Self-Organizing Systems

By:

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Introduction

One of the questions guiding subsets of physics, chemistry and biology research is Where does order come from? Following the general laws of thermodynamics it would seem that dynamic processes would find the path of least energy until the system found a low spot, a dead calm, and remained at equilibrium there until some obvious perturbation moved it from its complacency. For example, a pot of steaming sugar water will give off matter (water vapor) and energy (heat) until it reaches equilibrium with its environment. Cooling, evaporation and crystallization, governed by simple physical and chemical laws, will drive the system to a point of least energy, and we should find rock candy in the bottom of a dry pot.

Yet the world abounds with systems and organisms that maintain a high internal energy and organization in seeming defiance of the laws of physics. As spin glasses cool, ferromagnetic particles magnetically align themselves with their neighbors until the entire lattice is highly organized. Water particles suspended in air form clouds. An ant grows from a zygote into a complex system of cells, and then participates in an organized, structured hive society. What is so fascinating is that the organization seems to arise spontaneously from disordered conditions, and it doesn't appear driven by known physical laws. Somehow the order arises from the multitude interactions of the simple parts, and the laws that may govern this behavior are not well understood. It is clear, though, that the process is nonlinear, using positive and negative feedback loops among components at the lowest level of the system and between them and structures that form at higher levels.

For landscape ecology, an SOS perspective might reveal how spatial and temporal patterns such as patches, boundaries, cycles, and succession might arise in a complex, heterogeneous community. Understanding SOS mechanisms might enable models to be more informative and accurate. Early models of pattern formation use a 'top-down' approach, meaning the parameters describe the higher hierarchical levels of the system. For instance, individual trees are not made explicit in patch models, but clumps of trees are. Or individual predators are absent in a predation model, but a predator population is programmed as a unit that impacts a prey population. In this way, the population dynamics are controlled at the higher level of the population, rather than being the results of activity at the lower level of the individual.

The problem with this top-down approach is that it violates two basic features of biological phenomena: *individuality* and *locality*. By modeling a rodent population as a mass of rodent with some growth and behavior parameters, we obviate any differences that might exist between individual rodents. Some are big, some are small, some reproduce more, some get eaten more. These small differences can lead to larger differences such as changes in the population gene frequencies, size or location that might have cascading effects at still larger scales. For instance, a moving rodent population might draw their predators with them, away from environments where the predators have some other important ecological role.

The tenet of locality means that every event or interaction has some location and some range of effect (Kawata and Toquenaga 1994). Tree gaps in the tropics have resultant ecological changes that are extremely limited by the location and the size of the gap. Obviously, not every seed in the forest has an equal chance of germinating in the gap, but gap models assume that seeds are perfectly evenly distributed throughout the forest, and that the major influence on germination success is a species' relative abundance in the seed bank. Ignoring locality obscures the factors that might contribute to spatial and temporal dynamics. For instance, seedlings located on a high water table might grow better than those located on arid soil, and as they grow they might increase the moisture-holding capacity of that area, creating new landscape patterns. This is a simple illustration of the ecological principle that pattern affects process (Watt 1947, Huffaker 1958).

To say that a system is self-organized is to say it is not governed by top-down rules, although there might be global constraints on each individual component. Instead, the local actions and interactions of individuals is the source of the higher-level organization ofland the system into patterned, ordered structures with recognizable dynamics. Since the origins of order in SOS are the subtle differences among components and the interactions among them, system dynamics cannot be understood by decomposing the system into its constituent parts. Thus the study of SOS is *synthetic* rather than *analytic*.



