muller, 2007; Fontaine and Rounsevell 2009).

Under these two lines of theory, an agent "calculates" the suitability of a given location for a certain purpose as a function of variables that represent both absolute and relative locations (Manson 2006). There is certain degree of arbitrariness in choosing the (usually linear) relationships between the decision(s) and the related distance variables. Also more justification is needed for the arbitrary (usually equal) weights of different distance variables (e.g., Loibl and Toetzer, 2003).

3.3 Cognitive models

Agents make decisions based on their own cognitive maps (e.g., concepts) or abilities (e.g., memory, learning, and innovation), beliefs or intentions, aspirations, reputation of other agents, and social norms (e.g., Simon, 1955, 1960; Ligtenberg et al., 2004; Fox et al., 2002). There are a few models along this line that are worth mentioning as they aim to "[represent] the net effect of people's thought processes" (Bithell et al., 2008).

First, the actor-centered structuration theory states that actors influence, and simultaneously are influenced by, social structures, which reflects the concept of duality of structure (Giddens, 1984). Structuration theory conceptualizes a recursive social reproduction, which is in line with what is termed as circular causality in many complex adaptive systems such as CHANS (Janssen and Ostrom, 2006; Feola and Binder, 2010). Another related theory is the theory of interpersonal behavior, which posits that intentions, habit, physiological arousal, and contextual factors exert impacts on agent decisions (Triandis, 1980). In one example inspired by these two theories, an Integrative Agent-Centered Framework was developed to predict potato producers' pesticide use in Boyacá, the Colombian Andes. Binomial and multinomial logistic regressions were carried out to derive probability of using certain pesticides based on survey data that represent contextual (e.g., socio-economic and political) factors, habit of performing the act of interest, behavioral intention, and physiological arousal variables (Feola and Binder, 2010).

Second, fuzzy cognitive maps (FCM) are potentially very useful in modeling human decisions and behavior in CHANS. The FCMs, derived from cognitive maps that were originally introduced by psychologists to model complex human or animal behaviors (Tolman, 1948), are graphs that contain a set of nodes (concepts) and a set of directional edges (each edge representing the influence of a concept on another). FCMs are more used to describe and compute agent behavior in biological or ecological studies (e.g., predator-prey simulation, Gras et al. 2009). FCM related empirical research devoted to simulating human-environment interaction in CHANS has been minimal.

Third and last, computational organization theory is also potentially useful in modeling human decisions in CHANS. With input from social psychology, this theory claims that individual agents learn about their environments along pre-conceived biases, and influence other peer agents to adopt the same biases (Weick, 1979). Chen et al. (2011; this issue) report that a 10% reduction in neighboring households who participate in a conservation program, regardless of reasons, would decrease the likelihood that the household would participate in the same program by an average of 3.5 %. At the Caparo Forest Reserve in Venezuela, land occupation decisions are strongly influenced by imitation and social learning among individual landowners as a way to secure a "better way of life" (Teran et al. 2007).

Along this line, more research should be devoted to the role of social networks in affecting human decisions. The quality of social network (e.g., some members in the network have higher influences on other members) may determine how actions may arise from interactions (e.g., Barreteau and Bousquet, 2000; Acosta-Michlik and Espaldon 2008). Also in understanding recreational decisions, cognitive assessment models (e.g., Kaplan’s Information Processing Model; Kaplan and Kaplan 1982) are useful.

They provide fundamental understanding of how humans evaluate landscape quality and make subsequent decisions (Deadman and and Gimblett 1994).

3.4 Institution-based models

To a large extent, such models are inextricably linked to the above cognitive models because institutions can be considered as a special type of social norm that is established through law or policy. Institutions can explain why there are similarities across agents. Institutional theory postulates that agents in the same environment copy each other either because they are forced to (government regulation) or to gain legitimacy from copying other same-environment members' strategies (DiMaggio and Powell, 1983). For example, a person agent may consider marriage at a certain probability at the age of 22, the minimum age for marriage legally mandated in China (An et al., 2005). In another CHANS, the household agents could not perform their production activities outside their own ejidos (land management and ownership units) or sell land to outsiders before the neoliberal policy shift in the southern Yucatán (Manson, 2006).

