Environmental Literacy in Science and Society

From Knowledge to Decisions

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Chapter

14 - Integrated systems modeling of complex human–environment systems

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Chapter 14

Integrated systems modeling of complex human–environment systems

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Chapter overview

The definition of environmental literacy in Chapter 2 included: (i) the proper presentation and representation of the state of the environment and its dynamics; (ii) the understanding of the human impacts on the environment and environmental feedbacks; (iii) the identification of options for actions for mitigating unwanted impacts; and (iv) the generation of knowledge for successfully coping with (i) to (iii). This chapter shows how integrated systems modeling can serve to generate this knowledge. This is done by first specifying the nature of complementarity of human and environmental systems. HES are conceived as inextricably coupled complex systems.

One challenge here is to deal properly with different types of complexity and fundamental system traits such as continuity and discontinuity. Another challenge is to acknowledge that the human factor is also forming the processes of the natural environment. Humankind has become a geological factor and thus environmental systems from the micro to the macro scale require an anthropocenic redefinition.

We deal with modeling as an efficient scientific reasoning tool for gaining a better understanding of the system elements, their relations, and interactions, thus allowing for anticipating dynamics of complex HES. We summarize the epistemic requirements arising from the attempt to understand coupled HES comprehensively. From this we demonstrate the potential contributions of different modeling approaches to meet these requirements.

The essence of this chapter is to reveal what additional insights into HES can be attained by different types of modeling, which goes beyond what we can describe without making reference to formal modeling and what is essential for understanding HES.

The second part of this chapter appraises fundamental key ideas of selective modeling approaches. We make explicit how these approaches, and in particular integrated systems modeling can genuinely establish interdisciplinarity by integrating subsystems or variables that are dealt with in different disciplines. Thus, integrated modeling is considered a mode of "knowledge integration." The essence of this chapter is to reveal what additional insights into HES can be attained by different modeling approaches, (qualitative) insights that go beyond what we can describe without making reference to formal modeling techniques, but which are essential for understanding HES.

14.1 Integrated modeling of coupled HES

Given the fact that the human is a major agent in world material flows and the biosphere, environmental literacy requires the analysis and management of inextricably coupled human and environmental systems. This analysis has to take into account that these interactions

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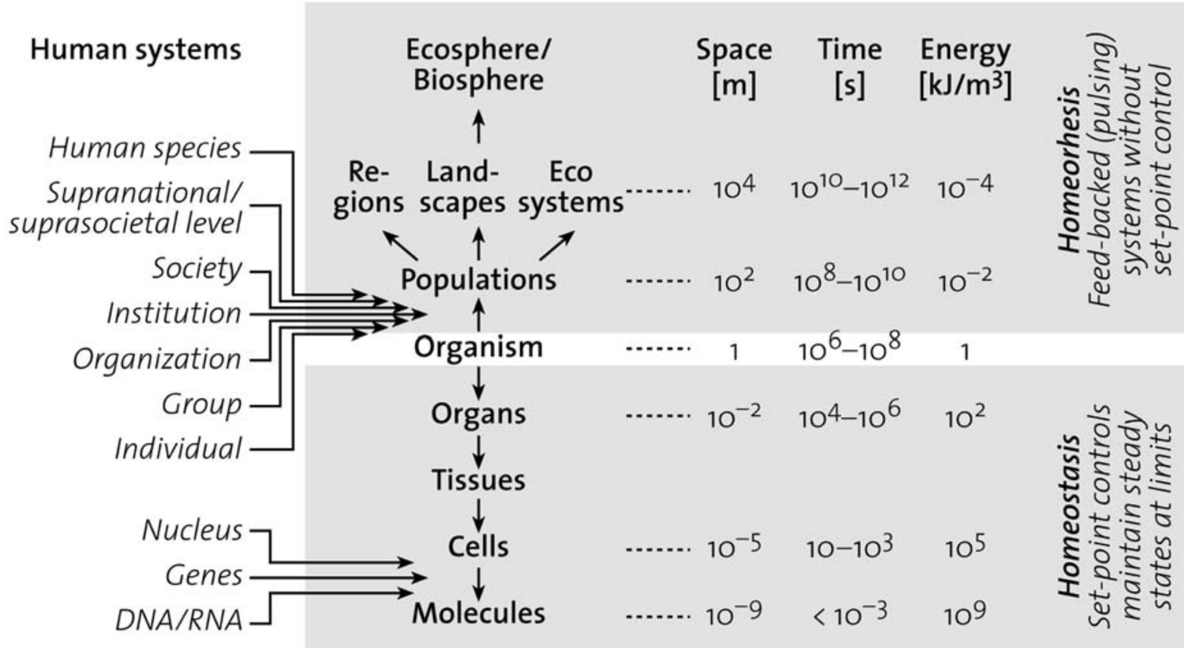

Figure 14.1* The hierarchy levels of human systems (left upper fringe scales; see Table 16.2) as part of the organism–ecosystem hierarchy (see Figure 8.2; Jørgensen *et al.*, 2007; Odum, 1996).

take place at different hierarchical levels and that they are often intrinsically systemic, dynamic, complex, and subject to evolutionary change. The systems' dynamics embodies feedbacks and non-linearities, possibly causing – under certain conditions – "critical transitions" which can also qualitatively change the system's structure. Understanding complexity in HES is a problem deserving particular attention.

We argue that mathematical modeling can be considered a "microscope" for investigating HES, allowing for the anticipation of possible dynamic patterns of complex systems. Mathematical models that can be used to investigate HES range from linear models, systems thinking, and system dynamics to complex multiagent and adaptive systems, each providing specific contributions to these investigations.

14.1.1 Starting from an anthropocenically redefined environment

We have shown (see in particular Chapter 13) that human activities and technology have caused fundamental global change of many kinds. We are facing, for instance, innumerable new chemical elements, new technologies producing never-seen engineered nanoparticles or genetically modified species, changed water and biogeochemical cycles, fundamentally modified Earth surface structures and accelerated climate dynamics causing scarcity, pollution, and detrimental social dynamics. Biologists acknowledge that large parts of the patterns of terrestrial systems are formed by human activities (O'Neill, 2001; Turner, 1990; Vitousek *et al.*, 1997).

Human-made changes show the same gravity as classical natural hazards, many of which are also already strongly affected by human activities. Paul Crutzen called this new period the age of the anthropocene (Crutzen, 2002a). Facing the changing world, Crutzen infers that:

> … humankind is … a noticeable geological force, as long as it is not removed by diseases, wars, or continued serious destruction of Earth's life support system … (ibid. p. 10/4)

Following this diagnosis, we speak about an anthropocenic redefinition of the environment. Considering the major impact humankind has had on the entire biosphere since the onset of agriculture and on the shape of land since the Middle Ages, the start of the anthropocene can be set even earlier than Crutzen suggests (Küster, 1999; see also Box 14.1). Today, many dynamics of lithosphere, hydrosphere, atmosphere, and biosphere are fundamentally affected by human activities. The human is a major agent in world material flows and the biosphere. This means that environmental literacy requires the analysis of inextricably coupled human and environmental systems, at least if we deal with the anthroposphere, the relevant environment of human life.

A critical issue is that the dynamics of HES are affected by processes that take place on a broad range of temporal–spatial scales. Figure 14.1* presents the scope of systems, ranging from the molecular level to the world level, represented by the ecosphere and biosphere. The two scales at the left fringe represent human systems above the scale of the individual, which builds the kernel of this book, and few levels between molecule and cells, which are essential to understand life and the interaction of the immune system with the environment. As shown in Chapter 5, systems above the individual are – in general – not assumed to be governed by homeostasis – that is, set-point controls which maintain steady states at limits – but rather a homeorhesis, that is pulsing systems returning to and following trajectories. Thus, to keep the environment within limits adequate for human living, intentional control and governance that affects the trajectories can become necessary. A simple example of what the governance of limit management with respect to inflow and outflow of material (and financial) resources looks like is presented in Box 14.2.

14.1.2 Complexity in HES

In the time of the anthropocene, the environment and thus most environmental problems have been shaped by human systems and history. It is not that humans usually directly cause flooding, but that flooding is the result of human settlement and related alterations of rivers and land, and, in particular, whether or not humans build levees. Global warming becomes a problem because of human production and fossil energy use, and soil fertility because of agriculture. All these problems are overly complex, in particular if they are investigated in real-world settings. In addition, we are facing multiple causalities. In general, what caused Chernobyl, Seveso, or the impact of hurricane Katrina does not refer to one single “cause” only. Cross-scale or cross-level interactions play a challenging role in complex HES, because reciprocal effects and (first and higher order) feedback loops are frequent and can establish tricky rebound effects. Thus, coping with multiple impacts and interactions is a special challenge.

Responses of a system’s environment may be delayed, and developments can go on hidden from awareness or evolve in a manner too slow and distributed to be easily recognized (Liu *et al.*, 2007a, b).

Box 14.1[1] Climate impacts of the agrarian society: pest impacts?

Until 2003, researchers thought that the anthropocenic era had begun 150–200 years ago, when the industrial revolution began producing CO_2 and CH_4 at rates sufficient to alter their compositions in the atmosphere. However, in 2003, Ruddiman (2003) proposed that the first human influences on the climate occurred thousands of years ago. His hypothesis is based on three arguments. First, cyclical variations in CO_2 and CH_4 driven by Earth-orbital changes during the last 350 000 years show predictable decreases throughout most of the Holocene. However, as shown in Figure 14.2 (left), the CO_2 trend began an anomalous increase 8000 years ago, and the CH_4 trend did so 5000 years ago. Second, published explanations for these mid- to late-Holocene gas increases based on natural forcing can be rejected based on paleoclimatic evidence. Third, a wide array of archeological, cultural, historical, and geologic evidence points to viable explanations for climate change that are tied to anthropogenic changes resulting from early agriculture in Eurasia, including the start of forest clearance about 8000 years ago and of rice irrigation about 5000 years ago. In recent millennia, the estimated warming caused by these early gas emissions reached a global mean value of 0.8 °C and roughly 2 °C at high latitudes. Based on analyses from two kinds of climatic models, this rate of warming was large enough to prevent a predicted glaciation in North-eastern Canada. Ruddiman (2007) also proposes that CO_2 oscillations of ~10 ppm in the last 1000 years are too large to be explained by external (solar–volcanic) forcing, but they can be explained by outbreaks of bubonic plague that caused historically documented farm abandonment in western Eurasia (see Figure 14.2b). His studies suggest that forest regrowth on these abandoned farms sequestered enough carbon to account for the observed CO_2 decreases. Moreover, plague-driven CO_2 changes are also thought to have been a significant causal factor in temperature changes during the Little Ice Age (1300–1900 AD).

[1] This box has been written together with Bastien Girod.

Box 14.1 *(cont.)*

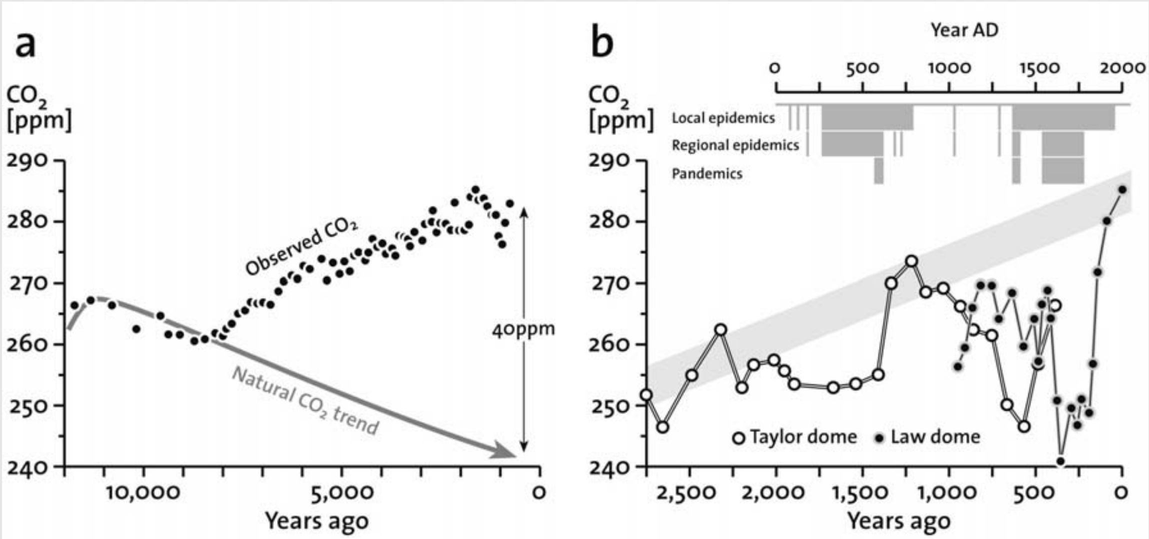

Figure 14.2 Early anthropogenic hypothesis. (a) Human activities during the late Holocene caused increases in CO_2 in contrast to the downward trends during previous interglaciation. Late Holocene greenhouse gas increases prevented much of the natural cooling that occurred in previous interglaciations (from Ruddiman, 2007, p. 2). (b) Rising CO_2 trend during the Holocene (light grey) interrupted by decreases during the past 2000 years. Several of the CO_2 drops may have been caused by reforestation, resulting from massive mortality during pandemics (from Ruddiman, 2007, p. 3).

Nearly every aspect of this early anthropogenic hypothesis has been challenged: the accuracy of the timescale and therewith the resulting anomalies in CH_4 and CO_2 emissions, the issue of use of the isotopic stage 11, the ability of human activities to account for the gas anomalies, and the impact of the pandemics. However, Ruddiman's response to this criticism (2007) reconfirms that the late Holocene gas trends are anomalous in all ice timescales; greenhouse gases decreased during the closest isotopic stage 11 insolation analog; disproportionate biomass burning and rice irrigation can explain the methane anomaly; and pandemics explain half of the CO_2 decrease over the past 1000 years. However, Ruddiman (2007, p. 1) admits that "only ~25% of the CO_2 anomaly can be explained by carbon from early deforestation." Considering the influence on the global climate of early agriculture, Kutzbach *et al*. (2009) conclude that a full test of the early anthropogenic hypothesis will require models that include ocean and land carbon cycles (see also Box 4.10). Calculations of the radiative forcing of climate with special resolutions support Ruddiman's thesis on the anthropogenic influence of epidemics and even population decline through warfare on the climate. Pongratz *et al*. (2009) point out that although some affected regions may be too small to have caused impacts on global climate, local climate may have been altered significantly.

This confronts us with legacy effects and time lags. A system may experience sudden changes, which in fact have evolved subliminally until a certain threshold is reached. These critical tipping points have to be explored to understand non-linear behavior. General characteristic properties of complex systems are circular causality, feedback loops, the issue that small change can cause large impacts, as well as emergence and unpredictability (Érdi, 2008; Matthies, Malchow & Kriez, 2001; Allen & McGlade, 1989). We can see that complexity has many origins and, as Allenby (2009) stressed, is not a unitary concept. We distinguish five types of complexity.

