TOWARD PHILOSOPHIES AND METHODS FOR PLANNING, DESIGN AND
MANAGEMENT OF ENVIRONMENTAL SYSTEMS

by

HAROLD JEFFREY TURK

(Under the Direction of DAVID K. GATTIE)

ABSTRACT

This work builds a qualitative and quantitative case that additional planning, design and
management philosophies other than those based on reduction are necessary to begin to holistically and
benignly integrate current human constructions into nature. Further it makes a substantive case that
ecological systems fall into a unique category of system types, *interdependent complex systems*, which
differ significantly from the system types that typically describe mechanistic systems. Thus, contextually
contrasting ecological systems and mechanistic systems using the Socratic Method by dialectically
comparing mechanism versus ecology through reductive versus system thinking dichotomies and direct
versus indirect causalities each indicating how mechanical and living systems are opposite ends of a
spectrum. It identifies that the current Newtonian stratagem of analysis and hence design are inadequate
for the planning and construction of natural living systems. Further, this work significantly looked at the
proliferation of system connectivity and interdependence as the system operates over time by examining
a Neuse River Estuary, NC model and various other models of ecological systems. These models
evidence increasing connectivity or coupling of ecological system components providing the quantitative
weight that further substantiates that planning and design of ecological systems requires different
methods other than those often employed in engineering design. It suggests that the methods needed are
the diametric opposite of those used in traditional engineering. Thus, building on the qualitative and quantitative evidence presented in this work which indicated that ecological systems had qualities and behaviors that are the opposite of traditionally engineered systems, this work extrapolates that argument to planning and design and proposes a design philosophy, axioms, and corollaries for environmental systems. Lastly, this work investigated eigenvalues as the key mathematical quantities that map to system emergent properties. The investigation and the resulting data indicated, however, that matrices of similar size, components, inputs, stocks, and outputs with identical eigenvalues returned a variety of network properties. Nonetheless, eigenvalues and inverse matrix methods still perhaps provide an initial step toward the planning and design of environmental systems.

INDEX WORDS: Design, Interdependent complex system, Environmental systems, Eigenvalues, Network properties, Dialectic, Connectivity.
TOWARD PHILOSOPHIES AND METHODS FOR PLANNING, DESIGN AND MANAGEMENT OF ENVIRONMENTAL SYSTEMS

by

HAROLD JEFFREY TURK

BS, Florida Atlantic University, 1987
ME, Florida Atlantic University, 1996

A Dissertation Submitted to the Graduate Faculty of The University of Georgia in Partial Fulfillment of the Requirements for the Degree

DOCTOR OF PHILOSOPHY

ATHENS, GEORGIA

2012
TOWARD PHILOSOPHIES AND METHODS FOR PLANNING, DESIGN AND
MANAGEMENT OF ENVIRONMENTAL SYSTEMS

by

HAROLD JEFFREY TURK

Major Professor:  David K. Gattie
Committee:  Bernard C. Patten
            E. William Tollner
            Caner Kazanci
            John Schramski

Electronic Version Approved:

Maureen Grasso
Dean of the Graduate School
The University of Georgia
December 2012
DEDICATION

I would like to dedicate this document to the memory of my parents,
Harold Bryson Turk (1918 – 2002) and Mary Claudine Clark Turk (1921 – 2011)
ACKNOWLEDGEMENTS

I would like to thank my committee members including my major professor Dr. David Gattie and committee members Dr. Bernard Patten, Dr. Ernest Tollner, Dr. Caner Kazanci, and Dr. Nadia Kellam. Also, special thanks to Zachary Miller for computer programming assistance and Anita Turlington for assistance in formatting and editing this document.
# TABLE OF CONTENTS

<table>
<thead>
<tr>
<th>CHAPTER</th>
<th>PAGE</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACKNOWLEDGEMENTS</td>
<td>v</td>
</tr>
<tr>
<td>LIST OF TABLES</td>
<td>viii</td>
</tr>
<tr>
<td>LIST OF FIGURES</td>
<td>x</td>
</tr>
<tr>
<td>1 INTRODUCTION TO SYSTEMS AND DISSERTATION</td>
<td></td>
</tr>
<tr>
<td>OVERVIEW</td>
<td>1</td>
</tr>
<tr>
<td>2 DESCRIPTION, CAUSALITY AND COMPARISONS OF SYSTEMS</td>
<td>25</td>
</tr>
<tr>
<td>3 SYSTEMS SCIENCE: THE SIGNIFICANCE OF ECOLOGICAL THEORIES AND NETWORK ANALYSES</td>
<td>58</td>
</tr>
<tr>
<td>4 INDIRECTNESS AND ECOLOGICAL SYSTEM PROPERTIES</td>
<td>106</td>
</tr>
<tr>
<td>5 DESIGN AND ECOLOGICAL SYSTEMS</td>
<td>155</td>
</tr>
<tr>
<td>6 IN SEARCH OF A METHOD</td>
<td>203</td>
</tr>
<tr>
<td>7 DISSERTATION SUMMARY</td>
<td>225</td>
</tr>
<tr>
<td>REFERENCES</td>
<td>229</td>
</tr>
<tr>
<td>APPENDICES</td>
<td></td>
</tr>
<tr>
<td>A COMPUTER CODE</td>
<td>245</td>
</tr>
<tr>
<td>B EXAMPLE COMPUTER RUNS, SUMMER 1988</td>
<td>254</td>
</tr>
<tr>
<td>C STATISTICAL DATA</td>
<td>262</td>
</tr>
<tr>
<td>D MODEL #23 AND RUN #634</td>
<td>271</td>
</tr>
</tbody>
</table>
E  GENERIC CONCEPTUAL DESIGN DATA .................................................................275
F  TEN SAMPLE RUNS, SPRING 1988 .................................................................281
LIST OF TABLES

Table 1.1: System type versus possible component action and system characteristic.....................24
Table 2.1: The mapping of causality to system type .........................................................................50
Table 4.1: Modeled intercompartmental flows, \( f'_{hi} \) boundary inputs, \( z_i \), boundary outputs, \( y_i \),
and standing stocks, \( x_i \), for nitrogen flow for the summer 1998, Neuse River Estuary,
North Carolina, USA ..................................................................................................................117
Table 4.2: Parallel equations of throughflow for macroscale measures
and microscale derivations .............................................................................................................143
Table 4.3: Input environs for summer 1988 Neuse River Estuary
network model ..............................................................................................................................144
Table 4.4: A comparison of the flow (F) and integral (N) matrix of the Neuse
River Estuary input driven analysis model summer 1989 .........................................................148
Table 4.5: A comparison of the flow (F) and integral (N) matrix of the Neuse
River Estuary input driven analysis model winter 1988..........................................................149
Table 4.6: A comparison of the flow (F) and integral (N) matrix of the
Intertidal Oyster Reef ecosystem model .....................................................................................150
Table 4.7: A comparison of the flow (F) and integral (N) matrix of the
Georgia salt marsh model ............................................................................................................151
Table 4.8: A comparison of the flow (F) and integral (N) matrix of the oxygen cycling in an
algae-Daphnia microcosm ..........................................................................................................152
Table 4.9: A comparison of the flow (F) and integral (N) matrix of the aquatic terrestrial transport of nitrogen by Lontra canadensis

Table 5.1: Some positive effects of reductionism in mechanistic design

Table 5.2: Comparing complex living systems and traditionally engineered systems

Table 6.1: Statistically comparing network properties of 5040 artificially derived network models to the actual summer 1988 network model of the Neuse River Estuary
## LIST OF FIGURES

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figure 4.1</td>
<td>Digraph of Neuse River Estuary model for both input-environ and output-environ analysis</td>
<td>112</td>
</tr>
<tr>
<td>Figure 4.2</td>
<td>Left to right: Flow from input-receiving compartment $j$ to arbitrary compartment $i$ for output-environ analysis. Right to left: Back trace of output generating compartment $h$ to arbitrary compartment $i$ for input-environ analysis</td>
<td>115</td>
</tr>
<tr>
<td>Figure 4.3</td>
<td>Amended general network unit for Network Environ Analysis</td>
<td>129</td>
</tr>
<tr>
<td>Figure 4.4</td>
<td>Comparison of total input-environ throughflow, output-environ throughflows, and average environ throughflow</td>
<td>134</td>
</tr>
<tr>
<td>Figure 5.1</td>
<td>Suh’s (1990) three types of applicable design matrices and matching types of systems</td>
<td>164</td>
</tr>
<tr>
<td>Figure 5.2</td>
<td>Three types of applicable design matrices and matching types of systems</td>
<td>188</td>
</tr>
<tr>
<td>Figure 6.1</td>
<td>Connectivity of an artificial model/conceptual design with network properties within 10% for the Neuse River Estuary spring 1988</td>
<td>222</td>
</tr>
</tbody>
</table>
CHAPTER 1
INTRODUCTION TO SYSTEMS AND DISSERTATION OVERVIEW

Purpose of Study

The overarching purpose of this dissertation is to describe and to build a case that additional planning, design and management philosophies other than those based on reduction are necessary to begin to holistically and more benignly integrate current human constructions into nature, and manage, and perhaps design, the essence and interdependent aspects of ecological systems. An additional purpose is to investigate a preliminary philosophy and strategy in a newly oriented design path that addresses the holistically connected interdependent aspects of living systems. This work’s primary hypotheses is that different philosophies, schema and axioms from those used in traditional engineering of mechanistic systems is necessary for environmental systems, secondarily this work hypothesizes that those new philosophies etc. will be the diametric opposite of those used in traditional mechanistic design and lastly this work hypothesizes that eigenvalues are the key mathematical parameter necessary in the predictable and repeatable design of network properties for environmental systems.

How This Study is Original

The goals of the work are fivefold: First, further from first principles the qualitative understanding for the need of new philosophies, strategies, methods, and ways of thinking in the design and management of complex interdependent natural systems and to build a case that a new philosophy and methods are required for management, integration into, and design of
ecological systems. Secondly, the work will illustrate that need quantitatively. The third goal is to facilitate greater understanding of systems, particularly ecological systems. The next and fourth goal is to search for and propose design philosophies, paradigms, schema, and strategies that assist in integrating human constructions more benignly into the natural world, aid in the holistic management of ecological systems, and begin to incorporate the connected and interdependent aspects of natural systems into design methods. Lastly, to determine if eigenvalues are the exact mathematical key to reproducing network properties in the planning and management of natural systems.

**Expected Results and Dissertation Overview**

It is expected that new philosophies, axioms, and methods for the planning and design of environmental systems will emerge from this work. To that end, **Chapter 1** begins with introductory observations, then immediately delves into tough and debatable subjects such as what constitutes a system and how to describe them. Further, some additional qualifiers of systems are proposed and the chapter addresses the description of the often fleeting and nebulous subject of complexity, seeking to ameliorate to some degree part of its intangibility by proposing a delimiter on when complexity exists.

**Chapter 2** is devoted to contextually describing ecological systems by a form of the Socratic Method or dialectical comparisons, including reductive versus system thinking, direct versus indirect causality, and mechanical versus living systems. The purpose of this chapter is to advance the case that the current Newtonian stratagem of analysis and hence designs are inadequate for the management and design of natural living systems.

**Chapter 3** is a discussion of mathematics and description of some of the current analysis techniques available today that are not reduction based, that is, those that retain system
connectedness during the analysis. This chapter often describes their qualitative precision over their quantitative accuracy and why this is significant. **Chapter 4** in part is a comparative analysis of the Neuse River Estuary using the environmental analysis technique, Network Environ Analysis (NEA), to illustrate and describe various aspects of the ecological system that do not fit or lend themselves to analysis or design based on the Newtonian paradigm of reduction. This chapter provides quantitative weight based on the analysis of the Neuse River Estuary and other ecological models to ascertain that planning and design of ecological systems requires an opposite strategy than that often used in the design of mechanistic systems.

**Chapter 5** surveys of some current engineering design methods and discusses their relevance or lack of same when managing or designing ecological systems. This chapter proposes that they are in fact inadequate but serve an important purpose as dichotomous dialectic illustrations of what is necessary for appropriate holistic management and design of ecological systems. This chapter goes further, proposing a new strategy for the design of environmental systems including an initial statement and philosophy for the planning and design of these systems. This line of thought continues with proposed design axioms and corollaries. **Chapter 6** examines the applicability of eigenvalues as the mathematical key to system wide properties and as a precise means to achieve the goals of the proposed design axioms of **Chapter 6**. Lastly, **Chapter 7** provides a short dissertation summary.

**Systems Introduction**

Creating a design to meet a societal need is generally the aim and function of the engineering process where analyses based on engineering science are requisite to meet objectives, provide control and reliability, and ensure the public’s safety (Gattie, Tollner & Foutz, 2005, p.1645). According to Mitsch (1996, 1998), “the design of sustainable ecosystems
that integrate human society with its natural environment for the benefit of both” defines the new field of *ecological engineering* (Mitsch and Jørgensen, 2003, p. 23). Mitsch and Jørgensen proposed that ecological engineering combines the sciences, theoretical and applied, for the restoration, design and construction of ecosystems. Further, they have submitted that the goals of ecological engineering are the restoration of natural systems disturbed by human activity and the construction of new ecosystems that have mutual benefit to nature and human society. In both situations, emphasis is placed on nature’s self-organizing characteristics as a primary method to achieve those goals. Additionally, they proposed that ecological engineering distinguishes itself from other fields such as environmental engineering in that, ecological engineering bases itself on the self-designing capacities of natural systems, relies on system sciences, seeks to conserve non-renewable resources, promotes conservation, and may serve to solidify or debunk current ecological theories. Mitsch and Jørgensen (2003) have further suggested that ecological engineering differs from the focus on unit processes within the field of environmental engineering but occupies itself with meeting human needs through restoring, creating or redesigning these systems based on the principles of nature. Sustainability for the planet needs ecological engineering to address current environmental problems including losses of natural capital and biodiversity. The earth as a closed system implies that matter resources are limited, and the earth as a system closed to matter exchanges makes remediation of pollutants often only their redistribution. Thus, significant indirect effects of pollution may be affecting the planet’s biochemical cycles (pp. 15, 35). Mitsch and Jørgensen (2003) further stated that ecological engineering is being carried out by various practitioners today both formally and informally within various fields, but they have suggested that theory has lagged and often not connected adequately with practice and frequently without sufficient peer review (p. 19). Not only is their
judgment correct, but there exists the further possibility of negative unintended consequences without a firm theoretical basis and greater peer review within ecological engineering. However, perhaps a far greater threat to the environment is design that does not consider or actually believes it is generally isolated from nature’s processes. The word “design” is used loosely here in that engineering design bases itself on the sciences and is applied through the profession of engineering but often design is only indirectly based on science or not at all. Design or engineering of nature occurs on a dramatic scale every day, ranging from the accumulated effects of artificially sustaining lawns, to the construction of shopping malls and subdivisions, slash and burn practices used in clearing rainforests for agricultural enterprises to the constructions of mega engineering projects such as the Three Gorges Dam Project in China. The latter has resulted in a new, voluminous reservoir that is approximately 0.7 miles in average width and 410 miles long. As such, it is causing a total redesign of the regional ecosystems in the Yangtze River valley of China (Allin, 2004). In our quest for energy, food and shelter, humankind has used its mastery of the sciences to create machinery that tends dramatically to control and in a way enslave nature to satisfy human desires on grand scales. However, humanity has failed fully to consider that in the process, we are redesigning nature, and the human population as a whole is largely ignoring the long-term implications of our actions. For these reasons, the articulation of design principles that allow our constructed systems to more benignly integrate into the natural world is a pressing need within science and engineering.

It is the position of this work, however, that the current state of engineering is insufficient to adequately analyze, manage, integrate into, and design living systems because the predominant methodologies used to investigate ecological systems are based on the reduction of systems of wholes into pieces. In part, this may be a reflection of society’s worldview; thus, the
question is just as sociologically significant and challenging for our collective wisdom as a
society as it is for the sciences. The predominant worldview today is very anthropocentric, and
consciously or perhaps unconsciously, its aim and goal is to master and exploit nature. The
primary scientific philosophy and methodology employed to accomplish those goals bases itself
on the reduction of wholes to small isolated sets, which may be controlled, studied and
ultimately exploited. It is a view promoted by Francis Bacon to enslave nature by human
ingenuity and a view of nature that René Descartes metaphorically saw as clockworks of isolated
and replaceable components (Capra, 1996, p. 20). With his Philosophiae Naturalis Principia
Mathematica, (Smith 2008), Newton in many ways, provided the intellectual tools to facilitate
the control of nature and seemingly confirmed the propositions and metaphors of Bacon and
Descartes. Today’s Newtonian philosophy of scientific investigation, reductionism, is very
enticing to science because of its precision, relative ease, and because its outcomes have in many
ways been seen to temporally improve the human condition. So, similar to arguments for legal
precedence known as stare decisis, great care and reflection should occur before embracing a
philosophical change or expansion of current scientific paradigms. Reflectively, though, it seems
that a change must occur to ensure the long-term survival of the biosphere and perhaps the
human species. However, for a change of philosophy that sinks deeply into the fabric of science
and permeates many disciplines, including engineering, fully to occur, may require a concurrent
societal change in worldviews. That is, a shift must occur away from an isolated anthropocentric
societal worldview to a more holistic worldview. Regrettably, this is not easy, and even in
science, many disciplines may rhetorically promote a worldview of holism, while they are still
fundamentally driven and ruled by market forces of the scientific juggernaut reductionism.
Often, and perhaps due to its conceptual and technical difficulties, our attempts at holism are
somewhat superficial and evidenced in that we tend to minimize the importance of the system sciences that might allow us to delve into the deep interconnectivity and interdependencies of complex systems. What is needed is a worldview that gives homage to and includes “systemness” and its requisite interdependencies, which would begin to address many of the planet’s environmental issues. This work tries to build that case from first principles through examinations of systems, epistemology, causality, analyses of networks, and engineering design methodologies. In addition, this work will often employ a form of dialectic comparison to expose any inadequacies in current scientific and engineering paradigms used for the analysis and design of natural living systems. And just as Newton’s mechanics were found to be limited in scale within the physics discipline, it is proposed that design methodologies based on reduction will be found to be a limited paradigm and insufficient for ecological systems. As other scientists and engineers also read and ponder what is truly required to construct within, manage and engineer natural living systems, perhaps they will agree that the current methods are lacking, and they will also seek additional knowledge to initiate an exchange of information that assimilates into a critical mass necessary for holistic systems management and design.

Systems

Some common characteristics of systems (White, Motterhead & Harrison, 1994, pp. 9-10) include 1) that all systems show a degree of integration; 2) that they are human idealizations or abstractions of an ontic world; 3) that systems function in some fashion, having functional and structural relationships between constituents; 4) that their function implies transfer of some material requiring an energy source as the driving force; and 5) that systems have structure or organization. Thermodynamically systems delimit into three categories in terms of matter and energy flows: isolated, closed and open systems. In isolated systems, there are no transfers of
matter or energy across system boundaries. Generally, isolated systems are manufactured systems that only exist in laboratories; however, they are still quite useful in the study and development of thermodynamic principles. Closed systems are those systems that allow transfers of energy across system boundaries, but these systems close to transfers of matter across their boundaries. Closed systems are rare in nature although the earth itself for practical purposes often approximates a closed system. A closed system in engineering called a control mass consists of a fixed amount of mass where no mass crosses the system boundary, but heat or energy may and where the volume in a control mass is not fixed. Much thermodynamic theory has been developed in terms of closed systems, and at times components of natural physical systems may lend themselves to this type of thermodynamic analysis, that is, when the larger system can be reduced to simpler non-complex parts that behave as a system closed to matter exchange with its environment. However, this will not be the case for living systems.

Living systems are examples of a third type of thermodynamic system called open systems, where both energy and matter may cross the system boundary. In engineering, these systems are often termed control volumes and selected as a region of space where mass and energy may flow through. In natural open systems, the transfers of matter are often also transfers of energy where the matter itself may also contain organized chemical potential energy. All ecological systems are open systems where the constant throughputs of energy and matter maintain the system’s structure and push the system away from thermodynamic ground and toward increasing levels of organization, complexity, and information (Prigogine, 1984; Sneider & Kay, 1994; Cengel &Boyles, 2002).

Isolated systems, as mentioned, are normally systems constructed and controlled in laboratory settings; however, they may serve a purpose in understanding ecological systems. Not
only may thermodynamic principles be inferred from isolated systems, but they may serve as dialectical comparisons to the other end of the thermodynamic system spectrum; that is, in many ways and at the correct scale of observation, thermodynamic behavior of isolated systems tends to be opposite of thermodynamically open systems. Thus, they may help elucidate thermodynamic characteristics of ecological systems through dialectical comparisons and inferences. And as previously mentioned, the use of dialectical comparisons will be an often employed stratagem throughout this work in inferring the direction for the management and design of ecological systems.

Closed systems may have applicability in a similar fashion, that is, to provide insight into thermodynamic principles and as a dialectical comparison to open systems. Additionally, there perhaps are physical systems embedded temporally within larger open living systems which are best described through a closed system thermodynamic analysis. This is profoundly true for mechanically engineered systems that embed within larger open ecological systems. The thermodynamic characteristics of these open or “closed” engineered systems may often, directly or indirectly, affect the behaviors of the ecological system in which they are embedded. Unfortunately, that impact often obscures itself at temporal or spatial scales that are out of the normal purview of human observation.

As open systems, ecosystems may operate as dissipating systems in contrast to isolated systems that are always describable mechanically by the second law of thermodynamics with increases of system entropy and a movement toward thermodynamic equilibrium. This is not true for the thermodynamically open ecological systems where the energy gradients across the system allow it to reduce its local entropy as it organizes interdependently and moves away from thermodynamic ground or the zero energy gradients where all matter and energy flows would...
cease (Jørgensen, 2002; Schneider & Kay, 1994). This ability of living open systems to reduce their local entropy has profound implications and allows the system to grow and develop (Ulanowicz, 1997, pp. 7-8) into the complex ecological systems surrounding humankind.

Describable in terms of boundary exchanges, systems are also describable as varying in size, organization and intricacy. It is the view of this work that the variation depends on several factors, including the number of components, component connectedness, and the amount of functional and relational coupling of components within the system. Generally, systems are entities that show organization within the scale or purview of human observation. As mentioned, one would not typically consider a pile of rocks a system; however, those same rocks organized into a rock wall constitute a system. If the scale were increased or decreased, the pile of rocks arguably exhibits system or system component characteristics. At human scales, common simple systems perform relatively few functions and have relatively few components connected in a manner that minimizes distributive function, information content, and functional and relational coupling. One may describe systems more intricate than simple systems as complicated systems. Complicated systems may perform several functions and may have several to many connected components and correspondingly higher information content. Complicated systems are generally additive, exhibiting superimposed or accumulated behaviors. However, complicated systems are still relatively free of functional coupling and markedly free of relational coupling. Both common simple and complicated systems are described as systems of interacting and perhaps interrelated components where the direct establishment of cause and effect typically may occur. On the other hand, complex systems are highly intricate and range from relatively small numbers of articulating coupled components to large numbers of interacting components that, in each case, tend toward high and increasing levels of information through relational connectivity or by
overwhelming numbers of components and actions. Complex systems may have components that are interdependent and distribute function, and functionally and relationally couple. Complex systems may also be systems with very large component numbers acting relatively independently of other system components. In either case, highly complex systems are information rich systems where direct cause to effect tends to be intractably difficult to infer. This is the result of system interdependent composite behavior or the result of a large number of independent component actions that are impractical if not impossible to track. Interdependent complex systems may efficiently perform several functions simultaneously, and toward this end, these complex systems may distribute function and couple components physically, functionally, and relationally to encourage beneficial systemic properties not evidenced in the parts. As interdependent complex systems, ecological systems are self-organizing, coupled, information rich systems that are the result of energy gradients, which have driven them away from thermodynamic equilibrium. These systems not only have interacting and interrelated components but have prolific and intertwined physical, functional and causal relationships (Fath & Patten, 1999; Jørgenson, 1999, 2002; Patten, 1984, 1991; Patten, Bosserman, Finn & Cale, 1976; Ulanowicz, 1997, 2000), decentralized control (Schramski et al., 2006, Gattie, Kellam & Turk, 2007, p.35), and interdependencies that lead to highly emergent properties that allow the system to evolve over time. Further, the synthesis of function and relationship, the scale, and the hierarchical nature of these complex systems tend to make the analysis of these interdependent systems intractably difficult to compute and to date unpredictable to design.

The 4 C’s for Systems

Systems seem to exist in quite numerous and varying forms, but perhaps there exist some common general invariance in these forms that may allow some general categorization of system
types. Warren Weaver (1948, pp. 536-538) in his works in science and complexity introduced three domains for problems. He recognized a gap between what he termed the casually direct organized simplicity or two variable problems consisting of no more than four objects that submit to direct mathematical analyses and what he described as disorganized complexity where the objects are numerous, disorganized, and distributed, and where their behaviors only yield to statistical mechanics and probability theory. Weaver also recognized a third category that did not fit well within the models of the previous two, and he termed this category “organized complexity,” that is, systems with sufficient numbers that did not submit to simple analyses and where their behavior was collective and organized instead of seemingly random and disorganized and thus not yielding to statistical analysis and where the collective behavior of system constituents was more than the sum of the individual behaviors. Weinberg (1975) further develops these relationships where he delimits simple machines into the domain of organized simplicity, aggregates into the domain of disorganized complexity, and systems as organized complexity (Gattie, Kellam & Turk, 2007, p. 28). Later, Bar-Yam (2004, pp. 51-59) described systems as simple, complicated, or complex. This work, however, building on the work of Weaver, Weinberg, Bar-Yam and others, endeavors to further parse and delimit systems, and although the demarcation between these types of systems may at times be blurred, the following four general classifications are logical: common simple systems, complicated systems, complex independent systems, and complex interdependent systems. These comprise the 4 C’s for systems. Common simple systems are those systems that perform few functions and consist of few components. The components of common simple systems may interact but do not necessarily integrate, nor are they functionally and relationally interdependent on other components or their environment. Examples of human constructed common simple systems
include the wheel, a hammer and chisel, mortar and pestle, nail, ball bearing, a bucket, etc.

*Common simple systems* perform a relative minimum of functions, have few components, and the requisite information needed to describe the system is small. Cause and effect largely are directly inferable in *common simple systems*. *Complicated systems* are more intricate than simple systems and may vary in the degree of their complication. *Complicated systems* may have multiple functions and may consist of larger component numbers, necessitating a greater amount of information to describe these systems. *Complicated systems* often physically couple or integrate into systems that to some degree exhibit an accumulated or superimposed behavior; however, the system components are still relatively free of interdependencies associated with functional coupling and are particularly free of relational coupling of components. These systems are often relatively free of dependencies to their environment. Cause and effect are also largely directly inferable in *complicated systems*. Examples of complicated mechanical systems include an oven, a bicycle, an automobile, a dishwasher, etc.

Complex systems are a third type of system. Complex systems are highly intricate systems that may range from relatively small to extremely large numbers of components. Complex systems may come in two varieties. One type, *complex independent systems*, consists of a very large number of components that exhibit many seemingly independent or disorganized actions. One could argue that at human scales, some of these systems may show disorganization over organization and thus are not systems. Often, however, the seemingly disorganized behaviors of these entities show trends that appear as organization at other scales; thus, it may be useful to consider these entities as systems. It is notable, at this point, that the Newtonian paradigm does fit and does work quite well for simple and complicated systems. However, long known within the disciplines of physics and engineering, Newtonian mechanics is insufficient to
describe and predict the many-bodied problems of complex independent systems, such as molecular motion, often encountered in nature. Thus, cause and effect are not directly inferable in these many-bodied systems. To describe and successfully predict these natural phenomena, physicists have, quite successfully, turned to the laws of averages and statistical mechanics to isolate, control, and predict the many-bodied problems (Gattie, Kellam & Turk, 2007, pp.28-29).

A second type complex system, which this work calls complex interdependent systems, consists of smaller component numbers where the components are interdependently connected, exhibiting composite highly integrated actions, functions and behaviors. In both types of complex systems, cause and effect tend not to be directly traceable or inferable; that is, the first require statistical analyses and the second require analyses that keep the system connected to account for the integrated composite interdependent relationships between components. Some examples of nonliving interdependent complex systems include neural networks and weather systems. Living systems at all levels are complex interdependent systems. In reference to the study of living systems, Gattie, Kellam & Turk (2007, pp. 27-28) wrote that Ludwig von Bertalanffy (1952, 1969), who developed a General Systems Theory, and Paul Weiss (1969) suggested a need for holism in the study of the biology of organisms. Furthermore, Weiss (1969) suggested that in living systems the informational sum of individual system constituents was less than the sum of information for the whole system. Thus, both Bertalanffy and Weiss also imply the need to analyze these complex interdependent systems as connected wholes.

**Complexity and Complex Systems**

Consensus in defining complexity, or when it exists, has not occurred; therefore, the term complexity has various meanings and interpretations depending on definer and audience. Complexity generally has the following characteristics or features: non-linear relationships,
feedback loops, open, relational memories, nested, reactionary, anticipatory, random, nebulous boundaries, and dynamic multiplicity (Weaver, 1948; Science, 1999, Complex Systems, Vol. 284, pp. 79-109). Kay’s (1983, 1984) definition of complexity distinguishes between structural complexity and functional complexity, where structural complexity defines the number of interactions between a system, and functional complexity refers to the distinct functions carried out within or by the system (Jørgensen, 2002, pp. 123-186). Often, many relate complexity to high informational content. For instance, according to Shannon’s communication theory, information is a measure of complexity (Shannon & Weaver, 1948, 1949; Jørgensen, 2002, p. 127). While that statement and the other characteristics of complexity described above are all valid, it is the position of this work that high informational content is also a characteristic of complexity, and the other aforementioned characteristics only describe aspects of complexity without completely capturing the general essence or holism of interdependent complexity. The true essence of complex interdependent systems is likely a nondescriptive synthesis of all the characteristics mentioned and more. However, is there a relatively crisp demarcation of complex independent and interdependent systems from complicated or common simple systems? To facilitate understanding and consistency of thought throughout, this work will propose not a definition of the essence of complexity, but a general description of when complexity exists: system complexity exists when cause and effect are not directly traceable or inferable.

Complexity may occur in two contradictory ways. First, complexity in a system may exist due to highly independent causes or seemingly individualistic component behavior. Some have described this as random complexity caused by disorder (Jørgensen & Muller, 2000, pp. 5-18), which would also fit with Shannon’s measure of complexity in that it would take an impossibly large amount of information to describe the system. It is a “herding of cats” problem, where a
relatively high number of causes, actions, system components, etc. exhibit seemingly highly independent behaviors or trajectories that are impractical if not impossible to directly track. Systems that exhibit these characteristics may have many component actions with separate causes and many components with many differing trajectories, which negate one's ability to make a deterministic analysis of direct cause to effect. An example of this type of complexity is Brownian motion that occurs in a diffusion process. Brownian motion, named after the botanist Robert Brown, refers to the physical phenomenon where minute particles, immersed in a fluid or floating on its surface, seemingly move about randomly (Brown, 1828). The results or effects of these random independent actions are intractably difficult to determine until one increases the scale and can empirically measure a trend or stochastically determine a correlation between cause and effect. Interestingly, the complexity seems to increase with increasing independent behavior at the scale of the independent behavior; however, the complexity of the system decreases at the higher scales (Bar-Yam, 2004, pp. 61-70) of these independencies; that is, at a higher scale, component trajectories and trends may be determined empirically or inferred stochastically. Furthermore, the greater number of independent components increases the sample size at the higher scale, thereby increasing the likelihood of trends and the reliability of the data and as a result the ability to make stochastic and empiric inferences, thus further reducing complexity at the scale of the stochastic analysis. Analogously, for example, if one considers Eulerian versus Lagrangian descriptions of flow of fluids, the Eulerian method uses a field concept for the description of fluid flow, where the requisite descriptions of fluid properties are functions of space and time. From this method, one may empirically determine large-scale fluid properties at a fixed point on space as fluid flows past those fixed points, thereby reducing the system complexity at the macro scale. However, the Lagrangian method, at fine scales, requires
impractically following the many individual fluid particles to determine the associated properties as functions of time, as the individual particles move about (Young, 2004, p.110). Further, at these fine micro scales, cause and effect are impractically difficult to ascertain because of the large number of particles and trajectories; thus, the system may be described as highly complex at the micro-scale.

The second type of complexity exists in systems of functionally and relationally interdependent components. This can be described as an “opaque box problem” where the system exhibits emergent behaviors, and cause to effect of the emerging properties masks in the composite interdependencies within the system. Further, it is the position of this paper that interdependent complexity is the most profound and highest form of complexity. As mentioned, complexity also depends on the scale of observation. For complexities that are the result of interdependent actions, the complexity decreases as interdependencies increase at the scale of the interdependencies (Bar-Yam, 2004, pg. 61-70). That is, observable patterns may develop at the actionable scale, but at higher scales the complexity increases in the form of composite emergent behaviors.

To assist in understanding these differences in complexity and scale, consider a large environmental science lecture and lab course to be a system of instructor and students where the student component is a system nested within the larger system, the lecture course. If the students are all very independent and individualistic, having their own study times, locations, methods, attendance patterns, ancillary materials etc., it is difficult to determine the primary mode of study and learning of the class until one moves up in scale and can stochastically determine patterns of the entire class. In other words, complexity is relatively high at the level of the independent actions but decreases as the scale increases where stochastic or empirical inferences to
correlation occur. On the other hand, if the students are interdependent, they may form study
groups to solve problems, tutor each other, etc. Here, the complex pattern of student study and
learning decreases at the scale of the interdependencies; that is, the patterns are observable at the
scale of the interdependent patterns. However, the complexity of the system increases at higher
scales because the ability to observe the patterns fades and blends into composite forms as the
scale is increased. For instance, at the administrative scale, emergent system properties or
behaviors of the system may be observed, such as increased class enrollment, attendance,
participation, enthusiasm, retention, comprehension, a better class average etc.; however, the
causes of these emerging system properties are likely hidden as composite forms to the
administrator.

In actuality, at some scale all components within a system exhibit some degree of
interdependence. For example, any component that contains mass is interdependent to some
degree on all other masses within the universe through Newton’s law of gravitational attraction
or in actuality through the warping of space time by all mass in the universe. However, the
magnitude of these types of interdependencies is very small at the scale of the actions considered
and where other interdependencies or independent actions often overshadow the former. At
human scales, direct electromagnetic coupling through conservative transfers, such as energy,
matter, and momentum are the essence of interdependent coupling. However, non-conservative
transfers, such as relational coupling at a network distance are perhaps at least as important to the
essence of component interdependence.

In terms of ecological systems, Jørgensen (2002, p. 31) suggested that complexity in
these systems might take several forms. Those forms include many different components (i.e.
high numbers of organisms and species), resulting high numbers of possible connections and
relations, very high numbers of feedback and damping regulations that are constantly changing, the hierarchical nature of components and processes, tendencies toward high temporal and spatial dynamism, and evolutionary tendencies toward higher complexities.

4 I’s of System Component Action

In the environmental science course mentioned, four general categories of component actions and relations within the system appear to be possible—interaction, integration, independence, and interdependence. System constituents may perform more than one of these types of actions concurrently. As mentioned, the student component of the environmental science course is a system within the larger system, and it consists of a number of components or individual students that as a group spontaneously interact with each other, the other component (instructor) within the larger system, and the system environment. Interactions, for instance, may include determination of seating within the classroom, distribution of class handouts, etc. where the degree of contacts are of a low magnitude and have little significance in individual comprehension and class performance. The individual students may also integrate into a larger whole of the student component of the environmental science course. The integration facilitates the collective functions of the student component, such as course evaluation, instructor evaluation, class participation, performance, etc. Integration of system constituents may often be a physical integration, particularly in the case of mechanical systems, or it may be a functional integration in which system components perform a common or collective task where each system constituent performs relatively independently of other system constituents. Functional integration requires individual systems constituent participation to achieve the collective functional response for the whole, but each constituent performs its task relatively independent of other constituents. In mechanical terms, common simple systems and complicated systems often show interaction
and integration of system constituents. For example, the constituents of the *common simple system*, a hammer and chisel, interact but do not integrate into a physically coupled whole. However, some *common simple systems* physically integrate, such as the wheel or shovel. For *complicated systems*, particularly for mechanical systems, the components often integrate into a physical whole and exhibit a degree of functional integration that is a superposition of system constituent function; examples included the dishwasher, the automobile etc.

In the environmental science class mentioned, the student component of the system may also exhibit complex actions within the system. The complex actions may range in degree and type exhibited within the system. To illustrate, the class may be fragmented with the students highly disconnected, individualistic, and relationally uncoupled, where all perform their studies independently and in many varying ways.

Alternatively, the students may show high levels of functional and relational interdependence through study groups, tutoring each another, etc. The latter, being a quite interdependent complex system, where the performance of the system is often enhanced through functional and relational reinforcement and feedback loops, is more than the sum of its parts, and where the performance of individual students is often optimized and dependent upon other students. Further, complex interdependent systems may or may not integrate physically but will exhibit high degrees of functional integration, which gives rise to a relational integration into the complex whole. Relational integration with corresponding high levels of functional integration makes these systems interdependent. Therefore, this analysis suggests that there exist within systems four general patterns of system component action: low-level *interaction* with other components, *integration* of components into a physical or functional whole, *independent*
component actions, and *interdependent* component actions through functional and relational interdependencies. This work will refer to these as the “4 I’s” of system component actions.

**4 P’s of Living “Systemness”**

Many consider ecosystems a fundamental unit of study within the field of ecology (Odum, 1980; Jørgensen & Müller, 2000). According to Jørgensen and Müller (2000), many authors (Odum, 1980; Stugren, 1986) and others suggest that ecosystems must meet several requirements. Those include: “internal cycles of matter, emergent behavior, energy flow in food webs that produces biodiversity and nutrient cycles, inorganic substances, organic substances, climatic factors, producers, consumers and decomposers in a spatial unit, spatial and temporal borders, a higher internal connectedness than external connections, the ability for self-regulation and self-organization” (Jørgensen & Müller, 2000, pp. 7-8). Thus, from these characteristics, it can be inferred that ecosystems have an ontic reality separate from human perception; that is, they have some common invariant characteristics independent of human thought and characterization. However, quantum mechanics seems to suggest that true ontology may not exist. For example, Heisenberg’s Uncertainty Principle implies that electrons are not in a particular location until observed. Moreover, if extrapolated to human scales, this theory suggests that the reality observed perhaps actually consists of the collapse of an infinite number of possibilities in perhaps higher dimensions to a particular reality through our actions. If that were to be the case, then it suggests that all reality may be more a form of epistemology. Others such as Bohm et al. (1987) also suggest that the observer cannot be separated from the observed due to the indivisible nature of the universe, further suggesting a blurring between ontology and epistemology (Jørgensen, 2002, p. 26; Patten, in progress). Whether there is a true ontology or if all are degrees of epistemology is unclear; however, Capra (1996, pp.160-161) identified three
key criteria of a living system that seem to generalize many of the characteristics necessary for living systems: These include pattern of organization, which Capra described as the “configuration of relationships that determine the systems essential characteristics”; structure, “the physical embodiment of the system’s pattern of organization;” and life process, “the activity involved in the continual embodiment of the system’s pattern of organization”. However, this work proposes that these general characteristics of living systems may be further expanded and delimited into four key ontic or at least epistemological criteria for living “systemness:” pattern (organization), parts (structure), process (activity of the system pattern), and plasticity, where plasticity describes the living system’s unique ability to sense, self-organize, conform and adapt to larger systems in which it embeds. For example, ecological systems over time have an ability to evolve and adapt synergistically with their environment, conforming to their circumstances. Perhaps this is a most significant characteristic, one where the system senses, models and physically, as well as relationally, molds itself to its surroundings, often resulting in a physical reorganization, change of constituents, and a modification of function. This may be best thought of as ecosystem plasticity where the system continually adapts to its changing actual or perceived surroundings. And it is the position of this work that although the four characteristics described are necessarily intertwined, each of these four describes generalized invariant qualities needed to begin to adequately represent the essence of any living system, that is parts, pattern, process, plasticity, or the 4 P’s of Living“Systemness”.

The plasticity of ecological systems, in many ways, transcends the analysis of any focal system because it couples to the hierarchical macro scale external environment of the system over long temporal scales. Thus, it is perhaps beyond current analysis techniques, whereas the parts, process and patterns of a system are more discernible. The parts and to a degree many
processes within a system are often to a large degree obtainable by observation while patterns of systems may range from empirically obvious and observable to concealed and hidden. To appreciate this, if we again consider the environmental science course as an illustrative complex system, generally its parts, processes, and some patterns are ascertainable through empiricism. The course has the same students engaged in a process of learning through lecture and lab, the course meets in the same room, the same days and times of the week, the lecture format is consistent, students generally sit in the same locations for each class, etc. Though perhaps some are trivial, all are parts, process or patterns observable in the system. Patterns are trends, consistencies, and as discussed, many are determinable by observation. However, often the essence of highly complex interdependent systems are the hidden processes and patterns which are perhaps more subtle and more difficult to discover. For example, what is the predominant pattern of student comprehension in the course? Was it the interdependencies of students and instructor during lecture, laboratory experiences, assigned reading, selected homework problems, ancillary materials, tutors, questions and interactions of student and instructor, or was it the interdependencies associated with the student system within the system? Was the process one direct pattern, or was it the sum of many small indirect patterns? Whatever the answer may be, the one thing it is not is obvious. Thus, a challenge of parsing out the pattern from a collage of interactions, integrations, independencies and interdependencies associated with the system remains. Normally, at this point, we embrace the scientific method and reductionism to uncouple the system and analyze how each part affects the whole. However, in doing so, we lose vital contextual information relating to the dependent nature of these types of complex systems. To reveal the hidden patterns of interdependent complex systems, a methodology is needed that embraces the connectedness and interdependent relationships within the system. That is, a
method that keeps the network intact but still parses and reveals the hidden trends and subtleties of the system. The system sciences and mathematical methods, such as network analysis, provide a framework by which one may uncover general system properties and uncover mathematical trends that describe and parse out the physical and relational patterns of complex systems. Ecological systems are very interdependent complex systems and contain patterns that range from very observable to patterns which are hidden and not directly observed. Empiricism, experimentation, and reduction have gone a long way in noting observable interacting, integrating, and perhaps independent component patterns of natural systems but have fallen short in the ability to note the complexity or subtle interdependencies within the system. This also portends that management and engineering of complex living systems has insufficiencies if the science used as the basis for the design, integration, and management of ecological systems is not adequate to describe all aspects of the system. Consequently, it appears that current management and engineering related to these systems is insufficient and in need of additional insights. This work will add weight to that proposition as we further examine these complex systems and current state of engineering in relation to those systems. Essential concepts about systems developed in this chapter are diagrammed in Table 1.1.

Table 1.1. System type versus possible component action and system characteristic.

<table>
<thead>
<tr>
<th>(Possible Component Action)</th>
<th>(System Type)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interact</td>
<td>Common Simple</td>
</tr>
<tr>
<td>Integrate (Physical)</td>
<td>✓</td>
</tr>
<tr>
<td>Integrate (Functional)</td>
<td>✓</td>
</tr>
<tr>
<td>Independent</td>
<td>✓</td>
</tr>
<tr>
<td>Interdependent</td>
<td>✓</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>(System Characteristic)</th>
<th>Common Simple</th>
<th>Complicated</th>
<th>Complex Independent</th>
<th>Complex Interdependent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parts</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Pattern</td>
<td>✓</td>
<td>✓</td>
<td>✓ (statistical)</td>
<td>✓</td>
</tr>
<tr>
<td>Process</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Plasticity</td>
<td></td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>
CHAPTER 2
DESCRIPTION, CAUSALITY, AND COMPARISONS OF SYSTEMS

Introduction

Established disciplines with high levels of consensus, such as mechanics and traditional engineering, often need less explanation; thus, descriptions and published works in traditional engineering may be inherently shorter with less background information. However, engineering management and design of ecological systems based on what may require at minimum, an augmentation of the Newtonian paradigm, requires thorough explanation from first principles, comparisons, and even qualified conjecture to justify and advance the field. In addition to the need for both qualitative and quantitative explanation of theory and methodologies, the question is perhaps more primary: Does the design and management of ecological systems need to be fundamentally and distinctly differentiated from traditional science and engineering?

Consequently, will the explanation and justification for the engineering management and design of ecological systems require a paradigm shift in the current philosophy of investigation and design used in science and engineering? A shift from the traditional atomistic, mechanist and reduction based views of the world. That is a shift from the clockwork metaphors of René Descartes and the domination of nature espoused by Francis Bacon, to a holistic vision of the world as a personification of what human beings find ourselves embedded within and surrounded by; the natural world and its inherent complexity. Conceivably, a further recognition of our current worldview as a society, which is predominantly anthropocentric and based largely upon
the desire to control and use nature, is necessary to move forward. This recognition should precede and color how we view the world scientifically.

Why do the objective disciplines of science and engineering readily embrace reductionism? The answer to this question is likely multifaceted and complex. Is it because of its relative ease, history of success, market forces, etc? Perhaps embedded within the answer is a subconscious human centered view that wants to control nature for our purposes. Thus, for a shift of philosophic and scientific paradigms to fully find a way into mainstream scientific thought, recognition of the need for an eco-centric worldview is focal and ultimately benefits humankind. Consequently, the successes and limitations of the atomistic view of science need explanation in that context, described in a way that 1) clarifies the need for a fundamentally new theoretical framework for the consideration of natural systems and 2) directs current thinking toward a theoretical basis on which engineering design and management of natural systems might address some of the pressing environmental problems facing society today. That theoretical framework should be a systems science that promotes systems thinking, analysis and a systems view of the world. However, Ervin Laslo (2002, p. vi), in paraphrasing Mark Twain, wrote, “Everyone talks of a new worldview of the sciences, but nobody quite knows what it is”. That statement acutely rings true today. A systems view has not been fully embraced in many areas of science and engineering, particularly in how human constructions meld with natural systems and their complexity. According to Gattie, Kellam & Turk (2007, pp. 26-28), Klir (1991) presented a history of the system sciences and its basic tenets and methods, followed by a summary of system science literature that addresses the scientific bases, appropriateness and use of reductionism on nature and its systems. The dialectical comparisons in this work are intended to further clarify the system sciences as applied to ecological systems and demonstrate the need
for system sciences in the management and design of ecological systems. Toward that end, this work will attempt to justify itself from first principles and to seek a philosophical framework as well as new strategies and methods by which the management and design of ecological systems should proceed.

**Dialectical Comparisons**

Embedded within the theoretical framework of systems science are several relevant questions which may serve as the foundation by which one may qualitatively explain a need for different strategies, methods, and ways of thinking in the design and management of natural living systems. Some of those questions are compared to, or contrasted with, established ideas in the Newtonian view of the world. In many cases, the discussions of this work take a form of comparative dialectical inquiry. Plato first wrote about the dialectic through his observations of Socrates. From his observations, Plato penned this important philosophical concept and method to arrive at the truth (Woodruff, 2010; Lazlo, 2002, p. 26). The dialectic may be broadly defined as “an exchange of propositions and counter-propositions resulting in a synthesis of the opposing assertions or at least a qualitative transformation of the direction of the dialogue” (Merriam-Webster, 2012). A secondary definition states that the dialectic is “the juxtaposition or interaction of conflicting ideas, forces, etc”. Questioning and dialectical comparisons, i.e., the Socratic Method (Woodruff, 2010), may result in an advance qualitatively toward a need for new philosophies, methodologies and different ways of thinking in the design and management of ecological systems. Often, dialectical comparison results in a synthesis of contradictory ideas. Hegel promoted this method to arrive at the truth. The Hegelian dialectic is defined as “an interpretive method, originally used to relate specific entities or events to the absolute idea, in which some assertible proposition (thesis) is necessarily opposed by an equally assertible and
apparently contradictory proposition (antithesis), the mutual contradiction being reconciled on a higher level of truth by a third proposition (synthesis)” (Merriam-Webster, 2012). Thus, the comparisons or synthesis of competing ideas may result in better understanding of nature’s attributes and processes for the management and design of ecological systems.

Reductive versus Systems Thinking

A system is generally a collection of articulating components that interact at some level, and as explained in Chapter 1, ecological systems are thermodynamically open systems consisting of articulating interdependent components that couple in a non-linear way, resulting in a move of the system from thermodynamic ground. Natural living systems connect across spatial and temporal scales, and natural living systems are complex where interdependencies give rise to system wide properties not evidenced in the parts. These properties are emergent properties.

However, Ludwig von Bertalanffy (1969, p. 32), the originator of General Systems Theory, said, “There appear to exist general system laws which apply to any system of a particular type, irrespective of the particular properties of the systems and the elements involved. Compared to the analytical procedure of classical science with resolution into component elements and one-way or linear causality as basic category, the investigation of organized wholes of many variables requires new categories of interaction, transaction, organization, teleology...” I previously suggested that systems categorize in several ways, usually depending on the context of the discussion. This work, based on the work of many others, suggested the 4 C’s of systems (common simple, complicated, complex independent and complex interdependent systems). In addition, the 4 I’s of system component action (interaction, integration, independence, interdependence) are proposed, as well as the recognition that natural living systems at
appropriate scales consist of four fundamental invariant characteristics called the 4 P’s of natural living systems: plasticity, parts, processes, and patterns. The 4 P’s of a system are described as plasticity to mold itself to its environment, parts or system constituents, process as the functional aspects of the collective and its components, and pattern as the system organization. Thus, systems seem to possess these and perhaps other general collective characteristics, as Bertalanfy suggested, that dissolve when the collective dissolves. However, reduction as a scientific philosophy tries to take often-large complex entities and reduce them to smaller, isolated sets for the purposes of understanding. Reduction based thinking is often called mechanistic or atomistic and it focuses on the parts. Nevertheless, whatever name is used, reduction has been and is the dominant scientific philosophy and tactic of our time, and for good reason: it has had enormous success in describing parts of nature and engineering our modern society for the temporal benefit of humankind. Employed since Newton’s age, this scientific method is successfully used in all scientific fields, including ecology, where it has also been instrumental in finding some governing relationships in nature, such as primary production versus radiation intensity and mortality versus concentrations of toxic substances (Jørgensen & Müller, 2000, p. 13) etc. So, similar to the concept of stare decisis or the doctrine of precedence in our legal system, the abandonment or augmentation of reduction based methodologies in science should not occur without careful consideration.

However, reduction seems to be insufficient to describe the connected and relationship driven natural systems that envelop humanity and quoting Jørgensen & Müller (2000), “the reductionistic methods have obvious shortcomings, when the entire ecosystems are to be investigated” (p.13). Obviously, this work is not the first to consider the implications of a reductionist view of the world. Many, including Patten, Jørgensen, Ulanowicz and many others,
have considered the philosophical implications of reductionism within the field of systems ecology, suggesting that ecological systems that show properties including hierarchy, complexity, and emergent properties fall outside the precision of Newtonian worldview (Patten, 1976; Allen, 1982; Ulanowicz, 1999; Kay, 1994; Jørgensen, 1992; Gattie, Kellam & Turk, 2007). Further, Ulanowicz presents a thoughtful and concise case for more appropriate philosophies of science (Ulanowicz, 1990, 1997, 1999, 2001, 2004a, 2000b, 2005; Gattie, Kellam & Turk, 2007, p. 29). However, it is the intention of this work to advance these discussions particularly within the engineering disciplines, which ultimately transform our world as much as or more than any other human endeavor.

Natural living systems consist of components with high interdependent patterns of organization and plasticity, giving these systems the ability to mold and reorganize themselves over time. Without component interdependencies, this ecological plasticity would likely revert to an ecological rigidity and leave the system without the ability to adapt and thus vulnerable to changing environmental conditions. The analytical reduction of these complex systems to parts largely ignores interdependencies. The subsequent analysis of analytically reduced systems to individual constituents results in a change in the behaviors of the components and thus a loss of the true contextual and systemic behaviors. Those characteristics however seem to be a most essential feature in the sustainability of the system. In contrast, holism focuses philosophically on the holistic, systemic and ecological whole, the characteristics of the whole and its emergent properties in context of its environment (Capra, 1996, pp. 17-36); this framework seems much more appropriate and promising as a scientific philosophy for the study of natural systems.

System thinking is a holistic way of viewing the world and humankind embedded within that world. It is a way of structuring or perhaps restructuring our knowledge from parts to wholes,
from isolation to interdependence, from things to relationships, that also transcends the spatial and temporal scales of these relationships. Systems’ thinking is contextual.

Epistemology is a human invented branch of philosophy that investigates the methods and nature of human knowledge; in contrast, ontology, at least in our spatial and temporal dimensions, is more focused on the essence of the object of interest. Thus, epistemology is a subjective way of knowing and only one method of knowing about nature, which suggests the possibility of philosophical flaws in certain situations. Thus, reduction as epistemology is subjective and potentially flawed in some circumstances. Reduction versus systems thinking in some ways is analogous to the contrast between quantity and quality in natural systems. Often the quantitative characteristics of natural systems are less important than their qualitative attributes. For example, the qualitative interpretations of Network Environ Analysis, such as, dominance of indirect effect, network homogenization, and other interpretations (Patten, 1978, 1982, 1984; Fath & Patten, 1999) seem to be significantly more important than the quantitative measure of matter or energy flows through ecological networks. Similarly, analysis versus synthesis in natural systems, where analysis separates the systems into components for an individual decoupled analysis, and synthesis brings the pieces together, suggests another contrast of reduction and systems thinking. Analysis is usually sequential or linear and works well with decoupled constituents. Synthesis, however, is iterative, often non-linear and perhaps in some ways the dialectical opposite of analysis; that is, synthesis combines constituent elements into a whole. Reductive decoupling implies component independence whereas synthesis prescribes interdependence. Moreover, what is independence versus interdependence in relation to natural living systems? All components within a system show a degree of both independence and interdependence at particular scales of interest. However, the magnitudes of each may be quite
different. For example, the previously mentioned Brownian motion of gas molecules at the molecular level is an example of highly independent or decoupled component action where the components may *interact* but show a very low functional or relational *interdependence* to other system components. At human scales, natural living system components show high degrees of interdependence or coupling, and if removed from these contexts, are fundamentally changed. Further, these interdependent systems at increasing scales often have unique system wide emergent properties that are preeminent in the study and understanding of their quintessence.

However, a systems view of nature is dependent on a qualitative understanding of invariance within ecological systems. Lazlo (2002, pp. 24-58) noted that 1) natural systems are wholes with irreducible properties (that is, wholes versus heaps); 2) natural systems maintain themselves in a changing environment; 3) natural systems create themselves (self-organize); and 4) systems within a larger complex system act as coordinating interfaces collectively behaving and interfacing into a larger whole. Often, however, the processes of reductionism results inevitably in oversimplification. For instance, the Principle of Parsimony (Zalta, 2011) often known as “Occam’s razor,” states “Don't multiply entities beyond necessity;” in other words, don’t make more assumptions than necessary, and if all other things are equal, then the simplest answer is correct. However, this principle appears in contrast to the way in which living systems operate, that is to grow and develop, increasing complexity and information content (Ulanowicz, 1990, 1997, 1999, 2001, 2005; Gattie, Kellam & Turk, 2007, p. 28). The Principle of Parsimony, however, is necessary and fundamental in scientific efforts to build models; without it all models would be unmanageable and inevitably as complex as the actual system. Conversely, though, complexity in nature abounds with increasing levels of information as ecosystems grow and develop (Ulanowicz, 2000b). Thus, with ecological hypotheses, such as dominance of indirect
effects (Patten, 1978, 1982, 1984; Higashi & Patten, 1989; Fath & Patten, 1999; Jørgensen, 2002, pp. 234-245) indicating greater levels of complexity and information required to analyze and describe ecological systems, one is faced with a tension and paradox that perhaps should be reflected upon at some point in the design and management of natural systems. Perhaps, these dilemmas can be addressed through scales of observations and deciding whether the intention and purpose of the parsimony is to decouple nature or synthesize a system model.

