PERGAMON

Geoforum 32 (2001) 405–414

GEOFORUM

www.elsevier.com/locate/geoforum

Simplifying complexity: a review of complexity theory

Steven M. Manson

Graduate School of Geography, Clark University, 950 Main Street, Worcester, MA 01610-1477, USA

Received 5 August 1999; in revised form 7 September 2000

Abstract

Complexity theory has captured the attention of the scientific community to the extent where its proponents tout it as a dominant scientific trend. Geographers, and environmental, human, and regional planners have applied complexity theory to topics ranging from cultural transmission and economic growth to the braiding of rivers. While such a wide array of applications is heartening because it speaks to the utility of complexity theory, it is necessary to move beyond the hyperbole and critically examine the nature of complexity research. The author therefore provides an overview of the evolution of complexity research, establishes a preliminary typology of complexity approaches with their advantages and drawbacks, and identifies areas of further research.

Keywords: Complexity theory; Chaos; Self-organization; Emergence

1. Introduction

"Complexity theory is destined to be the dominant scientific trend of the 1990's ... This revolutionary technique can explain any kind of complex system – multinational corporations, or mass extinctions, or ecosystems such as rainforests, or human consciousness. All are built on the same few rules." (Lewin, 1992: back cover). Whether over-exuberance or merely aggressive advertising copy, this bold pronouncement has yet to be fulfilled. Growing acceptance of complexity is evidenced by a recent section on complex systems in the journal Science (1999) and the increasing amount of complexity research. This interest is countered by concern that complexity is an over-hyped fad (Sarder and Ravetz, 1994). Does complexity merit the title of a "dominant scientific trend" or are ill-advised scientists rushing to capitalize on its cachet? What value does complexity theory hold for geographic research?

Advocates of complexity theory see it as a means of simplifying seemingly complex systems. The actual practice of complexity theory, however, is anything but simple in that there is no one identifiable complexity theory. Instead, a number of theories concerned with complex systems gather under the general banner of complexity research. The exact nature of complexity research is hard to discover due to the large degree to which complexity ideas are traded across disciplinary boundaries. Thrift (1999), for instance, examines what complexity theory means to, and traces interactions among, managerial science, the social and natural sciences, and new age philosophy. There is also a propensity for disciplines to borrow techniques from other disciplines or to speculate naively on subjects typically seen as outside their purview (Horgan, 1995; Lo Presti, 1996). In either case, exciting academic cross-fertilization occurs at the expense of potentially false leads.

In sum, any definition of complexity is beholden to the perspective brought to bear upon it. While it is possible, therefore, to examine complexity on a discipline-by-discipline basis, breaking complexity research into three major divisions affords a more coherent understanding of complexity theory. "Algorithmic complexity", in the form of *mathematical complexity theory* and *information theory*, contends that the complexity of a system lies in the difficulty faced in describing system characteristics. "Deterministic complexity" deals with *chaos theory* and *catastrophe theory*, which posit that the interaction of two or three key variables can create largely stable systems prone to sudden discontinuities. "Aggregate complexity" concerns how individual elements work in concert to create systems with complex behavior.

Why have these three divisions if there is an identifiable body of complexity theory? The simplest answer is

E-mail address: smanson@clarku.edu (S.M. Manson).

0016-7185/01/$ - see front matter
PII: S0016-7185(00)00035-X

that there are separate kinds of complexity that have different and sometimes conflicting assumptions and conclusions. This said, algorithmic, deterministic, and aggregate complexity share more than just the "complexity" label. To a certain extent, they share the same historical antecedents, as explored below. In disciplinary terms, researchers often apply different kinds of complexity to a single problem with the understanding that these approaches are complementary. Similarly, given that all three kinds of complexity are interested in the often mathematically intractable aspects of systems, they regularly rely on computational settings of non-linear mathematics and software simulation. Most importantly, all three kinds of complexity are concerned with how the nature of a system may be characterized with reference to its constituent parts in a non-reductionist manner.

Taken together, these three kinds of complexity research are a recent body of work. Complexity theory, however, may be traced back to conceptual antecedents such as the "philosophy of organism" (Whitehead, 1925), neural networks (McCulloch and Pitts, 1943), cybernetics (Wiener, 1961), and cellular automata (von Neumann, 1966). Complexity theory also owes much to general systems theory given shared foci of anti-reductionism and holistic appreciation of system interconnectedness (von Bertalanffy, 1968). The link between general systems theory and complexity is seldom recognized (Phelan, 1999), possibly because the former was largely rejected by academics. During the rise of general systems theory, some geographers found it potentially useful as a means of modeling environmental systems (Bennett and Chorley, 1978). Others, however, considered it irrelevant to social concerns (Chisholm, 1967) and, in general, geographers have abandoned systems theory (Johnston, 1994).

If complexity theory is an outgrowth of previous work and of general systems theory in particular, what does complexity research offer that previous efforts did not? First, complexity often concerns non-linear relationships between constantly changing entities. Systems theory, in contrast, studies static entities linked by linear relationships defined by flows and stocks (e.g., of energy, information). Second, this stocks-and-flows perspective emphasizes quantities of flow and not necessarily their quality. Complexity research employs techniques such as artificial intelligence to examine qualitative characteristics such as the symbolic content of communication. Third, complexity research concerns how complex behavior evolves or emerges from relatively simple local interactions between system components over time. Systems theory instead favors simplification and parameterization of flows and stocks, a process that assumes that the system exists in equilibrium and therefore negates the need to examine changing relationships between system elements. Complexity research contends that systems have emergent or synergistic characteristics that cannot be understood without reference to sub-component relationships. Of course, this idea can be traced back to Aristotle, so it is important to note that complexity research is also concerned with how systems change and evolve over time due to interaction of their constituent parts.