First, *static complexity*; this type of complexity (which others might call "complicatedness"; see Ottino, 2004) is defined by the number of system elements and their relations. In environmental sciences this complexity can often be taken from system graphs, such as Forrester's world model (see Box 16.7), or a flow chart representation of technical systems such as a nuclear power plant (see Box 16.11). Referring to the "architecture of knowledge" we conceive this type of knowledge

Box 14.2 Societal complexity, unsustainable resource flows, and indebtedness: the western Roman Empire

The rise and fall of the western Roman Empire reveals the difficulty that societies have in establishing sustainable resource flows. The great successes at the beginning of the Roman Empire (starting around 27 BC) stemmed from its expansions and the economic returns during the conquering phases. The return rates during this military and warfare-based expansion phase were initially very high. The accumulated resources of the conquered land increased the wealth of the mother country. However, the returns declined after the military process ended and was followed by an expensive administrative phase, in which the conquered country had to be organized and the defeated were no longer exploited to such a high degree. In short, the high return during expansion was only possible by ongoing conquering of new land and by taking resources from the defeated. Once this process decelerated or stopped, what was left was the huge Empire whose management caused large internal costs.

The late Roman Empire tried to solve these problems no longer by additional expansion but through its primary problem-solving institutions, i.e. the government and the armed forces which increased in complexity, size, power, and cost. "It became a coercive, omnipresent state that tabulated and amassed all resources for its own survival" (Tainter, 2000, p. 21).

What the Romans did not foresee was that their military and administrative growth was no longer complemented by growth in wealth (from external sources). Instead, beginning with Nero (in 64 AD) they tried to solve the problem by debasing their currency several times. This "was a rational solution to an immediate problem" (Tainter, 2000, p. 34) because the costly metals, especially silver, for the denarius coins became scarce. In the long term, however, the costs of self-sustaining of the empire exceeded its capabilities, because it stopped expanding while its enemies grew in number and strength.

A society must create a sustainable regime and prevent a consumption of its own substance. This is reflected by the devaluation of the money (see Figure 14.3), which represents the indebtedness of a system that has not found a sustainable flow of resources. The path the Romans were on meant "increasing the size, complexity, power, and the costliness of the primary problem-solving" systems, which in turn increased the vulnerability of the whole empire (Tainter, 2000, p. 23). Thus, the "Roman Model" of problem-solving led to unsustainable development, with increasing complexity and costs that had been subsidized by new resources through further expansion. The currency debase was a viable strategy only in the short term; but the ongoing use of the same strategy ("more of the same"; Dörner, 1989) led to bankruptcy (see Figure 14.3).

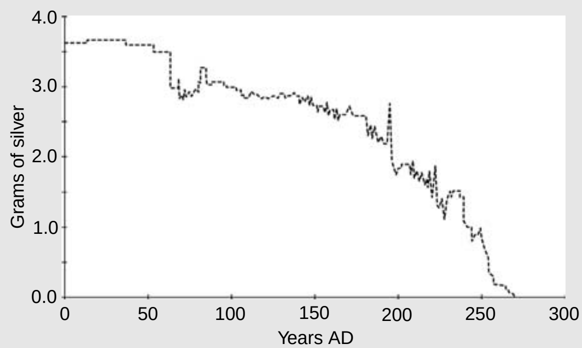

Figure 14.3 Debasement of the denarius to 269 AD (With kind permission from Springer Science + Business Media: Tainter, 2000, p. 21).

as "conceptual complexity," which represents the cognitive process of *begreifen* (conceptualizing; see Box 2.6). A static system model asks for definition of system boundaries and usually includes qualitative statements about cause–impact relationships, which already include a dynamic, temporal dimension and is linked to *erklären* (explaining; see Box 2.6).

Second, *dynamic complexity* arises if factors among the systems interact and induce temporal changes. Unexpected behavior emerges by the continued actions of positive feedback loops in the system. Capturing complexity of this type requires definition of quantitative relationships in the language of mathematics. We thus speak about formal models which serve to explain the complexity of systems through simplified representations of the system. The dynamic aspect of complexity is very pronounced in modern societies with accelerating technological development and information communication.

We distinguish two types of dynamics. One is predictable, gradual, and "continuous," while the other is a seemingly unpredictable, unsteady, "chaotic" process in which the fundamental system properties may change.

Third, according to Allenby (2009), *wicked complexity* emerges from the imponderabilities involved in human systems and the fuzzy goal definition when

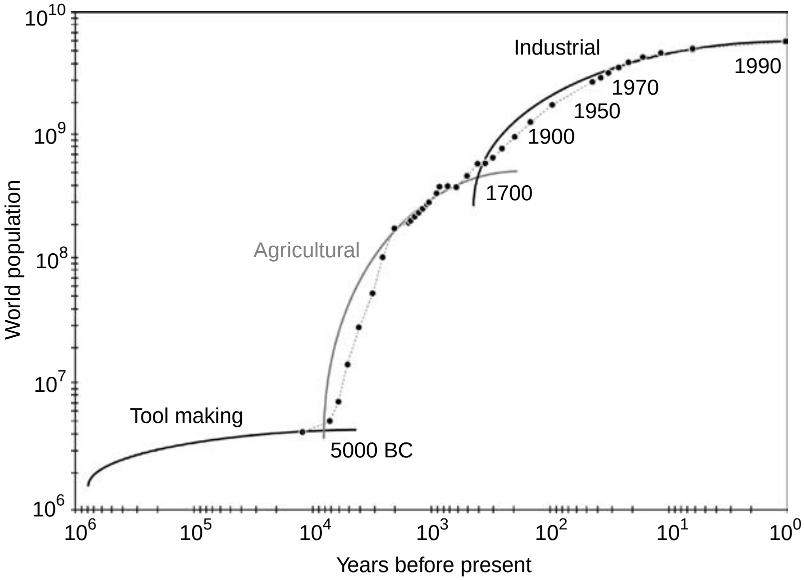

Figure 14.4 Logarithmic population growth in transitory successions of human social system. Adapted from Deevey, 1960 with permission. © 1960 Scientific American, a division of Nature America, Inc. All rights reserved. (Data from Kates, 1997; United Nations (UN), 1993).

dealing with transitions, for instance, towards sustainable development, of real-world systems. That is, the problems are ill-defined and sometimes there is no consensus what the problem *is* or which *goal* one wants to achieve (Dörner, 1989; Scholz & Tietje, 2002). This type of complexity is highly dependent on the socio-political structure and dynamics that constantly and inherently interacts with natural systems to general emergent behavior of coupled HES.

Fourth, *complexity of scale* emerges as we are dealing with HES on completely different spatiotemporal scales (see Table 9.1).

> [That] the Anthropocene arises because humans are impacting not just local environments and resource regimes but the global framework of physical, chemical, and biological systems is new and challenging, in that no discipline or intellectual framework enabling rational understanding at that scale yet exists (Allenby, 2009, p. 176).

The different temporal dynamics of the interacting systems can lead to interferences between subsystems and supersystems (see the Interference Postulate P3; Chapter 16.4). Further, the behavior of these systems can be qualitatively distinctive at different phases of development (see Figure 14.4). If we refer to Holling's adaptive cycle, critical issues are in particular revolting subsystems in highly connected mature supersystems in the conservation stage (see Figure 5.16). To understand this type of complexity, investigations focus on the connectivity of different systems' elements, their interactions, and their organization across various scales.

Fifth, we face *historic complexity*. This results from the cumulative, historic nature of systems, including path dependency. How a system is reacting or how and what a decision-maker is factually doing is not only dependent on the situation but also on the way they got there. Each increment of complexity is built on preceding steps, so that complexity seems to grow exponentially in time. Moreover, an increasing complexity because of technological and societal advances demands more complex societies to manage such complex systems (Tainter, 2000).

14.1.3 Non-linearities and "critical transitions"

There is no absolute linearity in real-world systems. Thus, non-linear functions or stepwise approximation by linear functions seem to be the most reasonable strategies to investigate relationships between certain variables. But in many systems, phases of relative continuity are following discontinuity. This can be exemplarily seen when modeling the population growth of human systems (see Figure 14.4). The population growth suggests that there were fundamental system transitions between the food-gatherers and hunters, the plowmen and herdsmen of the agricultural society, and the fuel-driven engine users in the industrial society. Here the invention of technologies such as the wheel, plow or steam engine can be seen as drivers of

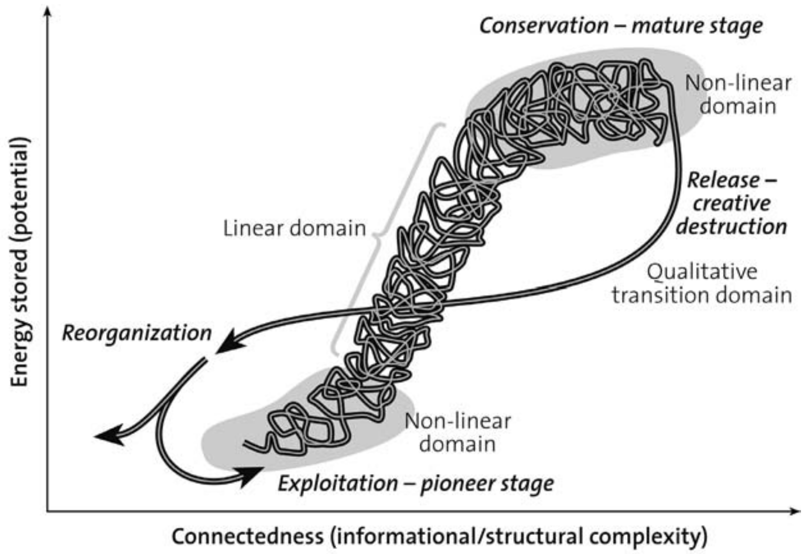

Figure 14.5 Energetic potential as a function of structural complexity in the development (succession) of ecosystems (based on Jørgensen *et al.*, 2007, p. 158, © Elsevier).

regime shifts (see Chapter 13). The growth at each level of society seems to be limited by the environmental constraints and the technological capacity to utilize these resources efficiently, and the type of social organization (see Figure 8.5*). Assuming that the trajectories of population growth at each stage of society follow law-like regularities, one could postulate that:

> … we are in the midst of the final doubling of … the third great surge of the population. (Kates, 1997, p. 37)

Another type of dynamics has been presented in Holling's conception of adaptive cycles. Figure 14.5 illustrates the maturation process as it has been presented for ecological (see Figure 5.16) and social systems along the dimension connectedness, which means structural complexity and stored exergy (i.e. the maximum amount of usable energy), which also is denoted as potential. The graph illustrates further that there is a kind of erratic or stochastic nature. We can distinguish three types of domains: a middle domain in which the relation can be described by a mean – apparently stochastic – linear relation between "potential" and "connectedness;" and the upper and lower bounds of the linear domain where we face a non-linear mean relation. Also, there is the domain of collapse. If a certain level of saturation is attained, one can observe a "critical transition," which means here an abrupt decline of potential.

Clearly these regime shifts are most difficult to anticipate. We know many examples from the real world of such releases or collapses, such as the shift of the Sahel-Sahara from a region that had abundant vegetation during the mid-Holocene to desertification nowadays, the 1929 Wall Street stock market crash, or abrupt changes in political systems such as the fall of the Soviet Union. Some of these "critical transitions" may be described by dynamic systems theory, such as chaos (Mandelbrot, 2004), catastrophe (Thom, 1970) or the bifurcation theory. Yet, we are still at the very beginning of understanding qualitative "critical transitions" (Scheffer, 2009; Sornette, 2003), which are an important component for environmental literacy.

14.1.4 What and what not to expect from modeling

> It is commonly held that mathematics began when the perception of three apples was freed from apples and became the integer 3. (Davis & Hersh, 1981, p. 127)

Numbers, lines, variables, and functions are abstractions or mental models or constructs. A model strips away everything that is sensible and transforms a system from a concrete real-world system to an abstracted model. Mathematical modeling means to switch from experience to mathematics; for instance, from our intuitive spatial understanding to geometry (Aristotle, 350 BC). If we use the language of Jakob von Uexküll (see Chapter 4.12) in modeling we are operating on the (abstract) sign level. In the conception of this book, models are part of the socio-epistemic world.

Models serve to better conceptualize, understand, explain, and anticipate reality and they do it in

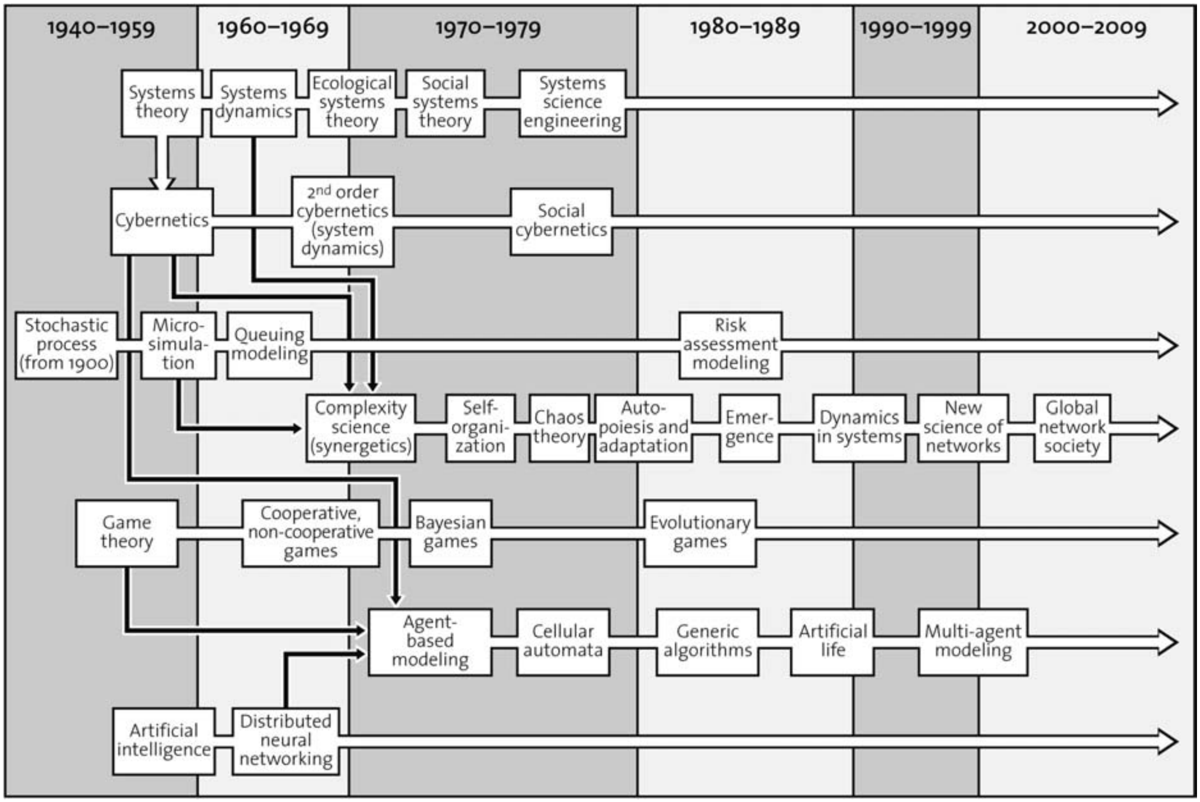

Figure 14.6 Development lines of human literacy in system complexity (modified from Wikipedia http://en.wikipedia.org/wiki/Complexity).

a systematic manner (Epstein, 2008). Figure 14.6 gives an overview of the development of different branches of *modeling* as a tool to enhance human literacy in system complexity. This holds true for a material model of a ship, which is used in a flow channel to explore flow resistance. It also holds true for conceptual or mathematical models on cause–impact relationships or dynamics of complex systems. In natural or engineering sciences, scientists are often formed by the idea that the truth is in the model. We call this the Newton and Leibniz way of thinking or knowledge integration, which comes from the belief that the laws of classical mechanics are universally valid and omnipotent models. From our perspective this is not true. We follow the understanding that each theory or model has a prototypical domain of intended applications in which the model can almost perfectly describe what is ongoing in the environment (Sneed, 1971). But for each model there are fringes where other factors and laws are at work. For instance, Hooke's law that the power of any spring is proportional to the extension of a spring is only "approximately valid" in a tiny domain of relatively small deformation of certain springs. Models are not copies of the world but constructs of our mental capability to better understand certain aspects of reality.