Reductionism and emergence are considered to be dichotomous: reductionists think that complex systems can be completely understood from their most fundamental elements and processes, whereas systems science and emergence suggests that the underlying organization of the system is at least as important as the constituent parts and processes. To advance this dialogue, we can consider the human brain as a complex system developed through billions of years of nature’s evolutionary engineering. Each human brain can be broken down into various parts; generally, each person has the same parts, and to some degree science understands the function of each part; thus, extrapolating from a reductionist, point of view, each person would then be the same, differing only in experiences. However, is this true? Does this explain why one person is outgoing while another is reserved, or why one person is musically talented and another a talented athlete? Does this point of view explain individual personality? What seems to be missing from the discussion is that though each person’s brain has the same general parts and billions if not trillions of connections, each brain part at the microscopic level articulates differently. Some connections genetically hardwire, and other connections develop in the first few years of life through various interactions with the physical world through sensory input and output. So, just as importantly as parts are the context and connections which give rise to emergent behaviors such as consciousness, personalities, and other traits of the human mind.
Thus, the contexts, which influence the connections and the patterns of organization, perhaps reflect more of the essence of the system than do the parts. Interestingly, current research to understand how the savant’s brain differs from the typical person uses induced magnetic fields near the skull. Preliminary research results indicate that targeted magnetic fields may temporarily “turn off” certain connections within the brain. Consequently, the brain’s circuitry temporarily rewires, and first results indicate more savant-like right hemisphere analytical skills and induced creative abilities in the volunteers (Snyder, 2009, p. 1399). As another example, there has long been a debate over the benefits of “open source code” versus “language code” at the highest levels of the computer and software industries. That is, a program compiled from languages based code is understandable to a programmer. However, when converted into machine code, it then becomes nearly impossible to reverse engineer and find the original program. Companies such as Microsoft only release their code in a compiled format so that reverse engineering is virtually impossible; that is, the machine code is nearly impenetrable because it lacks context of input parameters and language and thus could represent practically an immeasurable number of programs in various programming languages. In fact, without the context, even the developer often does not understand the program in its final form of 1’s and 0’s from the trillions of operations it may perform in response to a perhaps infinite number of input scenarios. That is, the meaning of the code is concealed in the code’s contextual language and in the code’s organization (http://nanobound.blogspot.com/2005/12/philosophy-in-science-reductionism.html. Web page retrieved: October 2008). This is somewhat analogous to just viewing nature as pieces and then trying to understand its ontology, meaning, and purpose. Thus, without the ecological context juxtaposed with the system’s organizational principles, nature too perhaps will remain as
significantly impenetrable and puzzling to science as machine code is without its organizational principles.

In summary, reduction is a scientific philosophy by which one tries to take often-large complex entities and reduce them to smaller isolated sets for the purposes of understanding. Reduction-based thinking focuses on the parts. However, reduction seems to be philosophically inadequate to describe the connected and relationship driven natural ecological systems that envelop humankind. On the other hand, holism focuses philosophically on the complete, contextual, systemic and ecological whole as well as the characteristics of the whole and its emergent properties in relationship to its environment (Capra, 1996, pp. 17-36); holism is therefore much more appropriate and promising as a scientific philosophy for the study of natural systems. However, many system components show scale related degrees of interdependent and independent aspects and behaviors; therefore, both reductionism and system science are likely requisite to fully understand nature. The current discussion implies that reduction as a scientific philosophy is perhaps very appropriate for the analysis and design of complicated mechanical systems but perhaps is equally inappropriate or insufficient for complex living systems management and design. Thus, a more thorough examination and comparison of mechanical systems and living systems is in order, which may substantiate that notion.

**Mechanical versus Living Systems**

A dialectical comparison of mechanical and ecological systems may serve further to inform the discussion of ecological design and management. From this comparison of machine and ecosystem, we may begin to infer whether mechanical analysis and design principles are appropriate for ecosystems or if a different paradigm is necessary. Mechanisms are human constructed and generally closed systems that are at or near steady state and increase in entropy
with time. Generally, these systems also tend toward the following characteristics: operational simplicity, decoupled, computable, rigid, transparent, often parallel, direct causalities, controllable, predictable, and the whole is the sum of the parts (Mikulecky, D.C., 2005a). The characteristic of operational simplicity refers to the tendency of human constructed systems to meet a set of parameters with the minimum effort, information and cost, etc. Generally, optimums are systems that achieve those goals, and systems that meet objectives outside of predetermined parameters and objectives are unnecessarily complex. Optimized mechanical systems are largely decoupled systems wherein functions of these systems generally operate independently decoupled from other functions (Suh, 1990, p. 48). This tends to minimize information, time and cost for construction and maintenance of the system while increasing predictability, reliability and minimizing unintended consequences. Mechanical systems are usually computable from an abstract mathematical model called a control element, considered elementary and homogeneous; the behavior of the control element under known conditions is computable and thus aptly leveraged into the design of safe and predictable systems. Thus, system boundaries of these designs must be rigid and remain closed to material and energy flows not accounted for in the control element (Gattie, Kellam & Turk, 2007, pp. 29-30). Mechanical systems are non-literally transparent, meaning that the purpose of the system, as are the purposes of the system constituents in relation to the system, is clear, unambiguous, directly deducible and computable. Mechanical systems often can be constructed, considered, and operated as parallel but unconnected processes. For example, in an assembly line system, the individual processes are designed and run in parallel and generally have no connectivity until assembled into a final product. Mechanical systems are generally complicated systems where cause and effect is largely directly determinable, thus making the system a superposition of the parts and their
functions. For example, the automobile and its ability to provide transportation services is
simplistically the additive assemblage of an energy source, plus an engine, plus a transmission,
plus a drive shaft, plus a differential, plus wheels equals motion. Further, this allows the system
construction within a certain tolerance of predictability, reliability and minimal unintended
consequences (at the scales of the system).

Living systems on the other hand are locally entropy reducing, self-organizing systems
that have moved far from thermodynamic equilibrium. They generally have the following unique
set of characteristics that tend to be inconsistent and paradoxical to mechanical systems:
*component coupling, intertwined, indirect and interdependent causal relationships, plastic,
intractability of computation, informational richness, emerging properties* that are not evidenced
1999; Jørgensen, 2002; Mikulecky, 2005a). Components of living systems tend to functionally
*couple*; for example, fungus on the tip of tree roots is necessary for the tree’s uptake of water and
nutrients, and the fungus is equally dependent on the tree root for its survival; thus, cause and
effect between the tree and the fungus is *intertwined* and *interdependent*. Ecological systems
have moldable or contextual *plastic boundaries* open to varying matter and energy flows. For
instance, if we consider Biscayne Bay, Florida or the Neuse River Estuary, North Carolina as
ecological systems, each is open to transfers of matter and energy from outside the system; for
example, a tropical storm or hurricane will cause each system to mold and conform itself to the
changing conditions imposed on it from the external environment. Hence, these aforementioned
characteristics (interdependence, plasticity etc) of ecological systems render a certain level of
intractability in the analytical computation of the system and its properties. Lastly, ecological
systems grow and develop, increasing their information content (Ulanowicz, 1990, 1997, 1999,
2001, 2004a, 2005; Jørgensen 2002, p. 245; Gattie, Kellam, & Turk, 2007, p. 29), and thus develop emergent properties not evidenced in the parts, such as dominance of indirect effects, homogenization, ascendency, etc. (Patten et al, 1976; Patten, 1981; Patten & Auble, 1981; Fath & Patten, 1999; Ulanowicz, 1990, 1997, 1999, 2001, 2004a. 2005; Gattie, Kellam, & Turk, 2007). Therefore, if we compare the list of mechanistic characteristics to the above list of living system characteristics, they tend to be diametric opposites. In fact, we can propose quoting Frank Golley that “Machines are not ecosystems and actually are poor representations of ecosystems” (Jørgensen & Müller, 2000, p. 31).

One of the beginning hints of insufficiency in a Newtonian view of the world, where force and mass were often primary and inherent in causal change, was suggested by von Uexüll (1926). Jacob von Uexküll was one of the first in biology to propose through the application of “function circles” that living systems are inherently semiotic entities that are able to perceive and affect their environment (Gattie et al., 2006, p. 196). Niels Bohr and Albert Einstein further reduced the applicability of the Newtonian view of the world with their works in quantum mechanics and relativity, thus rendering Newtonian mechanics precise only within a narrow range of scales. The work of Warren Weaver (1948) and Gerald Weinberg (1975) suggested that instead of Newtonian mechanics, appropriate ecosystem consideration is through the lens of a systems worldview (Gattie, Kellam, & Turk, 2007, p. 29). They proposed that ecological systems are neither machines nor are they aggregate. Aggregates refer to organized systems of individual parts that are similar in structure, function and composition. For example, a brick wall considered an aggregate would differ from what some would call a heap. In this case, a heap would be a random pile of the bricks (Lazlo, 2002. p. 25). Weaver and Weinberg though considered ecosystems as organized complex composites that are composed of various
subsystems where the function and composition of system and subsystems should not just reduce to an analysis of the parts (Gattie, Kellam & Turk, 2007, p. 28).

Further, Gattie, Kellam & Turk (2007, p. 37) summarized several diametrically contrasting characteristics of the Newtonian worldview employed in traditional engineering and science and the systems worldview of living systems suggested by Weaver and Weinberg among others. Those contrasting characteristics include: mechanical versus organic, closed versus open, objects and elements versus systems and subsystems, isolation versus connections and relationships, reduction versus synthesis and integration, control versus emergence and self-organization, prediction versus insight and understanding, functional decomposition versus relationally non-decomposable, control volume versus network environs, and increasing entropy versus ascendancy.

Causality: Direct versus Indirect

The following section references and builds on the works of Bunge (1979), Patten, Bosserman, Finn, & Cale, (1976), Rosen (1991) and others. This section discusses causality in various forms and proposes to map causality in terms of differing types of systems. Although in strict philosophical terms causality is quite difficult to adequately and fully explain, causality does in informal terms imply a necessary relationship between one event called a cause and a subsequent event called an effect where the effect is a clear consequence or result of the cause. Aristotle was one of the first in Western society to begin to characterize causality, and these discussions and descriptions have continued into present day literature (Ulanowicz, 1990; Gattie, Kellam, & Turk, 2007, p. 29; Falcon, 2011). For instance, cause and effect are often described in terms of events, but other descriptions are given in terms of processes, properties, variables, facts, and even state of affairs and to date there isn’t a universally accepted relationship in
academia. Further, recent theoretical developments of relativity and quantum mechanics and anticipatory systems have further “entangled” many of the propositions of causality such as antecedence, which assigns temporal priority to cause and a further “entanglement”, associated with the spatial concept of contiguity (Rosen, 1991, pp. 108-138; Mikulecky, 2005a). However, at human scales, causality in some form seems to remain a valid way to describe becoming (Patten, Bosserman, Finn, & Cale, 1976, pp. 459-471).

Causality according to Mario Bunge (1979, p. 3) is simultaneously a doctrine, a principle and a category. He writes that causation is the epistemological categorizing of cause into effect through the causal bond but also as an ontic characteristic of the universe which adheres to the fundamental principle that summarizes to “same causes, same effects”. He writes further that causality as a doctrine holds that these are the exclusively valid principles of determination (Patten, Bosserman, Finn, & Cale, 1976, pp. 459-460; Bunge, 1979, pp. 3-4).

The determinism doctrine is based on two principles: the principle of lawfulness and the genetic principle (Lucretius, ca 58 B.C.; Patten, Bosserman, Finn, Cale, 1976, p. 461) and may be stated as “Omne quod movetur ab alio movetor”, that is, “Everything is lawfully produced by something else and lawfully produces something else” (Aristotle 1930; Patten, Bosserman, Finn, & Cale, 1976, p. 461).

The meaning of determination has three facets that include the properties or characteristics of a thing as a necessary connection, relationship or association between things, and lastly as a lawful way of becoming. However, conceptually, these three facets of determination may take several forms of which causation is only one. The forms include quantitative self-determination, causal determination, interaction, mechanical determination, statistical determination, structural or holistic determination, teleological determination, and
dialectical determination (Bunge, 1979, pp. 17-20; Patten, Bosserman, Finn, & Cale, 1976, pp. 460-461). Quantitative determination refers to the continual successive unfolding of mathematical states; causal determination is the observation that a unique effect is caused by a unique external cause; interaction as determination by internal action; and mechanical determination as the combination of the previous three with matter and/or energy as the agent of determination. Statistical determination is determined by the joint action of multiple independent antecedents where often many of them are determined by other kinds of determination. Holistic determination suggests that the whole determines the parts and their behavior. Teleological determination is the determination by a goal function, and lastly dialectical determination is determination by or through the strife and/or eventual synthesis of opposites. As mentioned, dialectical comparisons are an often-employed strategic methodology of inference; this work perhaps will yield a dialectical determination toward a synthesis of the Newtonian philosophy of science and a systems philosophy of science, perhaps showing both as necessary but distinct management, integration and design tools for ecological systems.

Aristotle believed that each thing or event has more than one reason that explains what, why, and where it is. He recognized these as four categories of causes: the material cause, the matter out of which a thing is made, the efficient cause, the source of motion, generation or change, the formal cause, the essence or essential nature of the thing, and the final cause, the goal, or purpose of the thing. These four categories of causality seem to fit naturally with a state theoretical model of the causal bond where “Being is based on what has been” (Patten, Bosserman, Finn, & Cale, 1976, p. 465; Gattie, Kellam, & Turk, 2007, p.29).

The state concept is central to today’s systems theories wherein the state of a system is the link between its history and its future; it is a way or thing to transform cause into effect.
Zadeh’s (1969; Patten, Bosserman, Finn, & Cale, 1976, p. 465) state space systems theory is particularly applicable to ecological systems and is fundamental in Patten’s Network Environment Analysis (NEA) method for ecological networks.

Patten and others refer to the thing that transforms past to future or cause into effect as the *holon* (Koestler, 1967; Patten, Bosserman, Finn, & Cale, 1976, p. 466) which consists of two “sides”-- a *creaon* or the receptor side and the *genon* as the effector side, where the two sides in juxtaposition make up the causal bond (Patten, Bosserman, Finn & Cale, 1976). Zadeh’s (1969, Patten, Bosserman, Finn, & Cale, 1976, p. 465) state theory is an applicable way to permit the causal production of effects and has general properties for *holons* that allow this to occur. Those properties are closure under segmentation, covering, and closure under truncation, uniqueness, continuation, and nonanticipation, all of which are embodied in the concept of state (Patten, Bosserman, Finn, & Cale, 1976). State is the sufficient concept uniquely carrying causes into effects. The causes or inputs are received by the *holon’s* receiving side; the *creaon* and time is mapped into states by a mathematical state transition function where the *holon’s* output side acts on this function to map the inputs into outputs which may be juxtaposed as the holon’s response function. State-space theory provides an effective way to compute and describe an entity’s response to input. It is a way that mathematically describes an entity’s behavior to stimulus. That is, inputs received into state create a new state and produce a subsequent output. The response function and the state transition function mathematically constitute the makeup of the state space model of the causal bond where \( Z \) is input, \( X \) is state and \( Y \) is output.

\[
Z_t \times X_t \rightarrow Y_t \tag{2.1}
\]
\[
Z_{t+1} \times X_{t+1} \rightarrow Y_{t+1} \tag{2.2}
\]
State-space theory provides proven mathematics that may describe system behavior (Zadeh, 1969; Patten, Bosserman, Finn & Cale, 1976; Patten, 1981; Patten & Auble, 1981; Fath & Patten, 1999) where it takes serial sequences of causal bonds using the holon and its environment as reciprocal and inseparable pairs to investigate the propagation of cause within ecological networks. Thus, when receiving states that articulate to a next state, then the output of the first state becomes the input of the next and so on. Patten’s environ theory describes this as an input environ, which gives rise to a new state and a new output environ and in well-connected systems, the output can potentially cycle back around, at a later time reentering original components again as input. This mechanism is something that the biologist von Uexull (1926) described as function circles. Thus, this phenomenon of the generated output becoming the generating input of a system through feedback is a foundation of the co-evolutionary behavior of systems (Patten, Bosserman, Finn & Cale, 1976, p. 569; Patten, 1981; Patten & Auble, 1981; Fath & Patten, 1999, Gattie, et al., 2006). Thus, the structure and function of the system drives the system behavior where structure refers to relative network position and connections of system components and function refers to the type of conservative transfers through the system connections.

In terms of Aristotle’s four causes, efficient cause corresponds to exogenous input or endogenous coefficients of the system, the material cause corresponds to the conservative transfers of energy or matter of efficient cause, formal cause or the essential nature of a thing corresponds to state, and final cause corresponds to output, the teleological end, goal, or purpose. The endogenous coefficients and exogenous inputs of efficient cause in the form of serial dependency sequences known as causal chains have variable direct dependency of cause and effect. However, more significantly they show indirect cause and effect dependency of system
variables through the combinations of causal chains using the algebra of signal flow graph theory. Two important properties of signal flow graphs are the addition rule and the transmission rule. The addition rule states that a signal at a node is the algebraic sum at a node, and the transmission rule states that each outgoing branch operates upon the signal at a node independently. Therefore, by graph reduction, signal flow graphs of networks are always reducible to a canonical form consisting of only input and output nodes and the branches that connect them. The reduction consists of $n$ number of combined transmissions or transmittances representing the enfolded causal chain history of the network etc. Aristotle further suggested reciprocal or circular causality in the forms of mutual relationships of dependence, action or influence embedded within cause and effect. Today, ecological network analysis techniques have at their foundation, state-space theory and the combination of causal chains but quite importantly also include feedback through the use of graph theory to examine the canonical transmittances of networks, illustrating more explicitly the importance of this circular or indirect causality.

Furthermore, as philosophers and scientist have considered cause and effect over the centuries, some in the field of ecology have contemplated the implications and ramifications of cause and effect in their search for a general ecological systems theory, and some consider causality in terms of modern state space theory as a possible foundation for theories. State theory is the mathematical model of becoming (Zadeh, 1969; Patten, Bosserman, Finn & Cale, 1976, p. 470, pp. 567-576; Patten, 1981; Patten & Auble, 1981; Fath & Patten, 1999) where the mathematical syntax in the form of abstract differential equations may be understood though semantic interpretations. Thus, it is the interest and challenge of ecological systems science to uncover the perhaps subtle mathematical descriptions of the perceived order, harmony, and community observed in nature.
In comparing linear causation and closed causal loops, where causality is in the form of the casual bond, linear causation is a sequential chain of events or causes, which are tractable, and using the earlier description of the existence of complexity, the system is non-complex. On the other hand, closed causal loops are a form of causation that is non-linear, not easily or directly tractable (hence complex) where the non-linearity and complexity is due to causal feedback loops (indirect causality) within the system (Bunge, 1979; Patten, Bosserman, Finn & Cale, 1976; Patten, 1981; Patten & Auble, 1981; Fath & Patten, 1999).

The often universally employed linearity of causation was criticized by Bunge (1979, pp. 31-52) from which he differentiated several alternative types of causation: *simple causation, conjunctive multiple causation, disjunctive multiple causation*. Bunge suggests that simple causation, such as single cause $C$ maps to a single effect $E$, may also involve a set of finite causes ($C_i$) and a finite set of effects ($E_i$) where each set represents a bundle of independent non-interfering causal lines. This type of causality maps quite well to the *common simple systems* referred to and described in Chapter 1. Bunge (1979) went on to assert multiple causations or the plurality of causes and a diversity of effects that he distinguished into two categories. He argues that the conjunctive plurality of causes or *conjunctive multiple causation* is a type of causation that may be reducible to simple causations when the causal lines are discrete. That is, the effect(s) are additive from the simple causes which form an accumulated or superimposed effect. For example, causes $C_1 + C_2 \ldots \ldots C_n$ map discretely to effect $E$ where each cause $C$ may have its own weighting factor on the effect $E$. This type of causality appears to map to the *complicated systems* as described in Chapter 1. Further, Bunge identified the case where non-reciprocal relationships that exist in large numbers where there is a set of causes and a set of effects and the characteristic of linear causation is lost as variables become intermixed yielding
only to a non-causal statistical correlation. Though perhaps very tedious to implement, network analysis techniques may also show correlative effects of these relationships. Bunge also distinguished a second type of multiple causation or *disjunctive multiple causation* where separate distinguishable causes achieve the “same” effect. Bunge describes this as genuine multiple causation. This type of genuine multiple causation does not occur with joint causes but with alternative causes. The example he uses is that an effect heat may have several disjunctive causes such as friction, combustion, or nuclear reaction; although each may vary in intensity, each yields the same effect—heat. The obvious counter argument here is that the scale of observation is inadequate to distinguish differing causality and differing effects, though at certain scales disjunction seemingly exists. Further, he argues that multiple causation is not strictly causal and hence the linear causal chain ceases to be a general paradigm. That is, one cause equals several effects or multiple causes equal one effect. Therefore, Bunge seems to suggest three cases where the general paradigm of linear causation seems to be incomplete. Firstly, when the linear causal chain loses its meaning after a few branchings and secondly that disjunctive causation is non-additive where the joint action of causes each alone may cause the effect or vice versa. Lastly, as the number of causes reaches a certain level of complexity, it goes over into statistical correlation, particularly if the causes are of the same type and if intensities are of the same magnitude. These types of causation appear to map to the *complex independent systems* described in Chapter 1 (Bunge, 1979, pp. 31-52). However, in Bunge’s view, strict causality does not adhere to in these types of system. However, though seemingly very tedious or impractical, perhaps given sufficient time and instrumentation to move across temporal and spatial scales, a linear chain of causes is determinable for these types of systems. Note that ecological systems do not fall into any types of causality mentioned above. This is because as *complex interdependent*...
systems, ecological systems are non-linear and dynamic; hence, they do not sufficiently map to a static step-by-step chain of linear causation. Modern general systems theories have shown that the state of a system is a connection between the system’s past and its future and further that state plays a role in transforming cause into effect. Systems as a collection of interacting or interdependent objects lend themselves to analyses using the causal bond and state diagrams. Zadeh’s (1969) state based theory lends itself particularly well to ecological systems and as mentioned is a foundation of Patten’s Network Environ Analysis (Zadah & Desoer, 1963; Zadeh, 1969; Patten, Bosserman, Finn & Cale, 1976; Patten, 1981; Patten & Auble, 1981; Fath & Patten, 1999). Hutchinson first suggested the concept of circular causality in ecological systems from his observations of biochemical cycling within ecological systems (Hutchinson, 1948; Patten, Bosserman, Finn, & Cale, 1976, p. 494; Patten, 1981; Patten & Auble, 1981; Fath & Patten, 1999), and much research since has shown this to be true through the analyses of nutrients cycling within ecosystems. Patten, Bosserman, Finn, & Cale (1976) with this information coupled with theorems of Zadeh’s (1969) state based theory proposed, “The state variables of ecosystems are all mutually dependent and thus subject to the same set of causes” (p. 494). Called the property of causal closure, that is, “every system variable that is a parameter is an element of the sequential dependency set of every state or output variable and every output is sequentially dependent upon every state variable and parameter”. The complex interdependent systems described in Chapter 1 map to this type of causality. Thus, we begin to note a distinguishable causal difference between common simple, complicated and complex independent systems versus complex interdependent systems, and that difference is the general direct causality experienced by the former versus the additional subtle indirect causality experienced by the latter.
In addition, Patten and others through systems theories based on state and graph theory have also addressed the difficulties of cause losing its meaning after several branchings. That is using a system analysis that allows the parsing out of individual constituents from the composite flows of matter or energy through ecological networks (Patten, Bosserman, Finn, & Cale, 1976; Patten, 1981; Patten & Auble, 1981; Fath & Patten, 1999). For example, Gattie, Schramski & Bata (2007) were able to parse out microdynamic flows within an ecological network of composite flows. An interesting accusation against linear causation by Bunge deals with continuity or the sometimes lack of it. Bunge (1979, pp. 58, 85, 137) considers continuity a hypothesis with a limited but still wide range of validity and describes cases that refute universal continuity including instability, quantitative discontinuity, and qualitative discontinuity. Stable states provide many examples of continuity where small causes map to small effects; however, in unstable states small perturbations may lead to dramatic changes of state or even a range of states as shown in chaos theory. Thus, the cause or perturbation is a trigger only to a process that the cause does not control. An example of this includes the “butterfly effect,” or another example would be nonlinear oscillators where systems driven at natural frequencies begin to oscillate at dramatically increased amplitudes. Therefore, instabilities occur even in classical physics often and perhaps even more so at quantum levels where at this scale physical discontinuities may occur regularly; however, at human scales there is often a perception of continuity. Quantitative discontinuities occur when the effect is not a continuous function of cause over the whole range of the variable. For example, Bunge describes a function of this type as \( \tan y \) where at certain critical values the sign changes suddenly (1979, p. 142). However, mathematical discontinuities often arise in engineering mechanics; for example, when constructing shear and bending moment diagrams the function may abruptly jump or is discontinuous at certain locations. However, the
reason in this case for the mathematical discontinuity is that physically there is a point load applied at the location of the discontinuity. **Qualitative discontinuities** also seem to appear in nature; otherwise, categorization would be impossible (Bunge, 1979, pp. 141-143). The fossil record though indicating a gradual evolution from simple to complex species over time indicates many abrupt changes often through a process known as punctuated equilibrium.

Thermodynamically Prigogine and others (Prigogine, 1972; Nicolis & Babloyantz, 1972; Prigogine & Stengers, 1984, Gattie, Kellam, & Turk, 2007, p. 32) would perhaps describe discontinuities as bifurcation points. In terms of ecological systems, many may describe qualitative discontinuities as the emerging properties of the system or that the system is more than the sum of its constituent characteristics. These emerging new levels to date block our abilities to completely track continuously back to cause. However, ecological network analyses may allow the description of trends associated with discontinuities. Bohm in his “implicate order” view of existence would view these properties, bifurcations, and discontinuities even at the quantum level as embedded but to date hidden in the system waiting and only waiting for the correct conditions to occur (Bohm, 1980; Jørgensen, 2002, p. 26; Patten, in progress).

Though linear causality in its current form may work for many situations, it should not be a universal method to determine cause and effect. The determination of cause has been improved in ecological systems through the use of systems theory and particularly through ecological network analyses where, in addition to direct causes, circularity or the propagation of indirect causes may be traced by unfolding network transmittances and tracing feedback loops (Patten, Bosserman, Finn & Cale, 1976. pp. 564-576; Patten, 1981; Patten & Auble, 1981; Fath & Patten, 1999).
It is the consideration of this work that the use of state based theory and graph theory, coupled with causal feedback loops will enable one explicitly to more adequately uncover temporally and spatially distal causes for interdependent ecological systems. This is true even more so than stochastic methods, in that stochasticism may only assert correlation, not cause. Although correlation and cause are connected, and correlation does suggest cause, it does not explicitly demonstrate it as network analysis methods may. For example, in the realm of engineering design, particularly in terms of “mechanistic systems”, and explicitly to avoid unintended consequences, employment of constrained distal causality maximizes control of systems. (See Table 2.1).

Table 2.1. The mapping of causality to system type.

<table>
<thead>
<tr>
<th>(Possible Component Action)</th>
<th>Common Simple</th>
<th>Complicated</th>
<th>Complex Independent</th>
<th>Complex Interdependent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interact</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Integrate (Physical)</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Integrate (Functional)</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Independent</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Interdependent</td>
<td></td>
<td></td>
<td></td>
<td>✓</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>(System Characteristic)</th>
<th>Common Simple</th>
<th>Complicated</th>
<th>Complex Independent</th>
<th>Complex Interdependent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parts</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Pattern</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Process</td>
<td></td>
<td></td>
<td></td>
<td>✓</td>
</tr>
<tr>
<td>Plasticity</td>
<td></td>
<td></td>
<td></td>
<td>✓</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>(Linear/Direct Causation)</th>
<th>Common Simple</th>
<th>Complicated</th>
<th>Complex Independent</th>
<th>Complex Interdependent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simple</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Conjunctive Multiple</td>
<td></td>
<td></td>
<td></td>
<td>✓</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>(Non-Linear Direct Causation)</th>
<th>Common Simple</th>
<th>Complicated</th>
<th>Complex Independent</th>
<th>Complex Interdependent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Disjunctive Multiple</td>
<td></td>
<td></td>
<td></td>
<td>✓</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>(Non-Linear Indirect Causation)</th>
<th>Common Simple</th>
<th>Complicated</th>
<th>Complex Independent</th>
<th>Complex Interdependent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Circular</td>
<td></td>
<td></td>
<td></td>
<td>✓</td>
</tr>
</tbody>
</table>

This is realized often through the functional and relational uncoupling of system component functions to optimally consider and work exclusively (at least on human scales) with direct causes to effects. Dialectically disparate to mechanical systems, living systems operate where the components often are functionally and relationally coupled to the advantage of the system in which they are embedded. Further, causality at a distance, indirect causality, and non-linearity
appear not only plausible in these systems but seem to be the norm (Patten, Bosserman, Finn & Cale, 1976, p. 564-576; Patten, 1981; Patten & Auble, 1981; Fath & Patten, 1999).

Engineering design, though long familiar with control elements and feedback loops within the element, has failed to recognize or perhaps chosen not to consider that our control elements are not entirely isolated systems. They are at best spatially and temporally scale dependent closed systems or in some cases, open systems. Often engineering design has not fully recognized the indirect effects or circular causality of our work in that even our best-closed system control elements couple causally into the environment in sometimes direct and most certainly in indirect ways. Further, as our designs are also components in a larger environmental system, they are coupling into the function circles of the environment, establishing feedback loops that may be serving to amplify and distribute the effects across the biosphere. This is perhaps the most compelling reason that the new fields of study, such as ecological engineering, should leverage the system sciences into the design process to begin mitigating these potentially non-innocuous effects which are often manifest out of the purview of routine human spatial and temporal observations.

Efficient Cause: Open versus Closed Causality

Ulanowicz (1990, 1999; Gattie, Kellam, & Turk, p. 29), based on an apparent insufficiency in the Newtonian view of the world for ecological systems, proposed that Aristotle’s formal, material, efficient, and final causes be revisited to rethink formal cause and readmit final causality back into the scientific discussion. Gattie, Kellam & Turk (2007, p.29) discussed Aristotle’s causes in terms of the emerging field of ecological engineering where within traditional engineering efficient cause is directed by the Newtonian view of the world, one that considers nature to be machine like and thus subject to the scientific method and traditional
engineering design methods based on the reduction of wholes to parts and vice versa. Thus, efficient cause of design directly driven by the needs and desires of human society seeks to implement solutions to those wants through engineering. They go on to suggest that within this paradigm natural resources map to Aristotle’s material cause and that formal cause is the use and rearrangement of those matter and energy resources to meet the perceived needs of society. Thus, society within this human centered paradigm of nature is the agent of final cause. In meeting a need of human society, a mechanistic solution to that need may be designed and constructed where each of the four Aristotelian causes is discrete and the first three causes sufficiently answered by the question “how?” and the last, the final cause answered by the question “why?”, that is, to meet a human need. However, complex systems including ecological systems behave in ways that substantially differ from mechanistic systems. The four causes for complex systems are no longer discrete but intertwined (Rosen, 1991; Mikulecky, 2005a) and thus significantly the question “why?” is entailed in all four causes and this is perhaps the fundamental philosophical insufficiency of reductionism for complex interdependent systems. Robert Rosen (1991, pp. 108-138) suggested that final cause for complex living systems connotes anticipation based on the sensing, modeling of their environment, and using this model of environment to make relatively open-ended adjustments in their behavior for current and anticipated events, what can be called the plasticity of ecological systems. Certainly, this is a distinguishing characteristic from mechanistic systems. Further, this anticipatory characteristic suggests that causality in a way has a both a forward and backward temporal directionality for anticipatory systems. Rosen (1991, pp. 244-252) further suggests that relational descriptions of machines are inherently different from organisms in that they are direct sums of disjoint states, whereas organisms are not direct sums and that in fact direct summation for organisms is not even
available, thus reflecting the non-fractional essence of components of an organism. He writes that machines are disadvantaged by the entailment of organisms in two ways: firstly, the complete segregation of causal entailment into distinct direct sums but even more importantly the absence of closed chains of efficient causation. This is similar to what Patten and others may refer to as function circles, circular causation and indirect effects (Patten, Bosserman, Finn, & Cale, 1976; Patten, 1981; Patten & Auble, 1981; Fath & Patten, 1999). Thus, for machines, efficient causation is open and tied with the final cause of something outside the machine, which is as Voltaire (Shank, 2010) said, “a clock argues a clock maker” (Paley, 1802). Living systems, however, with their closed chains of efficient causation, differ in that final cause embeds within the system and its self-organizing characteristics. Thus, ecological systems being closed to efficient cause seemingly do not require a clockmaker but are entities that create over significant temporal scales their own parts, processes, patterns and as living and thus anticipatory systems have the additional ability to continually mold plastically to their contextual dynamic environment.

Discussion

The methodology to further the qualitative need for new strategies, methods and ways of thinking in the design and management of natural systems poses dialectical questions related to a systems view of humankind’s role as the only known ecosystem component with awareness of his place in the system. As the only known form of intelligence with this capacity, what are the ramifications and implications of the human species embedded within and perhaps transcending the local and natural environment? What role should we play in the grand scheme? Is the human species a tangential fluke of nature trying to maximize our exploitation of the world’s natural capital soon to be selected against by nature’s protective and optimizing principles?
Alternatively, are we as a species just in a rebellious exploitative adolescent stage but still the product of nature’s long ascendant evolutionary wisdom and self-organizing principles? Perhaps nature’s purpose for our complex organization is ironically for ensuring the survival of life and a biosphere. Our advances in technology may spread life and spare the planet’s biosphere from future cataclysmic events. Alternatively, our technology could almost certainly extinguish it today. Futurists suggest that the coming century will be critical; will we transition from what they call a \textit{type 0 civilization} depending on indirect energy sources to a \textit{type 1 civilization} with more direct access and control of energy sources (Karadashev, 1963, p. 217; Lemarchand, 1992) or will our adolescent behaviors destroy us? One could perhaps make either case effectively as our technologies may have the potential to destroy or save the planet’s biosphere from cataclysm.

This section posed several dialectical lines of thought, such as, direct versus indirect causality, open versus closed causation, mechanism versus living systems, and reductionism versus system thinking in the quest to find direction for the design and management of ecological systems. Other useful comparisons might include a discussion of equilibrium thermodynamics versus non-equilibrium thermodynamics. Closed to both energy and matter transfers isolated thermodynamic systems differ from closed thermodynamic systems, which are open to energy transfers only. Both types follow the second law of thermodynamics: where total entropy increases, the state of the system tends to disorder and the systems tend toward thermodynamic equilibrium. In contrast, open systems are systems which are open to matter and energy exchanges at the system boundary where these systems may be described by levels of energy dissipation which increase the system’s distance from thermodynamic equilibrium and allow/prescribe greater system organization (Kay, 1990). A comparison of axiomatic mechanical
design versus self-organization suggests further clarity in the design and management of ecological systems where the axiomatic design process seeks to simplify and standardize the design process for systems. In so doing, the process has two main axioms: the *independence axiom* and the *information axiom* (Suh, 1990, p. 48). The intent, based on reductionism, of the *independence axiom* is to uncouple the functional requirements of the system whenever possible. The results are simpler, more transparent and controllable designs. Similarly, the *information axiom* seeks to minimize the information required to complete a design and likewise reduces the complexity of the resulting design while minimizing unintended consequences as the requisite information is reduced (Suh, 1990). Self-organization, on the other hand, seems the antithesis of axiomatic design because self-organizing systems are highly coupled, information rich systems that have prolific and intertwined and interdependent functional and relational causal bonds in which reduction is inadequate to describe (Mikulecky, 2005a). Examinations of both thermodynamics and axiomatic design will occur in more detail in later chapters. Another dialectical comparison concerns environmental engineering versus deep ecology, which readers may wish to consider. Generally, environmental engineering is a traditional engineering discipline based on a mechanistic view of the world. Often, environmental engineering is reactive and seeks to ameliorate human induced problems in the environment with a temporally relative symptom alleviating solution. The intention is not a criticism in that symptoms of a problem often need addressing. However, deep ecology implies non-superficial ways to examine problems from a holistic, systems or “Gaia-like” perspective, seeking to find solutions to problems at causality’s root and thus eliminate all its potential symptoms.

Gattie, Kellam & Turk (2007, p. 37) identified several contrasting characteristics of the Newtonian worldview employed in traditional engineering and science to the systems worldview
of living systems suggested by Weaver and Weinberg and others. Those contrasting characteristics include: mechanical versus organic, closed versus open, objects and elements versus systems and subsystems, isolation versus connections and relationships, reduction versus synthesis and integration, control versus emergence and self-organization, prediction versus insight and understanding, functional decomposition versus relationally non-decomposable, control volumes versus network environs, and increasing entropy versus ascendancy among others.

The holistic management and design of ecological systems may support and help facilitate a transition to a type 1 civilization, but it is still somewhat nebulous and in the beginning phases of a solidification process. Thus, it is imperative to build consensus, add clarity through comparisons, and increase standardization from “First Principles”. The foundation should be a philosophical underpinning that serves as the theoretical framework by which further principles may be overlaid. Needed is a scientific philosophy that suggests and elucidates a qualitative and quantitative paradigm augmentation and shift allowing the design and management of ecological systems to reach its full potential? Various dialectical inquiries and comparisons were employed to highlight the need for new and different methods, ways of thinking and strategizing in the design and management of natural systems suggesting a necessary philosophical shift that accomplishes those goals? The necessary shift materializes within systems science. This argument for systems science is not new to this work; many in various fields of science and primarily within the science of ecology have presented compelling arguments for the system sciences. However, a holistic systems view of the world is relatively new to engineering, which has principally based its analyses, designs and constructions on a reducible and controllable view of the world. Though I have often been critical here of a
Newtonian view of the world, it should be acknowledged for its great accomplishments and benefits to the human condition; however, it should not be the singular paradigm; its boundaries should be demarcated, and those boundaries should not be exceeded. Comparisons of mechanical systems and ecological systems show that they are fundamentally and inherently different and in many ways, they are ontological and epistemological opposites. Thus, the philosophies and scientific methods of Descartes, Bacon and Newton are perhaps sufficiently complete for mechanical systems but are insufficient for a complete holistic descriptions and analyses of living systems. Therefore, they are equally insufficient in the management and design of ecological systems.
CHAPTER 3
SYSTEMS SCIENCE: THE SIGNIFICANCE OF ECOLOGICAL THEORIES AND NETWORK ANALYSES

Introduction

Gattie, Kellam & Turk (2007, p. 31) suggest four areas of research and study, that are most applicable as a foundation for the young discipline of ecological engineering in developing parameters to manage ecological systems. The four areas are systems ecology theories including 1) environ, ascendency, exergy, and emergy; 2) ecological network analyses; 3) ecological modeling; and 4) systems science. In this chapter, several of these areas will be examined, seeking out their relevance to the understanding, management and planning of ecological systems. Although the Ionians were perhaps the first known to have considered systems and wholes in western society, Fredric Clements (1916), Jan Christian Smuts (1926) and Jacob von Uexkull (1926) were some of the first in the modern era to do so. Later, E.P. Odum (1969) suggested that energy flows within the system facilitated ecosystem development, and his brother H.T. Odum (1983, 1996) developed a solar-based energy valuation system for energy quality in ecosystems. In 1978, Patten put forth a systems approach to environment, and Ulanowicz (1980) proposed concepts of ascendancy, autocatalysis and average mutual information in ecological systems. Jørgensen and Mejer (1979) and Jørgensen (1992) expanded thermodynamic theories of ecological systems with the development of ecoexergy (Gattie, Kellam & Turk, 2007, pp. 32-33). According to Gattie, Kellam & Turk (2007, pp. 31-32),
systems theory and systems science began to surface more in the mainstream of science in the mid-1990s as insufficiencies in some areas of science became evident. However, they suggest that academic and scholarly institutions where discipline specific individuals, often with similar backgrounds and perspectives, are located in isolated departments and thus find it difficult to break the mold of reductionism and address the holistic nature of systems in an interdisciplinary fashion. Referencing Banathy and Jenlink (2004), they further state that systems sciences were a response to the inadequacies of the fragmented science disciplines to deal with complex issues facing human society; the system sciences facilitate the exploration of general laws, principles and properties of self-organizing complex systems. They suggest that founders of the system sciences including Ludwig von Bertalanffy, William Ross Ashby, Margaret Mead, Gregory Bateson, Jay Forrester, Kenneth Boulding, Anatol Rapoport, James Grier Miller, Ralph Gerard and George Klir laid a foundation of systems science of ecosystems with properties and characteristics including complexity, emergence, holism, hierarchy and information.

Generally, the study of systems as a collection of articulated constituents using the general analytical tools of network analysis often uncovers and quantifies direct and indirect effects, among other properties within systems. The analysis at its foundation is based on conservative transactions of a common currency that passes through the interconnected system constituents. Ecological Network Analysis (ENA) techniques provide methods to uncover subtle interdependencies of complex natural systems and use a currency, such as matter or energy to track flows within systems. Methods of ENA include Network Thermodynamics, Ascendancy, and Network Environ Analysis, among others. Network Environ Analysis (NEA) is an environmental application of Liontief’s economic input-output method, which uses a currency of matter or energy, and provides a general analytical tool to study objects as part of a
connected system. It has the ability to investigate and map ecosystems as individual compartments within a connected system, thus providing a method to understand the connectedness of nature and to uncover various system properties including cycling index, total throughput, turnover time and rate, and often-relational interactions between components within the system. Using graph theory, the methodology allows the parsing of effects revealing direct and indirect quantities, furthering both the quantitative and qualitative understanding of the system. For example, the qualitative precision of NEA reveals the dominance of indirect effects in many natural systems. That is, in highly cyclic ecological networks, indirect effects, which are those separated by a path length greater than one, rapidly begin to outweigh the direct effects of singular path lengths. NEA also reveals other hidden system properties, including synergy, unfolding, homogenization, trophic dynamics, and amplification (Patten & Auble, 1981; Patten et al., 1989; Whipple & Patten, 1993; Fath & Patten, 1999; Fath & Patten, 2001; Ulanowicz et al., 2006; Gattie, Kellam & Turk, 2007, pp. 32-33). Implementing NEA and other analysis techniques that retain system connectedness reveals patterns as mathematical trends that correspond to subtle physical realities and the essence of interdependent complex natural systems. This chapter briefly reviews network thermodynamics, ascendency and network environ analysis in the context of system sciences and their applicability in the design and management of natural systems.

**Mathematical Patterns and Trends**

Before examining network analysis techniques, a discussion and reflection on the mathematical trends and patterns observed in the mathematical analysis of ecological networks is needed to frame and clarify their significance. Do the trends actually exist; are they “rightly viewed,” as Bertrand Russell implies, or are they artifacts and inventions of the human mind? In
general, the implications of mathematical patterns and trends are in many ways central to the philosophical debate of mathematics. This philosophy often questions, debates and reflects on the implications, assumptions, foundations, and significance of mathematics. First, however, a discussion of the nature of mathematics is in order. Wigner (1960, p. 2) writes, “Mathematics is the science of skillful operations with concepts and rules invented just for this purpose” where the principal emphasis is on the invention of the concepts. According to Sarukkai (2005), Wigner has ignored some important contributions of philosophy to mathematics. Where Wigner’s view seemingly stresses the importance of rules created through and by human activity, Sarukkai goes on to imply that Wigner, with a view of mathematics as driven by rules, is a cause of his analysis of its "unreasonable effectiveness" in his paper “The Unreasonable Effectiveness of Mathematics in the Natural Sciences”. Where Wigner (1960, p. 2) writes that the cryptic effectiveness of mathematics, guided by rules and influenced as humans by beauty and elegance maps correctly the descriptions and mechanisms of nature, Sarukkai (2005, p. 416) suggests that Wigner though right in his characterization of mathematics is incomplete.

Historically, western philosophies of mathematics originated with the ancient Greeks; Plato, for example, significantly influenced by the Pythagoreans, was interested in the ontological status of mathematical objects. The Greek philosopher Aristotle was concerned with issues related to infinity and logic. Later, Gottfried Leibniz shifted the philosophical debate forward to the relationships between mathematics and logic, and this view dominated until the late 19th and early 20th centuries, where the dominant philosophical interests became formal logic, set theory. Three schools of thought arose in the 20th century: Formalism, Intuitionism, and Logicism. During this time, questioning of fundamental axioms such as those of Euclid gave rise to Hilbert’s Metamathematics. The middle of the 20th century saw the emergence of category
theory as the natural mathematical language; however, toward the end of the century, opinions began again to differ, and the philosophy today tracks along several different lines of thought and inquiry. These include mathematical realism, intuitionism, constructivism, fictionalism, and embodied mind theories, among other traditional and non-traditional categories (Horsten, 2012; Sarukkai, 2005, pp. 416-417). The realists hold that mathematical entities exist independently of the human mind and emphasize mathematical discovery, not invention; for example, the realists hold that things such as geometric entities exist independently of the mind’s perception. Both Gödel and Erdős considered themselves mathematical realists, and several variations of mathematical realism exist today, ranging from Platonism to Logicism, Empiricism, and Formalism. Though each is unique, central to each is a view that mathematical entities exist independent of human perception.

The alternative views, Intuitionism, Constructivism, Fictionalism, and Embodied Mind Theories, hold that all mathematical truths are experienced (Horsten, 2012; Sarukkai, 2005). Sarukkai in a 2005 paper discussed several of the major mathematical philosophies, such as Platonism, that originate with Plato and are perhaps the dominant realist views of mathematics. The Platonists view mathematical entities and relations as independent entities wherein the reality of a world explains the universality of mathematical truth (Sarukkai, 2005, pp. 416-417). Although, seemingly popular with many mathematicians and scientists, Platonism does not adequately explain how these platonic non-spatial or temporal entities relate and map to the spatial and temporal physical world.

Another significant view in mathematics, Logicism suggests that logical arguments permeate the structure and validity of arguments and reduces mathematics generally and completely into deductive reasoning statements (Sarukkai, 2005, pp. 416-417). Thus, many
philosophers and logicians feel that all mathematical concepts reduce or derive purely from laws of logic. However, others suggest that the role of choice or the axiom of infinity and its incompatibility with set theory suggests flaws or anomalies within this viewpoint. Formalism, another prominent view of mathematics, which is largely associated with David Hilbert and German mathematics, suggests that rules and the formal manipulations of symbols and terms according to the rules are the essence of mathematics. Further, there are no meanings attached to the objects of mathematics, operations, or the equations above the formal manipulations (Sarukkai, 2005). The example that Sarukkai (2005, p. 417) discusses is that mathematics for the formalists is analogous to the game of chess having objects (e.g., pawns, bishops, kings) and rules of movement and that the formalists would argue that mathematics, like chess, has no meaning outside the game. However, Sarukkai goes on to state that the formalists’ problem is in accepting math as just a game; its applicability to the sciences, then, would appear to be, at best, completely arbitrary. If this were the case, why then is chess not equally applicable to the natural world? He writes further that another significant viewpoint, largely influenced by French mathematics, including the mathematician Brouwer, Intuitionism holds that mathematics is created, not discovered, and accepts the ideas of philosopher Immanuel Kant that involve ideas of intuition and a priori truth of mathematics in that mathematical entities are similar to physical entities. According to Sarukkai (2005, p. 417), Gödel suggests, “that we can perceive mathematical objects like sets in a manner similar to our perception of objects in our world”. Further, “this is an intriguing way of understanding perception; namely, perception of something is not the reason for it being true, but recognizing the truth of something actually suggests its perceptibility”. Sakrkkai (2005) suggests critics, though, would find intuitionism counter-
intuitive concerning the general understanding of perception; further, intuitionists find concepts of the infinite awkward and problematic.

Others consider mathematics a language and therefore a product of human imagination to describe our physical world so that examining the relations between the world, humans, and mathematics occurs in varying ways (Sarukkai, 2005, p. 417).

Thus, it all seems to suggest there are perhaps no simple and pithy answers to the question, what is mathematics? Galileo was one of the first to combine mathematics with experimentation, and that differentiated him from previous natural philosophers. Galileo believed that correct discernment of phenomena occurs through the application of mathematics. Sarukkai (2005) discusses Galileo’s mathematics as one of number sequences where he discovered, for example, through critical observation that the distance travelled by a free falling object is proportional to the square of the time of the fall. Without knowing any physical laws or complex mathematics, he noted by observation a pattern that the distance fallen is in multiples of 4.9. Thus, a pattern of free fall motion was discernible through observation and measurement of a certain parameter distance, but the pattern itself was not discernible until the combination of both the observation and measurement. Further, this application played an important role in Newton’s formulation of the gravitational force law; that is, observation and measurement of certain parameters led to the mathematization of the phenomenon (Sarukkai, 2005, pp. 417-418). Sarukkai suggests that the numbers alone were not enough for Newton to mathematize the problem; he also needed an appropriate set of operations. Further, Sarukkai asks whether we would have better descriptions of nature if discovery of new operations or numbers took place. For instance, Newton also needed the concepts of force, mass and acceleration to mathematize the Second Law of Motion, but describing the acceleration as the second derivative of position.
came only after the physical intuition of acceleration as a physical property of movement. Thus, according to Sarukkai, Wigner’s (1960) “miracle” in his paper discussing the mysterious unreasonable effectiveness of mathematics, was in this case not Newton’s use of second derivative but the discovery of the physical concept of acceleration. Contributing further to the mystery though, Sarukkai (2005, pp. 418-419) suggests that scientists often stumble upon a mathematical idea that appropriately describes a physical concept only to find that mathematicians have derived the concept previously. Sarukkai describes several instances of this phenomenon ranging from complex numbers and functions in the formulation of Hilbert space and their application in quantum mechanics to Newton’s law of motion based on sparse observation and that it contained the non-intuitive idea of the second derivative. The heart of the question for ecological engineering regarding mathematical trends and patterns observed in Ecological Network Analyses concerns their reality or invention and whether the question is itself significant.

A mathematical realism seems to be the more widely held view today. However, an important argument here is that mathematical concepts are not accidentally useful but are necessary in the sense that they are the “correct language” of nature (Sarukkai, 2005, p. 419). Sarukkai believes that mathematics is a product of human creation through our interaction with the world, and he infers that nature catalyses mathematical ideas and concepts. Though he believes that not every mathematical entity or operation connects to our activities, it does imply that the world of mathematics and the physical world are not far removed. Further, he goes on to suggest that the relationships between the natural world, humans and mathematics may be analyzed in different ways, suggesting that the world of mathematics and the physical world are not different worlds but one and the same. He further implies that there are two general ways of
describing nature: through language and through idealized models, suggesting that models and
language provide a way to mediate between nature and mathematics.

For example, he describes Newton’s Second Law of Motion (F=ma), which was
originally written by Newton in this way: “The change in motion is proportional to the motive
force impressed; and is made in the direction of the right line in which that force is impressed”
(Sarukkai, 2005, p. 419; Smith, 2008). Sarukkai (2005) suggests that F=ma is just the shorthand
for this longer linguistic statement by Newton, that force, mass, and acceleration are physical
ideas, not mathematical ones, and that Newton’s genius was in relating the physical ideas first
before mathematizing them. Thus, the mystery in Wigner’s (1960) unreasonable effectiveness
was not the relations of the physical but the accuracy and precision of coupling the non-intuitive
mathematics of the second derivative to the physical concepts. Sarukkai (2005, p. 417, 419)
would argue therefore that mathematics, including its symbolizations, applies to a language
describing nature and not to nature itself; in addition, mathematization is the application of
mathematics to idealized models where the accurate correspondence of the mathematical to the
physical is not immediate but a refinement process that over time settles to a stable type of
description. He goes on to imply that the available mathematics today is much larger than the
applications for it and that this surplus perhaps models the universe in ways that are different and
possibly contradictory to our physical universe, suggesting that mathematics may be indifferent
to realities. However, this work tends to disagree in part, though Gödel’s Incompleteness
Theorems imply that we can never find an all-encompassing mathematical system, which is able
to prove all mathematical truths, but no falsehoods. That is, if an axiomatic system proves to be
consistent and complete from within itself, then it is then incomplete, suggesting that we can
never completely mathematically describe a mathematical theory until we are able
mathematically to move outside the theory. Nevertheless, it does not preclude the human imagination mathematically moving outside of the phenomenon; thus, perhaps the great variety of mathematics today, which seems to have to no connection to our physical universe, has application outside the universe we perceive. String and M-Theory imply many and perhaps an infinite number of universes known as the multi-verse existing in ten dimensions. Many physicists believe the multi-verse contains four levels of universes where the level four universes behave with completely different physical laws (Tegmark, 2003, p. 1). If true, this may imply that the overabundance of mathematics available compared to observable physical reality today suggests a transcendence of mathematics beyond the known universe. Currently, experiments designed for the Large Hadron Collider (LHC) and the observations of what has been termed *dark flow* may begin to substantiate empirically the existence of other dimensions and a multi-verse.

Whatever future discovery may hold for mathematics and its philosophies, as scientists and engineers today we must be diligent to ensure that the mathematics we employ is appropriate to phenomena we describe. This becomes more difficult as we aspire to describe and even design complex systems where clear linear causation muddles in the circular complexity of the system. However, a person with a systems view might look at the current mathematical conundrums and suggest finding the answer to the paradox of discovery versus invention of mathematics within the framework of scale and duality; that is, perhaps both discovery and invention of mathematics happens. Duality appears to be one of the emerging threads in this work; for instance, in addition to the wave–particle and space–time duality seen in nature, other dualities seem to exist, such as reduction and emergence (synthesis/integration), independence and interdependence, mechanism and ecosystem, macro-scale and micro-scale, and now perhaps the duality of perception and
reality (discovery). Ulanowicz (1986) similarly noted several dialectical tensions, including growth versus development, input versus output, and size versus organization, the Yin and Yang as Jørgensen (2002, p. 248) suggests. Thus, in a complex systems analogy, components of a system articulate at fine scales with other components of the system to give rise to large-scale system level properties. Current thinking suggests that extremely small vibrating trans-universal, trans-dimensional strings and “branes” are the fundamental units or components of the universe(s). Research implies that these strings and “branes” may articulate back to themselves (self-loop) and to other strings/branes, thus suggesting that the corresponding connections and various modes of vibration give rise to the physicality of our universe(s) as a membrane(s) in ten dimensions. If so, this seems to suggest that there would be system patterns and thus rules by which strings articulate, which might give rise to the differing modes of vibration and subsequently differing physical objects at larger scales. It is unclear whether those logical rules would be binary or tertiary; would fall within set theory, category theory, or something yet unknown; or whether they are deterministic and/or probabilistic. However, connected or coupled components with rules of articulation may form a structured and functionally complex system. Complex systems at larger scales develop systemic characteristics or emerging properties, possibly as the macro-scale physical structures found within the universe. Furthermore, just as we observe and perceive the larger scale emergence of physical entities from the various superstring articulations and modes of vibrations such as stars, galaxies, and life itself at large scales, perhaps the fine scale rules of superstring articulation have larger scale emergent mathematical forms that the human mind may epistemologically observe and perceive (e.g., geometry, trigonometry, calculus, etc.). That is, the human mind perhaps perceives at larger scales emergent mathematical forms of the fine scale fundamental logic of superstring
relationships and/or perhaps invents descriptions to describe those emergent forms. Thus, are mathematical discovery and/or its invention potentially two sides of the same coin?

Some would argue the same foundational organization principles likely have given rise to the physical universe as well as less tangible concepts such as thought and mathematics. Thus, as the mind may independently invent mathematical patterns of organization, the abilities of the mind are but in many ways the emergent forms of its organization. Thus, it would seem logical that patterns, including observed mathematical patterns, are at least a reflection of the mind’s organization and in turn a reflection of nature’s organization, making therefore the point of Wigner’s (1960) statements regarding the “unreasonable” effectiveness of mathematics perhaps invalid. Moreover, what of that mathematics that may be contrary to our physical universe, such as complex numbers. As mentioned, String Theory suggests higher dimensions other than the space-time we experience. The higher dimensions suggest multiple universes with differing initial conditions, thus differing physical laws, suggesting potentially an infinite number of possibilities and perhaps the overabundance of applicable mathematical space we find is relevant in those universes. This would perhaps imply that mathematics exists in higher dimensions outside of our space-time. The Platonists would likely chime in now suggesting that mathematics then has a reality outside of human perception, that is, that mathematics is non-abstract and consists of tangible entities existing in higher dimensions.

