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Use of Complex Adaptive Systems for Modeling Global Change

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ABSTRACT

Global modeling has been used for decades to assess the possible futures of humanity and the global environment. However, these models do not always satisfactorily include the adaptive characteristics of systems. In this article, a general approach is used to simulate change and transition at a macrolevel due to adaptation at a microlevel. Tools from complex adaptive systems research are used to simulate the microlevel and consequently determine parameter values of the equation-based macrolevel model. Two case studies that applied this approach are reviewed. The first study assessed the efficacy of efforts to control malaria, whereas the second study used an integrated model to construct climate change scenarios by using various possible views on the nature of the climate system.

Key words: complex adaptive systems; global change; climate change; malaria; multiagent modeling; adaptation; coevolution; genetic algorithms.

INTRODUCTION

We live on a human-dominated planet. Human activities transform the land surface, alter the major biogeochemical cycles, and add or remove species and genetically distinct populations in most of the earth's ecosystems (Vitousek and others 1997). The expected growth of the human population and the associated economic activities will likely accelerate the scale and intensity of human-induced changes. To assess these global changes, there is a long tradition of global modeling in order to visualize various possible future scenarios [for example, see Meadows and others (1972), IPCC (1996), and UNEP (1997)]. Because of the complexity of global change, qualitative insights that improve the decision-making process, rather than specific quantitative predictions, are the main focus of these model efforts. One of the main drawbacks of models that assess global change is their mechanistic approach. In fact, from this perspective, an unsustainable development could be defined as a system change out of its (natural) equilibrium. On the other hand, it is known that, in the history of life, organisms have adapted to many changes. From an evolutionary perspective, we may define a sustainable development as sustaining the ability of systems to adapt to a changing environment. From an anthropocentric perspective, sustainable development might then be seen as coevolution between human activities and environment at a rate that makes adaptation possible (Janssen 1998).

As Levin (1998) has noted, the global biosphere is a prototypical example of a complex adaptive system, because its components adapt and reorganize themselves in response to interventions. Complex adaptive systems research provides us with modeling tools that enable us to study the coevolutionary development of humankind and our environment. It is not easy, though, to apply those tools to the analysis of global change and global modeling. They have been successfully applied to various issues in natural and social science [for example, see Anderson and others (1988) and Langton (1995)], but in the context of global change, complex adaptive systems models lead us to the everlasting dilemma of how to link macrolevel and microlevel modeling. On the one hand, we are interested in the long-term developments of large-scale political and economic

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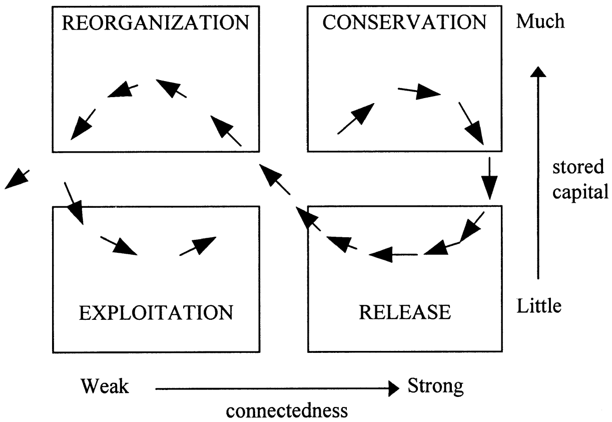

Figure 1. The adaptive cycle [based on Holling (1986)].

institutions, and the impact of human activities on the global environment. On the other hand, we know that decisions are actually made by the very small actors (households and individuals), and individual species are the entities that survive or perish in a changed (local) environment.

In this article, several applications of complex adaptive systems research to modeling global change are discussed. I begin by outlining a general modeling approach.

A General Approach

To explain the use of complex adaptive systems to model system change, I use a framework introduced by Holling (1986). He proposed that four basic functions are common to all complex systems, and that system development follows a spiraling evolutionary path through these functions (Figure 1). This idea emphasizes a system's trajectory, from conservation through phases of destruction and reorganization, in which innovation and change assume a dominant role. The reorganization phase occurs when a rare and (un)expected intervention or event can shape a new future. If the system is not able to adapt, it will reorganize into a new system. With respect to global change, we are interested in how systems may adapt, or not, to human-induced disturbance.