Mechanisms of self-organization

Several mechanisms and preconditions are necessary for systems to self-organize (Nicolis and Prigogine 1989, Forrest and Jones 1995). These mechanisms are somewhat redundant and somewhat undefined, but they are useful intuitive indicators of the potential for self- organization:

Thermodynamically open

First, the system (a recognizable entity such as an organ, an organism, or a population), must be exchanging energy and/or mass with its environment. In other words, there must be a nonzero *flow* of energy through the system. Adding heat to a pot of water or food to a fish tank are examples of energy flows. A system must be thermodynamically open because otherwise it would use up all the available *usable* energy in the system (and maximize its corollary, entropy) and reach what is known as heat death. A nicer name for this is thermodynamic equilibrium. It is often said that SOS are "far from" thermodynamic equilibrium, but that's not necessarily the case. They only need be far enough to avoid collapsing into a local equilibrium condition, and sometimes that's not very far.

Dynamic behavior

If a system is not at or near equilibrium, the only other option for its behavior is that it is dynamic, meaning the system is undergoing continuous change of some sort. One of the most basic kinds of change for SOS is to import usable energy from its environment and export entropy back to it. The idea of "exporting entropy" is a technical way of saying that the system is not violating the second law of thermodynamics because it can be seen as a larger system-environment unit. This entropy-exporting dynamic is the fundamental feature of what chemists and physicists call dissipative structures. Nobel Laureate <u>Ilya Prigogine</u> believes dissipation is the defining feature of SOS. There are <u>some</u>, though, who disagree with him.

Local interaction

Because all natural systems have inherently local interactions, this condition is noted because it is an important mechanism for self-organization that must be incorporated into models of SOS.

Nonlinear dynamics

A system with positive and negative feedback loops is modeled with <u>nonlinear</u> equations. Self-organization can occur when feedback loops exist among component parts and between the parts and the structures that emerge at higher hierarchical levels. In fact, self-organization, <u>fractals</u>, <u>chaos</u>, and many other interesting dynamical phenomena are often studied jointly at a large number of university and private institutes and centers, such as at <u>Los Alamos National Lab</u>, and <u>The University of Copenhagen</u>. In chemistry, when an enzyme catalyzes reactions that encourage the production of more of itself, it is called auto-catalysis. It's possible that auto-catalysis played an important role in the <u>origins of life</u>.

Many parts

Since the magic of self-organization lies in the connections, interactions, and feedback loops between the parts of the system, it is clear that SOS must have a large number of parts. Cells, living tissue, the immune system, brains, populations, hives, communities, economies, and climates all contain hundreds to trillions of parts. These parts are often called *agents* because they have the basic properties of information transfer, storage and processing. An agent could be a ferromagnetic particle in a spin glass, a neuron in a brain, or a firm in an economy. Models that assign agency at this level are known as <u>individual-based models</u>, such as SFI's <u>ECHO</u>. They use computer simulations to observe how local, nonlinear interactions of many agents can develop into complex patterns. In contrast, traditional system models place agency at the group level by using group-level parameters such as population growth rates (Huston et al. 1988)

Emergence

Probably the most nebulous concept of the bunch (Crutchfield 1994), the theory of emergence says the whole is greater than the sum of the parts, and the whole exhibits patterns and structures that arise spontaneously from the parts. Emergence indicates there is no code for a higher-level dynamic in the constituent, lower-level parts (Green 1993). Convection currents, eddies, cellular dynamics, 'mind,' forest patches, and food webs are examples of emergent phenomena. (See <u>Jim Crutchfield's paper</u> on this topic.) Some believe emergence is nothing more than a trick of perception, when the observer's attention shifts from the micro- level of the agents to the macro- level of the system. Emergence fits well into hierarchy theory as a way of describing how each hierarchical level in a system can follow discrete rule sets.

Multi-scale effects

Emergence also points to the multiscale interactions and effects in self-organized systems. The small-scale interactions produce large-scale structures, which then modify the activity at the small scales. For instance, Specific chemicals and neurons in the immune system can create organism-wide bodily sensations which might then have a huge effect on the chemicals and neurons. Prigogine (1984) has argued that macro- scale emergent order is a way for a system to dissipate micro- scale entropy creation caused by energy flux, but this is still not theoretically supported.