However, this work suggests that it may just be the imaginative powers of the human mind transcending the restriction surrounding space-time, yet the fine-scale rules of superstring articulation are still perhaps tangible. Extending this discussion to Gödel’s Incompleteness Theorem (Gödel, 1986), mathematics as a self-referencing system may be an emergent form of superstring articulation. Like other complex interdependent self-referencing systems, such as the
mind which has characteristics that are emergent but paradoxical in that the mind apparently knows it is self but seemingly can never absolutely know or understand why it seemingly knows. Mathematics in a similar fashion may indicate that it is, but as Gödel suggests, it can never fully show that it is. Jørgensen (2002) describes this as “infinite truth can never be condensed in a finite theory” (p. 57).

Returning to the core of the question for ecological engineering regarding mathematical trends and patterns observed in Ecological Network Analysis concerns their reality or invention and whether the question is itself significant. From an ecological engineering perspective, the answer seems to be both no and yes. That is, this work suggests that it does not matter whether mathematics is reality or just trends experienced by humans overlaying a perceived order onto the natural world as long as the perceptions are precise at appropriate scales and not a product of imagination or preconceptions. However, it may matter, in that if mathematics is a purely constructed human epistemology of the physical universe, then as all human constructions have inconsistencies, some mathematical artifacts may then have no physical meaning.

However, as noted, others might argue that the same organizational principles that give rise to nature also have given rise to human intelligence. This tends to counter the argument that the human mind may be overlaying a perceived but false organization structure upon nature because one could argue that the same organizational principles have given rise to both the human mind and nature and thus perception of organization, if pursued logically without emotion and prejudice, would result in a logical ontology of reality. This then provokes another question, that is, how then does one distinguish between emotionally or prejudicially perceived trend and reality? Unfortunately, questions remain, although time and the filter of the peer review process should lead to more and more correct perceptions of reality.
It is the position of this dissertation that though our perception may at times be inaccurate or that meaning obscures in complexity, mathematical trends, at some scale, and possibly, what we now describe as mathematical “artifacts,” could have connections to some physical and tangible reality in a multi-verse. However, this does not necessarily mediate the current dilemma faced in the management and engineering of ecological systems, that is whether our mathematical descriptions of complex systems allow the accurate description of emergent systemic properties. How can we ensure that mathematical trends map to and implicate a physical reality?

One of the most influential philosophers and mathematicians of western society, René Descartes, known for the phrase “I think, therefore I am” and the namesake of the Cartesian coordinate system, believed that physics was a branch of mathematics (Hatfield, 2011; Sarukkai, 2005, pp. 418-419). Consequently, it was his belief that physics needed no other principles than those found within mathematics. For example, Descartes considered mass to be extensional and non-pointlike whereas Newton, years later, considered mass to be pointlike. Furthermore, Descartes was actually on the verge of discovering Newtonian physics, but his misconception that physics was just an extension of mathematics seemingly prevented him from doing so (Sarukkai, 2005). So, how did Newton get it right? Newton’s tactic was a mathematization of the problem through a dynamic interplay between the natural world and mathematical ideas. For instance, in Newton’s derivation of Kepler’s law, Newton considered a pure mathematical non-physical system, and from this mathematical model, Newton subsequently mathematically derived the other laws of Kepler. Newton then compared this imaginary mathematical world to the physical world, which required him then to adjust and account for physical realities. Thus, successive iterations of this tactic each time accounted for more aspects of the physical
phenomenon. However, Newton found that his mathematics was only an approximation of the actual physical phenomenon. For example, the two-body planetary motion problem only approximates the more complex interplay of all mass of our solar system and beyond. Thus, Newton realized the need for verification through observation coupled with the need for approximation in his mathematical models of the physical world (Sarukkai, 2005, p. 419).

Today’s quantum mechanics and the theories of relativity suggest that Newton’s approximation does not apply at near light speed or in the realm of the very small where a continual exchange of matter and energy occurs and thus perhaps in some ways vindicating Descartes. However, Newton’s approximation at appropriate scales remains highly useful.

How does this relate to the mathematical descriptions of ecological systems? How do we verify the mathematics with a corresponding physical reality? How do we iterate between mathematical models and physical reality to understand and describe the intertwined emergent nature of complex systems? Observation and empiricism alone will not be sufficient to compare mathematical models to the physical in that emergent behaviors of complex systems veil themselves in composite forms, and direct cause and effect at this point in science for complex systems is tangled. The system sciences give indications of these properties through mathematization of the system, but just as Newton’s insight was to observe and mathematize, then compare to reality and iterate until he reached an acceptable approximation of reality, this work proposes that one way to refine our understanding of complex systems is through designed and simulated ecological systems. In the case of the intertwined complex systems, employment of a somewhat reverse approach from Newton should occur, using empirical data first to construct an idealized system model. This is in some ways working backward from Newton’s approach by first using direct observation and measurement of system properties to mathematize
the system but then using the subtleties of the mathematics to reveal hidden physical characteristics and qualities of the natural system. It should be of note that reverse approaches and opposite characteristics are an embedded theme and foreshadow the directions of this work. Next working in a reverse direction, employ these revealed mathematical characteristics as simulation and design parameters for artificial systems to adjust iteratively the understanding of these complex systems. That is, these models often reveal suspected systemically embedded and often hidden mathematical trends of reality. This perhaps suggests another clear demarcation between reductionism and the systems sciences. Newton seemingly was able to observe and reduce nature to discrete physical concepts such as mass, force, and acceleration and conceptually mathematize the problem and iterate between physical observation and the mathematical model until achieving an acceptable approximation of reality. However, for complex systems, many physical concepts conceal in the scale and complexity of the system, requiring a mathematical synthesis to first uncover the hidden physical realities and systemwide properties as mathematical trends. This is consistent with and further illustrates the dialectical tension between reductionism and the system sciences and the appropriateness of each. However, just as Newton iterated to achieve good approximations, the understanding and precision of using iteratively uncovered mathematical trends associated with complex systems, one may use these as design or simulation parameters of systems to verify further their existence and to adjust iteratively our understanding of the workings and emergent characteristics of these systems.

The following sections are mathematical descriptions of complex systems that retain system connectedness; summarizing several of these approaches will further the case that systems science provides a consistent basis on which design and management of ecological systems should begin. Though each method is unique and thus provides uniquely different
insights of interdependent complex systems, all suggest that analyses of connected systems are essential to understand holistically the workings of the system. Therefore, insights from a connected analysis of ecological systems become a requisite knowledge set in the design and management of natural systems and the synthesis of design to refine the understanding of nature’s hidden characteristics.

**Network Thermodynamics**

One ecological network analysis technique bases itself on network thermodynamics. The first law of thermodynamics, often called the conservation of energy principle, implies neither the creation nor destruction of energy but that all energy transactions must balance, suggesting that energy may only change in form. The mathematical statement of the first law is given by:

$$dU = \delta Q - \delta W \quad (3.1)$$

where $dU$ is the infinitesimal increase in the internal energy of the system, $\delta Q$ is the infinitesimal amount of heat added to the system, and $\delta W$ is the infinitesimal amount of work done by the system on the surroundings. Further, no known process may occur that disobeys this law; however, satisfying this law alone does not ensure that the process will take place. For example, a hot cup of tea placed in a cooler room will eventually cool with the room, becoming slightly cooler at equilibration; hence, this process would satisfy the conservation of energy principle. However, if we consider the opposite case, that is, the hot cup of tea extracting energy from the cooler room, though this would not violate the first law of thermodynamics, it is obvious that this could not take place (Cengel & Boyles, 2002, p. 245), at least not in this universe. Thus, processes have a certain direction, which, coupled with energy quality, is the essence of the Second Law of Thermodynamics. Formally, the most widely used description of the second law of thermodynamics is from Rudolf Clausius proposed that the entropy of an isolated system not in equilibrium will tend to increase over time, approaching a largest value at equilibrium.
Thus, entropy or thermodynamic disorder (no energy gradients) of the universe will tend toward the maximum.

Therefore, for isolated systems, that is, systems where neither matter nor energy crosses the system boundary, the total energy within the system, according to the first law, is constant. The second law applied to isolated systems reveals that differences in heat, pressure, etc will with time, equalize within the isolated system. Stated another way, the second law tells us that the entropy within the isolated system will increase with time, approaching thermodynamic equilibrium where no gradients exist.

For closed systems, the first law of thermodynamics informs that conservation of energy must occur; thus, energy into the system must equal energy out of the system. The energy out of the system may take various forms, such as work, heat, degraded energy, etc. However, the increasing entropy of the second law does not necessarily apply within the closed system; that is, entropy within a system without a thermal boundary does not have to increase. In other words, removing heat from the system reduces system entropy (although entropy of the surroundings increases). The utility of a second law closed system analysis of a heat engine will help to illustrate these points. Heat engines range from the internal combustion engines, gas turbines, to power stations that generate electricity. An important characteristic of a heat engine is that it operates in a cycle. For example, a coal-fired electric generating station takes heat from a furnace, moves that heat to a boiler, and turns water into steam. The steam in a high energetic state turns the blades of a turbine that rotate a shaft that couples to a generator that produces electricity. Thus, in the system one wants energy in the form of work extracted from the steam to operate the system cyclically. That is, the system should operate in a steady-state cycle where the
same water continuously passes through the same thermodynamic states and where the water returns to the original thermodynamic state. In other words entropy \( S_2 = S_1 \), that is, for one cycle:

\[ \Delta S = 0 \] (3.2).

Now, at a well-insulated turbine, the expansion of the steam against the turbine blades is considered adiabatic and thus by the second law, the change in entropy at the turbine will be greater than zero. That is, the entropy of the water increases at the turbine and for equation (3.2) to hold true as the water cycles, the entropy of the water must reduce. Thus, a heat exchanger downstream of the turbine removes heat from the water (Cengel & Boyles, 2002, pp. 247-248).

This is significant because it implies that not all of the energy (heat) taken from the furnace was converted to work at the turbine. That is, no heat engine can operate at 100% efficiency because heat removal occurs in completing the cycle. The upper limit of this efficiency is known as the \textit{Carnot efficiency} and typically, a heat engine generating electricity is only about 30% efficient (Cengel & Boyles, 2002). This means that only 30% of the energy extracted from the boiler converts to useful work. The remaining 70% of the energy deposits outside the system or into the environment, usually into aquatic environments by the cooling water used in the cooling stage of the cycle. This example, chosen for a particular reason, illustrates a problem; clearly, this is an example of a “closed” mechanical system embedded within a larger open ecological system.

Though the components of the power generating plant may be highly decoupled within the closed system, the closed system itself is coupling into the larger scale natural system. That is, the power generating plant, through a manifestation of the second law, is depositing entropy into the larger natural system. Further, Jørgensen (2002, p. 124) correctly identifies the environmental crises of our time as crises of entropy, that is, pollution (heated water in the case of the power plant) creates higher levels of disorder within larger natural systems. Moreover, at some
unknown threshold, this may cause a significant reduction in large-scale system organization and complexity, thus making less exergy, the available amount of useful energy, available for use in the biosphere. Further, Jørgensen (2002) goes on to say that as we attempt to create higher degrees of order within our often closed mechanical systems, paradoxically, the resulting byproduct is increasing entropy and disorder transferred by second law principles to our most important system, the environment. However, Jørgensen (2002, p. 124) suggests ways, by which the reduction of the inevitable results of the second law may occur, such as shortened energy chains, increased thermodynamic efficiencies, reuse of waste heat, etc.

For open systems, conservation of both matter and energy take place, that is, open systems like all known systems must follow the first law of thermodynamics. In addition to energies absorbed from thermal radiation, often, for open ecological systems, the matter consists as a form of useful chemical potential energy. The Second Law of Thermodynamics takes a significant and profound form in open systems. Where the first law led to the introduction of internal energy of the system that determines permissible changes, it does not identify the spontaneous changes that do occur. The changes, which do occur, follow the second law and the concept of entropy. Mathematically, entropy has the form:

\[ dS = \frac{\partial Q}{T} \]  \hspace{1cm} (3.3)

and for isolated systems:

\[ dS \geq 0 \]  \hspace{1cm} (3.4)

However, according to Jørgensen (2002, p. 124), processes that have energy transformations will not occur spontaneously without an accompanying degradation of organized energy to a less organized or more random form, that is, all energy transformations involve the degradation of
energy from a higher quality to a lower quality where the quality of the energy measured by the state variable entropy. In other words, the higher the quality of energy, the lower the entropy state, and vice versa. Some open physical systems, however, may create and maintain a high state of internal order (low entropy). The second law seems to explain how ecological systems maintain their order; that is, normally a system tends naturally to move toward greater randomness or toward thermodynamic ground. However, living systems may move away from thermodynamic ground when subjected to consistent high quality energy gradients. In other words, the systems degrade high quality energy to increase their spiraling ascent from thermodynamic ground and toward greater organization and complexity while dissipating energy and matter in the form of heat (increasing entropy) to the larger environment. Thus, they within their systems seemingly violate the second law, but in reality do not because entropy of the larger isolated system (the universe) is still increased (Snyder & Kay, 1994). Jørgensen (2002) has in fact taken this phenomenon of second law thermodynamics for ecological systems and penned an *Ecological Law of Thermodynamics*. From Jørgensen (2002, p.186), “If a system has a throughflow of exergy, it will attempt to utilize the flow to increase its exergy, i.e. to move farther away from thermodynamic equilibrium; if more combinations and processes are offered to utilize the exergy flow, the organization that is able to give the system the highest exergy under the prevailing conditions and perturbations will be selected”. In the statement, exergy refers to high quality, low entropy useable energy. Jørgensen bases the concepts on far-from-equilibrium thermodynamics. According to Gattie, Kellam & Turk (2007, p. 33), Prigogine and others (Prigogine et al., 1972; Nicholas & Prigogine, 1977, 1989) first developed this concept known as far-from-equilibrium thermodynamics or non-equilibrium thermodynamics. Open dissipative systems, which by definition may have material and energy gradients across their
system boundaries, tend to make use of these gradients to move to ever increasingly ordered steady states. Schneider and Kay (1994) (Gattie, Kellam & Turk (2007, p. 33) extrapolated these ideas of Prigogine to open living systems where they postulate that ecosystems use exergy to build system order and structure as the system moves away from thermodynamic ground.

**Network Thermodynamics for Ecological Systems**

This section explores the significance of network analysis techniques in relation to ecological systems. One method, based on the thermodynamics of networks, begins to reveal the importance and the qualitative essence of network thermodynamics for living systems. Much of the discussion is a review and based on Donald Mikulecky’s work in his 1993 book *Applications of Network Thermodynamics to Problems in Biomedical Engineering* and some of his papers, such as his 1991 paper *Network thermodynamics: a unifying approach to dynamics living system and A Network Thermodynamic Two-Port Element to Represent the Coupled Flow of Salt and Current*. Extending the discussions of this work beyond the complexity of ecological systems to other complex systems, in this case, biologic organisms, broadens the weight of evidence that analyses of complex systems as connected whole are fully essential to understand and manage these systems. Further, as there seems to be many parallels and analogs to other natural living systems, this work will suggest extending the biomedical network thermodynamic descriptions and insights of biologic systems analysis into the description of other complex systems. Though omitting a majority of the quantitative explanation, the analytical information is fundamental for a complete application of the material presented. Albeit the information discussed is quantitatively incomplete, one can begin to grasp the importance of network thermodynamics and note a common thread throughout. That is, that structure and function are inseparable and describing this connectedness by the laws of non-equilibrium thermodynamics requires new

Network thermodynamics is a relatively new synthesis of the formalism of non-equilibrium thermodynamics of Prigogine (1972) and others and electrical network theory. In 1963, Kedem and Katchalsky (Mikulecky, 1991, p. 73) first began applying the phenomenological laws of non-equilibrium thermodynamics and circuit analysis, based on Kirchoff’s laws, to complex systems. Ecological systems are complex interdependent systems that by their very nature are connected systems dependent on both structure and function. The use of Kirchoff’s laws allows one to encode the topology or connectedness of the system and essential relations that may, for example, describe resistance of flow across boundaries of constituent elements of the network (Mikulecky, 1991, p. 82, 1993, 2005b, pp. 119-120).

In the mid-19th century, Gustav Kirchoff (1847) (Mikulecky, 1991, p. 78, 1993) developed simple rules for the analysis of complex electric circuits: the junction rule and the loop rule. The junction rule states that the sum of currents entering any junction in a circuit must equal the sum of the currents leaving that junction. The loop rule states that the sum of the potential differences across all elements around any closed circuit loop must equal zero. The junction rule is a statement of the conservation of charge in electric circuits, and its mechanical analog exists in the conservation of mass. For example, in fluid mechanics the conservation of mass ensures that the water flow in a single pipe, which branches, must equal the water flow in
The loop rule in circuit analysis follows from the conservation of energy (Kirchoff, 1847; Mikulecky, 1991, pp. 78-79, 1993).

The network thermodynamic approach first applied to simple systems and represented as series and parallel circuits, later extended to analyze highly organized systems (Mikulecky, 1991, p. 79, 1993). In the thermodynamic analysis of these organized systems, such as ecosystems, a network of relatively simple, homogeneous structures and the laws that govern them combine within a flow-force relation of a network. That is, the essential relations describing the force-flow relations in network elements combine in a way dictated by the morphology of the ecosystem plus the functional relationships within the system (Mikulecky, 1993).

According to Mikulecky (1991, p. 71, 1993), other representations of systems, such as bond graphs (Karnopp and Rosenberg, 1968, 1975; Thoma, 1975; Wyatt, 1978; Breedvelt, 1984; Imai, 1989, Mikulecky 1993), are useful in many ways. Leonardo Peusner (1986) was one of the first who represented thermodynamic networks as schematic linear graphs and found that the resistive linear, graphical networks used to represent the energy transducers of linear, steady state non-equilibrium thermodynamics are a canonical representation. In other words, they define a coordinate system and a metric for the distance between states in entropy or energy space (Mikulecky, 1991, 1993, 2005b, p. 119).

Kirchoff’s use of graph theory systematically encodes a systems component connectedness into a mathematical form of incident matrices, coupled with Tellegen’s theorem (Mikulecky, 1991, p. 75, 1993, 2005), opened complex systems to analysis and is the basis of network thermodynamics. Similarly, Network Environ Analysis depends on the study of objects as part of a connected system in determining direct and indirect effects (Fath & Patten, 1999). Both network thermodynamics and Network Environ Theory indicate that an ecosystem is more
than a collection of concentrations, energy gradients, or flows, but is a synthesis of connected
and relationship-dependent components that may show emergent properties that are not evident
in the components. Graph theory suggests that emergent properties evident in network
thermodynamics (Mikulecky, 1993) and in network environ theory (Fath, Patten & Choi, 2001)
are seemingly tied to the topology of the system.

This work and others have proposed that modern science and engineering have had a very
strong bias toward reductionism and empiricism. For example, there is a strong tendency to
reduce ecological systems into simple mechanisms to fit current theories and modeling
techniques, a tendency to identify ecological systems as “warehouses” holding an inventory of
differing species, and lastly a very strong reliance only on observation and experience as the
means to understanding systems organization. Perhaps, these tendencies are a result of the
difficulty in the requisite rigor of systems theory or simply the unawareness of complex systems
theories. In any event, ecosystems are open, non-linear systems, and the analysis of non-linear
systems requires an analysis of how the components relate to the whole. Therefore, just as
Kirchoff did with circuit theory, the management and design of ecological systems must
relinquish the exclusiveness and additive tendencies of reductionism and embrace the
mathematics of graph theory, fractal geometry, and catastrophe theory to begin to determine the

In many sciences, the reduction of systems occurs to fit a limited Newtonian view of the world.
However, network thermodynamics applies theory originating in electronics and applies it to
complex connected systems, such as the encoding of ecosystems to predict their behavior.
Therefore, a holistic ecology with an adequate formalism is required. Robert Rosen (1985, 1991,
pp. 202-212, 244-252) made a distinction between two classes of objects: simple mechanisms
and complex systems. Newtonian formalism adequately describes mechanisms, but complex systems, such as ecosystems, require additional formalism for an adequate description. Rosen suggests that a mechanistic description of living systems can only be local (Rosen, 1985, 1991; Mikulecky, 1993). However, a local representation does not adequately describe the holistic contextual behavior of ecological systems. Though the modeling of ecological systems often begins with mechanistically represented components, it connects them functionally and relationally such that the whole becomes more than the sum of its parts. Therefore, it is the context, the mechanistic description (component properties), and the component connectedness which make an ecosystem. This further implies that connectedness is also a property of the system. According to Mikulecky (1991, pp. 79-81, 1993), an important contribution of network thermodynamics is to combine thermodynamic and kinetic modeling to illustrate their relationship through networks and thereby suggest a way to move from simple mechanistic models to complex system models.

**Thermodynamics and Dynamic Systems**

According to Mikulecky (1991, p. 71, 1993, 2005, pp. 141-144), the work of Oster, Perelson, and Katchalsky (1971, 1973) introduced new dynamic systems theory into network thermodynamics. Contrary to the historical approaches, they made a case that the best study of equilibriums occurs at “end points” of dynamic processes. For instance, a rigorous treatment of non-equilibrium thermodynamics by deGroot and Mazur (1962) (Mikulecky, 1993) started with rigorous continuum formulations of the laws of conservation of energy and momentum to derive the Gibb’s equation in a form that involves the second order tensor products in hydrodynamic processes. Further, they then replaced the differential expression with time derivatives (Mikulecky, 1993). However, he writes that a relatively new approach yields consistent results to
those of deGroot and Mazur. The approach does not rely on reductionism but embraces the mathematics of topological reasoning. According to Mikulecky (1991, p. 77, 82, 1993), Peusner (1986) described the difference between the approaches as geometric versus topological. That is, the systems properties historically base on system measurements whereas the new approach considers the connectedness of the system and that the geometric properties of systems have a relatively simple characterization. A collection of these properties, called the systems component’s constitutive properties, and the mathematical expressions, are the constitutive laws (Mikulecky, 1991, p. 82, 1993). Oster, Perelson and Katchalsky (1974) (Mikulecky 1993, 2005b, pp. 118, 122), provided a methodology to determine and express these laws based on the idea that dynamic system theory should start with a dynamic theory and under the proper constraints drive it to the established equilibrium theory. This is in contrast (hence a somewhat reverse approach) to the traditional method of taking equilibrium relationship in differential form and then turning the differentials into rates (Mikulecky, 1991, 1993). In addition, perhaps this further suggests the dialectic paradox between complicated and complex systems and the need for opposite approaches in the analysis and design of these differing types of systems.

Graph theory encodes a systems topology, and Leonhard Euler was one of the first to use graph theory in 1736 to solve a local riddle. Later, Kirchoff, (Mikulecky, 1991, 1993) first represented current flow pathways and connection nodes graphically and incorporated this reasoning into electronic theory. Network thermodynamic theory is based on the generalization of Kirchoff’s (Mikulecky, 1991, p. 75, 1993) current and voltage laws, but perhaps even more importantly it is his representation of networks as “trees” that allows network thermodynamics to combine with kinetics (Mikulecky, 1993, 2005b, pp. 125-126).
Graph Theory

In graph theory, connection points are called nodes or vertices and the lines connecting them are called branches or edges. Formally, Mikulecky suggests that graph theory can be stated as given a set which consists of a collection of points \( V = \{v_i\} \) in \( E_n \) which will be called vertices and another set which is a collection of simple curves \( E = \{e_{ij}\} \) which will be called edges.

Secondly, having a mapping such that every curve in \( E \) contains precisely one point in \( V \), and that every open curve contains precisely two points of \( V \) and these are its ending points. Lastly, the curves in \( E \) have no common points other than in \( V \) (Milulecky, 1993). Therefore, any edge or pathway in \( E \) may be designated by the use of two subscripts where the subscripts denote the ending points of the edge, which are members of \( V \). For example, \( \{E\} = \{e_{ij}\} \) and if an order is assigned to the pairs of \( V \) consisting of the ending points of the members of \( E \), it is a directed graph or digraph in which \( e_{ij} \neq e_{ji} \) where \( e_{ij} \) has the direction from \( i \) to \( j \) and \( e_{ji} \) has the direction from \( j \) to \( i \) (Mikulecky, 1993, 2005b, pp. 126-127).

The topological information of a graph’s connectedness and direction lies within its incidence matrix (Mikulecky, 1991, p. 92, 1993). An incident matrix is an array of ones and zeros for a non-directed graph and an array of ones, zeros, and minus ones for a directed graph where each row of the matrix corresponds to one of the nodes, and the columns refer to the branches. For example, the entry in the \( i^{th} \) row and \( j^{th} \) column will be 1 if branch \( j \) is incident on node \( i \) and flows into it. If the flow is out of node \( i \), the entry will be -1 and it will be zero if it is not incident (Fath and Patten, 1999).

A network is often represented as a directed graph with particular mapping associated with it where each branch of the graph is a network element. The elements describe by their constitutive relations and range from “1-port” (simple, independent, dissipative processes) to “n-
port” elements. According to Mikulecky, in a network the concept of through and across variables leads to a system’s description as a network by the following procedure. Subdivide the system into homogeneous subsystems or volume elements where the network will reflect this subdivision as often dictated by the morphology of the system. Then represent the pools of materials or other subdivisions as nodes, and connect the nodes with flow pathways. According to Mikulecky (1991, p. 93, 1993, 2005b, pp. 130-132), these are analogous to resistors, conductors, and represent the storage or depletion as capacitors from the compartment’s node to a reference or “ground” node. Lastly, represent inertia as an inductance. Flow is a time derivative, which implies that its time integral is also an important quantity. The amount of flowing material in the time interval from zero to t for an electrical circuit is the amount of charge. In mass flow, it is mass or moles; in volume flow, it is volume, etc. By integrating, the associated force with respect to time introduces a new variable: the primitive momentum (Oster, Perelson & Katchalsky, 1973; Mikulecky, 1991, 1993, 2005b, pp. 130-132). Therefore, the complete picture is comprised of two time integrations and the set of binary relations between resulting variables, that is, resistance is the binary constitutive relation between flow and force, capacitance corresponds to the relationship between amount and force, inductance relates flow and momentum, and something called “memristance” (Chua, 1971) relates momentum and amount (Mikulecky, 1993).

Multiple Ports

The “1-ports” (simple systems) are special cases of the more general n-ports. The n-ports are network elements that have a number of terminals so that pairs of these terminals can be the input and output routes for particular flows. Therefore, the essential essence of an ecological application describes as follows: the linear, coupled processes in steady state described by a set
of linear algebraic equations, which are the constitutive relations of the components of the ecological system as mentioned above. These define the linear n-ports constitutive laws, where n is the number of independent flows and forces that couple to each other in the system. Therefore, a network is simply a connected set of n-ports abstracted as a linear graph (Mikulecky, 1993).

Again, Kirchoff recognized that flows that go through an object enter along one path and leave along another because of the difference in some quantity across the terminal, that is, a driving force (Mikulecky, 1993, 2005, pp. 131-133).

**Power and Energy**

Power and energy are important aspects of thermodynamic equilibrium theory. They are formulated products of the dynamic analogs of the intensities and displacements comprised by the various free and internal energies (Mikulecky, 1993). Further, Mikulecky suggests that if power is the principle variable of interest in steady state, then it must be the product of two things that are quite different, and the flows and forces of non-equilibrium thermodynamics fit this requirement well. This is particularly true in isothermal steady state, for in this case, the dissipation function has the units of power, but the concept is more general. For example, the far from equilibrium ideas of Prigogine and Stengers (1984) (Kay, 1994, p. 7; Tollner, & Kazanci, 2007; Gattie, Kellam & Turk, 2007, p. 33) suggest that this is a range which shows some of the most interesting types of dynamic systems behavior (Mikulecky, 1991, 1993). Therefore, for this reason and others, it is desirable to begin with power instead of dissipation before extending the dynamics beyond steady state (Mikulecky, 1993). Therefore, power in the steady state in any part of the system is a product of the flow through that part and the effort across it that drives the flow. Pairs of flows such as these are called conjugate as in non-equilibrium thermodynamics, and one should also note that forces would be the differences in potentials (concentrations,
pressure, etc) across a part of the system (Mikulecky, 1993, 2005b, pp. 126-127). The part represents as a branch, and the potentials assign to the nodes at the ends of the branches. In defining the force, the first subscript i will denote a particular entity.

\[ X_i = V_{ij} - V_{ik} \quad (3.5) \]

The second subscripts j and k will denote the nodes that represent compartments in the system (Mikulecky, 1993).

**Steady State Linear Systems**

In the prediction of behavior of a network and graph of a dynamic, non-steady state system, knowing the initial conditions is often the objective. The behavior is the time path and the ultimate steady state or equilibrium values of the unclamped node potentials and/or forces across the branches plus the unclamped flows through the branches (Mikulecky, 1993; 2005, p. 130). Many matrix methods exist to determine the description of the system’s behavior. SPICE® and MATLAB® are examples of simulation packages that provide an easy method for the solution of networks. A formal discussion of those matrix methods will not be presented here but can be found in many linear algebra texts and the works of Mikulecky and Peusner (network thermodynamics), similar to the works of Patten (Network Environ Analysis) and others which will be presented in the next chapter.

**Dynamic Linear Systems**

Mikulecky (1993) states as capacitors incorporate into a network, the network becomes time dependent, and that it becomes a dynamic system. The general capacitive constitutive law is capacitance multiplied by the rate of potential change equals the storage flow. In other words, when a capacitor to ground and two dissipative branches connect to the same node, the capacitor
will charge or discharge due to the imbalance between the two dissipative flows, and the potential will continue to change until achieving steady state. When the two dissipative flows are equal, the capacitive flow stops. This shows the relative roles of energy storage and dissipation in dynamic systems. The steady state only involves dissipation whereas the dynamic system involves both. Thus, the capacitors in fact are not necessary in a steady state (Mikulecky, 1993). The previous statements describe the discrete version of the continuity equation:

\[
\frac{dc}{dt} = -\frac{dJ}{dx} \quad (3.6)
\]

\(J\) is the branch vector flow, \(x\) is the branch force, \(c\) is concentration, and \(t\) is time. It is here that the non-equilibrium formalism enters the picture, and from the network thermodynamic perspective, it is only the study of dissipators. Their mathematical description comes from their constitutive relations, that is, the phenomenological equations. This supplies the flows in the continuity equation, and it supplies the dissipators in any network whether it is in steady state or not. Therefore, a steady state network is extendable to non-steady state situations. Thus, the use of non-equilibrium thermodynamic information of multiple port dissipators is possible in the analysis of any linear dynamic system (Mikulecky, 1993, 2005b, pp. 130-133). Similar to other biologic systems, a dominant characteristic of ecological systems is that they involve multi-port elements. N-port systems are those that are represent a box with \(n\)-pairs of external terminals or ports where the flow entering one terminal of each port is equal to the flow leaving the second terminal. One finds that \(n\)-ports have particular utility in complex, interacting systems like ecological systems. One may use \(n\)-ports to represent a variety of processes. The \(n\)-port developed for coupled processes provides new thermodynamic insights into their description and analysis. Furthermore, the scope of linear, steady state non-equilibrium thermodynamics fits within this model and extends to kinetic and non-linear processes (Mikulecky, 1993).
concepts of self-organization and the tremendous amount of ordering within living systems seem to contradict the laws of thermodynamics as evidenced in simpler systems. However, ecosystems are complex, requiring new methods of description. The n-port is a means by which ordering events arise naturally through coupling to degrade energy, which assures an overall increase in entropy (Mikulecky, 1993, 2005, p. 134). In addition, a large number of problems arise from the study of living systems where understanding occurs more clearly through network thermodynamics and n-ports.

**Ecological Circuit Theory**

What arises from the applications of network thermodynamics by Peusner, Mikulecky and others is the idea of a biologic circuit theory, which seems to extrapolate equally as well to an ecological circuit theory. This theory bases itself on the fundamental concepts of electronic network theory and extends progressively from simple to complex ecosystems. Perhaps this analog is at best foreign to many in science, but it is an idea, along with others, with the potential to lay a foundation of organizing principles for the analysis and management of complex ecological systems.

Current division and voltage division are simple requisite principles of electronics and are often in the network configuration of living systems. For example, the current divider involves a flow source feeding into a pair of branching paths consisting of elements with resistive properties. The analysis of such networks consists of standard network or graph theory techniques that combine the use of incident matrices and Kirchoff’s rules with a set of constitutive relations describing the network elements in the branches (Mikulecky, 1993). The procedure for this simple example and the construction and manipulation of the associated matrices found in numerous texts on electronic theory and not repeated here. Furthermore, it
would be a relatively simple matter to extend the result to n-port systems of dissipators/resistors described by non-equilibrium thermodynamics, where the equations for the simple example still apply by recognizing that the network solution found for 1 port will apply to n-ports with the same topology (Mikulecky and Thomas, 1977). However, the actual behavior of the n-port current dividers is not a simple extrapolation of the 1-port case even though the mathematical analysis does extrapolate. Kedem and Katchalsky (1963) in their work on series and parallel combinations of membranes observed the appearance of non-additive terms in certain representations of constitutive relations in these membrane systems (Mikulecky, 1993, 2005b, pp. 119-134). They note that the combination of what appeared to be linear objects was more than just superposition but more analogous to parallel combinations of resistors in electronics. They observed new properties dependent on the simple topology of the connections. Peusner later established through network thermodynamics that the topological connectedness directly relates to the form of the constitutive equations and established a metric associated with the network representation (Peusner, 1986; Mikulecky, 1993). In network terms, varying combinations of n-ports resulted in new n-ports with an entirely different metric and results in very acute evidence for a form of emergence (Mikulecky, 1993, 2005b, pp. 119-120). It would not be a far stretch to believe that ecological systems behave similarly to the membrane combinations, showing emergent properties and requiring an entirely different metric based on the topologically parallel or series combinations of components.

The 2-port networks are by nature non-linear because of the dependence upon concentrations in the interior compartments of the system. However, when analyzed as isolated systems, the non-linearity is often not evident (Mikulecky, 1993, 2005b, p. 130). Therefore, in general the complete determination of these systems by through and across variables is not
possible. In addition, the reference state needs specification. When studied in isolation, the reference state can be kept constant, then the through and across variables are uniquely related to that reference state, and when the elements are combined in networks the property often is lost, and the system behavior becomes much more complex (Mikulecky, 1993). The question arises for other natural systems: Can ecological systems be completely determined by through and across variables? One might infer that the general and complete determination of ecosystems requires more than the study of through and across variables but also the topology of the connected elements.

Reference State, Kinetics, and Non-Equilibrium Thermodynamics

According to Milulecky (1993, 2005b, p. 135), Onsager gave two examples of irreversible processes to illustrate his inference about the thermodynamics of irreversible processes (Onsager 1931a & b). An examination of Onsager’s “triangle reaction” illustrates a number of points that establish a general approach for connecting kinetics to thermodynamics and will set the table for a network formulation of kinetic problems (Mikulecky, 1993, Kay, 1994). Although Onsager’s work is consistent with empirical evidence, the nature of his work is very restrictive. That is, the assumptions in his work were far from valid, according to Mikulecky (1993, 2005b, pp. 135-136). In general, Onsager showed that when a system is at equilibrium, each step in the sequence of events must also achieve equilibrium independently. This point demonstrated the way by which microscopic reversibility relates to the macroscopic. It followed that all the flows stopped at equilibrium, therefore obtaining a set of equilibrium concentrations, and these equilibrium concentrations allow the formulation of relations between kinetic description and the formalism of non-equilibrium thermodynamics (Onsager, 1931; Katchalsky & Curran, 1965; Mikulecky, 1993; Kay, 1994, p. 7). Then, by utilizing the equilibrium
conditions of detailed balance, the relations made linear between the thermodynamic attributes, and the kinetic descriptions, the flows substitute for their kinetic equivalents (Mikulecky, 1993). Therefore, the kinetic relationships are written now in terms of a thermodynamic variable(s) that is linear. Katchalsky and Curran (1965) Kay (1994, p 7), and Mikulecky (1993, 2005b, pp. 135-136) suggested that this principle of microscopic reversibility as presented above and according to the methods should be derivable by statistical mechanics. However, if one looks at the network approach for the same system, it becomes evident that microscopic reversibility is not readily evident as is implied by traditional non-equilibrium thermodynamics. Mikulecky (1993) suggests that the validity of Onsager’s proof has little to do with statistical thermodynamics but is dependent upon topological considerations through Kirchoff’s rules. In other words, microscopic reversibility provides the topological connectedness synonymous with Onsager’s reciprocity Sauer’s (1973, 1977) nonlinear theory of non-equilibrium thermodynamics stated the need for additional constraints defined by reference states to describe completely these systems; the reference states provide additional clarity and fit naturally in Peusner’s network thermodynamic models of kinetic systems (Sauer’s, 1973, 1977; Peusner, 1986; Mikulecky, 1993, 2005b, pp. 136-137). Peusner’s (1986) network representation of thermokinetic systems represents kinetic steps by a resistor to obtain network thermodynamic structure.

Examples of these dissipative structures include resistance in electrical circuits, hydraulic conductivity, and resistance to diffusion, where the value of the each resistor can be determined from rate constants where they have the specific constitutive relations to the flow and force variables (Mikulecky, 1993). The nodes are compartments and are the connection points with additional network elements where the elements are branches with a corresponding constitutive relation. According to Mikulecky, Peusner’s work repeatedly revealed uniformity between
Onsager’s reciprocity and the connectedness of networks (Peusner, 1986; Mikulecky, 1991, p. 73, 1993; Kay, 1994). In many instances, the connectedness of passive and purely resistive networks results from the application of detailed balance. That the network is passive is fundamental; otherwise, the sources will generally destroy the reciprocity. In many cases, the pseudo-first order rate constants do not obey microscopic reversibility; however, the second order rate constants embedded within the first order do and therefore at equilibrium and at a relatively small region near equilibrium, sources “vanish” (Mikulecky, 1993). Further, the reference state needs specification because nonlinear systems usually have a more complicated thermodynamic description than the linear systems. Mikulecky (1993) suggests an experimental strategy that fixes a reference state and then considers the flow-force relationship for each reference state, that is, any relation between the forces and flows is reference state dependent. The consideration of the relationship between Peusner’s (1986) networks and the choice of reference state for a simple, nonlinear system having only one degree of freedom extends to single degree systems with more than one state. In addition, it would include completely coupled versions of more complicated systems since coupled systems have only one cycle (Mikulecky, 1993). Kirchoff’s criteria for independent loop flow are applicable in making the determination of the number of degrees of freedom. Examples (Mikulecky, 1993) show a general method for finding a linear, reciprocal, reference state dependent coordinate system for thermokinetic descriptions. The examples also show that these model dependent networks will all smoothly merge into more general model independent thermodynamic networks near equilibrium, and they provide a canonical representation of the Onsager (1931a.,b.; Mikulecky, 1991, p. 73, 1993, 2005b, pp. 128-130) systems in an orthogonal coordinate system plus the applicable metric structure (Mikulecky, 1993).
When considering the ecological importance of network thermodynamics, one must consider the needs in the study of natural systems to apply the results of reductive analyses into a holistic perspective. The typical information acquired in modern science has a somewhat limited value until it combines with network topological information of the natural system. Network thermodynamics is a means by which the systematic assembly of reductionism-based components in an ecosystem can be assembled into a network where the whole becomes more than the sum of its parts; for example, differing connections among electrical components result in differing emerging system properties. Considering the network representation of linear n-ports as a canonical coordinate system for expressing the metric between states in entropy and/or energy space (Mikulecky, 1993, 2005b, pp. 131-140). Thus, if two simple linear n-ports combine, they produce a new n-port with new properties, which requires a new metric. The new n-port will likely show new emergent properties. Network thermodynamics encompasses all of classical and non-equilibrium thermodynamics, plus it combines these with kinetic and topological reasoning to form a holistic description of natural systems.

A key point that one should take from this discussion of network thermodynamics is that it is not enough to learn more about parts of a system in isolation, but one must learn more about the context in which the parts exist to begin to understand the true nature of ecological systems. Further, as engineers begin to ponder how to best manage and design these systems, that point must be taken acutely that it is both the parts and the context, and in the case of ecosystems, the context is an open system that is internally and externally interdependent at many levels, characterized by its plasticity, parts, processes, and patterns. Furthermore, network thermodynamics using electronic simulation software is one way by which complex interdependent system properties may be determined. Thus, it is a potential way by which design
and management of ecological systems could follow in trying to understand, manage and emulate these systems properties.

**Ascendency**

The next section is a discussion of the ecological network analysis technique called *Ascendency*. Developed by Robert Ulanowicz to quantify the growth and development of an ecosystem, Ascendency serves as an instantaneous measure of the size and organization of the system. Ulanowicz (1997, 2000) captured the growth and development in the measure *Ascendency*, but it bases on the ecological concept of succession explained by E.P. Odum (1969) as a biological organization resulting from the system’s interaction with the physical environment as it takes in energy and builds internal structure. Odum (1969) suggested that succession of ecological systems results in a stable system, such as the ending point of succession, climax communities maintaining symbiotic function and system biomass. Odum identified trends such as web-like food chains, closed mineral cycles, internal symbiosis, and a high resistance to external perturbations, low entropy and high levels of information (Odum, 1969; Gattie, Kellam, & Turk, 2007, pp. 32-33). Ascendency (Ulanowicz, 1997, 2000) intends to capture in a single quantitative index the aforementioned attributes of ecological systems by using the mathematics developed in Claude Shannon’s (1948) communications theory to quantify changes in probability. Ascendency suggests consideration as both a quantitative and qualitative description of the attributes of ecological systems and the interactions of their tropic networks. Ecosystems are represented through various degrees of sophistication and often in terms of their tropical interactions (Lindemann, 1942; Hutchinson, 1948). However, even the most detailed and sophisticated of these representations is at best minimalist compared to the subtleties and intricacies of the actual physical system. However, at an appropriate scale, these
simplified representations lead to pertinent system characteristics at immediate scales that may be useful for the design and management of ecological systems. For instance, \textit{Ascendancy} quantifies a system's ability to survive in the face of ecological disturbances. In other words, Ascendancy suggests that there is an operating range for sustainable ecosystems, and those which fall below this range tend to fall apart as a viable system; those which are above this range tend to "break" in the face of ecological disturbance. Ulanowicz calls this operating range the "window of vitality" (Ulanowicz, 1997, 2000, 2002; Jørgensen, 2002, pp. 245-279; Gattie, Kellam, & Turk, 2007, pp. 32-33) for ecological systems.

Mathematically, Ascendancy is the product of the systems throughput ($T$), the summation of all flows through the system and the systems information ($I$), or the “effects that impart order and pattern to the system” (Ulanowicz, 1997, p. 65). It is based on the far-from-equilibrium thermodynamics of Prigogine (1972) for living systems, where systems increase their order through a self-organizing autocatalytic process as a result of indirect mutualism within the network (Gattie, Kellam, & Turk, 2007, p. 33).

\begin{equation}
\text{Ascendancy} = T \ast I
\end{equation}

\begin{equation}
T = \sum_{j=0}^{n} \sum_{i=1}^{n+2} T_{ji}
\end{equation}

\begin{equation}
I = \sum_{j=0}^{n} \sum_{i=1}^{n+2} \left( \frac{T_{ji}}{T} \right) \ast \log \left( \frac{(T_{ji} \ast T)}{T_{i} \ast T_{j}} \right)
\end{equation}

Jørgensen (2002, p. 247), in describing and paraphrasing Ulanowicz and Norden (1990), writes that “Everything that grows is also constrained by temporal, spatial, or material factors. Such
constraints serve to keep the system *Ascendency* within its limits.” Perhaps this work might further extrapolate that statement to suggest relations as an additional constraint. Nevertheless, the abovementioned statement describes a natural optimization process of checks and balances to attempt to keep ecosystems within the “window of vitality” (Ulanowicz, 1997, 2000, 2002).

Stated another way, ecosystem growth may be naturally driven by maximization but is constrained to optimization, or it ceases to be sustainable, which may have important applicability as design strategies for ecological systems are considered. Further, this may have implications for human society’s tendency to maximize the exploitation of natural capital to achieve maximum profits. If so, does this tendency need effective constraints that select against human maximization for optimizations to occur? However, Hardin (1968, p. 1243) in “Tragedy of the Commons” suggests that these classes of problems likely do not have technical solutions but requires extension in morality.

The incremental tendencies of ecosystems to calm disorder describe mathematically by the use of information theory where a formula for the description of order or disorder may be used and is a measure of the systems processes. Ecosystem processes are the pathways of energy and material flows through the system. The complexity of the system relates directly to the system’s information, which is equivalent with the number of possible system events or connections within the system. Boltzman (1905) (Jørgensen, 2002, p. 126) determined that the possibility for each event combination contributes to the overall complexity (or information) as the negative logarithm of the probability that a particular combination will occur. In equation form

\[ s = -k \log p. \]  

(3.10)
Thus, $s$ is the contribution to overall complexity, $p$ is the probability that a particular combination or configuration will occur, and $k$ is Boltzman’s constant of proportionality. If a particular system combination or configuration occurs very frequently, its probability of occurring moves closer to unity (1), and as system probabilities approach 1, its complexity measure goes to zero, that is, $\log(1) = 0$. On the other hand, the more uniquely a system behaves, the lower the probability that its configuration and thus the contribution to overall complexity increases as its probability reduces. However, the overall complexity of a system averages over all the potential states of the system by summing all the weighted complexity contributions ($s_i$), where the weighting of each occurs by its probability ($p_i$). Thus, as increasing event combinations generate complexity through decreasing probabilities, constraints begin to inform systems by establishing patterns, bias, and trends, thereby increasing event probabilities and subsequently decreasing complexity (Bar-Yam, 2004, pp. 31-40).

In terms of ecological systems, Ulanowicz (1997, 2000, and 2002) determines that the most indeterminate and thus complex networks are those that have flows to and from every other compartment.

Ulanowicz weights the changes in probability assignment by the fraction of total system throughflow comprised by the actual flow and does the same for each flow in the network, ultimately summing all these contributions to what he calls the average mutual information or AMI of the flow structure. “AMI measures the average amount of constraint exerted upon an arbitrary quantum of currency in passing from any one compartment to the next” (Ulanowicz, 1997, p.73). Ascendency calculates as a product of TST, which is a measure of system growth, and AMI, which is a measure of system development.
It should be noted that equation 3.7 represents an instant in time or a systems size and organization at a time \((t)\); thus, to extrapolate the equations above for a depiction of system growth and development, several determinations at discrete times are required (Jørgensen, 2002, pp. 247-248). Equation 3.8 algebraically rearranges to parse out dialectical restrictions on a systems ascendency. Thus in two forms,

\[
\text{Ascendency} = T \sum_{j=0}^{n+2} \sum_{i=0}^{n+2} (T_{ji}/T) \log(T_{ji}/T) - (-T \sum_{j=0}^{n+2} T_{ji}/T) \log(T_{ji}/T)) \quad (3.14)
\]

\[
C = T \sum_{j=0}^{n+2} \sum_{i=0}^{n+2} (T_{ji}/T) \log(T_{ji}/T) \quad (3.15)
\]

The term inside the bracket in equation 3.14 represents a systems overhead (Jørgensen, 2002; Salines, 1986), which measures the system's conditional entropy or uncertainty. Parsing the ascendency equation above into two non-negative terms reveals an upper bound to the systems ascendency in the first term, which Ulanowicz calls the development capacity \((C)\) of a system. Since the equation for development capacity is algebraically limited, this limit on growth is also by default a limiter to a systems ascendency. In other words, input and the number of compartments \((n)\) limit TST. A greater number of constituents would tend to increase a systems ascendency, but as the flow distributes between greater numbers of constituents, the average throughflows at some constituents will become so small that changes within or external to the system may cause these flows to cease (Ulanowicz, 1997, 2000, 2002; Jørgensen, 2002, p. 248. Ulanowicz uses probability theory to inform the analysis of steady-state systems of the propensity for intercompartmental exchanges within the system and further informs the analysis.
of dynamic systems through information theory’s ability to determine changes in the conditional probabilities. A change of system size coupled with exchange probabilities between compartments results in systemic measure of the systems size and organization and implicates the system’s ability to move or maintain its distance from thermodynamic ground. Ulanowicz (1995) contends that it serves as a measure of a system’s ability to sustain its level of organization (Gattie, Kellam, & Turk, 2007, pp. 32 -33). Thus, in summary, Ascendency integrates the growth of system activity and the degree of organization of system constituents through processes of indirect mutualism to capture the dynamics of systems as they grow, self-organize and increase in complexity.

Gattie, Kellam, & Turk (2007) suggested that ecosystem growth, development, and organization well encapsulate within the ecological theory of Ascendency (Ulanowicz, 1997, 2000). It is the position of this work that a network’s Ascendency measure suggests use as a design orientor or parameter to determine optimally sustainable network configurations. In other words, ecological systems design and management and the integration of mechanistic systems into the natural environment that facilitate system organization and size remaining within Ulanowicz’s “window of vitality” seem to suggest a possible design direction, parameter or constraints to achieve sustainable systems that can continue to succeed when faced with disturbance. Perhaps it may be used to some degree to determine limiting resources for system constituents. Such applications investigated to some degree, for instance, by Pahl-Wostl (1990), who amasses species into functional groups based on the network’s Ascendency as it relates system function, location and time attributes (Jørgensen, 2002, p. 249). In addition, in comparing tropic chain length, and number of cycles within two ecosystems, Schneider and Kay (1990, 1994; Jørgensen, 2002, p. 251) suggested that the greater the number and/or length of cycles
within a food web facilitates more opportunities for systems to degrade energy. Further, the number of effective tropic levels will increase, facilitating a greater likelihood of energy degradation as the energy transfers up the food chain degrade more than energy that exports directly to detritus. Higher tropic level may only exist with a concurrent increase in energy efficiencies, and lastly, increasing number or length of cycling allows greater and more tightly constrained niches within ecological systems that also increases the number of energy pathways and subsequently facilitates more degradation (Jørgensen, 2002). These concepts and ideas will resurface again as this work begins to formulate and discuss design and management strategies for ecological systems in later chapters.

Network Environ Analysis

Patten and colleagues, making extensive use of the mathematics of Zadeh’s (Zadeh & Desoer, 1963; Fath & Patten, 1999) general system theory and using Zadeh’s fundamental idea that causation is a determinate and nonanticipatory relation between two constituents of a system introduced the holon (Koestler, 1967; Patten, Bosserman, Finn, & Cale, 1976, p. 472) as a subsystem within any level of a hierarchical layered ecological system. Further, they determined that any holon consists of two separate environments, one that looks backward in time and thus delineates the input environment of the holon and the other, which looks forward in time and delineates the output environment. Thus, Patten (1978) defined these in mathematical terms and termed them input and output environs (Fath & Patten, 1999). Furthermore, Patten and colleagues (1976) extended Zadeh’s fundamental ideas of causation to develop a theory of causal networks based on causal bonds and causal sequences within the network, where causal networks were used to suggest that ecological systems were coevolutionary (Fath & Patten, 1999).
Further, they combined these ideas with Leontief’s (1936, 1951, 1966) analyses of industrial interdependence within economic systems (Miller & Blair, 1985; Fath & Patten, 1999). With those of Hannon (1973), who used input–output analysis to determine direct and indirect flows of energy between constituents of an ecological system, and who further suggested that this type of analysis lends itself to determination of system goal functions based on total direct and indirect storages of the system (Hannon, 1979, Fath & Patten, 1999). However, Patten and colleagues reversed the orientation of the analyses used by Leontief and Hannon in order to calculate output generated from each unit of input and derived additional methods to determine total system throughflow, average pathlength, and cycling index (Finn, 1976; Fath & Patten, 1999). All of these ideas incorporate into and apply to ecological systems where Patten (1978) put forward three key ideas that would make up the underpinnings of Network Environ Analysis (NEA). First, any object within a system has two distinct quantifiable environments, which he termed *input environs* and *output environs*. Second, the internal causation of a system necessarily is determined from its external reference state. Last, flow propagation between system constituents is unique in its pathway; thus, an accounting of all direct and indirect flow may be accurately achieved (Patten, 1978, 1982a, 1984; Fath & Patten, 1999; Gattie, Kellam, & Turk, 2007, pp. 31-32).

Fath & Patten (1999) state that NEA has significant fundamental differences from other network analysis techniques, including that environment parses into *input* and *output environs*. Further, it employs both the inverse and the matrix power series to enumerate structural pathways and that both the input and output orientations are applied to flows, net flows, in both storage and throughflow models. Furthermore, primacy of flows over storage is significant to NEA in that flows articulate the *output environ* of one system constituent to the *input environ* of
another system constituent, and thus flow creates the system pattern and structure, which gives rise to direct and indirect system behaviors and holistic properties (Fath & Patten, 1999). Patten and associates (Patten et al., 1976) suggested the importance of indirect effects for cyclic systems and further suggested environs as a fundamental conceptual unit of nature and proposed a theory of environment based on this fundamental unit coupled with von Uexkull’s (1926) function circles (Patten, 1978, 1982a, 1984; Gattie, Kellam, & Turk, 2007, p. 32) called environ theory. Environ theory implicates ecosystems as articulated constructions of compartments, each with input and output environs (Fath and Patten, 1999), and Gattie et al. (2006) constructed a general network unit for analyzing the output environs of the Neuse River Estuary system constituents, which indicates a microdynamic organization for environs. A more thorough mathematical presentation and discussion of NEA and indirect effects occurs in the next chapter.

Discussion

Historically embedded within a Newtonian framework, science has often reduced and isolated the study of organisms from their context. This has been partly due to the difficulties associated with a holistic contextual study of system components within their natural environment. The significance of network analyses is their ability to investigate systems holistically, capturing both direct and indirect quantities and the intertwined interdependent aspects of systems and the relationships of components. These systemic properties and relationships include indirect effects, ascendancy, indirect mutualism and utility, network relationships, information, and organization, and though each property is unique, each has the common property of being empirically intractable (Gattie, Kellam, & Turk, 2007, p. 33). Thus, the design and management of open, interconnected and interdependent, self-organizing systems that exhibit these emergent properties, which have been typically out of the purview of normal
human observation and analyses, not only requires significant philosophical thought but also poses substantial technical challenges. Systems science, graph theory, network mathematics and various network analysis techniques (Gattie, Kellam, & Turk, 2007, pp. 33-34) may be prime candidates to serve as the philosophical and analytical basis for the design and management of ecological systems. In particular, ecological network analysis (ENA) techniques including network environ analysis, network thermodynamics, and ascendency, coupled with empirical observations, ecological theory, physical theory and simulations, may provide a first step toward more holistic management and less destructive integrations of human constructed systems into the environment while serving as a basis on which design methods for natural systems should proceed.
CHAPTER 4
INDIRECTNESS AND ECOLOGICAL SYSTEM PROPERTIES

The overall intent of this work has been and is to show that engineering complex natural systems requires new ways of thinking and new deliberations when considering the requisite level of accuracy and precision needed in the planning and management of ecological systems. To that end, this work intends to put forward several design goals and will use information gleaned from an input-environ analysis of the Neuse River Estuary, NC and other models of ecological systems to begin to both circumstantially and quantitatively illustrate distinct ecological characteristics that will lead to a proposed philosophy for the planning and management of ecological systems in following chapters. The particular purpose of this chapter is to reveal some unique characteristics of ecological systems and to most generally illustrate mathematically their interdependent and indirect aspects. An initial observation during a presentation of Axiomatic Design, an engineering design and optimization process, led this work to hypothesize, that design methods for traditional engineered systems are perhaps the opposite in many regards of what is needed in design and management of ecological systems. For instance, the Axiomatic Design (Suh, 1990, pp. 46-48) method manipulates design matrices toward an optimal configuration through decoupling or one to one mapping of design parameters to functional requirements. In other words, the method optimally seeks a functional independence of system components. This is quite different from the results observed in the network analyses of ecological systems. In these analyses of ecological systems initial
independent functional mappings decrease as the system operates toward a generalized functional \textit{interdependence} of system components. Bernard Patten and associates describe this as \textit{Network Proliferation} etc (Patten, 1978, 1982a.b., 1984; Higashi and Patten, 1986, 1989). These observations led this work to hypothesize that current engineering methods are insufficient for the construction and understanding of ecological systems and that a need exists for new intellectual paradigms in their management and design. Further, this work suspects that design axioms and corollaries used in traditional design methods to optimize an engineered system may in fact be the opposite of those necessary for the design and management of ecological systems. The following is a model analysis of the Neuse River Estuary (Turk, Gattie, Schramski, & Bata, 2012) which will show, unlike \textit{Axiomatic Design}, a proliferation of network connections as well as other interdependent system properties useful in the understanding, design and management of ecological systems. It will be followed by a summative commentary that will show that this proliferation of network connections is common if not general thus significantly and naturally leading to the overarching propositions of this work in chapters to follow.