Institutions may take a number of forms. In modeling location and migration decisions of firms (agents), subsidies, tax reductions, and/or environmental standards (enforced by governments) play a critical role in impacting the mobility of small and medium size firms (Maoh and Kanaroglou 2007). The pastoralist enterprises in Australian rangelands, through conforming to policies from governments and/or land brokers, may adopt different strategies (e.g., selling, destocking, or restocking cattle; Gross et al. 2006). In the simulation model of whale-watching tours in the St. Lawrence Estuary in Quebec, Canada, boat agents are required by regulation to share whale location information among other agents (Anwar et al. 2007). Buyer and seller agents make land transactions, subject to local policy and regulations (e.g., minimum parcel size), in the process of seeking maximum economic returns (Lei et al. 2005).

3.5 Experience- or preference-based decision models (rules of thumb)

Experience- or preference-based decision models are usually effective real-world strategies that can be articulated or inductively derived from data (both quantitative and qualitative), direct observations, ethnographic histories (e.g., "translating" narratives or life histories from the field into a computerized model; Huigen, 2004; Huigen et al., 2006; Matthews, 2006), or "stylized facts abstracted from real-world studies" (Albino et al. 2006). They are often simple, straightforward, and self-evident without much need for additional justification.

Examples using this type of decision model are many. When a new house (agent) is set up, the vegetation in its location and surrounding area is cleared up (An and Liu 2010). When clearing forests, the households in the southern Yucatán will "clear secondary forest when the primary forest is too far from my location" (Manson and Evans 2007). Human agents living with the hunter-gatherer lifestyle "first search for animals in their present location (cell) to hunt, and if successful, consume the animal. Otherwise… [they]move to adjacent cells to hunt." (Wainwright, 2008). In deciding what to plant or simply fallow, household agents check their subsistence needs, soil quality, capital, and labor in a hierarchically connected manner (Deadman et al. 2004). In the Caparo tropical forest reserve in Venezuela, a settler agent performs subsistence-oriented activities such as "slash and burn" after he/she takes possession of a parcel of land in the reserve (Moreno et al. 2007).

Along this line, artificial intelligence algorithms (e.g., learning classifier; Holland and Holyoak, 1989), often combined with expert knowledge and some degree of fuzzy logic, have been developed to solicit agents' decision rules in a manner consistent with our understanding of reality (e.g., Roberts et al., 2002; An et al., 2005; Wilson et al., 2007). Such rules or strategies are often dynamic and subject to evolution (See Section 3.8 for one way to capture such evolution). In modeling prehistoric settlement systems (e.g., Kohler et al. 2002) or human-environment interactions (e.g., Axtell et al. 2002), most of the decision rules (if not all) are derived this way unless there are historically documented analogs.

3.6 Participatory agent-based modeling

A variant in the family of experience- or preference-based decision models (Section 3.5) is the so called participatory ABM, in which real people directly tell the modeler what they will do (Purnomo et al. 2005; Simon and Etienne, 2010). In modeling CHANS, it is often a challenge to communicate between specialists (e.g., ABM modelers) and non-specialists. Agents are considered as individuals with autonomy and intelligence, who keep learning from (thus updating their knowledge base), and adapting to, the changing environment (e.g., “primitive contextual elements”; Tang and Bennett 2010) and other agents (e.g., Bennett and Tang, 2006; Le et al. 2010). Participatory agent-based modeling has arisen in this context, which is conceptually similar to “companion modeling” in the ecology literature. Participatory modeling involves stakeholders in an iterative process of describing contexts (e.g., local environment), soliciting decisions, and envisioning scenarios arising from the corresponding decisions.

Participatory agent-based modeling incorporates on-site decision making from real agents, facilitating “information sharing, collective learning and exchange of perceptions on a given concrete issue among researchers and other stakeholders” (Ruankaew et al., 2010). A particular application is role playing of real stakeholders, which has been successfully used in soliciting decision rules through direct observation of the player’s behavior. Success of using this approach has been reported from several study regions such as Northeast Thailand (Naivitit et al., 2010), the Colombian Amazonian region (Pak and Brieva, 2010), Senegal (D'Aquino et al., 2003), and Vietnam (Castella et al., 2005b; see D'Aquino et al., 2002 for review).

