



Effectively Extending Intention into a Complex World:

Limits to Predictive Understanding &
Strategic Actions Toward Sustainability

By:

Andrew Thomson

Andrew_Thomson@mac.com

Supervised by:

Barry Ness

Barry.ness@lucsus.lu.se

&

Henrik Thorén

henrik.thoren@lucid.lu.se

Lund University Center for Sustainability Studies Geocentrum 1, Sölvegatan 10 P.O. Box 170,
SE-221 00 LUND, Sweden Phone: +46 (0) 46 222 48 09 www.lucsus.lu.se

*A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in Environmental
Studies and Sustainability Science (LUMES) at Lund University, June 1st, 2011*

Abstract	3
1.0 Introduction	4
1.1 Research Questions	5
1.2 Paper Structure	5
1.3 Methodology and Theoretical Framework	6
1.4 Definitions	8
2.0 Limits to Predictive Understanding	11
2.1 Concept #1 - Sensitive Dependence on Initial Conditions	11
2.2 Concept #2 - Nonlinear Dynamics	14
2.3 Concept #3 - Aggregate Complexity	18
3.0 Summary of Concepts	22
4.0 Discussion	23
4.1 Valid Predictive Constructs and the Realization of Intentions	23
4.2 Extending Effective Intention	24
4.3 Sustainability Science: Intentional and Active	26
4.4 Strategic Implications	27
4.5 Reprioritization of Sustainability Aims	27
5.0 Conclusion	30
References	32
Appendix A	36

Abstract

Sustainability Science is an active and intentional field of study; part of its research aims to move beyond explanation and into prescriptive and strategic realms. In order to be effective in our intentional actions toward sustainability, they must be based on valid predictive understanding of the effects of those actions. Complex Systems Theory is used as a framework to analyze our ability, as cognitive agents, to develop valid predictive understanding within our complex world. A review of Complex Systems Theory literature has yielded three concepts that erode our ability to build valid predictive constructs have been identified. Namely: Sensitive Dependence on Initial Conditions, nonlinear dynamics, and Aggregate Complexity. An investigation into these concepts has identified three potential axis upon which our predictive capacity can be said to erode:

- 1) *Temporal Scale*- long-term predictive claims tend to be less valid than short-term predictive claims.
- 2) *Non-linear dynamic shifts*- predictive constructs lose validity as the dynamics of a system change in novel ways.
- 3) *Aggregate Complexity*- coupled complex systems are more difficult to predict.

These dimensions are utilized to critique the degree to which we can expect our intentional actions to be effective. The strategic implications of this investigation are explored as they relate to Sustainability Science. A strategic re-prioritization of our intentions is offered to place our focus on those Sustainability Science aims that are more likely within the reach of our intentional actions.

Key words:

Complexity Science, Strategy, Sustainability Science, Predictive Constructs, Intentional Actions

Word Count:

13,432

Acknowledgments:

I would like to thank Barry Ness and Henrik Thorén for acting as my thesis advisors. Their guidance, critical assessments and encouraging support over the past months has allowed me to take full advantage of the thesis process. In addition, I would like to thank my classmates for an endless series of discussions and critical debates that have aided the development of my ideas and enriched my experience of writing this thesis.

This paper is a personal exploratory investigation that is grounded in the discourse of Complex Systems Theory. My thesis is concerned with investigating potential limits to the efficacy of our intentional actions within our unavoidably and imperceptibly complex world.

1.0 Introduction

“The universe is not only queerer than we suppose, but queerer than we can suppose”
J.B.S Haldane

To echo the notion of evolutionary biologist J.B.S Haldane, the world is not only more complex than we suppose, it is more complex than we can suppose. We wake up each day a face an unimaginably complex world. We endeavour to navigate that complexity by attempting develop a better understanding of our environment. We, as individuals, can appeal to reason; that is, to our mental constructs, in an attempt to effectively guide our actions to effectively pursue that which we value.

Similarly, Sustainability Science, as an intentional field of study, is focused “on the design and running of processes linking *knowledge* with *action* to deal with persistent problems” that “have a high degree of complexity” (Jager 2009, p.3). A part of Sustainability Science is interested in the actual “implementation” of sustainability ideals (Jager 2009, p.3). Put another way, it is concerned with building knowledge that can effectively guide actions in pursuit of a more sustainable world (Kates, 2001, p.641).

Mitchell (2009, p. 86) argues that in “both individual choice and social policy contexts, we consider the consequences of our actions along with the values attached to those consequences in order to determine which actions we expect to best promote our values.” The actions we chose to take, in order to effectively promote that which we value, must be based upon valid predictive understanding of the consequences our actions have on that which we value. If we do not hold valid predictive understanding of the consequences of our actions, our choices will be misguided and our intentional actions ineffective. Sustainability values, however vaguely defined, represent a normative ideal toward which we act intentionally.

Hafsi & Thomas (2005, p.516) write that “ultimately, action is a series of decisions”. My paper is an investigation into some potential limits to predictive understanding and resulting limits to effective intentional actions within our complex world. I have utilized Complex Systems Theory, as a theoretical framework, to investigate these potential to limits our ability to build valid predictive constructs. Allen & Strathern (2003, p.9) argue that Complex Systems Theory

offers a “basis on which to consider knowledge, strategy and action”. Three concepts from the field of complexity science are discussed to illustrate three distinct challenges that limit our ability to be predictive.

Sustainability Science is an active and intentional field of study, that is, part of it’s research aims to move beyond explanation and into more prescriptive normatively bound realms; we pursue an unavoidably normative conception of a more sustainable future. The limits that I argue for directly relate to, and pose a significant challenge to, some of the explicit aims of Sustainability Science. From a pragmatic stance, it is hoped that the efficacy of our intentional actions can be improved by exploring the characteristics of complex systems that erode the validity of our predictive constructs. An acknowledgement and definition of that which is beyond our ability to predict can be useful for shaping strategic priorities. My thesis concludes with strategic recommendations for Sustainability Science that are based on the results of my investigation and discussion. I suggest a re-prioritization of our intentions to place our focus on those Sustainability Science aims that are more likely within the effective reach of our actions.

1.1 Research Questions

- i) In what ways are we limited in developing valid predictive constructs within complex socio-ecological systems?
- ii) How do limits to predictive understanding influence the degree to which we can be effective in our intentional actions toward sustainability?
- iii) In what ways can we, as individuals and Sustainability Scientists, strategically react to the limited efficacy of our intentional actions within our complex world.

My research questions are explored in a sequential manner. The investigation into (i) potential limits to predictive understanding offers the basis upon which I discuss (ii) limits to effective intentional actions and, finally, my (iii) strategic recommendations.

1.2 Paper Structure

I ground my investigation into potential limitations to predictive understandings in Complex Systems Theory. My review of complexity literature has identified three separate concepts, each highlighting different aspects, or conditions, which can be said to decrease or completely occlude our ability to construct valid predictive constructs. The first two concepts are illustrated by utilizing mathematical deterministic models, firstly, the Horseshoe Transformation Model and secondly, the Lorenz Strange Attractor Model. The third concept, Aggregate Complexity, as defined by Manson (2001, p. 409).

My investigation summarizes some of the ways in which our ability to form valid predictive constructs within complex socio-ecological systems (SES) is eroded. However, the three concepts that I investigate are not representative of an exhaustive list of the ways in which we are limited in developing predictive insights. That being said, we can view our ability to develop predictive capacity as being eroded on three distinct axes:

- 1) *Time* - Long-term predictions tend to be less valid than short-term predictions.
- 2) *Non-linear Dynamics* - Non-linear changes in the dynamics of a system reduce our ability to effectively predict.
- 3) *Aggregate Complexity* - The concept of aggregate complexity, that is the coupled nature of complex systems, is seen to reduce our ability to gain predictive understanding.

I frame my discussion around the concepts outlined above. Firstly, I explore the need for valid predictive constructs in order to make intentional actions effective at promoting our valued outcomes and the challenges cognitive agents in complex systems face when attempting to differentiate between valid and invalid predictive claims. The efficacy of our intentions is conceptualized within a three-dimensional abstract space by synthesizing the ways in which our predictive capacity is eroded with a predict-act model of intentional action. I argue that our intentions are limited in the degree to which they can effectively extend into the abstract space proposed. I then discuss the explicit aims of Sustainability Science in relation to the limitations outlined. My discussion ends with a strategic reframing of sustainability priorities in the hope that doing so might increase the effectiveness of our intentional actions.

1.3 Methodology and Theoretical Framework

This thesis is bound to, and operates within, the discourse of Complex Systems Theory. As such, it is ultimately dependent on the validity of Complex Systems Theory as a framework for discussing knowledge and actions. As mentioned above, Allen & Strathern (2003, p.9) argue that Complex Systems Theory offers a “basis on which to consider knowledge, strategy and action”. I have purposefully chosen not to write my thesis based on a wider survey of the field of Philosophy of Science. I have chosen Complex Systems Theory as potentially useful alternative framework for discussing the efficacy of intentional actions within our world. There are modern philosophers of science that similarly choose to employ a complexity framework to discuss knowledge and action (Mitchell, 2009). My choice to employ complex systems theory as a framework to discuss predictive knowledge is not claim to the superiority or the exclusivity of the theoretical framework. Rather, I argue that it is one, potentially useful, framework to structure an investigation into predictive knowledge and efficacy of intentional actions.