\textbf{Comparative Analyses of Microdynamic Environ Flows in an Ecological Network}

Network Environ Analysis (NEA) has two mathematical forms that provide differing perspectives by which the connectivity of ecological systems may be quantitatively determined. The methodologies are similar; however, one examines flows within a system from an input-driven perspective whereas the second examines the system flows from a perspective driven by output. Independently, the two methods, at coarse scales, reveal quantitatively precise results, but at fine scales, some quantitative differences emerge, perhaps suggesting interpretation of the differing roles that input and output environment may play in the dynamics of ecological systems. Thus, the contrasting fine scale environ results of the “forward looking” output-environ
analysis and the “backward looking” input-environ analysis of the seven-compartment model of nitrogen flows within the Neuse River Estuary, North Carolina, USA has led this work to separate and further refine several terms of each NEA method. The terms environ throughflow and total environ throughflow (Gattie, Schramski, & Bata, 2006, p. 189) are perhaps more aptly termed input-environ throughflow, total input-environ throughflow, output-environ throughflow, and total output-environ throughflow. Further, the quantitative input- and output-driven fine scale environ result differences uncovered suggests subtle mechanisms by which the dynamics of the system may operate. This implies a critical need for decision makers to carefully consider and reflect upon these subtleties and others involved in ecological systems when determining goals and prediction of emerging outcomes of natural system management and design.

Introduction

Empiricism, experimentation, and reduction have gone a long way in noting observable interacting, integrating, and perhaps independent component patterns of natural systems but have fallen short in the ability to note the complexity and subtle interdependencies within the system. On the other hand, the ecological input-output analysis techniques that have emerged over the last several decades provide methodologies to examine connected systems as matter and energy flows across an open boundary. Originally, Leontief (1936) developed an economic modeling technique to analyze the supply or input required to meet a particular economic demand or output. Later, Hannon (1973) extrapolated Leontief’s original method to ecological systems, using matter and energy as the currency but with a reverse orientation, that is, the determination of output generated by a particular input. Many differing network analytical techniques exist today with varying metrics used to parse out the subtleties of complex systems (Gattie, Schramski, & Bata, 2006, p. 190). Bernard Patten and associates developed Network Environ
Analysis (NEA) as an ecological analysis method based on Leontief’s and Hannon’s input-output analysis techniques, and it serves to provide a general analytical tool to study ecological objects as part of a connected system (Patten, 1978, 1982a., 1984; Higashi and Patten, 1986, 1989). The NEA method has the ability to investigate and map ecosystems as individual compartments within a connected system and provides a method to understand the connectedness and emergent properties of nature. By graph theory, the methodology allows the separation of effects, revealing the direct and indirect quantities furthering the quantitative and qualitative understanding of the system. Significantly, NEA and other analysis techniques, which retain system connectedness, allow the investigation between components of a system without removing them from the system setting. In addition, they suggest network ecological patterns as mathematical trends (see Chapter 3) that correspond to subtle physical realities and perhaps begin to approach the essence of interdependent complex natural systems. Conceivably, these patterns revealed are useful as tools or targets for the planning and management of ecological systems.

Patten’s (1982b) technique uses “environs” as the ecological unit of nature to pursue cause and effect within ecosystems. Often, cause and effect propagate indirectly within connected systems (Higashi and Patten, 1989), and perhaps this is the essence of what constitutes an interdependent complex system. Interdependent complexity seems to exist when cause and effect conceal within composite interdependencies and therefore cannot be directly inferred. Thus, environs seem to provide a method to parse out trends such as the causally circular indirect effects and allow one to pursue composite causes and effects within a system where, as an entity changes state, the composite causes are the input environs of the entity, and the composite effects are the entity’s output environs (Gattie, Schramski, & Bata, 2006, pp. 190-191).
Network Environ Analysis (NEA) has two mathematical forms that provide differing perspectives by which the connectivity of ecological systems may be quantitatively determined. The methodologies are similar; however, one examines flows within a system from an input-driven perspective whereas the second examines the system flows from a perspective driven by output. Independently, the two methods, at larger scales, reveal quantitatively precise results, but at fine scales, some quantitative differences emerge, suggesting an interpretation of the differing roles that input and output environment may play in the dynamics of ecological systems. The contrasting fine scale environ results of the “forward looking” output-environ analysis and the “backward looking” input-environ analysis of the seven-compartment model of nitrogen flows within the Neuse River Estuary, North Carolina, USA are examined and compared.

Analyses of Microdynamic Environ Flows

The Neuse River Estuary, North Carolina, USA, examined at steady-state using NEA to investigate the subtle indirect causes and effects within the system that maintain it at a steady state. The system, examined using the input-environ method of NEA (input-environ analysis), which is a “reverse looking perspective”, determining what input is required or instigated by a certain output. Comparing the results to a “forward looking” perspective or output-environ analysis performed on the same data set (Gattie, Schramski, & Bata, 2006), the two methods determine independently and quantitatively nitrogen flows within the system. This work will note any quantitative similarities and differences in these flows within the system as determined by the differing methods. Lastly, it will speculate qualitatively on those differences, if any. As mentioned, the output-environ analysis was previously performed on the same data set and for comparative consistency, this work draws upon and will parallel the format and structure of that analysis. This work suggests that interested readers should refer to the paper by Gattie,
Schramski & Bata (2006) for more detail of the general analysis technique of the Neuse River Estuary model particularly regarding the output-environ analysis. The input-environ analysis presented here, however, the requisite equations, the corresponding results, the comparisons of, and inferences from the two differing methods for the Neuse River Estuary model, are independent to this work. The graphical models for both methods are identical, but the analyses differ in that the input-environ analysis considers what input is required to cause a particular output whereas the output-environ analysis examines what output is generated by a particular input. As mentioned, the models are compared quantitatively, using similarities or differences to suggest qualitative interpretations of the system and applicability to the planning and management of ecological systems.

It is assumed, the system open to the environment is, at coarse scales maintained near a steady state by the fine scale interdependencies examined within the system’s network. It is these fine scale causes and effects that constitute the subtle interdependencies that reflect the essence of the system and its complexity. Understanding these will be requisite in determining a philosophy for effective design and management of complex natural systems.

**Method and Material**

Using data collected by R. R. Christian and C.R. Thomas (2000) during the summer of 1988, this work analyzes nitrogen flow of the Neuse River Estuary model by the use of Network Environ Analysis (NEA). The model (Figure 4.1) analyzes the input-environ flows of nitrogen of the system and for comparative purposes, the analysis uses the same conceptual model with identical connectivity of components, flows between components, and standing stocks as used in the output-environ analysis of the same data set (Gattie, Schramski, & Bata, 2006. p. 189).
Figure 4.1: Digraph of Neuse River Estuary model for both input-environ and output-environ analysis (after Gattie et al., 2006, p. 191). Note: $f_{ij}$ for the output-environ analysis and $f'_{hi}$ for the input–environ analysis.

Model Structure

The topology of a system may be encoded using theoretical graphical methods. Graph theory identifies connection points as nodes or vertices and the lines connecting these as branches or edges. System structure represents mathematically as a graph of the component interconnection and a corresponding incident matrix designates arrays of ones and zeros for a non-directed graph and an array of ones, zeros, and minus ones for a directed graph, where each row of the matrix
corresponds to one of the nodes and the columns refer to the branches. For example, the entry in the $i^{th}$ column and $h^{th}$ row will be “1” if branch $i$ is incident on node $h$ and flows into it. If the flow is out of node $h$, the entry will be “-1” and it will be “0” if it is not incident. Thus, topological information of a graph’s connectedness and direction may lie within its incidence matrix. For example, in tropic relationships if prey $i$ is eaten by predator $h$, the actual or physical flow of material is from $i$ to $h$. (Patten, 1978, 1982a., 1984; Higashi and Patten, 1986, 1989; Mikulecky, 1993; Fath and Patten, 1999). Another representation of system structure is an adjacency matrix which indicates which nodes or vertices of a system are adjacent to other nodes etc. The adjacency referred to in the following model is the result of empirically observed flows, and the presence of such observed flows between compartments (nodes) is represented (Equation 4.1) as an entry of “1” in the matrix. Thus, the network modeled here is a directed graph with a particular mapping associated with it. In this case, a binary adjacency matrix was constructed of model components where $a'_{hi} = 1$ represents in this model that nitrogen may flow between and from $i$ to $h$. If $a'_{hi} = 0$, nitrogen flow is not possible from $i$ to $h$ without first traveling through another intermediate compartment. Therefore, the adjacency matrix indicates where direct connectivity exists between model compartments, which corresponds to a path length of $m = 1$. This work will compare a network-input environ analysis of the same data used by Gattie, Schramski, & Bata (2006, p.191) in a previous output-environ analysis of the same Neuse River Estuary data. In this paper, prime quantities will be used to specifically denote assigned and derived quantities of the input-environ analysis and non-prime values will be for terms common to both analyses and/or the output-environ analysis. Gattie, Schramski & Bata (2006) used an adjacency matrix $A$ in the output-environ analysis of the summer 1998 Neuse River Estuary, for the input-environ analysis of the same data the adjacency matrix will be designated $A'$ and is
shown in Equation 4.1. It should be noted that the adjacency matrix for the output-environ analysis (Equation 4.2) differs from the adjacency matrix for the input-environ analysis in respect to the direction of the analysis. In other words, the focal compartments $i$ (Figure 4.2) remain the same in each analysis, and other compartments within the model for the output-environ analysis and the input-environ analysis also remain the same. The difference only arises in respect to the direction that each analysis considers. Hence, for the input-environ analysis, the output or flows from the focal compartment $i$ (columns) to $h$ (rows) determine the requisite input into focal compartment $i$. This differs from the output-environ analysis where the flows are considered from $j$ (columns) to the focal compartments $i$ (rows) and determine the requisite output of focal compartment $i$.

$A' = \begin{bmatrix}
0 & 1 & 1 & 1 & 0 & 0 & 1 \\
0 & 0 & 1 & 1 & 0 & 1 & 1 \\
0 & 1 & 0 & 0 & 1 & 1 & 0 \\
1 & 1 & 0 & 0 & 0 & 0 & 0 \\
1 & 1 & 1 & 0 & 0 & 0 & 0 \\
1 & 1 & 1 & 0 & 1 & 0 & 0 \\
0 & 1 & 1 & 0 & 0 & 0 & 0 \\
\end{bmatrix}

h \quad 4.1$: For Input-environ analysis

$A = \begin{bmatrix}
0 & 0 & 0 & 1 & 1 & 1 & 0 \\
1 & 0 & 1 & 1 & 1 & 1 & 1 \\
1 & 1 & 0 & 0 & 1 & 1 & 1 \\
1 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 1 & 0 \\
0 & 1 & 1 & 0 & 0 & 0 & 0 \\
1 & 1 & 0 & 0 & 0 & 0 & 0 \\
\end{bmatrix}

i \quad 4.2$: For Output-environ analysis
**Figure 4.2.** Left to right: Flow from input-receiving compartment \( j \) to arbitrary compartment \( i \) for output-environ analysis. Right to left: Backtrace of output generating compartment \( h \) to arbitrary compartment \( i \) for input-environ analysis. Note: The focal compartment \( i \) remains the same in each analysis, as well as, the other compartments within the model for the output-environ analysis and the input-environ analysis. The difference arises in respect to the direction that each analysis considers. Hence, for the input-environ analysis, the output or flows from the focal compartment \( i \) (columns in the adjacency matrix \( A' \)) to \( h \) (rows in the adjacency matrix \( A' \)) determine the requisite input into focal compartment \( i \). This differs from the output-environ analysis where the flows are from \( j \) (columns in the adjacency matrix \( A \)) to the focal compartments \( i \) (in the adjacency matrix \( A \)) and determine the requisite output of focal compartment \( i \). Prime values will be used to signify quantities both assigned or derived in the analysis based on flows from the focal compartment \( i \) (input-environ analysis) and non-prime values will denote assigned or derived quantities based on the analysis of flows to the focal compartment \( i \) (output-environ analysis) or common to both analyses.

\( A^m \) is a power series of \( A \) (for the output-environ analysis) and \( A'^m \) is a power series of \( A' \) (for the input-environ analysis), both of which enumerate the pathways between \( j \) and \( i \) and \( i \) and \( h \), respectively, where \( m \) is the path length. The \( a_{ih}^m \) entry of \( A'^m \) is a non-negative integer representing the number of pathways from \( i \) to \( h \) of length \( m \). The power series will diverge as shown (Equation 4.3) and corresponds to a proliferation of pathways in the extended network. Pathways of \( m > 1 \) have particular significance in ecological networks in that these pathways represent the causally circular and distributed indirect effects at work within the system and are significant in developing a mathematical framework by which the importance of these quantitative indirect effects are used to enhance the description of the system (Patten et al., 1976;

\[ A^0 + A^1 + A^2 + A^3 + \ldots = \text{Divergent (as } m \to \infty) \]  

(4.3)

Of the 42 possible connections of path length 1, Figure 4.1 reveals that nitrogen flow exists in 22 adjacent connections. The adjacency matrix indicates the measured or empirical flows; however, there exists embedded within these flows a component of flow where the path lengths are \( m > 1 \). That is, there often exists within empirical flows a component, which is the result of indirect connections between compartments. Indirect connections are those connections that have path lengths \( m > 1 \); moreover, these indirect connections provide additional flow information with regard to indirectness and cycling within the model. One should note that elements along the diagonal of the \( A' \) matrix would refer to potential connections or flows from individual compartments back to themselves.

Network Flows

The system is analyzed as a steady state system (or near steady state system) using the following matrix parameters: \( f'_{hi} \) as the intercompartmental flows from \( i \) to \( h \) in mmol/m\(^2\) per season, \( z_i \) as the boundary input flows (mmol/m\(^2\) per season), \( y_i \) as the boundary output flows (mmol/m\(^2\) season), and \( x_i \) (mmol/m\(^2\)) as the standing stocks of the system’s compartments (Table 4.1). The throughflow (\( T' \)) is dependent upon the system’s flow parameters and is a measure of compartmental flow activity within the system. That is, throughflow is the sum of either the inflows or outflows of a compartment within the system.
Table 4.1. Modeled intercompartmental flows, $f'_{hi}$ boundary inputs, $z_i$, boundary outputs, $y_i$, and standing stocks, $x_i$, for nitrogen flow for the summer 1998, Neuse River Estuary, North Carolina, USA (Christian and Thomas, 2003). Units for $f'_{hi}$, $z_i$, and $y_i$ are mmoles-N/m²•season, and for standing stocks are mmoles-N/m².

<table>
<thead>
<tr>
<th>Summer 1988</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flows</td>
</tr>
</tbody>
</table>
| $F' = \begin{bmatrix}
0 & 0 & 0 & 446 & 446 & 2438 & 0 \\
2419 & 0 & 260 & 372 & 34 & 2034 & 696 \\
218 & 2 & 0 & 0 & 2 & 54 & 218 \\
666 & 151 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 33 & 0 & 0 & 386 & 0 \\
0 & 4772 & 119 & 0 & 0 & 0 & 0 \\
22 & 894 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}$ |
| Boundary Inputs |
| $Z = \begin{bmatrix}
1 \\
4 \\
8 \\
27 \\
64 \\
23 \\
5
\end{bmatrix}$ |
| Boundary Outputs |
| $Y = \begin{bmatrix}
6 & 0 & 90 & 26 & 1 & 7
\end{bmatrix}$ |
| Standing Stocks |
| $X = \begin{bmatrix}
24 \\
22 \\
1300 \\
78 \\
7 \\
5 \\
24
\end{bmatrix}$ |
In equation form: $T_i$

$$T_i^{in} = T_i = z_i + \sum_{j=1}^{n} f_{ij}, \quad i=1,2,3,\ldots,n, \quad (4.4)$$

$$T_i^{out} = T_i' = y_i + \sum_{h=1}^{n} f_{hi}', \quad i=1,2,3,\ldots,n, \quad (4.5)$$

In the equations above, $n$ represents the number of compartments within the system and at steady state the throughflow is a property of compartments within the system as well as the system in general. Further, at steady state, throughflow out ($T_i^{out}$) will equal the throughflow in ($T_i^{in}$). For system throughflow, the total flow activity of the system or Total System Throughflow (TST) has the following analytical form:

$$TST = \sum_{i=1}^{n} T_i^{out} = \sum_{i=1}^{n} T_i^{in} \quad (4.6)$$

Living systems organize and maintain a distance from thermodynamic ground where all gradients are zero and thus matter and energy flow is impossible (Jørgensen, 2002). White (et al., 1992) identifies three types of systems: open, closed and isolated. Isolated systems are those that close to matter and energy exchanges with the external environment. Closed systems are those systems, which allow exchanges of energy but not matter with the external environment, and open systems are those that allow exchange of both matter and energy with the external environment. Living systems are open systems; this openness to matter and energy exchanges at
the system boundaries is requisite for these systems to minimize their entropy or organize and distance themselves from the zero gradients at thermodynamic ground. The Neuse River Estuary examined in this work is an open system. Open systems, however, do not maintain an exact or true equilibrium, but the system as a whole is in a stationary or steady state open to boundary exchanges \(z_i\) and \(y_i\). Although, at a macroscopic scale, the system may be empirically determined, analyzed and interpreted as a steady state system, but in reality is a collection of dynamic microenvironments that maintain its macro-scale steady state. In other words, there exists embedded within the empirically determined values of intercompartmental flows \(f'_{hi}\) and standing stocks \(x_i\) components from the boundary exchanges that are developed from and through the network’s extended pathways as enumerated by higher powers of \(A^m\). These smaller scale flow components were termed and referenced as microdynamic environ flows by Gattie, Schramski, & Bata (2006, p. 192).

**Analytical Methodology**

The output-environ analysis (Gattie, Schramski, & Bata, 2006) illustrated how boundary input at individual compartments may contribute to flow within the network and how any boundary input \(z_i\) may contribute to individual compartmental flows. This is also true for the input-environ analysis; however, it is boundary output at individual compartments that reflects flow within the network and where any individual boundary outputs \(y_i\) are due to prior individual compartmental flows over direct or indirect pathways. This is very significant in that it illustrates how indirect relationships develop along pathways of increasing length as input or output from the system’s boundary causes and distribute flow to compartments within the system. In other words, any flow \(f'_{hi}\) in a network potentially affects any boundary input or output to the system through indirect connections that in turn result in the potential distribution of input to all system
compartments. In the output-environ analysis, Gattie, Schramski, & Bata (2006, p. 193) illustrated a generalized network focal compartment \( i \) where the compartments in the input environ of \( i \) are \( j \) and compartments in the output environ of \( i \) taken as \( h \). This focal element \( i \) and its input and output environ connections represent its local environment and consists of all other objects within the system with which it interacts. Accordingly, the element dissects into mutually exclusive halves where one comprises the inflow and the other outflow. (von Uexküll, 1926; Patten 1978, 1982a, 1982b, 1984; Higashi & Patten 1986, 1988; Fath & Patten, 1999; Gattie, Schramski, & Bata, 2006, p. 193).

In the output-environ analysis, the contribution at any compartment \( j \) to the throughflow at focal compartment \( i \) is \( f_{ij} \), of the throughflow \( T_j \) at the donor compartment and \( g_{ij} \) is the dimensionless ratio of \( f_{ij} \) by \( T_j \) or the flow intensity for the output-environ analysis. Thus, each of these (flow intensities) may be determined and assembled into an \( n \times n \) matrix denoted as \( G \), where each element of the matrix represents the fraction of throughflow at the donor compartment \( j \) distributed to \( i \). For the input-environ analysis, the focal compartment remains \( i \); however, the contribution at any compartment \( h \) from the throughflow at \( i \) is \( f'_{hi} \) of the throughflow at the recipient compartment and the ratio of \( f'_{hi} \) by \( T_h \) will be denoted the dimensionless flow intensity \( g'_{hi} \) (Equation 4.7), which may also be assembled into an \( n \times n \) matrix, \( G' \). Thus, to analyze the significance of these flow distributions there is a need to partition the throughflow into fractional components assembled into a dimensionless \( n \times n \) matrix form \( G \) for the output-environ analysis and \( G' \) for the input-environ analysis, each of which represents the fractions of throughflow (Patten 1982a, 1982b; Fath & Patten, 1999; Gattie, Schramski, & Bata, 2006, p. 193). For the output-environ analysis, the fraction of throughflow at donor compartment \( j \) distributed to \( i \), and for the input-environ analysis the fraction of
throughflow at the recipient compartment $h$ distributed by the focal compartment $i$. Further, the throughflow may be readily partitioned using the above ratios $g_{ij}$ and $g'_{hi}$ and Gattie, Schramski, & Bata (2006, p. 193) referenced $g_{ij}$ the \textit{throughflow partitioning coefficient}. That terminology will also apply to the input-environ analysis contained herein. Thus, $g'_{hi}$ \textit{(Equation 4.7)} for the input-environ analysis:

$$g'_{hi} = \frac{f'_{hi}}{T'_{h}} \quad (4.7)$$

The reader will be reminded that flows $f'_{hi}$ are empirically measured flows, which may be an integration of all boundary inputs, outputs and standing stocks within the system over both a direct and indirect pathway structure. As integrated flows, the indirect contributions from inputs, outputs and standing stocks to these flows hide in the composite structure and cannot be empirically determined, but derive mathematically.

The \( n \times n \) matrices $G$, $G'$ and the adjacency matrices $A$ \textit{(Equation 4.2)} and $A'$ \textit{(Equation 4.1)}, and the flow matrix $F'$ \textit{(Table 4.1)} have the same connectivity. This is significant in analyzing the distribution of nitrogen to and from the focal compartment $i$. That is, as the $A'$ matrix enumerated into higher powers $A'^{m}$ \textit{(Equation 4.3)} to reveal the number of pathways from $i$ to $h$, so also the $G'$ matrix enumerates to reveal the fraction of throughflow from compartment $i$ distributed to compartment $h$ over all pathways of length $m$. For the input-environ analysis $G'$:

$$G'^{0} + G'^{1} + G'^{2} + G'^{3} + \ldots + G'^{m} \quad (4.8)$$
Both \( G^m \) (Gattie, Schramski, & Bata, 2006) and the \( G'^m \) (Expression 4.9) matrix elements are coefficients that will, respectively, mathematically partition throughflow at compartment \( j \) into flows along network pathways from \( j \) to \( i \) or partition throughflow at compartment \( h \) into flows along the network pathways from \( i \) to \( h \) in each case, partitioning along path lengths \( m \) as similarly enumerated by \( A^m \) or \( A'^m \) (Equation 4.3). The two analysis techniques continue to diverge and it is significant and should be noted at this point that the coefficients of the expansions will differ for \( G \) and \( G' \). This is due to the differing path structure when “looking forward” through the system as opposed to “looking backward” through the system. However, the analyses will converge again when each returns the same Total System Throughflow. It should also be noted that Total System Throughflow (TST) increases but is not fully returned until the complete summation of the throughflow coefficients is achieved at \( m = \infty \) where both the \( G \) (output-environ analysis) and \( G' \) (input-environ analysis) expansions returned a Total System Throughflow (TST) of 16814 mmol/m\(^2\) season.

The power series for \( A \) and \( A' \) are divergent, but because of the fractional structure of the components of \( G \) and \( G' \) matrices, both will converge when expanded and may be summed to yield the integral matrices \( N \) for the output-environ analysis (Gattie, Schramski, & Bata, 2006) and \( N' \) for the input-environ analysis (Equation 4.12). Equation 4.13 shows the explicit formulation under transitive closure conditions (Ore, 1962) for \( N' \). Further, the components of \( N \) and \( N' \) represent the partitioning coefficients for mapping boundary output and input, respectively, at any compartment \( k \), into flows from \( j \) to focal compartment \( i \) or from focal \( i \) to \( h \) along all path lengths \( m \). Focusing on \( N' \) of the input-environ analysis (Equation 4.13) and manipulating Equations 4.10 & 4.11, results in a relatively simple equation used in network input-environ analysis for mapping boundary output \( Y \) (Equation 4.14) into compartmental
throughflow $T'$ which may be further used to decompose throughput flow into smaller scale network flows (Gattie, Schramski, & Bata, 2006).

$$T' = Y(G'_{0} + G'_{1} + G'_{2} + G'_{3} + \ldots + G'_{m} + G'_{\infty})$$  \hspace{1cm} (4.9)

$$\sum_{n=0}^{\infty}G'^{n}$$

$$\sum_{m=0}^{n}G'^{m} = N'$$  \hspace{1cm} (4.10)

$$T' = \frac{YG'_{0}}{N'} + \frac{YG'_{1}}{N'} + \frac{YG'_{2}}{N'} + \frac{YG'_{3}}{N'} + \ldots + \frac{YG'_{m}}{N'}$$  \hspace{1cm} (4.11)

Note: After Gattie, Schramski, & Bata (2006, p. 194). Normally, one considers input as generating output and in the output-environ analysis does describe the partition of throughput flow as generated from input, in contrast, the input-environ analysis of this work is interested in the input caused by a particular output. However, it is proposed that “generate” is also the appropriate term to describe the flow inducing phenomenon for both the output-environ or the input-environ and, as such, is the incorporated term in Equation (4.9). Further, $N'$ below represents the summation of the infinite power series of $G'$ to embody the partitioning coefficients, which map boundary output at any compartment $k$ into flows from $i$ to $h$ over all pathways and path lengths $m$.

$$N' = \sum_{m=0}^{\infty}G'^{m} = G'^{0} + G'^{1} + G'^{2} + G'^{3} + \ldots G'^{m}$$  \hspace{1cm} (4.12)
\[ N' = (G^0 - G') \quad (4.13) \]
\[ T' = YN' \quad (4.14) \]

Mathematical Derivations, Results and Discussion

By substituting back into preceding equations, Equation 4.14 then provides an explicit mapping of boundary output back to the systems throughflow. The throughflow \((T = NZ)\) for the output-envir analysis (Gattie, Schramski, & Bata, 2006) is mapped from input; however, the throughflow \((T')\) for input-envir analysis will return the same value as \((T)\) but is derived and calculated differently, foreshadowing the need for further investigation into the composition of these flows. For now, Equation 4.14 expands to a series of equations (Equations 4.15) which are the compartmental throughflows. These throughflows are the boundary outputs at compartments \(y_k\) transferred from compartment \(i\) along all path lengths \(m\).

\[
T'_i = y_in'_{i1} + y_{i2}n'_{31} + y_{i3}n'_{32} + \ldots + y_{ik}n'_{k1} \\
T'_2 = y_{i1}n'_{12} + y_{i2}n'_{22} + y_{i3}n'_{23} + \ldots + y_{ik}n'_{k2} \\
T'_3 = y_{i1}n'_{13} + y_{i2}n'_{23} + y_{i3}n'_{33} + \ldots + y_{ik}n'_{k3} \quad i=1, 2, 3 \ldots n. \quad (4.15)
\]

Hence, one may decompose the total system throughflow mathematically to reveal a general expression for individual compartmental throughflow as functions of boundary output \(T''\) (Equation 4.16) and \(T_i\) as functions of boundary input. Therefore, the throughflow (Equation
4.16) is a summation of terms $y_k n'_k$ for the input-environ analysis where the partition of output at a specific compartment $k$ is distributed as throughflow at a specific focal compartment $i$.

$$T'_i = \sum_{k=1}^{n} y_k n'_k = T_i = \sum_{k=1}^{n} n_{ik} z_k \quad i=1, 2, 3…n \quad (4.16)$$

Gattie, Schramski, & Bata (2006, p. 195) designated compartmental throughflow in the output-environ analysis as $T_i$ and noted that throughflow is unique to the model and is therefore a network property that may change as the network or model changes. Consequently, one should consider the significance and quantitative accuracy of throughflow in that light. Though quantitative exactitude may depend on the accuracy of information observed and modeled, the qualitative precision of throughflow, that is its composite character of the network and other embedded network parameters, may lead to many useful uncovered qualifying trends, descriptions and interpretations of system properties.

Throughflow partitions into constituent flows at scales smaller than the empirical observed flow $f'_{hi}$. Moreover, similar to the manipulation of Equation 4.7, it yields the observed flows in the input environs as partitions of throughflow (Equation 4.16). By substituting Equation 4.17 into Equation 4.18, a unique expression (Equation 4.19) for the observed flow as partitions of boundary inputs, which this paper will term the microdynamic input-environ flows is revealed. Note: Gattie, Schramski, & Bata (2006, p. 196), described these type flows as microdynamic environ flows in the output-environ analysis. It is now proposed that these should be revised and referred to as microdynamic output-environ flows for the output-environ analysis and microdynamic input-environ flows for the input-environ analysis. The reader will also note that the focus has now shifted from considering the empirical and observed flow $f'_{hi}$, that is, the flow from the focal compartment $i$, to considering $f_{ij}$ the flow into focal compartment $i$. This is
the mathematical quantity necessary for the “backward looking” analysis, which seeks to mathematically parse out the input caused by a particular output. Therefore, the flows into the focal compartment \(i, f_{ij}\), will be of central concern and are determined accordingly. Thus from equation 4.16, the throughflow at \(i\) will have the same value in each case \((T = T')\), similar to Equation 4.7, a mathematical equation for \(f_{ij}\), based on \(T'\) and the partitioning coefficients \(g_{ij}\) forms.

\[
f_{ij} = g_{ij} T'_i, \quad (4.17)
\]

And applying Equation 4.17,

\[
f_{ij} = g_{ij} \sum_{k=1}^{n} y_{ik} n'_{ki}. \quad (4.18)
\]

The *microdynamic input-environ flows* are partitions of \(f_{ij}\) generated by boundary output at compartment \(k\), for the input-environ analysis and may be mathematically determined by Equation 4.19. Significantly, Gatnie, Schramski, & Bata (2006, p. 196) show in the output–environ analysis of this data that observed flows partially constitute by boundary input at each compartment \(x_i\) for the output-environ analysis and extrapolating this reasoning to the input-environ analysis where then observed flows are partially constituted by boundary output, in this case, at each compartment \(x_i\) (Figure 4.3).

\[
\varepsilon'_{ij,k} = g_{ij} y_{ik} n'_{ki} \quad (4.19)
\]

The operations above, beginning with Equation 4.10 take the terms of integral matrix \(N'\), and mathematically partitions the boundary output matrix \(Y\) terms respectively into observed compartmental throughflow, \(T'\), and *total input-environ throughflow*, \(TET'\). In the output-
environ analysis, this quantity was termed total environ throughflow, \( TET \). However, due to the fine scale quantitative differences determined between the output-environ analysis and input-environ analysis, each of the total environ throughflows should now be separated into distinct terms. Thus, for the output-environ analysis, \( TET \) should refer to the total output-environ throughput and for total input-environ throughput, \( TET' \).

The throughflow partitioning coefficient matrix \( G' \) decomposes the throughflow into the microdynamic input-environ flow \( \varepsilon'_{ij,k} \) where the summation of the microdynamic input-environ flow returns the observed intercompartmental flow \( f_{ij} \) in the input environs of the focal compartment \( i \) (Equation 4.20).

\[
f_{ij} = \sum_{k=1}^{n} \varepsilon'_{ij,k} \quad (4.20)
\]

Equation 4.20 is quite significant because it reveals that macroscopic empirically derived or observed flow \( f_{ij} \) is a sum of very fine scale flows, that is, the microdynamic input-environ flows. This is somewhat analogous to an Eulerian versus Lagrangian description of flow of fluids where the Eulerian method uses a field concept for the description of fluid flow, describing the requisite fluid properties as functions of space and time. From this method, one may determine large-scale fluid properties at a fixed point on space as fluid flows past those fixed points. The Lagrangian method, at fine scales, mathematically tracks individual fluid particles and determines the associated properties as functions of time, as the individual particles move about (Young, 2004).

Similarly, in the Neuse River model, the observed flows may be decomposed into unobservable but mathematically derivable, fine scale particulate analogs, microdynamic input-environ flows \( \varepsilon'_{ij,k} \) which represents flows in the extended pathways of the network’s input environ,
respectively. Therefore, empirical flows, \( f_{ij} \), in the input-environ are in actuality composite flows through the focal compartments \( i \). This, combined with the output-environ analysis, reveals that in fact both the flows in the input and output environs of the focal compartments \( i \) are composite flows and are partially reflected in Gattie, Schramski, & Bata’s (2006, p. 197) figure of the output-environ analysis. The figure revised here (Figure 4.3) to reflect differing symbols, total system throughput as a combined collection of microdynamic output and input-environ flows, \( e_{bi,k} \) and \( e'_{ij,k} \). And further, both the boundary inputs and outputs of focal compartment \( i \) are depicted as composite collections of input and output environ boundary flows \( \hat{z}_{i,k} \) and \( \hat{y}_{i,k} \).

These microscale derivations may serve as the basis for developing understanding and insight into the connectedness and interdependencies between network compartments where these interdependencies and interconnections are not observable or inferable directly from empirical observations alone. Gattie, Schramski, & Bata (2006), developed terms and metrics for the description of parameters associated with the output-environ analysis. Correspondingly, a similar and amended table of equations and metrics which contains symbols for the input-environ analysis is listed in Table 4.2. The microdynamic input-environ flows, \( e'_{ij,k} \), refers to the flow over all pathways of length \( m \) from compartment \( j \) to compartment \( i \) because of boundary output at compartment \( k \).

This differs from the input-environ flows \( e'_{i,k} \), which refer to the flow to the focal compartment \( i \) from all other compartments \( j \) within the network generated by boundary output at compartment \( k \). In addition, \( \hat{z}_{i,k} \) represents the partition of boundary input at compartment \( k \) that enters the system at compartment \( i \). Initiated by boundary output at compartment \( k \) for the
Amended genera


Figure 4.3 Amended general network unit for Network Environ Analysis (after Gattie et al, 2006, p. 197).

input-environ analysis, $\theta_{i,k}'$ represents the partition of throughflow at compartment $i$. It is important to note that the partitions of throughflow may not be solely due to direct links between compartments $i$ and $k$. In other words, it may also indicate relationships between these compartments over indirect network pathways. This suggests that the network compartments of the Neuse River Estuary model are functions of both boundary inputs and outputs and the
connectivity between compartments. That is, each compartment receives nitrogen at the system boundary, which may affect compartmental throughflow $\theta_i'$ (for the input-environ case), throughflow at other network compartments, and the total system throughflow, $\Omega$. In other words, the boundary condition(s) at each compartment has an effect on the throughflow of the system. In the input environs, compartments of the model also receive nitrogen from other compartments within the system by way of direct or indirect intercompartmental microdynamic flows. As such, the compartments within the model each affect the throughflow of the system by way of their connections along both direct and indirect pathways within the system. Note: The magnitude of $\theta_i$ (compartmental flow for the output-environ analysis) should equal $\theta_i'$; that is, the flow through each focal compartment is constant at any time $t$ for both the backward looking output and forward looking input-environ analyses.

**Analysis of the Microdynamic Input-Environ Flows**

Similar to Gattie, Schramski, & Bata’s (2006) output-environ analysis, the nitrogen flow of the Neuse River Estuary model during the summer of 1988 indicates 22 direct intercompartmental flows out of a possible 49 direct or adjacent connections, which corresponds to a connectivity of 0.45. This indicates that empirical observation alone does not lead to relationship information between the other 27 possible connections within the network. In both the adjacency and flow matrices, these entries are zero. These twenty-seven relationships were not attainable from empirical information, although Network Environ Analysis indicates that all compartments within the system connect either directly or indirectly over extended network pathways. Therefore, for the input-environ analysis, quantitative information for these relations in the form of microdynamic input-environ flows, $\epsilon_{ij,k}'$, and input-environ boundary flow $\hat{z}_{i,k}$ are derivable and listed in Table 4.3. The input environs of Table 4.3 are in terms of input-environ
flows, $\varepsilon'_{i,k}$ and input-environ boundary flow, $\hat{\varepsilon}'_{i,k}$, both of which directly or indirectly are reflected in output, for the summer season of 1998. Noting that the table interprets as column and rows separately where the column analysis reflects the contribution of one compartment’s input, $k$, to throughflow at other compartments and the sum of the columns refers to the total input-environ throughflow $\Theta'_k$. The analysis of the rows yields the contribution of output at all compartments to throughflow at a single compartment where the sums of the rows refers to the compartmental throughflow.

**Input-Environ Analysis Results**

The input-environ method of analyzing the nitrogen flow of the Neuse River Estuary was completed. For the model examined, Table 4.3 indicates a total output of 132 mmoles-N/m$^2$ ·season from the network generated by a total system throughflow of 16814 mmoles-N/m$^2$ ·season. Compartmental throughflows ranged from 483 to 5819 mmoles-N/m$^2$ ·season at NO$_x$ and PN-Hetero, respectively. Boundary outputs at compartment Sediment by far generated the highest total input-environ throughflows of 11509.5 mmoles-N/m$^2$ ·season (68.5 %) and followed by DON at 3254.8 mmoles-N/m$^2$ ·season (19.4 %), PN-Abiotic 908.4 mmoles-N/m$^2$ ·season (5.4 %), PN-Phyto 768.04 mmoles-N/m$^2$ ·season (4.6 %), NH$_4$ 259.7 mmoles-N/m$^2$ ·season (1.5 %), NO$_x$ 113.5 mmoles-N/m$^2$ ·season (0.68 %), and PN-Hetero had no boundary output. Interestingly, PN-Hetero’s boundary output contributed 0 % to total system throughflow, but it was the largest contributor to input-environ flow within the system, accounting for 5819 mmoles-N/m$^2$ ·season (34.6 %). NH$_4$, also a small contributor to total system throughflow as generated by boundary output, was the second largest contributor to input-environ flow within the system, 4914 mmoles-N/m$^2$ ·season (29.2 %). PN-Phyto was also a significant contributor to input-environ flow within the system, 3331 mmoles-N/m$^2$ ·season (19.8 %). The other
compartments, Sediment, DON, NOx, and PN-Abiotic combined to make up the remaining 16.4% of input-environ flow within the system.

Table 4.3 contains shaded cells which represent the input-environ flows, \( \varepsilon_{i,k}' \) and the boundary input environ boundary flows, \( \hat{\varepsilon}_{i,k} \) generated over the indirect pathways of the Neuse River Estuary model. The decomposition of total system throughflow reveals that 38% of the total system throughflow consists of input-environ flow and input-environ boundary flow over the indirect pathways between compartments. Again, neither is directly inferable from the empirical data, \( f'_{hi} \) and \( y_i \). The analysis of the input-environ of Sediment and DON revealed the most significant contribution to the indirect flow relationships and interdependencies within the system for the “backward looking” input environs; combined, they accounted for 31.34% of total system throughflow through indirect flows generated from boundary output at those compartments.

**Comparisons of the Analyses**

Two distinct analyses, one output driven and the other input driven, of the summer 1998 Neuse River Estuary model, using the same empirically determined data, revealed similar large scale results but differing fine scale environ information for the input driven versus output driven analysis. Further, the contrasting results of the “forward looking” output-environ analysis and the “backward looking” input-environ analysis has necessitated that this paper add and additionally qualify several terms, including the following: environ throughflow and total environ throughflow into more distinct terms, including *microdynamic input-environ flow*, *microdynamic output-environ flow*, *input-environ throughflow*, *

*output-environ throughflow*, *average environ throughflow* (see nomenclature). For example, the output-environ analysis of the same data (Gattie, Schramski, & Bata, 2006), as expected, revealed the same total system

132
throughflow for the 1998 summer model of Neuse River Estuary, of 16,814 mmol N/m² season from a total input of 132 mmol N/m² season as did the input-environ analysis. Further, the compartmental throughflows, as expected, matched for both the input-environ analysis and output-environ analysis where they ranged from 483 mmol N/m² season at compartment NOₓ to 5819 mmol N/m² season at compartment PN-Hetro. Interestingly, though, the fine scale boundary output driven input-environ throughflows and input driven output-environ throughflows were significantly different at each compartment. The highest total output-environ throughflows, as a result of boundary inputs, occurred at compartment DON, NOₓ, and NH₄ where DON generated 3410.2 mmol N/m² season (20.3%), NOₓ generated 8279 mmol N/m² season (49.2%) and NH₄ generated 2990.1 mmol N/m² season or 17.8% of the total system throughflow. The remaining compartments, PN-Phyto and PN-Hetero, generated, from boundary input, the remaining 12.7% of total system throughflow. Even though these compartments were not major contributors to total system throughflow from boundary inputs, they were substantial contributors to environ flow within the system, contributing 3331 mmol N/m² season (19.8%) and 5819 mmol N/m² season (34.6%) of total system throughflow, respectively. NH₄ generated 4914 mmoles-N/m² season or 29.2% of total system throughflow. Thus, NH₄ both substantially imports nitrogen at the boundary; as well, it substantially distributes nitrogen to other compartments through environ flows within the system (Gattie et al., 2006). These results are significantly different from the input-environ analysis (Figure 4.4). Here, boundary outputs at compartment Sediment, by far generated the highest total input-environ throughflows of 11509.5 mmoles-N/m² ·season (68.5%) followed by DON at 3254.8 mmoles-N/m² ·season (19.4%), PN-Abiotic 908.4 mmoles-N/m² ·season (5.4%), PN-Phyto 768.04 mmoles-N/m² ·season (4.6%), NH₄ 259.7 mmoles-N/m² ·season (1.5%), NOₓ 113.5 mmoles-N/m² ·season (0.68%), and
PN- Hetero had no boundary output. Although PN-Hetero’s boundary output contributed 0 % to total system throughflow, it was the largest contributor to input-environ flow within the system, accounting for 5819 mmoles-N/m²-season (34.6 %). NH₄, also a small contributor to total system throughflow as generated by boundary output, was the second largest contributor to environ flow within the system, 4914 mmoles-N/m²-season (29.2 %). PN- Phyto was also a significant contributor to environ flow within the system, 3331 mmoles-N/m²-season (19.8 %). The other compartments, Sediment, DON, NOₓ, and PN-Abiotic combined to make up the remaining 16.4 % of input-environ flow within the system.

![Figure 4.4](image.png)

**Figure 4.4.** Comparison of total input-environ throughflow, output-environ throughflows, and average environ throughflow.

Compartment k
Discussion

In hindsight, the differing total input-environs throughflows ($\Theta'_{k}$) and output-environs throughflow ($\Theta_{k}$) (Gattie, Schramski, & Bata, 2006) is not surprising, in that the “forward looking” network structure differs from the “backward looking” network structure. However, the interpretations and implications are perhaps more difficult to resolve. The 16,000km$^2$ watershed of the Neuse River along with the substantially smaller Trent River watershed constitutes the freshwater flows into the Neuse River Estuary. The 400km$^2$ estuary flows into Pamlico Sound, which serves as the interface to the Atlantic Ocean. The large size of Pamlico Sound results in relatively long residence times of freshwater in the sound and brackish water, with salinities ranging from one-half to two-thirds of typical seawater salinities (Giese et al., 1979; Schramski et al., 2006). Furthermore, the water level in the sound, dominated more by wave action and river discharge and to a significantly lesser extent, tidal action (Schramski et al., 2006). This seven-compartment nitrogen flow model consists of inputs that are dominated by fluctuating loadings of dissolved organic nitrogen, nitrates and nitrites, and ammonium through precipitation and heterotrophs. The outputs went to sediment, respiratory loss through denitrification and downstream into Pamlico Sound (Schramski et al., 2006). Subsequently, interpreting the contrasting fine scale results of the environ analyses should be reflected upon in this context. Does the differing fine scale environs results of the output driven versus the input driven environ analysis perhaps provide hints of differing flow mechanisms at work within the system? Do the results suggest a possible system wide pulse-like action? Does it imply even greater subtlety of interconnectivity and component dependencies, not only within but external to the system? Though examined at steady state, the differing environ results seem to indicate that not only does the system propagate inputs indirectly throughout the system over an extended pathway.
structure, but it perhaps reveals information regarding the potential for a dynamic pulse within the system? Perhaps it is a yin and yang or a “push” and “pull” through the system, where components of the system play varying roles of importance in each case. If true, this would have implications regarding the role that environment plays in system analysis; where system flows seem influenced in different ways by their input environment and their output environment respectively. However, questions may arise regarding the similar total flows in the two separate analysis methods but differing input-environ throughflow and output-environ throughflow. The conflict is resolved when one recognizes that the large scale data used in both analyses is a snapshot in time, and therefore each analysis, whether “forward looking” or “backward looking,” should return a similar total system throughflow and similar total compartmental throughflows. However, the two methodologies of environ analysis, though one input driven and the other output driven, both use a fine scale unit pulse, or unit input “pushed” through the system for the output-environ analysis or a unit pulse “pulled” through the system for the input-environ analysis to determine compartmental environ throughflow coefficients. The results bear out that those coefficients differ for each method because of the differing flow structure for the input versus output environs, that is, one normalized by receiver and the other normalized by contributor compartments. May this difference be reconciled in the different afferent and efferent characteristics of environment? Moreover, does it further implicate the duality of environment in the dynamics of the system? This might be further borne out in the differing environ flows that each analysis yields and possibly suggests a forward and backward internal system dynamic, a potential for a system pulse-like action. Therefore, a snapshot of flows at a time \((t)\) may only be examining either a “push or pull” of nutrients through the system, the parsing of the system through environs perhaps allows one to see the possible mechanics of flow for either case.
through the system. For instance, if one were to take a photograph of coastal tidal flux one, with an appropriate reference standard in the picture, may determine the relative height of the tide from the picture. However, from the snapshot, one could not necessarily infer whether the tide was advancing or retreating. Nonetheless, the height measurement would still be valid and models and analyses that return the measured height whether it is a model of the physical dynamics at work causing the advancement of the tide or the physical dynamics at work causing the retreat of the tide would both have validity and significance. In the case of the Neuse River Estuary, example causes for a potential “push” and “pull” through the system may include also high versus low tides, day versus night, summer versus winter, or drought versus flood, inordinate nutrient influx versus lack of nutrient input etc. It is likely that state of each models input and output environment will suggest if the forward or backward looking model dominates and is more appropriate. If the “push” and “pull” are equally at work in the system, average values of the fine scale input and output dynamics of the system would have worth in describing large scale system dynamics. For instance, the frequencies of vibrating systems are often the simultaneous integration of macro-frequencies and micro-frequencies of the system where, for example, a wave crest if examined at finer scales is assemblage of finer scale crests and troughs. Further, there exist other analogs; for example, alternating current in electrical systems is a type of pulsating flow of energy, a varying high pressure “push” and low pressure “pull” resulting in flow of electrical energy. In this case, the frequency of the pulsation is very large; that is, for an electromagnetic wave the magnitudes of the frequencies range up to $10^{22}$ hertz. The frequency of pulsation of nutrients through an ecological system obviously would have a frequency many orders of magnitude lower, perhaps, hours, days, seasons, or years. Additionally, each of the causes of flows through an ecosystem may have various timings and orders of magnitude of
influence on the system; each may have a unique amplitude and frequency. One could infer that any potential dynamic and its frequency through the system is a composite with several differing micro-frequencies of the system integrated and embedded within large scale flow frequencies of the observed flows of the system. These embedded oscillations may only come into focus as the scale decreases and one begins to examine the dynamics of component environs of the system. Perhaps neither the discrete push nor pull scenarios are fully sufficient. We often have difficulty assigning cause to many physical phenomena; for example, we often think that the moon exerts a gravitational pull on the oceans and the tides rise and fall. However, this is not correct in that there is no true or discrete “pull,” but it is rather a relationship between masses of the earth and moon and the resulting curvature of space-time. In fact, this is a complex many-bodied problem that also includes the sun and all mass of the universe. Thus, in a similar fashion, perhaps in our ecosystem it is neither a “push” nor “pull” through the system but a relationship that encompasses both, and for this reason, perhaps necessitating the term average environ flow. Further, it is likely that the causality of flow through an ecological network is an interconnected relationship between the “push” and “pull” through the system. For example, in predator and prey relationships, hunger is a driver of the pull of matter and energy through the system. However, it also to some degree takes the “push” of the prey entering the predator’s territory to complete the transaction. Though basic average values likely do not reflect the correct proportional influences of “push” and “pull” through the system, it does begin to represent an integrated interaction. Further research may lead to a closer approximations and additional qualifiers that may lead to weighted averages. However, the work of parsing and uncovering microenviron flows from a unit input or output pulse is valuable to reveal precise qualitative information gained through quantitative measures for these complex systems. Moreover, the
microdynamic input and output environ flows seemingly give a qualitative picture of a coin with two sides. Though, the system analyzed in a snapshot of time, and thus, an accurate determination of whether the system influenced at that time by its output, input or a relationship between them is not fully evident. It is still significant that the internal workings of the connected system upon an indirect examination reveal qualitative similarities and plasticity to its environment but quantitative differences depending on the focal direction suggesting the dual and intertwined role of environment in the system and its potential dynamics.

**Nomenclature (including amended nomenclature of output-environ analysis after Gattie et al., 2006 (p. 189) and input-environ analysis nomenclature of this work):**

\( i = \) the focal compartment;

\( j = \) any compartment in the input environs of the focal compartment \( i \), from which energy or material flows to \( i \);

\( h = \) any compartment in the output environs of the focal compartment \( i \), to which energy or material flows from \( i \);

\( n = \) number of network model compartments;

\( f_{ij} = \) empirically determined flow from compartment \( j \) to the adjacent focal compartment \( i \) (mmoles/m\(^2\)•season); using NEA, \( f_{ij} \) is shown to be constituted by the summation of input-environ flows, \( \varepsilon'_{ij,k} \), over all network pathways of all path lengths from compartment \( j \) to compartment \( i \), generated by boundary output at all compartments \( k \);

\( f'_{hi} = \) empirically determined flow from the focal compartment \( i \) to adjacent compartment \( h \) (mmoles/m\(^2\)•season); using NEA, \( f'_{hi} \) is shown to be constituted by the summation of output environ flows, \( \varepsilon_{hi,k} \), over all network pathways of all path lengths from compartment \( i \) to compartment \( h \), generated by boundary input at all compartments \( k \);
$Z = n \times 1$ vector of boundary inputs at each compartment;

$z_i =$ boundary input at the focal compartment $i$ (mmoles/m$^2$•season);

$Y = I \times n$ vector of boundary outputs at each compartment;

$y_i =$ boundary output from the focal compartment $i$ (mmoles/m$^2$•season);

$X = n \times 1$ vector of standing stocks for each compartment;

$x_i =$ standing stock at the focal compartment $i$ (mmoles/m$^2$)

$G = n \times n$ matrix of dimensionless throughflow output-environ partitioning coefficients;

$G' = n \times n$ matrix of dimensionless throughflow input-environ partitioning coefficients;

$g_{ij} =$ dimensionless partitioning coefficient for distributing throughflow at $j$ into output-environ flows from $j$ to $i$;

$g'_{hi} =$ dimensionless partitioning coefficient for distributing throughflow at $i$ into input-environ flows from $i$ to $h$;

$N = $ matrix of dimensionless partitioning coefficients for mapping boundary output into compartmental throughflows for the output-environ analysis;

$N' = $ matrix of dimensionless partitioning coefficients for mapping boundary output into compartmental throughflows for the input-environ analysis;

$n'_{ki} =$ dimensionless partition coefficient for mapping boundary output at compartment $k$ into throughflow at compartment $i$;

$n_{ik} =$ dimensionless partition coefficient for mapping boundary input at compartment $k$ into throughflow at compartment $i$;

$k =$ compartment whose boundary input or output is to be traced along all possible network pathways of all path lengths $m = 1:\infty$;
\[ \mathcal{E}_{ij,k}^{\prime} = \text{(microdynamic input-environ flow) flow over all network pathways of all lengths } m \text{ to the focal compartment } i \text{ from a particular compartment } j \text{ generated by boundary output at a particular compartment } k \text{ (mmoles/m}^2\text{•season);} \]

\[ \mathcal{E}_{hi,k} = \text{(microdynamic output-environ flow) flow over all network pathways of all lengths } m \text{ to the focal compartment } i \text{ to a particular compartment } h \text{ generated by boundary input at a particular compartment } k \text{ (mmoles/m}^2\text{•season);} \]

\[ \mathcal{E}_{i,j,k}^{\prime} = \text{(input-environ flow) flow to the focal compartment } i \text{ from all other compartments, } j, \text{ within the network, generated by boundary output at a particular compartment, } k \text{ (mmoles/m}^2\text{•season);} \]

\[ \mathcal{E}_{i,k} = \text{(output-environ flow) flow from the focal compartment } i \text{ to all other compartments, } h, \text{ within the network, generated by boundary output at a particular compartment, } k \text{ (mmoles/m}^2\text{•season);} \]

\[ \hat{y}_{i,k} = \text{(output environ boundary flow) boundary output from compartment } i \text{ generated by boundary input at a particular compartment } k \text{ (mmoles/m}^2\text{•season);} \]

\[ \hat{z}_{i,k} = \text{(input environ boundary flow) boundary input to compartment } i \text{ generated by boundary output at a particular compartment } k \text{ (mmoles/m}^2\text{•season);} \]

\[ \theta_{i,k} = \text{(output-environ throughflow) partition of throughflow at compartment } i \text{ generated by boundary input at a particular compartment } k \text{ (mmoles/m}^2\text{•season);} \]

\[ \theta_{i,k}^{\prime} = \text{(input-environ throughflow) partition of throughflow at compartment } i \text{ generated by boundary output at a particular compartment } k \text{ (mmoles/m}^2\text{•season);} \]

\[ T_i = \text{(compartmental throughflow in terms of observed flow) summation of inflows from compartment, } i \text{ (mmoles/m}^2\text{•season);} \]
\( T'_{i} = \) (compartmental throughflow in terms of observed flow) summation of outflows from compartment, \( i \) (mmoles/m\(^2\)•season);

\( \theta_i = \) (compartmental throughflow in terms of input-environ or output-environ flow) the integrated input environ or output environ flow response over network pathways of a particular compartment, \( i \), from boundary outputs or inputs at all compartments, \( k \), in the system (mmoles/m\(^2\)•season);

\( \Theta_k = \) (output-environ throughflow) the partition of total system throughflow, TST (\( \Omega \)), derived from boundary input at a particular compartment, \( k \) (mmoles/m\(^2\)•season);

\( \Theta'_k = \) (input-environ throughflow) the partition of total system throughflow, TST (\( \Omega \)), derived from boundary output at a particular compartment, \( k \) (mmoles/m\(^2\)•season);

\( \Theta_{k\ avg} = \) (average environ throughflow) the partition of total system throughflow, TST (\( \Omega \)), averaged from boundary output-environ throughflow and input-environ throughflow at a particular compartment, \( k \) (mmoles/m\(^2\)•season);

\( \Omega = \) (TST-total system throughflow) a metric of ecosystem network response to material and energy exchange at the ecosystem boundary, as indicated by the cumulative network response of its individual compartments (mmoles/m\(^2\)•season);

\( TET' = \) total input-environ throughflow (mmoles/m\(^2\)•season);

\( TET = \) total output-environ throughflow (mmoles/m\(^2\)•season);
### Table 4.2 Parallel equations of throughflow for macroscale measures and microscale derivations (after Gattie et al. 2006)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Notation and Description</th>
<th>Macroscopic Measures Associated with Figure 4.1 and Table 4.1 (Observable &amp; Empirically Determined)</th>
<th>Microscopic Derivations Associated with Figure 4.3 (Non-observable, Mathematically Derived by NCA)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observed Intercompartental Flow</td>
<td>$f_{hi}$</td>
<td>Empirically determined flow from compartment $i$ to compartment $h$</td>
<td>$e_{i,i} = g_{i,2}Y_{i}h_{i}$&lt;br&gt;(Equation 4.19) Flow to compartment $i$ from a particular compartment, $j$, generated by boundary output at a particular compartment, $k$,</td>
</tr>
<tr>
<td></td>
<td>$E_{i,j}$</td>
<td>Flow from compartment $i$ to compartment $j$</td>
<td>$E_{i,j} = \sum_{j=1}^{n} E_{i,j}$&lt;br&gt;(Equation 4.21) Flow to compartment $i$ to all other compartments, $j$, within the network, generated by boundary output at a particular compartment, $k$,</td>
</tr>
<tr>
<td>Observed Boundary Input</td>
<td>$z_{i}$</td>
<td>Empirically determined boundary input flow to $i$</td>
<td>$z_{i,j} = Y_{i}h_{j} - Y_{j}h_{i}\sum_{j=1}^{n} E_{i,j}$&lt;br&gt;(Equation 4.22) Boundary input to compartment $i$ generated by boundary output at a particular compartment, $k$,</td>
</tr>
<tr>
<td>Throughflow</td>
<td>$T_{i}^{\text{out}} = T_{i}^{\text{in}} = z_{i} + \sum_{j=1}^{n} f_{ji}$</td>
<td>(From Equation 4.4) Summation of empirically determined flows, $f_{ji}$, out of compartment $i$ and boundary output, $z_{i}$, from compartment $i$</td>
<td>$\theta_{i,j} = \sum_{j=1}^{n} E_{i,j} + z_{i,j}$&lt;br&gt;(Equation 4.23) Partition of throughflow at compartment $i$ generated by boundary output at a particular compartment, $k$,</td>
</tr>
<tr>
<td></td>
<td>$T_{i}^{\text{in}} = T_{i}^{\text{in}} = z_{i} + \sum_{j=1}^{n} f_{ji}$</td>
<td>(From Equation 4.5) Summation of empirically determined flows, $f_{ji}$, into compartment $i$ and boundary input, $z_{i}$, into compartment $i$</td>
<td>Throughflow&lt;br&gt;$\theta_{i} = T_{i}^{\text{in}} = \sum_{k=1}^{n} \sum_{j=1}^{n} E_{i,j} + z_{i,j}$&lt;br&gt;(Equation 4.24) Throughflow at compartment $i$ generated by boundary output at all $k$ compartments</td>
</tr>
<tr>
<td></td>
<td>$\Theta_{i} = \sum_{j=1}^{n} \sum_{k=1}^{n} E_{i,j,k} + \sum_{k=1}^{n} z_{i,k}$&lt;br&gt;(Equation 4.25) Partition of Total System Throughflow in the network generated by boundary output at a particular compartment, $k$</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 4.3. Input environs for Summer 1988 Neuse River Estuary network model where, $\epsilon'_{j,k} = \sum_{k=1}^{n} \Theta'_{j,k}$.