Even knowing that self-organization can occur in systems with these qualities, it's not inevitable, and it's still not clear why it sometimes does. In other words, no one yet knows the *necessary* and *sufficient* conditions for self-organization.



Complexity at the edge of chaos

SOS often display a highly complex kind of organization. Hives have obvious patterns and regularities, but they are not simple structures. Certainly stochastic (random) elements affect the structure and dynamics of a hive, but it's not likely that in a completely deterministic hive the patterns would be simple. Likewise clouds, weather patterns, ocean circulation, community assemblages, economies and societies all exhibit complex forms of self-organization. If so many SOS are characterized by complexity, it's fair to ask What is complexity?

What is complexity?

There is no good general definition of complexity, though there are <u>many</u>. Intuitively, complexity lies somewhere between order and disorder, between the glassy-calm surface of a lake and the messy, misty turbulence in gale-force winds. Complexity has been measured by logical depth, metric entropy, information content, fluctuation complexity, and many other techniques. These measures are well-suited to specific physical or chemical applications, but none describe the general features of self-organization. Instead, we must settle for the dictionary definition which pulls relative intractability (i.e. we can't understand it yet) and intricate patterning into a conceptual taffy. Obviously, the lack of a definition of complexity doesn't prevent researchers from using the term.

Langton's cellular automata

A polite way to talk about complexity when it is so poorly defined is to describe the boundary between order and chaos - where complexity would feasibly reside - as the edge of chaos (Packard 1988, Langton 1990, Kauffman 1991, 1993). <u>Chris Langton</u> (1990) conducted a computer experiment with <u>cellular automata</u> (CA) in which he attempted to find out under what conditions a simple CA could possibly support "computational primitives," which he defines as the transmission, storage, and modification of information.

In his experiment, a one-dimensional CA is composed of 128 cells connected in a circle. Each cell is capable of four possible internal states. Each cell takes as its input the states of the cells in its region, known as its neighborhood. Langton's neighborhoods consist of five cells: an automaton is considered a member of its own neighborhood along with the two neighborhood and some transition function which describes which internal state it should move to given a neighborhood state. Thus the neighborhood state is associated with transmission, the automaton internal state with storage, and the transition function with modification of information.

To examine how order and chaos affect computation, he formulates a *lambda* value which describes the probability that a given neighborhood configuration will lead to one particular, arbitrary internal state, called the "quiescent state." When lambda = 0, all neighborhood states move a cell to the quiescent state, and the system is immediately completely ordered. When lambda = 1, no neighborhood states move to the quiescent state, and the CA will not settle into any ordered regime of states and transitions.

When 0 < lambda < 1, the fun begins. As lambda increases, the time series graphs of the linear CA exhibit longer and larger streams of cell transitions called *transients*. (In the time series, t=1 is the top row, and time flows down.) Transients supposedly demonstrate the CA's ability to compute. The patterns that transients exhibit also hint of that elusive quality complexity. Thus computation seems to be possible at the edge of chaos.

Langton has made an <u>interactive CA site</u> that allows you to perturb the lambda value up or down from the default value of 0.25. When you use it, **run** the CA and check out the resulting time series. Note how long and intricate the transients are. Then adjust the lambda value (go up first) and hit **perturb lambda**. It will run again and you'll see how the transients have changed.

Langton claims that as lambda is increased, the CA undergoes a *phase transition* from ordered states to chaotic regimes. When average transient length is graphed against lambda, there is a spike of extremely long transients at lambda = 0.50. Langton shows that the average mutual information (a kind of complexity measure) of the CA is maximized at the lambda value at which the phase transition occurs, called its *critical* value. If lambda exceeds the critical value the average mutual information decays as the system becomes more chaotic. Langton suggests that because computation is associated with this critical value at the phase transition, a SOS will need to maintain itself at the "edge of chaos" in order to compute its own organization:

One of the most exciting implications of this point of view is that life had its origin in just these kinds of extended transient dynamics.... In order to survive, the early extended transient systems that were the precursors of life as we now know it had to gain control over their own dynamical state. They had to learn to maintain themselves on these extended transients in the face of fluctuating environmental parameters, and to steer a delicate course between too much order and too much chaos, the Scylla and Charybdis of dynamical systems.