2. Algorithmic complexity

Algorithmic complexity theory makes two relatively ancillary contributions to complexity theory overall. One measure of algorithmic complexity calculates the effort required to solve a mathematical problem. In some cases, a problem is so complex or specified in such a way that it is unsolvable. Spatial statistics and geographic information science face this kind of complexity. Some problems, such as enumerating all permutations in a resource allocation situation or finding the shortest path through a network, are very hard to solve in non-trivial cases. This first form of algorithmic complexity is useful because it guides practitioners in their choice of technique.

The second, more touted aspect of algorithmic complexity lies in information theory (Chaitin, 1992). This body of work identifies complexity as the simplest computational algorithm that can reproduce system behavior. With information theory, one may condense the myriad interactions between system components into simple measures. The use of information theory ranges from classifying remotely sensed imagery (Eastman, 1999) to considering the role of ecological community structure on biodiversity (Norton and Ulanowicz, 1992). Information theoretic concepts of complexity take an epistemological cast when mental experiments establish limits to knowledge. The brain, for instance, is a computing device with a limited information processing capacity and is therefore limited to answering to certain kinds of problems (Traub, 1996).

The key difficulty in applying algorithmic complexity to social or environmental phenomena, especially when positing computational limits of knowledge, is that it may incorrectly equate data with knowledge. Vast realms of human endeavor, such as lived experience and meaning given to it, lie beyond algorithmic expressions. Even broad forms of description, such as language, are necessarily vague because meaning lies in varying inscriptions and readings of texts, landscapes, or experience (Barnes and Duncan, 1991). Critics of geographic information science raise a similar issue with the shortcomings of computational representation of spatial phenomena (Pickles, 1995). Algorithmic conceptions of complexity allow demarcation of the boundaries of certain types of knowledge but certainly not others.

3. Deterministic complexity

Deterministic complexity lies in chaos and catastrophe theories. In some respects, these theories are different, but they are similar in use and import. Chaos theory holds that there exists a "true" chaos in keeping with popular usage and a "robust" chaos that is seemingly random but in fact is the manifestation of some accessible, underlying order. Catastrophe theory deals with systems that experience large and abrupt changes in some characteristic due to a small change in another.

3.1. What makes complexity deterministic?

Deterministic complexity has four key characteristics: (1) the use of deterministic mathematics and mathematical attractors; (2) the notion of feedback; (3) sensitivity to initial conditions and bifurcation; and (4) the idea of deterministic chaos and strange attractors.

3.1.1. Deterministic mathematics and attractors

One may describe, and potentially understand, chaotic or catastrophic systems in simple mathematical terms. The term deterministic complexity refers to the premise that a few key variables related through a set of known equations can describe the behavior of a complex system. Consider the equation for the standard logistic model of population growth, as one might find in an introductory human geography or ecology course:

$$X_{t+1} = \alpha X_t(1 - X_t), \tag{1}$$

where future population X_{t+1} is dependent on the current population X_t $(0 < X < 1)$ and a growth rate parameter α $(0 < \alpha < 4)$. This formula, for the most part, is useful for projecting population and does not seem very complex.

May (1976) found that for parameter values of α ranging from 1 to 3, the population settles on a single value equal to $(1 - 1/\alpha)$ regardless of the initial size of the population. For example, when $\alpha = 2$, the population settles on the value of 0.5 after several generations. This value $(1 - 1/\alpha)$ is termed an *attractor*, a value towards which a system variable tends to settle over time. Other attractors for this equation are the population dying out (X becomes zero when $\alpha < 1$) and the population expanding endlessly (X approaches infinity when $\alpha > 4$).

3.1.2. Feedback

The simple mathematic equations of deterministic complexity allow for dynamic behavior by incorporating feedback. In our example, the future population (X_{t+1}) is dependent on the present population (X_t). Negative feedback occurs when changes in one variable forces itself or other key variables to settle on a stable value. This is the case when the population settles on the attractor of $(1 - 1/\alpha)$. Positive feedback is self-reinforcing and results in one or more variables moving rapidly towards a point of no return, as when population dies out or grows indefinitely. To provide an illustrative (and simplistic) example, Malthusian population dynamics rely on positive feedback for explosive growth and negative feedback, due to resource shortages, for population decline.

3.1.3. Sensitivity to initial conditions and bifurcation

The overall state of chaotic or catastrophic systems are sensitive to small, incremental changes in key variables. At first glance, this tendency is at odds with the use of simple formulae to describe deterministic systems. In the example used here so far, changing the value of α in the range $1 < \alpha < 3$ by a small amount changes the overall result by a correspondingly small amount. The system is completely insensitive to the initial values of either α or X when $\alpha < 1$ or $\alpha > 4$. Once set in motion, the outcome never varies, just the rate at which the population arrives at zero or expands endlessly.

Under certain conditions, however, the system is *sensitive to initial conditions*. This term refers to situations where small changes in the initial system configuration may lead to large, non-linear effects. The popular term "butterfly effect" exemplifies sensitivity to initial conditions, whereby the flapping of a butterfly's wings can influence far removed weather systems. With the values of α examined so far, population converges on a single attractor $(1 - 1/\alpha,\ 0 \text{ or } \infty)$. When $3 < \alpha < 4$, however, the system oscillates between multiple attractors. The population moves through cycles of boom and bust. Small shifts in the value of α lead to large and sudden shifts in the attractors for the value of X, completely changing the periodicity of the population.