My thesis is based on an exploratory review of literature related to “Complex Systems Theory”, as defined by Manson (2001). During the reading process I reflected and took notes on concepts that were seen to related to the idea of prediction and to predictive capacity within complex systems. I identified conceptual themes and then focused my critical exploration on those concepts. The iterative process between identifying concepts and critiquing the relevance of those concepts allowed me to limit my thesis to only three concepts that speak to limits of predictive capacity. The three general concepts I chose to focus on are: Sensitive Dependence on Initial Conditions (SDIC), nonlinear-dynamic shifts, and aggregate complexity. In an attempt to communicating and discuss these concepts with readers that have not been previous exposed to them, I identified two illustrative mathematical models that had peer reviewed articles discussing their relationship with the concepts of interest. I chose the Horseshoe Transformation Model to illustrate the concept of SDIC because I found multiple references

that offered an interpretation of the model. For similar reasons, I chose to utilize the Lorenz Strange Attractor Model to illustrate the concept of non-linear dynamical shifts within complex systems. The concept of aggregate complexity refers to a more general area of study within the field of complex systems theory and, as such, my illustration of the concept will appeal more directly to the literature in question (Manson 2001, p.409).

Literature from the field Strategic Management Studies is also appealed to within my thesis. I argue that, as a field of study interested in strategic purposeful actions within complex environments, it has the potential to provide transferable knowledge for my investigation concerning strategic actions toward sustainability.

I am aware of the non-conventional and ambitious nature of my thesis; this was a conscious choice. I have chosen this research topic, not because I think I am most qualified or capable to answer it, but rather I chose it because I believe it to be central to how I experience, interpret and interact with the world around me. This of course is an experientially based justification, but it is my sincere hope that my investigation, can be a useful exploration of strategy and action for myself and others pursuing a more sustainable future.

1.3.1 Methodological Individualism

I maintain that the only scale at which conscious thought is experienced is within the individual. The experience of strategy is important to my project as the self awareness of human agency is argued to allow for the potential of actively critical and reflexive reasoning. While it is acknowledged that intersubjectively constructed forms of social or shared strategy exist, this paper focuses on individual agents, as the act of choosing to share, combine and coordinate efforts is one that could fall within the purview of a critical assessment of intentional choices. Choosing to combine individual intentions into a collective form can generate an organizational strategy that is dissociated with individuals intentions (Mintzberg & Waters, 1985 p.260). We exist within and interact with, societies, organizations, governance and policy structures. However, reflection and choice is ultimately only experienced as a separate individual, and we, at any given time, can only rely on our personal understandings to guide actions. Organizations and governance structures do make choices and act toward predefined aims, however it is often the case that those organizational intentions emerge out of a wider base and collective of individuals acting upon individual intentions (Mintzberg & Waters, 1985, p. 257). It is for these reasons that I investigate intentional action from the perspective of an individual.

Ultimately, if we are concerned with conscious or self-aware agency, we must feature the individual as the constituent element of our complex human society. We, as individuals, conceptualize the world, we place a sense of certainty on our understandings and label them as legitimate. As this paper will explore the intentional actions we must look at the experience of understanding at the only scale that is self aware; the individual, the conscious agent.

1.4 Definitions

Complex Systems Theory is diverse and is employed by many different academic fields, as a theoretical framework of analysis and as an area of study, in and of itself. As a field of study, Complexity Science has developed and evolved over the past sixty years and has many complementary and competing schools of thought (see Appendix A).

There are a diverse set of definitions for key terms within complexity science. It is not my aim to synthesize differing definitions of a single term or make claim to one definition's superiority over another. However, it is necessary to define the way in which I utilize some key terms. Namely: complex system, predictive construct, agency, and intentional action. These definitions, while being drawn from a diverse set of reading, are personal conceptualizations. I neither claim to be the sole author of them nor am I making a claim that these definitions are representative of wide agreement within the academic community.

1.4.1 Complex System

There are many, and significantly varied, definitions of complexity and what constitutes a complex system (Manson, 2001, p. 405). In the interest of clarity, I will attempt to broadly outline a working definition for this paper. Foote (2007, p. 410) offers the following description:

“In recent years the scientific community has coined the rubric “complex system” to describe phenomena, structures, aggregates, organisms, or problems that share some common themes: (i) They are inherently complicated or intricate, in that they have factors such as the number of parameters affecting the system or the rules governing interactions of components of the system; (ii)... state parameters or measurement data may only be known in terms of probabilities; (iii) mathematical models of the system are usually complex and involve nonlinear, ill-posed, or chaotic behavior; and (iv) the systems are predisposed to unexpected outcomes (so-called “emergent behavior”). Familiar examples include weather systems, biological and chemical systems, social networks, transportation and engineering infrastructure systems, and the Internet”

(Foote, 2007. P. 410)

Systems are characterized by diverse and distributed interactions and relationships between entities that generate non-linear behaviour patterns and are capable of spontaneously exhibiting novel emergent phenomena. It has been said that “complexity starts when causality breaks down” (Editorial, No man is an Island, Nature Physics, 2009 5:1). This paper frames the manifold of socio-ecological systems that are of interest to Sustainability Science as being complex systems (Liu, 2009).

1.4.2 Predictive Construct

Predictive constructs make claims, whether valid or invalid, to understanding causal relationships over time. Causal associations that are projected over a time period are the basis of predictive claims, whether they are a projection of previous trend lines or are generated within a model, or mental construct, that utilizes previously observed corollaries. Constructs do not have to be consciously experienced and are often implicit in our reasoning. In this way, predictive constructs can be latent to our conscious reasoning and still affect, or guide, our actions.

Path and Pattern Predictive Claims:

It will be useful for the purpose of clarity to detail two different types of predictive understandings differing only in the quality, or resolution, of the predictive claims. Predictive understanding can be characterized as holding claims to path predictability, or that of pattern predictability. Path predictability is the stricter version of the two types, as it reconstructs a causal chain of outcomes. That is, a claim that A will lead to B which will then lead to C. On the other hand, pattern predictability represents causal associations, or recognizable patterns of organization, over time that are not order specific.

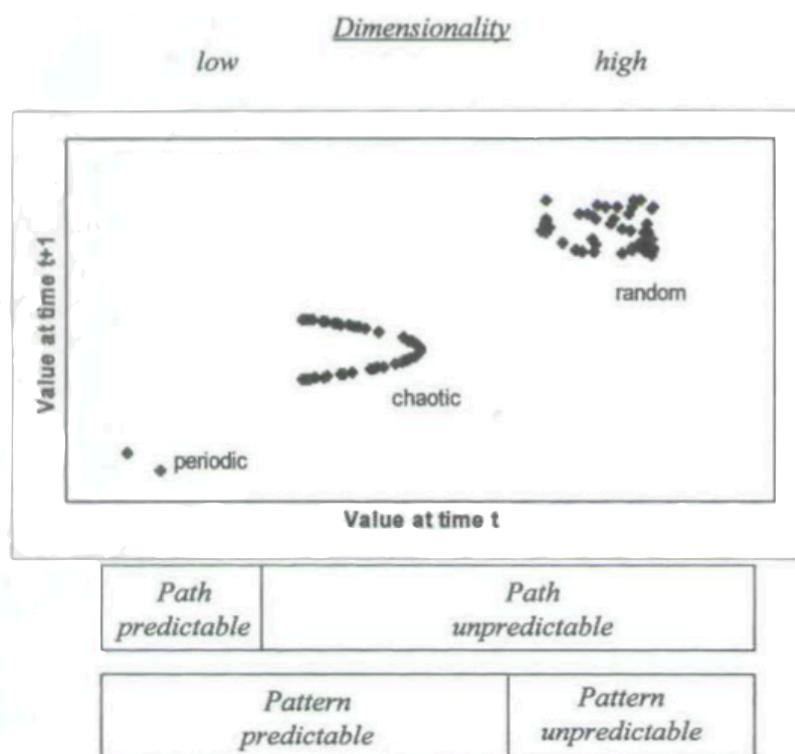


Figure #1 - Differentiation of Path Predictability and Pattern Predictability
(Dooley & Van De Ven 1999, p. 360)

The figure above illustrates the two types of predictive claims. The important distinction within the figure is that it is possible to hold pattern predictability constructs without having strict path predictability. This could be said to be analogous to making claims to the expected outcome of flipping a coin many times. It would be reasonable to claim that on average the outcome of the coin toss will be 50% heads and 50% tails (i.e. pattern) but not a claim to the specific order of heads and tails (i.e. path).

Functional Validity of Predictive Constructs:

I refer to predictive constructs as being “valid” when they are functional in the context in which they are held. I do not use the word valid to represent a single “true” way of understanding. I am pluralistic in my conceptualization of validity in complex systems in that I accept there are multiple ways of making sense of an environment that are functional. I think that two predictive constructs can differ yet both be valid. As a result, I speak to a functional and pluralistic conception of predictive construct, as opposed to validity referring to the one “truth”.

“What is important about intellectual ideas [i.e. predictive constructs] is their ability to recover order; they help arrest our feelings of unrest and lack, but they are in no way true because of that, and, should we come to believe them as true above all other ways of thinking about the world, much mischief follows”

(Chia, & Holt, 2011, p. 114)

Conceptual understanding of observed and interpreted phenomena will be said to be “predictive” if it, within the context of it being held, is able to effectively “recover order” from the environment; that is, be functional in relation to our values.

Perceived Legitimacy of Predictive Constructs:

It is important that I distinguish between perceived validity and the functional validity of predictive constructs within complex systems as it will be important in my discussion. We, as cognitive agents, do not directly experience the functional validity of our predictive constructs instead we form, socially and individually, a sense of “legitimacy” with regard to the validity of our constructs. It is important to distinguish our confidence in a construct, that is, the legitimacy we label it with, as being potentially distinct from the actual functional validity. The point that we can have false confidence in our constructs might seem self evident, but it is important to note, as “perceived legitimacy” and “functional validity” can diverge significantly within complex systems.

As my paper centers on predictive constructs within complex systems, I have outlined three sets of terms that can be utilized to describe our predictive constructs. Predictive constructs can vary in their nature, being path or pattern oriented. Predictive constructs can be functionally valid or invalid and the validity linked to the context within which they are held. Finally, predictive constructs can be labeled as legitimate, or illegitimate, but that label can differ from the actual validity it aims to represent.