-- Langton (1990)

Phase transitions

Phase transitions are mathematically interesting. They differ from standard transitions in the sharpness, or steepness, of the break between two phases or states. The transition from freezing to boiling temperatures for a liquid is general: it is a gradual slope from one to the other. But the transition from boiling-temperature liquid to boiling-temperature gas occupies a small space between the two phases (e.g., some particular pressure-temperature combination). After the gradual heating, there is an abrupt change to the gas phase so that the two phases are clearly distinct, separated by the boundary at the phase transition conditions. Such boundaries are very useful for predicting the properties of a system or substance in different conditions. Phase transitions are also often the site of interesting dynamics that don't appear in the phase regions. For instance, a simple solid will absorb much more energy per unit mass and will dissolve chemical bonds at melting.

A phase transition also occurs in large networks when the connectedness between cells reaches a critical value. The degree of connectedness (i.e. number of connections) determines the probability that a patch of connected cells spans the entire lattice. When such a lattice-spanning patch exists, it is said the system *percolates*. The boundary between sparsely connected and percolating networks is well-known to be a phase transition: with a very large number of runs or a very large lattice, the boundary region becomes so thin it is approximated by a point. Percolation allows for *long-range correlations* between cells, so that distant cells are linked through the highly- connected network.

Phase transitions and percolation occur frequently in nature. For instance, the ranges of two tree-dwelling squirrel species in New Mexico is divided by the phase-transition border between forest patches whose canopies are disjointed or percolated. Langton's work on phase transitions is compelling because it hints of ways to measure and perceive the special conditions under which self- organization might be possible.



Self-organized criticality

So far we've described the general mechanisms and features of SOS and illustrated Langton's experiment which demonstrated a thin region of complexity between order and chaos at which self-organization might be possible. Before continuing, it's important to note that these postulates are not proven, and in fact are under intense scrutiny (Mitchell, Hraber and Crutchfield 1993, Horgan 1995, Sigmund 1995) because of the many assumptions the models make and the many profound conclusions drawn from them. Research in this area continues, though, because of the appeal of a theory of self-organization that could help us understand the origins of order and life, and perhaps the process of evolution as well.

Bak's sandpile

Bak et al. (1988) studied the behavior of spatially extended dynamical systems using computer simulations of their 'sandpile' model. In this model, sand is poured onto a table in a continuous stream. At a certain point, the pile is as large as it can get, and more sand falls off the sides. The pile is very sensitive to perturbation (if the table is jostled sand falls). Yet it cannot be too sensitive, or the maximum slope would not be a regular value, but would fluctuate depending on initial conditions and disturbance. Because of this precarious yet stable balance, Bak et al. say that the system is *critical*. Further, they note that the system self-organizes to this critical state. Linking this with "1/f" noise and fractal self-similarity, they speculate that self-organized criticality (SOC) "might be *the* underlying concept for temporal and spatial scaling in dissipative nonequilibrium systems."

While this claim is still unproved, some have recognized the diagnostic use of linking SOC with fractal self-similarity and "1/f" noise. In other words, self-similar structure and dissipation at all scales might be indicators that a system is at SOC.

Empirical tests: rainforests and ant colonies

Sole and Manrubia (1995) use Bak's theories to examine whether a rainforest exhibited SOC. Knowing that treefall and gap formation are vital to rainforest dynamics, they claim that the distribution and abundance of forest gaps are indicative of the organizational state of the forest. They hypothesize that the gaps in the Barro Colorado Island forest in Panama will show self- similar, multiscale distribution. With both the empirical data

and a simulation of gap distribution called the Forest Game, their hypothesis is supported. Further, in the simulation biomass also shows fractal properties. Knowing that in the simulation the system starts with an arbitrary set of trees, Sole and Manrubia note that the system self-organizes to a state with self-similar structure characterized by "1/f" distribution of gaps and biomass. They conclude that this is suspiciously akin to Bak's critical state, and might indicate that the forest has evolved to SOC.