The potential for system variables to jump suddenly from one attractor to another is termed *bifurcation* (Feigenbaum, 1980). Researchers have examined a variety of chaotic systems for bifurcation (Nijkamp and Reggiani, 1990; Byrne, 1997). Catastrophic systems in particular are defined more by bifurcation than other characteristics of deterministic complexity. Catastrophic attractors are two-dimensional curves or three-dimensional surfaces defined by the interaction of two or three system variables. Along most of a catastrophic attractor, any change in one variable typically results in a change of similar magnitude in other variables. Catastrophic attracters, however, have occasional discontinuities where a small change in one variable results in a large "catastrophic" change in another. Catastrophe attractors have been largely used to describe changes in natural phenomena, with the exception of a few attempts to portray change in social systems in catastrophic terms (Renfrew and Cooke, 1979; Lowe, 1985; Brown, 1995).

3.1.4. Deterministic chaos, strange attractors, and fractals

For any initial pairing of α and X examined so far, it is possible to identify distinct attractors. There is, however, one key exception. When $\alpha = 3.8$, the population variable, X, becomes completely random and chaotic with no discernable attractor. There is no reason as such for this particular value; it is simply inherent to the system. In terms of chaos theory, the system is not truly chaotic because a single deterministic equation underlies seemingly random behavior, so we term the system *deterministically chaotic* given its behavior when $\alpha = 3.8$. Of course, there are millions of seemingly chaotic systems and discovering if an equation can describe any given system is difficult. Fortunately, while a deterministically chaotic system may lack normal attractors, it does possess at least one *strange attractor*, a value or set of values towards which system variables tend towards over time but never quite reach. To determine if a system possesses a strange attractor, one draws a *Poincaré graph*, which simply refers to removing time as one of the axes of a graph and instead plotting data points (sampled at a regular temporal interval) along dimensions described by system variables (see Mainzer, 1996). A Poincaré graph of a truly chaotic system appears random. The graph of a deterministically chaotic system, however, traces system variables moving along endlessly different paths that are simultaneously constrained to a regular, geometric region of the graph. This region is the strange attractor for the system. Just as normal attractors are values towards which system variables tend, strange attractors roughly delimit the possible values of system variables.

Finally, there are fractals, complicated self-referential patterns that also happen to be strange attractors whose patterns remain unchanging regardless of the scale of observation. The structure of a tree, for instance, is fractal because the same branching arrangement is apparent at scales ranging from the entire tree down to the veins in its leaves. This property of fractals, scale-invariance, has led geographers to look for fractal patterns in phenomena ranging from urban form to coastlines (White and Engelen, 1993; Pecknold et al., 1997). Researchers hope to understand phenomena that have fractal patterns because the processes that give rise to these patterns may be operating across scales. If so, understanding how a system works at one scale may lead to understanding how it works other scales (Mandelbrot, 1977).

3.2. Reflections on deterministic complexity

Deterministic complexity is an interesting but marred concept. It is hard to explain a seemingly chaotic system when we are limited to two or three key variables that define deterministically complex systems. In the population growth example, for instance, where are the variables for culture, the state, or migration? If we could find and defend appropriate choices, how would we pick just two or three? Similarly, a large amount of time series data is required to prove that a system has deterministic complexity. Even when data exists, fewer systems than anticipated are in fact deterministically chaotic (Zimmer, 1999) or catastrophic (Back, 1997) because characterizing a human system through a few simple variables or deterministic equations is often just too, in a word, simplistic (Kellert, 1993). There are also hazards in conflating pattern with process, as visited in debates over urban form or city rank-size rules. Urban land use, for instance, may have a fractal pattern but this knowledge only goes so far in aiding our understanding of how it came to be that way.

Admittedly, effects such as sensitivity to initial conditions or strange attractors can spur new thinking about accepted phenomena, especially when used in an analogical manner. Postmodernists have embraced deterministic complexity in this way (Hayles, 1991). Deterministic complexity is characterized by contextuality, complexity, and contingency; these themes exemplify postmodernism (Warf, 1993). Sensitivity to initial conditions and bifurcation undermine totalizing discourses by supporting unpredictability and the search for fragmentation and discontinuity. Cartwright (1991), for instance, argues that urban planning should take into account chaos theory. Given the potential for small changes in one place to result in large changes elsewhere, planning must be sensitive to the transformative effect of local interactions. Postmodern techniques such as deconstruction may also draw on chaos theory through a shared focus on iteration and recursion as a means of destabilizing systems (Hayles, 1989).

The postmodern concern for focusing on local interactions influences geographic concepts of scale. A commonly accepted notion of scale is the nested hierarchy, a set of areal extents in which it is assumed that the sum of all components of one level, such as counties or consumers, produces one component at a larger scale, such as states or households (Haggett, 1965). In this kind of spatial hierarchy, local context fine-tunes large-scale processes. In light of the butterfly effect, however, a local action may directly affect those at a larger scale without moving through intermediary scales. Similarly, local action, instead of being dampened out, may become amplified through the non-linear interactions between components across scales. The impact of individual currency speculators on the economies of entire countries exemplifies this interaction, as individual actions are quickly scaled up through financial networks to have profound effects on large-scale phenomena (Jeanne, 1997).