Mathematical parameters, variables, and functions are means of describing what is happening. They cannot explain, for instance, a causal relationship, but can only describe it. Explanations emerge from theories. Thus we conceive modeling and mathematical modeling in particular as a tool or language, which helps us to utilize an abstract representation for describing more precisely and gaining insight into the dynamics and interactions of systems. The knowledge that can be gained by modeling goes beyond verbal or graphical (maximum four-dimensional representation, including time in an animated 3D graph).

Models allow us to represent our assumptions about causalities, but do not explain them. To explain we need conceptual systems, which include terms whose role and interaction can be described, for instance, by mathematical formula. Here it makes sense to distinguish between conceptual and abstracted systems or models. Conceptual systems are built by terms from normal languages. Abstracted systems are: (i) formal, mathematical systems presented in a formal, symbolic language, that (ii) refer explicitly to natural or social science theories (Miller, 1978; Sneed, 1971).

14.1.5 Mathematical models as a "microscope"

A critical question with respect to environmental literacy is whether and in what manner models can help us to better access critical properties of HES. Can we magnify our image and penetrate what is ongoing – for example – in current or future food or energy supply on a world system level? We have seen in the history of microbiology and molecular biology, that the microscope has been the major instrument promoting progress in understanding the structure and function of microstructures of the organism (see Figure 5.1). Clearly, the data and signs from the microscope have to be interpreted. Similarly we can postulate that mathematical modeling provides new data, which can help to better describe, understand, and explain dynamism, trajectories, and regulatory mechanisms in HES.

Simulation, i.e. the imitative representation of the functioning of a real-world system by mathematical signs, can help to mimic complex systems without intervening into the real-world setting, which is often impossible for various reasons. We shed light on major modeling approaches and exemplarily reveal what core ideas they provide for an extended environmental literacy. Simulation, in particular, offers the opportunity of anticipating and investigating possible future dynamics of a complex system. As such, it is considered a tool for sustainability learning.

14.1.6 Epistemic requirements to analyze HES

The previous sections and chapters have demonstrated that a variety of epistemic requirements arise from the attempt to understand coupled HES comprehensively. These include the following epistemic operations:

- Capture complexity
- Include and quantify uncertainty
- Acknowledge complementarity of human and environment systems, including hierarchies of systems and potential interferences between them
- Take into consideration the dichotomy of agency and structure
- Understand decision-making of different actors, taking into account alternative, potentially conflicting, strategies
- Include feedbacks in human and environment systems
- Adopt a long-range view and anticipate potential future developments
- Capture non-linearities and "critical transitions," including self-organization of systems and emergent properties
- Capture heterogeneity of states and processes in space and in time, coupling multiple human and environmental agents
- Provide reliable evidence with limited availability of data and information.

These requirements pertain to properties of complex systems in general and to characteristics of HES in particular. Perhaps these requirements do not all apply at the same time but depend on the phenomenon at hand.

14.1.7 A taxonomy of models for HES

It has been argued that modeling is a promising approach to analyze HES. Here we present a taxonomy of models, referring to the epistemic requirements stated above. It will be demonstrated that the different modeling approaches show specific strengths with regard to these requirements (Table 14.1). We start with the "linear model," which is based on linear equations or transformations. These are the basic fundamentals of modeling and date back to 2000 BC (Struik, 1987). Systems thinking and system dynamics models, as the next important tool to model complex non-linear systems, go beyond linear models and are based on differential calculus, which was developed in the time of Leibniz (1646–1716) and Newton (1643–1727). Scenario analysis, and, in particular, formative scenario analysis, are options to address complex problems in case a cardinal operationalization of the variables and/or functional relationships among the variables cannot (yet) be provided.

Other than differential equation-based models, which are essentially deterministic, stochastic processes are non-deterministic in the sense that they include random processes. A system element or variable is called random if there is no way to predict its outcome exactly. This leads to uncertainty, probability

Table 14.1 Strengths of various modeling approaches with respect to epistemic requirements for understanding the dynamics of HES (indicated by x).

Epistemic requirements	Linear model	System dynamics	Probability, stochastics, risk	Game and decision theory	Cellular automata	Multiagent system
Uncertainty	x		x	x	x	
Complexity:	x	x		x	x	x
static complexity		x		x	x	x
dynamic complexity						x
wicked complexity						
complexity of scale						
historic complexity						
Complementarity of human and environment systems	x	x		x		x
Hierarchy, interference of systems		x		x		x
Agency/structure dichotomy		x				x
Conflicts, alternative strategies		x		x		x
Understanding decision-making		x	x*	x		x
Feedback		x			x	x
Anticipation, long range view		x				x
Non-linearity, thresholds		x			x	x
Self-organization and emergence		x			x	x
Heterogeneity: - in space		x		x	x	x
- in time				x	x	x
Dealing with limited availability of data and information	x	x	x	x		

* This refers to risk.

distributions, and risk assessment. As we will see, uncertainty and probability modeling is ubiquitous. Thus, as we can learn from physics and chemistry, unforeseeable dynamics of systems, qualitative change of structures, "critical transitions" or unforeseeable collapses can also result from non-stochastic system dynamics. We briefly touch on this under the label self-organization, instability, and chaos.

With game and decision theory, actors, together with their strategies, interests, and rationales, are introduced explicitly. While game theory offers the opportunity to formalize and to understand conflictive situations and social dilemmas, decision theoretical models address the mental process within individual actors prior to action. Finally, we focus on multiagent systems, which have their root in game theory, cellular automata, and artificial intelligence. Other than in system dynamics, multiagent models operate at the level of individual agents following a set of decision rules, resulting in emergent properties of the system at the level of the observed phenomena. The issue here is that this way of modeling allows for the modeling of coupled material bio physical and social systems, and thus is an interesting approach to HES.

To conclude this overview on different modeling approaches, we would like to point out that beyond these requirements there are further challenges for interdisciplinary modeling to take into consideration. These pertain in particular, first, to reconciling different disciplinary views with regard to model validation, and second, to the problem of leaving space for the unknown when addressing future developments. These challenges have to be kept in mind and investigated further when applying modeling approaches for the analysis of HES.

14.1.8 Key messages

- The anthropocenic redefinition of the material–biophysical environment systems acknowledges the strong human impact in all environmental systems, from the atomic–molecular to the global biogeochemical–cycle level. This requires incorporation of the human factor in (modeling) the material (natural) environment dynamics
- Human and environmental systems are seen as hierarchically layered, multiscaled, historically shaped, partly predictable, inextricably coupled complex systems, which may face linear, smooth or non-linear qualitative system transitions
- Modeling is considered a promising approach to analyze HES that has the potential to comply with a range of epistemic requirements that arise from the attempt to understand these systems thoroughly.

14.2 The world of the linear model

14.2.1 The linear model: the working horse for systems modeling

The key concept of the linear model is *proportionality*, which simply means that one variable x has a constant ratio to another y, which means x/y = constant = a. Historically, the linear model developed early and is the simplest approach of quantitatively relating different variables.

The linear model is still a powerful tool of many sciences, including the environmental sciences. Practical work with the *IPAT* model ($I = P \times A \times T$; see Chapter 9.3) refers to the linear model. When calculating the environmental impact per person ($P = 1$), the environmental impact I, which is often measured by CO_2, depends linearly on the affluence A, which is often represented by the GDP and the level of technology, which is taken as a constant.

For instance, life cycle analysis (LCA; Heijungs & Wegener Sleeswijk, 1999; Udo de Haes & Heijungs, 2009), material flow analysis (Baccini & Bader, 1996), and all variants of input–output analysis (Hendrickson *et al.*, 1998; Leontief, 1966) are based on linear algebra, the mathematical field dealing with linear transformations. To understand the idea of the linear model in LCA, the reader can think about vector Y as all relevant environmental impacts that can result from one product (or process), X as all material, biophysical input resources needed to produce this product, and the cells of the variables $A = a_{i,j}$ to denote in what way the input resource x_i affects y_j. This idea also runs under the term input–output analysis (Leontief, 1966).

14.2.2 The key idea

The linear model is presumably the most simple and most frequently used approach to gain insight into the mutual relationship between two or more system variables. In the elementary case we consider two variables x and y that can be defined or measured by rational (or real) numbers and where the values of the one variable are proportional to that of another. We can represent this by the simple equation (see Figure 14.7):

$$y = ax + b \tag{14.1}$$

In general, we can denote the linear model as a rough, simple but in many cases useful and beneficial instrument or tool of modeling the interaction of variables in HES and other systems. The wide range of use of the linear model is revealed by the terminology. Depending on the context of application, the variable y is also called the dependent, response, observed, measured, explained or outcome variable. The variable x is called the independent, manipulated, exposure, predictor or input variable.

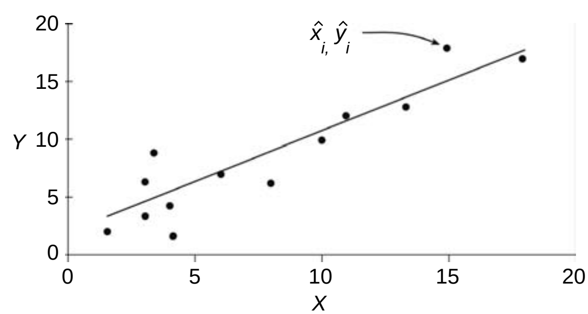

Figure 14.7 A linear regression of two variables x and y.

In the following, we want to sketch how environmental literacy is fundamentally extended by the linear model using four examples. These are: (1) the utilization of matrix algebra to represent how multiple variables (linearly) transform a vector of resources in environmental impacts. (2) We demonstrate how complexity measurements can be reduced by linear correlation and regression. This is done by the use of the linear model in statistics, which includes methods such as regression analysis, factor analysis, and analysis of variance. Here, we exemplarily illustrate how the complexity of a model and measurements can be reduced by (3) factor analysis. Finally, (4), we briefly illuminate the interaction of variables, which can be considered as the entrance of multivariate literacy before we sketch the linear programming models.

14.2.3 Representing multiple linear processes

We are often not only interested in one or more dependent variables y_j which are considered as being a function of a set of other variables x_i. The dependent variables can be different types of emissions. The reader can think about the vector $Y = (y_1,\ldots y_j,\ldots y_m)$ as a set of relevant environmental damages that can result from $X = (x_1,\ldots x_i,\ldots x_n)$, which are different material resources needed to produce a product.

If we assume that the values of the variables y_i can all be assessed by a linear combination of the vector of variables $X = (x_1, ..., x_i, ..., x_n)$(e.g. $y_j = \sum_i a_{i,j} x_i$), we can present this complex transformation by the simple equation

$$Y = XA + B \tag{14.2}$$

where $B = (b_1,\ldots,b_j,\ldots,b_m)$. Here A is a matrix with m lines and n rows and each cell $a_{i,j}$ describes by what amount the variable x_i contributes to y_j.

We should note that the linear model is powerful and widely applied as it is often reasonable to transform non-linear relationships into linear ones by suitable functions. If variable x_i has a multiplicative impact on a dependent variable, then logarithmization or other transformations may linearize these relationships.

14.2.4 Regression analysis for data complexity reduction

An important field using the linear model is statistics, for instance (linear) correlation and regression analysis. Let us assume that we have a certain set of $k = 1,\ldots k,\ldots,K$ observations $(\hat{x}_i, \hat{y}_i)$ of the variables x and y (see Figure 14.7). If we assume a linear "stochastic" relationship this leads to a linear correlation and related methods. The correlation coefficient tells us how strong the relation between the two variables is. If all points are on the straight line, we have a perfect correlation and the correlation coefficient is 1. If there is absolutely no linear relationship, the coefficient is 0. The term "stochastic" refers to a fundamental assumption of linear regression that the variables show factually a linear correlation, but random factors affect the values of the (measurement of the) variables. If we consider ε as a stochastic error term, the equation (14.1) turns into:

$$\hat{y} = a\hat{x} + \varepsilon \tag{14.3}$$

Clearly, we can also work with more than one dependent and independent variable, which leads to different variants of multiple regression analysis (Bortz, 2005; Draper & Smith, 1998).

14.2.5 Finding a minimum number of system variables

An important and widely applied approach is factor analysis. The issue is again complexity reduction. Let us assume that we have a large number of random variables $Y = (y_1,\ldots,y_i,\ldots,y_m)$. For each of these variables we have a set of observations or measurements of system states (i.e. $\hat{y}_{i,1},\ldots,\hat{y}_{i,m}, m \geq n$). Factor analysis is a means of reducing the number of initial variables by postulating a small number of k factor variables $F = (f_1,\ldots, f_e,\ldots,f_k)$ which incorporate all variables y_i as a linear combination (i.e. $y_i = \sum_i w_i f_e, w_i$ are called factor scores).

The key idea of factor analysis is reflected in the term "principle component analysis," which is often synonymously mentioned. This procedure provides for a larger number of correlated variables a reduced number of uncorrelated variables, principle components, which can predict all variables by linear combination.

If we can find few variables f_e (i.e. factors or principle components) that can well explain the variation of the dependent variables or observed measurements $\hat{y}_{i,1}$ then we may have reduced the structural complexity.

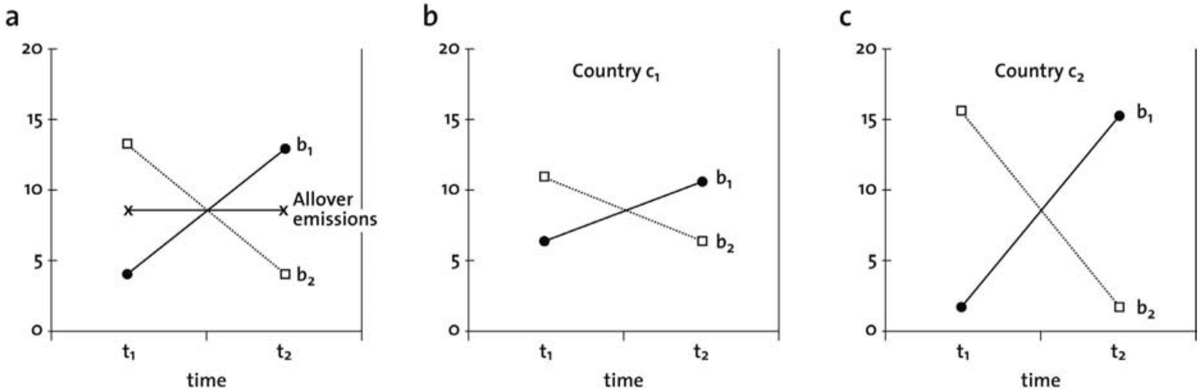

Figure 14.8 Graphical representation of first order and second order interactions of two variables by representing the means *x* and *y* over time *t*.