Sole and Miramontes (1995) followed a similar approach with *Leptothorax* ant colonies, determining whether actual and simulated ant colonies would exhibit self-similar structure with "1/f" noise at a critical value. They find that they do at a critical density of ants, at which the connections between individuals allows for maximum information capacity of the colony. When the density is reached, the colony shows pulses of activity that exhibit self-similarity. Sole and Miramontes point out that the key parameter in determining the critical value of density is simply the number of automata in their model. This is corroborated with empirical observation: in actual colonies, when the number of ants increases substantially (towards a critical density), ants change the colony boundaries to achieve the critical density value for the new colony size. Thus Bak's SOC is evident again in a biotic system.



Evolution to the edge

The previous section explored the concept of self-organized criticality as a place on the edge of chaos where self-organized complexity and computation are possible, and where self-similar fractal structure with "1/f" noise are evident. Next we must investigate why and how a system can move itself to that state from some other state in the order-chaos spectrum.

Adaptation

For biotic systems, one important addition to the list of mechanisms and conditions for SOS is the ability of agents to *adapt*. This means agents are capable of changing their internal information processing functions. This kind of system is known as a complex adaptive system (CAS, Forrest and Jones 1995). In Langton's model, cells would be able to change their transition rules. If this were possible, CA would be able to tune their transition rules (thus their lambda values) along the order-chaos spectrum. In *Leptothorax* ant colonies it means ants which do not respond to changes in density or respond in an adverse way will adapt to a response which leads to SOC. A series of questions about SOS arise when adaptation is considered: what are the mechanisms of adaptation? Under what conditions are they possible? How do systems choose which direction to move among their adaptive choices? And do adaptive systems always move towards SOC?

In evolutionary terms, the How of SOC would be the conditions for evolution (individual phenotypic variation, excess reproduction, and heritability of traits). A population would be able to adapt through the inheritance of genetic variations due to mutation and recombination. The Why of SOC would be natural selection. A population might evolve towards a critical state because natural selection removes variants of the system that are farther from the critical state. This is the basic idea of a population adapting to a particular condition. SOC theory might be a sound statistical theory of evolution if, as the above experiments suggest, populations exhibit the diagnostic qualities of Bak's SOC.

Connectivity

Stuart Kauffman (1991, 1993, 1995) has developed a Boolean network called a coupled fitness landscape to model CAS. In his model N units, each capable of A states, and each connected to K other agents, are mapped into a K-dimensional "landscape" which topographically expresses all possible system states. Kauffman assigns fitness values to each of the A unit states, so that when system states are calculated through the K connections between the N agents, fitness "peaks" appear in the landscape which represent optimal system states. Each landscape then can represent an agent in an adaptive system: a genome, a population, a niche type. He then links several of these landscapes together to study coevolution. One of his findings is that K is a major determinant of how orderly or chaotic the system dynamics are. David Green at ANU also believes <u>connectivity</u> is a pattern determinant in landscapes. In highly-connected landscapes, information travels very quickly and the system becomes more chaotic, whereas in sparsely-connected ones the system quickly settles onto a stable or periodic state. He suggests that the number of connections to each unit in a self-organizing system might be the sole

parameter that determines the self-organizing dynamics of the system.

Still, in order to drive the system across its fitness landscape towards higher fitness, Kauffman invokes a rule by which landscapes can move to nearby system states that offer higher system fitness (i.e., towards local fitness peaks), but they cannot move "down" to states with lower fitness. This arbitrary rule is in line with the evolutionary Why of SOC, and the structure of his many-state landscapes, which closely resembles Langton's CA, offer the How. But this evolutionary explanation becomes less convincing when other systems not driven by genes are considered, particularly communities, biomes, and of course abiotic systems (such as mountain ranges or climates).