Contrary to the postmodern view of the importance of sensitivity to initial conditions, structuralist and modernist conceptual frameworks contend that the ability of strange attractors to describe key system characteristics reduces the significance of sensitivity to initial conditions. Approaches grounded in historical materialism, for instance, link bifurcation to emancipatory social transformation and identify the Fordist mode of regulation with the boundedness of strange attractors (Harvey and Reed, 1994; Byrne, 1997). In this view, socioeconomic systems are largely fixed in their mechanisms but can exist in several states, each having an associated attractor. Fundamentally changing how the system plays out in a given locality lies less with individual actions and more with attempts to change the size of attractors and opportunities for bifurcation (Byrne, 1998). Research on foreign trade and international development also uses the concept of strange attractors and deterministic complexity (Savit, 1993; Keen, 1997), as does work attempting to explain the decline of political systems in catastrophic terms (Renfrew and Cooke, 1979; Lowe, 1985).

Despite some advances, deterministic complexity is still difficult to apply to social phenomena. Convincing examples are largely limited to work in natural science or physical geography (Prigogine and Stengers, 1984; Philips, 1993). Social science has been far less forthcoming with convincing applications, although there are some thought provoking exceptions (e.g., Wong and Fotheringham, 1990; Krider and Weinberg, 1997). Instead, deterministic complexity serves as an intellectual foil. There is a limit, however, as seen in the tension between those who see deterministic complexity as a means of understanding complex systems through attractors and others who contend that sensitivity to initial conditions limits understanding and prediction. In conclusion, deterministic complexity is interesting but marred by shortcomings.

4. Aggregate complexity

Complexity research increasingly considers systems of linked components, or aggregate complexity. Algorithmic and deterministic complexity rely on simple mathematical equations and a number of assumptions of how complex systems work. Aggregate complexity instead attempts to access the holism and synergy resulting from the interaction of system components.

4.1. Key attributes of aggregate complexity

In order to understand aggregate complexity, it is necessary to explore a key set of interrelated concepts that define a complex system: relationships between entities; internal structure and surrounding environment; learning and emergent behavior; and the different means by which complex systems change and grow.

4.1.1. Relationships

The heart of aggregate complexity lies in relationships between components. In an economy, for example, components are consumers, firms, and the state. In turn, they exchange and redistribute information, matter, and energy. In ecology, key entities are flora and fauna with relationships largely defined through matter and energy exchanges.

A complex system is defined more by relationships than by its constituent parts. A single person in an economy can consume and produce goods and knowledge, boycott firms, and contribute to the underground economy. A tree in an ecosystem is important to biogeochemical processes. Understanding and tracing the relationships of a single entity is difficult, while tracing them in an entire system verges on the impossible. Given the number and variety of these relationships, they extend beyond simple feedback into higher order, nonlinear processes not amenable to modeling with traditional techniques (Costanza et al., 1993).

Sub-systems and individual components typically have functions or goals, but given the complexity of relationships between components, it is impossible to characterize the system on the whole as having a unified purpose. This is apparent for either an economy or ecosystem. They may serve functions such as resource redistribution or maintenance of an atmosphere but they lack design.

Similarly, sub-systems and components are largely limited to local interactions. There is no omniscience or constantly updated common body of information. Apart from Gaia theory, it is hard to argue that any one ecological component or sub-system "knows" what other components are doing. Similarly, the notion of the all-knowing, rational *homo economicus* is increasingly under siege for its assumption of ubiquitous information and insensitivity to local context (Cook and Levi, 1990).

4.1.2. Internal structure

The components of a system and their relationships are not an undifferentiated mass. Relationships of differing strengths between component parts define the internal structure of a system. Components with especially tight connections form sub-systems, so even homogenous components can support internal diversity through realignment of relationships to create non-identical sub-systems. Economic entities form sub-systems according to their relationships in space, competitive niches, and shared consumer preferences. Ecological entities form sub-systems within species or outside of species (e.g., an ecotope). Any given component can belong to multiple sub-systems. A single person, for instance, can simultaneously be part of a family, union, investment club, and regional economy. A tree is part of a larger community of trees through mechanisms such as seed dispersal and has symbiotic relationships with other plants and animals (Allen and Hoekstra, 1992).

4.1.3. Environment

A complex system owes its existence to relationships with its environment, defined as anything outside of the system, although this division may not be sharp. Natural resources, international markets, and human desires may be considered external to a national economy but the boundaries are permeable. External to an ecosystem are abiotic aspects of the earth such as its crust and climate. Regardless of the actual boundary between a system and the environment, the former passes information, matter and energy through its internal structure. The actions and interactions of system components eventually create outflow from the system into the environment.

4.1.4. Learning and memory

A complex system is not beholden to the environment – it actively shapes, reacts, and anticipates. A system "remembers" through the persistence of internal structure (Holland, 1992). Components and sub-systems with the capacity to accommodate the influx of energy, matter, and information from the environment will grow. Regularly occurring external relationships encourage the growth of the same set of components and sub-systems. The memory of an economic system exists in various places, such as business plans and the experience of individuals. Ecological information lies largely in the form varying configurations and density of relationships between and within species.

A complex system can deal with truly novel situations because it has a wide array of internal components and sub-systems linked by complex relationships. Some subset of these components may have some ability to accommodate a novel relationship. In the rare cases when no suitable components or sub-systems exist, the system cannot respond to new relationships with the environment, with potentially catastrophic results. Concern for this kind of system collapse lies in the drive to protect biodiversity. The destruction of complex, diverse internal relationships may lead to a lack of resilience and adaptability in ecosystems. When monocrops replace mixed agriculture or forest, for instance, the ecosystem is more susceptible to rapid and potentially adverse shifts in the environment, such as the introduction of foreign species or climate change (Wilson, 1988).