Column-wise analysis reflects the contribution of output at a single compartment, $k$, to throughflow at all other compartments, and column sums represent total environ throughflow, $\Theta'_{j}$. Row-wise analysis reflects the contribution of output at all compartments to throughflow at a single compartment with row sums representing compartmental throughflows, $\Theta'_{i}$. Values in parenthesis represent percentage of total system throughflow. (<) indicates existence of values less than 0.5%. Shaded table cells denote the quantitative information between compartments that are zero in the F and A matrices (i.e. non-adjacent, indirect relationships). Shaded table cells combine to represent 6382 mm N m$^{-2}$ season$^{-1}$ (38%) of TST (after Gattie et al. 2006).

<table>
<thead>
<tr>
<th>Total System Throughflow (Ω) generated by 132 moles-Nm$^{-2}$-season of total output at all compartments, k</th>
<th>Boundary output at PN-Phyto</th>
<th>Boundary output at PN-Hetero</th>
<th>Boundary output at Sediment</th>
<th>Boundary output at DON</th>
<th>Boundary output at NO₃</th>
<th>Boundary output at NH₄</th>
<th>Boundary output at PN-Ab</th>
<th>Boundary output at PN-Abotic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Throughflow, $\Theta'<em>{i}$, generated from boundary output at compartment k, $\theta'</em>{i,k} + \epsilon'_{j,k}$</td>
<td>Boundary output at PN-Phyto</td>
<td>Boundary output at PN-Hetero</td>
<td>Boundary output at Sediment</td>
<td>Boundary output at DON</td>
<td>Boundary output at NO₃</td>
<td>Boundary output at NH₄</td>
<td>Boundary output at PN-Ab</td>
<td>Boundary output at PN-Abotic</td>
</tr>
<tr>
<td>$\epsilon'_{1,1}$</td>
<td>$\epsilon'_{1,2}$</td>
<td>$\epsilon'_{1,3}$</td>
<td>$\epsilon'_{1,4}$</td>
<td>$\epsilon'_{1,5}$</td>
<td>$\epsilon'_{1,6}$</td>
<td>$\epsilon'_{1,7}$</td>
<td>$\epsilon'_{1,8}$</td>
<td>$\epsilon'_{1,9}$</td>
</tr>
<tr>
<td>155.6 (9.22)</td>
<td>0.05</td>
<td>0</td>
<td>0</td>
<td>2272.1 (13.5)</td>
<td>0.684</td>
<td>651.1</td>
<td>0.186</td>
<td>22.01</td>
</tr>
<tr>
<td>$\theta'_{1,2}$</td>
<td>$\theta'_{1,3}$</td>
<td>$\theta'_{1,4}$</td>
<td>$\theta'_{1,5}$</td>
<td>$\theta'_{1,6}$</td>
<td>$\theta'_{1,7}$</td>
<td>$\theta'_{1,8}$</td>
<td>$\theta'_{1,9}$</td>
<td>$\theta'_{1,10}$</td>
</tr>
<tr>
<td>265.9 (1.92)</td>
<td>0.183</td>
<td>0</td>
<td>0</td>
<td>3978.7</td>
<td>2.376</td>
<td>1122</td>
<td>0.772</td>
<td>39.4</td>
</tr>
<tr>
<td>$\theta'_{2,3}$</td>
<td>$\theta'_{2,4}$</td>
<td>$\theta'_{2,5}$</td>
<td>$\theta'_{2,6}$</td>
<td>$\theta'_{2,7}$</td>
<td>$\theta'_{2,8}$</td>
<td>$\theta'_{2,9}$</td>
<td>$\theta'_{2,10}$</td>
<td></td>
</tr>
<tr>
<td>18.62</td>
<td>0.302</td>
<td>0</td>
<td>0</td>
<td>3657.9</td>
<td>5.92</td>
<td>78.4</td>
<td>1.269</td>
<td>2.83</td>
</tr>
<tr>
<td>$\theta'_{3,4}$</td>
<td>$\theta'_{3,5}$</td>
<td>$\theta'_{3,6}$</td>
<td>$\theta'_{3,7}$</td>
<td>$\theta'_{3,8}$</td>
<td>$\theta'_{3,9}$</td>
<td>$\theta'_{3,10}$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>36.6</td>
<td>1.211</td>
<td>0</td>
<td>0</td>
<td>540.96</td>
<td>17.87</td>
<td>179.1</td>
<td>5.918</td>
<td>5.3</td>
</tr>
<tr>
<td>$\theta'_{4,5}$</td>
<td>$\theta'_{4,6}$</td>
<td>$\theta'_{4,7}$</td>
<td>$\theta'_{4,8}$</td>
<td>$\theta'_{4,9}$</td>
<td>$\theta'_{4,10}$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>19.50</td>
<td>2.98</td>
<td>0</td>
<td>0</td>
<td>285.44</td>
<td>43.61</td>
<td>81.6</td>
<td>12.47</td>
<td>3.64</td>
</tr>
<tr>
<td>$\theta'_{5,6}$</td>
<td>$\theta'_{5,7}$</td>
<td>$\theta'_{5,8}$</td>
<td>$\theta'_{5,9}$</td>
<td>$\theta'_{5,10}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>22.9</td>
<td>1.062</td>
<td>0</td>
<td>0</td>
<td>334.24</td>
<td>15.71</td>
<td>94.85</td>
<td>4.46</td>
<td>33.4</td>
</tr>
<tr>
<td>$\theta'_{6,7}$</td>
<td>$\theta'_{6,8}$</td>
<td>$\theta'_{6,9}$</td>
<td>$\theta'_{6,10}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>39.8</td>
<td>0.217</td>
<td>0</td>
<td>0</td>
<td>634.3</td>
<td>3.36</td>
<td>198.9</td>
<td>0.918</td>
<td>5.92</td>
</tr>
<tr>
<td>$\Theta'_{1}$</td>
<td>$\Theta'_{2}$</td>
<td>$\Theta'_{3}$</td>
<td>$\Theta'_{4}$</td>
<td>$\Theta'_{5}$</td>
<td>$\Theta'_{6}$</td>
<td>$\Theta'_{7}$</td>
<td>$\Theta'_{8}$</td>
<td>$\Theta'_{9}$</td>
</tr>
<tr>
<td>762.04</td>
<td>6.00</td>
<td>0</td>
<td>0</td>
<td>11419.5</td>
<td>90.0</td>
<td>3228</td>
<td>20.0</td>
<td>112.5</td>
</tr>
</tbody>
</table>
Conclusion

Ecological systems in their quest to grow and develop seem to facilitate self-organization through the distribution of function, often through the physical, functional, and relational coupling of dissipative structures. This connectivity and associated indirectness within ecosystems is analytically challenging, but as ecological engineers search for appropriate management tools, design strategies and tactics, these system properties appear to be essential to accurately replicate natural systems and effectively manage the beneficial emergent system properties of these complex systems. Connectivity of ecological systems is often embedded within the fine scale composite interactions between system components. These interactions, often in terms of flows between compartments, may only be revealed through a mathematical description of the very fine scale component interactions. Network Environ Analysis and the corresponding input-environ and output-environ flows provides one method to begin to parse out and describe the very subtle interdependencies within the system. Further, the analysis presented in this paper provided reinforcing evidence of these subtle connections and interdependencies of an ecological system, the Neuse River Estuary. Subsequently, the contrasting fine scale results of the comparative environ analyses provide hints, perhaps, of a system dynamic that suggests even greater indirect interconnectivity and component dependencies not only within but external to the system. Though the system was analyzed in a snapshot of time, and thus, an accurate determination system dynamics is not evident, it is still significant and intriguing that the internal workings of the connected system upon an indirect examination reveal quantitative differences depending on the focal direction. This perhaps suggests a dual but intertwined role of environment by way of the input and output drivers of the systems dynamics. For the system designer, it perhaps is simultaneously revealing, aweing and ultimately daunting, suggesting that
design targets for ecological systems will be quite multi-faceted and further that an intertwined system “push” coupled with a “pull” of the system, if ultimately true, should be a noted characteristic of any analysis, design and management strategies.

Chapter 4 Summary

This chapter focused on comparatively analyzing microdynamic environs flows of the Neuse River Estuary model. The analysis showed that observed flows within the system and observed flows in and out of the system are in actuality composite flows from many components and directions that integrate together to form the observable flows. Illustrating that the system modeled is substantially more than the observable direct interactions, but is in fact significantly influenced by indirectness. The comparison of the analysis “driven” by output versus the analysis driven by “input” further implicates that system context is also factor when determining system behavior and complexity.

There have been several other analyses of the Neuse River Estuary that have uncovered examples of system properties within the Neuse River Estuary models including: the proliferation of network pathways which shows how the number of pathways increase as the length of the transactions increase, dominance of indirect effects over direct effects or known as network nonlocality, the homogenization of resource, and network amplification where the system benefits more than just by the magnitude of system inputs.

Each of these measures indicates a systems propensity for holism as evidenced in the models of the Neuse River Estuary. The models also indicate that significant indirect effects occur relatively quickly and do not need extended pathways to become major factors. The models also indicate a holistic controlling relationship that has embedded within the systems organizational interdependent complexity. These have been referred to as distributed control (Schramski et al.,...
2006). These examples of system properties and others of the Neuse River Estuary are likely desirable system properties that perhaps should be characteristics emulated in the design and management of similar systems.

In summary, the model analysis of the Neuse River Estuary illustrated several things; ecological systems are complex, contextual, and cyclic, where the model of the microdynamic input-environ flows of the Neuse River Estuary indicated that the system’s network grew or proliferated over time, was nonlocal where indirect effects outweighed direct effects, the network over time began to homogenize and because of feedback and associated circular causalities show a tendency toward uniform distribution of causality where system components were or became functionally interdependent. Quite significantly for purposes of this work and the logic behind the design axioms and corollaries that are to be proposed in the next chapter is that the model analysis showed that network structure expanded and homogenized over time. This phenomenon was not isolated to the preceding model analysis or to a particular time period. Below are portions of additional model analyses, at differing time periods, of the Neuse River Estuary and models of other ecological systems. Tables 4.4 – 4.9 show for several systems empirically measured flow matrices (F), and the integral matrices (N) which mathematically account for all flows transferred over extended connections or pathways. The analysis of the data was performed by EcoNet software (Kazanci, 2007). The reader will note the seemingly more independent system components as indicated by the measured flows (F) versus the resulting and contrastingly highly interdependent system components as the network’s proliferated into integral matrices (N).
Table 4.4: A comparison of the flow (F) and integral (N) matrix of the Neuse River Estuary input driven analysis model for the summer of 1988.

**Neuse River Estuary Model, Flow Matrix (F), Summer 1988**

<table>
<thead>
<tr>
<th></th>
<th>PN_phyto</th>
<th>PN_hetero</th>
<th>N_sed</th>
<th>DON</th>
<th>NOx</th>
<th>NH4</th>
<th>PN_abiotic</th>
</tr>
</thead>
<tbody>
<tr>
<td>PN_phyto</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>446.03</td>
<td>446.005</td>
<td>2438.07</td>
<td>0</td>
</tr>
<tr>
<td>PN_hetero</td>
<td>2419.08</td>
<td>0</td>
<td>260.002</td>
<td>372.004</td>
<td>33.9995</td>
<td>2034.06</td>
<td>696.019</td>
</tr>
<tr>
<td>N_sed</td>
<td>217.999</td>
<td>2.00008</td>
<td>0</td>
<td>0</td>
<td>1.99993</td>
<td>54.0015</td>
<td>217.998</td>
</tr>
<tr>
<td>DON</td>
<td>666.02</td>
<td>151.012</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>NOx</td>
<td>0</td>
<td>0</td>
<td>32.9942</td>
<td>0</td>
<td>0</td>
<td>386.011</td>
<td>0</td>
</tr>
<tr>
<td>NH4</td>
<td>0</td>
<td>4772.13</td>
<td>119.003</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>PN_abiotic</td>
<td>22.0015</td>
<td>894.017</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

**Neuse River Estuary Model, Integral Matrix (N), Summer 1988**

<table>
<thead>
<tr>
<th></th>
<th>PN_phyto</th>
<th>PN_hetero</th>
<th>N_sed</th>
<th>DON</th>
<th>NOx</th>
<th>NH4</th>
<th>PN_abiotic</th>
</tr>
</thead>
<tbody>
<tr>
<td>PN_hetero</td>
<td>44.7056</td>
<td>45.7479</td>
<td>37.305</td>
<td>44.6557</td>
<td>45.0336</td>
<td>43.4018</td>
<td></td>
</tr>
<tr>
<td>NOx</td>
<td>3.20082</td>
<td>3.26887</td>
<td>2.75145</td>
<td>3.13222</td>
<td>4.19712</td>
<td>3.30101</td>
<td>3.12155</td>
</tr>
<tr>
<td>NH4</td>
<td>37.564</td>
<td>38.4213</td>
<td>31.5718</td>
<td>36.7847</td>
<td>37.5217</td>
<td>38.8344</td>
<td>36.508</td>
</tr>
<tr>
<td>PN_abiotic</td>
<td>7.03965</td>
<td>7.19611</td>
<td>5.86951</td>
<td>6.89176</td>
<td>7.03124</td>
<td>7.08802</td>
<td>7.82741</td>
</tr>
</tbody>
</table>
Table 4.5: A comparison of the flow (F) and integral (N) matrix of the Neuse River Estuary input driven analysis model for the winter of 1989.

<table>
<thead>
<tr>
<th></th>
<th>PN_phyto</th>
<th>PN_hetero</th>
<th>N_sed</th>
<th>DON</th>
<th>NOx</th>
<th>NH4</th>
<th>PN_abiotic</th>
</tr>
</thead>
<tbody>
<tr>
<td>PN_phyto</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>190.018</td>
<td>189.998</td>
<td>679.013</td>
<td>0</td>
</tr>
<tr>
<td>PN_hetero</td>
<td>748.021</td>
<td>0</td>
<td>1.00032</td>
<td>173.991</td>
<td>137.005</td>
<td>625.013</td>
<td>268.997</td>
</tr>
<tr>
<td>N_sed</td>
<td>91.0026</td>
<td>0.999975</td>
<td>0</td>
<td>26.0042</td>
<td>4.99988</td>
<td>41.0033</td>
<td></td>
</tr>
<tr>
<td>DON</td>
<td>212.006</td>
<td>79.0022</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>NOx</td>
<td>0</td>
<td>0</td>
<td>22.004</td>
<td>0</td>
<td>0</td>
<td>180.003</td>
<td>0</td>
</tr>
<tr>
<td>NH4</td>
<td>0</td>
<td>1457.02</td>
<td>15.0075</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>PN_abiotic</td>
<td>12.0003</td>
<td>293.999</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>PN_phyto</th>
<th>PN_hetero</th>
<th>N_sed</th>
<th>DON</th>
<th>NOx</th>
<th>NH4</th>
<th>PN_abiotic</th>
</tr>
</thead>
<tbody>
<tr>
<td>PN_phyto</td>
<td>4.29959</td>
<td>3.49588</td>
<td>0.844499</td>
<td>3.70187</td>
<td>3.7226</td>
<td>3.87568</td>
<td>3.12502</td>
</tr>
<tr>
<td>N_sed</td>
<td>0.582466</td>
<td>0.532328</td>
<td>1.13087</td>
<td>0.528039</td>
<td>0.601701</td>
<td>0.564829</td>
<td>0.607577</td>
</tr>
<tr>
<td>DON</td>
<td>1.13444</td>
<td>1.00232</td>
<td>0.230665</td>
<td>2.01286</td>
<td>1.01372</td>
<td>1.05993</td>
<td>0.89448</td>
</tr>
<tr>
<td>NOx</td>
<td>0.701813</td>
<td>0.75682</td>
<td>0.297703</td>
<td>0.688393</td>
<td>1.69143</td>
<td>0.842046</td>
<td>0.691631</td>
</tr>
<tr>
<td>NH4</td>
<td>5.18891</td>
<td>5.6983</td>
<td>1.25358</td>
<td>5.13609</td>
<td>5.08231</td>
<td>6.36941</td>
<td>5.07764</td>
</tr>
<tr>
<td>PN_abiotic</td>
<td>1.08509</td>
<td>1.17972</td>
<td>0.24232</td>
<td>1.06867</td>
<td>1.05674</td>
<td>1.11705</td>
<td>2.04896</td>
</tr>
</tbody>
</table>

In each of the analysis of Neuse River Estuary data presented, the models begin with 21 direct of independent flow connections but in each case as the model was allowed to run over time the 21 direct connections became 49 direct and indirect flow connections indicating the
interdependence of all components within the network. The interdependence indicated by the homogenization at work within the network and the proliferation of its network has not been an isolated occurrence. Below are additional network models performed by EcoNet software of several other systems (http://eco.engr.uga.edu/Examples/examples.html, Web page retrieved November 2012). Note: Some EcoNet (Kazancı, 2007) models are based on the MATLAB® model written by Fath and Borrett (2004).


<table>
<thead>
<tr>
<th>Filter_Feeders</th>
<th>Dep_Detritus</th>
<th>Microbiota</th>
<th>Meiofauna</th>
<th>Dep_Feeders</th>
<th>Predators</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>15.7505</td>
<td>0</td>
<td>0</td>
<td>4.24188</td>
<td>1.87404</td>
<td>0.364422</td>
</tr>
<tr>
<td>0</td>
<td>8.17457</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0</td>
<td>7.27736</td>
<td>1.2064</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0</td>
<td>0.59814</td>
<td>1.2064</td>
<td>0.661135</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0.598121</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.169495</td>
<td>0</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Filter_Feeders</th>
<th>Dep_Detritus</th>
<th>Microbiota</th>
<th>Meiofauna</th>
<th>Dep_Feeders</th>
<th>Predators</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0.536075</td>
<td>1.38644</td>
<td>0.277137</td>
<td>0.778867</td>
<td>1.09901</td>
<td>0.65821</td>
</tr>
<tr>
<td>0.197122</td>
<td>0.509813</td>
<td>1.10191</td>
<td>0.286399</td>
<td>0.40412</td>
<td>0.242032</td>
</tr>
<tr>
<td>0.204578</td>
<td>0.529096</td>
<td>0.253341</td>
<td>1.29723</td>
<td>0.41941</td>
<td>0.251187</td>
</tr>
<tr>
<td>0.0594573</td>
<td>0.153774</td>
<td>0.189818</td>
<td>0.164315</td>
<td>1.12189</td>
<td>0.073004</td>
</tr>
<tr>
<td>0.0185103</td>
<td>0.0105707</td>
<td>0.0130485</td>
<td>0.0112954</td>
<td>0.07712</td>
<td>1.00502</td>
</tr>
</tbody>
</table>
In the Oyster Reef Ecosystem model, 12 direct flow connections are in actuality are 31 direct and indirect flow connections. The pattern continues in the Georgia Salt Marsh model below which shows a direct flow connectivity of 15 components but in actuality is substantially more connected.

**Table 4.7:** A comparison of flow (F) and integral (N) matrices of the Georgia salt marsh model by C. Small. Based on model by Teal, John M. (1962) Energy flow in the salt marsh ecosystem of Georgia. Ecology 43:614-624.

### Georgia Salt Marsh Flow Matrix (F)

<table>
<thead>
<tr>
<th></th>
<th>Spartina</th>
<th>algae</th>
<th>Insects</th>
<th>Detritus</th>
<th>bacteria</th>
<th>spiders</th>
<th>nematodes</th>
<th>mudcrabs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spartina</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Algae</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Insects</td>
<td>1.04053</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Detritus</td>
<td>15.6079</td>
<td>0.704286</td>
<td>0.594587</td>
<td>0</td>
<td>3.61136</td>
<td>0.099098</td>
<td>5.40531</td>
<td>0.060059</td>
</tr>
<tr>
<td>Bacteria</td>
<td>0.052026</td>
<td>0</td>
<td>0</td>
<td>6.52065</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Spiders</td>
<td>0</td>
<td>0</td>
<td>0.148647</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>nematodes</td>
<td>0</td>
<td>0.704286</td>
<td>0</td>
<td>6.52065</td>
<td>0.072227</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>mudcrabs</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.090088</td>
<td>0</td>
</tr>
</tbody>
</table>

### Georgia Salt Marsh Integral Matrix (N)

<table>
<thead>
<tr>
<th></th>
<th>Spartina</th>
<th>algae</th>
<th>insects</th>
<th>detritus</th>
<th>bacteria</th>
<th>spiders</th>
<th>nematodes</th>
<th>mudcrabs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spartina</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Algae</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Insects</td>
<td>0.010983</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Detritus</td>
<td>0.255998</td>
<td>0.371067</td>
<td>0.990094</td>
<td>1.48514</td>
<td>0.828235</td>
<td>0.990094</td>
<td>1.11233</td>
<td>0.990094</td>
</tr>
<tr>
<td>Bacteria</td>
<td>0.064549</td>
<td>0.092767</td>
<td>0.247523</td>
<td>0.371285</td>
<td>1.20706</td>
<td>0.247523</td>
<td>0.278082</td>
<td>0.247523</td>
</tr>
<tr>
<td>Spiders</td>
<td>0.001569</td>
<td>0</td>
<td>0.142857</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>nematodes</td>
<td>0.064709</td>
<td>0.236643</td>
<td>0.250243</td>
<td>0.375365</td>
<td>0.220323</td>
<td>0.250243</td>
<td>1.28114</td>
<td>0.250243</td>
</tr>
<tr>
<td>mudcrabs</td>
<td>0.000799</td>
<td>0.002922</td>
<td>0.003089</td>
<td>0.004634</td>
<td>0.00272</td>
<td>0.003089</td>
<td>0.015817</td>
<td>1.00309</td>
</tr>
</tbody>
</table>
Table 4.8: Oxygen cycling in an algae-Daphnia microcosm by J. Shetsov and E. Susko based on unpublished data from Frieda Taub.

Oxygen cycling in an algae-Daphnia microcosm, Flow matrix (F)

<table>
<thead>
<tr>
<th></th>
<th>Algae</th>
<th>Daphnia</th>
<th>Detritus</th>
<th>CO2</th>
<th>O2</th>
<th>H2O</th>
<th>Nutrients</th>
</tr>
</thead>
<tbody>
<tr>
<td>Algae</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>169.727</td>
<td>158.043</td>
<td>80.1012</td>
<td>33.5272</td>
</tr>
<tr>
<td>Daphnia</td>
<td>47.226</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.015171</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Detritus</td>
<td>0</td>
<td>14.7689</td>
<td>0</td>
<td>0</td>
<td>0.000994</td>
<td>1.92E-05</td>
<td>0</td>
</tr>
<tr>
<td>CO2</td>
<td>158.8</td>
<td>1.40258</td>
<td>27.8459</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>O2</td>
<td>155.973</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>H2O</td>
<td>79.3999</td>
<td>0.70129</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Nutrients</td>
<td>0</td>
<td>30.3737</td>
<td>3.15342</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Oxygen cycling in an algae-Daphnia microcosm, Integral Matrix (N)

<table>
<thead>
<tr>
<th></th>
<th>Algae</th>
<th>Daphnia</th>
<th>Detritus</th>
<th>CO2</th>
<th>O2</th>
<th>H2O</th>
<th>Nutrients</th>
</tr>
</thead>
<tbody>
<tr>
<td>Algae</td>
<td>2.67842</td>
<td>2.25887</td>
<td>1.46458</td>
<td>1.32712</td>
<td>1.35128</td>
<td>2.67842</td>
<td>2.67842</td>
</tr>
<tr>
<td>Daphnia</td>
<td>0.286615</td>
<td>1.24172</td>
<td>0.156723</td>
<td>0.142013</td>
<td>0.144647</td>
<td>0.286615</td>
<td>0.286615</td>
</tr>
<tr>
<td>Detritus</td>
<td>0.089597</td>
<td>0.388154</td>
<td>1.04899</td>
<td>0.044394</td>
<td>0.04522</td>
<td>0.089597</td>
<td>0.089597</td>
</tr>
<tr>
<td>CO2</td>
<td>1.05259</td>
<td>1.19819</td>
<td>1.47384</td>
<td>1.52154</td>
<td>0.531058</td>
<td>1.05259</td>
<td>1.05259</td>
</tr>
<tr>
<td>O2</td>
<td>0.946449</td>
<td>0.798195</td>
<td>0.517525</td>
<td>0.468951</td>
<td>1.47749</td>
<td>0.946449</td>
<td>0.946449</td>
</tr>
<tr>
<td>H2O</td>
<td>0.486055</td>
<td>0.424762</td>
<td>0.265778</td>
<td>0.240833</td>
<td>0.245219</td>
<td>1.48605</td>
<td>0.486055</td>
</tr>
<tr>
<td>Nutrients</td>
<td>0.193373</td>
<td>0.837759</td>
<td>0.207463</td>
<td>0.095813</td>
<td>0.097591</td>
<td>0.193373</td>
<td>1.19337</td>
</tr>
</tbody>
</table>

Finally, the Oxygen Cycling Model above and Nitrogen flow model below both show complete connectivity as the analysis is performed in contrast to their somewhat sparse initial direct connectivity.
This work from Chapter 1 has shown that ecological systems are philosophically and sensibly dissimilar from the typical mechanistic system designed and constructed by humankind.

In fact they have tended to have the reverse or opposite characteristics. The quantitative results from this chapter are very significant in that ecosystem components tend to interdependently and prolifically connect as was shown in the various integral matrices (N) above. As this work
attempts to make a strong scientific and circumstantial case for design philosophies, axioms and principles in the next chapter these interconnected and interdependent characteristics of ecological systems will be central to that rationale.
CHAPTER 5
DESIGN AND ECOLOGICAL SYSTEMS

An initial observation during an Axiomatic Design presentation and discussion led this work to its overall hypothesis, that the philosophy and design methods for traditional engineered systems are perhaps the opposite in many regards of what is needed in the design and management of ecological systems. For example, the Axiomatic Design (Suh, 1990, p. 48) method manipulates design matrices toward an optimal configuration through decoupling on the way to a one to one mapping of design parameters to functional requirements. This is quite different from flow matrices observed in the network analyses of ecological systems. In these analyses of ecological systems initial mappings proliferate as the system operates as was illustrated by the analyses and examples in Chapter 4. These types of observations led this work to hypothesize that current engineering methods are insufficient for the construction and understanding of ecological systems and that a need exists for new intellectual paradigms in their management and design. Further, the initial hypothesis of this work suspects that design axioms and corollaries used in traditional design methods to optimize an engineered system may in fact be the opposite required for the design and management of ecological systems. Seeking to use first principles, this work has attempted to make that case often through descriptions, philosophical methods and dialectical comparisons of the qualitative and quantitative characteristics and essence of mechanical systems versus living systems. Chapter 1 made a strong case that ecological systems, different from traditionally engineered mechanistic systems,
fall into unique classes of systems that are functionally and relationally interdependent. Chapter 2 went further and discussed causality and strongly asserted that living systems had unique circular functional and relational causalities through system direct and indirect feedback mechanisms that differ from typically engineered systems, and also that Aristotle’s four causes for complex self-organizing interdependent systems intertwine around the question why and thus are disparate from systems typically engineered by humankind. In qualitative terms, Chapter 3 suggested that mathematical trends and characteristics revealed through the analysis of ecological systems using the system sciences and network analysis provide a potentially precise way forward in accounting for contextual and interdependent characteristics of living systems. Further, this chapter discussed how the mathematization of the problem for ecological systems requires a somewhat reverse approach from the way Newton mathematized the physical world. Additionally, suggesting that this type of opposite approach used iteratively in the design and management of ecosystems will further provide for greater understanding of ecological systems while concurrently adding greater precision and accuracy to the planning and management of these systems. Chapter 4 used Network Environ Analysis to examine the microdynamic flows within the Neuse River Estuary and other model examples of system connectivity. These examinations added quantitative weight to the argument that ecological systems are highly cyclical, interdependent, relational and contextual systems that survive not by minimizing connectivity but through a proliferation of coupling of system components. These systems are indeed highly intertwined causally, as evidenced in the composite flows uncovered, and these systems are uniquely contextual (plastic) as indicated by different composite microdynamic flows that were uncovered, depending on whether the system drivers were input or output mechanisms. In Chapter 5, a specific discussion of design, some current engineering design
methods, and their applicability to the management and design of ecological systems will add further clarity and weight to the argument that design of ecological systems may in fact require opposite axioms, corollaries and methods from those often used in the engineering of traditional mechanistic systems.

The word "design" carries implications ranging from arguments for the existence of a supreme being as the direct causal agent for all aspects of our natural world, to relativistic measures of humanly created aesthetics. The Scottish philosopher David Hume addressed the religious argument that the order and purpose found in the natural world must implicate a divine designer. Hume (1777, 1779), though, was critical of this argument, suggesting that for the "design argument" to be valid and further even feasible, then it must be true that order and purpose only result from the typical understanding of design. Hume argues that human actuated design accounts for only a small portion of the order and purpose observed. He moreover makes the point that observation of order and purpose in our universe has no comparative analogy to distinguish it from disorder and lack of purpose. In other words, a comparison to another universe where disorder and lack of purpose are the norm would be necessary to distinguish a machine-like ordered universe from universes that were not. Further, Hume suggests that if order and purpose must implicate a designer, then the designer also requires a designer who also requires a designer, etc. Thus, based on the metaphor of nature as a machine, open to efficient causation and requiring final causation from outside, an infinite regress and expansion of the machine system is required to explain final cause. Supposing one could then choose to be content with an unexplainable self-organized divine mind as final cause, and responsible for all observed order, or based on closed efficient causation and embedded final cause from within living systems, one would be perhaps sufficiently logical in defending order as a self-organizing
principle in the natural universe. In fact, the work of Prigogine (1980, p. 260), Prigogine & Stengers (1984), Peusner (1986) and others in the field of non-equilibrium thermodynamics does support ideas that self-organization of the natural world is not only plausible, but it is what science tends to observe. Thus, contrary to the “designer argument,” science seems to imply that order arises spontaneously, self-designing or self-organizing in the natural world. Examples range from crystals, snowflakes, and cyclones to the evolutionary self-organization of living systems. Thus, the science-of-the-designer argument based on evidence within the physical world seemingly has flaws and inconsistencies, as science tends to implicate self-organizing principles, and only faith, not science, is necessary to require a designer from outside the physical universe to generate those organizing principles.

The American Heritage Dictionary (2012) defines “design” as: “To conceive or fashion in the mind; invent,” and "To formulate a plan", and defines engineering as: "The application of scientific and mathematical principles to practical ends such as the design, manufacture, and operation of efficient and economical structures, machines, processes, and systems”. Generally, design may be thought of as the act of bringing into being something that did not exist before. Design or planning in the context of this discussion, ecological systems, may be thought of as the intentional shaping of matter, energy, processes and systems to meet some perceived environmental need. In the next sections, three standard design philosophies or strategies will be explained and discussed in terms of their applicability or lack thereof in managing and designing natural systems.

**Axiomatic Design**

Axiomatic design is a systematic process developed by Nam Suh at Massachusetts Institute of Technology where Suh (1990, pp. 17-19) considers it as theory and methodology that
seeks to simplify, standardize and ultimately optimize the design process. An axiom is defined as a self-evident truth or universally accepted principle or rule that requires no proof. Thus, some often argue that an axiomatic approach may not exist in design because of the arbitrary and subjective nature of the process. Suh (1990, pp. 17-19, 47) in his book *The Principles of Design* suggests that axioms may in fact exist in the “artificial” domain of the synthesis process just as axioms exist in the natural sciences. Suh cites several examples to make this point: force, entropy and energy are themselves not primary quantities in the natural world but must be determined indirectly, using axioms describing nature. For instance, force is determined from axioms related to acceleration of a mass, deflection of a spring or measurement of weight, etc. Hence, Suh notes his fundamental approach in promoting axioms for the design process as a basic set of existing principles that determines good design practice, and he seeks to both quantify and qualify those practices. He goes on to write in his book, “The knowledge in a given field can be axiomatized when a set of self-consistent logic based on the axioms can yield correct solutions to all classes of problems” (Suh, 1990, p.18). Further, Suh describes design as interaction between what is wanted and how to achieve it and the design objective as in a *functional domain* while how to achieve it is in a *physical domain*. The two domains connect at the hierarchical level of the design process. Further, the two domains are independent and are only coupled to each other in the manifestation of the design. Design objectives are defined in terms of specific requirements and called the *functional requirements* (FRs) within *axiomatic design*. The *functional requirements* satisfy by a physical manifestation and characterize by a set of *design parameters* (DPs). Thus, the design process, according to Suh, involves relating or mapping the functional requirements of the functional domain to the design parameters of the physical domain. He formally defines the design process “as the creation of synthesized solutions in the
form of products, processes or systems that satisfy perceived needs through the mapping between
the FRs in the functional domain and the DPs of the physical domain, through the proper
selection of DPs that satisfy FRs. This mapping process is non-unique; therefore, more than one
design may ensue from the generation of the DPs that satisfy the FRs” (Suh, 1990, p. 27).
Therefore, there may be an endless number of design solutions possible, and those solutions will
vary in degree of acceptability; thus, one of Suh’s objectives is to offer a method of comparison
and selection. He further states that the selection of the FRs defines the design problem and
requires the designer’s judgment. One should note that in many engineering design methods, the
problem definition is paramount and often done in consultation with stakeholders. After defining
the need and gathering pertinent information, generation and comparison of differing ideas that
seemingly meet the perceived need occurs through the analysis of these potential solutions to see
how efficiently they meet the functional requirements. This often requires iteration that fine-
tunes the design to meet best the need(s) defined. The designer next specifies materials, shapes,
sizes, and components along with their temporal and spatial relationships. This may take the
form of equations, working drawings, software, circuit diagrams, or flow charts and often
culminate in the construction of a prototype. All of these are general steps found in most
engineering design processes. Suh (1990, p. 48) seeks at this point to begin qualifying good
designs as those that satisfy the determined need with a minimal set of independent FRs. He
argues, correctly in my opinion, that as the number of FRs increases so does the complexity of
the design; thus, it is important and necessary to satisfy only those FRs that achieve the desired
outcome. Otherwise, cost, control, predictability, and precision may make the design ineffective,
dangerous or unsustainable. Suh (1990, pp. 64-67) further writes that FRs should be independent
of each other and that when they become dependent, it adds additional complexity to the design
without additional benefit. At this point, in the opinion of this work, is where Suh’s method, though beneficial for the optimization of “mechanistic” designs, becomes non-axiomatic when applied to design and management of natural living systems. Further elaboration on this subject occurs in later sections. However, Suh (1990, p. 28) goes on to state quite correctly that “the designer must be familiar with manufacturing processes, the laws of nature, and basic scientific principles. Nothing substitutes for knowledge”.

Designs are often constrained, and designers along with customers or clients often have to specify and weigh those constraints, including size, aesthetics, cost, weight, and safety etc. However, unlike FRs, designs are considered acceptable in terms of constraints if the constraints are not exceeded, noting that the constraints may be dependent on other constraints and the FRs. However, the FRs in Suh’s method should remain independent. Interestingly and for future work and discussions of ecological systems design, this methodology indicates that the greater the number of constraints, the narrower the range of FRs, but is this what nature tends to promote?

The axiomatic design process promotes two main axioms: the independence axiom and the information axiom. Suh (1990, p. 48) introduces these design axioms as an effort to systematize and to answer rationally and formally questions regarding making correct and optimal design decisions; in other words, how to quantify good designs and how to choose good designs physically constructed from a near infinitude of possibilities. Suh’s intent, based philosophically on hierarchical reduction of the independence axiom, is to uncouple the functional requirements of the system whenever possible, resulting in simpler, transparent and controllable designs. Similarly, the information axiom seeks additional controls by minimizing the information required to complete a design, thereby reducing the complexity of the resulting design and thus minimizing unintended consequences as requisite information is reduced (Suh, 1990). However,
the normal subjective process of design is creative and often based on the designer’s knowledge and in theory may lend itself to countless possible solutions. For example, the problem of transferring automobiles from one side of a river to another subjectively solves in a variety of ways, such as various types of bridges, tunnels, ferries, etc. It is the intent of Suh’s work, however, through his two axioms, to make the process more deterministic and less subjective. The use of the independence and information axioms and subsequent corollaries in tandem with an analytical methodology allow one to decide if a solution is appropriate and optimized. The theory of axiomatic design makes use of the advantages and benefits of reductionism to uncouple components of a system and reduce the requisite information content of the design. Therefore, it optimizes the independent operation of function, which tends to result in the following summarized general positive effects (Table 5.1.) for the systems designer.

**Table 5.1. Some positive effects of reductionism in mechanistic design**

<table>
<thead>
<tr>
<th>increased operational simplicity</th>
<th>increased distinction of causal relationships</th>
</tr>
</thead>
<tbody>
<tr>
<td>increased transparency of the design</td>
<td>increased control</td>
</tr>
<tr>
<td>simpler to change the design</td>
<td>the whole becomes the sum of the parts</td>
</tr>
<tr>
<td>increased parallelism in the design</td>
<td>easier to compute (i.e. analytic = synthetic)</td>
</tr>
</tbody>
</table>

Design quality also relates to manufacturability, and Suh (1990. p. 41) cites Stoll’s (1986) review of design rules for manufacture, which include the following:

- Minimize the total number of parts.
- Develop a modular design.
- Use standard components.
- Design parts to be multifunctional.
• Design parts for multi-use.
• Design parts for ease of fabrication.
• Avoid separate fasteners.
• Minimize assembly directions.
• Maximize compliance.
• Minimize handling.

However, Suh considers this non-general and thus only applicable for certain cases; in other instances, they violate the axioms he has proposed. The axioms he promotes are as follows (Suh, 1990, p. 48):

• “Axiom 1 The Independent Axiom

  Alternate Statement 1: An optimal design always maintains the independence of FRs.

  Alternate Statement 2: In an acceptable design, the DPs and FRs are related in such a way that specific DPs adjust to satisfy corresponding FRs without affecting other functional requirements.

• Axiom 2 The Information Axiom

  Alternate Statement: The best design is a functionally uncoupled design that has the minimum information content.”

Suh separates designs into three distinct states: uncoupled, decoupled and coupled. An uncoupled design state completely satisfies the independence axiom and is considered optimum whereas in a coupled design many, if not all, FRs are dependent on each other. A coupled design may be decoupled to minimize functional interdependencies when the coupling is caused by an inadequate number of DPs as compared with FRs (see Fig.5.1):
As an example of an uncoupled design, a multipurpose Swiss Army knife may have several functions such as a long blade, short blade, can opener, corkscrew, saw blade, etc. Each of these functions on the knife is functionally independent in that each is its own functionally independent device though each function physically integrates into a whole. In other words, one could break the blades, but the can opener would still function. At this point, physical coupling does not imply functional coupling. In fact, it is often desirable to physically couple components if their functions remain independent because of the often-reduced complexity and information content of a physically coupled design. For instance, if we consider a single ½ inch wrench with a boxed end and an open end, it has two independent functions embodied physically in a single part. Accomplishing functional independence while minimizing information, in other words, more information and specificity are required to design and construct two physically separate wrenches instead of one. Thus, Suh (1990, p.52) developed corollaries, which he has inferred from his original axioms:

Corollary 1: “Decouple or separate parts or aspects of a solution if FRs are coupled or become interdependent in the design proposed.”
Corollary 2: “Minimize the number of FRs and constraints.”

Corollary 3: “Integrate design features into a single physical part if FRs can be independently satisfied in the proposed solution.”

Corollary 4: “Use standardized or interchangeable parts if the use of these parts is consistent with the FRs and constraints.”

Corollary 5: “Use symmetrical shapes and/or arrangements if they are consistent with the FRs and constraints.”

Corollary 6: “Specify the largest allowable tolerance in stating FRs.”

Corollary 7: “Seek an uncoupled design that requires less information than coupled designs in satisfying a set of FRs.”

Generally, the overarching mathematical method employed in axiomatic design consists of matrix manipulation to optimally achieve an uncoupled design, or if complete uncoupling is not possible, to achieve a decoupled design. According to Suh (1990, p.54), the matrix consists of design matrix \([A]\) which is mapping DPs in the physical domain to FRs in the functional domain (Equation 5.1).

\[
[A] = \begin{pmatrix}
A_{11} & A_{12} & \cdots & A_{1n} \\
A_{21} & A_{22} & \cdots & A_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
A_{m1} & A_{m2} & \cdots & A_{mn}
\end{pmatrix}
\]  

(5.1)

An entry in any element \(A_{ij}\) of the design matrix \([A]\) relates a component of the DP vector to the FR vector where

\[
A_{ij} = \frac{\partial FR_i}{\partial DP_j}
\]  

(5.2)

Unless \(A_{ij}\) is a constant, it should be evaluated at a unique point in design space, and \(A_{ij}\) may vary with both FR\(_i\) and DP\(_j\) for the nonlinear case. If the design matrix is not square, Suh (1990)
considers it a coupled or redundant design. Both cases are non-ideal, requiring adjustment of the design. Thus, ideally \( m=n \) in matrix \([A]\). In equation form the design equation is as follows

\[
\{\text{FR}\} = \{A\}\{\text{DP}\}.
\]

(5.3)

where the left-hand side of the equation represents the design goals, and the right-hand side represents how to achieve those goals. The simplest case in which the independence axiom is fully satisfied involves the case where all entries of matrix \([A]\) are zero except along the diagonal, implying that each FR independently maps only to one DP, and Suh (1990, pp. 54-56) considers it an uncoupled design. That is

\[
\text{FR}_i = A_{ij}\text{DP}_j \quad \text{where } i=j.
\]

(5.4)

A highly coupled design matrix \([A]\) would conversely have nonzero entries in most of the matrix elements (Figure 5). A fully coupled four-dimensional design matrix would have the following set of relationships between functional requirements and design parameters:

\[
\begin{align*}
\text{FR}_1 &= A_{11}\text{DP}_1 + A_{12}\text{DP}_2 + A_{13}\text{DP}_3 + A_{14}\text{DP}_4 \\
\text{FR}_2 &= A_{21}\text{DP}_1 + A_{22}\text{DP}_2 + A_{23}\text{DP}_3 + A_{24}\text{DP}_4 \\
\text{FR}_3 &= A_{31}\text{DP}_1 + A_{32}\text{DP}_2 + A_{33}\text{DP}_3 + A_{34}\text{DP}_4 \\
\text{FR}_4 &= A_{41}\text{DP}_1 + A_{42}\text{DP}_2 + A_{43}\text{DP}_3 + A_{44}\text{DP}_4
\end{align*}
\]

(5.5)

A change of any DP results in an alteration of all FRs, implying that each function is coupled or interdependent to or with the other functions of the design. However, manipulation of coupled designs occurs in a manner that may result in a decoupled design. Consider a special case, the triangular or decoupled design matrix (Figure 5.1). Here the FRs can be maintained independently of the other FRs through the adjustments of DPs in a particular order. In other words, if \( \text{DP}_1 \) is varied first, then that fixes \( \text{FR}_1 \) although \( \text{FR}_2 \) and \( \text{FR}_3 \) are affected. However, \( \text{DP}_2 \) manipulates to fix \( \text{FR}_2 \) and \( \text{DP}_3 \) will fix \( \text{FR}_3 \); changes to this order would not allow the adjusting of each FR or set by only one corresponding DP.
The above derivations are for the linear case, but many systems will be non-linear, and evaluation should occur in correspondingly proper operating ranges. Further, Suh’s methods do evolve to more mathematically sophisticated forms as he gives further details and examples for both the linear and non-linear cases. However, the current information presented is sufficient to represent the purposes of axiomatic design and for a general understanding of the fundamental themes and directions of his theory and axioms. In summary, they are to maintain functional independence and minimize information in the design of systems. Further, designs, which are highly coupled with mostly nonzero entries in the design matrix, may manipulate in a manner that results in only nonzero entries along the diagonal of that matrix (uncoupled) or manipulate to a triangular form with only nonzero entries along the diagonal and below (decoupled).

My first exposure to Suh’s methods occurred while attending a lecture in a graduate course in 2005. His methods proposed a possible way to begin to quantify and specify design of ecological systems. However, I found it strikingly odd and mentioned it at the time that the intent of Suh’s methodology was quite different and in fact, the opposite of observed tendencies in nature. In Suh’s ideal design matrix, manipulations occur to achieve only nonzero entries along the diagonal; natural systems however tend to do quite the opposite, that is, to fill in all the nonzero entries of their flow and storage matrices. For example, in Chapter 4, the examination of flows in the Neuse River Estuary based on measurements performed by Christian and Thomas (2003) resulted in the following flow matrix with several zero entries:
Chapter 4 showed that as the network interacts through indirect feedback loops that zero entries in the flow matrices become nonzero quantities (Table 4.3-4.9). This is quite the opposite of Suh’s design matrix, which optimally manipulates to achieve zero quantities off the diagonal. Ecologists have known that nature tends toward interdependence for some time, but the disparate functioning of traditional engineered systems, which tries to avoid these complexities, versus ecological systems, perhaps has not seen such a stark quantitative contrast of nature’s interdependence with the desired control of mechanistic system through independence until now. I suspected at the time that the methods employed by Suh might in fact be the opposite of what should occur to achieve a trajectory for the planning and management of ecological systems. This work has tried formally to make that case from first principles. 

**Evolutionary Systems Engineering**

Generally, systems engineering has been a method to organize design or build a large or highly intricate system where the system reduces or separates into vital parts. This method typically assigns particular parts to a group to design or build in coordination with groups working on the other pieces with the intent of ultimately putting the pieces together to form the system. The groups often take the vital parts and further separate them into even smaller pieces, often until individuals have a particular piece that they are designing. As the individual pieces
are completed, they are coordinated and integrated back into larger and larger pieces until the complete system assembles. Although this seems inherently simple to accomplish, it becomes logarithmically more difficult as the systems designed become increasingly more complex. In other words, in large or intricate designs, no one person seems or is able to have the information or understanding of how the individual pieces coordinate and integrate into a whole. Yaneer Bar-Yam in his 2004 book *Making Things Work* identified this problem. However, although he does acknowledge that this traditional system engineering does work when the complexity of the system desired is not very great, he notes that the cost, effort and time required starts to become increasingly non-linear as highly complex systems designs are attempted. I have experienced this as a mechanical designer in the aviation industry where each engineer has his or her own particular “widget” to design and engineer often at a conceptual level.

These “widget” designs pass to detail designers and ultimately integrate and assemble into a virtual and then physical prototype. Regularly, the designer of an individual piece has a very limited understanding of the whole. That is, of other pieces and how the pieces integrate and form the operational whole. Though the use of computer aided design and manufacture has extended the capabilities of individuals, there is still an inherent limit of understanding of any one individual. This is particularly true today in the military industrial complex, where information is available on a “need to know” basis and this, coupled with the inherent increasing complexity of completed systems, is one reason that design of a new tactical aircraft for example often takes the efforts of thousands of engineers, decades, and billions of dollars.

Bar-Yam (2004, pp. 221-240) recognizes that the traditional systems engineering of the past is becoming insufficient to pragmatically meet the challenges of today’s complex systems design in large part because many engineered systems today must have many interdependent
parts mutually interacting with other system components that often give rise to unintended consequences as a result of their collective behaviors. Engineers are aware of the difficulties associated with component interdependencies and employ several techniques to ameliorate some of these difficulties. These range from Suh’s axiomatic design, which tries systematically to remove functional interdependences, to concepts such as modularity, abstraction, scaling, and layering. Modularity is a reductionist approach to the design of intricate systems that reduce larger systems into smaller constituent parts designed independently with the intent of assembling these individual parts into the system. Engineers often take a system and abstract or simplify the specificity of the system to reduce its complexity to a level that is immediate and manageable. The use of hierarchical scaling and layering in the design of systems is an approach that often intertwines with modularity and abstraction to initiate a design at a particular scale with the hope of filling in the details at other hierarchical levels at later stages (Bar-Yam, 2004, pp. 227-228). Each of these methods has been successful to a degree for relatively low levels of system complexity, but each has its weaknesses in terms of the design of highly interdependent systems. Those weaknesses include the loss of description and control of emergent properties, loss of component interface specificity, discounting important indirect properties and relationships.

Bar-Yam (2004, p. 228) identifies two theorems in engineering complex systems: 1) the Law of Requisite Variety (Ashby, 1957), and 2) the Theorem of Functional Complexity. The Law of Requisite Variety entails a relationship between the complexity of the system engineered and the complexity of the task the system performs. The theorem of functional complexity indicates that testing of complex systems is pragmatically impossible. He further indicates that in regards to these two theorems and their conditions, the instigation of new strategies and
approaches must occur to alleviate these difficulties, such as simplifying objectives and through what he calls *enlightened evolutionary engineering* (Bar-Yam, 2004, p. 221). Simplifying objectives has some parallels to Suh’s (1990) axiomatic method in that it seeks to limit the complexity of the design objectives. Many modern engineered systems have increased in complexity as components increasingly are integrated, multifunctional and have high informational constraints. However, when high complexity is necessary, Bar-Yam identifies specificity as one of the design issues; in other words, large and often unrealistically large amounts of information may be requisite for acceptably adequate control and predictability of some systems. To mitigate some of these difficulties, he proposes a different design approach for complex systems called *enlightened evolutionary design*, which implements a process to create an environment that allows the system to evolve over time. Thus, a mechanism is provided by which systems through a feedback structure may incrementally undergo relatively rapid improvement through adaptive modification to changing circumstances. Further, the systems as they evolve require constant monitoring and evaluation to ensure the correct trajectory of the system to its desired design target.

In summary, Bar-Yam (2004, pg. 240) states “The wide applicability of evolutionary change is a fundamental expression of the unique status it has as the only mechanism we know by which systems that are both effective and highly complex may arise. To solve complex problems we need effective complex systems. Therefore, we can expect that evolution will play an increasing role in our everyday activities.”

**Design of Complex Living Systems**

Generally, science and the engineering design of mechanistic systems are thought by many to be philosophically different. That is, science has as its foundation the goal of describing
the way nature is whereas engineering design traditionally has as a goal the description and construction of things, which have never been (Goldman, 1990, p.135). On the surface, this appears to be true, but if we increase our scale, we find that these engineering designs of things that never existed before are in many instances controlled, decoupled mechanical replications of things nature long ago mastered. These include locomotion, temperature regulation, flight, calculation, perception, etc. Thus, we begin to see hints that in many ways science and engineering design are perhaps not so philosophically different, thus foreshadowing a philosophy for the design of living systems, in that, the philosophical differences between mechanistic systems design and the philosophy of scientific investigation seem to converge as we move closer to the design of complex natural systems. For example, design of complex ecological systems is in many ways an attempt to describe, model and replicate nature. As such, the philosophical contrast between the description of nature and the description and construction of things that have never been seems to be less valid. Further, and perhaps more fundamentally, we should ask the question, do living systems require a manager/designer, or do living systems preclude or exclude the need for a manager/designer (Rosen, 1985, pp. 245-253)? As mentioned previously, Hume (1777, 1779) would philosophically argue that order does not imply a designer by axiom at least in terms of the limited human experience with creating order. Hume would propose that order exists in a variety of random seemingly mindless processes such as ripples in beach sand, to snowflakes, to quartz crystals. Furthermore, science suggests that living systems appear to self-organize, creating order, growing, developing and continually adjusting that order to changing conditions.

Perhaps the arguments for an explicit designer of the universe or the arguments against
each intertwine and entail an infinite “chicken or egg” circularity. However, ironically we find by analogy some solace in an inside versus outside dichotomy. One important philosophical theorem of mathematics is Gödel’s Theorem (Hofstadter, 1989; Kennedy, 2011) which states generally that any effectively produced theory capable of expressing elementary arithmetic cannot be both consistent and complete thus we are left with the “chicken and the egg”.

Traditional mechanistic design of systems has generally focused on a method that is concerned with “how” a system works using a Newtonian and Cartesian paradigm that generally prescribes avoidance of the questions of “why” a system functions. Aristotle persistently asked the question “Why?” about the world, and deduced four categories of answers to those questions in the form of four causes: material cause, efficient cause, formal cause, and final cause (Bunge, 1962; Rosen, 1985). As described in Chapter 2, these world paradigms of Bacon, Descartes, and Newton seem to work very well within the first three causes because the “how” for each cause separates for mechanistic systems, and final cause can be and is ignored. It is ignored because, to date, science and engineering have generally not been concerned with why, and consequently are silent concerning its description (Rosen, 1985). However, at fine scales, interdependent complex systems are philosophically divergent from mechanistic systems as consideration of final cause is necessary in that material, efficient, formal, and final cause may be interdependently related. Then the concern of “why” perhaps more than “how” becomes the relevant question (Rosen, 1985, pp. 244-253).