3.7 Empirical- or heuristic rules

Agents are assigned rules that are derived from empirical data or observations without a strong theoretical basis or other guidelines. Models using rules of this type are sometimes called "heuristic rule-based models" (Gibon et al. 2010). Even though also based on data, researchers usually have to go through relatively complex data compiling, computation, and/or statistical analysis to obtain such rules, not as straightforward and self-evident as that in Section 3.5. Some demographic decisions are usually modeled in a stochastic manner. For instance, male adults may move to the Gulf of Guinea basin to find jobs during the dry season at a certain probability (Saqalli et al., 2010); children between 16-20 may go to college or technical schools at a probability of 2% per year (An et al., 2005). Zvoleff et al. (in preparation) uses statistical models (e.g., regression) to make links between fertility behavior choices and different pre-determined socioeconomic and land use variables (the choice of these variables still depends on theory).

Neural network or decision tree methods, largely black- or grey-box approaches (usually little mechanistic explanations or theories are provided, if any), are sometimes used to derive or "learn" rules from empirical data. In modeling strategies of ambulance agents that aim to save victims, experts were provided with a set of scenarios that increase in information complexity (e.g., location and number of hospitals, ambulances, and victims, whether there is enough gasoline). Then the set of criteria or decision rules, usually not elicitable or elicitable only with difficulty, was learned through analyzing the experts' answers under the above scenarios using a machine-learning process (e.g., a decision tree; Chu et al., 2009). This type of black- or grey-box approach, though statistics-based, is different from many other instances in which statistical analyses (e.g., regression) are used under theoretical (e.g., microeconomics or others reviewed above) guidance.

When data on deterministic decision making processes are unavailable, it is sometimes a practical way to group agents according to a certain typology (e.g., one derived from survey data). Such typologies usually account for differences in making decisions, performing some behavior, or encountering certain events (e.g., Antona et al., 1998; Loibl and Toetzer, 2003; Mathevet et al., 2003). In some instances, each agent type may be assigned a ranking or scoring value for a specific decision or behavior type (out of many types) according to, e.g., experts' knowledge or empirical data (e.g., the 'Who Counts' matrix in Colfer et al., 1999).

Examples of this type of decision model are numerous. In one example focusing on land use decisions, five types of farmers (i.e., hobby, conventional, diversifier, expansionist-conventional and expansionist-diversifier) were identified based on both the willingness and ability of farmers in terms of farm expansion and diversification of farm practices. For each type, empirical probabilities were found for optional activities such as "stop farming" or "buying land" (Valbuena et al., 2010). In modeling land use decisions at a traditional Mediterranean agricultural landscape, Milington et al. (2008) adopt a classification of "commercial" and "traditional" agents. These agents make decisions in different ways: commercial agents make decisions that seek profitability in consideration of market conditions, land-tenure fragmentation, and transport; while traditional agents are part-time or traditional farmers that manage their land because of its cultural, rather than economic, value. Similar efforts include the agent profiling work by Acosta-Michlik and Espaldon (2008) and the empirical typology by Jepsen et al. (2005), Acevedo et al. (2008), and Valbuena et al. (2008).

Deriving rules this way (i.e., exposing empirical data to statistical analysis), modeling needs can be temporarily satisfied. However, questions related to why decisions are so made are largely left unanswered. For instance, Evans et al. (2006) point out that many statistical tools can be employed to correlate particular agent attributes (e.g., age) with specific land-use decisions, which may be "useful for policy purposes. However, this practice does not necessarily identify why landowners of a certain age make these decisions." Hence it would be ideal that beyond those empirical or heuristic rules, actual motivations, incentives, and preferences behind those decisions can be derived. This will not only provide *ad hoc* solutions to the specific problem under investigation, but also advance our generic knowledge and capacity of modeling human decisions in complex systems (CHANS in particular).