4.1.5. Emergence

The capacities of a complex system are greater than the sum of its constituent parts. A system can have *emergent* qualities that are not analytically tractable from the attributes of internal components (Baas and Emmeche, 1997). Emergence is a function of synergism, whereby system-wide characteristics do not result from superposition (i.e., additive effects of system components) but instead from interactions among components (Lansing and Kremer, 1993). An economy has emergent qualities such as volatility and investor "herd behavior" that are commonly attributed to irrationality or imperfect markets but in fact are intrinsic to rational, local interactions and their non-linear consequences (Andreoni and Miller, 1995).

Emergent phenomena may lie beyond our ability to predict or control. There is certainly enough understanding of an economy to allow for intervention in major sub-systems with an eye towards changing some emergent quality, such as regulating a major industry in order to stabilize prices. It is difficult, however, to anticipate changes beyond the short term because other components of the system adjust to this intervention in addition to other changes in the environment (Youssefmir and Huberman, 1997). Similarly, as we increasingly discover to our chagrin, any single change to an ecosystem can have far-reaching, large-scale effects due to not understanding emergence from complexity (Lansing and Kremer, 1993).

4.1.6. Change and evolution

A complex system constantly changes, largely through three different types of transition. First, a key characteristic of a complex system is *self-organization*, the property that allows it to change its internal structure in order to better interact with its environment. Self-organization allows a system to learn through piecemeal changes in internal structure.

Second, a system becomes *dissipative* when outside forces or internal perturbations drive it to a highly unorganized state before suddenly crossing into one with more organization (Schieve and Allen, 1982). Economies can be dissipative when confronting large shifts in the nature of their relationships with the environment. Introduction of new technologies, such as in the industrial revolution, can spur radical change in the internal structure of an economy (Harvey and Reed, 1994). The work of Holling (1978, 1995) illustrates how small disturbances such as pest infestations or fire can trigger large-scale redistribution of resources and connectivity within the internal structure of an ecosystem.

Third, the term *self-organized criticality* refers to the ability of complex systems to balance between randomness and stasis. Instead of occasionally weathering a crisis, a system can reach a critical point where its internal structure lies on the brink of collapsing without actually doing so (Bak and Chen, 1991). Self-organized criticality is a form of self-organization where the rate of internal restructuring is almost too rapid for the system to accommodate but necessary for its eventual survival (Scheinkman and Woodford, 1994). Research on self-organized criticality is largely restricted to ecological and biogeophysical systems (e.g., Andrade Jr. et al., 1995; Correig et al., 1997) but there is a small and growing body of work on urban and economic systems (Sanders, 1996; Allen, 1997).

4.2. Reflections on aggregate complexity

The chief value of aggregate complexity is its challenge to conventional notions of stability and change. Science in general sees systems of interconnected elements, such as economies or ecologies, as stable entities. This view has been critical to the success of science. It is also useful, however, to see complex systems as constantly changing their internal structure and external environment through self-organization, dissipative behavior, and self-organized criticality.

Mainstream economics, for instance, studies stability and repeated patterns, while complexity research is interested in "multiple equilibria, non-predictability, lock-in, inefficiency, historical path dependence, and asymmetry" (Arthur, 1999, p. 108). Complexity also questions the long-held assumption that ecosystems evolve towards an unchanging "climax" structure (Worster, 1985). It may be more fruitful to consider ecological landscapes as existing in a constant state of flux (Goerner, 1994; Philips, 1999).

Unfortunately, it is difficult to employ insights granted by aggregate complexity. Defining the boundaries and components of a system is problematic. It is also necessary to adequately defend and characterize what constitutes learning, self-organization, and adaptation (Rapport, 1991). A conceptually coherent view of a complex system is hard to link to reality. Equilibrium-oriented mathematics is not suited to dynamic, historically dependent or transient phenomenon. Emergent social phenomena can disappear when one reduces the system into components or uses too many statistical assumptions (Arthur, 1994).

A potential answer to these methodological difficulties is the increasing sophistication of computer simulation tools that allow "exploratory simulation" (Conte and Gilbert, 1995; 4). Silicon-based simulation is a manifestation of possible system outcomes that are not preordained and deterministic (Thrift, 1999). This said, model results can reflect underlying programming more than the phenomena modeled. Much work remains undone on means of classification, measurement, and validation, particularly when distinguishing legitimate results from modeling artifacts (Huberman and Glance, 1993).

Aggregate complexity is not limited to computer simulations. Postmodern and poststructural perspectives link complexity to knowledge, language, and epistemology. Several authors leverage the resonance between self-organized criticality and the view of forces of Lyotard (1984), creating social diversity and novelty through dissension and destabilization of the status quo (Funtowitcz and Ravetz, 1994; Cilliers, 1998). The constant repositioning of entities and relationships within a complex system supports the postmodern view of a multiplicity of localized, yet networked, social and political discourses. The meaning of language and knowledge is not crystallized and centralized but instead distributed and created through the interaction and competition of different viewpoints (Clifford, 1988; Cilliers, 1998). Similarly, aggregate complexity illustrates how relationships are more important than attributes in defining the nature of components. This insight supports reconceptualization of identity and representation, whereby a person is not limited to a singular identity but instead is situated in a web of relative power relations (Gibson-Graham, 1993).