14.2.6 Understanding interactions among variables

To understand the interaction of three or more variables is an important aspect of environmental literacy. We introduce the idea through a simple example: consider the situation where one dependent variable y (e.g. environmental emissions) depends on two independent variables, which may be time t and different branches $b = b_1, b_2, \ldots$ of industry. A survey conducted by environmental scientists may be interested in the question of how the emissions y from different branches b change over time.

This is exemplarily shown in Figure 14.8a. The middle line shows that the total emissions do not differ between the two points in time t_1 and t_2. However, there is an interaction between the variable time t and the branches b. Whereas for branch b_1 the emissions are increasing between time and, the emissions are decreasing for branch b_2. This is called first order interaction among the independent variables t and b on the dependent variable y.

A slightly more sophisticated interaction is demonstrated in Figure 14.8b–c. Here we consider besides t and b a third variable c, which can represent countries, for example. In our example we consider only two countries, c_1 and c_2. As can be seen from Figure 14.8b and Figure 14.8c, in both c_1 and c_2 the emissions are increasing for b_1 and decreasing for b_2. One may diagnose (and often statistically verify) that the decrease–increase difference is (significantly) smaller under c_1 than under c_2. Here we are facing a second order interaction of three variables, t, b, and c on a dependent variable y. There are many other cases with variables of different levels of scale. The theory of interaction is a field of statistics, in particular the analysis of variance (ANOVA; see Cox *et al.*, 1984; Hays, 1963).

14.2.7 How is interdisciplinarity achieved

In a rigid sense, interdisciplinarity is established by merging concepts or methods. Thus it is essential how and which variables are related. We can see two major forms of merging. One is by establishing causality between two variables originating in different disciplines. For example, when we face the emotional response of anxiety regarding a nuclear power plant and this response can also be measured by increased bloodflow to the amygdala, then this is a case of neuropsychological research about the perception and evaluation of new technologies. This example shows organized interdisciplinarity by integrating variables from different disciplines, which are neuropsychology and technology assessment, in a (linear) model. A second option is given by integrating variables from different disciplines in a (linear) model.

14.2.8 Key messages

- The linear model allows multiple system variables to be related, and is a quantitative representation of how a multitude of input variables affect outputs, given certain presuppositions

- The linear model can be generalized by various means, e.g. by linearizing the variables (by scale transformations) or by logarithmization of multiplicatively related variables. There is a large set of statistical models developed under the heading generalized linear models
- The linear model in statistics is a basic model for reducing complexity by interacting, reducing, and empirically testing interactions between system variables.

14.3 Systems theory, systems dynamics, and scenario analysis

14.3.1 Rationale and historical background

Systems thinking, system dynamics, and the theory of dynamic systems seek to understand and to describe the behavior of complex systems over time.

Box 14.3 Dynamic patterns in coupled HES: collective irrigation management

Water is a primary natural resource and, as such, a fundamental condition for increasing agricultural productivity in rural areas to improve food security and to generate additional income streams for farmers through the cultivation of cash crops (Molden, 2007; Norton & Food and Agriculture Organization of the United Nations, 2004). Farmer-managed, collective systems are widespread and have been found to operate often very efficiently (Vermillion & Sagardoy, 1999). In many cases, however, cooperation may fail, leading to deterioration of irrigation infrastructure, tensions between upstream and downstream users, and possibly violent conflicts. Hence, the question is, whether and under what conditions cooperation can be successful. This problem is considered an example of a coupled HES, where human actions (decisions with regard to cooperation in collective irrigation management) and the effects of these actions (condition of the irrigation system and water productivity) are integrated into a dynamic feedback system. To study possible dynamic patterns in collective irrigation management, a system dynamics model has been developed (Gallati, 2008).

This model refers to the theory of a critical mass in collective action (Granovetter, 1978; Oliver & Marwell, 2001; Schelling, 1978), and includes a number of influence factors that have been found conducive for successful common property resources management (Baland & Platteau, 1996; Lam, 1998; Ostrom, 1990; Wade, 1988). The model is based on case studies in Kyrgyzstan and Kenya. The fundamental feedback structure of the model is shown in Figure 14.9.

The model has two equilibria: the first corresponding to successful, and the second corresponding to unsuccessful cooperation. Model results are presented for the Kyrgyz case, showing a decline of cooperation, and in turn of condition of irrigation infrastructure (Figure 14.10a). This decline has been observed between the early 1990s and 2005. Variation of initial conditions or of specific functional relations, representing for example the effect of receiving sufficient water on farmers' decisions for cooperation, may shift total cooperation to the upper equilibrium.

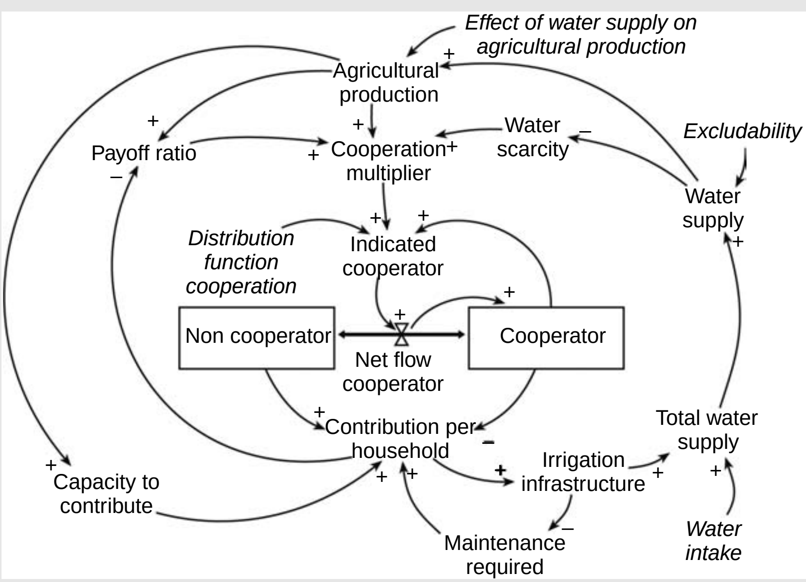

Figure 14.9 Fundamental feedback structure of the system dynamics model for collective irrigation management. The number of users intending to cooperate in future depends (i) on the number of current cooperators, (ii) on the performance of the irrigation system (water supply), and (iii) on the capacity of the users to contribute. Distribution function cooperation refers to an overall distribution of users' thresholds for participation in collective action, shaped by prior experiences as well as by individual economic resources.

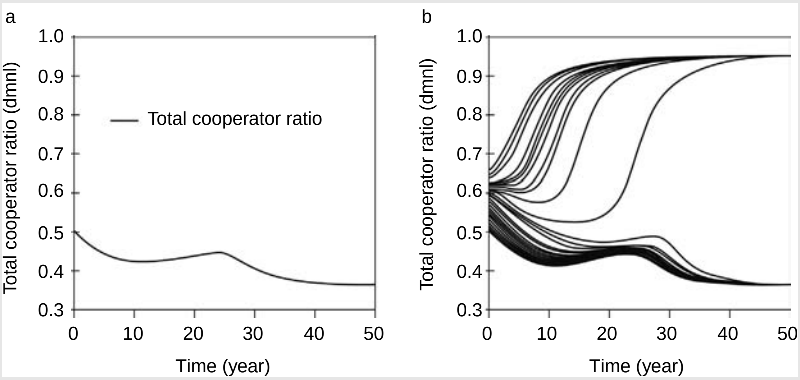

Figure 14.10 (a) Decline of cooperation and settle to the lower equilibrium of unsuccessful cooperation. (b) Slightly higher initial cooperation may result in successful cooperation (upper equilibrium). Note: *x* axis, time; *y* axis, total cooperation ratio (dmnl: dimensionless).

Historically, these approaches refer to physics and the description of the motion of physical bodies using – and further developing – the mathematical language and tools available at that time. The 17-year-old Galileo, for instance, was interested in finding a law describing the swing of a pendulum. He could see that the wider the swing, the faster the motion was. He was surprised, when using his pulse as a chronometer, that it took the same number of pulse beats for a pendulum to complete one swing no matter how far it moved (Ginoux, 2009). This led to the invention of pendulum clocks but also to differential equations. The term was first used by Leibniz in 1684 and Newton to describe the Galileo pendulum using a second order differential equation. In its simple form, a (first order) ordinary differential equation describes the change dx of a target object (or variable) x within an infinitesimally small time dt. Mathematically this reads:

$$\frac{\mathrm{d}x}{\mathrm{d}t} = g\ \ x(t),\vartheta \qquad (14.4)$$

where g is a continuous function describing the change, t is time, and ϑ a vector describing location, motion, and other state variables.

Mathematics became a major tool in the search for knowledge. The primary domain in which mathematical theory developed was the investigation of properties of motion of physical bodies in idealized settings, ignoring some environmental constraints such as air resistance. The concepts used were those of idealized entities of "space, time, weight, velocity, acceleration, inertia, force, and momentum" (Kline, 1985, p. 98). One challenge was to identify the right variables, the other to develop the mathematical apparatus to describe the behavior of these entities over time. These were differential equations, which became a powerful tool to describe behavior of nature. Social scientists, in particular economists, utilized these tools to describe dynamics of economic and social systems.

However, the description and analysis of a system by means of differential equations also has its limitations, which arise on the one hand from mathematical properties of (non-linear) dynamic systems and on the other from the modeling process itself. Even elementary dynamic systems, such as the motion of three celestial gravitationally related objects, show unstable, chaotic behavior, as has been pointed out by Poincaré (1892). Moreover, it has been recognized that chaotic behavior is a property of many non-linear dynamic systems (Lorenz, 1963; Schuster & Just, 2005). Thus, the world of systems described with differential equations is not as "smooth" as one might expect. On the other hand, one has to be aware that a model of a complex problem is always only one of many possible descriptions that is valid from a particular perspective.

In the late 1940s, cybernetics evolved as a theory of (feedback) control of a system with regard to the environment (Wiener, 1948), and in the late 1950s system dynamics was developed to describe and analyze feedback mechanisms in socioeconomic systems (Forrester, 1961, 1969, 1971a, b, 2007a, b; see Box 16.7; Sterman, 2000). General system theory (von Bertalanffy, 1955) addresses characteristics of systems from a more general point of view. Finally, scenario analysis is an approach to deal with an uncertain future in a qualitative, yet meaningful, way.

14.3.2 Cybernetics

Cybernetics is a theory of control systems based on communication (transfer of information) between system and environment and within the system, and control (feedback) of the system's function in regard to the environment. (von Bertalanffy, 1968, p. 21)

In cybernetics, which concentrates on the regulatory mechanisms in systems, we find mathematicians (Wiener, 1948), organizational scientists (Beer, 1959), social scientists (Bateson, 1979), and psychiatrists (Ashby, 1956). In this book, we widely subsume cybernetics under systems theory. It is relevant in our context as one of the main targets of environmental literacy is the identification of regulatory mechanisms. However, we should mention that modern control theory is a new, mathematical domain in engineering that deals with modeling of feedback systems in engineered systems (Åström & Murray, 2008; Brogan, 1990). This approach is dealt with in some detail in Chapter 16.5 (Feedback Postulate P4).

14.3.3 Systems theory

Systems theory originated in the 1920s from biology when explaining the interrelationship between organisms and their related ecosystems by a "discovery of the principles of organization at its various levels" (von Bertalanffy, 1968, p. 12). Besides the hierarchical structure and the inner organization, the interaction with the environment (see Figures 3.3* and 17.1*) has been a key topic.

> Living systems are open systems, maintaining themselves in exchange of materials with environment, and in continuous building up and breaking down of their components. (von Bertalanffy, 1950b, p. 23)

This distinction between *open* and *closed* systems was particularly important and led to further investigation of open systems and irreversible processes in physics, chemistry, and biology. The cell and the organisms, for example, are open systems and thus can never attain true chemical equilibrium.

Systems theory is general, as we can speak about physical, biological, human, social, technical, and many other systems. Systems are described verbally or with formal, mathematical languages, and a distinction between concrete real-world systems, abstracted verbally described and abstracted mathematically described systems has been introduced. Systems theory has been formed by giants of thinking, among them biologists (Miller, 1978; von Bertalanffy, 1950a), economists (Boulding, 1956; Parsons, 1951), psychologists (Rapoport, 1996), or physicists (Capra, 1996; Nicolis & Prigogine, 1989; von Foerster, 1987), who all made important contributions to the philosophy of science.

14.3.4 System dynamics

System dynamics provides a set of concepts and tools that enable us to better understand the structure of complex systems. Designing effective policies has been the mission of the founders of system dynamics (Forrester, 1961, 1969, 1971a, b, 2007a, b; see Box 16.7; Sterman, 2000). Causality and feedbacks among variables in dynamic systems build the basic constituents.

As a modeling approach, system dynamics relies on three major constituents: first, the concept of feedback loops, including autocatalytic processes; second, computer simulation which allows us to utilize differential equations as a descriptive tool; and third, the notion of mental models which allows the participation of people concerned in utilizing these bodies of science for a better understanding of societally relevant phenomena (see Box 14.3).

The concept of feedback loops involves the collection of information about the state of the system, followed by some influencing action, which in turn changes the state of the system (Lane, 2000). The essence of the feedback concept is a circle of interactions that provides a closed loop of action and information. The patterns of behavior of any two variables in such a closed loop are linked, each influencing, and in turn responding to, the behavior of the other (Richardson, 1991b). Delays and non-linearities are essential properties of system dynamics models. Non-linearities, in particular, are necessary to cause shifts in the dominant structure of a model. This means that different parts of a system become dominant at different times (Richardson, 1991b). An extended discussion on feedback loops is provided in Chapter 16.5.

Computer simulation is the major tool used to describe the dynamic behavior of the system and to anticipate possible future states. Computer simulation is essential in particular for uncovering unanticipated side-effects (Sterman, 2000) and counterintuitive behavior. We should note that computer simulation is not a pure analytic formula-based activity but is based on many constraints, assumptions, and errors underlying the numerical, algorithmic approximation. Thus there is a second layer of modeling and simplification underlying simulation (Oliviera & Stewart, 2006).

The third element of system dynamics has to do with the involvement of practitioners and people who are facing specific problems in the modeling process. We call these people case agents and deal with the collaboration between case agents and scientists in Chapter 15, on transdisciplinarity. It has been recognized that one of the major contributions of a system dynamics modeling process is to stimulate learning processes amongst involved people (Morecroft & Sterman, 1994). It can also be said that the goal of a system dynamics intervention is to create shared inter-subjective meaning (Vennix, 1996) and to provide insight to key agents in a presumed functioning of the system, for instance for anticipating potential policy actions:

> The goal of a system dynamics policy study is understanding – understanding the interactions in a complex system that are conspiring to create a problem, and understanding the structure and dynamic implications of policy changes intended to improve the system's behavior. (Richardson, 1991b, p. 164)

This understanding is built around a dynamic hypothesis, which is the idea that a certain causal structure explains a certain dynamic behavior (Lane, 2000). This notion of a "dynamic hypothesis" is fundamental and is closely connected to the endogenous perspective adopted in system dynamics. The system dynamics model thus belongs to the category of causal, theory-like models claiming to generate the "right output behavior for the right reasons" (Barlas, 1996, p. 186). Thus, we consider a major benefit of system dynamics modeling to be that it shows the dominance of the underlying system's structure over the effect of a change of single variables to achieve a desired system change.