3.8 Evolutionary programming

This type of decision making, in essence, belongs to the category of empirical or heuristic decision models (Section 3.7). It is separately listed as its computational processes are similar to natural selection. Agents carry a series of numbers, characters, or strategies (chromosomes; Holland 1975) that characterize them and make them liable to different decisions or behaviors. The selection process favors individuals with the fittest chromosomes, who have the capacity of learning and adaptation. Copying, cross-breeding, and mutation of their chromosomes are critical during the adaptation or evolution process. Under this umbrella, genetic algorithms (Holland, 1975) have emerged and found applications in a range of ecological/biological studies (see Bousquet and Le Page, 2004 for review) as well as studies on emerging social organizations (Epstein and Axtell, 1996). In CHANS research, few but increasing empirical studies fall into this category. Below are examples that illustrate this line of modeling decision making.

In the human-environment integrated land assessment (HELIA) model that simulates households' land use decisions in the southern Yucatán (Manson and Evans, 2007), household agents use their intricate function f(x) to calculate the suitability when siting land use in a "highly dimensional stochastic" environment (Manson 2006). This function f(x) is considered to consist of usually multi-criteria (and likely multi-step) evaluation processes that are unknown or inarticulate. Through some symbolic regression (genetic programming in particular) between land change data (**Y**, response variable) and spatial predictor variables (**X** $=\{X_{1,}\ldots X_n\}$), an empirical function $\hat{f}(x)$ can be estimated to approximate f(x) (e.g., through minimizing the residuals between data and estimated suitability). During the estimation process, multiple parental land use strategies or programs (similar to the above chromosomes) compete and evolve to produce offspring strategies through imitating/sharing, interbreeding, and mutation (Manson 2005).

Strategies computed through genetic programming are found to be consistent with those obtained from general econometric models or rules of thumb solicited from local interviews (Manson and Evans, 2007). This consistency increases the reliability of genetic programming on the one hand; at the same time it necessitates more explorations for why and when genetic programming should be used in place of traditional modeling approaches. A variant under this type of studies is the concept of tag (a sort of numerical code that explains skills or behavior). Agents, through comparing and adopting each other's tags, interact with each other and are collectively (usually unwittingly) accountable for the emerging patterns (Riolo et al., 2001).

3.9 Assumption and/or calibration-based rules

Hypothetical rules can be used in places where inadequate data or theory exists. In public health or epidemiology field, daily activity routines are important for researchers to model the diffusion of infectious diseases; human agents are infected in a stochastic manner that involves untested assumptions (e.g., Muller et al. 2004; Perez and Dragicevic, 2009). Specifically in Perez and Dragicevic (2009)'s model, it is assumed that the length of time for out-of-house daily activities for an individual is 10 hours (time of high risk of being infected), which includes two hours for public transportation and eight hours in work places, study places, or places for doing some leisure activities. People within this 10-hour window are assumed to have the same risk of infection, which may be subject to changes if new observations or theories arise. Temporarily, such untested hypothetical rules are accepted to operationalize the corresponding model.

Similarly, time-dependent human activities, varying across different land use or agent types (e.g., rice growers, wine growers, hunters) or time windows, are documented and assumed constant over time. Such data, including the constancy assumption, are used to simulate how likely humans may be infected by Malaria over space and time assuming constant mosquito (*An. Hyrcanus*) biting rate (Linard et al. 2009), or how likely hunters may capture game animals (Bousquet et al. 2001). In another instance, "[At] an age *specified by the user* (the user has to make these assumptions related to decision rules), children leave the house in search of an independent livelihood or other economic opportunities" (Deadman et al. 2004). There are many other simulation studies that similarly document the timing and location of different human activities, and assume a certain activity, location, or time may subject the associated agents to certain events (e.g., Roche et al. 2008; Liu et al. 2010) or strategies (e.g., Roberts et al. 2002) at the same probability.

Alternatively, calibration-based rules are used to choose among candidate decision models. Specifically, such candidates are applied to the associated ABM, which may produce various outcomes. By evaluating the defensibility of the outcome or comparing the outcome with observed data (if available), the modeler decides what decision model is most likely to be useful. For instance, in Fontaine and Rounsevell (2009)'s model that simulates residential land use decisions, several values, usually ranging from low to high, are chosen for a set of carefully selected parameters (e.g., weight for distance to coastline or road network). Then all the combinations of these parameter values are entered into the model for simulation runs. Then the set of parameter values that give rise to resultant household patterns most similar (e.g., in terms of correlation coefficient) to real data at a certain aggregate level are retained. In some instances decision or behavior patterns of economic agents per se are of interest, and this approach is used to detect the most plausible one(s) (e.g., Tillman et al. 1999).