The notion of aggregate complexity creating emergence potentially addresses the micro–macro distinction in issues such as the relationship between agency and structure. Social institutions, for instance, are both artifacts and dynamic processes that constitute, and are constituted by, regularized behavior of their component parts (Ostrom, 1990). There is a growing body of research linking aggregate complexity to institutional and organizational behavior using computer simulations based on systems of software agents (Conte et al., 1997).

Another significant body of research lies in exploring emergence with cellular automata. These tessellations (e.g., grids) represent how the state of some phenomenon changes in time according to rules based on localized interactions of entities. Geographers have readily adopted cellular automata given a conceptual resonance with cellular geography (Wagner, 1997) and GeoAlgebra (Couclelis, 1997). Cellular automata are used to model phenomena ranging from ecosystems (Hogeweg, 1988; Ermentrout and Edelstein-Keshet, 1993) to urban morphology (White and Engelen, 1993; Clarke et al., 1996; Couclelis, 1997).

Although research on how macro-scale phenomena arise from micro-interaction continues apace, less examined is the effect of macro-structure on the micro-scale. Seeing social norms as emerging from agent interaction, for instance, does not adequately address how norms affect agents (e.g., Blume, 1996; Gintis, 1997). Some definitions of emergence go so far as to necessitate that lower level elements are unaware of their role in emergent phenomena (Forrest, 1991). As a result, complexity-based human system surrogates can fail because they do not allow reflexivity or individuals who reason about features of which they are part.

As with other forms of complexity, aggregate complexity offers insight at a cost. It offers valuable commentary on emergence, equilibrium, and change. At the same time, despite the potential of simulation, aggregate complexity must overcome methodological shortcomings. More importantly, its conceptual contributions to the larger body of science are still unclear. On one extreme, aggregate complexity dovetails well with postmodern conceptions of the world. On the other, a sociobiological form of aggregate complexity holds that the evolution of social structure evolves from the imperative of individual survival (Dawson, 1996; Pearson, 1996). The discordance between these views underlines the need to couple complexity-based research with other conceptions of human agency and the role of social phenomena such as institutions and culture.

5. Conclusion

The value of complexity exists in the eye of its beholder. For some it is merely a passing fad, for others an interesting complement to accepted conceptual frameworks, and for others it is a pioneering break from a moribund Newtonian worldview. Identical findings or phenomena can lead to radically different interpretations. How far can we extend the epistemological corollaries of algorithmic complexity? Does deterministic complexity allow or prevent prediction and control of complex systems? Does aggregate complexity support the role of individuality and creativity or does it point to biological determinism in human affairs?

Answering these questions and others should be a priority for geographers and planners. Our work offers both the theoretical dimensions and empirical knowledge necessary to conduct complexity research. Key issues surrounding complexity in general include: (1) the need to understand better the different kinds of complexity theory; (2) provision of data and techniques amenable to complexity research; (3) proper interpretation of complexity theory, especially with regard to human systems; and (4) exploration of the ontological and epistemological corollaries of complexity. In return for addressing these issues, complexity offers a host of new approaches to the study of economic, political, social and environmental systems.

Acknowledgements

This work is supported in part by National Science Foundation Grant Number 9521914 through the Carnegie Mellon University Center for Integrated Study of the Human Dimensions of Global Change. The author gratefully acknowledges the assistance of Dr. D.P. Angel and Dr. B.L. Turner II. Responsibility for the opinions expressed is solely that of the author.

References

Allen, P.M., 1997. Cities and Regions as Self-Organizing Systems: Models of Complexity. Gordon and Breach, London.

Allen, T.F.H., Hoekstra, T.W., 1992. Toward a Unified Ecology. Columbia University Press, New York.

Andrade Jr., J.S., Wainer, I., Moreira, J.E., 1995. Self-organized criticality in the El Nino southern oscillation. Physica A 215 (3), 331–338.

Andreoni, J., Miller, J.H., 1995. Auctions with artificial adaptive agents. Games and Econ. Behav. 10, 39–64.

Arthur, W.B., 1994. Inductive reasoning and bounded rationality. Am. Econ. Rev., Papers Proc. 84 (2), 406–411.

Arthur, W.B., 1999. Complexity and the economy. Science 284 (5411), 107–109.

Baas, N.A., Emmeche, C., 1997. On Emergence and Explanation. Santa Fe Institute, Santa Fe, NM.

Back, K.W., 1997. Chaos and complexity: Necessary myths. In: Eve, R.A., Horsfall, S., Lee, M.E. (Eds.), Chaos, Complexity, and Sociology. Sage, Thousand Oaks, CA, pp. 39–49.

Bak, P., Chen, K., 1999. Self-organized criticality. Sci. Am. January, 46–53.

Barnes, T., Duncan, J., 1991. Writing Worlds: Discourse, Text, and Metaphor. Routledge, London, UK.

Bennett, R.J., Chorley, R.J., 1978. Environmental Systems: Philosophy, Analysis, and Control. Princeton University Press, Princeton, NJ.

Blume, L.E., 1996. Population Games. Santa Fe Institute, Santa Fe, NM.

Brown, C., 1995. Chaos and Catastrophe Theories. Sage, Thousand Oaks, CA.

Byrne, D., 1997. Chaotic places or complex places: Cities in a post-industrial era. In: Westwood, S., Williams, J. (Eds.), Imagining Cities. Routledge, London, pp. 50–72.

Byrne, D., 1998. Complexity Theory and the Social Sciences. Routledge, London.