System dynamics makes the fundamental claim that the evolutionary behavior of a social system over time is explainable in terms of feedback loops and state variables (Richardson, 1991b). The concept of feedback thinking in system dynamics is intimately linked with the concepts of interdependence and circular causality, with a rich history in the social sciences (Richardson, 1991a). This observation points to a substantial affinity between system dynamics and the social sciences. System dynamics allows "that the environment that controls human decision making is *itself* made by human decisions" (Lane, 2000; emphasized in the original) is to be taken into account. Lane (2001), with reference to Giddens' structuration theory (see Figure 9.1), considers system dynamics an approach that has the potential to implement agency and structure integrating theories as it acknowledges the relevance of agency as well as of structure in their mutual (dynamic) relationship. Thus, by describing and analyzing such reflexive structures (see Figure 16.13), system dynamics has the potential to contribute to the social sciences.

This may illustrate that in the context of environmental literacy the roots of system dynamics are more related to social science and to the "systems movement" (Schwaninger, 2006) than to cybernetics. Richardson (1991a) argues that the origins of system dynamics are to be found in the servomechanical thread, oriented towards the combination of economics and engineering, and interested in understanding complex problems with feedbacks, rather than in adjustment processes and information transfer, as it applies to cybernetics.

14.3.5 How is complexity reduced

Reduction of complexity is achieved, first, by structuring "messy," ill-defined or "wicked" problems, second, by evaluating and exploring individual components of the models and thus assessing their influence on the behavior of the whole model, and third, by attempting to discern model structures that are as simple as possible yet which still generate the essential dynamics of the system. Such model structures are referred to as "generic models" (Lane & Smart, 1996), although a rigorous definition of generic structures is still missing.

The first point includes problem definition, which comprises the definition of the system boundaries and the problem-solving focus by a guiding question. This is an important step in structuring messy problems. This process of problem-forming, however, is shaped by perspectives and knowledge of the people involved. As such, it can be considered a first step in a mutual learning process creating a shared reality among the people involved (Checkland, 1981; Eden *et al.*, 1983; Phillips, 1984; Vennix, 1996).

The second and third points are intimately related to the primary focus of system dynamics on structure, generating a certain observed behavior. A (system dynamics) simulation model offers the opportunity to assess the influence of individual components of a model, and also of alternative model formulations, on the behavior of the model. As such it can be considered an experimental design that can be used to explore the effect of individual parts on the overall model behavior, possibly leading to a reduction in complexity. Generic models in particular seek to identify models that concentrate on the minimum structure necessary to create a particular mode of behavior (Forrester, 1968).

14.3.6 How is interdisciplinarity achieved

System dynamics is considered a valuable candidate for interdisciplinary and transdisciplinary studies for several reasons. From its origin the method is not related to any specific discipline and, as such, it qualifies for interdisciplinary studies – on the condition that the problem can be properly described in a way that is adequate to system dynamics (by means of state variables, feedbacks, and causal relations). In particular, it is possible to construct causal relations between variables that belong to different disciplinary-rooted domains. In practical modeling, however, one has to take into consideration that, owing to the high level of aggregation, these relationships may represent pure (non-linear) correlations or contingencies rather than genuine causal explanations.

With its orientation towards creating a shared and improved understanding of a problem, system dynamics contributes to interdisciplinary and transdisciplinary studies, providing both a language and a process of group interaction (Lane, 2000). In this perspective the process of building a model starts from the different perceptions of the participants and, by systematically eliciting and sharing their "mental models," aims at creating a more complete problem representation.

14.3.7 Semiquantitative system analysis by scenario analysis

When dealing with complex systems such as regional or organizational systems, we are often able to identify the key system elements or variables that we consider essential for describing the state and the systems change without being able to represent the dynamics and the interrelationship between aspects by differential equations or real number-based mathematical functions. This is the situation in which scenario analysis can be applied (Scholz & Tietje, 2002).

The method of scenario analysis was developed after World War II in strategic military and business planning. The initial idea was that scenario analysis was to describe what alternatives may emerge and how a system develops (Kahn & Wiener, 1967).

In simple terms, scenario construction is built on incorporating all essential variables that are necessary to describe the current state and the future development of a system. Here, we can distinguish between endogenous, action-based variables involved which represent the measures of the key case agents. In addition, there are exogenous variables that represent the salient changes in the environment. A critical question to be answered in scenario construction is whether the action scenarios, which describe the decision alternatives or strategies of the case agents based on endogenous variables, and the frame scenarios have to be defined separately or whether they are incorporated in an integrated model.

To describe the current state of a system and possible future states (both of action and frame scenarios), scenario analysis uses a set of variables or descriptors $D = (d_1,\ldots,d_i,\ldots,d_n)$. These descriptors are not necessarily seen as many variables, but they can also be seen as discrete variables which can have two or very few levels. These descriptors are called impact factors and should have the capability of describing the current state and the future changes of a system adequately and sufficiently.

In the case of urban development, for instance, the variables can come from the social (e.g. values, social classing), economic (e.g. income, energy prices), or environmental (e.g. emissions, impacts on ecosystems) side. If we can define different levels of each of these impact factors (e.g. d_i^1 = low income, d_i^2 = high income) we can define scenarios: a scenario is simply a "complete combination of levels of impact factors" (Scholz & Tietje, 2002, p. 105).

14.3.8 Formative scenario analysis

A formative scenario analysis (FSA) provides, on the one hand, a strictly organized method to construct scenarios that include the same specifying information on a fixed set of variables. This is already included in the above definition of scenarios. FSA also includes techniques to select a small set of scenarios that represent the possible states in a sufficient manner. This can be done by consistency analysis, i.e. by only selecting those scenarios whose combination of levels of impact variables are considered possible or not overly unlikely (Tietje, 2005). On the other hand, the term *formative* indicates that the process of defining scenarios is giving form to the case for which the scenario is built. This can be understood in an epistemic mental way, as has been described above for system dynamics. In particular, when future scenarios are jointly formed by stakeholders and scientists in a transdisciplinary process (see Chapter 15, Box 15.1), the forming of scenarios may have an impact on the case itself as all act with a desired or undesired future scenario in mind. Factually, this has been the case in many transdisciplinary case studies on sustainable transformations of regional, organizational, and political settings and processes (Scholz *et al.*, 2006). Thus, the process of scenario construction may have a formative component.

The FSA approach includes various techniques to construct mental models of how the impact factors are related, what relative importance they have in changing the status quo scenario, and what combinations and future scenarios are considered impossible because of (logical) inconsistencies between the levels that subsets of scenarios can take (Scholz & Tietje, 2002).

14.3.9 Intergovernmental Panel on Climate Change scenarios

The scenario technique became famous by the Intergovernmental Panel on Climate Change (IPCC) scenarios. These scenarios are a combination of different assumptions about key impact variables with regard to different social, economic, and technological developments. The scenarios have changed since 1990 regarding underlying assumptions and applied methods (Girod *et al.*, 2009). Based on these scenarios, the future development of greenhouse gas emissions, temperature, and precipitation in different regions have been calculated with classical differential equation-based models.

> Future greenhouse gas (GHG) emissions are the product of very complex dynamic systems, determined by driving forces such as demographic development, socio-economic development, and technological change. Their future evolution is highly uncertain. Scenarios are alternative images of how the future might unfold and are an appropriate tool with which to analyze how driving forces may influence future emission outcomes and to assess the associated uncertainties. They assist in climate change analysis, including climate modeling and the assessment of impacts, adaptation, and mitigation. The possibility that any single emissions path will occur as described in scenarios is highly uncertain (Intergovernmental Panel on Climate Change. (IPCC), 2000, p. 3)

The last sentence of this quote stresses that there is no technique which allows for describing the likelihood of scenarios.

14.3.10 Key messages

- Systems thinking contributes to an improved, reflexive understanding of feedback structures of coupled HES by providing mental models on how systems may evolve. System dynamics supports this exploration by providing quantitative simulation models, focusing on explaining model behavior by its underlying structure
- One goal of systems thinking and system dynamics is understanding and anticipating implications of human policy and its changes
- System dynamics is a *descriptive tool*. The current practice involves and relates variables of material–biophysical systems with those of social–epistemic systems in an open way. Special attention should be paid to reflecting causalities and different rationales of human and environmental systems as well as discontinuities
- Formative scenario analysis is a coarsened system model in which only levels of impact factors (and not real value-based functions) serve for system description and for constructing possible future states.

14.4 Self-organization, "critical transitions," and chaos

In this section we come back to non-linear dynamic systems. These systems can be described by differential equations, as has been stated above, and be classified according to their equilibrium states, which may be stable fixed points or limit cycles. A third possibility is that the system might show an erratic, aperiodic behavior and settle onto a "strange attractor" (Strogatz, 1994, 2001). Under the condition that the system is also sensitive to initial conditions, chaotic behavior is generated (Schuster & Just, 2005). This sensitive dependence on the initial conditions is called the "butterfly effect" (Lorenz, 1963), which reads in its classic shape that the flapping of the wings of a butterfly in South America today could result in a typhoon in Japan next month. Thus, non-linearity is a necessary, but not a sufficient, condition for the generation of chaotic behavior. "The observed chaotic behavior is due neither to external sources of noise nor to an infinite number of degrees of freedom" (Brown, 1996, p. 53), but precisely because of this property of separating initially close trajectories. For these reasons, this behavior has been termed deterministic chaos (Schuster & Just, 2005).

Different routes to chaos have been investigated mathematically and verified experimentally (see Schuster & Just, 2005). To illustrate a particular route, we refer to the one proposed by Grossmann and Thomae (1977), Feigenbaum (1978), and Coullet and Tresser (1978). They noticed that in simple difference equations, such as the logistic difference equation (equation 14.5) used to describe populations in ecology, the equilibrium states of the system change, depending on an external parameter. At a distinct value of this parameter,

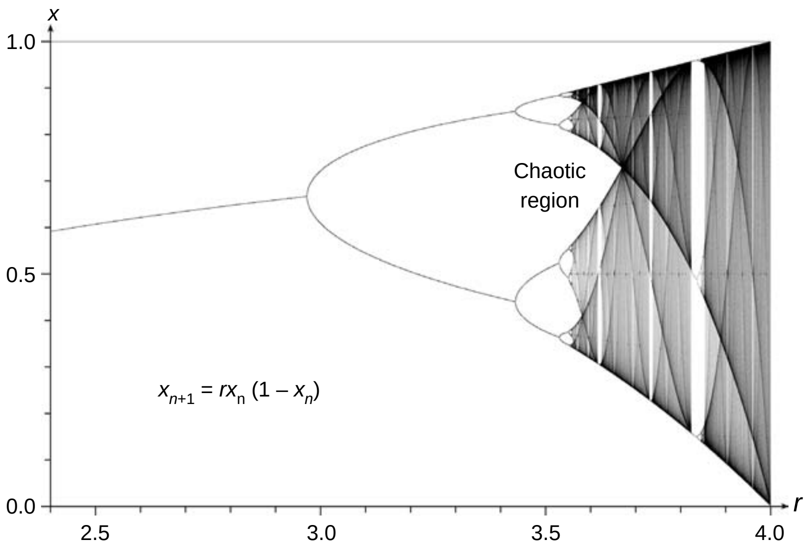

Figure 14.11 A route to chaos: bifurcation diagram of the logistic difference equation. Convergence to fixed point for $r < 3$, oscillation for $r > 3$, with x_n oscillating between four, eight and, finally, an infinite number of values, which means chaos.

the single stable fixed point becomes a limit cycle, where the population oscillates between two values. This transition is called a bifurcation. With increasing values of the external parameter, the population oscillates between four, eight and, finally, an infinite number of fixed points, where the variation in time of the population becomes irregular and chaos is attained (Schuster & Just, 2005; see also Figure 14.11, which shows a bifurcation diagram of the logistic difference equation).

The logistic difference equation reads as follows, with r as the external driving parameter:

$$x_{n+1} = rx_n\left(1 - x_n\right) \tag{14.5}$$

Though the cradle of these theories is definitely in the natural sciences, in particular physics and chemistry, there are many attempts to apply the key concepts and dynamics to social systems. The idea is that – from a complexity perspective – fundamental system principles, which govern certain material–biophysical systems dynamics, also govern the dynamics of socio-epistemic processes in human systems (Helbing, 2007; Schweitzer, 1997; Sornette, 2000; Weidlich & Haag, 1983). To illustrate this we focus here on selected aspects of the theory of non-linear systems that are relevant for the study of HES, in particular on "critical transitions" and hysteresis as well as on pattern formation, self-organization, and emergence.

The study of transitions between different dynamic states is at the heart of non-linear dynamics. If a system has alternative stable states, "critical transitions" and hysteresis may occur (Scheffer, 2009). Critical transitions take place if these alternative stable states are separated by an unstable equilibrium and no "smooth" transition is possible (see Figure 16.10). Hence, if the environmental conditions change, the system may undergo a "catastrophic" shift to an alternative stable state. It has to be noted that, owing to this configuration, the "forward" and the "backward" shift between these states do not occur at the same environmental conditions. This property, known as hysteresis, implies, first, that such critical transitions are not easy to reverse, and second, that the history of the processes matters.

An interesting issue is that we face a seemingly analog property in the perceptual processes with respect to ambiguous figure-ground configuration. If we look from the left to the right of Figure 14.12, the figure-ground configuration flips later than when starting from the right side (Haken, 1996).

It was one of the major objectives of the theory of non-linear systems to describe the formation of (temporal, spatial and spatiotemporal) patterns and to discern general principles governing self-organization of elements in systems independent of their nature (Érdi, 2008). Haken has proposed a theory of self-organization, for which he coined the term "synergetics," as "a theory of the emergence of new qualities at a macroscopic level" (Haken, 1996, p. 23). One of the central concepts in this theory is the concept of order parameters, which says that, close to the transition or instability points, the behavior of a complex system can

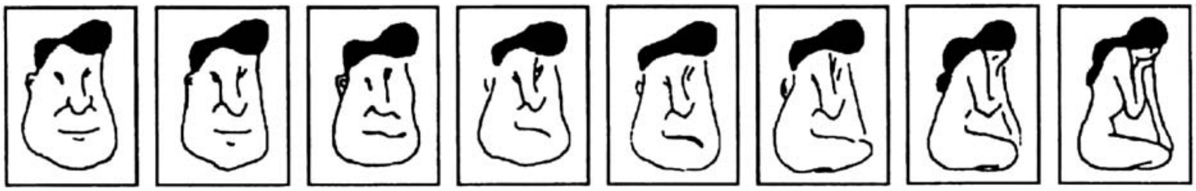

Figure 14.12 Hysteresis in human perception. A switch from a human face to a kneeling woman or vice versa takes place later if your eyes move from the left to right compared to if they move from right to left.

be characterized by only a small number of parameters. An example of self-organization in biology is presented in Box 14.4, with a transition of amoebae-like cells to a single, larger organism.

Self-organization and emerging structures in social systems have been widely investigated (Gilbert, 1995), and it has been recognized that in social systems certain properties on a societal level emerge from the local rules that individual actors follow. A well known example is the segregation model of Schelling (1971), showing segregation of different groups of agents because of local preferences about their neighborhood. The issue of emerging properties in complex systems will be further pursued in Chapter 14.7.