1.4.3 Intentional Action

I talk of intentional action as those actions that are taken, as conscious cognitive agents, in pursuit of predefined and normatively bound aims. I limit the use of the term “intentional

action” to an instrumental conceptualization as it is my belief that purposeful action is the means by which we extend our will onto the world.

“Reason is, and ought only to be the slave of the passions, and can never pretend to any other office than to serve and obey them”

David Hume

Our capacity as individuals to reason with, and act intentionally within, our shared complex environment is central to my arguments. Intentional actions are born of *reason* pursuing *passion*.

2.0 Limits to Predictive Understanding

In this section I investigate three concepts that arose out of my review of complexity literature. I attempt to give definition to pervasive and inherent limits to predictive understanding within complex SESs. The three concepts are investigated to highlight some, but not all, of the ways in which the validity of our predictive constructs can be said to erode.

The first concept is illustrated through exploring a deterministic mathematical model called the Horseshoe Transformations Model. I provide a summary of the model and the dynamics that govern its behaviour to illustrate the concept of Sensitive Dependence on Initial Conditions (SDIC) and its relationship with our capacity to be predictive.

The second concept is illustrated through another classic example of a deterministic mathematical model called the Lorenz Strange Attractor Model. This model is used to illustrate the concept of nonlinear shifts, or bifurcations, within system dynamics. The effect non-linear dynamics have on our ability to build valid predictive constructs is then explored.

The third and final concept is distinct from the first two, in that it is a broader investigation into aggregate complexity and the associated limits to predictive capacity. Manson (2001, p. 409) defines aggregate complexity as an area of study within complexity research that focuses on “access(ing) the holism and synergy resulting from the interactions” of systems. The SES’s of interest to Sustainability Science are highly interconnected, or coupled. I discuss the challenges faced when attempting to build valid predictive constructs from within the aggregate complexity of coupled SES’s.

2.1 Concept #1 - Sensitive Dependence on Initial Conditions

Mathematical models can be useful to illustrate the dynamics complex systems display. In this section I discuss the the Horseshoe Transformation Model which was first devised by Smale (1965). My aim is to illustrate the concept of Sensitive Dependence on Initial Conditions (SDIC) and the ways in which it erodes our ability to hold long term predictive constructs. The Horseshoe Transformation Model, while not technically defined as a complex system, exhibits

SDIC argued to exist in the SES's of interest to sustainability science such as anthropogenic climate change (Parker, 2010, p. 264).

SDIC refers to, in a general sense, the notion that small changes in the initial characteristics of a system can result in very different subsequent states of the system. This extreme sensitivity to initial conditions is sometimes referred to as the “butterfly effect” (Thietart, & Forgues, 1995, p.26). The analogy invoked is one of a butterfly flapping its wings which ultimately results in the formation of a hurricane forming half a world away that would not have formed if not for the butterfly's action (Manson, 2001, p.407). In essence, SDIC, or the butterfly effect, describes the divergence of system behavior patterns that start out as identical, save for the smallest detail in initial conditions.

To be clear, the inclusion of this mathematical model is intended to illustrate the concept of SDIC, it is not intended to be a representative model of a real world observed system. The Horseshoe Transformation Model is an idealized deterministic model, as the laws that govern its behaviour are both, known in their entirety, the system is precisely deterministic. This model can be said to be governed entirely by known deterministic functions. The initial state of the systems dictates the next state and so on in an infinitely deterministic causal chain of events. The dynamics of this model will be interpreted to highlight challenges when making predictions that can exist even within ideal conditions of full knowledge.

Many have offered different analogous explanations of how the model operates, but I will follow Michel Baranger (Undated, p.8) in using the analogy of stretching and folding pastry dough. The image Baranger evokes to illustrate the model dynamic is that of a piece of dough stretched to the exact width of a table which is then folded over on itself and re-stretched to its original width. This “stretching and folding” of the dough in iterative and continues indefinitely.

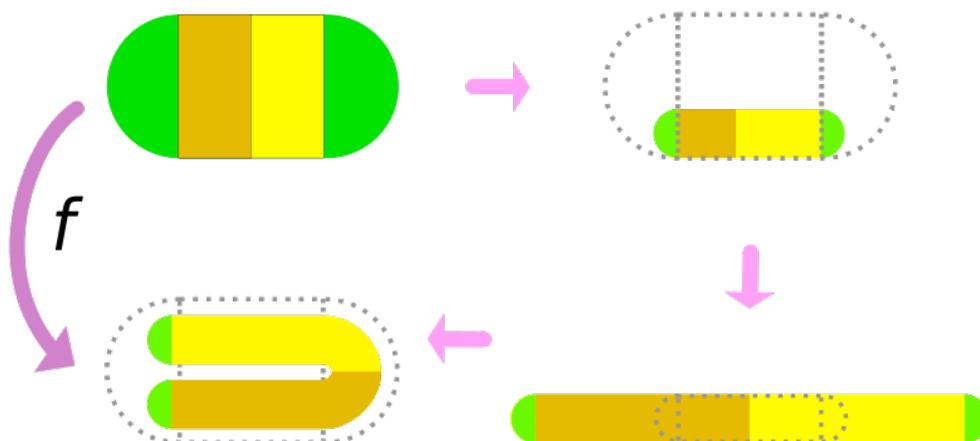


Figure #2 - The Smale Folding Horseshoe Transformation Model - Illustration of one iteration of the system (<http://commons.wikimedia.org/wiki/File:Action.svg>)

If a raisin were to be placed on top of the dough and its location measured and documented. One could expect to predict where the raisin will be on the next iteration of stretching and folding. However, the divergence within the system, generated by the stretching and folding lead to SDIC. In this illustrative model we can imagine placing two raisins right next to each other on the dough. Within the first few iterations of the system we can expect the raisins to track each other's movements closely, but as more iterations of the system stretch and expand the original distance between the two raisins, they begin to move independently and increasingly in an uncorrelated way (see figure #3).

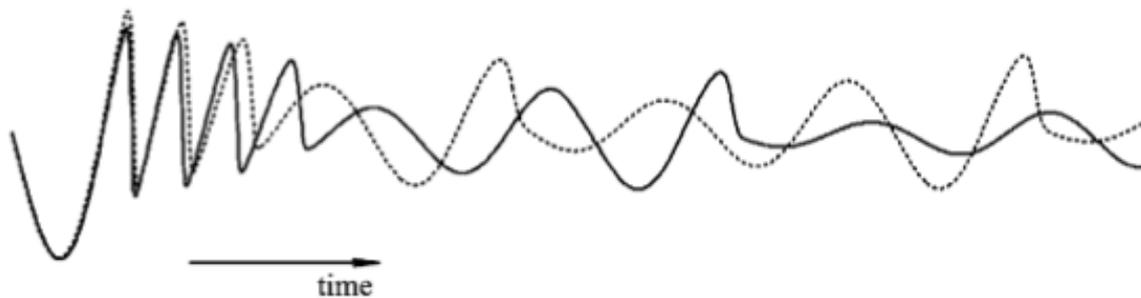


Figure #3 - Illustration of SDIC - The separation of neighbouring trajectories over time.
(Retrieved from: Helbing, 2009, p.42)

Now imagine that instead of two raisins, there was only one and an observer of the system wished to make a prediction about where the raisin will be in the dough after successive iterations of stretching and folding. That observer could measure the initial location and, for the purposes of illustration, we can assume that the observer could measure the location accurate to $1/100^{\text{th}}$ of a mm. Even with the precise information of the initial condition and full knowledge of the laws that govern the system, the smallest of uncertainties in the initial position are amplified with each iteration of the model. A predictive model of the system could, at least initially, be relatively accurate at predicting where the raisin will be in the dough but over time the predictive capacity is eroded. Predictive capacity is lost completely when the original error bars in measurement, however small, result in hypothetical future states that could exist anywhere over the full range of the dough. In this way the efficacy of statistical modeling to give meaningful probabilistic claims to potential future states also breaks down over time, or in this case, iterations of the system.

The point of this discussion is not to highlight the importance of raisins in pastry. Rather, it is to illustrate that even in idealized systems, where there is full knowledge of the governing laws, predictive capacity is eroded over time. The passage of time, or in this case, the iterations of stretching and folding, can lead to wildly different “states” of the system for two raisins, even when the initial position, or “initial conditions”, were very similar. This model therefore, could be said to exhibit a SDIC.

In summary, this model illustrates that even in simple, deterministic, fully understood systems that exhibit SDIC, observers lose predictive capacity over time and potentially very quickly; that

is when the difference in time between the observational measurement and the time at which the prediction is attempting to represent increases.

Three interesting discussion points arise:

i) Lower Limits to Sensitivity:

Within the model outlined there is no lower limit to the sensitive dependence. That is, the most minuscule difference in initial condition, or uncertainty of measurement, will be amplified over successive iterations of the system until the resulting potential states of the system exist over the entire area.

ii) Erosion of Predictive Validity:

Making causal associations over time becomes difficult or impossible. Even though, in this model, we can say that the mechanisms that govern its behaviour are deterministic and fully understood, the ability to predict and retrospectively associate an outcome with an initial condition becomes impossible. A causal chain of system states represented by $A \rightarrow B \rightarrow C$, might not be possible to reconstruct accurately. In this way, when a system exhibits SDIC and the timeframe of A and C are sufficiently separated, we cannot say with any degree of certainty that A will lead to C, or conversely, that C is a result of an earlier state A. Therefore, we lose the ability to construct valid predictive constructs of causal associations for any extended period of analysis.

iii) SDIC in Complex Systems

The concept of SDIC challenges attempts to attain valid predictive constructs through “totalizing discourses” or conceptual models and instead suggest inherently unpredictable systems (Manson, 2001, p.408)(Cartwright, 1991). While recognizable order might exist within systems that exhibit SDIC the potential of complex systems to be highly sensitive to initial conditions preclude the ability to strictly predict the state of the system far into the future.