Rosen was intrigued with the question “What is life?” and in his quest to answer it, he found that perhaps the question itself was nebulous and that the more pertinent question is “Why organisms are different from machines?” The pursuit of the answer to this question led him to develop a relational theory for living systems that addresses the unique properties of living
systems; in particular, he identified living systems with a “nonfractionability” of components. Rosen determined that a material system is an organism if it closes to efficient causation (1985, pp. 244-253). Rosen also identified replication as a higher order function of a system that often produces by metabolism and repair functions operating together. Mikulecky (2005a) explains how these concepts of Rosen match with the image of life as “achieving organizing and disorganizing capacities simultaneously” (Fiscus, 2001, 2002). Rosen ultimately concluded that living systems do not fit within the current Newtonian scientific descriptions for the following reasons: unlike a machine, life is not divisible, life closes to efficient causation, and the model of life that meets the requirement of closure to efficient cause must and does include the interrelated functions of metabolism and repair.

Thus, why living systems have interrelated functions compared with how they are related may be the pertinent question. The answer to the question of why for interdependent complex systems may often lie in the fact that they are living systems and as such incorporate a level of model making, perhaps distributive model making, of their environment. Further, this model making ability allows one to infer that as living systems they may have an anticipatory characteristic and when feedback loops are present have the potential to self-organize or self-design into interdependently acting components within a system (Rosen, 1985, pp. 244-253).

Philosophically, one may successfully argue that mechanistic systems at fine scales may be fragmented and reduced, and in reverse mechanistic systems can also be designed using the reductionism paradigm where the efficient cause of the mechanistic system is always open and thus suggests a designer when the question “how” is asked. However, natural systems are more abstract and are quite different from machines in that they may form a closed causal loop (Chapter 2) in the form of non-linear distributed functions, relationships, self-repair, self-
replication, self-organization, etc. This implies that living systems are closed to efficient cause and as such seem not to require an external designer or manager.

Fiscus (2001, pp. 248-250; 2002, pp. 94-95), by principally synthesizing work of Lotka (1925), H.T. Odum (1970), Rosen (1991), Ulanowicz (1997), has developed an interesting hypothesis that may add to the design discussion. He first prefaces his comments with the following often-cited concepts of living systems: life is an emergent property of physical and chemical dynamics that emerged from a bifurcation point as these physical and chemical systems were driven away from thermodynamic ground by a continuous energy gradient where bifurcations resulted in new system states and behaviors. He hypothesizes that bifurcations result in two new states of functional processes; molecular string composers that he suggests are proto-autotrophs, and string decomposers, that he suggests are proto-heterotrophs. The composer function is to absorb and use solar, chemical, or thermal energy to form chemical bonds and build molecular strings, and the decomposer function is to harness energy from the chemical bonds and break molecular strings into component parts. He suggests that the two systems states derived from the bifurcation had a unique relationship in that they were interdependent though this work would argue that they were both independent and interdependent to some degree. In any event, the combination had a greater capacity to exist than either component had in isolation where the collective capacities provided a greater ability to endure as a dynamical process in a changing environment.

Moreover, these coupled composer-decomposer systems are necessary and sufficient for life to persist to counter the two opposing tendencies to break down life, that is, disorganization and over-organization. He also postulates that the ecosystemic organization of life from its beginning is more fundamental than the cellular or organismic forms of organization and that
composer-decomposer system is the forerunner of the metabolic and genetic processes of molecular string composition and decomposition. Further, cells were generated later through a process called "encapsulation and miniaturization" (Odum, 1970). Thus, Fiscus (2001, 2002) asserts that the ecosystem as an integrated system of autotroph and heterotroph and is the most general self-perpetuating form of life, and that cells and organisms are special cases of this life in that they cannot persist in isolation. This work would suggest here that persistence is perhaps a temporally relative attribute; that is, components of complex ecosystems cannot sustain themselves in isolation for extended periods.

Fiscus’s hypothesis if correct suggests life’s capacity for open-ended evolution, which too implicates the lack of necessity for a designer. Further, his suggestion that simple molecular forms of composer and decomposer operate as a team and are mutually causal, that is each helps create and evolve the other, further implicating the highly interdependent nature of ecological systems where the entropic and syntropic forces are in a continual and harmonious interplay. Further, Fiscus (2001, pp. 248-250; 2002, pp.94-95) paraphrases his hypothesis: “life achieves its independence through interdependence”.

Considering the information discussed in the last several pages of this work, the question for the ecological engineer perhaps changes from “Do interdependent complex living systems require management and design?” which in the opinion of this work is no, to "Will complex interdependent living systems allow a designer?” Apparently, the answer is yes because ecosystems are intentionally and unintentionally designed or initiated on a trajectory every time something (including man) disturbs them on a relatively large scale. In the human case, this is not necessarily a good or correct action, and philosophers, ethicists, and theologians should assist in determining the ethics or morality of intentional disturbances/designs of living systems.
For the present discussion, the engineer or ecologist can surmise that nature does not need but also does not preclude intentional planning or management. However, though an intentional designer may not be necessary, eternalness does often play a role in the “self-design” process, often providing the push or need for system reorganization through changing environmental conditions.

Design normally consists of three main attributes that judge the quality design: performance, control, and prediction. The previously discussed evolutionary design is an iterative design methodology using feedback as a mechanism that continually adjusts the trajectory of the design toward a predefined or necessary goal or outcome. This is in many ways a science of “muddling through” (Bar-Yam, 2004, pp. 227-240), but the human race has since it first constructed a tool or shelter used a version of this approach in the form of trial and error and heuristics to design some common simple systems, complicated systems, and perhaps some minimally complex systems, and over time this method eventually provided many useful outcomes. In addition, the evidence that nature provides obviously makes evolutionary ordering a viable method to achieve a desired outcome over time.

However, the time factor is problematic in this design methodology; for example, evolution typically has occurred not on human or even historical time scales but on geologic time scales of millions of years. Additionally, biological evolution seems to have a component of randomness associated with it; human constructed evolutionary designs, however, are generally not random and therefore are perhaps pseudo-evolutionary and as such reduce the requisite time periods for a successful outcome. Still, the time from goal definition to desired outcome may be quite impractical from the standpoint of a typical control-theory problem in nature. Further, effective designs by man through heuristics and engineering science by necessity incorporate a
degree of control and predictability in the processes and outcomes of designs. Evolutionary design may reduce that control and predictability over long temporal scales. Moreover, tragically, individuals and systems have suffered when the control and predictability have been neglected or flawed. As mentioned, engineering science and the science of engineering design have been effective ways to reduce uncertainties and their effects, increase control and predictability, and enhance the performance of mechanistic system designs. The theory of axiomatic design takes advantage of the benefits of reductionism to uncouple components of a system and reduce the requisite information content of the design. A summary of its benefits for the systems designer occurred previously in Table 5.1. The use of the axiomatic method is an effective way to take advantage of these benefits to increase control and optimize the design of common simple systems and complicated systems where complex system behavior is not present or desired. However, the self-organization evident in nature seems to be the antithesis of axiomatic design because self-organizing systems are highly coupled, information rich systems that have prolific and intertwined and interdependent functional and relational causal relationships. Nature is obviously very complex, and the design of complex systems should account for the distinctions between complex systems and common simple, and complicated mechanistic systems. Complex systems have the following characteristics (Mikulecky, 1995a) which differ from mechanistic systems:

- the components of the systems couple;
- the systems tend to be natural and living systems;
- the system may not be fragmented without seriously affecting the system;
- the systems tend to be intractably difficult to compute;
- the system has prolific and intertwined and interdependent causal relationships;
- the systems tend to be information rich;
- the analytical reduction of the system does not equal the system synthesis and integration;
- the system as a whole has beneficial emergent systemic properties.

Reductionism and mechanistic approaches both are seriously lacking in the ability to describe or implement the characteristics of complex systems listed above.

Thus, it is the position of this work that mechanistic design and management methodologies based on reductionism are not appropriate for interdependent complex systems. This then begs the question, how does one begin to design complex coupled natural systems and avoid the inadequacies of mechanistic design methods and the shortcomings of evolutionary design? Obviously, coupled designs execute successfully, for they are prolific in nature. However, the scaling laws and the predictive ambiguities for coupled systems tend to be difficult to manage. For example, hierarchical layers, pathway proliferation, and emerging properties are but some of the difficulties that must be addressed. Needed are design strategies and methodologies that address and transcend these difficulties. First, however, the overarching purposes of design within the field of ecological engineering need mentioning. It is my opinion that formal design of ecological systems has four purposes. The first purpose is to provide a means by which society’s products, processes and systems may integrate harmoniously and benignly into the natural living environment. Since the industrial revolution, the effects of human constructions have had dramatic effects on natural systems.

Currently, human constructions are in effect designing ecological systems in increasingly dramatic ways and with alarming effects such as the at least one-hundred-fold increase in species extinction rates since the industrial revolution to altering the planet’s biochemical, and physical
cycles. A second purpose of ecological design is to provide insight and means by which natural systems manage holistically and naturally. Thirdly, to increase the understanding of ecological systems, and fourthly provide a knowledge set by which severely damaged ecosystems restore while providing the beginning knowledge set by which complete ecosystem planning, design or management may occur.

Mitch and Jørgensen (2004, pp. 94-102) derived, from the experience of field observation and ecological theory and science, ecological design principles that were used as decision guidelines when engineering, managing or restoring ecological systems. The first principle they identified is that forcing functions of the system determine ecosystem structure and function. Though some disagree by submitting that the forcing functions are not as important as the structure of the system, Mitch and Jørgensen (2004, pp. 94 - 102) contend that though structure does alter the function of the system, it is the forcing functions that ultimately give the systems their trajectories. Their second principle, based on conservation principles, identifies the energy inputs and available storage of matter within an ecosystem; that is, though systems often are artificially augmented by other energy and matter resources, it is only solar energies and the in situ resources available that will make the system sustainable over time.

The third principle, based on the second law of thermodynamics, indicates that ecosystems are open and dissipative systems, which are dependent on a continual supply of energy. Principle four states that attention should be given to a limited number of resources, that is, those resources which are most critical in restoring an ecosystem or preventing ecosystem degradation through pollution. Fifth refers to an ecosystem’s ability to attenuate strongly variable inputs. However, this homeostatic ability is limited and so is the system’s buffer capacity;
changes in these capacities may dramatically change or collapse the system. Principle six relates the matching of available cycling pathways and the amounts of resources or pollution acted upon or utilized. They suggest that this may be accomplished using ecological models. Principle seven suggests that ecosystems vary from day to day, season-to-season and that design should account for pulsations within ecosystems. For example, refer to the discussion of the Neuse River Estuary in Chapter 4. The eighth principle states that ecosystems are self-designing or self-organizing systems that adjust well to prevailing conditions using natural regulation mechanisms to maintain a system pattern. The ninth principle refers to the correct management of spatial and temporal scales within and surrounding ecosystems.

The next principle suggests that biodiversity should be maintained at a level that contributes successfully to the system’s ability to regulate, organize and sustain itself. Biodiversity is the system’s storehouse of information available to find solutions to changing parameters and conditions and limited biodiversity makes the system susceptible to collapse. Principle eleven suggests that ecological systems need transition zones as buffers from “undesirable” characteristics of adjacent systems. Ecosystems should be coupled wherever possible is the next principle suggested by Mitch and Jørgensen (2004, pp. 94-102), that is, the ecological engineer should not try to isolate the system because it is an open system requiring a perpetual supply of energy to maintain itself. In addition, as interconnected open systems, regional and global connections and effects need consideration.

Building on Principle Twelve above, the thirteenth principle states that ecosystems as connected components form a network with network properties where the indirect effects, biomagnifications, etc. may outweigh the direct effects and as such, the designer should consider these possibilities. Ecosystems also have a history of development, which constitutes the
fourteenth principle; that is, components of an ecosystem have millions of years of evolutionary experience in selecting components which are best suited for the conditions present. As such, the structural aspects and characteristics of mature ecological systems should be sought after though they likely cannot be achieved quickly. Principle Fifteen proposes that ecosystems and individual species are vulnerable near the edges of system viability and that more sustainable designs should target middle ranges of tolerance. Maintenance of landscape diversity because ecosystems are part of a hierarchical continuum is Principle Sixteen. Principle Seventeen states that both the physical and biologic processes need to be understood and integrated into a cohesive dynamic whole. Further, Principle Eighteen suggests that ecological design requires an integrated and holistic approach that considers and intertwines parts and processes as far as possible. Finally, Mitsch and Jørgensen (2004, pp. 94-102) put forward that information in ecosystems is stored in component structures that allow the system to degrade energy, increase organization and decrease entropy.

It is the opinion of this work that management of ecological systems and design of ecological systems may both benefit from the design principles put forward by Mitsch and Jørgensen. Though often overlapping in many aspects, management and design of ecological systems differ in that management focuses on the sustainability of current natural systems. Whereas design may be focused toward regeneration of damaged or destroyed systems, integrating human constructed systems, processes or products into the natural environment in a way that minimizes changes to the natural system and its processes, and lastly, if the human species survives long enough, perhaps the design and construction of complete systems on other worlds.
Management of ecological systems has benefited from technology in the form of better sensors, additional ways to collect data, etc: however, Wolfgang Sach (1992) (Van Der Ryn and Cowan 1996, p. 6) observes that the things such as satellite images used as global management tools “construct a reality that contains mountains of data, but no people.” Van Der Ryn and Cowan (1996, p. 6) suggest that data do not explain why for example, the Tuaregs are driven to exhaust their water holes. Nor does it indicate who owns the timber shipped from the Amazon or which industry flourishes because of a polluted Mediterranean sea, and they are mute about the significance of forest trees for Indian tribes, or what water means to an Arab country. In short, these technologies provide a knowledge which is faceless and placeless; “an abstraction that carries a considerable cost: it consigns the reality of culture, power and virtue to oblivion” (Van Der Ryn & Cowan, 1996, p.7). Thus, technology may provide society more data and a means to transcend scales of observation; however, it should be noted that technology still only provides sterile data which is missing a tremendous amount of contextual and relationship driven information necessary for ecological systems to persist. David Orr (Van Der Ryn & Cowan, 1996, p.7) noted several points related to sustaining ecological systems. Firstly, humans are finite and fallible with limited abilities to comprehend and manage scale and complexity, a sustainable world can only be built from the bottom up, traditional knowledge coevolves out of culture and place, and nature is more than a bank of resources but is the best source of information for the design issues and problems faced. However, who are or would be ecological designers? Certainly, engineers, architects, city planners, and landscape architects, but so are farmers, builders, foresters, and on a small scale so are homeowners. According to Van Der Ryan & Cowan (1996, p. 9), the environmental crisis is in large part a design crisis in the way that human
constructed products, processes and systems use an epistemology that is incompatible with nature’s own.

It is the position of this work that we have tried to design and engineer based on a flawed reductionist model of trying to decouple, isolate and control our designs from their surroundings. Although these designs are controlled in some aspects, they still in other aspects couple into the environment at some spatial or temporal scale. These designs tend to effectively meet short term narrowly defined human wants and needs but fail to consider the needs of the other components and species of the living system of which humans are a part, thus degrading the system and ultimately by extension the human species. We cannot fully separate our design decisions from ecological cost. Wendell Berry states, “A solution that causes a ramifying series of new problems, the only limiting criterion being, apparently, that the new problems should arise beyond the purview of the expertise that produced the solution” (Berry, 1981, Van Der Ryn & Cowan, 1996, p. 9). Since the industrial revolution, our power to design has increased logarithmically and so has our degradation of the environment as humankind has for example taken vast complex and diverse landscapes, reducing them to somewhat sterile templates of minimal biologic diversity and information. Moreover, at some point a loss of this biologic information may reach a critical mass and significantly affect the planet’s biosphere’s ability to respond effectively to changing environmental conditions. Van Der Ryn & Cowan (1996, p. 9) suggest that if society adds a richness of ecological parameters into the epistemology of design and moves away from design that blindly optimizes toward convenience and cost, there would be a significant amelioration of environmental problems. They (pp. 26-27) further put forth a set of contrasting characteristics of conventional design versus characteristics they feel should be endemically incorporated in ecological design. Though some differences are proposed, Table
5.2 below modifies and summarizes those characteristics while including some metaphorical comparisons put forth by Gattie, Kellam, and Turk (2007, p. 26).

**Characteristics, Use and Design Solutions**

In keeping with our discussions and comparison of conventional design and ecological design, let us return to the axiomatic design method put forth in Suh’s (1990, p.48) *Principles of Design* where he put forth *The Independence Axiom* and *The Information Axiom*.

- **Axiom 1 The Independence Axiom**
  
  *Alternate Statement 1:* An optimal design always maintains the independence of FRs.

  *Alternate Statement 2:* In an acceptable design, the DPs and FRs are related in such a way that specific DP can be adjusted to satisfy its corresponding FR without affecting other functional requirements.

- **Axiom 2 The Information Axiom**

  *Alternate Statement:* The best design is a functionally uncoupled design, one that has minimal information content.”

It is my judgment that Suh’s method has merit as an efficient method to optimize a mechanical system, process or product. It is hoped that this work has made the case through the juxtaposition of conflicting ideas of mechanistic systems and ecological systems using dialectical arguments and further reinforced by the work of others has led to the precipice of potential axioms for ecological design. As was presented, characteristics of mechanical systems and ecological systems are often contradictory. If we extrapolate this line of reasoning to design, it would suggest that contradictory ideas for ecological systems design would be appropriate, and perchance we find in that contradiction a general direction for the design of ecological systems.
Thus, instead of trying to facilitate the independence of function of mechanistic design, we should embrace the interdependence of function instead of trying to control and minimize information within design; ecological design should allow information within ecological systems to increase. Perhaps at this point we can begin to form some initial statements for ecological design such as, ecosystems are complex energy degrading open system entities that will not fragment without loss of system properties. Ecological systems in their quest to survive and thrive seem to facilitate self-design and organization often through the distribution of function, and often the physical, functional, or relational coupling of dissipative structures. As such, design of ecological systems should embrace complexity, increasing levels of information, distributed function and the physical, functional and relational coupling of system components to allow the emergence of systemic properties. Moreover, ecological engineers should not impede but include, predict and efficiently use emergent system properties to meet or enhance the design and management objectives. Complex natural system design should perhaps consider and hold paramount certain inherent truisms that differ from some traditional design methods, such as, interdependence of system components, increasing information content of self-organizing living systems, and the inherent beneficial emergent properties of the system (Turk, 2005). Suh (1990, p. 52) further identified several corollaries in his axiomatic design, which might also under the dialectical microscope yield useful information regarding the design of ecological systems. That is, if we presume from dialectical comparisons of natural and mechanistic systems that Suh’s corollaries are opposites of the way natural systems self-organize and using what we have learned of ecological organization, perhaps we can infer ideas that will be useful in the design and management of natural systems. Axiomatic Design corollary 1 suggests that designs that have functional interdependencies should adjust in a way to uncouple the functional
interdependencies. Nature, however, tends to couple functions in the quest to survive and organize.


<table>
<thead>
<tr>
<th>Complex Living Systems Design</th>
<th>Mechanical Systems</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Living systems</td>
<td>1. Mechanical systems</td>
</tr>
<tr>
<td>2. Coupled</td>
<td>2. Decoupled, Uncoupled</td>
</tr>
<tr>
<td>3. Complex</td>
<td>3. Complicated</td>
</tr>
<tr>
<td>4. Open</td>
<td>4. Closed</td>
</tr>
<tr>
<td>5. Systems and subsystems</td>
<td>5. Isolated objects and elements</td>
</tr>
<tr>
<td>6. Holism, synthesis, integration</td>
<td>6. Reduction</td>
</tr>
<tr>
<td>7. System thinking</td>
<td>7. Newtonian</td>
</tr>
<tr>
<td>8. Connectivity, relationships</td>
<td>8. Isolation</td>
</tr>
<tr>
<td>9. Manage</td>
<td>9. Control</td>
</tr>
<tr>
<td>12. Relationship proliferation</td>
<td>12. Minimize relationship</td>
</tr>
<tr>
<td>14. Direct and indirect effects</td>
<td>14. Direct Effects</td>
</tr>
<tr>
<td>15. Ascendancy</td>
<td>15. Increasing Entropy</td>
</tr>
<tr>
<td>17. Non-equilibrium thermodynamics</td>
<td>17. Classical thermodynamics</td>
</tr>
<tr>
<td>18. Exergy and energy</td>
<td>18. Energy</td>
</tr>
<tr>
<td>19. Renewable and nondestructive energy source (wind, solar etc)</td>
<td>19. Nonrenewable and destructive energy sources (fossil fuels)</td>
</tr>
<tr>
<td>20. Use of recycled materials and cycles where waste becomes food or input</td>
<td>20. Clumsy use of high quality materials and energy</td>
</tr>
<tr>
<td>21. Designed for flexibility, recycling, durability, and ease of repair</td>
<td>21. Discards low quality (often toxic) materials into the environment</td>
</tr>
<tr>
<td>22. Minimizes and matches any pollutants which are generated to the ecosystem’s ability to absorb or treat them.</td>
<td>22. Widespread and abundant pollution generated</td>
</tr>
<tr>
<td>23. Minimal use of toxic substances</td>
<td>23. Unnecessary use of toxic substances</td>
</tr>
<tr>
<td>25. Embraces ecology and takes a long term ecological and economic view</td>
<td>25. Perceived opposition and short term view of ecology and economics</td>
</tr>
<tr>
<td>26. Design criteria for success include human and ecosystem health and integrity</td>
<td>26. Often used design criteria for success are convenience, cost, etc.</td>
</tr>
<tr>
<td>27. Design is integrated with local environment, culture, climate, topography, etc.</td>
<td>27. Standardized design templates are imposed universally</td>
</tr>
<tr>
<td>28. Preserves native biodiversity.</td>
<td>28. Facilitates or instigates use of non-native or invasive species.</td>
</tr>
<tr>
<td>29. Respects traditional local knowledge, environment, culture &amp; technology.</td>
<td>29. Homogenizes toward a global culture and environment.</td>
</tr>
<tr>
<td>30. Optimizes energy and material throughput feedback loops.</td>
<td>30. Tends toward high energy and material throughput.</td>
</tr>
<tr>
<td>31. Integrates an assortment of scientific and other knowledge</td>
<td>31. Employs a highly reduced and narrowly focused knowledge set.</td>
</tr>
<tr>
<td>32. Transcends spatial and temporal scales.</td>
<td>32. Focused on the immediate spatial and relatively short temporal scales.</td>
</tr>
<tr>
<td>33. Works with whole systems and respects system “boundaries”.</td>
<td>33. Reduces, divides and unnaturally demarcates systems.</td>
</tr>
</tbody>
</table>
Figure 5.2: Three types of applicable design matrices and matching types of systems. Columns represent functional requirements of the design and rows represent design parameters. An $X$ represents coupling of function to design parameter and $O$ represents non-coupling of function to design parameter.

Figure 5.2 above illustrates graphically the connectivity differences between mechanistic and what this work believes ecological design should entail. Axiomatic design corollary 2 seeks to minimize the number of functional requirements and constraints. However, nature tends to maximize functions and in the process of maximization, optimization occurs through constraints. The third corollary seeks to integrate design features into a single physical part if the functional requirements can be satisfied independently. Ecological systems, however, tend toward increasing interdependently functioning biodiversity; though some species may be considered keystone species, there are also many niche species which are all intertwined in the grand
functioning of the system. The fourth corollary seeks to use standardized or interchangeable parts if the parts are consistent with functional requirements and constraints, but again nature increases its organization through often highly specialized biodiversity. In other words, nature tends to hedge its bet in that increasing biodiversity increases the odds that life and systems will continue regardless of changing environmental conditions. Corollary 5 proposes the use of symmetrical shapes and/or arrangements if they are consistent with the functional requirements and constraints. However, though nature uses symmetry at the species level; at the ecosystem scale components are of various shapes, sizes, and arrangements. The sixth axiomatic corollary of Suh’s axiomatic design seeks to specify the largest allowable tolerance when stating functional requirements; that is, to ensure reliability, resilience and durability of the mechanical system it is desirable that it operate under the greatest variety of conditions while minimizing the information or specificity required for construction. Tighter tolerances require exponentially increasing levels of information or complexity; however, tolerances which are to loose require increasing level of information and complexity in the form of maintenance and repair. Nature seems also to be interested in reliability, resilience and durability but tends to achieve those goals differently through the use of biodiversity and redundancy of function. Axiomatic corollary seven seeks uncoupled designs because less information is required for uncoupled designs than coupled design in satisfying functional requirements. Nature however tends to seek coupled designs that give rise to emerging system properties that are beneficial to the system.

The design process of sustainable complex ecological systems will likely be similar to natural complex systems themselves; that is, the designs will be scale dependent and the design process will require a collection of human talents and capabilities interacting, integrating and ultimately interdependent on one another for the successful design and management of a
complex system. In addition, the design methodology will likely consist of various tools both new and established to custom generate a particular complex design from generalities. However, unlike ecological systems, which appear to self-organize from the bottom up, an artificially instigated design of self-organizing systems will have an initial top downward organization. That is, first will be the correct identification of the complex system and scale desired and the corresponding interdependent components of the system. Secondly, a methodology is needed to organize the system so that systemic emergent behavior is facilitated, predicted, and directed to some degree.

Thirdly, the system may consist of systems within the complex system that may or may not be complex. If the system(s) within the system are complex, steps one and two will need repetition. If the system within the system is a minimally complex system, that is, a common simple or complicated system, tools and methods, such as, modularity, observable patterns, and axiomatic design may be employed to design this component. At this point empirical and theoretical ecologists, hydrologists, soil scientists, biologists, chemists and others should be incorporated into the process to begin to add detail, and the design should be simulated in various ways, including various network analysis techniques, to determine its potential outcomes. These steps iterate until the design reaches a desired base level of components and desired spectrum of outcomes. Lastly, the method should utilize the benefits of feedback used in evolutionary design to continually manage and fine-tune the system toward desired goals. However, a methodology that uses and collaborates with nature using nature’s evolutionary design intelligence but “leap frogs” over temporal scales evolution normally involves reducing the period and capriciousness of natural organization by targeting a trajectory toward a desired
spectrum of outcomes less random and more predictable. At this point, the designed ecological system is allowed to optimally self-organize toward the spectrum of identified outcomes.

As in most processes, the first step is critical; in this case, the correct identification of the complex systems desired. Further, a successful identification will depend on the goals, skills, and experience of the designer. This work, however, will not at this time focus toward system identification but on a method to organize the system after identification. That is how to integrate mechanical systems more benignly into the natural world, and how to use system emergent properties to aid in the planning and management of natural systems. It must organize, manage, and integrate systems in a manner that facilitates the targeting of a design trajectory toward desired systemic emergent behavior, increasing the predictability of system properties while decreasing degradation of the biosphere.

**Discussion**

Design implies organization, and organization exists in various entities ranging from institutions to electrical and mechanical products to ecosystems. Several design methodologies were discussed which seek to formalize the design process. Axiomatic Design Theory attempts to formalize the design process into a science and searches for a unified design theory (Suh, 1990). The axiomatic method began as comparisons of designs through relativistic measures of design effectiveness. Further, axiomatic design theory and the associated axioms of independence and information seek to provide a scientific basis for the understanding of design organization through decomposition and the structured mapping of uncoupled and decoupled systems. Traditional systems engineering is also in many ways design using decomposition. This method tends to abstract a high-level description of the system into components that design to some degree separately. However, this paper proposes that design of complex interdependent
systems is beyond the scope of both axiomatic design and traditional systems engineering. Furthermore, though enlightened evolutionary design proposed by Bar-Yam seems more in line with design of ecological systems, it has temporal and predictability shortcomings.

It is the opinion of this work that design of complex natural systems requires an additional new methodology or methodologies to target and encompass the complexities associated with component interdependencies and their dependencies to environment. The research and comparisons to mechanical systems led this work to suspect an overarching philosophical statement for ecological design where ecological design embraces the interdependence of function and instead of trying to control or minimize information within a design; ecological design should allow information within ecological systems to increase. Perhaps at this point an overarching philosophy of ecological design begins to emerge: *Ecosystems are complex energy degrading open system entities that do not fragment without loss of system properties. Ecological systems in their quest to survive and thrive seem to facilitate self-design and organization, often through the distribution of function, and often the physical, functional, or relational coupling of dissipative structures. As such, design of ecological systems should embrace complexity, increasing levels of information, distributed function and the physical, functional and relational coupling of system components to allow the emergence of beneficial systemic properties (e.g. resilience, ascendancy, network proliferation etc). Moreover, ecological engineers should not impede but include, predict and efficiently use emergent system properties to meet or enhance design and management objectives. Complex natural system design should perhaps consider and hold paramount certain inherent truisms that differ from some traditional design methods, such as, interdependence of system components, increasing information content of self-*
organizing living systems, and the potential inherent beneficial emergent properties of the system (Turk, 2005).

Based on the original hypothesis, the comparisons made in this work, and the philosophy for ecological design, it is proposed that axioms for ecological design likely will be the opposite in many ways of axioms for mechanistic design. Thus based on the dialectical evidence presented in previous chapters, this work proposes three potential axioms and several associated corollaries inferred from the preceding statements and discussions for the design, planning and management of ecological systems:

- **Axiom 1: The Interdependence and Distributed Function Axiom:** Though physically, biologically, chemically, functionally, or relationally constrained to optimum levels, an ecological system tends toward maximizing interdependence of function.

- **Axiom 2: The Information and Perception Axiom:** The best design is a functionally coupled design and one that optimizes its perception of environment and information content by striving toward maximum information content as the ecological system grows and develops under physical, functional and relational constraints (Jørgensen, 2002).

- **Axiom 3: The Emergence Axiom:** Functional, relational and physical coupling will often give rise to emergent system properties that are desirable and necessary for effective and sustainable ecological designs.

These axioms are followed by subsequent corollaries:

- Seek to couple ecological functions when organizing ecological systems.
Maximize functions and in the process of maximization optimization is achieved through natural physical, biologic, chemical, functional and relational constraints.

Ecological systems should tend toward increasing and maximization of information. Optimization will result through natural physical, biological, chemical, functional and relational constraints.

Ecological design should increase its perception and organization through high levels of unique biodiversity.

Ecosystem scale components should be of various shapes, sizes, organizations and arrangements.

Achieve reliability, resilience, and durability of design through increasing biodiversity and redundancy of function.

Embrace emerging system properties through component relational, functional and physical coupling that benefit the system.

The above axioms and corollaries result in systems with several desirable emerging properties. These properties sought in ecological designs serve as potential quantifiable planning and design targets and beneficial characteristics of the system. It is of note that many of the above statements are a contradiction to principles promoted for traditional engineering design. However, this work has hypothesized and made a substantial case that ecological systems and mechanistic systems are opposite ends of a spectrum, and thus one infers that their design principles also would be opposites. The following are additional characteristics and potential design targets:

- Design for ecosystem pathway growth.
- Design for dominance of indirect effects.
- Design tendencies for the ecosystem’s uniform distribution of causality, resources.
- Design for the dominance of indirect over direct utility.
- Design for dominance of indirect control in ecosystems. (Schramski, et al., 2006)
- Design for proliferation matter and energy transfer levels.
- Design for obtaining more than direct values of ecosystem boundary inputs.
- Design for indirect utilities becoming more positive than direct utilities.

- Design for internal order exceeding external disorder of the ecosystem.

- Design for the iterative incorporation of ecosystem indirect causes into direct causes.

- Design for the coevolution of wholes and parts.

The following are additional pertinent and potentially overlapping ecological design principles as laid out by Mitsch and Jørgensen (2003, pp. 94-102):

- Though structure does alter the function of the system, it is the forcing functions, which ultimately give the systems their trajectories.

- The conservation principles identify the energy inputs and available and storage of matter within an ecosystem; that is, though systems may be artificially
augmented by other energy and matter resources, it is only solar energies and the in situ resources available that will make the system sustainable over time.

- Based on the second law of thermodynamics, ecosystems are open and dissipative systems that are dependent on a continual supply of energy.

- Attention should be given to a limited number of resources; that is those resources that are most critical in restoring an ecosystem or preventing ecosystem degradation through pollution, etc.

- Ecosystems attenuate strongly variable inputs, but this homeostatic ability is limited and so is the system’s buffer capacity. Thus, changes in these capacities may dramatically change or collapse the system.

- Relate the matching of available cycling pathways to the amounts of resources or pollution to be utilized or acted upon. This may be accomplished using ecological models.

- Ecosystems vary from day to day, season to season, and that design should account for pulsations within ecosystems. See discussion of Neuse River Estuary in Ch. 4.

- Ecosystems are self-designing or self-organizing systems that adjust well to prevailing conditions using natural regulation mechanisms to maintain a system pattern.

- Correctly manage the spatial and temporal scales within and surrounding ecosystems.

- Biodiversity should be maintained at a level that contributes successfully to the system’s ability to regulate, organize and sustain itself. Biodiversity is the system’s
storehouse of information available to find solutions to changing parameters and conditions, and limited biodiversity makes the system susceptible to collapse.

- Ecological systems need transition zones as buffer from “undesirable” characteristics of adjacent systems.
- Ecosystems should be coupled wherever possible; that is, the ecological engineer should not try to isolate the system because it is an open system requiring a perpetual supply of energy to maintain itself. As interconnected open systems, regional and global connections and effects need to be considered. (See axioms and corollaries).
- Ecosystems are connected components and form a network with network properties where the indirect effects, biomagnifications, etc. may outweigh the direct effects and as such, the designer should consider these possibilities (See number 9).
- Ecosystems also have a history of development; components of an ecosystem have millions of years of evolutionary experience in selecting components that are best suited for the conditions present. As such, the structural aspects and characteristics of mature ecological systems are or should be sought after, though they likely cannot be achieved quickly (See number 16 and 18).
- Ecosystems and individual species are vulnerable near the edges of system viability, and more sustainable designs should target middle ranges of tolerance.
- Maintain landscape diversity because ecosystems are part of a hierarchical continuum.
- Physical and biologic processes need to be understood and integrated into a cohesive dynamic whole.
• Ecological design requires an integrated and holistic approach that considers the intertwined parts and processes as far as possible.

• Information in ecosystems is stored in component structures that allow the system to degrade energy, increase organization and decrease entropy.

A further extension of design principles, based on the information in Table 5.2 (Van Der Ryn & Cowan, 1996, pp. 26-27; Gattie, Kellam & Turk, 2007, p. 27) of this work, promotes criteria applicable for both ecological designs and traditional mechanistic designs that seek to less intrusively and less destructively integrate human constructed systems into the natural world. The above authors suggested several ways that this may be accomplished; first by seeking designs that take advantage of nature’s living systems, ideally these systems which are native to the immediate ecosystem to perform functions and processes that human society currently constructs a mechanistic system to perform. Several things should be considered when constructing living systems to meet a need within human society, first an understanding of systems thinking and the constructed systems complexity and how this complexity is often a function of system component coupling, perhaps coupling at several hierarchical scales where subsystems may embed within larger systems. Further, realizing that these constructed systems will be open systems exchanging matter and energy internally within the system but also with its input and output environment. This connectivity to environment may have other ramifications which must be examined and accounted using sophisticated ecological accounting and analysis techniques such as network analysis, non-equilibrium thermodynamics, emergy, and exergy etc. Often for these constructed open systems a waste by product of human civilization may be the systems input and a beneficial byproduct of systems processes, a system output. Though
necessarily, one must carefully match the system’s ability to absorb and treat input with the level of input anticipated. Furthermore, energy and material throughput should be optimized by promoting feedback loops within the system. While an examination of and a subsequent level of understanding of the endogenous and exogenous connectivity that not only results in functional bonds but often additional relational bonds develop that lead to adjusted system growth and development will be necessary. Feedback loops precipitate a proliferation of the network connectivity and often this results not only in direct but indirect effects through system cycling. These factors lead to both a short term and long term trajectory of the constructed system that must be considered and projected. One then must consider the systems eventual transcendence of immediate spatial and temporal scales. However, the design should also work in tandem with nature’s ability to self-organize and optimize itself while concurrently increasing the designers understanding of the workings of the system, one that includes a process to iteratively monitor and adjust the system based on this newly acquired knowledge. Pluralism within and of designs would be desirable to mimic natures often high levels of biodiversity and subsequent sustainability.

With today’s level of understanding of natural systems and the level of understanding of the design of complex natural systems a less desirable mechanistic solution to meet a human need may often still be required. If a living system design cannot be implemented perhaps some guidelines that mitigate the negative effects of mechanistic design can be found. Sometimes it may be as simple as just considering environment, that is not only immediate human health but also the health and integrity of the ecosystem when planning human constructions or simply choosing renewable and non-destructive energy sources or minimizing the use of toxic substances. These will ameliorate many problems because often we think of human constructed
mechanistic systems as controlled, closed systems within the natural environment. In many instances this is not true, particularly, at significantly smaller or larger spatial scales than the scale of the mechanistic design and perhaps quite often not true over long temporal scales. These systems designed to be uncoupled from environment in actuality are generally at some level or time coupling to the natural world. Some of these effects can be mitigated by implementing long term ecological and economic considerations while considering how best the mechanistic design will integrate with a minimum of impact with the environment. Lastly, many negative effects from human constructions to “fix a problem” could be eliminated by not focusing on a fix for a symptom of a problem but uncovering and focusing on eliminating the root cause (Van Der Ryn & Cowan, 1996, pp. 26-27; Gattie, Kellam & Turk, 2007, p. 27).

In summary, the work has proposed that traditional engineering design is in a variety of ways the opposite way by which natural ecological systems organize and grow. This work has made a strong case for this dialectic. In that, ecological systems often have beneficial emergent properties gained through interdependencies developed through system component coupling. However, some may argue that a complex system continually reduced the components would at some level the components begin operating under mechanistic principles and thus could be design based on traditional engineering design methodologies. I must concede that this could be true; however, in getting to this level using our current understanding of the workings of nature, I suggest that vital information is lost. Information is lost because we do not yet understand the specifics of interdependent coupling of system components and how this translates into beneficial system-wide properties. Perhaps, over time this will change as science begins to fully understand complexity and design of ecological systems can begin from fundamental components and thus designed layer by layer and associated with each hierarchical step a precise
prediction of the resulting system-wide properties. As was mentioned in Chapter 3, with today’s understanding working “backward” from Newton’s approach to mathematize from the observation of the physical phenomenon, but to first mathematize and determine the system-wide physical properties and then work toward systems and components that exhibit those properties and their typical trajectories gives one a potential way forward in the planning, design and management of ecological systems. The next chapter will begin a discussion of some of those reverse methods toward the design and management of natural systems.
CHAPTER 6
IN SEARCH OF A METHOD

Initial observations of the underlying foundations for many engineering methodologies has led this work to made a strong case that the philosophy for the planning, design and management of ecological systems is distinctly different from the philosophies and methods typically undertaken in engineering. In fact this work has proposed and made a powerful case that they are often opposite ends of a spectrum. Building on this proposition and the qualitative and quantitative information presented in Chapters 1-4, Chapter 5 outlined a philosophy for design of ecological systems and identified several characteristics of ecological systems as planning and management objectives that map toward design axioms and corollaries. In this chapter, an initial approach will be examined as a method by which these characteristics may be targeted. In all likelihood this may only serve as a preliminary starting point for further investigation and research toward a mathematical and methodological basis by which the planning, design or management of ecological systems may be fulfilled. With that said, it is suggested that eigenvalues as characteristic roots of the equations that connect ecosystem components are also requisite mathematical parameters for the precise and repeatable design of system wide properties of environmental systems. These system wide properties are evidenced as mathematical trends from much modeled empirical data by many which have consistently revealed a qualitative and quantitative precision in the patterns of connected constituents within a natural system.
Therefore, it is proposed that eigenvalues are the mathematical quantity that establishes, with a degree of mathematical repeatability, the direction in direct ecological planning and design of these systems. Thus, if so, the first preliminary steps toward establishment of quantitative design methodologies of environmental systems may then proceed. Toward that end this work hypothesizes that matrices of identical size, component numbers, inputs, outputs and stock values plus the same set of eigenvalues will return identical network properties.

Eigenvalues, Eigenvectors and Matrix Decomposition

The eigenvectors of a matrix are those that do not vary in direction when transformed by the matrix. Further, a point on an eigenvector can move up or down the vector when transformed by the matrix, but it will stay along that vector and the amount that the point moves is given by the associated eigenvalue. An $n \times n$ matrix will generally have $n$ linearly independent eigenvectors, and often the eigenvalue of the greatest absolute value along with its associated eigenvector have special significance in many physical problems. That is, whatever process is represented by the linear transformation in many cases acts repeatedly feeding output from the last transformation back into another transformation which gives every arbitrary (nonzero) vector converging on the eigenvector associated with the largest eigenvalue (Nobel & Daniel, 1977, pp. 263-267). Thus, the long term behavior of the system of equations is determined by the eigenvectors. In factor analysis, the eigenvectors of the covariance matrix correspond to the factors and the eigenvalues the factor loadings. In rigid body mechanics, the eigenvectors of an inertia tensor matrix calculate the axes of inertia and the corresponding eigenvalues are the moments of inertia. In vibration analysis, of a bridge for example, the smallest eigenvalue corresponds to the natural frequency of the bridge and the eigenvectors correspond to the modes of vibrations. Similarly, eigenvalues are used to tune radios and can be used to explain
harmonies in music and in the design of concert halls (Deken, 2007). In ecological systems, such as, the differential equations relating the population of predator to prey the eigenvector reflects the ratio between predator and prey (Jørgensen et al., 2000). Thus, it is speculated that the range of eigenvalues might be a valuable measure of ecosystem behavior. In particular, perhaps eigenvalues/eigenvectors will give a measure of system emergent behaviors through the use of ecological modeling techniques, such as, Network Environ Analysis. Perhaps, there exists an analogous “natural frequency” of an ecosystem with various “modes”, if so, perhaps eigenvalues and eigenvectors will quantify those characteristics and serve as design tools that inform the design process toward desirable system properties.

Mathematical Background and Methods

Using MATLAB ® coding, the eigenvalues and eigenvectors of the matrix C below are determined.

\[
C = \begin{bmatrix}
3 & 0 & 2 & 1 \\
1 & 5 & -5 & 2 \\
0 & 3 & -5 & 0 \\
2 & -2 & 1 & 6 \\
\end{bmatrix}
\]  \hspace{1cm} (6.1)

\[
[V, D]=\text{eig}(C) 
\]  \hspace{1cm} (6.2)

\[
V = \begin{bmatrix}
0.2789 & 0.8790 & -0.4315 + 0.0357i & -0.4315 - 0.0357i \\
-0.5122 & 0.1050 & -0.7908 & -0.7908 \\
-0.8078 & 0.0416 & -0.2422 + 0.0136i & -0.2422 - 0.0136i \\
-0.0851 & -0.4632 & -0.2968 - 0.2005i & -0.2968 + 0.2005i \\
\end{bmatrix}
\]  \hspace{1cm} (6.3)
The matrix $V$ above represents the eigenvectors of $C$; the diagonal matrix $D$ represents the eigenvalues. The first two eigenvectors are real and the other two vectors have complex conjugates of each other. All four vectors are normalized to have Euclidean length equal to one.

The matrix $C$ is from a series of equations $Y = CX$ where $C$ is a 4x4 square matrix. And, where $X$ is a vector of dimension 4 and the product $Y = CX$ is a linear transformation from 4 dimensional space back onto itself. The scalars $\lambda$ (the eigenvalues) exist for a non-zero vector $X$, that is:

$$CX = \lambda X \quad \text{(6.5)}$$

Now, a linear transformation $F(X) = CX$ will map $X$ onto the $\lambda X$‘s. Hence, we call $X$ the eigenvector that corresponds to the eigenvalue $\lambda$.

Further;

$$(C - \lambda I)X = 0 \quad \text{(6.6)}$$

where, $I$ is the identity matrix (a 4x4 matrix in this case).

The eigenvalues ($\lambda$) are the roots of the characteristic polynomial equation (6.6).

$$P(\lambda) = \det(C - \lambda) \quad \text{(6.7)}$$

Now, to find the eigenvectors, solve the system of linear equations given by the equation. (Nobel & Daniel, 1977, pp. 264-265).

Matrix $C$ can also be decomposed into a special product of other matrices or another which is geometric that gives a geometrically transparent description of the linear
transformation. The eigenvectors and eigenvalues are numbers and vectors associated with square matrices that together provide an eigen-decomposition which analyzes the structure of the matrix (Nobel & Daniel, 1977, p. 271). Eigen-decompositions do not exist for all square matrices, but it has a particular simple expression in matrices of multivariate analysis, such as, correlation, covariance, and cross-product matrices. Summarizing, Abdi (2007, pp. 8-10) below, the eigen-decomposition allows one to find minimum or maximum functions involving these statistical matrices. That is, eigen-decomposition problems involve problems of optimization, such as, in principal component analysis where in a matrix C where the rows are observations and the columns are variables describing the observation. The goal will be to find the factors and magnitudes that explain the variance in the matrix. Therefore, the factors will be

\[ F = CP \quad (6.8) \]

and constrained such that

\[ F^T F = P^T C^T C P \quad (6.9) \]

is a diagonal matrix and that

\[ P^T P = I \quad (6.10) \]

where \( P^T \) is an orthonormal matrix. Further, one way to solve this problem is to introduce a Lagrangain multiplier \( \Lambda \). Therefore,

\[ \Lambda (P^T P - I) \quad (6.11) \]

and thus

\[ \mathcal{L} = F^T F - \Lambda (P^T P - I) - P^T C^T C P - \Lambda (P^T P - I) \quad (6.12) \]

To find the values of \( P \) which give the maximum values of \( \mathcal{L} \), take the derivative of \( \mathcal{L} \) with respect to \( P \).

\[ \frac{\delta \mathcal{L}}{\delta P} = 2C^T C P - 2 \Lambda P \quad (6.13) \]
and setting the derivative equal to zero

\[ C^T CP - \Lambda P = 0 \iff C^T CP = \Lambda P \quad (6.14). \]

In the equation above, \( \Lambda \) is diagonal. Thus this is an eigen-value decomposition problem where \( \Lambda \) is the matrix, in descending magnitude, of eigenvalues of the semi-definite positive matrix \( C^T C \) and \( P \) is the matrix of eigenvectors of \( C^T C \). Thus the factor matrix is

\[ F = P \Lambda^{1/2} \quad (6.15) \]

and the variance of the factors magnitude is equal to the eigenvalues:

\[ F^T F = \Lambda^{1/2} P^T P \Lambda^{1/2} = \Lambda. \quad (6.16) \]

Further, the trace of \( C^T C \) is equal to the sum of the eigenvalues. Therefore, the first factor magnitude extracts as much of the original data’s variance as possible, and the second extracts as much as left unexplained by the first and the third as much as was left unexplained by the second etc. Abdi (2007, pp. 8-10).

Additionally, Singular Value Decomposition is another useful factorization technique used in various fields, such as, signal analysis and statistics and is a similar but more general than the above eigen-decomposition. However, it should be noted that the diagonal elements of the matrix \( \Lambda^{1/2} \) are the singular values of matrix \( C \) and the standard deviations of the factors magnitude.

**Eigenvalues, Inverse Eigenvalue Methods and Network Properties**

An inverse eigenvalue problem concerns the reconstruction of a matrix from prescribed spectral data. The spectral data involved may consist of the complete or only partial information of eigenvalues or eigenvectors. Thus, can the original matrix be determined by the sequence of its eigenvalues or partial information of its eigenvalues? Inverse eigenvalue problems arise in a
variety of applications. In particular, there is a variety of purposes related to nonnegative or positive matrices. These uses encompass economics, Markov chains (stochastic matrices), theory of probability, probabilistic algorithms, numerical analysis, game theory, discrete distributions, categorical data, group theory, matrix scaling, theory of small oscillations of elastic systems among others (http://ri.conicyt.cl/575/article-14121.html, Web page retrieved: October, 2012).

The investigative method proposed here is to use a variation of the goals of inverse eigenvalue and eigenvector methods to first construct matrices similar to those used in Network Environ Analysis (NEA) of the Neuse River Estuary, NC. Further, the constructed artificial matrices related to the original Neuse River models will have the same eigenvalues as the actual modeled system. Subsequently, taking those artificially derived matrices and using NEA (EcoNet) to examine those matrices, which have identical eigenvalues as those of the actual system model, and compare network properties of the actual system to the models, based on artificially derived matrices. If the network properties are similar, this may be the first key to unlocking a level of mathematical precision in targeting and planning environmental systems initiated on a trajectory toward network properties such as dominance of Indirect Effects, Synergy, Development Capacity, Ascendency and Homogenization among others. The following is a general discussion of the scientific method toward that end.

As noted, this chapter seeks to find a first step toward a consistent mathematical method for planned and designed ecological systems with precise and predictable network properties. Thus, a tertiary hypothesis of this work is that eigenvalues are key mathematical network quantities that will provide at minimum, a part of the mathematical precision needed to predictably plan, manage and design environmental systems. It is predicted that through matrix manipulation a family of artificial coefficient and flow type matrices can be generated from the
eigenvalues of actual modeled environmental systems that will reproduce the same modeled and desirable system properties as those of the actual system. To that end, a family of matrices with the same eigenvalues as the Neuse River Estuary, North Carolina models will be generated. The methods will first look at the coefficient and flow type data and corresponding matrix for the summer 1988 Neuse River model (Gattie, Schramski, & Bata, 2006) and use that matrix to generate artificial matrices of the Neuse River model resulting in a 7 factorial family of matrices. Each of these 5040 matrices will be generated by programming code and subsequently entered into EcoNet (Kazanci 2007) software to determine the network properties of each artificial model. Each of the 5040 artificial models will be run using an adaptive time-step method with a total time (t) of 20 and a sensitivity of 0.01.

The results will be further controlled by using the same input, output, and stock values as used in the actual model. As mentioned, each model will be analyzed using a consistent total time for the run and consistent model sensitivity. The network properties of the artificial matrices will be compared to the network properties of the original. To confirm and replicate results obtained from the summer of 1988 artificial models, 50 randomly selected artificial matrices with identical eigenvalues as the actual model will be derived from several sets of coefficient and flow type data of the Neuse River Estuary, NC over differing seasons and years of the collected data (Christian, R.R. and Thomas, C.R. 2000). The randomly selected matrices will again use the corresponding input, output and stock data from the actual model as controls and will be entered into EcoNet modeling software. The network properties of the actual models will be compared to the properties of the artificially derived models. Finally, the results will be analyzed to determine if the results substantiate the hypothesis that identical eigenvalues will produce identical system properties and thus are the key mathematical parameter to reproducing network
properties and a step toward the predictable planning and design of environmental systems.
Conclusions will be drawn suggesting eigenvalue importance and applicability in the design of environmental systems.

Generating a New Matrix with the same Eigenvalues

Eigenvalues can be used to construct different matrices with the same eigenvalues as the original. Let \( \nu \) & \( \lambda \) be the eigenvectors and corresponding eigenvalues of a square matrix \( A \)

\[
A \nu = \lambda \nu \quad (6.17)
\]

Let \( B \) be a square non-singular matrix of the same size as \( A \). Then let

\[
H = BAB^{-1} \leftrightarrow HB = B \quad (6.18)
\]

Claim: \( H \) and \( A \) have the same eigenvalues. Thus letting \( \gamma \) be the eigenvalues of \( H \) then:

\[
H \mu = \gamma \mu \quad (6.19)
\]

Then

\[
BAB^{-1} \mu = \gamma \mu \quad (6.20)
\]

Or

\[
B^{-1}BAB^{-1} \mu = \gamma \mu \quad (6.21)
\]

Where

\[
B^{-1}B = I \quad (6.22)
\]

Then by rearranging

\[
A(B^T(-1) \mu) = \gamma(B^T(-1) \mu) \quad (6.23)
\]

Thus

\[
(B^{-1} \mu) = \nu \quad (6.24)
\]

But

\[
A \nu = \gamma \nu \quad (6.25)
\]
Therefore, $\gamma$ is also an eigenvalue of $A$.

Thus, the above proof indicates that a method by which a matrix similar to the original matrix and with identical eigenvalues of the original matrix may be generated. Further, one may apply this method using MATLAB® as seen below:

$$K = \text{rand}(5) \quad (6.26)$$

$$K = \begin{bmatrix}
0.3500 & 0.3517 & 0.2858 & 0.0759 & 0.1299 \\
0.1966 & 0.8308 & 0.7572 & 0.0540 & 0.5688 \\
0.2511 & 0.5853 & 0.7537 & 0.5308 & 0.4694 \\
0.6160 & 0.5497 & 0.3804 & 0.7792 & 0.0119 \\
0.4733 & 0.9172 & 0.5678 & 0.9340 & 0.3371
\end{bmatrix} \quad (6.27)$$

$$\text{eig}(K) = \begin{bmatrix}
2.3807 \\
0.2185 + 0.3446i \\
0.2185 - 0.3446i \\
0.1165 + 0.0484i \\
0.1165 - 0.0484i
\end{bmatrix} \quad (6.28)$$

The above values are the eigenvalues of a randomly generated 5 x 5 matrix ($K$) using MATLAB®. Then generating another random 5 x 5 matrix ($H$), one may manipulate the matrix ($H$) by multiplying ($H$) by the original matrix ($K$) and by the inverse of ($H$) to generate a third matrix ($K_1$). That is, $K_1 = (H*K*\text{inv}(H))$ and then taking the eigenvalues of ($K_1$) a set of eigenvalues are found that duplicate the eigenvalues of ($K$).

$$H = \text{rand}(5) \quad (6.29)$$

$$H = \begin{bmatrix}
0.1622 & 0.6020 & 0.4505 & 0.8258 & 0.1067 \\
0.7943 & 0.2630 & 0.0838 & 0.5383 & 0.9619 \\
0.3112 & 0.6541 & 0.2290 & 0.9961 & 0.0046 \\
0.5285 & 0.6892 & 0.9133 & 0.0782 & 0.7749 \\
0.1656 & 0.7482 & 0.1524 & 0.4427 & 0.8173
\end{bmatrix} \quad (6.30)$$
\[
e^{i(H\ast K\ast \text{inv}(H))} = \begin{bmatrix}
2.3807 \\
0.2185 + 0.3446i \\
0.2185 - 0.3446i \\
0.1165 + 0.0484i \\
0.1165 - 0.0484i
\end{bmatrix} \quad (6.31)
\]

Where \(e^{i(H\ast K\ast \text{inv}(H))} = \text{eig}(K_1)\). Therefore, the claim is again substantiated that it is possible to generate from an original matrix and new matrix with identical eigenvalues.