14.4.1 Key messages

- Material–biophysical and socio-epistemic systems can show instability, chaos, processes of self-organization, and pattern formation
- Even deterministic systems can show unpredictable and chaotic behavior. As a consequence, non-linear modeling tools are required
- The history of a system matters: in non-linear systems hysteresis may occur, meaning that the response of a system to a certain cause depends on the previous development of this system.

14.5 Uncertainty, probability, stochastic processes, and risk assessment

We start with a clarification of the terms used in this section. *Uncertainty* appears if we have incomplete knowledge with respect to the state of a specific object or system. *Probability* is a key concept of the language of uncertainty and will be dealt with in some depth in Chapter 14.5.2. *Stochastic processes* are sequences of events where there is real or cognized indeterminacy about future states. *Risk* is a genuine concept that links the behavioral, decision-based dimension of human systems' actions with uncertain negatively evaluated environmental impacts emerging from these actions. All four concepts can be found in all domains of sciences and life. Coping with stochasticity and properly incorporating uncertainty and risk in decisions systems understanding opens a new perspective and is an essential aspect of complexity management. Here, we only briefly pinpoint key essentials of environmental literacy.

14.5.1 Uncertainty and ignorance

Uncertainty is in knowledge or in the data. This fundamental statement departs from the socio-epistemic vs. material–biophysical complementarity (see Figure 3.3*). It leads to a similar fundamental ontological question whether randomness or random processes are something that exist in material–biophysical systems. When answering this question, we can see only two fields where uncertainty is fundamental.

The *first* is radioactive decay. The standard quantum mechanics theory is that there is a genuine stochastic process on the atomic level. It is impossible to predict when a certain atom decays, though by the concept of half-life we can predict what percentage of a pool of atoms will decay in a certain period. The discussion about the hidden variable theory goes back to 1935 and is rooted in the assumption that there are unknown deterministic theories about decay inducing processes, which allow for a prediction. However, after 40 years of experimentation "a conclusive experiment falsifying in an absolutely uncontroversial way local realism [of stochasticity] is still missing," thus there "are strong indications favoring standard quantum mechanics" (Genovese, 2005, p. 385). We can conclude that quantum mechanics leaves the question open as to whether "nature," here meaning the material–biophysical dimension of the world, is intrinsically probabilistic or whether quantum mechanical random phenomena derived from our ignorance of some theories about hidden parameters and therefore underlying deterministic

Box 14.4 Emerging systems: slime mold

The slime mold appears to be a fungus-like organism, which can be found all over the world in soil, forest floors, mulch, and similar settings. It starts the life cycle as amoebae-like cells and spend most of its life as an amorphous setting of distinct single-cell units, each moving separately from the others. Under certain conditions, when the environment is less hospitable, the myriad of single cells coalesces into a single, larger organism. Some crawl across the floor, consuming rotting leaves and wood as they move. They are an example of equipotent cells, which may self-organize into well distinguished clusters and regions (Haken, 1983, p. 9).

The cellular slime mold (*Dictyostelium discoideum*) "forms a multi-cellular organism by aggregation of single cells. During its growth phase the organism exists in the state of single amoeboid cells. … these cells aggregate, forming a polar body along which they differentiate into other spores or stalk cells; the final cell types constitute the fruiting body" (Haken, 1983, pp. 11–12). The reason for this is that the cells emit specific chemicals (called adenosine 3′5 monophosphate, i.e. cAMP molecules) as pulses into their environment. These messenger molecules are perceived as stimuli by other cells, resulting in a collective emission process which leads to a concentration gradient of the messenger chemical. Thus the single cell can measure the direction of the gradient and migrate to the center. The resulting process is displayed in Figure 14.13a. Figure 14.13b shows how a sample of slime molds ("they") has become an organism ("it"). Slime mold can be taken as an example that the boundary between a protozoal being and an organism may be fuzzy (see Chapter 5.5 on the immune system as a cognitive system).

The process is an example for an environment-driven regulatory mechanism based on efficient, genetically programmed (cAMP emission-based) adaptation strategies. The process of slime molds can be mathematically programmed and visualized (Resnick, 1999).

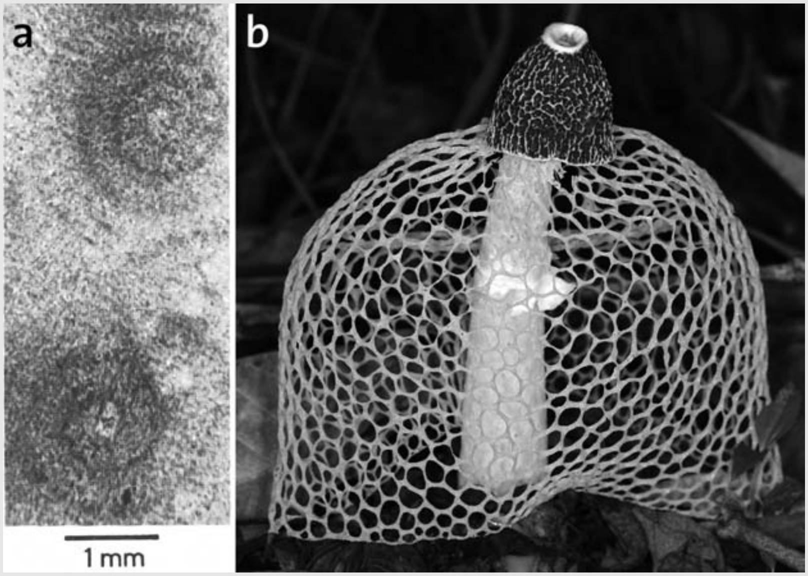

Figure 14.13 (a) Wave pattern of chemotactic activity in dense cell layers of slime mold (taken from Haken, 1983, p. 23, with kind permission from Springer Science + Business Media). (b) The tropical long net stinkhorn mushroom (*Phallus indusiatus borneo*) is up to 30-cm tall and girded with a net-like structure, the indusium (photo by David Kolba).

processes are at work. Einstein's famous quote does not give the answer:

> Quantum mechanics is certainly imposing. But an inner voice tells me that it is not yet the real thing. … I, at any rate, am convinced that *He* [God] does not throw dice. (Einstein, 1926/1971)

There is a *second* theorem of quantum mechanics, which is commonly seen as the materialist cradle of randomness that is the Heisenberg uncertainty principle. This principle states that we cannot determine both position and momentum of an electron and thus uncertainty in the knowledge is indispensable. However, this theorem does not make any statement about the intrinsic stochastic nature of the material world. The uncertainty refers to the unknowable ignorance and not to the stochasticity of the material–biophysical world.

14.5.2 Probability

As it is with many of our language terms, probability has many notions. We speak about the concept field of probability (Scholz, 1987). This field has a main dividing line between *objective* (data-oriented) and *subjective* (knowledge-oriented) probability. Both subfields have many subfacets. For instance, there is the Laplace probability, which is based on equal probability; there is the von Mises–Reichenbach frequentist probability, or area size-based probability; and there is the de Finetti definition of probability as a degree of belief. All these notions of probability have prototypical applications such as the toss of a coin or the throw of a dice, or being hit by a snowflake. All these concepts of probability also have in common that they meet the axioms of Kolmogorov (Fine, 1973; Hacking, 1975). Each notion or facet of probability is linked to an idea about the generation or mechanism of defining the likelihood of events.

At the fringes of the concept field we find quantitative conceptions of subjective probability, such as the Shafer–Dempster belief functions (Shafer, 1976), Baconian probability (Schum, 2001), or Cohen's probability theory (Cohen, 1977), which are variants of subjective probability. In accordance with Bayesian reasoning, these approaches provide conceptions on how the cognized uncertainty about the truth of a certain state can be meaningfully adjusted if new information and evidence is provided. However, the concepts at the fringes of the probability field do not follow the Kolmogorov axioms. For instance, the probabilities of all possible events may not add up to 1. This also holds true for the fuzzy set-based approach towards uncertainty (Zadeh & Kacprzyk, 1992).

An interesting variant of subjective probability is Walley's concept of imprecise probability. This approach assumes that the exact subjective probability is unknown but that the range in which it is located can be estimated if we take:

> … the lower probability to be the maximum rate at which you are prepared to bet on an event, and your upper probability to be the minimum rate at which you are prepared to bet against the event. (Walley, 1991, p. 3)

We should note that random variables usually map events to real numbers (or into a measurable space), and that probability distributions are a well established procedure to include uncertainties of such variables in modeling.

A critical question of stochastic modeling is what type of probability distribution is assumed to be adequate, for instance, for an environmental variable, say the air pollution in the vicinity of a heavy metal-emitting source of contaminants. The answer is that this depends on how the different terms causing variability are related. According to the central limit theorem, the sum of an infinite number of independent random variables (with about the same finite mean and variance) is normally distributed. In addition to such additive effects and in accordance to the central limit theorem, many small multiplicative effects lead to log-normally distributed variables. Both forms of variability stem from a variety of effects, each one acting independently.

14.5.3 Random processes

The theory of stochastic processes has been the backbone of statistical physics. Stochastic processes provide models for physical phenomena such as Brownian motion, which assumes a great number of independent and randomly moving and colliding molecules. Other examples are thermal noise, causing fluctuating voltage in electric networks or – if we refer to biology – the spatial spread and distribution of plant and animal communities or the spread of epidemics.

A critical question is whether random processes are also at work in socio-epistemic processes. Clearly, we can use Markov chains or more sophisticated operations such as the Langevin equation, which is central for Brownian motion, and apply these concepts to the study of human systems, e.g. the interaction of individuals on the stock market (Sornette, 2000, 2003). Still, the answer is no *and* yes. No means that the processes are affected by unforeseeable discrete events, which are not appropriately captured by the abovementioned concepts. Yes means that some dynamics of human system show definite similarities with material–bio physical dynamics, which as a consequence may provide a conceptual and mathematical framework to be applied to social systems.

14.5.4 Risk assessment and decisions

We focus here on a selected number of fundamental aspects of risk and risk assessment relevant for environmental literacy:

Risk is a component of decisions, because the riskiness of a decision alternative is incorporated into the evaluation of the desirability, attractiveness, and the anticipated satisfaction or utility of the outcomes related to a decision alternative.

Risk is a primitive, one of the simplest and most basic elements of a body of knowledge, and thus is a fundamental concept in the sense of Kant. Everybody knows that risk has something to do with the negative uncertain outcomes related to decisions.

We differentiate *risk* from *hazard* (Luhmann, 1990). If we talk about risk, the exposure of a human system depends on decisions and on how the human system is behaving. A hazard is given independent of an action.

Risk is a concept field. In this field we can distinguish between pure and speculative risk. Pure risk only focuses on the negative outcome. Speculative risk, however, weighs the negative and the positive outcomes, the prospective outcomes of a decision reflecting the common sense thought: if you are facing risk, there is a chance (to win). In economic terms we distinguish between benefit risk and cost risk. Which concept of risk, pure or speculative, is in the foreground, has varied historically and shifts between situations. The origins of the probability-based risk concept date back to the era of Chevalier de Méré (1607–1684), when it was the noblemen's dilemma to indulge in gambling with the objective of keeping losses to a minimum. Later, with the rise of the industrial age, it was merely the costs to gain access to the benefits tied to new technologies that were in the foreground. This led to the simple formula: risk is probability times losses. Risk is different from danger (see Chapter 6.19).

Risk can be formally defined. From a decision theory perspective, risk is a function of accessing the choice alternatives $A_i \in A$ and the probabilities $(p_{i,1},\ldots, p_{i,Ni}) = p_i \in P$, which are linked to the possible outcomes $(E_{i,1},\ldots, E_{i,Ni}) = E_i \in E$ resulting from choosing alternative A_i. These concepts describe a risk situation. A *risk situation* is a model that precisely describes the situation g when dealing with risk. A *risk function* r is a mapping from the set of all risk situations to the space of risk cognitions of a human system. The space of risk situations is $R = (A,P,E)$ and the image set represents what a certain decision-maker understands by risk in a specific situation. This can be quantitative risk scores, like the expected loss, the largest loss, or the probability of having a loss, to mention but three variants of the quantitative facets of the concept field of risk. But there can also be qualitative representations of risk, such as considering something dreadful and uncontrollable, as has been outlined by the psychometric paradigm (see Chapter 6.20).

Risk *assessment* is part of risk *management*. Contrary to risk *perception*, which denotes the psychological process of an individual in a risk situation, risk assessment is based on well defined methods, which define what situation (and thus what negative outcomes or hazards) we are facing. In the past few decades it has become a dominant scientific tool to protect public health and the environment.

14.5.5 Steps of risk assessment

In principle, risk assessment includes five stages (cf. Paustenbach, 2002; Scholz & Siegrist, 2010).

First, the risk situation is defined. This includes determining the specific alternatives that are looked at in a specific risk assessment. In public health this may mean that we have to define which people should be looked at in what place and at what time. The decision alternatives may result from distinguishing between being in a critical situation and being not in a critical situation.

Second, in the case of pure risk the negative effects have to be described. In the public health case this would require specifying whether we look at the general wellbeing, a specific dysfunction of an organ, or just at a critical concentration of a contaminant in a certain compartment or organism.

Third, for a given risk situation the factual exposure of a safeguard object has to be defined. This may mean that we have to define how much of the contaminant is ingested by food, breathing, or other paths, and in what circumstances.

Fourth, the dose–response relationship (i.e. the sensitivity) has to be assessed. This means clarifying how much the negative impacts depend on exposure.

Fifth, the risk has to be characterized by estimating the frequency and the meaning of a negative effect under the various conditions of exposure described and with respect to the object of interest.

A possible method of risk assessment is inductive–stochastic risk assessment. The idea behind this is that when we are facing a risk (resulting from action or of being exposed), we have to construct the impact from the source of the risk (e.g. a cadmium-contaminated ground) to a critical compartment in a safeguard object (e.g. the cortex of the kidney of a home gardener eating vegetables from this ground). Thus, we are viewing chains such as contaminated ground → contaminated plant (modeled by transfer coefficients) → contaminated food → intake of contaminated food (modeled by combining contaminants of the home garden) → adsorbing the contaminants → transporting it to the sensitive safeguard object (modeling toxicokinetics to the cortex of the kidney) → assessing the probability or

Box 14.5 The Prisoner's Dilemma: strategies and the emergence of cooperation

Robert Axelrod (1984a) developed a model based on the concept of an evolutionarily stable strategy in the context of the Prisoner's Dilemma game. This game is an embodiment of the problem of how to achieve mutual cooperation, and thus provides the basis for Axelrod's analysis. He performed multiple tournaments of such games (on a computer), with different strategies playing against each other: cooperation or defection. The payoff for T = temptation to defect is the highest, followed by mutual cooperation. The problem is, if both players want the highest return by defection, this leads to punishment (P; see Figure 14.14). These games can be played once or repeatedly. One result of these tournaments is that for the repeated games there seems to be a strategy that rules all others out in terms of reward. This strategy is called tit-for-tat, which means "cooperate as long the other cooperates and defect when or as soon as the other defects."

Axelrod believed that very sophisticated rules should not do better than the simple ones. Indeed, strategies that are too complex to be comprehended by the other "player" (or strategy) can be dangerous, leading to a worse payoff. However, Delahaye and Mathieu (1994) showed that more complex strategies can be superior to tit-for-tat. The authors added to some of their strategies the possibility of quitting the game (renunciation). This adaptation may also fit better with reality, because sometimes it is better to stop interaction with a player "that seems too weird or too aggressive" (Delahaye & Mathieu, 1994, p. 2). In their tournaments they found that renunciation in fact proved a successful extension. Only three of the first 40 strategies worked without renunciation.