Cartwright, T.J., 1991. Planning and chaos theory. J. Am. Planning Assoc. 57, 44–56.

Chaitin, G.J., 1992. Information, Randomness, and Incompleteness. World Scientific, Singapore.

Chisholm, M., 1967. General systems theory and geography. Trans. Inst. Br. Geographers 42, 45–52.

Cilliers, P., 1998. Complexity and Postmodernism: Understanding Complex Systems. Routledge, New York, NY.

Clarke, K.C., Hoppen, S., Gaydos, L.J., 1996. A self-modifying cellular automaton model of historical urbanization in the San Francisco Bay area. Environ. Planning B 24, 247–261.

Clifford, J., 1988. The Predicament of Culture. Harvard University Press, Cambridge, MA.

Conte, R., Gilbert, N., 1995. Computer simulation for social theory. In: Gilbert, N., Conte, R. (Eds.), Artificial Societies: The Computer Simulation of Social Life. UCL Press, London, pp. 1–15.

Conte, R., Hegselmann, R., Terna, P. (Eds.), 1997. Simulating Social Phenomena. Springer, Berlin.

Cook, K.S., Levi, M. (Eds.), 1990. The Limits of Rationality. University of Chicago Press, Chicago, IL.

Correig, A.M., Urquizu, M., Vila, J., 1997. Aftershock series of event February 18, 1996: an interpretation in terms of self-organized criticality. J. Geophys. Res. B 102 (12), 27407–27420.

Costanza, R., Wainger, L., Folke, C., et al., 1993. Modeling complex ecological economic systems: toward an evolutionary, dynamic understanding of people and nature. Bioscience 43 (8), 545–555.

Couclelis, H., 1997. From cellular automata to urban models: new principles for model development and implementation. Environ. Planning B 24, 163–174.

Dawson, D., 1996. The origins of war: biological and anthropological theories. History and Theory 35 (1), 1–28.