A possible approach to simulate adaptation is the coupling of macrolevel and microlevel in the following way. Dynamics at the macrolevel are usually described in terms of differential or difference equations. This equation-based approach can be formulated by describing the state variables x as a function of x: $dx/dt = F[x(t)]$. The function F( ) consists of a number of parameters that are assumed to be fixed. It might be that these parameters are only fixed in a limited area of the state space. The dynamics on the microlevel can now be coupled with those on the macrolevel by considering various parameters p( ) as outcomes of a rule-based tool like a genetic algorithm or cellular automata, tools to simulate complex adaptive systems (Holland 1992; Langton 1995): $dx/dt = F(x(t), p[x(t)])$. Examples of such parameters are aggregated values, such as the average birth rate, the average resistance, or the average worldview. On the microlevel of the model, characteristics of the agents are simulated and, at the macrolevel, only the average is used. Note that, due to possible aggregation errors, correction transformations might be necessary (Rastetter and others 1992; Cale 1995).

Suppose that we are interested in the evolution of a population in a changing environment. To imagine such a changing environment, consider the following example. During the second half of the 19th century, the countryside around the industrial cities of Great Britain darkened because of a large increase in pollutants from industrial activities. This change greatly affected moths that relied upon camouflage to protect them from being seen and eaten by insectivorous birds (Cox and Moore 1993). As long as the bark of the trees on which they rested remained pale, it was advantageous for the moths to be pale also. In 50 years time, though, the dark form of this moth became more common.

We can examine the evolution of two phenotypes, such as a pale moth and a dark moth, by using a simple biological model. Consider a species of population size N_t at time t, whose population size varies over time under the influence of the reproduction rate r and the density dependent death rate q (N_t/K), where K is the carrying capacity: $N_{t+1} = N_t (1 + r - q N_t/K)$. Values for the constants r, q, and K can be assumed to derive a deterministic population model. If we consider the moths from the aforementioned example, we may relate the fitness of the pale moth (F) to the level of pollution (P): $F = 1 + P/(P - 2)$ (Figure 2).

Assuming q equal to 1/F, K equal to 1, and r equal to 1.5, we derive a simple model that simulates the population size of the pale moth. If pollution increases from time step 40 onward, the fitness of the pale moth will decline and the resulting population size will drop to zero (Figure 3). The pale form of the moth vanishes. In reality, however, the pale form of the moth vanished but was replaced by the dark form of the moth. To simulate such a change, a genetic algorithm is used that simulates the adaptive processes of natural systems (Holland 1975, 1992; Goldberg 1989; Mitchell 1996). The basic construction is to consider a population of agents who produce offspring that are similar but not identical

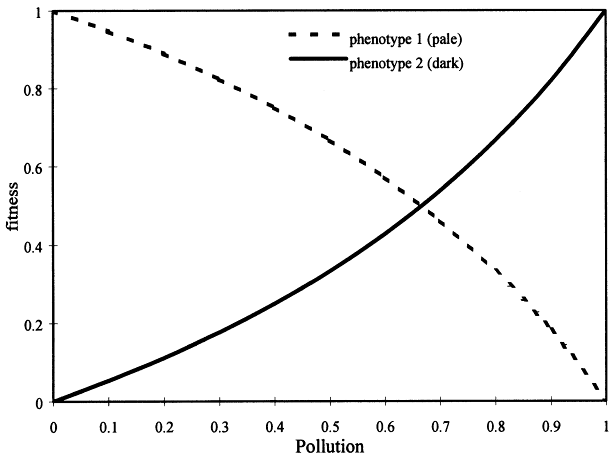

Figure 2. The assumed fitness functions of the phenotypes for pale moths and for dark moths.

to their parents. The number of offspring that an agent produces is determined by a fitness function.

The fitness function of the dark moth is assumed to be equal to $-P/(P - 2)$ (see Figure 2). The value of F on the macrolevel is now determined by the genetic algorithm. This algorithm simulates a population with diversity in genetic information. By taking the average fitness of the population, we derive an estimate of F on the macrolevel.