Therefore, it is proposed to take the coefficient and flow type matrix (CF) that generated the flow matrix of the Neuse River Estuary Model (Eqn. 6.32) for the summer of 1988 and use the methods outlined above to generate a corresponding family of matrices that have the same eigenvalues as the original coefficient matrix. The exception will be that the randomly generated matrix (R) will be not be completely random but of the form with only one numerical entry in each row and column. This is another experimental control to replicate similar component numbers of the original model. Lastly for this inquiry, the analysis technique will consider the output generated by a particular input and will make use of EcoNet software to perform the analysis of the models. For example, entering the coefficient and flow type matrix (CF) (Eqn. 6.33) that returned the Neuse River Flow matrix (F) (Eqn. 6.32) below, this information is used to generate the eigenvalues of (CF):

\[
F = \begin{bmatrix}
0 & 0 & 0 & 446 & 446 & 2438 & 0 \\
2419 & 0 & 260 & 372 & 34 & 2034 & 696 \\
218 & 2 & 0 & 0 & 2 & 54 & 218 \\
666 & 151 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 33 & 0 & 0 & 386 & 0 \\
0 & 4772 & 119 & 0 & 0 & 0 & 0 \\
22 & 894 & 0 & 0 & 0 & 0 & 0
\end{bmatrix} \quad (6.32)
\]
\[ CF = \begin{bmatrix}
0.00, 0.00, 0.00, 5.70, 63.7, 487.6, 0.00 \\
100.8, 0.00, 0.2, 4.80, 4.90, 406.8, 29.0 \\
9.10, 1.00, 0.00, 0.00, 3.000, 10.80, 9.10 \\
27.80, 6.80, 0.00, 0.00, 0.00, 77.2, 0.00 \\
0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00 \\
0.00, 216.9, 0.10, 0.00, 0.00, 0.00, 0.00 \\
0.10, 40.6, 0.00, 0.00, 0.00, 0.00, 0.00
\end{bmatrix} \] 
(6.33)

\[ \text{eig}(CF) = \begin{bmatrix}
(0.5386+0.0000j) \\
(-0.2642+0.3539j) \\
(-0.2642+-0.3539j) \\
(-0.0100+0.0000j) \\
(0.0000+0.0004j) \\
(0.0000+-0.0004j)
\end{bmatrix} \] 
(6.34)

\[ R = \begin{bmatrix}
1.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000 \\
0.0000, 1.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000 \\
0.0000, 0.0000, 1.0000, 0.0000, 0.0000, 0.0000, 0.0000 \\
0.0000, 0.0000, 0.0000, 0.0000, 1.0000, 0.0000, 0.0000 \\
0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 1.0000, 0.0000 \\
0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 1.0000 \\
0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000
\end{bmatrix} \] 
(6.35)
\[
J = \begin{bmatrix}
0.0000, 0.0000, 0.0000, 0.4876, 0.0000, 0.0057, 0.0637 \\
1.0008, 0.0000, 0.0002, 0.4068, 0.0290, 0.0048, 0.0049 \\
0.0091, 0.0001, 0.0000, 0.0108, 0.0091, 0.0000, 0.0003 \\
0.0000, 0.2169, 0.0001, 0.0000, 0.0000, 0.0000, 0.0000 \\
0.0001, 0.0406, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000 \\
0.0278, 0.0068, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000 \\
0.0000, 0.0000, 0.0000, 0.0772, 0.0000, 0.0000, 0.0000 
\end{bmatrix} \times 1000 \quad (6.36)
\]

\[
\text{eig}(J) = \begin{bmatrix}
(0.5386+0.0000j) \\
(-0.2642+0.3539j) \\
(-0.2642+-0.3539j) \\
(-0.0100+0.0000j) \\
(-0.0001+0.0000j) \\
(0.0000+0.0004j) \\
(0.0000+-0.0004j) 
\end{bmatrix} \quad (6.37).
\]

It is again substantiated that a new matrix, in this case from Neuse River Estuary data, can be generated from an original coefficient and flow type matrix (CF) that has the same eigenvalues as the original. At this point, the power of electronic computing will be employed using ideas and code (Appendix A) developed by Turk, H.J. & Miller, J.Z. (2012) to generate the 5040 combinations of a 7 X 7 matrix (R) with a value of one and only one in each row and column. Subsequently, the R matrices using the mathematics above will facilitate the construction of 5040 unique artificial coefficient and flow type matrices. Each of the artificial coefficient and flow type matrices will be entered in to EcoNet (Kazanci 2007) software to determine the network properties of each artificial model. These network properties of each matrix will be statistically compared to the properties of the original model. In addition, to the statistical analysis of the network properties, the computer coding will be used to determine the artificial coefficient and flow type matrices that have all network properties within 10% of the actual Neuse River Estuary models (Appendix C).
The network properties considered and compared between the original models and the artificial models are: *Total System Throughflow* and also known as Total System Throughput which is the sum of throughflows of all compartments: \( TST = T_1 + T_2 + \ldots + T_n \), *Finn's Cycling Index* which measures the amount of cycling in the system by computing the fraction of total system throughflow that is recycled, *Indirect Effects Index* which measures the amount of flow that occurs over indirect connections versus direct connections and when the ratio is greater than one, indirect flows are greater than direct flows, *Ascendency* which is a measure that quantifies both the level of system activity and the degree of organization (constraint) with which the material is being processed in ecosystems, *Aggradation Index* that measures the average path length., *Synergism Index* which is a system-wide index for pairwise compartment relations. Values larger than 1 indicate a shift toward positive interactions (mutualism), *Mutualism Index*, is a system-wide index for pairwise compartment relations. Values larger than 1 indicate a shift toward positive interactions (mutualism), *Homogenization Index* is a measure that quantifies the action of the network making the flow distribution more uniform. It should be noted that these network properties map back to the design *corollaries 8-18* and others proposed in Chapter 5. The statistical results of all 5040 artificial Neuse River Estuary models of the summer of 1988 data are summarized below.

**Data Analysis**

Table 6.1 presents data that indicates that the hypothesis that matrices of the same size, similar components numbers, inputs, stocks, outputs and identical eigenvalues returns a range of network properties. Suggesting that the hypothesis proposed is false.
Table 6.1: Statistically comparing network properties of 5040 artificially derived network models to the actual summer 1988 network model of the Neuse River Estuary.

<table>
<thead>
<tr>
<th>Total System Throughflow</th>
<th>Actual Neuse River Model</th>
<th>Network Value</th>
<th>Summer 1988</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Summary Statistics</td>
<td>( from 5040 Artificial Models)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>AVG</td>
<td>12780.7</td>
<td></td>
</tr>
<tr>
<td></td>
<td>STD</td>
<td>9298.17</td>
<td></td>
</tr>
<tr>
<td></td>
<td>MEDIAN</td>
<td>8552.7</td>
<td></td>
</tr>
<tr>
<td></td>
<td>MAX</td>
<td>39829.4</td>
<td></td>
</tr>
<tr>
<td></td>
<td>MIN</td>
<td>5819.37</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Actual Neuse River Model Network Value</td>
<td>Summer 1988</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Finns Cycling Index</td>
<td>Summary Statistics</td>
<td>( from 5040 Artificial Models)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>AVG</td>
<td>0.919615</td>
<td></td>
</tr>
<tr>
<td></td>
<td>STD</td>
<td>0.032825</td>
<td></td>
</tr>
<tr>
<td></td>
<td>MEDIAN</td>
<td>0.905015</td>
<td></td>
</tr>
<tr>
<td></td>
<td>MAX</td>
<td>0.98978</td>
<td></td>
</tr>
<tr>
<td></td>
<td>MIN</td>
<td>0.879145</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Actual Neuse River Model Network Value</td>
<td>Summer 1988</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Development Capacity</td>
<td>Summary Statistics</td>
<td>( from 5040 Artificial Models)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>AVG</td>
<td>20577.3</td>
<td></td>
</tr>
<tr>
<td></td>
<td>STD</td>
<td>14379.0</td>
<td></td>
</tr>
<tr>
<td></td>
<td>MEDIAN</td>
<td>14022.4</td>
<td></td>
</tr>
<tr>
<td></td>
<td>MAX</td>
<td>62332.2</td>
<td></td>
</tr>
<tr>
<td></td>
<td>MIN</td>
<td>9821.2</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Actual Neuse River Model Network Value</td>
<td>Summer 1988</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mutualism Index</td>
<td>Summary Statistics</td>
<td>( from 5040 Artificial Models)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>AVG</td>
<td>1.91455</td>
<td></td>
</tr>
<tr>
<td></td>
<td>STD</td>
<td>0.11176</td>
<td></td>
</tr>
<tr>
<td></td>
<td>MEDIAN</td>
<td>1.88235</td>
<td></td>
</tr>
<tr>
<td></td>
<td>MAX</td>
<td>2.063</td>
<td></td>
</tr>
<tr>
<td></td>
<td>MIN</td>
<td>1.7222</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Actual Neuse River Model Network Value</td>
<td>Summer 1988</td>
</tr>
</tbody>
</table>
### Aggradation Index

**Summary Statistics**  
(from 5040 Artificial Models)

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>AVG</td>
<td>122.65</td>
</tr>
<tr>
<td>STD</td>
<td>136.26</td>
</tr>
<tr>
<td>MEDIAN</td>
<td>64.73</td>
</tr>
<tr>
<td>MAX</td>
<td>665.96</td>
</tr>
<tr>
<td>MIN</td>
<td>44.08</td>
</tr>
</tbody>
</table>

**Actual Neuse River Model**  
**Network Value**  
**Summer 1988**  
(123.973)

### Synergism Index

**Summary Statistics**  
(from 5040 Artificial Models)

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>AVG</td>
<td>4.594</td>
</tr>
<tr>
<td>STD</td>
<td>0.16558</td>
</tr>
<tr>
<td>MEDIAN</td>
<td>4.67032</td>
</tr>
<tr>
<td>MAX</td>
<td>4.844</td>
</tr>
<tr>
<td>MIN</td>
<td>4.271</td>
</tr>
</tbody>
</table>

**Actual Neuse River Model**  
**Network Value**  
**Summer 1988**  
(4.42928)

### Indirect Effects Index

**Summary Statistics**  
(from 5040 Artificial Models)

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>AVG</td>
<td>125.37</td>
</tr>
<tr>
<td>STD</td>
<td>136.13</td>
</tr>
<tr>
<td>MEDIAN</td>
<td>62.99</td>
</tr>
<tr>
<td>MAX</td>
<td>668.14</td>
</tr>
<tr>
<td>MIN</td>
<td>49.17</td>
</tr>
</tbody>
</table>

**Actual Neuse River Model**  
**Network Value**  
**Summer 1988**  
(123.908)

### Ascendency

**Summary Statistics**  
(from 5040 Artificial Models)

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>AVG</td>
<td>11057.6</td>
</tr>
<tr>
<td>STD</td>
<td>7629.8</td>
</tr>
<tr>
<td>MEDIAN</td>
<td>7578.8</td>
</tr>
<tr>
<td>MAX</td>
<td>33253.1</td>
</tr>
<tr>
<td>MIN</td>
<td>5375.3</td>
</tr>
</tbody>
</table>

**Actual Neuse River Model**  
**Network Value**  
**Summer 1988**  
(14078.6)
### Homogenization Index

**Summary Statistics**
(from 5040 Artificial Models)

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>AVG</td>
<td>2.0478</td>
</tr>
<tr>
<td>STD</td>
<td>0.01006</td>
</tr>
<tr>
<td>MEDIAN</td>
<td>2.050995</td>
</tr>
<tr>
<td>MAX</td>
<td>2.059025</td>
</tr>
<tr>
<td>MIN</td>
<td>2.02161</td>
</tr>
</tbody>
</table>

### Actual Neuse River Model

**Network Value**

**Summer 1988**

(2.04589)

However, to replicate and generalize the results obtained from the analyses of the 5040 artificial Neuse River (note: the first 10 artificial models of this set is presented in Appendix F) models for the summer of 1988 summarized above, this work will use several seasons and years of Neuse River Estuary coefficient and flow type matrix (CM) data collected and modeled by Christian and Thomas (2000, 2003) and randomly generate 50 artificial network models from several sets of these data. Subsequently, the network properties of the artificial models are compared to the actual models. Examples runs of these artificial models are given in Appendix B and the statistical summary of network properties of each set of 50 randomly selected artificial models from the differing seasons and years is presented in Appendix C. The statistical data presented in Appendix C also clearly indicates that coefficient and flow type matrices of the same size, components, inputs, outputs, stocks and identical eigenvalues return a range of network properties.

Thus, the hypothesis is again falsified that matrices of the same size, similar components numbers, stocks, inputs, outputs and identical eigenvalues will return identical network properties, and thus eigenvalues are not the sole mathematical key to these network properties. However, similar to the results from the 5040 artificial matrices returned for the Neuse River Estuary data for the summer of 1988, the computer code returned for these data sets several artificial matrices that fall within a tolerance of 10% of the network properties of the actual
model. Thus, it is proposed that a planner or designer might use that information to initiate the first steps toward a conceptual design of an ecological system with similar network properties. For example, as an initial step toward the planning or design of environmental system, the planner could take one of the artificially generated coefficient and flow type matrices which returned network properties within a specified range of tolerance and use that network organization as a starting point toward planning an environmental system of the same size that would have similar network properties. For example, randomly choosing one of the artificial models that fall within that tolerance, (23_run634 in Appendix D) based on the actual Neuse River Estuary model for the spring of 1988; one could begin to conceptually configure a generic model with the following network structure. The conceptual model (Figures 6.1) consists of 7 generic compartments A, B, D, E, F, G, and H. Further, the connectivity of and flow coefficients and resulting network properties are described in the graph and information below.

**Connectivity and Flow Coefficients**

<table>
<thead>
<tr>
<th>From</th>
<th>To</th>
<th>Flow Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>E</td>
<td>A</td>
<td>4.595</td>
</tr>
<tr>
<td>F</td>
<td>A</td>
<td>17.2</td>
</tr>
<tr>
<td>G</td>
<td>A</td>
<td>316.667</td>
</tr>
<tr>
<td>A</td>
<td>B</td>
<td>1.0</td>
</tr>
<tr>
<td>H</td>
<td>B</td>
<td>34.5</td>
</tr>
<tr>
<td>A</td>
<td>D</td>
<td>7.273</td>
</tr>
<tr>
<td>B</td>
<td>D</td>
<td>7.25</td>
</tr>
<tr>
<td>F</td>
<td>D</td>
<td>3.7</td>
</tr>
<tr>
<td>G</td>
<td>D</td>
<td>4.667</td>
</tr>
<tr>
<td>H</td>
<td>D</td>
<td>0.08333</td>
</tr>
<tr>
<td>A</td>
<td>E</td>
<td>27.455</td>
</tr>
<tr>
<td>H</td>
<td>E</td>
<td>20.417</td>
</tr>
<tr>
<td>D</td>
<td>F</td>
<td>0.02846</td>
</tr>
<tr>
<td>G</td>
<td>F</td>
<td>59.667</td>
</tr>
<tr>
<td>D</td>
<td>G</td>
<td>0.01385</td>
</tr>
<tr>
<td>H</td>
<td>G</td>
<td>129.25</td>
</tr>
<tr>
<td>A</td>
<td>H</td>
<td>101.455</td>
</tr>
<tr>
<td>B</td>
<td>H</td>
<td>28.25</td>
</tr>
<tr>
<td>D</td>
<td>H</td>
<td>0.03846</td>
</tr>
<tr>
<td>E</td>
<td>H</td>
<td>2.167</td>
</tr>
</tbody>
</table>
F -> H c=10.2
G -> H c=149.667

Initial State

* -> A c=3
* -> B c=5
* -> D c=5
* -> E c=36
* -> F c=96
* -> G c=26
* -> H c=5

A -> * c=0.1818
B -> * c=2.667
D -> * c=0.09154
E -> * c=0.1786
F -> * c=0.1
G -> * c=1
H -> * c=0.3333

Initial values

A= 11, B= 12, D= 1300
E=84, F=10, G= 3, H= 12

Corresponding Network Properties of the Generic Design

- Link density: 3.14286
- Connectance:0.44898
- Total system throughflow (TST):7066.33
- Finn's Cycling Index (FCI): 0.854067
- Indirect effects index: 39.381
- Ascendency: 6444.9
- Development Capacity: 12623.9
- Synergism Index: 5.79434

221
- Mutualism index: 1.45
- Aggradation index: 40.1504
- Homogenization index: 2.13151
- Homogenization index -output based: 2.30525

**Figure 6.1:** Connectivity of an artificial model/conceptual design with network properties within 10% of the Neuse River Estuary for the spring of 1988.

Thus, the initial mappings of a network design may be based off of this diagram of connectivity and coefficients of flow as listed above. The full network characteristics and properties of the
conceptual design are included in Appendix E. It should be noted that the generic conceptual design is constructed from an artificial model derived by matrix manipulation and generation of an artificial coefficient and flow matrix based on an actual model of the Neuse River Estuary during the spring of 1988. The generation of the matrix was constructed by mathematically relating the original coefficient and flow matrix to a matrix of ones and zeros where there is a one and only one in each row and column. The reader should note that this returns a matrix with the same eigenvalues but also the same coefficients of flow but in differing network configurations. Thus, it may represent only a small initial step toward the understanding of precise planning and eventual constructions of ecological systems. However, just as the first manned flight was only a few feet, perhaps this will lead to further research and advancement to a robust and fuller understanding and the precise engineering of ecological systems.

Conclusion

The summary analysis of the data (Table 6.1 & Appendix C ) clearly show that matrices of the same size, similar numbers of components, stocks, inputs and outputs and with identical eigenvalues result in a range of network properties as identified through a network analysis of artificial models performed by EcoNet (Kazanci 2007) software. The data from the 5040 artificial models from the summer 1988 Neuse River Estuary model shows that Total System Throughflow ranges from a maximum of 39829.4 to minimum of 5819.4 with the actual model having a throughflow of 16353.4, the Finn Cycling Index ranges from a maximum of 0.98978 to minimum of 0.879145 with the actual model having a value of 0.947912, the Indirect Effects Index ranges from a maximum of 668.14 to minimum of 49.17 with the actual model having a value of 123.908, the Aggradation Index ranges from a maximum of 665.96 to minimum of 44.08 with the actual model having a value of 123.973, the Development Capacity ranges from a
maximum of 62332.2 to minimum of 9821.18 with the actual model having a value of 26238.3, the Synergism Index ranges from a maximum of 4.844 to minimum of 4.271 with the actual model having a value of 4.42928, the Mutualism Index ranges from a maximum of 2.063 to minimum of 1.7222 with the actual model having a value of 2.0625, the Homogenization Index ranges from a maximum of 2.059025 to minimum of 2.02161 with the actual model having a value of 2.04589, and lastly the Ascendency ranges from a maximum of 33253.1 to minimum of 5375.26 with the actual model having a value of 14078.6. Similarly, the network properties of the artificial models presented in Appendix C based on data of several years and seasons varied similarly as did the artificial models based on the summer of 1988 data.

Thus, a strict hypothesis that suggests that models with same eigenvalues and other controls mentioned above will result in an exact reproduction of network properties is falsified. However, in terms of design of ecological systems perhaps there is still a way toward a preliminary step with a requisite amount of precision in the quantitative and qualitative planning and design of environmental systems. The computer coding was also designed not only to check network properties and statistically compare those properties to the actual model, but it was also designed to pick out those artificial models which have network properties within 10% of the actual model. These coefficient and flow type artificial models suggest network internal structure and function which replicate an actual modeled system with a precision variance of 10% or less. Thus, an ecological planner or designer could pick one of these artificial coefficient and flow type models and under similar levels of inputs, outputs and stock values conceptually organize a system that would produce network properties within 10% of the actual Neuse River Estuary model. Several of these matrices that fall within that range are listed in Appendix C.
CHAPTER 7
DISSERTATION SUMMARY

The focal purpose and hypothesis of this dissertation was to build a qualitative and quantitative case that additional planning, design and management philosophies other than those based on reduction are necessary to begin to holistically and benignly integrate current human constructions into nature, and further to manage, plan and design the interdependent aspects of environmental systems. Secondarily, it was to seek a philosophy, axioms and methods for the planning and design of these systems.

The closing arguments of this work suggestes that the evidence is compelling and the verdict clear that the primary hypotheses suggesting that environmental systems require different philosophies, schema and axioms from those used in traditional engineering of mechanistic systems was strongly supported. For example, Chapter 1 made a substantive case that ecological systems fall into a unique category of system types, interdependent complex systems, which differ significantly from the system types which typically describe engineered mechanistic systems. Chapter 2 continued to support the primary hypothesis by contextually contrasting ecological systems and mechanistic systems using the Socratic Method by dialectically comparing mechanism versus ecology through reductive versus system thinking dichotomies, direct versus indirect causalities each indicating how mechanical and living systems are opposite ends of a spectrum. The chapter advanced the case that the current Newtonian stratagem of analysis and hence design are inadequate for the planning and construction of natural living
systems. Chapter 3 described some current analysis techniques available today that are not reduction based, that is, those that retain system connectedness during analysis and significantly why they and the mathematical trends they infer are more applicable for the understanding and modeling of connected systems. Chapter 4 significantly looked at the proliferation of system connectivity and interdependence as the system operates over time by examining the Neuse River Estuary model and various other models of ecological systems. This chapter provided the equivalent of a quantitative “smoking gun” implicating increasing connectivity or coupling of ecological system components providing the quantitative weight that further substantiates that planning and design of ecological systems requires different methods other than those often employed in the design and engineering of mechanistic systems.

Secondarily this work hypothesized that those new philosophies, axioms, and design strategies will be the diametric opposite of those used in traditional mechanistic design. Thus, Chapter 5 building on the weight of evidence presented in the preceding chapters, which furthered the understanding and contrast of environmental and mechanistic systems, investigated the philosophies, motives and goals of various engineering design schemes and methods. This chapter paid particular attention to Axiomatic Design and the underlying motives and goals of its methodology. Thus building on the evidence presented in the first four chapters of this work which indicated that ecological systems had qualities and behaviors that are the opposite of traditionally engineered systems, this chapter extrapolated that argument to design goals, axioms and corollaries. Further based on the evidence presented, this work believes it has substantiated the hypothesis that planning and design philosophies, axioms etc for ecological systems are in most cases the reverse of those for traditionally engineered mechanical systems. Toward that end, Chapter 5 proposed a design philosophy, axioms, and corollaries that are in many ways the
direct opposite of those used for mechanistic systems and traditional engineering design. Chapter 6 hypothesized that eigenvalues are the key mathematical quantities that map to system wide emergent properties of ecological systems and thus would establish, with a degree of mathematical repeatability, the direction in direct planning and design of ecological systems. However, the hypothesis that eigenvalues are alone the only mathematical quantity to map and return exact system wide ecological network properties was falsified. The data presented indicated that matrices of similar size, components, inputs, stocks, and outputs with identical eigenvalues returned a variety of network properties. Thus, an indirect goal of this work has furthered the understanding of the workings of these systems. That byproduct was the understanding that the mathematical keys to system wide properties are not solely the systems eigenvalues. However, all was not lost toward a method for the planning and design of these environmental systems. Chapter 6 also proposed that through the power of electronic computing, matrix and thus environmental system arrangements within a prescribed range of tolerance of network properties can be replicated. Accordingly, an initial step toward the mathematical and conceptual design of environmental systems may proceed. This was supported by an initial generic conceptual design of system arrangement that replicated with a specified tolerance the modeled system properties of the Neuse River Estuary.

Further research areas related to this work might include further refinement and expansion of the computer code that generates artificial matrix models to include greater flexibility and adjustment in parameters related to artificial model generation. Also, designing the code whereby one may easily increase or decrease the prescribed tolerance when searching for artificial models that fall within a range of system properties of an actual system. Further expansion of the code to store artificial model numbers that fall within the prescribed tolerance
and electronically comparing those models to other seasons and years of modeled data to parse out which artificial models fall within the prescribed tolerance for all seasons, years, and using both input and output environ analysis models may be useful. The R matrix of ones and zeros used in this study was required to tightly control the study. However, the code might be adjusted in the future to include a customization option for the R matrix used to generate matrices with identical eigenvalues. For example, it could be of interest to investigate the artificial matrices derived using increments of prime numbers, PI or incements of the Golden Ratio instead of ones as was used in this work. This coupled with a more thorough analysis over many seasons and years of data could provide additional insight toward resiliency and sustainability of system designs. These may ultimately lead toward more sophisticated, sustainable and practical designs. Another interesting study would be to take an actual model and holding the original connectivity constant vary iteratively the stocks, flow coefficients, inputs and outputs to see how these affect the systems eigenvalues and network properties. Lastly, though perhaps substantially more challenging, it would be of interest to examine the integral matrices using similar methods as was used in the work.
REFERENCES


Allin, Samuel Robert Fishleigh (2004). *An examination of China’s Three Gorges Dam project based on the framework presented in the report of the world commission on dams.*

Retrieved from Virginia Polytechnic Institute and State University website:


Brown, Robert (1828). A brief account of microscopical observations made in the months of June, July and August, 1827, on the particles contained in the pollen of plants; and on the general existence of active molecules in organic and inorganic bodies. *Philosophical Magazine* 4:161-173.


Hume, David (1779). *Dialogues concerning natural religion*. Published posthumously by his nephew, David Hume the Younger.


Kay, J. and Schneider, E.D. (1990). On the applicability of non-equilibrium thermodynamics to living systems. Internal paper, Waterloo University, Ontario, Canada.


Patten, B.C. Hololecology: The unification of nature by network indirect effects, Unpublished work.


Rosen, R. (1985a). Organisms as casual systems which are not mechanisms: An essay into the


(pp. 1-10).


88 (3)*.

Schneider, E.D. & Kay, J.J. (1994b). Life as a manifestation of the second law of

Schneider, K.J. (Ed.). (1994). Embracing complexity, the challenge of the ecosystem approach.*
*Alternatives* 20(3): 32-38.

Schramski, J.R., Gattie, D.K., Patten, B.C., Borrett, S.R., Fath, B.D., Thomas, C.R. & Whipple,
S.J. (2006). Indirect effects and distributed control in ecosystems: Distributed control in


APPENDIX A

COMPUTER CODE

This appendix contains computer code developed from ideas and programming knowledge of Turk, H.J. and Miller, J.Z. (2012). The code takes original modeled data and constructs artificial coefficient and flow type matrices and enters that matrix into EcoNet (Kazanci 2007) software to generate artificial models of environmental systems.

```python
import random
import StringIO, os
import urllib, urllib2
from itertools import permutations
import BeautifulSoup
import numpy

def get_5040():
    prep_mset = []
    ms = ['1,0,0,0,0,0,0',
          '0,1,0,0,0,0,0',
          '0,0,1,0,0,0,0',
          '0,0,0,1,0,0,0',
          '0,0,0,0,1,0,0',
          '0,0,0,0,0,1,0',
          '0,0,0,0,0,0,1']

    for m in permutations(ms):
        if m not in prep_mset:
            prep_mset.append(m)

    ## e = numpy.fromstring('1,0,0,0,0,0,0', sep=',')
    mset = []
    for prepped in prep_mset:
        a = numpy.fromstring(prepped[0], sep=',')
```

245
b = numpy.fromstring(prepped[1], sep=',')
c = numpy.fromstring(prepped[2], sep=',')
d = numpy.fromstring(prepped[3], sep=',')
e = numpy.fromstring(prepped[4], sep=',')
f = numpy.fromstring(prepped[5], sep=',')
g = numpy.fromstring(prepped[6], sep=',')
matrix = numpy.array([a, b, c, d, e, f, g])
mset.append(matrix)

return mset

def generator(n):
    orig = numpy.array([[0, 0, 0, 0.0057, 0.0637, 0.4876, 0],
                        [.1008, 0, 0.0002, 0.0048, 0.0049, 0.4068, 0.0290],
                        [0.0091, 0.0001, 0, 0.0003, 0.0108, 0.0091],
                        [0.0278, 0.0068, 0, 0, 0, 0, 0],
                        [0, 0, 0.0000, 0, 0, 0.0772, 0],
                        [0, 0.2169, 0.0001, 0, 0, 0, 0],
                        [0.0001, 0.0406, 0, 0, 0, 0, 0]])
    orig_eigen = numpy.linalg.eig(orig)[0]

    mset = get_5040()

    ECONET_CONSTANTS = ""
    # Initial State
    * -> PN_phyto c=1
    * -> PN_hetero c=4
    * -> N_sed c=8
    * -> DON c=27
    * -> NOx c=64
    * -> NH4 c=23
    * -> PN_abiotic c=5
    PN_phyto -> * c=0.25
    PN_hetero -> * c=0
    N_sed -> * c=0.06923
    DON -> * c=0.3333
    NOx -> * c=0.1429
    NH4 -> * c=0.4
    PN_abiotic -> * c=0.2917
    # Initial values
    PN_phyto = 24, PN_hetero = 22, N_sed = 1300
DON = 78, NOx = 7, NH4 = 5, PN_abiotic = 24

```python
runs = []
counter = 0
for r in mset:
    counter += 1
    j = r.dot(orig).dot(numpy.linalg.inv(r))

orig_out = StringIO.StringIO()
orig_eigen_out = StringIO.StringIO()
r_out = StringIO.StringIO()
j_out = StringIO.StringIO()
j_eigen_out = StringIO.StringIO()

numpy.savetxt(orig_out, orig, fmt='%1.4f', delimiter=',')
numpy.savetxt(orig_eigen_out, orig_eigen, fmt='%1.4f', delimiter=',')
numpy.savetxt(r_out, r, fmt='%1.4f', delimiter=',')
numpy.savetxt(j_out, j, fmt='%1.4f', delimiter=',')
numpy.savetxt(j_eigen_out, numpy.linalg.eig(j)[0], fmt='%1.4f', delimiter=',')

runs.append({
    'run': str(counter),
    'orig': orig_out.getvalue(),
    'orig_eigen': orig_eigen_out.getvalue(),
    'r': r_out.getvalue(),
    'j': j_out.getvalue(),
    'j_eigen': j_eigen_out.getvalue(),
    'j_array': j
})

LinkDensity_list = []
Connectance_list = []
TotalSystemThroughflow_list = []
FinnsCyclingIndex_list = []
IndirectEffectsIndex_list = []
Ascendency_list = []
DevelopmentCapacity_list = []
AggradationIndex_list = []
SynergismIndex_list = []
MutualismIndex_list = []
HomogenizationIndex_list = []

ten_percent = []

scale = 1000
```
nums = [1]
while len(nums) < 51:
    run = random.randint(2, 5040)
    if run not in nums:
        nums.append(run)

randomruns = []
for num in nums:
    randomruns.append(runs[str(num)])

print randomruns

for run in runs:
    f = open(os.getcwd() + '/results/run{0}.txt'.format(run['run'])), 'w')
    f.write('Run: {0}n'.format(run['run']))
    f.write('Original Matrix:n {0}n'.format(run['orig']))
    f.write('Original Eigenvalues:n {0}n'.format(run['orig_eigen']))
    f.write('R:n {0}n'.format(run['r']))
    f.write('J:n {0}n'.format(run['j']))
    f.write('J Eigenvalues:n {0}n'.format(run['j_eigen']))
    f.write('PN_phyto < PN_phyto c={};
'.format(run['j_array'][0][0] * scale))
    f.write('PN_hetero < PN_phyto c={};
'.format(run['j_array'][1][0] * scale))
    f.write('N_sed < PN_phyto c={};
'.format(run['j_array'][2][0] * scale))
    f.write('DON < PN_phyto c={};
'.format(run['j_array'][3][0] * scale))
    f.write('NOx < PN_phyto c={};
'.format(run['j_array'][4][0] * scale))
    f.write('NH4 < PN_phyto c={};
'.format(run['j_array'][5][0] * scale))
    f.write('PN_abiotic < PN_phyto c={};
'.format(run['j_array'][6][0] * scale))
    f.write('PN_phyto < PN_hetero c={};
'.format(run['j_array'][0][1] * scale))
    f.write('PN_hetero < PN_hetero c={};
'.format(run['j_array'][1][1] * scale))
    f.write('N_sed < PN_hetero c={};
'.format(run['j_array'][2][1] * scale))
    f.write('DON < PN_hetero c={};
'.format(run['j_array'][3][1] * scale))
    f.write('NOx < PN_hetero c={};
'.format(run['j_array'][4][1] * scale))
    f.write('NH4 < PN_hetero c={};
'.format(run['j_array'][5][1] * scale))
    f.write('PN_abiotic < PN_hetero c={};
'.format(run['j_array'][6][1] * scale))
    f.write('PN_phyto < N_sed c={};
'.format(run['j_array'][0][2] * scale))
    f.write('PN_hetero < N_sed c={};
'.format(run['j_array'][1][2] * scale))
    f.write('N_sed < N_sed c={};
'.format(run['j_array'][2][2] * scale))
    f.write('DON < N_sed c={};
'.format(run['j_array'][3][2] * scale))
    f.write('NOx < N_sed c={};
'.format(run['j_array'][4][2] * scale))
    f.write('NH4 < N_sed c={};
'.format(run['j_array'][5][2] * scale))
DIRTY_ECONET_CONSTANTS = "* -> PN PHYTO c=1;* -> PN HETERO c=4;* -> N SED c=8;* -> DON c=27;* -> NOx c=64;* -> NH4 c=23;* -> PN ABIOTIC c=5;PN PHYTO -> * c=0.25;PN HETERO -> * c=0;N SED -> * c=0.06923;DON -> * c=0.3333;NOx -> * c=0.1429;NH4 -> * c=0.4;PN ABIOTIC -> * c=0.2917; PN PHYTO = 24, PN HETERO = 22, N SED = 1300, DON = 78, NOx = 7, NH4 = 5, PN ABIOTIC = 24"

modeltext += DIRTY_ECONET_CONSTANTS

submitVars = {}

# Model Text

values = [('model_text', modeltext), ('model', 0), ('variable1', 30), ('variable2', 0.01)]

submitUrl = "http://eco.engr.uga.edu/cgi-bin/econetV2.cgi"
referer = "http://eco.engr.uga.edu/"
origin = "http://eco.engr.uga.edu"
ua = 'Mozilla/5.0 (Windows NT 6.1; WOW64) AppleWebKit/537.4 (KHTML, like Gecko) Chrome/22.0.1229.94 Safari/537.4'

submitVarsUrlencoded = urllib.urlencode(values)
submitVarsUrlencoded = submitVarsUrlencoded.replace('%2A','*')
req = urllib2.Request(submitUrl, submitVarsUrlencoded)
req.add_header('Referer', referer)
req.add_header('Origin', origin)
req.add_header('User-Agent', ua)

response = urllib2.urlopen(req)
thePage = response.read()
soup = BeautifulSoup.BeautifulSoup(thePage)
data = soup.findAll('td')

LinkDensity = float(data[49].renderContents())
LinkDensity_list.append(LinkDensity)

Connectance = float(data[50].renderContents())
TotalSystemThroughflow = float(data[51].renderContents())
FinnsCyclingIndex = float(data[52].renderContents())
IndirectEffectsIndex = float(data[53].renderContents())
Ascendency = float(data[54].renderContents())
DevelopmentCapacity = float(data[55].renderContents())
AggradationIndex = float(data[56].renderContents())
SynergismIndex = float(data[57].renderContents())
MutualismIndex = float(data[58].renderContents())
HomogenizationIndex = float(data[59].renderContents())

LinkDensity_list.append(LinkDensity)
Connectance_list.append(Connectance)
TotalSystemThroughflow_list.append(TotalSystemThroughflow)
FinnsCyclingIndex_list.append(FinnsCyclingIndex)
IndirectEffectsIndex_list.append(IndirectEffectsIndex)
Ascendency_list.append(Ascendency)
DevelopmentCapacity_list.append(DevelopmentCapacity)
AggradationIndex_list.append(AggradationIndex)
SynergismIndex_list.append(SynergismIndex)
MutualismIndex_list.append(MutualismIndex)
HomogenizationIndex_list.append(HomogenizationIndex)

f = open(os.getcwd() + '/results/run{0}stats.txt'.format(run['run']), 'w')
f.write('n
n### STATS ###

f.write('TotalSystemThroughflow:

f.write("AVG: {0:.5f} STD: {1:.5f} MED: {2:.5f} MAX: {3:.5f} MIN: {4:.5f}\n\n".format(
numpy.average(TotalSystemThroughflow_list),
numpy.std(TotalSystemThroughflow_list),
numpy.median(TotalSystemThroughflow_list),
max(TotalSystemThroughflow_list),
min(TotalSystemThroughflow_list))))
f.write('FinnsCyclingIndex:

f.write("AVG: {0:.5f} STD: {1:.5f} MED: {2:.5f} MAX: {3:.5f} MIN: {4:.5f}\n\n".format(
numpy.average(FinnsCyclingIndex_list),
numpy.std(FinnsCyclingIndex_list),
numpy.median(FinnsCyclingIndex_list),
max(FinnsCyclingIndex_list),
min(FinnsCyclingIndex_list)))
f.write('IndirectEffectsIndex:

f.write("AVG: {0:.5f} STD: {1:.5f} MED: {2:.5f} MAX: {3:.5f} MIN: {4:.5f}\n\n".format(
numpy.average(IndirectEffectsIndex_list),
numpy.std(IndirectEffectsIndex_list),
numpy.median(IndirectEffectsIndex_list),
max(IndirectEffectsIndex_list),
min(IndirectEffectsIndex_list)))
f.write('Ascendency:

f.write("AVG: {0:.5f} STD: {1:.5f} MED: {2:.5f} MAX: {3:.5f} MIN: {4:.5f}\n\n".format(
numpy.average(Ascendency_list),
numpy.std(Ascendency_list),
numpy.median(Ascendency_list),
max(Ascendency_list),
min(Ascendency_list)))
f.write('DevelopmentCapacity:
'
f.write("AVG: {0:.5f} STD: {1:.5f} MED: {2:.5f} MAX: {3:.5f} MIN: {4:.5f}\n\n".format(
numpy.average(DevelopmentCapacity_list),
numpy.std(DevelopmentCapacity_list),
numpy.median(DevelopmentCapacity_list),
max(DevelopmentCapacity_list),
min(DevelopmentCapacity_list)))
f.write('AggradationIndex:
'
f.write("AVG: {0:.5f} STD: {1:.5f} MED: {2:.5f} MAX: {3:.5f} MIN: {4:.5f}\n\n".format(
numpy.average(AggradationIndex_list),
numpy.std(AggradationIndex_list),
numpy.median(AggradationIndex_list),
max(AggradationIndex_list),
min(AggradationIndex_list)))
f.write('SynergismIndex:
'
f.write("AVG: {0:.5f} STD: {1:.5f} MED: {2:.5f} MAX: {3:.5f} MIN: {4:.5f}\n\n".format(
numpy.average(SynergismIndex_list),
numpy.std(SynergismIndex_list),
numpy.median(SynergismIndex_list),
max(SynergismIndex_list),
min(SynergismIndex_list)))
f.write('MutualismIndex:
'
f.write("AVG: {0:.5f} STD: {1:.5f} MED: {2:.5f} MAX: {3:.5f} MIN: {4:.5f}\n\n".format(
numpy.average(MutualismIndex_list),
numpy.std(MutualismIndex_list),
numpy.median(MutualismIndex_list),
max(MutualismIndex_list),
min(MutualismIndex_list)))
f.write('HomogenizationIndex:
'
f.write("AVG: {0:.5f} STD: {1:.5f} MED: {2:.5f} MAX: {3:.5f} MIN: {4:.5f}\n\n".format(
numpy.average(HomogenizationIndex_list),
numpy.std(HomogenizationIndex_list),
numpy.median(HomogenizationIndex_list),
max(HomogenizationIndex_list),
min(HomogenizationIndex_list)))

if (TotalSystemThroughflow < TotalSystemThroughflow_list[0] * 1.1 and
    TotalSystemThroughflow > TotalSystemThroughflow_list[0] * .9 and
    SynergismIndex < SynergismIndex_list[0] * 1.1 and
    SynergismIndex > SynergismIndex_list[0] * .9 and
    FinnsCyclingIndex < FinnsCyclingIndex_list[0] * 1.1 and
FinnsCyclingIndex > FinnsCyclingIndex_list[0] * .9 and
IndirectEffectsIndex < IndirectEffectsIndex_list[0] * 1.1 and
IndirectEffectsIndex > IndirectEffectsIndex_list[0] * .9 and
Ascendancy < Ascendancy_list[0] * 1.1 and
Ascendancy > Ascendancy_list[0] * .9 and
DevelopmentCapacity < DevelopmentCapacity_list[0] * 1.1 and
DevelopmentCapacity > DevelopmentCapacity_list[0] * .9 and
AggradationIndex < AggradationIndex_list[0] * 1.1 and
AggradationIndex > AggradationIndex_list[0] * .9 and
MutualismIndex < MutualismIndex_list[0] * 1.1 and
MutualismIndex > MutualismIndex_list[0] * .9 and
HomogenizationIndex < HomogenizationIndex_list[0] * 1.1 and
HomogenizationIndex > HomogenizationIndex_list[0] * .9):
APPENDIX B

EXAMPLE COMPUTER RUNS, SUMMER 1988

This appendix consist of examples runs of the computer program to generate a new matrix from the actual coefficient and flow type matrix (\textbf{CF}) of the original modeled data. The software generates an artificial coefficient and flow type matrix (\textbf{J}) and enters that data into Econet (Kazanci 2007) software to determine system wide properties. Note: These examples runs are taken from data provided by Kazanci, C. (2011) of the data collected and modeled by Christian and Thomas (2000, 2003). All models in appendix B are using the adaptive time-step method with a total time (t) of 50 and a sensitivity of 0.01.

# Neuse grand average

\begin{verbatim}
DON -> PN_phyto c=4.356  
NOx -> PN_phyto c=15.559  
NH4 -> PN_phyto c=133.778  
PN_phyto -> PN_hetero c=57.165  
N_sed -> PN_hetero c=0.1067  
DON -> PN_hetero c=5.141  
NOx -> PN_hetero c=9.881  
NH4 -> PN_hetero c=166.639  
PN_abiotic -> PN_hetero c=26.312  
PN_phyto -> N_sed c=7.188  
PN_hetero -> N_sed c=0.1094  
NOx -> N_sed c=1.119  
NH4 -> N_sed c=2.222  
PN_abiotic -> N_sed c=7.59  
PN_phyto -> DON c=16.035  
PN_hetero -> DON c=17.781  
N_sed -> NOx c=0.02365  
NH4 -> NOx c=28.806  
PN_hetero -> NH4 c=183.031  
N_sed -> NH4 c=0.03058
\end{verbatim}
Example Arificial Model Runs Based on the Neuse Grand Average Data:

Random Run: 1057
Original Matrix (CF):
0.0000,0.0000,0.0000,4.3560,15.5590,133.7780,0.0000
57.1650,0.0000,0.1067,5.1410,9.8810,166.6390,26.3120
7.1880,0.1094,0.0000,0.0000,1.1190,2.2220,7.5900
16.0350,17.7810,0.0000,0.0000,0.0000,0.0000,0.0000
0.0000,0.0000,0.0237,0.0000,0.0000,28.8060,0.0000
0.0000,183.0310,0.0306,0.0000,0.0000,0.0000,0.0000
0.6706,31.3280,0.0000,0.0000,0.0000,0.0000,0.0000

Original Eigenvalues:
(197.4573+0.0000j)
(-147.8591+0.0000j)
(-45.9734+0.0000j)
(-1.8248+0.3946j)
(-1.8248+0.3946j)
(0.0124+0.1939j)
(0.0124+0.1939j)
\[ R: \]
\[
0.0000, 1.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.0000, 0.0000, 1.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 1.0000
1.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.0000, 1.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.0000, 0.0000, 0.0000, 1.0000, 0.0000
0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 1.0000
\]

\[ J: \]
\[
0.0000, 5.1410, 26.3120, 57.1650, 0.1067, 9.8810, 166.6390
17.7810, 0.0000, 0.0000, 16.0350, 0.0000, 0.0000, 0.0000
31.3280, 0.0000, 0.0000, 0.6706, 0.0000, 0.0000
0.0000, 4.3560, 0.0000, 0.0000, 0.0000, 15.5590, 133.7780
0.0000, 0.0000, 7.5900, 7.1880, 0.0000, 1.1190, 2.2220
0.0000, 0.0000, 0.0000, 0.0000, 0.0237, 0.0000, 28.8060
183.0310, 0.0000, 0.0000, 0.0000, 0.0306, 0.0000, 0.0000
\]

J Eigenvalues:
\[
(197.4573+0.0000j)
(-147.8591+0.0000j)
(-45.9734+0.0000j)
(-1.8248+0.3946j)
(-1.8248+-0.3946j)
(0.0124+0.1939j)
(0.0124+-0.1939j)
\]

########################### ECONET MODEL ###########################

PN_phyto -> PN_phyto c=0.0;
PN_hetero -> PN_phyto c=5.141;
N_sed -> PN_phyto c=26.312;
DON -> PN_phyto c=57.165
;NOx -> PN_phyto c=0.1067
;NH4 -> PN_phyto c=9.881
;PN_abiotic -> PN_phyto c=166.639;
PN_phyto -> PN_hetero c=17.781;
PN_hetero -> PN_hetero c=0.0;
N_sed -> PN_hetero c=0.0;
DON -> PN_hetero c=16.035;
NOx -> PN_hetero c=0.0;
NH4 -> PN_hetero c=0.0;
PN_abiotic -> PN_hetero c=0.0;
PN_phyto -> N_sed c=31.328;
PN_hetero -> N_sed c=0.0;
N_sed -> N_sed c=0.0;
DON -> N_sed c=0.6706;
NOx -> N_sed c=0.0;
NH4 -> N_sed c=0.0;
PN_abiotic -> N_sed c=0.0;
PN_phyto -> DON c=0.0;
PN_hetero -> DON c=4.356;
N_sed -> DON c=0.0;
DON -> DON c=0.0;
NOx -> DON c=0.0;
NH4 -> DON c=15.559;
PN_abiotic -> DON c=133.778;
PN_phyto -> NOx c=0.1094;
PN_hetero -> NOx c=0.0;
N_sed -> NOx c=7.59;
DON -> NOx c=7.188;
NOx -> NOx c=0.0;
NH4 -> NOx c=1.119;
PN_abiotic -> NOx c=2.222;
PN_phyto -> NH4 c=0.0;
PN_hetero -> NH4 c=0.0;
N_sed -> NH4 c=0.0;
DON -> NH4 c=0.0;
NOx -> NH4 c=0.02365;
NH4 -> NH4 c=0.0;
PN_abiotic -> NH4 c=28.806;
PN_phyto -> PN_abiotic c=183.031;
PN_hetero -> PN_abiotic c=0.0;
N_sed -> PN_abiotic c=0.0;
DON -> PN_abiotic c=0.0;
NOx -> PN_abiotic c=0.03058;
NH4 -> PN_abiotic c=0.0;
PN_abiotic -> PN_abiotic c=0.0;

# Initial State
* -> PN_phyto c=17
* -> PN_hetero c=23
* -> N_sed c=28
* -> DON c=187
* -> NOx c=418
* -> NH4 c=82
* -> PN_abiotic c=37

PN_phyto -> * c=0.4353
PN_hetero -> * c=2.313
N_sed -> * c=0.08038
DON -> * c=0.4593
NOx -> * c=0.1864
NH4 -> * c=0.6389
PN_abiotic -> * c=0.5082

# Initial values
PN_phyto = 85, PN_hetero = 64, N_sed = 5200
DON = 270, NOx = 59, NH4 = 36, PN_abiotic = 61

### ECONET RESULTS ###

TotalSystemThroughflow: 6440.64
FinnsCyclingIndex: 0.897687
IndirectEffectsIndex: 60.8905
Ascendency: 5499.02
DevelopmentCapacity: 10858.6
AggradationIndex: 48.7699
SynergismIndex: 4.92808
MutualismIndex: 1.72222
HomogenizationIndex: 1.86865

Random Run: 4640
Original Matrix (CF):
0.0000,0.0000,0.0000,4.3560,15.5590,133.7780,0.0000
57.1650,0.0000,0.1067,5.1410,9.8810,166.6390,26.3120
7.1880,0.1094,0.0000,0.0000,1.1190,2.2220,7.5900
16.0350,17.7810,0.0000,0.0000,0.0000,0.0000,0.0000
0.0000,0.0000,0.0237,0.0000,0.0000,28.8060,0.0000
0.0000,183.0310,0.0000,0.0000,0.0000,0.0000,0.0000
0.6706,31.3280,0.0000,0.0000,0.0000,0.0000,0.0000
0.0000,183.0310,0.0000,0.0000,0.0000,0.0000,0.0000

Original Eigenvalues:
(197.4573+0.0000j)
(-147.8591+0.0000j)
(-45.9734+0.0000j)
(-1.8248+0.3946j)
(-1.8248+-0.3946j)
(0.0124+0.1939j)
(0.0124+-0.1939j)
R:
0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 1.0000
0.0000, 0.0000, 1.0000, 0.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.0000, 0.0000, 0.0000, 1.0000, 0.0000, 0.0000
0.0000, 1.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000
1.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 1.0000, 0.0000
0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 1.0000
0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000

J:
0.0000, 0.0000, 0.0000, 31.3280, 0.6706, 0.0000, 0.0000
7.5900, 0.0000, 1.1190, 0.1094, 7.1880, 2.2220, 0.0000
0.0000, 0.0237, 0.0000, 0.0000, 0.0000, 28.8060, 0.0000
26.3120, 0.1067, 9.8810, 0.0000, 57.1650, 166.6390, 5.1410
0.0000, 0.0000, 15.5590, 0.0000, 0.0000, 133.7780, 4.3560
0.0000, 0.0306, 0.0000, 183.0310, 0.0000, 0.0000, 0.0000
0.0000, 0.0000, 0.0000, 17.7810, 16.0350, 0.0000, 0.0000

J Eigenvalues:
(197.4573+0.0000j)
(-147.8591+0.0000j)
(-45.9734+0.0000j)
(-1.8248+0.3946j)
(-1.8248-0.3946j)
(0.0124+0.1939j)
(0.0124-0.1939j)

######################################################### ECONET MODEL ###################################################

PN_phyto -> PN_phyto c=0.0;
PN_hetero -> PN_phyto c=0.0;
N_sed -> PN_phyto c=0.0;
DON -> PN_phyto c=31.328
;NOx -> PN_phyto c=0.6706
;NH4 -> PN_phyto c=0.0
;PN_abiotic -> PN_phyto c=0.0;
PN_phyto -> PN_hetero c=7.59;
PN_hetero -> PN_hetero c=0.0;
N_sed -> PN_hetero c=1.119;
DON -> PN_hetero c=0.1094;
NOx -> PN_hetero c=7.188;
NH4 -> PN_hetero c=2.222;
PN_abiotic -> PN_hetero c=0.0;
PN_phyto -> N_sed  c=0.0;
PN_hetero -> N_sed  c=0.02365;
N_sed  -> N_sed  c=0.0;
DON  -> N_sed  c=0.0;
NOx  -> N_sed  c=0.0;
NH4  -> N_sed  c=28.806;
PN_abiotic -> N_sed  c=0.0;
PN_phyto  -> DON  c=26.312;
PN_hetero  -> DON  c=0.1067;
N_sed  -> DON  c=9.881;
DON  -> DON  c=0.0;
NOx  -> DON  c=57.165;
NH4  -> DON  c=166.639;
PN_abiotic  -> DON  c=5.141;
PN_phyto  -> NOx  c=0.0;
PN_hetero  -> NOx  c=0.0;
N_sed  -> NOx  c=15.559;
DON  -> NOx  c=0.0;
NOx  -> NOx  c=0.0;
NH4  -> NOx  c=133.778;
PN_abiotic  -> NOx  c=4.356;
PN_phyto  -> NH4  c=0.0;
PN_hetero  -> NH4  c=0.03058;
N_sed  -> NH4  c=0.0;
DON  -> NH4  c=183.031;
NOx  -> NH4  c=0.0;
NH4  -> NH4  c=0.0;
PN_abiotic  -> NH4  c=0.0;
PN_phyto  -> PN_abiotic  c=0.0;
PN_hetero  -> PN_abiotic  c=0.0;
N_sed  -> PN_abiotic  c=0.0;
DON  -> PN_abiotic  c=17.781;
NOx  -> PN_abiotic  c=16.035;
NH4  -> PN_abiotic  c=0.0;
PN_abiotic  -> PN_abiotic  c=0.0;

# Initial State
*  -> PN_phyto  c=17
*  -> PN_hetero  c=23
*  -> N_sed  c=28
*  -> DON  c=187
*  -> NOx  c=418
*  -> NH4  c=82
*  -> PN_abiotic  c=37

PN_phyto  -> *  c=0.4353
PN_hetero -> * c=2.313
N_sed -> * c=0.08038
DON -> * c=0.4593
NOx -> * c=0.1864
NH4 -> * c=0.6389
PN_abiotic -> * c=0.5082

# Initial values

PN_phyto = 85, PN_hetero = 64, N_sed = 5200
DON = 270, NOx = 59, NH4 = 36, PN_abiotic = 61

### ECONET RESULTS ###

Total System Throughflow: 25341.3
Finns Cycling Index: 0.977107
Indirect Effects Index: 289.951
Ascendency: 19738.6
Development Capacity: 40221.5
Aggradation Index: 289.92
Synergism Index: 4.48165
Mutualism Index: 1.57895
Homogenization Index: 1.85165
This appendix contains the resulting statistical data of 50 randomly selected artificial coefficient and flow type matrix models based on various years and seasons of the Neuse River Estuary data collected and modeled by Christian and Thomas (2000, 2003). Data provided by Kazanci, C. (2011). Statistics of network properties from 50 randomly generated artificial models determined from the coefficient and flow data of the Neuse Grand Average data.

TotalSystemThroughflow:
AVG: 9129.24078 STD: 6595.08151 MED: 6051.67000 MAX: 27038.70000 MIN: 4704.14000

FinnsCyclingIndex:
AVG: 0.89554 STD: 0.03904 MED: 0.87991 MAX: 0.98013 MIN: 0.85090

IndirectEffectsIndex:
AVG: 85.00150 STD: 81.44200 MED: 47.67210 MAX: 337.20800 MIN: 38.62160

Ascendency:
AVG: 7492.73824 STD: 5004.20065 MED: 5150.90000 MAX: 21121.20000 MIN: 4107.48000

DevelopmentCapacity:

AggradationIndex:
AVG: 82.12089 STD: 82.33051 MED: 45.83310 MAX: 334.01600 MIN: 35.63740

SynergismIndex:
AVG: 4.95841 STD: 0.25646 MED: 5.03139 MAX: 5.38660 MIN: 4.45807

MutualismIndex:
AVG: 1.56081 STD: 0.11916 MED: 1.57895 MAX: 1.72222 MIN: 1.33333
Homogenization Index:
AVG: 1.86328 STD: 0.00729 MED: 1.86454 MAX: 1.87507 MIN: 1.85030

Below are the artificial models run and matrix number of the 50 modeled from this data set that have network properties within 10% of the actual model. Note: the numbers correspond to the computer sequence number of the randomly generated 50 of the 5040 possible models. The number corresponds to the matrix number of the 5040 possible combinations

['1', '4152', '394', '1120', '2821', '2910', '4862', '4267', '4265']

Statistics of network properties from 50 randomly generated artificial models determined from the coefficient and flow data of the Neuse River Estuary data for the fall of 1986.

Total System Throughflow:
AVG: 9788.19431 STD: 6332.28426 MED: 6632.78000 MAX: 28779.40000 MIN: 4988.13000

Finns Cycling Index:
AVG: 0.90535 STD: 0.03379 MED: 0.89504 MAX: 0.98105 MIN: 0.86596

Indirect Effects Index:

Ascendancy:

Development Capacity:

Aggradation Index:
AVG: 84.53791 STD: 74.04933 MED: 50.24810 MAX: 353.99200 MIN: 37.78870

Synergism Index:
AVG: 5.19436 STD: 0.35665 MED: 5.18884 MAX: 5.74152 MIN: 4.53296

Mutualism Index:
AVG: 1.56888 STD: 0.12068 MED: 1.57895 MAX: 1.72222 MIN: 1.22727

Homogenization Index:
Below are the artificial models of the 50 modeled from this data set that have network properties within 10% of the actual model. Note: the numbers correspond to the computer sequence number of the randomly generated 50 of the 5040 possible models. Note: the first number in the parentheses corresponds to the run number. The second number corresponds to the matrix number of the 5040 possible combinations.

```
[(1, '1'), (12, '514'), (15, '722'), (25, '2914'), (33, '3426'), (34, '4142'), (39, '3048'), (40, '1230'), (47, '723')]
```

Statistics of network properties from 50 randomly generated artificial models determined from the coefficient and flow data of the Neuse River Estuary data for the fall of 1988.

- **TotalSystemThroughflow:**
  - AVG: 5138.73196
  - STD: 2844.08795
  - MED: 3890.33000
  - MAX: 13983.40000
  - MIN: 3212.78000

- **FinnsCyclingIndex:**
  - AVG: 0.84313
  - STD: 0.04648
  - MED: 0.82464
  - MAX: 0.96788
  - MIN: 0.79995

- **IndirectEffectsIndex:**
  - AVG: 48.35237
  - STD: 44.51674
  - MED: 31.31510
  - MAX: 203.76600
  - MIN: 27.35530

- **Ascendency:**
  - AVG: 5410.44627
  - STD: 2720.08417
  - MED: 4255.60000
  - MAX: 13811.90000
  - MIN: 3510.85000

- **DevelopmentCapacity:**
  - AVG: 9055.34490
  - STD: 4667.33329
  - MED: 7029.85000
  - MAX: 23481.00000
  - MIN: 5860.59000

- **AggradationIndex:**
  - AVG: 46.75029
  - STD: 44.58650
  - MED: 29.47210
  - MAX: 204.06300
  - MIN: 24.33930

- **SynergismIndex:**
  - AVG: 6.14632
  - STD: 0.45755
  - MED: 6.17854
  - MAX: 6.74875
  - MIN: 5.15787

- **MutualismIndex:**
  - AVG: 1.34713
  - STD: 0.14926
  - MED: 1.33333
  - MAX: 1.72222
  - MIN: 1.04167

- **HomogenizationIndex:**
  - AVG: 2.43332
  - STD: 0.02579
  - MED: 2.42490
  - MAX: 2.48112
  - MIN: 2.40169
Below are the artificial models of the 50 modeled from this data set that have network properties within 10% of the actual model. Note: the numbers correspond to the computer sequence number of the randomly generated 50 of the 5040 possible models. Note: the first number in the parentheses corresponds to the run number. The second number corresponds to the matrix number of the 5040 possible combinations.

\[[(1, '1')]\]

Statistics of network properties from 50 randomly generated artificial models determined from the coefficient and flow data of the Neuse River Estuary data for the spring of 1986.