2.1.1 Temporal Scale and Predictive Capacity

When a complex system displays a sensitivity to initial conditions the ability of our predictive constructs to remain valid over longer time horizons is eroded. The speed at which the validity of our predictive constructs erode can be slow or fast depending on the dynamics of the specific systems that we are concerned with, yet we can, in general, conclude that long-term predictive claims tend to be less valid than short-term predictive claims (Thietart & Forgues, 1995, p.21) (Cartwright, 1991, p.50). Both path and pattern predictability tend to erode as the timeframe of our predictive claims increase with regard to Complex SES's.

2.2 Concept #2 - Nonlinear Dynamics

As with the previous section I utilize an illustrative to discuss a concept derived from my review of complexity literature. This model is an example of an ideal mathematical system, as it is

deterministic and, as an observer, the governing laws are known exactly. I discuss the Lorenz Strange Attractor Model in an effort to illustrate the concept of non-linear dynamic shifts that characterize complex SESs of interest to Sustainability Science (Liu, et al. 2007). Our limited ability to predict the occurrence of non-linear shifts in system dynamics is discussed as well as our inability to forecast the dynamics of a systems after a non-linear shift. I illustrate how our predictive constructs lose validity as the dynamics of a system changes.

The Lorenz Strange Attractor model was developed in 1963 by Edward Lorenz, originally intended to model specific weather phenomena (Chia & Holt, 2011, p. 52). However, the novel dynamics exhibited by the model resulted in it becoming a formative model for Chaos Theory (Levy, 1994, p. 168), which has been very influential for complexity studies (Goldstein, 2000, p. 55). Chaos has been described by some as existing at the boundary of order and disorder, that is, at the very edge of recognizable order (Manson, 2001, p. 407)(Kaufman, 1993 cited in Levin, 2002, p. 12). I will describe the deterministically chaotic model and summarize some of the interpretations and resulting limits to predictive understanding outlined in the academic literature.

The model is comprised of three variables (X,Y &Z) that change over time as a function of the previous state of the system. As in the section above, the model is completely deterministic and governed by fully understood and precise laws. One state of the system can only lead to one next state. Stated in another way; state A can only lead to state B which can only lead to state C.

$$\begin{aligned} X' &= -\sigma X + \sigma Y, \\ Y' &= -XZ + rX - Y, \\ Z' &= XY - bZ. \end{aligned}$$

Figure #4 - Governing Equation of Lorenz Strange Attractor Model (Lorenz, 1963, p. 135)

As we can see from the equation above, the change in X, that is X', is a function of the previous states of X and Y. Y' and Z' have similar deterministic qualities.

Lorenz illustrated the behavioral dynamics of the systems by first graphing the value of Y over successive iterations of the model. The following graph shows the results of these iterations:

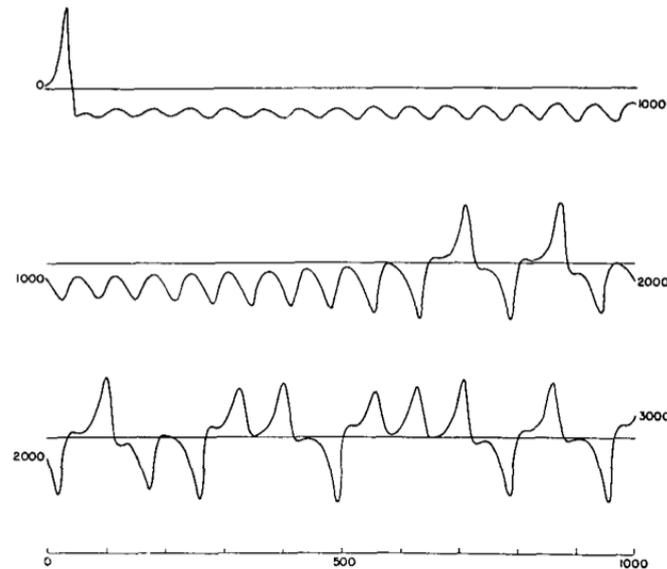


Figure #5 - Values of Y over 3000 iterations of the Lorenz Strange Attractor Model
(Lorenz, 1963, p. 137)

The oscillations of the system seem random and it is difficult to recognize any pattern over the first 3000 iterations. The values of Y jump unpredictably from lower to higher values. Lorenz then generated a Poincare Graph to represent the Values of Y and Z over time. A Poincare Graph refers to “removing time as one of the axis of a graph and instead plotting data points” (Manson, 2001, p.408). These data points sampled at regular intervals can form patterns representative of order through time.

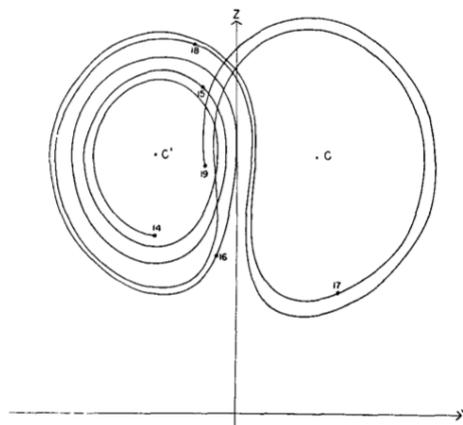


Figure #6- Poincare Graph of the Lorenz Strange Attractor Model on the X-Y Plane (Lorenz, 1963, p. 137)

There is clearly an order to the movement of the variable X and Y through time. The two points, labeled “C” in the graph above, represent the two points around which system dynamics tend to circle around. That being said, the SDIC exhibited by the system means that we are unable to predict when the system will shift from one orbit to the other (Thietart, & Forgues, 1995, p.20). The points C and C’ are referred to as “Strange Attractors” (Lorenz, 1963). Strange attractors have come to be defined more generally as “a value or a set of values towards which

system values tend towards over time” (Manson, 2001, p.408). The process of a system jumping from one attractor to another, or reorienting itself around new dynamics, has been described as “bifurcation” (Feigenbaum, 1980 as cited in Manson, 2001, p. 407)

Now, adding the last variable, we can see a 3-dimensional representation of the dynamics of the Lorenz Strange Attractor Model over time.

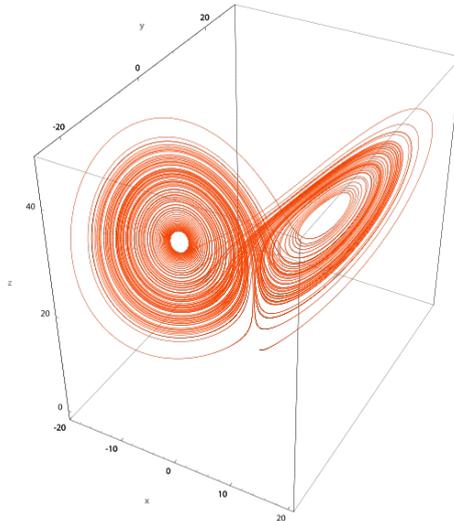


Figure #7 - Lorenz Attractor Model- Variables X,Y&Z represented in 3-Dimensional Poincare Graph State-space. (Image retrieved from: http://en.wikipedia.org/wiki/File:Lorenz_attractor_boxed.svg)

The Lorenz Strange Attractor Model exhibits dynamics that unpredictably oscillate between two points of attraction. The unpredictable shifts between attractors can be said to be illustrative of non-linear shifts in system dynamics.

2.2.1 Non-linear Shifts in Complex Systems:

The Lorenz Strange Attractor Model can serve as a useful model to illustrate the concept of non-linear shifts within complex systems. The model shows that chaotic systems that bifurcate between different Strange Attractors can exhibit retrospect order, while not being predictable. The unpredictable nature of this model could be said to result from two concepts, one, SDIC as discussed in the previous section, and two, internally generated non-linear shifts (Kellert, 1993, p. 12). Put another way, systemic changes can arise from “within” the system, with no need for external stimuli to initiate or direct the change. This has potential significant implications for those studying complex systems. More specifically, if someone was to, for instance, observe the behaviour pattern and corollaries of the Lorenz model during a set of iteration in which it was tending toward one Strange Attractor, they might develop a useful understanding of how the system operates. If the system unexpectedly, broke from its previous patterns of action and shifted to the other strange attractor, the observers previous constructs on the dynamics of the system might prove less useful. In this way, an observer has potentially lost both strict path predicability of how the system will be configured in the future, but also an understanding of the patterns of dynamics exhibited by the system. Correlates that might have been previously useful at making probabilistic projections (pattern predictability) fail to

correlate after the non-linear changes in system dynamics that are argued to occur within complex systems (Levy, 1994 p169)(Holling, 2001, p. 399). Thus, bifurcations are illustrative of systemic shifts, or tipping points, in complex systems that fundamentally change how variables are seen to correlate.

Edward Lorenz aptly concluded his seminal article by stating that, in the absence of exact knowledge of initial conditions, his results “indicate that prediction of the sufficiently distant future is impossible by any method” (Lorenz, 1963, p. 141). He goes on to say that the question of how long into the future can models be predictive, remains unanswered. I argue that, in a general sense, this question remain unanswered today. This is argued to be especially true for complex systems exhibiting non-linear behaviour pattern for which we do not have anything close to exact knowledge of the governing laws or current state of affairs. We instead rely on the assumption of some notion of the continuity of nature, that is that past dynamics are usefully representative of future dynamics, an assumption potentially invalidated by non-linear changes (Thietart, & Forgues, 1995, P.26)

2.2.2 Non-linear Dynamics and Predictive Capacity

Non linear dynamics within systems that exhibit multiple domains of attraction, as in the Lorenz model, become very difficult to predict. Predictive capacity is eroded for two reasons. One, there is disproportional responses to changes, as in a small change can make a huge difference in future states, and conversely large changes can result in small differences in future states of the system. And two, if a system jumps from one strange attractor, or domain of attraction, to another, the observable order within the system can radically change. Correlates and causal associations that form valid predictive construct within one domain of attraction might prove invalid within a new domain of attraction. Predicting when nonlinear shifts will occur in system dynamics are extremely difficult and the nature of the systems dynamics after a shift between domains of attraction is likewise unforeseeable. Helbing (2009, p.435) concludes that “the response of complex systems... can be very different from the intended or predicted one.” Thus, I argue non-linear dynamic shifts in Complex systems erode the validity of our predictive constructs that are, unavoidably, based on current or past dynamics of a systemic behaviour.