An illustrative experiment is shown in Figure 3, in which the distribution of phenotypes in the population changes due to stress on the system. Once the pollution increases, the fitness of the population drops, resulting in a decrease in the population. As pollution increases, the fitness of the dark moths increases relative to the pale moths. Due to genetic selection by the genetic algorithm, the share of dark moths increases until it dominates the population by time step 60. From that time on, the population's average fitness and the population size increase until they return to the original level.

This simple example demonstrates the possibility of coupling a rule-based model (genetic algorithm) with an equation-based model (population model) in order to simulate the changes in the population size of a species under stress. Using such a model, we may study the conditions under which and manner in which a system adapts.

In the following section, I provide a brief overview of two case studies that apply the modeling approach just discussed to global change research conducted at the National Institute for Public Health and the Environment (RIVM) in the Netherlands. The first case study examines the adaptation of biological agents responsible for malaria, whereas the second case study describes an integrated model of climate change with social agents who adapt mitigation policy to a changing climate.

Case Studies

Biological Agents

As the resistance of the malaria parasite to antimalarial drugs and the malarial mosquito to insecticides continues to increase, the efficacy of efforts to control malaria in many tropical countries is diminishing (Krogstad 1996; WHO 1996). This trend, together with projected climate change, may substantially increase the prevalence of malaria in the coming decades. Janssen and Martens (1997) applied genetic algorithms to simulate the adaptation of mosquitoes and parasites to the available pesticides and drugs. By coupling genetic algorithms to a dynamic malaria-epidemiological model, they derived a complex adaptive system capable of simulating adaptive and evolutionary processes within both the mosquito and the parasite populations. They used their approach to analyze malaria management strategies in regions exhibiting higher and lower degrees of malaria endemicity. The consequences of including adaptive processes is illustrated by the following example of a malaria control policy using antimalarial drugs in a region with high endemicity (Figure 4). If the malaria parasite does not evolve resistance to drugs, the incidence of malaria drops to zero after the control policy is started (year 2). If the malaria parasite can evolve drug resistance, however, malaria incidence increases following a brief period during which incidence is reduced. In this case, the control policy causes more people to become susceptible to malaria and fewer remain immune. If the malaria parasite becomes resistant, the increased number of susceptible people produces a higher incidence of malaria. This case clearly demonstrates that malaria eradication programs should be concerned with the adaptive capacity of malaria, for this ability strongly influences the success or failure of drug application policy. More generally, it demonstrates that policy can be vulnerable to adaptive processes, and that incorporating adaptive dynamics into policy-planning models can enhance their ability to assess policy robustness.

Social Agents

One can distinguish two main-stream approaches to the integrated assessment of climate change: the optimization approach that assumes that agents, who have perfect knowledge about the system, determine the optimal policy to balance costs and benefits [for example, see Nordhaus (1992)], and

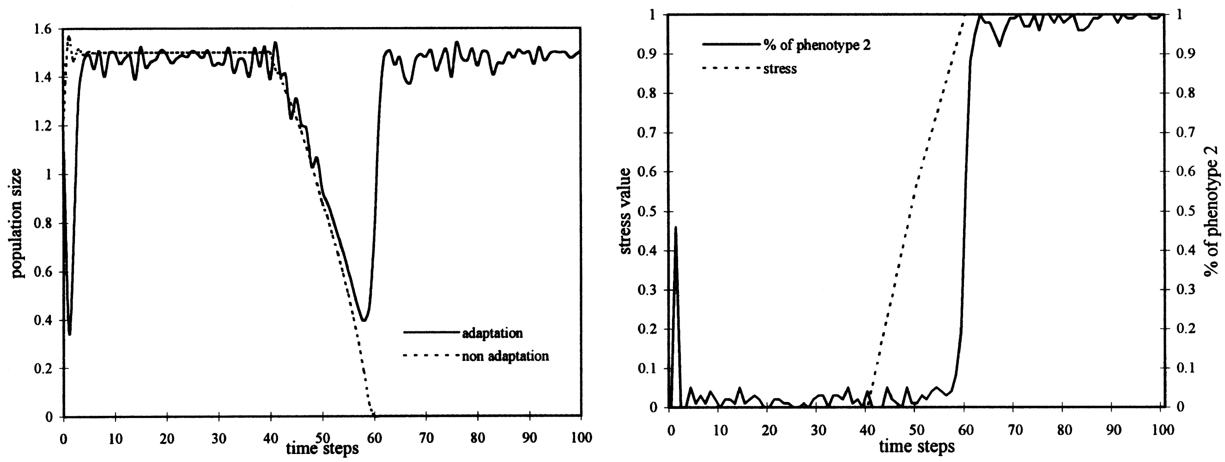

Figure 3. An experiment with the coupled micro–macro model where a stress on the system occurs that leads to a change in the distribution of phenotypes and the size of the population. In case of adaptation, the population size recovers.