Player A \ Player B	C Cooperation	D Defection
C Cooperation	R = 3 Reward for mutual cooperation	S = 0 Sucker's payoff
D Defection	T = 5 Temptation to defect	P = 1 Punishment for mutual defection

Figure 14.14 The Prisoner's Dilemma game as a matrix. The payoff to player A is illustrated by arbitrary numerical values. Per definition $T > R > P > S$ and $R > (S + T)/2$.

probability function of dysfunctions. The critical issue is that, for each "→," we have to define a probability distribution that models the uncertainty in the specific transfer, input–output, or cause–impact relationship (McKone & Bogen, 1991; Scholz *et al.*, 1992; Wallsten & Whitfield, 1986).

14.5.6 From risk assessment via vulnerability to resilience

While risk and risk assessment may be considered a static approach, risk management points to the dynamic, prospective aspects of risk. In this perspective, *vulnerability* and *resilience* of systems, which are inherently systemic and dynamic concepts, receive particular attention. Although vulnerability research is composed of several research streams, such as research on the vulnerability of socioecological systems, the sustainable livelihoods approach, and vulnerability to climate change (Adger, 2006), these strands have in common that vulnerability is based on exposure, sensitivity, and adaptive capacity of a system with regard to certain effects (see Polsky *et al.*, 2007). In the context of climate change, for example, vulnerability has been defined as:

> … the degree to which a system is susceptible to, or unable to cope with, adverse effects of climate change, including climate variability and extremes. Vulnerability is a function of the character, magnitude, and rate of climate variation to which a system is exposed, its sensitivity, and its adaptive capacity (McCarthy, 2001, p. 995).

Adaptive capacity relates to the means upon which a human system can rely to take adaptive actions aimed at avoiding or coping with the negative effects of a risk situation (Metzger *et al.*, 2006; Füssel, 2007). This means that when facing a risk situation, action can be taken that alters the exposure of that system to a specific hazard and/or the sensitivity with which the system is affected by this event. In other words, the decision-maker has the capability to change the risk situation. In that sense, vulnerability is a component of the wider concepts of risk governance (e.g. International Risk Governance Council (IRGC), 2009) and adaptive risk management (reference). The vulnerability concept can be defined quantitatively or qualitatively. As will be further elaborated in Chapter 14.8, on multiagent systems, the options of specific agents for adaptive actions are supported or constrained by their environment, which is made up of human components (e.g. political and institutional rules) as well as of biophysical components. This multifaceted challenge possibly leads the agents to explore new strategies qualitatively.

14.5.7 How is interdisciplinarity achieved

Risk assessment and management are highly interdisciplinary fields. Conceptualizing and defining the exposure is based on a behavioral model of the human system in relation to environmental hazards. Thus, exposure needs a coupled social and material–biophysical systems view. In addition, assessing sensitivity analysis (i.e. analyzing how much does the risk vary if some parameters vary) requires knowledge from the natural and social sciences. The system's sensitivity of an individual with respect to contaminants also depends on the mental (i.e. socioepistemic) processes and not only on the material–biophysical processes. The same holds true for risks of companies and financial markets.

14.5.8 Key messages

- Risk primarily represents the evaluation of trade-offs (i.e. negative environmental feedbacks) resulting from a decision under uncertainty
- Risk assessment provides a structured analysis of a risk situation, thus reducing the complexity of a case analysis
- Risk management and risk governance involving the concepts of vulnerability and resilience introduce a systemic and dynamic perspective. As such, risk is related to exposure, sensitivity, and adaptive capacity of a human system to a hazard.

14.6 Game and decision theory

14.6.1 Malignant and benign conflicts

When coping with environmental problems, there are often conflicts and social dilemmas among different human systems with respect to environmental resources. By social dilemma we mean situations in which a difficult choice has to be made between unfavorable alternatives between different agents or between individuals and collective interests (for an example in a contribution dilemma, see Box 14.5). Game theory can help us to conceptualize, describe, and understand these conflicts. We have dealt with risk perception in Chapter 6.18 and with the psychological foundations of decisions in Chapter 7.1. Here we only illuminate in what way game theory can provide insight into the *malignence* and *benignity* of certain situations and the different rationales of game theory. We define a situation to be malignant if, without transforming the situation, deterioration of some participants or systems or a progressive, unfavorable dynamic will result. A benign conflict is free of this peril.

Warfare situations or duels are usually represented as malignant situations, where, as a simplification, players can only win while (some of) the others are losing. Here we speak about antagonist conflicts or zero-sum games.

Decision theory can be considered a special case of game theory as there is only one player. Milnor (1954) also called decision situations as games against nature.

14.6.2 Historical background and basic concepts

Game theory originated in finding the best strategy in military conflicts and policy, and can be traced back to the Chinese art of war (e.g. Sun Tzu, 500 BC/1910) or ancient governance strategies (Thucydides, 550 BC/1910). The game of chess can be taken to illustrate the key elements of strategic games. A strategic game $\Gamma = (A,S,U)$ includes the definition of a set of players or actors $A = \{1,\ldots,n,\ldots,N\}$. Each player has a set of strategies $S_n = \{s_{1,n},\ldots,s_{k,j},\ldots\} \in S$ and of utility functions $u_n \in U$ which evaluates each outcome. Outcomes result when all players (N) have chosen a strategy and result from a strategy tuple $(S_{k1},\ldots,S_{kn},\ldots,S_{kN})$. The utility functions evaluate the attractiveness, relative satisfaction or desirability of the outcomes for each strategy tuple; that is, for all situations when all players have set up their decisions.

A strategy can also be defined verbally in the following way:

> A strategy of a player is a complete behavioral plan, which describes for each situation a player can come in, the behavior, i.e. the decision that is made in this situation. (translated from Burger, 1959, p. 10, translated by Scholz)

Chess is a finite game. Game theory shows that there is a win strategy for white, a win strategy for black, or strategies which compel a tie, as in any finite games there is a tie or one player wins (Burger, 1959). However, it is difficult to identify these win or tie strategies as, for instance, in chess a strategy includes more possible draws (i.e. decisions) than there are atoms in the universe (Mandecki, 1998). Thus, we can already see that game theory is mostly a theoretical approach.

This is not the place to go into the details of game theory. We just want to illuminate the broad range of (game) situations and their representation in game theory. We can discriminate between games in a normal form, which corresponds to the strategic games as defined above, and games in extensive form, which are presented as trees in which the nodes are the decisions the players have to make. There are 2- and *N*-person, zero- and non-zero-sum, and non-cooperative and cooperative games. In cooperative games, groups of players may enforce cooperation by coalition building. This aspect is of interest if we deal with supranational players, who have the power to induce cooperative behavior among loosely and voluntarily interacting nations. We make reference to this issue as the world game for climate mitigation is a non-cooperative game between the 192 nation-state players that are members of the United Nations; a solution seems easier if a supranational player is involved who represents penalties for not cooporating.

In extensive games (which can be represented by trees), there are games with *perfect* and *imperfect information* in which at least one player does not know all the actions of his opponent. We find games with *complete* or *incomplete information* in which the player does not exactly know against what player he is playing and what utilities may result. There are many excellent books about game theory and we recommend reading them to learn more on the subject (see for instance Gintis, 2009a,b; Osborne, 2004).

14.6.3 Contributions of game theory to interdisciplinarity

Game and decision theory provide an excellent language to describe the interaction between different agents or players. The language is general as it can be used to describe decisions at all levels of living systems, from the cellular level via the individual up to populations. Thus, game theory is genuinely interdisciplinary as games can include agents from different systems and the description of the different rationales of the agents – for instance, a virus that is attacking a human community – may have completely different behavioral repertoires and rationales.

We see the main benefit of game theory for interdisciplinarity in crisply describing the synergetic potential, conflict, or dilemma that is inherent in both human–environment interactions or in interactions between different levels of human systems. The latter refers to the commons dilemma problem, which is inherent in many problems of sustainable development.

14.6.4 Key messages

- Game and decision theory provide a general language to describe and classify the decision processes and conflicts involved in human–environment interactions as well as between different levels of human systems
- Game and decision theory denote human systems as decision-makers, agents, players, etc. who can choose among strategies which generate outcomes that are evaluated by preference or utility functions.

14.7 Modeling human–environment interactions with cellular automata

Cellular automata (CA) are identical cells that are arranged in a grid structure (comparable to a checkerboard). The cells can represent units of a biophysical environment or human individuals or collective actors (e.g. countries or states). Each cell is surrounded by other cells that build its environment. The cells (or CA) exist in one of a finite set of possible cell states. These states depend on the states of the surrounding cells. As time advances in discrete steps, each cell looks at its neighbor cells (whereas different kinds of neighborhood relations are possible, e.g. Moore or von Neumann neighborhood; see Gilbert & Troitzsch, 2005) and updates its own state depending on the implemented rules. The modeled system is homogeneous with respect to both (i) the set of possible states and (ii) the set of transition rules that apply to each cell. We briefly illustrate here a famous example of CA, the "Game of Life" of Conway (1970; see also Figure 14.15). The status of dark cells is "on" (or "alive"), that of light cells is "off" (or "dead"). Depending on the status of the neighbor cells, a cell in this game turns "alive" or "dead" when following certain rules. The results are often astonishing patterns. Figure 14.15a shows the initial random distribution. On the right (14.15b), the situation after some time steps is depicted. What one cannot see in these static pictures are the "movements" of living cells across the cellular grid.

The fundamental claim of CA is that temporal and spatial evolutionary behavior of systems can be

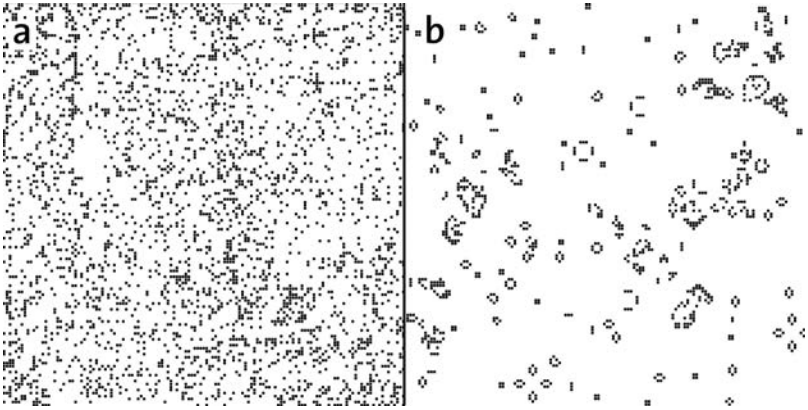

Figure 14.15 Game of Life. (a) Initial random distribution. (b) Situation after some time steps in generation 384. What one cannot see in these static pictures are the dynamics, caused by "movements" of on-cells across the grid, constantly forming new patterns (Wilensky, 1998).

explained in terms of local interactions of autonomous units. It is conceptually very simple and comprehensible compared to other approaches, but still produces emergent properties based on mimicking behavior of many constituent units of nature and society. Further, CA address the two fundamental properties that are inherent in real social and natural systems: parallel operation (synchronized self-control), and the important role of local variations in explaining the system dynamics. These features are new in comparison with the other modeling approaches described earlier in this chapter. In the context of environmental literacy, this may illustrate that new insights on regular patterns of human and environmental dynamics are rooted in diverse local actions.

The discrete nature of CA allows application of discrete mathematics, such as Markov processes, in the investigation of complex human and environmental dynamics. A Markov chain is a discrete random process where all information about the future is contained in the present state. If Markov processes are applied for CA models, cell states depend probabilistically on temporally lagged cell state values (Parker *et al*., 2003). In particular, CA have been applied successfully to several spatio-temporally explicit environmental dynamic models (e.g. landscape models of land use and land cover changes) that capture the macro outcomes emerging from millions of simple micro scale interactions. A classic example is the use of CA models to simulate residential discrete choices and land use conversion in urban areas. In the latter example, spatial housing patterns emerge from local decisions of single CA. These decisions depend on the neighbors' state (Hegselmann, 1998; Schelling, 1971).

In sum, CA have proven to be useful to model biophysical aspects of environmental dynamics, but they face challenges when incorporating complex human decision-making process. It is necessary to use heterogeneous, hierarchical rule-sets to differentiate between the kinds of decision-making that apply to groups of cells, such as resources tenure structure (Parker *et al*., 2003). Moreover, one has to be aware that pattern "movements" across the grid are not the results of autonomous agents but represent the succession of single cell states, each very restricted with regard to their decisions and spatially fixed. With respect to this, the multiagent system (MAS) approach offers additional potential.

14.8 Modeling human–environment interactions with multiagent systems

An MAS[5] is a community of agents, situated in an environment. "Agent" refers to autonomous decision-making entities within the system. "Environment" is the space that surrounds agents and supports or constrains their activities. "Community" refers to an organized collective of agents in which each agent plays specific roles and interacts with the environment (possibly including other agents). This interaction works according to protocols (rules) determined by the roles of the involved agents (Gilbert & Troitzsch, 2005; Zambonelli *et al*., 2003).

As an extension of CA, MAS provides all the fundamental features of CA; that is, macro phenomena that emerge from micro interactions, parallel operation, and the crucial role of local heterogeneity, and social networks. The concept of the agent originates in the so-called players of game theory.

[5] Sometimes MAS is also used for multiagent simulation.

In addition, compared to CA the agents in MAS can be more complex with regard to their structure and behavior. While CA are uniform in terms of the set of their state, the variable set of MAS agents can be different across agent typologies. Moreover, instead of being homogeneous with CA's rules, agent's rules can be specific for every agent typology. This heterogeneity is central to multiagent systems since it acts as a trigger initiating different behavior among agents in the system, sequentially leading to emerging system complexity (cf. Axelrod, 1997; Holland, 2006).

Behavioral rules of an agent can be rather simple causal if–then rules, in which behavioral decisions directly reflect the changing states of agents or their environment. However, agent behavior can also be driven by the evaluation of equations over particular state variables, or assessment of outputs of dynamic models encoded in the agent-based systems. Regarding this aspect, MAS can be understood as a decentralized system template in which multiple mathematical formalisms (e.g. simple causal if–then rules, linear functions, differential equations, and so on) can be concurrently embodied. Several types of agent architectures, based on different behavioral theories, were proposed. Most frequently, if–then rules are mixed with other kinds of behavior formalizations such as parameterized functions, or competitive tasks, or belief–desire–intention (BDI), or evolutionary metaphor-based (e.g. genetic algorithm) architectures (Bousquet *et al.*, 2004). This claim is different to that of earlier modeling approaches.

Environmental behavior of human agents is embedded in social interactions that are shaped by social networks. Informal institutional constraints or opportunities of environmental behavior (e.g. norms, collective attitudes, and behavior innovations), as well as their enforcement characteristics, are mediated by social networks. Social networks are important in understanding the dynamics of HES as they contribute significantly to resilience and adaptability by creating channels for information flows (Deffuant *et al.*, 2002), for management and distribution of resources (Epstein & Axtell, 1996), and for diffusion of technological innovations. MAS modeling is particularly relevant in representing social network structures and associated interaction rules, as well as the role of inequality of the individual agent within a network (i.e. nodes). With MAS, individual agents can form wide-ranging networks of many "weak ties" that facilitate information transfer and innovation diffusion, and ultimately promote economic development. Kohler and Gumerman (2000) showed that MAS approaches were particularly useful where there is evolution of social norms or social structure, or the presence of social dilemmas and common pool resource issues. Through connecting agent characteristics and knowledge of the position of agents in social networks, van Eck *et al.* (2011) demonstrated the important role of the network in mediating the impact of opinion leaders on diffusion processes of new products.