2.3 Concept #3 - Aggregate Complexity

Aggregate Complexity refers to coupled, or integrated, complex systems. As an area of study within the wider field of Complexity Science, it concerns itself with integrated observed biological, chemical, social and ecological systems (Manson, 2001, p. 409). My discussion of aggregate complexity in relation to predictive understanding will differ from the previous two sections outlined. This section will instead discuss the challenges associated with attempting to gain a sufficiently “holistic” understanding of complex SES's so as to have valid predictive understanding. In the previous sections the observer was an external “builder” of the system, this section discusses the challenge of trying to attain predictive understanding from within a non-centrally controlled complex SESs with only incomplete understanding of the governing

laws. In summary, this section will be limited to discussing how greater aggregate complexity, or coupled systems, effect our ability to hold valid predictive constructs.

My investigation of aggregate complexity focuses on two areas: one, the relative “permeability” of system boundaries and the associated need to expand boundaries of concern, or in other words the need to pursue a more holistic approach. And, two, the need to differentiate between the concept of probabilistic risk and that of uncertainty within complex systems.

2.3.1 “Permeable” System Boundaries

Permeable system boundaries can be described as the degree to which the outside “context” , or “environment”, affects the internal dynamics of the system or sub-systems. The greater degree to which we can say a system has permeable boundaries the more a “holistic” understanding is required to understand it’s dynamical behaviour. Elinor Ostrom has utilized the term “decomposable system” as a systems that has low permeability and thus more amendable to inquiry (Ostrom, 2007, p. 15181). Ostrom speaks of one aspect of decomposable systems as having “relatively separable sub-systems that are independent of each other in the accomplishment of many functions...”and refers to them as having “parallel functionality.” Ostrom is measured in the definition of decomposable systems as she acknowledges that it is a relative term and that the dynamics of one system will “eventually affect each others performance” (Ostrom, 2007, p. 15181). Highly permeable systems are more integrated with the functional dynamics “outside” itself. This integrated nature of two systems can also be called coupled systems or aggregate complexity.

Thus, when seeking predictive understanding within complex systems, permeable system boundaries demand for more integrated, or aggregated, systems to be included within boundaries of analysis or concern. Moving, what might have once been seen as a stable external “environment”, to a more integral dynamic element within an analysis. The process of globalization can be, seen through this frame, to increase the degree of interconnectivity of the global systems of interest to Sustainability Science (Kates, & Parris, 2003, p. 8064)(Janssen, & Ostrom, 2006, p. 238). The flow of materials, energy and ideas through our modern world happens at a historically unprecedented scale and rate (Homer-Dixon, 2000, 119) (Hägerstrand, 2001, p.35)

To take an integrated approach, we, in Sustainability Sciences, aim to be holistic. The pursuit of holism promotes widening the scope of our inquiry. We are, of course, never fully successful, but great attempts are made at integrating knowledge in interacting systems, as exemplified by the Earth System Governance research programme. The less “decomposable” the system, that is, the more permeable its system boundaries, the more I argue that we face uncertainty, and not probabilistic risk, while attempting to build functional predictive constructs.

2.3.2 Differentiating Risk and Uncertainty

In Sustainability Science we attempt to understand the largest and most complex aggregated SESs. In doing so, distinctive additional challenges arise from the highly integrated nature of the systems we are studying. We are limited in our ability to understand the aggregate manifold of complex systems that comprise our world. Unlike the previous two models outlined, we cannot prudently expect to have full understanding of, what exists, or what the governing relationships are in the integrated systems.

Path predictability, over any extended length of time, within aggregated complex systems it is often impossible to attain without the total, and accurate, un-reductive reconstruction of the elements of the entire system in question (Crutchfield, 1986 as cited in Chia, & Holt, 2011, p. 51)(Manson, 2001, p. 411). This is, of course, a challenge bordering on ludicrous to undertake. Even with the advances in computer science and social knowledge systems, it is imprudent to expect that we will be able to sufficiently recreate or model our global reality, in its entirety. Instead we often statistically represent pattern predictability within the discourse of risk, or probability (i.e. a specific action is “likely” to generate and particular valued outcome)

Greater aggregate complexity results in claims of valid predictive constructs becoming increasingly reductive and rely on assumptions of the continuity of nature. The classic statement in economics, that precedes many predictive statements, goes along the lines of “all else equal, we can expect the following”. The challenge that aggregated complexity forces upon those attempting to attain predictive constructs is that it is imprudent to assume that, “all else” will remain equal. The validity of these assumptions are fundamentally threatened by non-linear dynamics within complex systems (Cartwright, 1991, p. 53).

Our limited capacity to perceive the world around us combined with the aggregated nature of our modern world increasingly generates uncertainty, as distinct from risk. Callon et. al (2009) in the essay “Acting in an Uncertain World”, makes a useful distinction between the concept of “risk” or probability and that of “uncertainty”.

“The term ‘risk’ designates a well identified danger associated with a perfectly describable event or series of events. We do not know if this event or series of events will in fact take place, but we know that it may take place. In some cases, statistical instruments applied to series of systematic observations performed in the past make it possible to calculate the event’s probable occurrence, which will then be described as objective probability. In the absence of such observations, the probabilities assigned depend on the points of view, feelings, or convictions of the actors; these are called subjective probabilities. Whether objective or subjective, these probabilities have in common their application to known, identified events that can be precisely described and whose conditions of production can be explained.”

(Callon, et al., 2009, p.19)

The paper goes on to argue:

“It is easy to see why the notion of risk, thus defined, does not enable us to describe situations of uncertainty or to account for the modes of decision making in such contexts. In actual fact, science

often proves to be incapable of establishing the list of possible worlds and of describing each of them exactly. This amounts to saying that we cannot anticipate the consequences of the decisions that are likely to be made; we do not have a sufficiently precise knowledge of the conceivable options, the description of the constitution of the possible worlds comes up against resistant cores of ignorance, and the behavior and interactions of the entities making them up remain enigmatic. The conditions required for it to be relevant to talk of risk are not met. We know that we do not know, but that is almost all that we know: there is no better definition of uncertainty”
(Callon, et al, 2009, p.21)

Uncertainty is, thus conceived, an inability to recognize stable order within our environment. “Uncertainty is what is left when probabilistic reasoning lies exhausted, unable to reveal meaningful patterns” (Chia, & Holt, 2011, p.42). Uncertainty is what lays beyond the useful purview of the discourse of risk and probability. It refers to an eroded validity of statistical tools and representation of order through time, that is, beyond pattern predicability. The expansion of our interest into aggregated complex systems that are highly integrated forces us away from systems that are amendable to the discourse of risk (i.e. probabilistic) analysis and to areas of pervasive and unavoidable uncertainty (Lissack, 1999, p. 119)(Callon, 2009).

The more the functional elements of systems can be said to be integrated, forming aggregate complexity, the more we must increase the dimensionality of our predictive constructs, whether utilizing computer models or our minds, there are limits to our ability to the functional nature of our world. In other words, our environment of concern becomes “more complex than we can suppose”. Aggregated complex systems fosters a world of uncertainty, within which our ability to build valid constructs based on recognized patterns of predictable order is limited to pockets of stability. The validity of our predictive constructs become, at best, provisional, and inextricably linked to the contexts in which they are held. This poses a great challenge to the cognitive agent aiming to gain predictive understanding, as it becomes difficult to associate the retroactive validity of a construct with the future validity. In this way, “structure and knowledge”, or stable system order and valid predictive constructs, can co-emerge over time (Bulletin of the Atomic Scientists, 2011)(Allen & Strathern, 2003, p.14). Yet, as illustrated in the, Long-Term Capital Management example below, predictive constructs can be valid for a certain period of time and then be invalidated by uncertainty generated by unforeseeable non-linear shifts in coupled systems.

Illustrative example (Jorion, 2000):

The, ironically named, “Long-term Capital Management” hedge fund utilized sophisticated algorithms (i.e. constructs) to guide investment choices based in part on previously observed correlated movements in market values. The hedge fund quickly went defunct after an unexpected Russian financial crisis led to novel market fluctuations and ultimately to significant financial losses. The assumption that the model faithfully represented the dynamics of the financial system was largely functionally valid until the Russian financial crisis in 1998. Russia defaulting on their foreign debt caused a non-linear shift in the dynamics of market corollaries that invalidated the models predictive capacity resulting in the fund failing and “nearly blow(ing) up the world’s financial system” (Jorion, 2000, p.277).

2.3.4 Aggregate Complexity and Predictive Capacity

It is imprudent to expect anything close to full knowledge of the aggregated systems we attempt to study and, as such, are faced with the situation of holding reductive and incomplete understandings of systems that refuse to faithfully adhere to reductionist constructs. The aggregated complex nature material, energy and information interactions within the modern world leads to great predictive uncertainty when attempting to build valid predictive understanding within complex SES's. I argue the greater aggregated complexity leads to cognitive agents holding more reductive understandings that are less valid as predictive constructs.

3.0 Summary of Concepts

The areas outlined above suggest some potentially useful axes upon which it is reasonable to say that our predictive capacity is eroded. The Horseshoe Transformation Model illustrated the concept of Sensitive Dependence on Initial Condition (SDIC) and how our predictive capacity can be eroded over time. The Lorenz Strange Attractor Model illustrates the potential for complex systems to exhibit unpredictable non-linear behaviour patterns. Finally, the a discussion of how tightly coupled systems lead to greater aggregate complexity, making conceptual models of the aggregate less likely to hold predictive capacities. Thus, I propose that our predictive capacity is eroded by time, the aggregate complexity of coupled systems, as well as by non-linear shifts in system dynamics. This list is not represented as an exhaustive list of limits to predictive capacity.