the simulation approach that simulates the consequences of different scenarios of human activities on the environmental system without feedbacks to human activities [for example, see Alcamo (1994)]. Janssen and de Vries (1998) introduce an alternative approach by using a multiagent model with adaptive responses to climate change.

Janssen and de Vries assume that agents use different worldviews to interpret the climate change problem, and consequently agents having different worldviews favor different types of policies. Three active perspectives based on the Cultural Theory of Thompson and colleagues (1990) are used as a framework to classify possible worldviews: hierarchists, egalitarians, and individualists. These types represent extreme views where

- Hierarchists assume that nature is stable in most circumstances but can collapse if it crosses the limits of its capacity. Therefore, control is advocated as a management style.
- Egalitarians assume that nature is highly unstable, and the least human intervention may lead to complete collapse. A preventive management style is preferred.
- Individualists assume that nature provides an abundance of resources, and it is believed to remain stable under human interventions. An adaptive management style is advocated.

Janssen and de Vries modeled three possible worlds based on the three cultural perspectives of the Cultural Theory. The worlds differ in views on climate sensitivity, technological developments, mitigation costs, and damage costs due to climate change. The egalitarians, for example, assume a high climate sensitivity, high damage costs, low technological development, and low mitigation costs. For management styles, they assume different strategies for investments and reductions of emissions of carbon dioxide. The individualist, for example, assumes a strategy that maximizes economic growth, and emissions are reduced only if a certain threshold of economic damage is exceeded.

Suppose that all of the agents in a model world share one of the three extreme worldviews. If we assume that agents have perfect knowledge of their world, we can simulate their utopia. If their worldview is incorrect and they still apply their preferred management style, we can simulate their dystopia. An example is presented in Figure 5A. In the egalitarian utopia, emissions of carbon dioxide will be reduced to zero within a few decades, leading to a modest temperature change. However, if the individualistic worldview manages a world that actually operates according to the egalitarian worldview, emissions increase until climate change causes such an economic disaster that emission reduction policy is unavoidable.

By introducing a population of agents with heterogeneous worldviews, a complex adaptive system is produced. It is assumed that the better an agents' worldview explains the world's observed behavior, the greater is the chance that it will not change its worldview. On aggregate, there is a trend to change to the worldview that explains the observations in the most likely way. Suppose that reality is one of the three possible worlds and an agent obtains information over time that causes it to change (or not) its perspective on the climate change problem. We derive now three sets of projections in which agents adapt to a climate change (Figure 5B). Prior to year 2040, the observed climate change does not