A few other hypotheses exist for Why SOS move towards critical states, such as the law of maximum entropy production (Swenson 1989) and perpetual disequilibration (Ito and Gunji 1994), but these have yet to move beyond conjecture. Thus the two most likely mechanisms remain natural selection and physical laws such as the interplay between friction and gravity in Bak's sandpile.



Overviews for the nonspecialist

- Gell-Mann, M. 1994. The Quark and the Jaguar. W. H. Freeman, New York, USA.
- Kauffman, S. A. 1995. At Home in the Universe. Oxford Univ. Press, New York, USA.
- Prigogine, I., and I. Stengers. 1984. Order Out Of Chaos. Bantam Books Inc., New York, USA.
- Waldrop, M.M. 1992. *Complexity: the emerging science at the edge of order and chaos*. Simon & Schuster Inc., New York, USA.

Scientific papers

- Bak, P., C. Tang, and K. Wiesenfeld. 1988. Self-organized criticality. Physical Review A 38:364-374.
- Brown, J. H. 1994. Complex ecological systems. Pages 419- 443 in G. Cowan, D. Pines, and D. Meltzer, editors. *Complexity: metaphors, models, and reality*. SFI studies in the sciences of complexity, proc. vol. XIX. Addison-Wesley, Massachusetts, USA.
- Caswell, H., and J. E. Cohen. 1991. Communities in patchy environments: a model of disturbance, competition, and heterogeneity. Pages 97-122 *in* J. Kolasa and S. T. A. Pickett, editors. *Ecological Heterogeneity*. Springer, New York, USA.
- <u>Crutchfield, J. P. 1994.</u> Is anything ever new? *In* G. Cowan, D. Pines, and D. Melsner, editors. SFI studies in the sciences of complexity XIX. Addison-Wesley, Massachusetts, USA.
- Forrest, S., and T. Jones. 1994. Modeling complex adaptive systems with echo. Pages 3-21 in R. J. Stoner and X. H. Yu, editors. *Complex Systems: mechanisms of adaptation*. IOS Press, Amsterdam.
- <u>Green, D. G. 1993.</u> Emergent behaviour in biological systems. Pages 24-35 *in* D. G. Green and T. J. Bossomaier, editors. *Complex Systems From Biology to Computation*. IOS Press, Amsterdam.
- Hiebeler, D. 1994. The swarm simulation system and individual-based modeling. In Decision Support 2001: advanced technology for natural resource management.
- Horgan, J. 1995. From complexity to perplexity. Scientific American (June 1995):104-109.
- Huston, M., D. DeAngelis, and W. Post. 1988. New computer models unify ecological theory. *Bioscience* 38:682-691.
- Huffaker, C. B. 1958. Experimental studies on predation: dispersion factors and predator-prey oscillations. *Hilgardia* 27:343-383.
- Ito, K., and Y. Gunji. 1993. Self-organisation of living systems towards criticality at the edge of chaos. *BioSystems* 33:17-24.
- Johnson, A. R., J. A. Wiens, B. T. Milne, and T. O. Crist. 1992. Animal movements and population dynamics in heterogeneous landscapes. Landscape Ecology 7: 63-75.
- Jones, T., and S. Forrest. 1993. An introduction to SFI echo. E-print.
- Judson, O. P. 1994. The rise of the individual-based model in ecology. *Trends in Ecology and Evolution* 9:9-14.
- Kauffman, S. A. 1991. Coevolution to the edge of chaos: coupled fitness landscapes, poised states, and coevolutionary avalanches. *Journal of Theoretical Biology* 149:467-505.
- Kauffman, S. A. 1993. Origins of Order: self- organization and selection in evolution. Oxford Univ.

Press, New York, USA.