The validity of our predictive constructs are eroded by:

- 1) *Temporal Scale*- long-term predictive claims tend to be less valid than short-term predictive claims.
- 2) *Non-linear dynamic shifts*- predictive constructs lose validity as the dynamics of a system change.
- 3) *Aggregate Complexity*- coupled complex systems are more difficult to predict.

Valid predictive constructs can, and do, exist for “decomposable” subsystems, yet are eroded by time, permeable system boundaries and potential for non-linear breaks. These predictive constructs function in pockets of stable systemic order, but can be lost when unexpected non-linear breaks in system dynamics occur. Predictive conceptual models exist, but within uncertain and potentially unstable boundaries.

This is not to claim the complete invalidation of all predictive constructs. Instead, these axes are put forward as a potentially useful way to conceptualize the edges of uncertainty that surround us in our complex world. Historically, we are knowledgeable of our environment beyond the most ambitious hopes of previous generations. We have become very knowledgeable and adept at exploiting the order that exists, nested within stable pockets of system dynamics. However, when we attempt to push our knowledge into higher levels of

aggregate complexity, temporal dimensions, or beyond “compostable” sub-systems, we are likely to find the validity of our predictive claims absorbed by the turbulence of uncertainty.

4.0 Discussion

I have addressed the first of my research questions by illustrating three axes upon which the validity of predictive constructs erode. My subsequent discussion will provisionally accept the concepts outlined above as a useful basis upon which to frame for critiquing the efficacy of our intentional actions toward the values of sustainability. This section is of a strategic nature, in that it aims to investigate the connection between predefined normative aims, or our intentions, and the outcomes of our purposeful actions.

Research questions:

- i) In what ways are we limited in developing valid predictive constructs within complex socio-ecological systems?
- ii) How do limits to predictive understanding influence the degree to which we can be effective in our intentional actions toward sustainability?
- iii) In what ways can we, as individuals and Sustainability Scientists, strategically react to the limited efficacy of our intentional actions within our complex world.

4.1 Valid Predictive Constructs and the Realization of Intentions

Valid predictive constructs are what allows us to thread our intentions into our world through effective action. As cognitive agents we seek constructs that faithfully represent our environment and can functionally “recover order” (Chia, & Holt, 2011, p. 114). I want to reiterate that the predictive understanding I refer to here is that of a pluralistic and functionalist definition. There is no “one truth” to which agents seek greater knowledge, but rather an understanding that works within the context it is being employed in relation to the values that in an individual aims toward. In this way I take a pluralistic view of cognition as an agent’s attempt to functionally align the internal constructed reality with that of a shared external reality.

Mitchell (2009, p. 86) explains that in “both individual choice and social policy contexts, we consider the consequences of our actions along with the values attached to those consequences in order to determine which actions we expect to best promote our values.” To be effective in intentionally shaping our external environment we must hold constructed understandings that can function as valid predictive constructs. The constructs that we hold must sufficiently contrast expected outcomes between various actions to motivate us to act in one way over another. However, it is the functional validity of the constructs employed that dictate the efficacy of our intentional actions.

As conscious individuals we rely on our mental constructs to guide our choices and decide upon our actions. Our understanding of the environment must hold some predictive power to be effective at guiding our intentional actions. We must, to a certain degree, understand the

effect our intentional actions have on that which we value if we are to make effective choices. Valid predictive constructs are needed to effectively extend our intentions into our complex world. Yet, our world is more complex than “we can suppose”, and as our predictive constructs erode in the face of complexity, can we risk assuming that our intentions can still reach, without limitation into our world?

There are two final points I would like to make regarding these claims. One, I speak of predictive validity in non-absolute terms, and two, I recognize the significant challenge faced by cognitive agents within complex systems to differentiate between what could be called an external objective functional validity of a construct and the internally constructed notion of validity or legitimacy.

It is useful to view cognitive agents within complex systems as aiming to align the internal world with the ever-changing external world. There could be said to be two levels at which the “aligning” occurs; between the shared external reality and the functional effects of internal constructs, and, between the validity of our constructs and the legitimacy we assign to them. In this way, the task of building actionable strategic knowledge within complex systems faces the challenge of aligning perceived legitimacy of predictive constructs with the functional validity of predictive constructs. To the conscious agent within the uncertainty generated by complex system dynamics, it becomes extremely difficult to differentiate the experience of holding a valid predictive construct with that of holding an invalid construct.

We, as intentional agents, require a perceived contrast in the associated outcomes of our actions in order to make a reasoned choice. As agents within complex systems, we are ultimately uncertain of the edges of our certainty. It becomes increasingly difficult to differentiate the perception of legitimacy and the actual validity of our constructs in our complex world. I have no suggestions for how to differentiate between the actual functional validness and the perceived validness of predictive constructs experienced by agents, as that would require a more detailed and contextual investigation. However, the concepts outlined might serve as a basis to identify abstract conceptual realms where we can expect our intentional actions to effectively reach.

4.2 Extending Effective Intention

No absolute definable, or observable, boundaries exist between valid and invalid predictive constructs, but we, as active agents, can reasonably expect that on three axes, we lose our capacity to be predictive and consequently our capacity to effectively extend our intention within complex systems. We essentially lose the efficacy of our intentional action to the turbulence of complexity. In this section I will outline an alternative frame through which to view the expected efficacy of our predictive constructs for guiding action.

How far can our intentions effectively reach into our complex world?

Taken together, the arguments that I have made thus far, can form a framework through which to view the relative efficacy of intentional action. If we accept that functionally valid predictive

constructs are required to effectively align our intentions with outcomes, then we can, in general terms, say that our capacity to be predictive is eroded upon the three axes outlined above, namely; time, non-linear dynamical shifts, and aggregated complexity.

The following conceptualization (see figure #8) represents the degree to which we can reasonably expect our predictive constructs to be functionally valid in relation to three variables. Agents can be said to act intentionally toward desired outcomes that are separated from them in time, non-linear dynamics, and can be characterized as existing within different degrees of aggregate complexity. Intentional action is conceptualized, within this diagram, to exist at the centre of three intersecting axes. The ability and likelihood of our predictive constructs being functionally valid erodes as the value, separating action and outcome, of temporal span, potential for non-linear shifts, and degree of aggregate complexity increases. Our intentions can thus be said to only reach so far into this abstract space. Beyond our effective intentionality exist future realities, that our actions can be said to affect, but not in an intentional manner. In other words beyond our effective intention lays an unintentional emergent order.

I have chosen to represent our intentions in this way to offer an alternative to conceptualizing them as existing within a three-dimensional physical world. I suggest that it might be more strategically useful to view our intentions as existing within three abstract dimensions of a complex world. I propose that this abstract space can be utilized to critique, in a general sense, how far our intentional actions can effectively reach into our complex world.

The following conceptualization of effective intention within complex systems does not make reference to any quantified of exacting limits to our effective reach, rather it is intended to illustrate the tendency of our efficacy to erode along the axes identified.

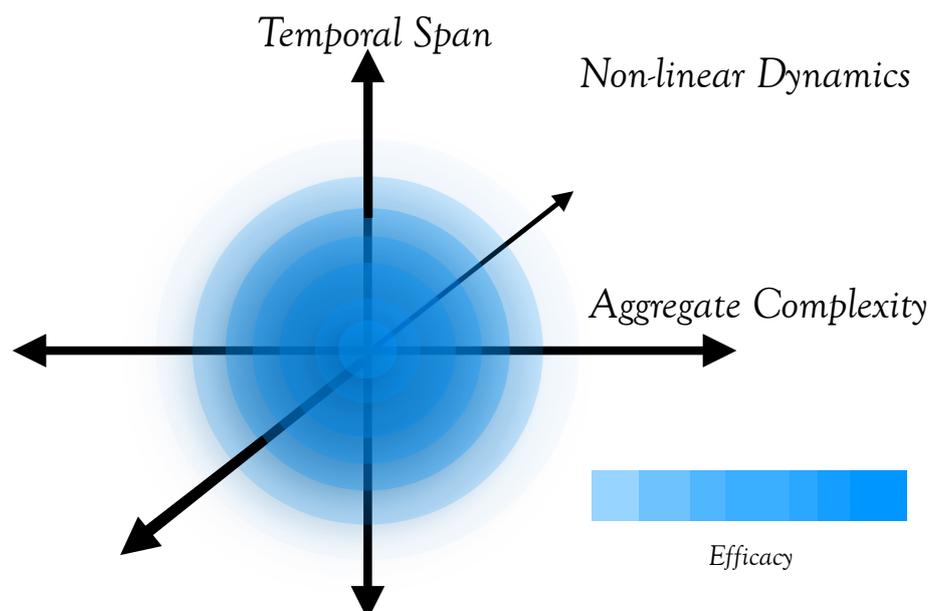


Figure #8 - Three-Dimensional Conceptualization of the Expected Efficacy of Intentional Actions in Relation to Temporal Span, Non-linear Dynamics, and Aggregate Complexity.

The following three sections summarize the arguments made above regarding the efficacy of our intentional actions within the alternative framework outlined:

4.2.1 Effective Intention Across Temporal Spans

The likelihood that our claims to predictive understandings are functionally valid, within the complex environment which they are held, is diminished as temporal scale increases. Causal associations between action and outcome, whether path or pattern oriented, are made increasingly difficult over longer time periods, eroding the functional validity of our predictive constructs.

4.2.2 Effective Intention Beyond Non-linear Dynamical Shifts

Effective acting toward ends that exist beyond unforeseeable non-linear shifts, or reorganizations of system dynamics are hard to accomplish. Predictive constructs lay on beds of previously observed order or the inductive patterns generated by appealing to previous associations. In all predictions there is an assumption of a continuity of those previously observed causal associations. The functional validity of predictive constructs are threatened by non-linear changes in system dynamics. Previously stable patterns of order are replaced with novel unpredictable forms. Non-linear dynamics make it extremely difficult for our studies to move beyond explanation and observation into prescriptive and predictive realms (Thietart & Forgues, 1995, p. 28).