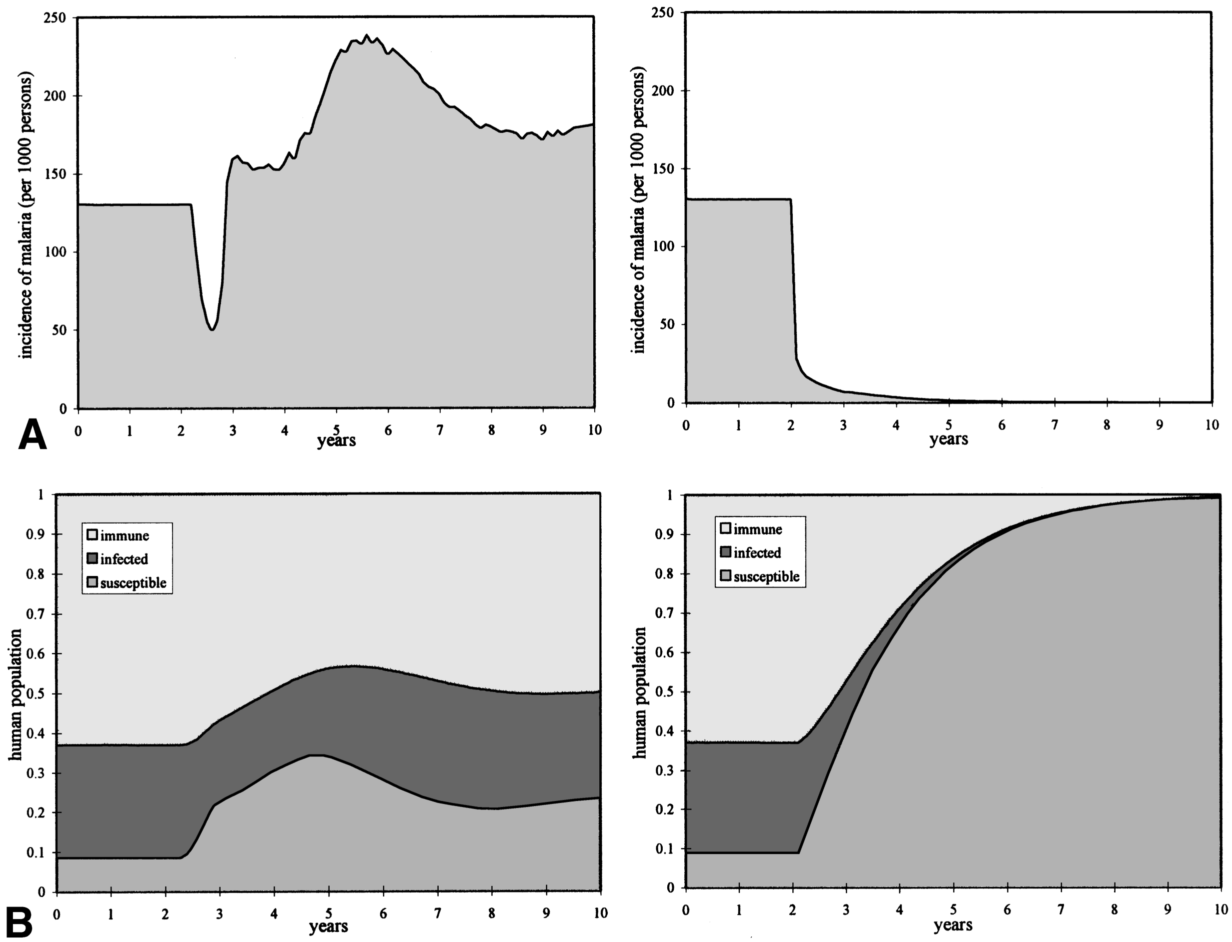

Figure 4. A Malaria incidence for a region of high endemicity where the malaria parasite becomes resistant (*left*) or not (*right*). B Distribution of immune, infected, and susceptible people that changes due to the use of antimalarial drugs and the drug resistance of the parasite (*left*).

lead to domination of one of the worldviews. After 2040, the climate signal becomes clear enough that one of the worldviews begins to dominate. In the event of the world functioning according to the egalitarian worldview, the emissions growth stabilizes on average in the coming decades and decreases to a level below half the present amount of emissions. However, this reduction policy can not avoid a global mean temperature increase of about 2.5°C in the coming century.

By modeling policy as something that emerges from a heterogeneous set of agents with changing beliefs, rather than a unchanging single actor, an alternative set of global climate change scenarios is developed that lay between extremes of perfect knowledge and no adaptation. I hope that the inclusion of human behavior in global models may lead to a better understanding of the possible tradeoffs among alternative policies.

Reflections

To assess the consequences of the current and ongoing global change of human activities, tools from complex adaptive systems research are essential. Since complex adaptive systems simulate the behavior of heterogeneous agents, it is not straightforward how to integrate this approach in the macrolevel global models. This article introduced the possible approach of coupling the equation-based macrolevel model with the rule-based microlevel model. Parameter values of the macrolevel equations are simulated then by a microlevel model. The case studies showed the possible use of this approach to simulate biological and social agents.