Eastman, R., 1999. IDRISI32. Clark University, Worcester, MA.
Ermentrout, G.B., Edelstein-Keshet, L., 1993. Cellular automata approaches to biological modeling. J. Theoret. Biol. 160 (1), 97–113.
Feigenbaum, M.J., 1980. Universal behavior in nonlinear systems. Los Alamos Sci. 1, 4–27.
Forrest, S. (Ed.), 1991. Emergent Computation: Self-Organization, Collective, and Cooperative Phenomena in Natural and Artificial Computing Networks. MIT Press, Cambridge, MA.
Funtowitcz, S.O., Ravetz, J.R., 1994. Emergent complex systems. Futures 26 (6), 568–582.
Gibson-Graham, J.K., 1993. Stuffed if I Know: Reflections on Postmodern Feminist Research. Department of Geology and Geography, University of Massachusetts, Amherst, MA.
Gintis, H., 1997. A Markov Model of Production, Trade, and Money: Theory and Artificial Life Simulation. Santa Fe Institute, Santa Fe, NM.
Goerner, S., 1994. The Evolving Ecological Universe. Gordon and Breach Science, New York.
Haggett, P., 1965. Locational Analysis in Human Geography. Edward Arnold, London.
Harvey, D.L., Reed, M.H., 1994. The evolution of dissipative social systems. J. Soc. Evol. Syst. 17 (4), 371–411.
Hayles, N.K., 1989. Chaos as orderly disorder: shifting ground in contemporary literature. N. Literary Hist. 20, 305–322.
Hayles, N.K., 1991. Complex dynamics in literature and science. In: Hayles, N.K. (Ed.), Chaos and Order: Complex Dynamics in Literature and Science. University of Chicago Press, Chicago, IL, pp. 1–33.
Hogeweg, P., 1988. Cellular automata as a paradigm for ecological modelling. Appl. Math. Comput. 27 (1), 81–100.
Holland, J.H., 1992. Complex adaptive systems. Daedalus 121 (1), 17–30.
Holling, C.S. (Ed.), 1978. Adaptive Environmental Assessment and Learning. Wiley, London.
Holling, C.S., 1995. Sustainability: The cross-scale dimension. In: Murasinghe, M., Shearer, W. (Eds.), Defining and Measuring Sustainability. The World Bank, Washington, DC, pp. 65–75.
Horgan, J., 1995. From complexity to perplexity. Sci. Am. 272, 104–109.
Huberman, B.A., Glance, N.S., 1993. Evolutionary games and computer simulations. Proc. Nat. Acad. Sci. 90 (16), 7716–7719.
Jeanne, O., 1997. Are currency crises self-fulfilling? A test. J. Int. Econ. 43 (3/4), 263–286.
Johnston, R.J., 1994. General systems theory. In: Johnston, R.J., Gregory, D., Smith, D. (Eds.), The Dictionary of Human Geography. Basil Blackwell, Oxford, UK, pp. 215–216.
Keen, S., 1997. From stochastics to complexity in models of economic instability. Nonlinear Dyn. Psychol. and Life Sci. 1 (2), 151–171.
Kellert, S.H., 1993. In the Wake of Chaos. University of Chicago Press, Chicago, IL.
Krider, R.E., Weinberg, C.B., 1997. Spatial competition and bounded rationality: retailing on the edge of chaos. Geogr. Anal. 29 (1), 17–34.
Lansing, J.S., Kremer, J.N., 1993. Emergent properties of Balinese water temple networks: coadaptation on a rugged fitness landscape. Am. Anthropol. 95 (1), 97–114.
Lewin, R., 1992. Complexity: Life at the Edge of Chaos. MacMillan, New York.
Lo Presti, A., 1996. Futures research and complexity: a critical analysis from the perspective of social science. Futures 28 (10), 891–902.
Lowe, J., 1985. The Dynamics of Collapse: A Systems Simulation of the Classic Maya Collapse. University of New Mexico Press, Albuquerque, NM.
Lyotard, J.-F., 1984. The Postmodern Condition: A Report on Knowledge. University of Minnesota Press, Minneapolis, MN.
Mainzer, K., 1996. Thinking in Complexity: The Complex Dynamics of Matter, Mind, and Mankind. Springer, New York.
Mandelbrot, B.B., 1977. Fractals. W.H. Freeman, San Francisco, CA.
May, R., 1976. Simple mathematical models with very complicated dynamics. Nature 261, 459–467.
McCulloch, W.S., Pitts, W., 1943. A logical calculus of the ideas immanent in nervous activity. Bull. Math. Biophys. 5, 115–137.
Nijkamp, P., Reggiani, A., 1990. Logit models and chaotic behaviour: a new perspective. Environ. Planning A 22, 1455–1467.
Norton, B.G., Ulanowicz, R.E., 1992. Scale and biodiversity policy: a hierarchical approach. Ambio 21 (3), 244–249.
Ostrom, E., 1990. Governing the Global Commons: The Evolution of Institutions for Collective Action. Cambridge University Press, Cambridge, UK.
Pearson, D.E., 1996. Sociology and biosociology. Am. Sociol. 27 (2), 8–20.
Pecknold, S., Lovejoy, S., Schertzer, D., et al., 1997. Multifractals and resolution dependence of remotely sensed data: GSI to GIS. In: Quattrochi, D.A., Goodchild, M.F. (Eds.), Scale in Remote Sensing and GIS. Lewis, New York, pp. 361–394.
Phelan, S.E., 1999. Note on the correspondence between complexity and systems theory. Systemic Practice and Action Res. 12 (3), 237–238.
Philips, J.D., 1993. Spatial-domain chaos in landscapes. Geogr. Anal. 25 (2), 101–117.
Philips, J.D., 1999. Divergence, convergence, and self-organization in landscapes. Ann. Assoc. Am. Geographers 89 (3), 466–488.
Pickles, J., 1995. Ground Truth: The Social Implications of GIS. The Guilford Press, New York.
Prigogine, I., Stengers, I., 1984. Order Out of Chaos: Man's New Dialogue with Nature. Bantam, New York.
Rapport, D.J., 1991. Myths in the foundations of economics and ecology. Biol. J. Linn. Soc. 44, 185–202.
Renfrew, C., Cooke, K.L. (Eds.), 1979. Transformations: Mathematical Approaches to Cultural Change.
Sanders, L., 1996. Dynamic modelling of urban systems. In: Fischer, M., Scholten, H.J., Unwin, D. (Eds.), Spatial Analytical Perspectives on GIS. Taylor and Francis, London, pp. 229–244.
Sarder, Z., Ravetz, J.R., 1994. Complexity: fad or future?. Futures 26 (6), 563–567.
Savit, R., 1993. Chaos on the trading floor. In: Hall, N. (Ed.), Exploring Chaos: A Guide to the New Science of Disorder. Norton, New York, pp. 174–183.
Scheinkman, J.A., Woodford, M., 1994. Self-organized criticality and economic fluctuations. Am. Econ. Rev. 84 (2), 417–421.
Schieve, W.C., Allen, P.M. (Eds.), 1982. Self-Organization and Dissipative Structures: Applications in the Physical and Social Sciences. University of Texas Press, Austin, TX.
Science, 1999. Complex systems. Science 284 (5411), 79–107.
Thrift, N., 1999. The place of complexity. Theory, Culture and Soc. 16 (3), 31–69.
Traub, J.F., 1996. The Unknown and the Unknowable. Santa Fe Institute, Santa Fe, NM.
von Bertalanffy, L., 1968. General Systems Theory: Foundation, Development, Applications. Allen Lane, London.
von Neumann, J., 1966. Theory of Self-Reproducing Automata. University of Illinois Press, Champaign-Urbana.
Wagner, D.F., 1997. Cellular automata and geographic information systems. Environ. Planning B 24, 219–234.
Warf, B., 1993. Postmodernism and the localities debate: ontological questions and epistemological implications. Tijdschr. Economische Sociale Geograf. 84 (3), 162–168.
White, R., Engelen, G., 1993. Cellular automata and fractal urban form: a cellular modelling approach to the evolution of urban land-use patterns. Environ. Planning D 25, 1175–1199.
Whitehead, A.N., 1925. Science and the Modern World. Macmillan, New York.

Wiener, N., 1961. Cybernetics: Or, Control and Communication in the Animal and the Machine. MIT Press, Cambridge, MA.
Wilson, E.O., 1988. Biodiversity. National Academy Press, Washington, DC.
Wong, D.W.S., Fotheringham, A.S., 1990. Urban systems as examples of bounded chaos: exploring the relationship between fractal dimension, rank-size, and rural-to-urban migration. Geogr. Ann. B 72 (3), 89–99.
Worster, D., 1985. Nature's Economy: A History of Ecological Ideas. Cambridge University Press, Cambridge, UK.
Youssefmir, M., Huberman, B.A., 1997. Clustered volatility in multiagent dynamics. J. Econ. Behav. Organ. 31 (1), 101–118.
Zimmer, C., 1999. Life after chaos. Science 284 (5411), 83–86.