4.2.3 Effective Intention within Aggregated Complexity

Integrated relationships between systems demand that boundaries of analysis be expanded. This expanded of scope of inquiry results in increasingly reductive constructs that are less likely to be functionally predictive. More tightly coupled complex systems generate uncertainty and therefore reduce our ability to develop valid predictive understandings.

4.3 Sustainability Science: Intentional and Active

Sustainability Science is an explicitly intentional field of study (Jager, 2009, p. 3)(Clark, 2009, p.3)(Jerneck, et al., 2010, p. 4). Its research problematic is defined externally by sustainability phenomena, including; climate change, global energy transitions, social justice, global health and global governance (Clark, 2009, p.11). These challenges are of undeniably critical importance to the welfare of humanity and the continued relationship between our species and our biological and physical environment.

“Sustainability” is an unavoidably value constrained concept. We all construct differing visions of what the principle of sustainability entails. Many of us justify our actions as a means to a sustainable future, even if only vaguely defined. The normative diversity with regard to the

specific aims or configurations of sustainability are pluralistic and no general consensus is agreed upon in academia or society. Sustainability Science is not restrictive, in that it does not demand the rigid adoption of one ideal of sustainability. Instead the diversity of ideals could be said to be a constituent part of building a pluralistic and interdisciplinary field of study. However, if an attempt to generalize the concept of sustainability were made, it could contain the following characteristics. Principles of sustainability apply a sense of justice and equity between the elements of the human and natural world. This sense of justice is applied to present systemic order and potential future ideals. The term could be said to often refer to a holistic and inclusive ideal existing at the emergent global scale.

“Sustainability”, as generally defined above, centers around long temporal horizons, faces the inevitable changes in current systemic order, and is inherently, holistic in scope. The fact that Sustainability Science is defined by observed and interconnected emergent global challenges that are difficult to gain predictive understanding, poses unique strategic difficulties. Challenges arise when the nature of our intentions exist within realms where the validity of predictive constructs are potentially low or absent.

4.4 Strategic Implications

If we want to guide “interactions along more sustainable trajectories” (Kates, 2001, p.641) we must critically question the efficacy of our intentional actions. Mitchell (2009, p.90) asks an undeniably practical question regarding strategy within complex systems; if our predictive constructs are potentially invalid and if “waiting to make decisions is not desirable, then how do we act in contexts of deep uncertainty? While I make no claim to hold the only possible answer to this question, I do have a suggested response to the “deep uncertainty” that we face while attempting to guide our complex world toward a more sustainable future.

We can choose to strategically reframe our intentions so they are more amendable to our ability to build functional predictive understandings that are useful for guiding choices. The aim in doing this is to discuss the construction of a reasoned strategy based, not on the pursuit of ever-greater “knowledge” of complex SESs, but rather shaped from the acceptance of the pervasive and unavoidable uncertainty that exists within complex systems.

4.5 Reprioritization of Sustainability Aims

We need to have the courage to de-prioritize some of the sustainability aims that we hold, and yet are unable to affect meaningfully. I do not suggest de-prioritizing these aims on the basis that they are not important, or that they are not of concern to ideals of sustainability, but rather that we may fundamentally lack the ability to address them, given limits to predictive understanding. I argue that we do a disservice to our global society and planet when we confound our concern regarding an observed sustainability challenge with our ability to effectively act toward addressing that challenge. Let those of us, concerned with a more sustainable future, choose to act strategically toward that which is within our effective reach.

The positive expansion of knowledge and the building of more holistic understanding is undeniably important, yet will invariably be unable to completely remove the pervasive uncertainty that surround our claims to predictive insights. We can reframe our strategic intentions in light of this and in doing so, modify the nature of our intentions rather than solely seeking a more complete understanding of our complex world. Placing our intentions within spheres that are more likely to yield to our predictive constructs is an alternative and practical reaction to the limits outlined.

If we accept that our uncertain future erodes our ability to be effective in our intentional actions, we can react in two ways. We can continue our attempts to gain an ever-more holistic and contextually detailed understanding of the complex world we live in to reduce uncertainty, which I argue is the more conventional approach. Or we can pragmatically reframe our strategic intentions so as to increase the likelihood of our predictive constructs being valid. In essence, we can make a strategic retreat in the ambition of our intentions in hope of being more effective at aligning our actions with desired outcomes.

I advocate that we pursue the second course, re-prioritizing our sustainability intentions, as the uncertainty faced is pervasive and ultimately, unavoidable. It is my belief that a positive expansion of knowledge is underway, and will continue far into the future, yet the limits to our predictive and thus prescriptive knowledge will never be complete. There is no “end of history” with regard to understanding complex systems. Indeed, Traub (1996, p.5) argues that some questions should be regarded as “unknowable”. We are bound to remain agents that exist within pockets of effective intention while being surrounded by uncertainty. In this light, I argue that we can utilize the three axes identified as guides for a practical re-prioritization of our sustainability aims. It is imprudent to expect our more ambitious aims to be useful at guiding our actions as the complexity that separates our actions and our intentions can render our efforts fruitless and ineffectual.

The following three sections offer suggestions of strategic priorities in an attempt to increase the efficacy of our intentional actions. Hafsi & Thomas (2005, p.517) state that it “takes deliberately deviant behaviour to innovate”; in this light, I hope these suggestions are found to be provocative while remaining true to the limits to the effective reach of our intention as conceptualized above in figure #8.

4.5.1 Time: Present Justice and Global Equity

Long-term predictive constructs tend to be less valid than short-term. If we are interested in increasing our ability to reach out and affect our world in a positive way based on our values, then we should focus on shorter time horizons. The generalized definition of sustainability offered above spoke of the notion that, at its core, sustainability is concerned with the concept of equity and justice between society and nature. In this light I argue that we should deprioritize actions based on achieving intergenerational equity or justice and instead focus our efforts addressing more immediate expressions of injustice and inequity. As an example, it might be more effective for us to focus on specific and immediate instances of illegal logging than it would be to attempt to build governance structures that will manage global forestry activities for the next 50 years. In essence, my recommendation is that we prioritize acting

toward fostering justice and equity in the short term over attempting to shape future states of global justice.

4.5.2 Non-linear Dynamics: Adaptive Capacity and Reflexive Learning Structures

Non-linear dynamics erode the capacity of our mental constructs to be predictive. Nonlinear shifts in dynamics within complex systems are unpredictable and can result in radically new forms of order. This suggests that the future will be characterized by unforeseeable changes that may fundamentally alter the dynamics of nature-society relationships. I recommend that we deprioritize our attempts to shape or guide emergent macro-scale phenomena and instead focus our attention on the development of localized adaptive capacity and reflexive learning structures. The capacity of society to react to changes is an important strategy to address non-linear dynamics (Holling, 2001, p.390)(Janssen & Ostrom, 2006, p237)(Folk, 2006, p.260) . Reflexive learning structures are a specific example of adaptive capacity, as they can increase the ability of society to reflect and learn from change. Both individually and collectively we must develop “flexible cognition for an increasingly complex and ill-structure world” (Spiro, 1996, p. 60).

An example of this strategic suggestion would be the deprioritization of efforts to mitigate global greenhouse gas emissions and instead focus on developing alternative farming methods tailored for warmer and more variable climates. To clarify, this recommendation is made on the basis of increasing the efficacy of our actions not based on a belief that climate change is unimportant.

4.5.3 Aggregate Complexity: De-aggregation of Coupled Systems

Aggregated complex systems that are tightly coupled, or “non-decomposable” systems have been shown to generate uncertainty that occludes our ability to be predictive. The uncertainty generated is argued to be pervasive and our predictive capacity only marginally responsive to the positive expansion of more holistic understanding. Mitchell, S.D. (2009, p.89) argues that “depending on the structure of the system and the nature of the complexity, knowing more about the system may in fact not reduce the uncertainty”. I suggest that we deprioritize our efforts toward more holistic mental constructs and modeling and instead focus on the “de-aggregation” of coupled systems.

De-aggregation of systems would make systems more “decomposable” and more amendable to the development of valid predictive constructs. As noted earlier, Ostrom (2007, p.15182) speaks of the concept of “parallel functionality” referring to subsystems that have many functions that are relatively independent or separable from other systems. An example of parallel functionality could be the operation of an off-grid solar power system and the relatively independent functioning of a continental electric grid. “Parallel functionality” might be thought of as a buffer or delay between the functioning of one system and that of another. An example of de-aggregation of a system of interest to Sustainability Science could be the decoupling of the global financial system and the food system by developing localized food production and distribution. In this case the core functions of the food system might be less susceptible to fluctuations in global food commodity markets. Rather than focusing on holistically

understanding the ways that the global food, water, climate, health and economic systems interact and evolve, we should focus on acting toward developing buffers that create parallel functionality. I argue that de-aggregating the core functional elements of SESs will result in greater resilience and in more successful efforts to build valid predictive constructs.

5.0 Conclusion

I have outline three dimensions along which we can reasonably expect the validity of our predictive constructs to erode:

- 1) *Temporal Scale*- The Horseshoe Transformation Model illustrated how sensitive dependence on initial conditions (SDIC) erodes our ability be make valid predictions over long time horizons. long-term predictive claims tend to be less valid than short-term predictive claims.
- 2) *Non-linear dynamic shifts*- The Lorenz Strange Attractor Model was shown as an example of non-linear dynamics and the associated predictive limits were explored. Predictive constructs lose validity as the dynamics of a system change in novel ways.
- 3) *Aggregate Complexity*- The concept of aggregate complexity was discussed in relation to our limited ability to develop valid predictive constructs within contexts of pervasive uncertainty. Coupled complex systems generate uncertainty and are therefore more difficult to predict.