The "environment" formalized in MAS largely depends on the object system that is to be modeled. In real-world applications, we often see three types of applied MAS models: (i) MAS for social systems; (ii) MAS for material–biophysical systems; and (iii) MAS for coupled HES. When MAS is used to represent a social system, the "environment" of an agent refers to other human agents, which can be similar or different in typology (Edmonds *et al.*, 2007). The real biophysical environment is often assumed to be static, without an important role in explaining the system dynamics, thus ignored in the formalism. With MAS applied to biophysical worlds, the "environment" is truly the material-bio physical environment, which consists of other natural agents (like fish, trees, or land units; cf. Grimm *et al.*, 2005), without human agents in it. In MAS designed for coupled HES, the "environment" of an agent (being either human or biophysical objects) becomes a coupled community of decision-making human agents and autonomous biophysical agents (Jager *et al.*, 2000).

In MAS, due to the autonomy of the agents, interactions in the system are no longer mathematically traceable. Thus we meet what is called mathematical intractability of processes in time and space, as we can also find them in the system dynamics approach (Axelrod, 1997).

14.8.1 Multiagent systems for coupled HES

A growing number of MAS models for coupled HES have been developed in the past decade. To exemplify we refer here to a specific class of models of this type that has been formulated to represent the coupled human–landscape systems in a highly integrative manner (e.g. Le, 2005; Le *et al.*, 2008; Matthews, 2006). Here we have the integration of different kinds of social agents (decision-making, politics, and organizations) and natural processes (e.g. regarding soil, crops, and climate). Therefore, "human agents" integrate attributes of social actors like environmental and policy knowledge and capabilities, whereas "land agents" represent the relevant parts of the environment with which the human agents interact (see Figure 14.17).

Box 14.6 Social dilemmas: contributing to a land reclamation system or not?

Using MAS as a means for representing real-world HES and understanding the complex system dynamics can be demonstrated by a case of farmers in the Odra region of Poland who are caught in a social dilemma. In the catchment, while, in principle, the existing land reclamation system (LRS) of ditches and canals can absorb the negative effects of extreme weather conditions, its proper functioning requires collective action with regard to maintenance. Thus it is important that the acquaintance and/or friendship relationships that exist amongst farmers are utilized appropriately. The agent-based model SoNARe (Social Networks of Agents' Reclamation of land, cf. Krebs *et al*., 2008a, b) simulates the collective decision-making (Olson, 1965; Ostrom, 1990; Dawes, 1980) of typical landowners in the catchment under fluctuating socioenvironmental boundary conditions. The model is coupled to a hydroagricultural model that simulates the hydrological dependencies that exist between farmers located along the LRS. In the model, landowners decide about investing in the maintenance of their local section of the LRS and are provided with feedback in terms of their attained crop yield under certain climatic conditions. Farmer agents keep a balanced attention to their attained crop yields and their social endorsement resulting from their opinion regarding LRS maintenance. Farmers find themselves in a twofold dilemma: (1) the working LRS is most pertinent under unpredictable extreme weather conditions because it protects crops against excess water stress; (2) the beneficial effects of the LRS may only be achieved by high degrees of mobilization of the involved farmers, and beneficial effects differ depending on the farmer's position along the channel.

The conditions encountered on individual land parcels depend highly on the amount of LRS maintenance performed on other (connected) land parcels. In wet periods, for example, LRS neglect leads to a loss of yield on neighboring land parcels upstream since the runoff of excess water is blocked, whereas LRS maintenance has the opposite, beneficial effect since it facilitates runoff. The latter effect arises even if the upstream neighbors do not themselves maintain their section of the LRS (free-riding). Maintenance of the LRS thus enables farmers to overcome environmental shocks like flooding with only reduced yields or even with no losses at all, but it requires a collective effort.

The effects of several possible combinations of the farmer agents' success can be simulated. Two extreme scenarios are described here in short: the first scenario suggests that under the assumption of selfish farmers who only consider their individual farming success, roughly one-fifth of farmers show free-riding behavior. This points in the direction of a social dilemma induced by the hydrological interdependencies of farmers' land parcels. Scenario 2 adds social influence to the decision process, which results in the emergence of a positive social lock-in. The results indicate that, under the given circumstances, the presence of an active social network and of mechanisms of social influence dampens phases of high volatility in opinion dynamics and instead leads to a coherence effect. The frequency of LRS volatility is reduced with the introduction of social influence and further social pressure leads to a positive lock-in that even prevents free-riding behavior. Figure 14.16 shows the yields of the farmer agents. Compared to scenario 1 (see Figure 14.16a), in the long run in scenario 2 (see Figure 14.16b) the average crop yields increase and the deviation between farmers decreases.

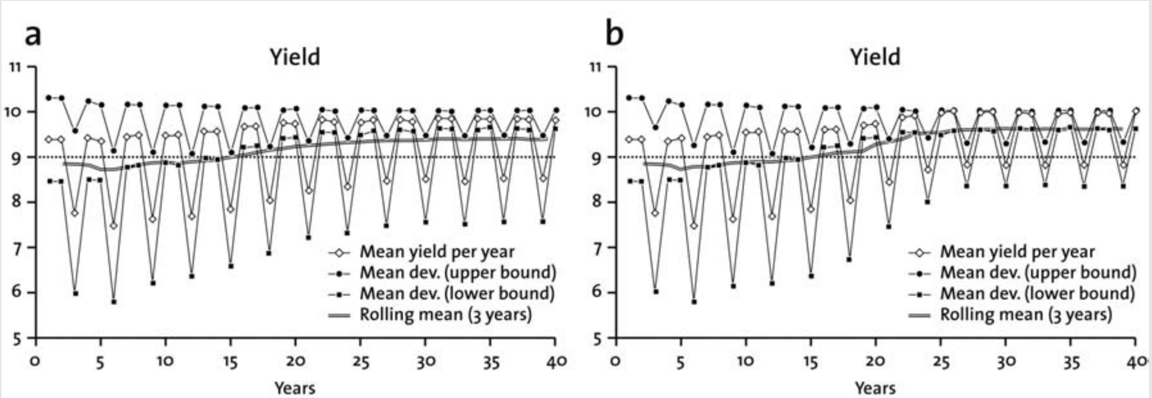

Figure 14.16 Average yields of farmers (*y* axis normalized, dimensionless) bounded by the mean deviation and the rolling mean over 3 consecutive years. The dotted line indicates the yield threshold. (a) Scenario 1; (b) scenario 2 (Adapted from Krebs *et al*., 2008b, p. 5 & 7).

Box 14.7 Interactive household and landscape agents: Vietnam deforestation

Assessment of future socioecological consequences of land-use policies can support decisions about what and where to invest for the best overall environmental and developmental outcomes. However, such assessment work is highly challenging because of: (i) the inherent complexity of coupled human–landscape systems; (ii) the long-term perspective; and (iii) the multidimensional criteria required for sustainability assessment. The Land-Use DynAmic Simulator (LUDAS) is a spatially explicit multiagent model developed to simulate land-use change and the interrelated socio-economic dynamics on the community/catchment scale (Le *et al*., 2008). The human community is represented by heterogeneous household agents, which integrate individual, environmental, and policy information into land-use decisions. The natural landscape was modeled as a group of landscape agents, which represent land units hosting natural processes that change in response to interventions by human agents. LUDAS embodies the material-social complementarity (see Figure 3.3*) within household agents, by for example coupling material household assets with a cognitive sub-model of land-use decisions ($H_m \Leftrightarrow H_s$), and within landscape agents, by for example representing the switch from biophysical land potential to perceived land utility ($E_m \Leftrightarrow E_s$). The model embodies the human-environmental complementarity ($H \leftrightarrow E$) by representing the impact of human systems on environmental systems ($H \rightarrow E$), for example a farmer's vegetation clearance, and the resulting benefits from the environment by crop production ($E \rightarrow H$) (Figure 14.17).

The model structure is designed by mimicking the common hierarchical levels (see Figure 14.1*) of land-use systems: household/farm – household group/landscape neighborhood – whole community/landscape. The interactions between the three layers occur through high-order feedback loops (vertical arrows in Figure 14.17). Household's land uses lead to a change in the larger human–landscape environment that reshapes the future decisions of household agents. Thus, the model represents the co-determination, and co-adaptation between human and environment systems. LUDAS illustrates many epistemological assumptions of HES described in Chapter 3.

As a virtual computational laboratory, LUDAS is able to systematically generate spatiotemporally explicit land-use change and interrelated socioeconomic dynamics resulting from land-use policy interventions. In the case of the Hong Ha catchment in Central Vietnam, comparative assessments of alternative future socioecological scenarios using LUDAS suggest that it is challenging to attain both community welfare and forest conservation by simply expanding current agricultural extension programs and subsidy schemes, without improving the qualities of these services. The results also provide new information about how policy interventions can strike a balance over the long term between 1) the need to strengthen enforcement of forest protection in critical areas of the watershed and 2) needs to simultaneously create incentives and opportunities for agricultural production in the less critical areas (Le *et al*., 2010).

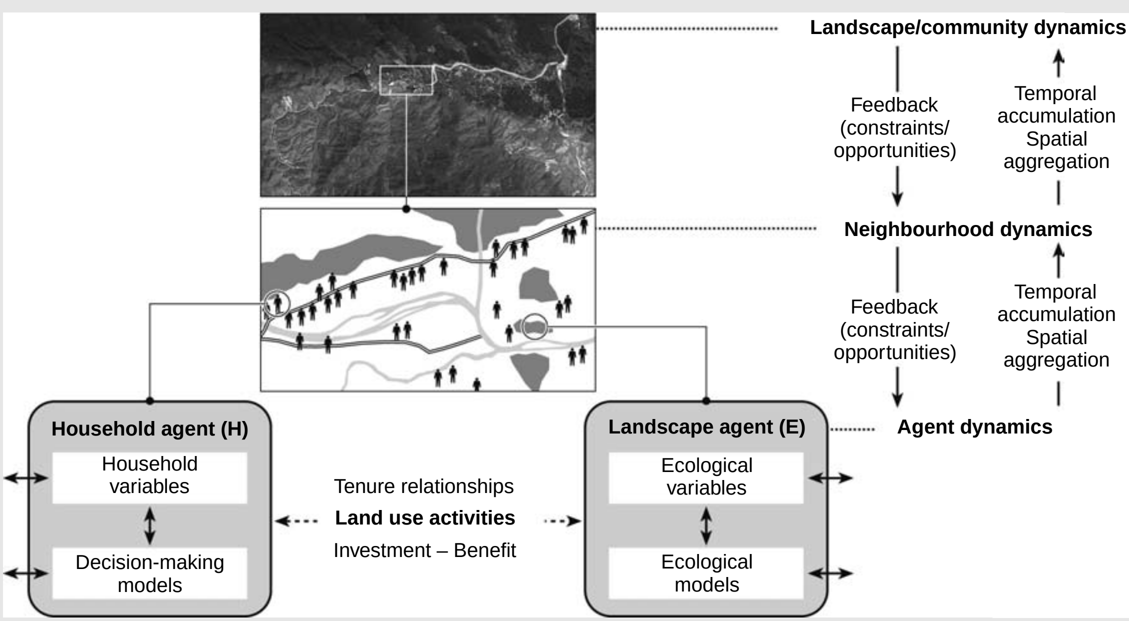

Figure 14.17 The LUDAS modeling framework mimicking natural ontologies of the coupled human–landscape system.

With MAS models for coupled HES, available models of different sociological/political/economic and ecological processes can be embodied into the structures of human and land agents. Integration of knowledge across disciplines in coupled models can be seen, for instance, in the case of MAS related to land use change (see Box 14.7 and Figure 14.17). By working as parallel subsystems that can host relevant processes possibly formulized by different analytical means, such a new class of MAS models offers a much higher degree of freedom to integrate not only knowledge from different disciplines, but also different conventional modeling methods into one integrated system model (see, for example, Box 14.6).

Within MAS for coupled HES, there are three major types of interactions: communicative interactions, physical interactions, and environment-mediated interactions. Communicative interaction means the exchange of messages among agents (e.g. concerning negotiations and exchanges of contracts, goods, or services).

Physical interactions, undertaken by agents, exert a physical action on others such as pushing or pulling. These kinds of interactions have been used in applications such as hydrology or soil physics. Environment-mediated interactions form the primary environmental feedback loop, in which human agents perceive the environment status and react to it, and the human action transforms the environment, with a retroactive effect on the decision-making process of itself and of other agents (see direct interactions between household and landscape agents in Figure 14.17). This illustrates the key advantage of MAS by mutual co-determination (Bousquet & Le Page, 2004; Krebs & Bossel, 1997) of the structure of the environment and the organization of the human agents' community.

Repeated agent interactions can lead to cumulative changes in social/economic and environmental conditions at larger scales and in the longer term. This may cause emergent changes of the whole system's performance after a delayed period (see vertical interlinks in Figure 14.17). The emergent change on the macro level has a two-path effect on the agent's behavior in the MAS: (i) it creates new opportunities or constraints for agent-based processes at the micro level; and (ii) it influences the behavior of politicians who frame policy issues that reshape interactive behavior of human and environmental agents. In this way, MAS represent secondary environmental feedback loops. By realizing these high-order environmental feedback loops, MAS models reveal the (complex) adaptive capacity of coupled HES. MAS can become complex adaptive systems (Holland, 1995, 2006); for instance, if we assume that the agents discover new rules that are more successful in dealing with an environment. This may be the case if changes in the political or climatic environment challenge household agents and/or landscape agents which have to adapt, e.g. by the mutation of rule-parts (and genetic algorithms; Holland, 1995 a,b). In this context evolutionary game theory is also relevant, as it deals with changing environments by variation of the strategy sets of the agents and subsequent adaptation (Axelrod, 1984; Smith, 1776/1961).

14.8.2 How interdisciplinarity is achieved

MAS models for coupled HES help to bridge the domains of natural and social sciences in many ways. First, like other integrated system model approaches, MAS provides feedback between variables (agents) with different ontological quality (e.g. variables of human, social, and financial assets of human individuals or organizations, and biophysical attributes of the landscape environment). Second, disciplinary knowledge in forms of available theories, models or rules/laws of different social and ecological processes can be implemented into the agents' structures (rule systems). MAS modeling also provides a kind of a meta-theoretical language in which every disciplinary statement must be reformulated. Developing MAS for coupled HES to inform and evaluate sustainability aspects (of several integrated scenarios) is a specific application of this approach. This kind of integrated modeling requires intensive discussions among the modelers from all the relevant disciplines (e.g. Barthel *et al.*, 2010; Lenz-Wiedemann *et al.*, 2010).

14.8.3 Key messages

- MAS is an interesting approach for understanding of HES as it integrates ideas from systems theory, game theory, theory of self-organization of complex systems, and allows for interdisciplinary, coupled systems modeling
- Agents' interactions within MAS allow the capture of both cross-scale (micro–macro) feedback loops and social and ecological heterogeneities. Thus, understanding self-organization and emerging structures in social and environmental systems forms a basic feature of MAS.