Obviously, the results are tentative in view of the many shortcomings of modeling agents and their environment. Specific shortcomings include ignorance of spatial and geographic characteristics in the

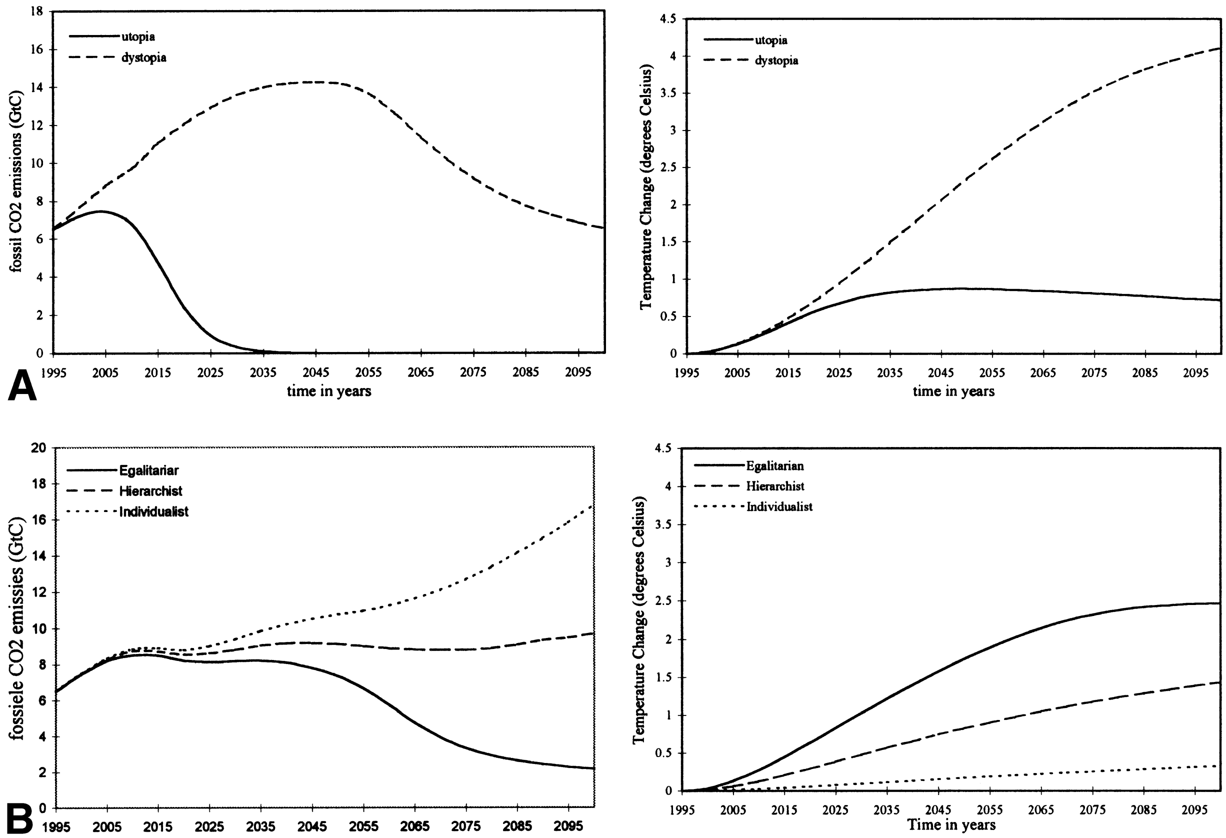

Figure 5. A Expected carbon dioxide emissions and temperature increase according to the egalitarian utopia and a possible dystopia (individualistic management style in an unstable global system). B Expected carbon dioxide emissions and temperature increase according to different views on the functioning of the global system. GtC, global temperature change.

malaria model, the nonvalidated fitness functions, and the exclusion of geopolitical regions in the integrated model for climate change. However, I feel that some basic aspects of the simulated adaptive behavior are operating in the real world, and the use of complex adaptive systems makes it possible to simulate the process of adaptation. Especially for the modeling of ecosystems, the inclusion of adaptation to (un)expected interventions is critically important. The use of complex systems approaches to model adaptive processes offers to improve our understanding of the consequences of human activities and therefore provides us with a framework to improve efforts in sustainable management of our human-dominated planet.

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