Valid predictive constructs are required to effectively guide our actions toward our intentions. Without the ability to have a meaningful understanding of the outcomes of our actions, we become ineffectual at reaching our intended aims.

I synthesized the concepts investigated with the idea that predictive capacity effectively threads our intentions into our complex world. In doing so, I have conceptualized the limits to the effective reach of our intentional action as existing within a three-dimensional abstract space characterized by temporal span, non-linear dynamics, and aggregate complexity.

In the interest of increasing the efficacy of our intentional actions toward sustainability, I have suggested a reprioritization of our aims.

- 1) Prioritize actions toward fostering justice and equity in the short-term over attempting to shape future states of global justice.
- 2) Deprioritize our attempts to shape or guide emergent macro-scale phenomena and instead focus our attention of the development of localized adaptive capacity and reflexive learning structures. Our challenge is developing the ability to react to a complex world that changes in unexpected ways.
- 3) Deprioritize our efforts toward developing more holistic predictive constructs and instead focus on the “de-aggregation” of coupled systems. Rather than focusing on attempting to predict the ways that the global food, water, climate, health, economic and natural systems interact and evolve, we should focus on developing buffers that create “parallel functionality.”

I began this paper stating that the world is not only more complex than we suppose, but more complex that we can suppose. The validity of our predictive constructs are bound to pockets of stability within our inconceivably complex world, and as such is both contextual and potentially ephemeral. We wake each day as cognitive intentional agents and attempt to navigate the uncertainty in order to pursue that which we value. I have attempted to define some limits to our ability to extend our intentions into a complex world by critiquing our capacity to develop valid predictive constructs.

We cannot effectively change that which we cannot develop valid predictive constructs around. Our efforts will achieve more real progress towards a more sustainable world by focusing on aims where we can expect to predict the outcome of our actions.

Let us seek the serenity to accept the things we cannot change,
The courage to change the things we can,
And the wisdom to know the difference.
(Adapted from: Reinhold Niebuhr)

References

Books:

Benton, T. & Craib, I., 2011. *Philosophy of Social Sciences: The Foundations of Social Thought*. London: Palgrave Macmillan.

Callon, M. et. al., 2009. *Acting in an Uncertain World*. London: The MIT Press.

Capra, F., 1996. *The Web of Life*. New York: Anchor Books.

Chia, R. & Holt, R., 2009. *Strategy Without Design: The Silent Efficacy of Indirect Action*. Cambridge: Cambridge University Press.

Kellert, S. H., 1993. *In the Wake of Chaos*. Chicago: University of Chicago Press.

Hagerstrand, T., 2001, A Look at the Political Geography of Environmental Management. In: *Sustainable landscapes and lifeways: scale and appropriateness*. Cork University Press. Ch 2.

Homer-Dixon, T., 2000. *The Ingenuity Gap*. Toronto: Random House of Canada.

Mitchell, S., 2009. *Unsimple Truths: Science, Complexity, and Policy*. Chicago: University of Chicago Press.

Online Material:

Bulletin of the Atomic Scientists. 2011. *Beyond our imagination: Fukushima and the problem of assessing risk* [Online]. Available at: <<http://thebulletin.org/web-edition/features/beyond-our-imagination-fukushima-and-the-problem-of-assessing-risk>> [Accessed April 2011]

Earth System Governance. 2011. *Earth System Governance: Conceptual Framework*. [Website] Available at: <http://www.earthsystemgovernance.org/about/concept>

Page, S. E., 2010. Understanding Complexity: lectures by Scott E. Page, Phd. [Video Lecture Series] Available at: <<http://www.thegreatcourses.com/>>

Stanford Encyclopedia of Philosophy, 2008. Chaos. Available at: <<http://plato.stanford.edu/entries/chaos/>>

Journal Articles:

Allen, P. & Strathern, M., 2003. Evolution, Emergence, and Learning in Complex Systems. *Emergence*, 5(4), pp. 8-33

- Barager, M., (Undated). Chaos, Complexity, and Entropy. *New England Complex Systems Institute, Cambridge, MA*, pp. 1-17
- Cartwright, T. J., 1991. Planning and Chaos Theory. *Journal of American Planning Association*. 57, pp. 44-56
- Cash, D. Et al., 2009. Knowledge Systems for Sustainable Development. *Proceedings of the National Academy of Sciences*, 100(14), pp. 8086-8091
- Clark, W.C. & Dickson, N.M., 2003. Sustainability Science: The Emerging Research Program. *Proceedings of the National Academy of Sciences*, 100(14), 8059-8061
- Clark, W.C, 2009. Sustainable Development and Sustainability Science. *Proposal for NSF*, pp. 1-21
- Dooley, K. & Van de Ven, A., 1999. Explaining Complex Organizational Dynamics. *Organizational Science*, 10(3), pp. 358-372
- Editorial, No man is an Island, *Nature Physics*, 2009 5:1
- Feigenbaum, M.J., 1980, Universal Behaviour in Non-linear Systems. *Los Alamos Science*, 7, pp. 16-39
- Folke, C. 2006. Resilience: the emergence of a perspective for socio-ecological systems analyses. *Global Environmental Change*, 16, pp. 253-267
- Foote, R. et al., 2007. Mathematics and Complex Systems. *Science* 318, pp. 410-412
- Goldstein, J., 1999. Emergence as a Construct: History and Issues. *Emergence*, 1(1), pp. 49-72
- Hafsi, T. & Thomas, H., 2005. The Field of Strategy: In Search of a Walking Stick. *European Management Journal*, 23(5), pp. 507-519
- Helbing, D. 2009, Managing Complexity in Socio-Economic Systems. *European Review*, 17(2), pp.423-438
- Heylighen, F. & Joslyn, C., 2001. Cybernetics and Second Order Cybernetics. *Free University of Brussels, Belgium*
- Heylighen, F., (undated) The Science of Self-Organization and Adaptivity. *Free University of Brussels, Belgium*. pp. 1-26
- Holling, C. S., 1973, Resilience and Stability of Ecological Systems. *Annual Review of Ecological Systems*, 4 , pp. 1-23

- Holling, C.S., 2001. Understanding the Complexity of Economic, Ecological, and Social Systems. *Ecosystems*, 4, pp. 390-405
- Homer-Dixon, T., 2009, The Newest Science. *Alternatives Journal*, 35(4), pp. 10-11, 38-39
- Jager, J., 2009. Sustainability Sciences in Europe. *Background paper prepared for DG Research*. pp. 1-16
- Janssen, M. & Ostrom, E., 2006. Resilience, vulnerability, and adaptation: A cross-cutting theme of the International Human Dimensions Programme on Global Environmental Change [editorial]. *Global Environmental Change*. 16, pp. 237-239
- Jerneck, A. et al. 2010. Structuring Sustainability Science. *Sustainability Science*. 1-14
- Jorion, P., 2000. Risk Management lessons from Long-Term Capital Management. *European Financial Management*, 6(3), pp. 277-300
- Kates, R.W. et. al., 2001. Sustainability Science. *American Association for the Advancement of Science*, 292, pp. 641-642
- Kates, R. W. & Parris, T., 2003. Long-term Trends and Sustainability Transition. *Proceedings of the National Academy of Sciences*, 100(14), pp. 8062-8067
- Levin, S., 2002. Complex Adaptive Systems: Exploring the Known, the Unknown and the Unknowable. *Bulletin of the American Mathematical Society*, 40(1), pp. 3-19
- Levy, D. 1994. Chaos Theory and Strategy: theory, Application, and Managerial Implications. *Strategic Management Journal*, 15, pp. 167-178
- Lissack, M. R., 1999. Complexity: the Science, It's Vocabulary, and it's relations to organizations. *Emergence*, 1(1), pp. 110-126
- Liu, J. et. al., 2007. Complexity of Coupled Human and Natural Systems. *Science*, 317, pp. 1513-1516
- Lorenz, E. N., 1963. Deterministic Nonperiodic Flow. *Journal of the Atmospheric Sciences*, 20, pp. 130-141
- Manson, S. M., 2001. Simplifying Complexity: A Review of Complexity Theory. *Geoforum*, 32, pp. 405-414
- Mintzberg, H. & Waters, J., 1985 Of Strategies, Deliberate and Emergent. *Strategic Management Journal*, 6(3), pp. 257-272
- Ostrom, E. et. al. 2007. Going Beyond Panaceas. *Proceedings of the National Academy of Sciences*, 104(39), pp. 16176-15178

- Ostrom, E., 2007. A Diagnostic Approach for Going Beyond Panaceas. *Proceedings of the National Academy of Sciences*, 104(39), pp. 15181-15187
- Parker W.S., 2010. Predicting Weather and Climate: Uncertainty, ensembles and Probability. *Studies in History and Philosophy of modern Physics*, 41, pp.263-272
- Perrings, C., 2007. Future Challenges. *Proceedings of the National Academy of Sciences*, 104(39), pp 15179-15180
- Smale, S., 1965. An Infinite Dimensional Version of Sard's Theorem. *American Journal of Mathematics*, 87(4), pp. 861-866
- Spiro, R. et. al., 1996. Two Epistemic World-views: Prefigurative Schemas and Learning in Complex Domains. *Applied Cognitive Psychology*, 10, pp. 51-61
- Stacey, R. D., 1995. The Science of Complexity: An alternative Perspective for Strategic Change Processes. *Strategic Management Journal*. 16, pp. 477-495
- Thietart, R.A. & Forgues, B., 1995. Chaos Theory and Organization. *Organizational Science*, 6 (1), pp. 19-31
- Traub, J.F., 1996. The Unknown and the Unknowable. *Santa Fe Institute, Santa Fe NM*.
- Walker, B. et al., 2004. Resilience, Adaptability and Transformability in Socio-ecological Systems. *Ecology and Society*, 9(2)

Appendix A

Historical Roots of Complexity Science over the past 60yrs.

(Castellani, Brian, Kent State University)

(Retrieved from: <http://www.personal.kent.edu/~bcastel3/>)