There are several disadvantages associated with this type of decision model: 1) researchers usually do not have all the possible candidate rules, thus the chosen one may not be appropriate; 2) only a limited number of rules should be set by calibration testing; errors in ABMs could cancel out each other and give rise to problematic calibration outcomes (e.g., ruling out a good candidate). Therefore rules of this type should be used with caution. Calibration in ABM is often cited as a weakness of ABM that needs to be improved (e.g., Parker et al., 2003; Phan and Amblard, 2007).

4. Conclusion

This paper does not mean to give a complete list of all human decision models used in CHANS research. It rather focuses on the ones that are relatively frequently used in the hope that CHANS modelers (especially beginners) may find them helpful when dealing with modeling human decisions. It is also noteworthy to point out that the above nine types of models are by no means exclusive. Actually in many instances, hybrid models are employed in simulating CHANS decision making processes.

According to this review, the decision or behavior models related to human decision making range from highly empirically-based ones (e.g., derived through trend extrapolation, regression analysis, expert knowledge based systems, etc.) to more mechanistic or processes-based ones (e.g., econometric models, psychological models). It is clear that both approaches for modeling human decisions along this gradient (from empirically-based to processes-based) have their own strengths and weaknesses, and should be employed to best suit the corresponding contexts (e.g., objectives, budget and time limitations) and complement each other.

The CHANS related complexity (as reviewed in Section 1) makes modeling of human decision highly challenging. Humans make decisions in response to changing natural environments, which will in turn change the context for future decisions. Humans, with abilities and aspirations for learning, adapting, and making changes, may undergo evolution in their decision making paradigm. All these features contribute to the above challenge. For instance, it is considered “something that is still far away” to incorporate realistic reasoning about beliefs and preferences into understanding and modeling human decision processes (Ligtenberg et al., 2004). Without more process-based understanding of human decision making (e.g., the wayfinding process model by Raubal 2001), it is very difficult to appreciate complexity at multiple dimensions or scales, achieving in-depth coupling of the natural and human systems.

This research thus advocates that while keeping up with empirically-based decision models, substantial efforts be invested in process-based decision-making mechanisms or models to better understand CHANS systems. In many instances, process-based models are the ones “capturing the triggers, options, and temporal and spatial aspects of an actor’s reaction in a [relatively] direct, transparent, and realistic way” (Barthel et al. 2008). During this pursuit, agent-based modeling will play an essential role, and will become enriched by itself. Whatever decision models are used, the KISS rule (“keep it simple, stupid”; Axelrod 1997, p.4-5) may still be a good advice given the complexity we face in many CHANS. By keeping the behaviors available to agents limited and algorithmic, we as modelers will be able to produce stories that, if not convincingly true, cannot be automatically “categorized as false because they contradict what we know of human capacities” (Luistick, 2000).

Modeling human decisions and their environmental consequences in ABM is still a combination of science and art. Comparison and cross-fertilization between ABM models developed by different researchers is a daunting task. Similar to the ODD (Overview, Design concepts, and Details) protocol for ecological studies (Grimm et al., 2006) and the agent-based simulation taxonomy for environmental management (Hare and Deadman 2004) it would be desirable to have similar protocols for CHANSoriented ABMs that aim at modeling human decisions. This paper thus advocates that generic protocols and/or architectures be developed in the context of the specific domain of research questions. Advancements in computational organization theory, such as behavioral decision theory and institutional theory, may provide useful insights for establishing such protocols or architectures (Kulik and Baker, 2008). Such protocols or architectures, though impossible to serve as panaceas, may be used as benchmarks or checklists, offering recommendations on model structure, choice of decision models, and a few key elements in modeling human decisions.

As in the past, CHANS modelers will continue to benefit from other disciplines such as ecological psychology (directly addressing how people visually perceive their environment; Gibson 1979), biology/ecology (e.g., genetic programming), sociology (e.g., organization of agents), political science (e.g., modeling of artificial societies), and complexity theory (e.g., complexity concept). It is hoped that research on how to model human decisions in CHANS will not only advance theories, but also bring forward new opportunities in advancing agent-based modeling.