- Kawata, M., and Y. Toquenaga. 1994. Artificial individuals and global patterns. *Trends in Ecology and Evolution* 9:417-421.
- Keitt, T. H., and A. R. Johnson. 1995. Spatial heterogeneity and anomalous kinetics: emergent patterns in diffusion-limited predatory-prey interaction. *Journal of Theoretical Biology* 172:127-139.
- Langton, C. G. 1990. Computation at the edge of chaos: phase transitions and emergent computation. *Physica D* 42:12-37.
- Langton, C. G., editor. 1994. Artificial Life III. Addison-Wesley, New York, USA.
- <u>Mitchell, M., P. Hraber, and J. P. Crutchfield. 1993.</u> Revisiting the edge of chaos: Evolving cellular automata to perform computations. *Complex Systems* 7:89-130.
- McCauley, E., W. G. Wilson, and A. M. de Roos. 1993. Dynamics of age-structured and spatially structured predator-prey interactions: individual-based models and population-level formulations. *American Naturalist* 142:412-442.
- Nicolis, G., and I. Prigogine. 1989. Exploring complexity. W. H. Freeman, New York, USA.
- Olson, R. L., and R. A. Sequeira. 1995. An emergent computational approach to the study of ecosystem dynamics. *Ecological Modelling* 79:95-120.
- Perry, D. A. 1995. Self-organizing systems across scales. Trends in Evolution and Ecology 10:241-244.
- Packard, N. H. 1988. Adaptation toward the edge of chaos. Pp. 293-301 *in* A. J. Mandell, J. A. S. Kelso, and M. F. Shlesinger, eds. *Dynamic Patterns in Complex Systems*. World Scientific, Singapore.
- Shugart, H. H., T. M. Smith, and W. M. Post. 1992. The potential for application of individual-based simulation models for assessing the effects of global change. *Annual Review of Ecological Systems* 23:15-38.
- Smith, T., and M. Huston. 1989. A theory of the spatial and temporal dynamics of plant communities. *Vegetatio* 83:49-69.
- Sole, R. V., and S. C. Manrubia. 1995. Are rainforests self- organized in a critical state? *Journal of Theoretical Biology* 173:31-40.
- Sole, R. V., and O. Miramontes. 1995. Information at the edge of chaos in fluid neural networks. *Physica D* 80:171-180.
- Swenson, R. 1989. Emergent attractors and the law of maximum entropy production: foundations to a theory of general evolution. *Systems Research* 6:187-197.
- Watt, A. S. 1947. Pattern and process in the plant community. Journal of Ecology 35:1-22.
- Yates, F. E., Editor. 1987. *Self-Organizing Systems: the emergence of order*. Plenum Press, New York, USA.

Miscellaneous SOS, SOC, CAS, CA & complexity links

- <u>Annotated A-life On-line Resources Bibliography</u> by Ezequiel A Di Paolos at the School of Cognitive and Computing Sciences at the university Sussex.
 - A good list of complexity, self-organization, evolution, and A-life links.
- <u>Complex Systems Research Links</u> maintained by Yogesh Malhotra at the University of Pittsburg. - An excellent links list of a multitude of topics by a complex business systems researcher.
- <u>Bookmarks</u> by Olivier Bousquet at L'Ecole Polytechnique in Paris.
- A seemingly exhaustive and expansive links list by someone with too much time on his hands.
- <u>Nonlinear Science e-Print Archive</u> at Los Alamos National Lab.
 A searchable archive of on-line, nonlinear-type papers.
- <u>Principia Cybernetica Web</u> by the Principia Cybernetica Project (PCP: how about that acronym?).
 An interesting collection of materials: "The Project's aim is the computer-supported collaborative development of an evolutionary-systemic philosophy. Put more simply, PCP tries to tackle age-old philosophical questions with the help of the most recent cybernetic theories and technologies." Trippy at times, but they have a great <u>links list</u>.
- <u>Chaos at Maryland</u>, by the Chaos Group at the University of Maryland at College Park.
 A good academic page by a very good program, with e-prints, a chaos database, and other institutional information.
- <u>Annotated Complexity Links List</u> maintained by Alex Mallet at the University of Pennsylvania. - A big, fun list of a wide array of complexity links.