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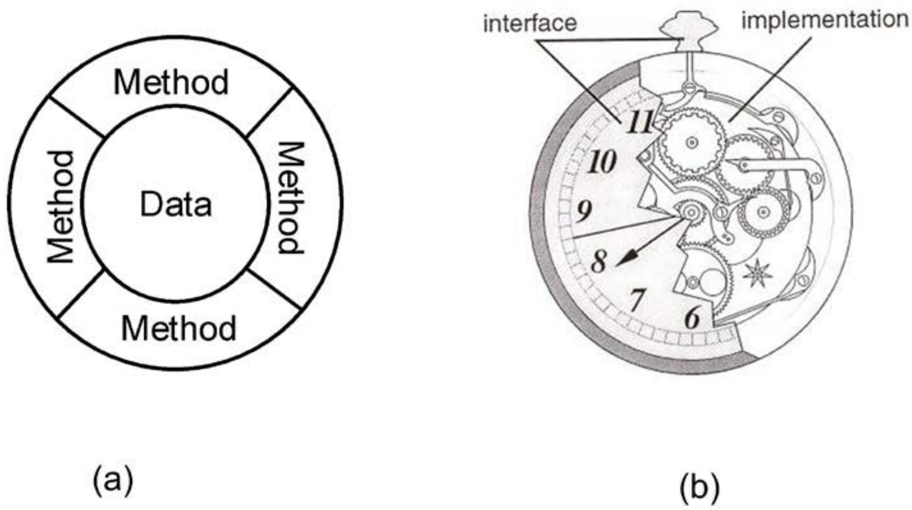
Figure legends

Fig. 1. Objective-oriented programming with separation between implementation and surface (reprint with approval from the publisher, see An et al. 2005).

Fig. 2. Dynamics of publications related to the ABM based on our search criteria (1994-2010).


Method
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11
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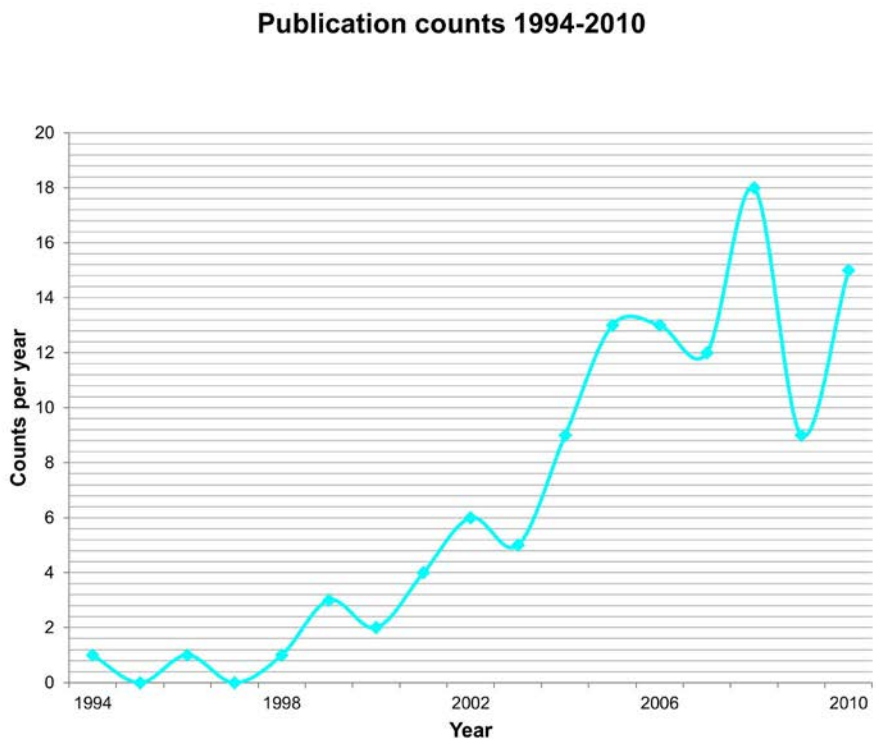
(a)
(b)

Figure 1


Publication counts 1994-2010
Counts per year
Year
0
2
4
6
8
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2006
2010

Figure 2