TotalSystemThroughflow:

FinnsCyclingIndex:
AVG: 0.91736 STD: 0.03098 MED: 0.90244 MAX: 0.98748 MIN: 0.88322

IndirectEffectsIndex:

Ascendency:

DevelopmentCapacity:

AggradationIndex:
AVG: 105.55872 STD: 111.29124 MED: 59.33330 MAX: 540.18900 MIN: 43.82910

SynergismIndex:

MutualismIndex:
AVG: 1.76619 STD: 0.14982 MED: 1.72222 MAX: 2.26667 MIN: 1.45000

HomogenizationIndex:
AVG: 1.81709 STD: 0.00586 MED: 1.81653 MAX: 1.82800 MIN: 1.80547
Below are the artificial model runs and matrix number of the 50 modeled from this data set that have network properties within 10% of the actual model. Note: the numbers correspond to the computer sequence number of the randomly generated 50 of the 5040 possible models. The first number in the parentheses corresponds to the run number. The second number corresponds to the matrix number of the 5040 possible combinations:

\[(1, '1'), (9, '2690'), (22, '2200'), (45, '2704')]\]

Statistics of network properties from 50 randomly generated artificial models determined from the coefficient and flow data of the Neuse River Estuary data for the spring of 1988.

- **TotalSystemThroughflow:**
  - AVG: 6298.21314
  - STD: 4023.25515
  - MED: 4557.14000
  - MAX: 17628.00000
  - MIN: 3515.84000

- **FinnsCyclingIndex:**
  - AVG: 0.86380
  - STD: 0.04983
  - MED: 0.84208
  - MAX: 0.98151
  - MIN: 0.81728

- **IndirectEffectsIndex:**
  - AVG: 69.33275
  - STD: 78.39979
  - MED: 35.66410
  - MAX: 359.86600
  - MIN: 30.60290

- **Ascendency:**
  - AVG: 5681.92745
  - STD: 3278.68713
  - MED: 4259.01000
  - MAX: 14911.70000
  - MIN: 3430.09000

- **DevelopmentCapacity:**
  - AVG: 11045.88549
  - STD: 6648.66743
  - MED: 8161.48000
  - MAX: 29694.40000
  - MIN: 6455.23000

- **AggradationIndex:**
  - AVG: 67.02976
  - STD: 78.44478
  - MED: 34.52380
  - MAX: 358.90900
  - MIN: 26.63510

- **SynergismIndex:**
  - AVG: 5.68798
  - STD: 0.35128
  - MED: 5.70128
  - MAX: 6.17584
  - MIN: 4.91313

- **MutualismIndex:**
  - AVG: 1.33568
  - STD: 0.15876
  - MED: 1.45000
  - MAX: 1.57895
  - MIN: 1.04167

- **HomogenizationIndex:**
  - AVG: 2.10396
  - STD: 0.02343
  - MED: 2.09701
  - MAX: 2.14657
  - MIN: 2.07021

Below are the artificial model runs and matrix number of the 50 modeled from this data set that have network properties within 10% of the actual model. Note: the numbers correspond to the computer sequence number of the randomly generated 50 of the 5040 possible models. The first
number in the parentheses corresponds to the run number. The second number corresponds to the matrix number of the 5040 possible combinations

\[
[(1, '1'), (4, '4473'), (23, '634'), (28, '1247'), (31, '4351')]\]

Statistics of network properties from 50 randomly generated artificial models determined from the coefficient and flow data of the Neuse River Estuary data for the summer of 1986.

**TotalSystemThroughflow:**
- AVG: 10653.74843
- STD: 9707.75685
- MED: 6129.61000
- MAX: 36893.80000
- MIN: 4224.90000

**FinnsCyclingIndex:**
- AVG: 0.89166
- STD: 0.04796
- MED: 0.86785
- MAX: 0.98617
- MIN: 0.83584

**IndirectEffectsIndex:**
- AVG: 104.65156
- STD: 133.20871
- MED: 44.69300
- MAX: 495.32300
- MIN: 3.56280

**Ascendency:**
- AVG: 10170.94549
- STD: 8816.24775
- MED: 6083.88000
- MAX: 34089.10000
- MIN: 4353.70000

**DevelopmentCapacity:**
- AVG: 18314.63784
- STD: 16014.18585
- MED: 10861.80000
- MAX: 61628.40000
- MIN: 7686.98000

**AggradationIndex:**
- AVG: 103.18998
- STD: 133.53486
- MED: 46.43610
- MAX: 494.15000
- MIN: 32.00680

**SynergismIndex:**
- AVG: 4.87487
- STD: 0.15737
- MED: 4.87738
- MAX: 5.14242
- MIN: 4.56920

**MutualismIndex:**
- AVG: 1.61580
- STD: 0.06982
- MED: 1.57895
- MAX: 1.88235
- MIN: 1.57895

**HomogenizationIndex:**
- AVG: 2.27369
- STD: 0.02508
- MED: 2.28953
- MAX: 2.29396
- MIN: 2.21487

Below are the artificial model runs and matrix number of the 50 modeled from these data sets that have network properties within 10% of the actual model. Note: the numbers correspond to the computer sequence number of the randomly generated 50 of the 5040 possible models. The
first number in the parentheses corresponds to the run number. The second number corresponds to the matrix number of the 5040 possible combinations.

\[(1, '1'), (5, '4256'), (13, '525'), (19, '2913'), (21, '988'), (27, '268'), (30, '22'), (31, '4850'), (34, '730'), (39, '4467'), (40, '4735')\]

Statistics of network properties from 50 randomly generated artificial models determined from the coefficient and flow data of the Neuse River Estuary data for the winter of 1987.

TotalSystemThroughflow:

FinnsCyclingIndex:
AVG: 0.87560 STD: 0.05853 MED: 0.84369 MAX: 0.97405 MIN: 0.82431

IndirectEffectsIndex:

Ascendancy:

DevelopmentCapacity:

AggradationIndex:

SynergismIndex:
AVG: 5.38277 STD: 0.34944 MED: 5.55909 MAX: 5.79051 MIN: 4.69184

MutualismIndex:
AVG: 1.39602 STD: 0.10651 MED: 1.3333 MAX: 1.72222 MIN: 1.22727

HomogenizationIndex:
AVG: 1.89717 STD: 0.07512 MED: 1.85281 MAX: 2.02136 MIN: 1.84164

Below are the artificial model runs and matrix number of the 50 modeled from this data set that have network properties within 10% of the actual model. Note: the numbers correspond to the computer sequence number of the randomly generated 50 of the 5040 possible models. The first
number in the parentheses corresponds to the run number. The second number corresponds to the matrix number of the 5040 possible combinations

\[
[(1, '1'), (5, '4481'), (11, '4492'), (15, '2176'), (18, '1572'), (19, '1885'), (20, '1889'), (21, '4010'),
(23, '2592'), (24, '1763'), (27, '446'), (32, '1855'), (37, '723'), (46, '1699'), (51, '3323')]
\]

Statistics of network properties from 50 randomly generated artificial models determined from the coefficient and flow data of the Neuse River Estuary data for the winter of 1989.

TotalSystemThroughflow:

FinnsCyclingIndex:
AVG: 0.85977 STD: 0.03061 MED: 0.84876 MAX: 0.92783 MIN: 0.82595

IndirectEffectsIndex:
AVG: 43.06732 STD: 17.55335 MED: 35.02120 MAX: 86.76730 MIN: 32.09310

Ascendency:

DevelopmentCapacity:

AggradationIndex:
AVG: 70.64889 STD: 80.51133 MED: 35.72900 MAX: 291.12300 MIN: 22.68690

SynergismIndex:

MutualismIndex:
AVG: 1.28708 STD: 0.08043 MED: 1.33333 MAX: 1.45000 MIN: 1.13043

HomogenizationIndex:
AVG: 1.82686 STD: 0.02939 MED: 1.81340 MAX: 1.89263 MIN: 1.80577

Below are the artificial model runs and matrix number of the 50 modeled from this data set that have network properties within 10% of the actual model. Note: the numbers correspond to the
computer sequence number of the randomly generated 50 of the 5040 possible models. The first number in the parentheses corresponds to the run number. The second number corresponds to the matrix number of the 5040 possible combinations

\[
[(1, '1'), (5, '4367'), (28, '3761'), (34, '13'), (39, '282')]
\]
APPENDIX D

MODEL #23 AND RUN #634

Artificial Model #23 and run #634 based on the original Neuse River Estuary coefficient and flow matrix for the spring of 1988.

Run: 634
Original Matrix (CF):
0.0000,0.0000,0.0000,4.5950,17.2000,316.6670,0.0000
101.4550,0.0000,0.0385,2.1670,10.2000,149.6670,28.2500
7.2730,0.0833,0.0000,0.0000,3.7000,4.6670,7.2500
27.4550,20.4170,0.0000,0.0000,0.0000,0.0000,0.0000
0.0000,0.0000,0.0285,0.0000,0.0000,59.6670,0.0000
0.0000,129.2500,0.0138,0.0000,0.0000,0.0000,0.0000
1.0000,34.5000,0.0000,0.0000,0.0000,0.0000,0.0000

Original Eigenvalues:
(204.0197+0.0000j)
(-100.2720+101.8946j)
(-100.2720+-101.8946j)
(-3.3712+0.0000j)
(0.1105+0.2377j)
(0.1105+-0.2377j)
(-0.3256+0.0000j)

R:
1.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,1.0000
0.0000,0.0000,1.0000,0.0000,0.0000,0.0000,0.0000
0.0000,0.0000,0.0000,1.0000,0.0000,0.0000,0.0000
0.0000,0.0000,0.0000,0.0000,1.0000,0.0000,0.0000
0.0000,0.0000,0.0000,0.0000,0.0000,1.0000,0.0000
0.0000,1.0000,0.0000,0.0000,0.0000,0.0000,0.0000

J:
0.0000,0.0000,0.0000,4.5950,17.2000,316.6670,0.0000
1.0000,0.0000,0.0000,0.0000,0.0000,0.0000,34.5000
7.2730,7.2500,0.0000,0.0000,3.7000,4.6670,0.0833
27.4550,0.0000,0.0000,0.0000,0.0000,20.4170
0.0000,0.0000,0.0285,0.0000,59.6670,0.0000
J Eigenvalues:
(204.0197+0.0000j)
(-100.2720+101.8946j)
(-100.2720+-101.8946j)
(-3.3712+0.0000j)
(0.1105+0.2377j)
(0.1105+-0.2377j)
(-0.3256+0.0000j)

############################ ECONET MODEL ############################

PN_phyto -> PN_phyto c=0.0;
PN_hetero -> PN_phyto c=0.0;
N_sed -> PN_phyto c=0.0;
DON -> PN_phyto c=4.595
;NOx -> PN_phyto c=17.2
;NH4 -> PN_phyto c=316.667
;PN_abiotic -> PN_phyto c=0.0;
PN_phyto -> PN_hetero c=1.0;
PN_hetero -> PN_hetero c=0.0;
N_sed -> PN_hetero c=0.0;
DON -> PN_hetero c=0.0;
NOx -> PN_hetero c=0.0;
NH4 -> PN_hetero c=0.0;
PN_abiotic -> PN_hetero c=34.5;
PN_phyto -> N_sed c=7.273;
PN_hetero -> N_sed c=7.25;
N_sed -> N_sed c=0.0;
DON -> N_sed c=0.0;
NOx -> N_sed c=3.7;
NH4 -> N_sed c=4.667;
PN_abiotic -> N_sed c=0.08333;
PN_phyto -> DON c=27.455;
PN_hetero -> DON c=0.0;
N_sed -> DON c=0.0;
DON -> DON c=0.0;
NOx -> DON c=0.0;
NH4 -> DON c=0.0;
PN_abiotic -> DON c=20.417;
PN_phyto -> NOx c=0.0;
PN_hetero -> NOx c=0.0;
N_sed -> NOx c=0.02846;
DON -> NOx c=0.0;
NOx -> NOx c=0.0;
NH4 -> NOx c=59.667;
PN_abiotic -> NOx c=0.0;
PN_phyto -> NH4 c=0.0;
PN_hetero -> NH4 c=0.0;
N_sed -> NH4 c=0.01385;
DON -> NH4 c=0.0;
NOx -> NH4 c=0.0;
NH4 -> NH4 c=0.0;
PN_abiotic -> NH4 c=129.25;
PN_phyto -> PN_abiotic c=101.455;
PN_hetero -> PN_abiotic c=28.25;
N_sed -> PN_abiotic c=0.03846;
DON -> PN_abiotic c=2.167;
NOx -> PN_abiotic c=10.2;
NH4 -> PN_abiotic c=149.667;
PN_abiotic -> PN_abiotic c=0.0;

# Initial State
* -> PN_phyto c=3
* -> PN_hetero c=5
* -> N_sed c=5
* -> DON c=36
* -> NOx c=96
* -> NH4 c=26
* -> PN_abiotic c=5

PN_phyto -> * c=0.1818
PN_hetero -> * c=2.667
N_sed -> * c=0.09154
DON -> * c=0.1786
NOx -> * c=0.1
NH4 -> * c=1
PN_abiotic -> * c=0.3333

# Initial values
PN_phyto = 11, PN_hetero = 12, N_sed = 1300
DON = 84, NOx = 10, NH4 = 3, PN_abiotic = 12

### ECONET RESULTS ###
TotalSystemThroughflow: 6471.38
FinnsCyclingIndex: 0.878885
IndirectEffectsIndex: 49.2563
Ascendency: 5838.38
DevelopmentCapacity: 11426.5
AggradationIndex: 49.0761
SynergismIndex: 5.61947
MutualismIndex: 1.45
HomogenizationIndex: 2.14657
This appendix contains the full network properties and results of a generic conceptual design from an artificially derived coefficient and flow type matrix (model #23 and run #634 in Appendix D). Note: this conceptual design was based on the actual model characteristics of the Neuse River Estuary model for the spring of 1988.

This file is automatically generated by EcoNet (Kazanci 2007) (http://eco engr.uga.edu).

Environmental inputs:

, A, 3
, B, 5
, D, 5
, E, 36
, F, 96
, G, 26
, H, 5

Environmental Outputs:

, A, 2.05642
, B, 30.9754
, D, 119.311
, E, 15.4197
, F, 1.01781
, G, 3.09116
, H, 4.12495

Initial storage values:

, A, 11
, B, 12
, D, 1300
, E, 84
, F, 10
, G, 3
Final storage values - assumed Steady-state:

\[ A, 11.3114 \]
\[ B, 11.6143 \]
\[ D, 1303.38 \]
\[ E, 86.3367 \]
\[ F, 10.1781 \]
\[ G, 3.09116 \]
\[ H, 12.3761 \]

Output throughflow:

\[ A, 1553.79 \]
\[ B, 443.283 \]
\[ D, 224.585 \]
\[ E, 599.229 \]
\[ F, 317.556 \]
\[ G, 1643.47 \]
\[ H, 2284.42 \]

Input throughflow:

\[ A, 1553.65 \]
\[ B, 443.286 \]
\[ D, 224.588 \]
\[ E, 599.237 \]
\[ F, 317.534 \]
\[ G, 1643.66 \]
\[ H, 2284.38 \]

Residence times:

\[ A, 0.00727989 \]
\[ B, 0.0262006 \]
\[ D, 5.80349 \]
\[ E, 0.14408 \]
\[ F, 0.0320513 \]
\[ G, 0.00188087 \]
\[ H, 0.0054176 \]

Link density:

\[ 3.14286 \]

Connectance:

\[ 0.44898 \]

Total system throughflow (TST):

\[ 7066.33 \]
Finn’s Cycling Index (FCI): 
,0.854067

Indirect effects index: 
,39.381

Ascendency: 
,6444.9

Development Capacity: 
,12623.9

Synergism Index: 
,5.79434

Mutualism index: 
,1.45

Aggradation index: 
,40.1504

Homogenization index: 
,2.13151

Homogenization index - output based: 
,2.30525

Stoichiometric matrix (SM): 
(Zero represents the environment)

```
Flows: 4->1,5->1,6->1,1->2,7->2,1->3,2->3,5->3,7->3,1->4,7->4,3->5,6->5,3->6,7->6,1-
>7,2->7,3->7,4->7,5->7,6->7,0->1,0->2,0->3,0->4,0->5,0->6,0->7,1->0,2->0,3->0,4->0,5->0,6-
>0,7->0
,A,1,1,1,1,-1,0,-1,0,0,0,0,-1,0,0,0,0,0,1,0,0,0,0,0,-1,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0
Flow Matrix (F):

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>G</th>
<th>H</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>396.717</td>
<td>175.063</td>
<td>978.867</td>
<td>0</td>
</tr>
<tr>
<td>B</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.426.975</td>
</tr>
<tr>
<td>D</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>38.2679</td>
<td>84.2037</td>
<td>0</td>
<td>14.4264</td>
</tr>
<tr>
<td>E</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>252.682</td>
</tr>
<tr>
<td>F</td>
<td>0</td>
<td>0</td>
<td>37.0941</td>
<td>0</td>
<td>0</td>
<td>184.44</td>
<td>0</td>
</tr>
<tr>
<td>G</td>
<td>0</td>
<td>0</td>
<td>18.0518</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1599.61</td>
</tr>
<tr>
<td>H</td>
<td>1147.6</td>
<td>328.104</td>
<td>50.1278</td>
<td>187.092</td>
<td>103.816</td>
<td>462.644</td>
<td>0</td>
</tr>
</tbody>
</table>

Normalized flow matrix (G):

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>G</th>
<th>H</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.662047</td>
<td>0.551282</td>
<td>0.59561</td>
<td>0</td>
</tr>
<tr>
<td>B</td>
<td>0.00727989</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.186907</td>
</tr>
<tr>
<td>D</td>
<td>0.0529466</td>
<td>0.189955</td>
<td>0</td>
<td>0</td>
<td>0.11859</td>
<td>0.00877803</td>
<td>0.000451448</td>
</tr>
<tr>
<td>E</td>
<td>0.199869</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.110611</td>
</tr>
<tr>
<td>F</td>
<td>0.00727989</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.186907</td>
</tr>
<tr>
<td>G</td>
<td>0</td>
<td>0</td>
<td>0.0803784</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.700225</td>
</tr>
<tr>
<td>H</td>
<td>0.738581</td>
<td>0.740168</td>
<td>0.223202</td>
<td>0.312221</td>
<td>0.326923</td>
<td>0.281505</td>
<td>0</td>
</tr>
</tbody>
</table>

Throughflow Analysis (N):

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>G</th>
<th>H</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.662047</td>
<td>0.551282</td>
<td>0.59561</td>
</tr>
<tr>
<td>B</td>
<td>0.00727989</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.186907</td>
</tr>
<tr>
<td>D</td>
<td>0.0529466</td>
<td>0.189955</td>
<td>0</td>
<td>0</td>
<td>0.11859</td>
<td>0.00877803</td>
<td>0.000451448</td>
</tr>
<tr>
<td>E</td>
<td>0.199869</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.110611</td>
</tr>
<tr>
<td>F</td>
<td>0.00727989</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.186907</td>
</tr>
<tr>
<td>G</td>
<td>0</td>
<td>0</td>
<td>0.0803784</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.700225</td>
</tr>
<tr>
<td>H</td>
<td>0.738581</td>
<td>0.740168</td>
<td>0.223202</td>
<td>0.312221</td>
<td>0.326923</td>
<td>0.281505</td>
<td>0</td>
</tr>
</tbody>
</table>

Normalized flow matrix - output oriented (G'):

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>G</th>
<th>H</th>
</tr>
</thead>
<tbody>
<tr>
<td>B</td>
<td>2.61989</td>
<td>3.25206</td>
<td>1.229</td>
<td>2.58599</td>
<td>2.48164</td>
<td>2.61745</td>
<td>2.72723</td>
</tr>
<tr>
<td>D</td>
<td>1.25772</td>
<td>1.22475</td>
<td>1.59228</td>
<td>1.22171</td>
<td>1.28955</td>
<td>1.25858</td>
<td>1.24606</td>
</tr>
<tr>
<td>E</td>
<td>3.45676</td>
<td>2.78678</td>
<td>1.55007</td>
<td>4.33986</td>
<td>3.1903</td>
<td>3.37842</td>
<td>3.36726</td>
</tr>
<tr>
<td>F</td>
<td>1.29075</td>
<td>1.13744</td>
<td>0.781199</td>
<td>1.27174</td>
<td>2.24106</td>
<td>1.40331</td>
<td>1.33625</td>
</tr>
</tbody>
</table>

Throughflow Analysis - output oriented (NP):
Partial turnover rate matrix (C):

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>G</th>
<th>H</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>-137.365</td>
<td>0</td>
<td>0</td>
<td>4.595</td>
<td>17.2</td>
<td>316.667</td>
<td>0</td>
</tr>
<tr>
<td>B</td>
<td>7.273</td>
<td>7.25</td>
<td>-1.7231</td>
<td>0</td>
<td>3.4667</td>
<td>0.08333</td>
<td></td>
</tr>
<tr>
<td>D</td>
<td>27.455</td>
<td>0</td>
<td>0</td>
<td>-6.9406</td>
<td>0</td>
<td>0.20417</td>
<td></td>
</tr>
<tr>
<td>E</td>
<td>0.366311</td>
<td>0.374931</td>
<td>0</td>
<td>0</td>
<td>0.167682</td>
<td>0.064236</td>
<td>0.00459202</td>
</tr>
<tr>
<td>F</td>
<td>0.518258</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.421679</td>
<td></td>
<td></td>
</tr>
<tr>
<td>G</td>
<td>0.0109839</td>
<td>0</td>
<td>0</td>
<td>0.973312</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>H</td>
<td>0.502359</td>
<td>0.143627</td>
<td>0.0219433</td>
<td>0.0818989</td>
<td>0.0454453</td>
<td>0.202521</td>
<td></td>
</tr>
</tbody>
</table>

Storage Analysis (S):

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>G</th>
<th>H</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.0709638</td>
<td>0.0541267</td>
<td>0.0306274</td>
<td>0.0673592</td>
<td>0.0640906</td>
<td>0.0681014</td>
<td>0.0652674</td>
</tr>
<tr>
<td>B</td>
<td>0.0686427</td>
<td>0.0852062</td>
<td>0.0322005</td>
<td>0.0677545</td>
<td>0.0650205</td>
<td>0.068579</td>
<td>0.0714553</td>
</tr>
<tr>
<td>E</td>
<td>0.498049</td>
<td>0.401519</td>
<td>0.223333</td>
<td>0.65286</td>
<td>0.459658</td>
<td>0.486762</td>
<td>0.485154</td>
</tr>
<tr>
<td>F</td>
<td>0.0413702</td>
<td>0.0364564</td>
<td>0.0250384</td>
<td>0.0407609</td>
<td>0.0718289</td>
<td>0.04549778</td>
<td>0.0428284</td>
</tr>
<tr>
<td>G</td>
<td>0.018151</td>
<td>0.0156728</td>
<td>0.00868499</td>
<td>0.0179321</td>
<td>0.0172301</td>
<td>0.020035</td>
<td>0.0189458</td>
</tr>
<tr>
<td>H</td>
<td>0.0738818</td>
<td>0.0637083</td>
<td>0.0347354</td>
<td>0.0730037</td>
<td>0.0700738</td>
<td>0.0738942</td>
<td>0.0771584</td>
</tr>
</tbody>
</table>

Partial Turnover Rates - output oriented (C'):

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>G</th>
<th>H</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>-137.365</td>
<td>0</td>
<td>0</td>
<td>35.0723</td>
<td>15.4766</td>
<td>5238</td>
<td>0</td>
</tr>
<tr>
<td>B</td>
<td>0.973921</td>
<td>-38.167</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>36.7628</td>
</tr>
<tr>
<td>D</td>
<td>0.0631191</td>
<td>0.0646043</td>
<td>-0.17231</td>
<td>0</td>
<td>0.0288933</td>
<td>0.0110685</td>
<td>0.000791252</td>
</tr>
<tr>
<td>E</td>
<td>3.59702</td>
<td>0</td>
<td>-6.9406</td>
<td>0</td>
<td>0.292671</td>
<td></td>
<td></td>
</tr>
<tr>
<td>F</td>
<td>0.0459769</td>
<td>0.0416008</td>
<td>3.20636</td>
<td>0.34576</td>
<td>0.0718289</td>
<td>0.0136601</td>
<td>0.0520775</td>
</tr>
</tbody>
</table>

Storage Analysis - output oriented (S'):

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>G</th>
<th>H</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.0709638</td>
<td>0.0555761</td>
<td>3.52909</td>
<td>0.514133</td>
<td>0.057669</td>
<td>0.0186106</td>
<td>0.0714106</td>
</tr>
<tr>
<td>B</td>
<td>0.0685266</td>
<td>0.0852062</td>
<td>3.61359</td>
<td>0.503663</td>
<td>0.05698</td>
<td>0.0187253</td>
<td>0.0761419</td>
</tr>
<tr>
<td>D</td>
<td>0.0633461</td>
<td>0.0633375</td>
<td>9.24077</td>
<td>0.46966</td>
<td>0.0584417</td>
<td>0.0173229</td>
<td>0.0686657</td>
</tr>
<tr>
<td>E</td>
<td>0.0652519</td>
<td>0.0540137</td>
<td>3.37153</td>
<td>0.625286</td>
<td>0.0541882</td>
<td>0.0174278</td>
<td>0.0695452</td>
</tr>
<tr>
<td>F</td>
<td>0.0459769</td>
<td>0.0416008</td>
<td>3.20636</td>
<td>0.34576</td>
<td>0.0718289</td>
<td>0.0136601</td>
<td>0.0520775</td>
</tr>
</tbody>
</table>
Utility series matrix (D):

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>G</th>
<th>H</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0</td>
<td>-0.00727989</td>
<td>-0.0529466</td>
<td>0.055453</td>
<td>0.112668</td>
<td>0.629987</td>
<td>-0.738581</td>
</tr>
<tr>
<td>B</td>
<td>0.02551740</td>
<td>0.189955</td>
<td>0.000251473</td>
<td>-0.0161424</td>
<td>-0.21861</td>
<td>0.0758534</td>
<td></td>
</tr>
<tr>
<td>D</td>
<td>0.366311</td>
<td>0.374931</td>
<td>0.0000251473</td>
<td>-0.0161424</td>
<td>-0.21861</td>
<td>0.0758534</td>
<td></td>
</tr>
<tr>
<td>E</td>
<td>-0.143789</td>
<td>0.0000251473</td>
<td>-0.0161424</td>
<td>-0.21861</td>
<td>0.0758534</td>
<td></td>
<td></td>
</tr>
<tr>
<td>F</td>
<td>-0.551282</td>
<td>0.00177849</td>
<td>0.0000251473</td>
<td>-0.0161424</td>
<td>-0.21861</td>
<td>0.0758534</td>
<td></td>
</tr>
<tr>
<td>G</td>
<td>-0.59561</td>
<td>0.0000251473</td>
<td>-0.0161424</td>
<td>-0.21861</td>
<td>0.0758534</td>
<td></td>
<td></td>
</tr>
<tr>
<td>H</td>
<td>0.502359</td>
<td>-0.0432803</td>
<td>0.0000251473</td>
<td>-0.0161424</td>
<td>-0.21861</td>
<td>0.0758534</td>
<td></td>
</tr>
</tbody>
</table>

Utility Analysis (U):

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>G</th>
<th>H</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.628343</td>
<td>-0.011156</td>
<td>-0.0330119</td>
<td>0.0386882</td>
<td>0.0118876</td>
<td>0.46993</td>
<td>-0.133904</td>
</tr>
<tr>
<td>B</td>
<td>0.05743280</td>
<td>0.926379</td>
<td>-0.175434</td>
<td>-0.00174233</td>
<td>0.0178702</td>
<td>-0.0360154</td>
<td>0.171605</td>
</tr>
<tr>
<td>D</td>
<td>0.178056</td>
<td>0.350177</td>
<td>0.921446</td>
<td>0.0138506</td>
<td>-0.00241435</td>
<td>0.164831</td>
<td>-0.138506</td>
</tr>
<tr>
<td>E</td>
<td>-0.0534333</td>
<td>-0.00174208</td>
<td>0.00496331</td>
<td>0.994389</td>
<td>0.0066865</td>
<td>-0.0757644</td>
<td>0.0922351</td>
</tr>
<tr>
<td>F</td>
<td>-0.0837941</td>
<td>-0.0145267</td>
<td>0.0199757</td>
<td>-0.0196569</td>
<td>0.0588612</td>
<td>0.65251</td>
<td>0.522784</td>
</tr>
<tr>
<td>G</td>
<td>-0.337255</td>
<td>-0.0305704</td>
<td>0.0019786</td>
<td>-0.000441963</td>
<td>0.0767044</td>
<td>-0.0748573</td>
<td>0.666747</td>
</tr>
<tr>
<td>H</td>
<td>0.3664197</td>
<td>0.0588871</td>
<td>3.662</td>
<td>0.0500848</td>
<td>0.0567325</td>
<td>0.020035</td>
<td>0.0758534</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.0675261</td>
<td>0.059787</td>
<td>3.65813</td>
<td>0.0509281</td>
<td>0.0576286</td>
<td>0.0184565</td>
<td>0.0771584</td>
</tr>
</tbody>
</table>

Control matrix I (CD):

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>G</th>
<th>H</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0</td>
<td>-0.00112505</td>
<td>-0.00289253</td>
<td>0.000186298</td>
<td>0.00160137</td>
<td>0.00148668</td>
<td>-0.00019968</td>
</tr>
<tr>
<td>B</td>
<td>0.00112505</td>
<td>0.00268091</td>
<td>0.00118309</td>
<td>0.00201645</td>
<td>0.000834478</td>
<td>0.00100465</td>
<td></td>
</tr>
<tr>
<td>D</td>
<td>0.00289253</td>
<td>0.00268091</td>
<td>0.000186298</td>
<td>-0.00112505</td>
<td>-0.00289253</td>
<td>0.000186298</td>
<td></td>
</tr>
<tr>
<td>E</td>
<td>-0.000186298</td>
<td>0.00118309</td>
<td>0.00201645</td>
<td>-0.00112505</td>
<td>-0.00289253</td>
<td>0.000186298</td>
<td></td>
</tr>
<tr>
<td>F</td>
<td>0.00160137</td>
<td>-0.00201645</td>
<td>0.000186298</td>
<td>0.00118309</td>
<td>0.00201645</td>
<td>0.000186298</td>
<td></td>
</tr>
<tr>
<td>G</td>
<td>0.000186298</td>
<td>0.00000000</td>
<td>0.00000000</td>
<td>0.00000000</td>
<td>0.00000000</td>
<td>0.00000000</td>
<td></td>
</tr>
<tr>
<td>H</td>
<td>0.000186298</td>
<td>0.00000000</td>
<td>0.00000000</td>
<td>0.00000000</td>
<td>0.00000000</td>
<td>0.00000000</td>
<td></td>
</tr>
</tbody>
</table>

Control matrix II (CR):

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>G</th>
<th>H</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>1.66533e-15</td>
<td>0.190357</td>
<td>0.516507</td>
<td>0.00000000</td>
<td>0.00000000</td>
<td>0.00000000</td>
<td>0.00000000</td>
</tr>
<tr>
<td>B</td>
<td>0.00000000</td>
<td>0.88178e-16</td>
<td>0.00000000</td>
<td>0.00000000</td>
<td>0.00000000</td>
<td>0.00000000</td>
<td>0.00000000</td>
</tr>
<tr>
<td>D</td>
<td>0.00000000</td>
<td>0.00000000</td>
<td>0.00000000</td>
<td>0.00000000</td>
<td>0.00000000</td>
<td>0.00000000</td>
<td>0.00000000</td>
</tr>
<tr>
<td>E</td>
<td>0.03128440</td>
<td>0.02020303</td>
<td>0.524479</td>
<td>1.22125e-15</td>
<td>0.00000000</td>
<td>0.00000000</td>
<td>0.00000000</td>
</tr>
<tr>
<td>F</td>
<td>0.282627</td>
<td>0.360189</td>
<td>0.571566</td>
<td>0.24779</td>
<td>7.77156e-16</td>
<td>0.207196</td>
<td>0.25682</td>
</tr>
<tr>
<td>G</td>
<td>0.02469330</td>
<td>0.141324</td>
<td>0.498642</td>
<td>0.00000000</td>
<td>0.00000000</td>
<td>0.00000000</td>
<td>0.00000000</td>
</tr>
<tr>
<td>H</td>
<td>0.00000000</td>
<td>0.163295</td>
<td>0.494138</td>
<td>0.00000000</td>
<td>0.00000000</td>
<td>0.00000000</td>
<td>0.00000000</td>
</tr>
</tbody>
</table>
APPENDIX F

TEN SAMPLE RUNS, SPRING 1988

This appendix includes 10 sample runs of the 5040 artificial models derived from the original model of the Neuse River Estuary for the spring of 1988.

Run: 118
Original Matrix:
0.0000,0.0000,0.0000,0.0000,0.0000,0.0057,0.0637,0.4876,0.0000
0.1008,0.0000,0.0002,0.0048,0.0049,0.0049,0.068,0.0290
0.0091,0.0001,0.0000,0.0000,0.0000,0.0000,0.0108,0.0091
0.0278,0.0068,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000

Original Eigenvalues:
(0.3484+0.0000j)
(-0.1892+0.0000j)
(-0.1482+0.0000j)
(-0.0095+0.0000j)
(-0.0015+0.0000j)
(0.0000+0.0004j)
(0.0000+0.0004j)

R:
1.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.0000,1.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,1.0000
0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,1.0000,0.0000
0.0000,0.0000,0.0000,1.0000,0.0000,0.0000,0.0000,0.0000
0.0000,0.0000,0.0000,1.0000,0.0000,0.0000,0.0000,0.0000
0.0000,0.0000,1.0000,0.0000,0.0000,0.0000,0.0000,0.0000

J:
0.0000,0.0000,0.0000,0.4876,0.0057,0.0637,0.0000,0.0000
0.1008,0.0000,0.0002,0.0048,0.0049,0.0049,0.068,0.0290
0.0091,0.0001,0.0000,0.0000,0.0000,0.0000,0.0108,0.0091
0.0278,0.0068,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.0000,0.2169,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.0278,0.0068,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.0000, 0.0000, 0.0000, 0.0000, 0.0772, 0.0000, 0.0000, 0.0000
0.0091, 0.0001, 0.0091, 0.0108, 0.0000, 0.0003, 0.0000

J Eigenvalues:
(0.3484+0.0000j)
(-0.1892+0.0000j)
(-0.1482+0.0000j)
(-0.0095+0.0000j)
(-0.0015+0.0000j)
(0.0000+0.0004j)
(0.0000+-0.0004j)

# ECONET MODEL #

PN_phyto -> PN_phyto c=0.0;
PN_hetero -> PN_phyto c=0.0;
N_sed -> PN_phyto c=0.0;
DON -> PN_phyto c=487.6
;NOx -> PN_phyto c=5.7
;NH4 -> PN_phyto c=63.7
;PN_abiotic -> PN_phyto c=0.0;
PN_phyto -> PN_hetero c=100.8;
PN_hetero -> PN_hetero c=0.0;
N_sed -> PN_hetero c=29.0;
DON -> PN_hetero c=406.8;
NOx -> PN_hetero c=4.8;
NH4 -> PN_hetero c=4.9;
PN_abiotic -> PN_hetero c=0.2;
PN_phyto -> N_sed c=0.1;
PN_hetero -> N_sed c=40.6;
N_sed -> N_sed c=0.0;
DON -> N_sed c=0.0;
NOx -> N_sed c=0.0;
NH4 -> N_sed c=0.0;
PN_abiotic -> N_sed c=0.0;
PN_phyto -> DON c=0.0;
PN_hetero -> DON c=216.9;
N_sed -> DON c=0.0;
DON -> DON c=0.0;
NOx -> DON c=0.0;
NH4 -> DON c=0.0;
PN_abiotic -> DON c=0.1;
PN_phyto -> NOx c=27.8;
PN_hetero -> NOx c=6.8;
N_sed -> NOx c=0.0;
DON -> NOx c=0.0;
NOx -> NOx c=0.0;
NH4 -> NOx c=0.0;
PN_abiotic -> NOx c=0.0;
PN_phyto -> NH4 c=0.0;
PN_hetero -> NH4 c=0.0;
N_sed -> NH4 c=0.0;
DON -> NH4 c=77.2;
NOx -> NH4 c=0.0;
NH4 -> NH4 c=0.0;
PN_abiotic -> NH4 c=0.0;
PN_phyto -> PN_abiotic c=9.1;
PN_hetero -> PN_abiotic c=0.1;
N_sed -> PN_abiotic c=9.1;
DON -> PN_abiotic c=10.8;
NOx -> PN_abiotic c=0.0;
NH4 -> PN_abiotic c=0.3;
PN_abiotic -> PN_abiotic c=0.0;

# Initial State
* -> PN_phyto c=1
* -> PN_hetero c=4
* -> N_sed c=8
* -> DON c=27
* -> NOx c=64
* -> NH4 c=23
* -> PN_abiotic c=5

PN_phyto -> * c=0.25
PN_hetero -> * c=0
N_sed -> * c=0.06923
DON -> * c=0.3333
NOx -> * c=0.1429
NH4 -> * c=0.4
PN_abiotic -> * c=0.2917

# Initial values
PN_phyto = 24, PN_hetero = 22, N_sed = 1300
DON = 78, NOx = 7, NH4 = 5, PN_abiotic = 24

### ECONET RESULTS ###
TotalSystemThroughflow: 8122.34
FinnsCyclingIndex: 0.900755
IndirectEffectsIndex: 60.3598
Ascendency: 7292.94
DevelopmentCapacity: 13402.7
AggradationIndex: 61.5013
SynergismIndex: 4.68707
MutualismIndex: 1.88235
HomogenizationIndex: 2.05215

Run: 119
Original Matrix:

0.0000, 0.0000, 0.0000, 0.0057, 0.0637, 0.4876, 0.0000
0.1008, 0.0000, 0.0002, 0.0048, 0.0049, 0.4068, 0.0290
0.0091, 0.0001, 0.0000, 0.0000, 0.0003, 0.0108, 0.0091
0.0278, 0.0068, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.2169, 0.0001, 0.0000, 0.0000, 0.0000, 0.0000
0.0001, 0.0406, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000

Original Eigenvalues:
(0.3484+0.0000j)
(-0.1892+0.0000j)
(-0.1482+0.0000j)
(-0.0095+0.0000j)
(-0.0015+0.0000j)
(0.0000+0.0004j)
(0.0000+-0.0004j)

R:
1.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000
0.0000, 1.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.0000, 1.0000, 0.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.0000, 0.0000, 1.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.0000, 0.0000, 0.0000, 1.0000, 0.0000, 0.0000
0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 1.0000, 0.0000
0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 1.0000

J:
0.0000, 0.0000, 0.0000, 0.4876, 0.0637, 0.0000, 0.0057
0.1008, 0.0000, 0.0002, 0.4068, 0.0049, 0.0049, 0.0290
0.0001, 0.0406, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.2169, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.0000, 0.0000, 0.0772, 0.0000, 0.0000, 0.0000
0.0091, 0.0001, 0.0091, 0.0108, 0.0003, 0.0000, 0.0000
0.0278, 0.0068, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000
J Eigenvalues:
(0.3484+0.0000j)
(-0.1892+0.0000j)
(-0.1482+0.0000j)
(-0.0095+0.0000j)
(-0.0015+0.0000j)
(0.0000+0.0004j)
(0.0000+0.0004j)

################################ ECONET MODEL ################################

PN_phyto -> PN_phyto c=0.0;
PN_hetero -> PN_phyto c=0.0;
N_sed -> PN_phyto c=0.0;
DON -> PN_phyto c=487.6
NOx -> PN_phyto c=63.7
NH4 -> PN_phyto c=0.0
PN_abiotic -> PN_phyto c=5.7;
PN_phyto -> PN_hetero c=100.8;
PN_hetero -> PN_hetero c=0.0;
N_sed -> PN_hetero c=29.0;
DON -> PN_hetero c=406.8;
NOx -> PN_hetero c=4.9;
NH4 -> PN_hetero c=0.2;
PN_abiotic -> PN_hetero c=4.8;
PN_phyto -> N_sed c=0.1;
PN_hetero -> N_sed c=40.6;
N_sed -> N_sed c=0.0;
DON -> N_sed c=0.0;
NOx -> N_sed c=0.0;
NH4 -> N_sed c=0.0;
PN_abiotic -> N_sed c=0.0;
PN_phyto -> DON c=0.0;
PN_hetero -> DON c=216.9;
N_sed -> DON c=0.0;
DON -> DON c=0.0;
NOx -> DON c=0.0;
NH4 -> DON c=0.1;
PN_abiotic -> DON c=0.0;
PN_phyto -> NOx c=0.0;
PN_hetero -> NOx c=0.0;
N_sed -> NOx c=0.0;
DON -> NOx c=77.2;
NOx -> NOx c=0.0;
NH4 -> NOx c=0.0;
PN_abiotic -> NOx c=0.0;
PN_phyto -> NH4 c=9.1;
PN_hetero -> NH4 c=0.1;
N_sed -> NH4 c=9.1;
DON -> NH4 c=10.8;
NOx -> NH4 c=0.3;
NH4 -> NH4 c=0.0;
PN_abiotic -> NH4 c=0.0;
PN_phyto -> PN_abiotic c=27.8;
PN_hetero -> PN_abiotic c=6.8;
N_sed -> PN_abiotic c=0.0;
DON -> PN_abiotic c=0.0;
NOx -> PN_abiotic c=0.0;
NH4 -> PN_abiotic c=0.0;
PN_abiotic -> PN_abiotic c=0.0;

# Initial State
* -> PN_phyto c=1
* -> PN_hetero c=4
* -> N_sed c=8
* -> DON c=27
* -> NOx c=64
* -> NH4 c=23
* -> PN_abiotic c=5

PN_phyto -> * c=0.25
PN_hetero -> * c=0
N_sed -> * c=0.06923
DON -> * c=0.3333
NOx -> * c=0.1429
NH4 -> * c=0.4
PN_abiotic -> * c=0.2917

# Initial values
PN Phyto = 24, PN Hetero = 22, N Sed = 1300
DON = 78, NOx = 7, NH4 = 5, PN Abiotic = 24

### ECONET RESULTS ###

TotalSystemThroughflow: 6317.33
FinnsCyclingIndex: 0.882083
IndirectEffectsIndex: 50.5904
Ascendency: 5843.69
DevelopmentCapacity: 10621.6
AggradationIndex: 47.8569
SynergismIndex: 4.75063
MutualismIndex: 1.72222
HomogenizationIndex: 2.05298

Run: 120
Original Matrix:

\[
\begin{bmatrix}
0.0000, & 0.0000, & 0.0000, & 0.0057, & 0.0637, & 0.4876, & 0.0000 \\
0.1008, & 0.0000, & 0.0002, & 0.0048, & 0.0049, & 0.4068, & 0.0290 \\
0.0091, & 0.0001, & 0.0000, & 0.0000, & 0.0003, & 0.0108, & 0.0091 \\
0.0278, & 0.0068, & 0.0000, & 0.0000, & 0.0000, & 0.0000, & 0.0000 \\
0.0000, & 0.0000, & 0.0000, & 0.0000, & 0.0000, & 0.0000, & 0.0000 \\
0.0000, & 0.2169, & 0.0001, & 0.0000, & 0.0000, & 0.0000, & 0.0000 \\
0.0001, & 0.0406, & 0.0000, & 0.0000, & 0.0000, & 0.0000, & 0.0000 \\
0.0000, & 0.0000, & 0.0000, & 0.0000, & 0.0000, & 0.0000, & 0.0000 \\
\end{bmatrix}
\]

Original Eigenvalues:

\[
(0.3484+0.0000j) \\
(-0.1892+0.0000j) \\
(-0.1482+0.0000j) \\
(-0.0095+0.0000j) \\
(-0.0015+0.0000j) \\
(0.0000+0.0004j) \\
(0.0000+-0.0004j)
\]

R:

\[
\begin{bmatrix}
1.0000, & 0.0000, & 0.0000, & 0.0000, & 0.0000, & 0.0000, & 0.0000 \\
0.0000, & 1.0000, & 0.0000, & 0.0000, & 0.0000, & 0.0000, & 0.0000 \\
0.0000, & 0.0000, & 0.0000, & 0.0000, & 0.0000, & 0.0000, & 1.0000 \\
0.0000, & 0.0000, & 0.0000, & 0.0000, & 0.0000, & 1.0000, & 0.0000 \\
0.0000, & 0.0000, & 0.0000, & 0.0000, & 0.0000, & 0.0000, & 0.0000 \\
0.0000, & 0.0000, & 0.0000, & 1.0000, & 0.0000, & 0.0000, & 0.0000 \\
0.0000, & 0.0000, & 1.0000, & 0.0000, & 0.0000, & 0.0000, & 0.0000 \\
0.0000, & 0.0000, & 0.0000, & 0.0000, & 0.0000, & 0.0000, & 0.0000 \\
\end{bmatrix}
\]

J:

\[
\begin{bmatrix}
0.0000, & 0.0000, & 0.4876, & 0.0057, & 0.0000, & 0.0637, & 0.0000 \\
0.1008, & 0.0000, & 0.0049, & 0.0048, & 0.0002, & 0.4068, & 0.0290 \\
0.0001, & 0.0406, & 0.0000, & 0.0000, & 0.0000, & 0.0000, & 0.0000 \\
0.0000, & 0.2169, & 0.0000, & 0.0000, & 0.0000, & 0.0000, & 0.0001 \\
0.0000, & 0.0000, & 0.0000, & 0.0000, & 0.0000, & 0.0000, & 0.0000 \\
0.0278, & 0.0068, & 0.0000, & 0.0000, & 0.0000, & 0.0000, & 0.0000 \\
0.0091, & 0.0001, & 0.0091, & 0.0108, & 0.0003, & 0.0000, & 0.0000 \\
0.0000, & 0.0000, & 0.0000, & 0.0000, & 0.0000, & 0.0000, & 0.0000 \\
\end{bmatrix}
\]
J Eigenvalues:
(0.3484+0.0000j)
(-0.1892+0.0000j)
(-0.1482+0.0000j)
(-0.0095+0.0000j)
(-0.0015+0.0000j)
(0.0000+0.0004j)
(0.0000+0.0004j)

######################## ECONET MODEL ########################

PN_phyto -> PN_phyto c=0.0;
PN_hetero -> PN_phyto c=0.0;
N_sed -> PN_phyto c=0.0;
DON -> PN_phyto c=487.6
;NOx -> PN_phyto c=63.7
;NH4 -> PN_phyto c=5.7
;PN_abiotic -> PN_phyto c=0.0;
PN_phyto -> PN_hetero c=100.8;
PN_hetero -> PN_hetero c=0.0;
N_sed -> PN_hetero c=29.0;
DON -> PN_hetero c=406.8;
NOx -> PN_hetero c=4.9;
NH4 -> PN_hetero c=4.8;
PN_abiotic -> PN_hetero c=0.2;
PN_phyto -> N_sed c=0.1;
PN_hetero -> N_sed c=40.6;
N_sed -> N_sed c=0.0;
DON -> N_sed c=0.0;
NOx -> N_sed c=0.0;
NH4 -> N_sed c=0.0;
PN_abiotic -> N_sed c=0.0;
PN_phyto -> DON c=0.0;
PN_hetero -> DON c=216.9;
N_sed -> DON c=0.0;
DON -> DON c=0.0;
NOx -> DON c=0.0;
NH4 -> DON c=0.0;
PN_abiotic -> DON c=0.1;
PN_phyto -> NOx c=0.0;
PN_hetero -> NOx c=0.0;
N_sed -> NOx c=0.0;
DON -> NOx c=77.2;
NOx -> NOx c=0.0;
NH4 -> NOx c=0.0;
PN_abiotic -> NOx c=0.0;
PN_phyto -> NH4 c=27.8;
PN_hetero -> NH4 c=6.8;
N_sed -> NH4 c=0.0;
DON -> NH4 c=0.0;
NOx -> NH4 c=0.0;
NH4 -> NH4 c=0.0;
PN_abiotic -> NH4 c=0.0;
PN_phyto -> PN_abiotic c=9.1;
PN_hetero -> PN_abiotic c=0.1;
N_sed -> PN_abiotic c=9.1;
DON -> PN_abiotic c=10.8;
NOx -> PN_abiotic c=0.3;
NH4 -> PN_abiotic c=0.0;
PN_abiotic -> PN_abiotic c=0.0;

# Initial State
* -> PN_phyto c=1
* -> PN_hetero c=4
* -> N_sed c=8
* -> DON c=27
* -> NOx c=64
* -> NH4 c=23
* -> PN_abiotic c=5

PN_phyto -> * c=0.25
PN_hetero -> * c=0
N_sed -> * c=0.06923
DON -> * c=0.3333
NOx -> * c=0.1429
NH4 -> * c=0.4
PN_abiotic -> * c=0.2917

# Initial values

PN_phyto = 24, PN_hetero = 22, N_sed = 1300
DON = 78, NOx = 7, NH4 = 5, PN_abiotic = 24

### ECONET RESULTS ###

TotalSystemThroughflow: 7593.1
FinnsCyclingIndex: 0.89412
Indirect Effects Index: 56.4987
Ascendency: 6880.75
Development Capacity: 12610.7
Aggradation Index: 57.5013
Synergism Index: 4.70242
Mutualism Index: 1.88235
Homogenization Index: 2.0577

Run: 121
Original Matrix:
0.0000, 0.0000, 0.0000, 0.0057, 0.0637, 0.4876, 0.0000
0.1008, 0.0000, 0.0002, 0.0048, 0.0049, 0.4068, 0.0290
0.0091, 0.0001, 0.0000, 0.0000, 0.0003, 0.0108, 0.0091
0.0278, 0.0068, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.2169, 0.0001, 0.0000, 0.0000, 0.0000, 0.0000
0.0001, 0.0406, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000

Original Eigenvalues:
(0.3484 + 0.0000j)
(-0.1892 + 0.0000j)
(-0.1482 + 0.0000j)
(-0.0095 + 0.0000j)
(-0.0015 + 0.0000j)
(0.0000 + 0.0040j)
(0.0000 + 0.0040j)

R:
1.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.0000, 1.0000, 0.0000, 0.0000, 0.0000, 0.0000
0.0000, 1.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.0000, 0.0000, 1.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.0000, 0.0000, 0.0000, 1.0000, 0.0000, 0.0000
0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 1.0000, 0.0000
0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 1.0000

J:
0.0000, 0.0000, 0.0000, 0.0000, 0.0057, 0.0637, 0.4876
0.0910, 0.0000, 0.0001, 0.0000, 0.0000, 0.0000, 0.0000
0.1008, 0.0002, 0.0000, 0.0048, 0.0049, 0.4068, 0.0290
0.0278, 0.0068, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0772, 0.0000
0.0000, 0.2169, 0.0001, 0.0000, 0.0000, 0.0000, 0.0000
0.0001, 0.0406, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000
J Eigenvalues:
(0.3484+0.0000j)
(-0.1892+0.0000j)
(-0.1482+0.0000j)
(-0.0095+0.0000j)
(-0.0015+0.0000j)
(0.0000+0.0004j)
(0.0000-0.0004j)

######################## ECONET MODEL ########################

PN_phyto -> PN_phyto c=0.0;
PN_hetero -> PN_phyto c=0.0;
N_sed -> PN_phyto c=0.0;
DON -> PN_phyto c=5.7
;NOx -> PN_phyto c=63.7
;NH4 -> PN_phyto c=487.6
;PN_abiotic -> PN_phyto c=0.0;
PN_phyto -> PN_hetero c=9.1;
PN_hetero -> PN_hetero c=0.0;
N_sed -> PN_hetero c=0.1;
DON -> PN_hetero c=0.0;
NOx -> PN_hetero c=0.3;
NH4 -> PN_hetero c=10.8;
PN_abiotic -> PN_hetero c=9.1;
PN_phyto -> N_sed c=100.8;
PN_hetero -> N_sed c=0.2;
N_sed -> N_sed c=0.0;
DON -> N_sed c=4.8;
NOx -> N_sed c=4.9;
NH4 -> N_sed c=406.8;
PN_abiotic -> N_sed c=29.0;
PN_phyto -> DON c=27.8;
PN_hetero -> DON c=0.0;
N_sed -> DON c=6.8;
DON -> DON c=0.0;
NOx -> DON c=0.0;
NH4 -> DON c=0.0;
PN_abiotic -> DON c=0.0;
PN_phyto -> NOx c=0.0;
PN_hetero -> NOx c=0.0;
N_sed -> NOx c=0.0;
DON -> NOx c=0.0;
NOx -> NOx c=0.0;
NH4 -> NOx c=77.2;
PN_abiotic -> NOx c=0.0;
PN_phyto -> NH4 c=0.0;
PN_hetero -> NH4 c=0.1;
N_sed -> NH4 c=216.9;
DON -> NH4 c=0.0;
NOx -> NH4 c=0.0;
NH4 -> NH4 c=0.0;
PN_abiotic -> NH4 c=0.0;
PN_phyto -> PN_abiotic c=0.1;
PN_hetero -> PN_abiotic c=0.0;
N_sed -> PN_abiotic c=40.6;
DON -> PN_abiotic c=0.0;
NOx -> PN_abiotic c=0.0;
NH4 -> PN_abiotic c=0.0;
PN_abiotic -> PN_abiotic c=0.0;

# Initial State
* -> PN_phyto c=1
* -> PN_hetero c=4
* -> N_sed c=8
* -> DON c=27
* -> NOx c=64
* -> NH4 c=23
* -> PN_abiotic c=5

PN_phyto -> * c=0.25
PN_hetero -> * c=0
N_sed -> * c=0.06923
DON -> * c=0.3333
NOx -> * c=0.1429
NH4 -> * c=0.4
PN_abiotic -> * c=0.2917

# Initial values
PN_phyto = 24, PN_hetero = 22, N_sed = 1300
DON = 78, NOx = 7, NH4 = 5, PN_abiotic = 24

### ECONET RESULTS ###

TotalSystemThroughflow: 33025.8
FinnsCyclingIndex: 0.982871
Indirect Effects Index: 395.899
Ascendency: 27776.7
Development Capacity: 51951.4
Aggradation Index: 392.298
Synergism Index: 4.28803
Mutualism Index: 2.0625
Homogenization Index: 2.02601

Run: 122
Original Matrix:
0.0000, 0.0000, 0.0000, 0.0057, 0.0637, 0.4876, 0.0000
0.1008, 0.0000, 0.0002, 0.0048, 0.0049, 0.0290, 0.0000
0.0091, 0.0001, 0.0000, 0.0000, 0.0003, 0.0108, 0.0091
0.0278, 0.0068, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.2169, 0.0001, 0.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.0406, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000

Original Eigenvalues:
(0.3484+0.0000j)
(-0.1892+0.0000j)
(-0.1482+0.0000j)
(-0.0095+0.0000j)
(-0.0015+0.0000j)
(0.0000+0.0004j)
(0.0000+-0.0004j)

R:
1.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.0000, 1.0000, 0.0000, 0.0000, 0.0000, 0.0000
0.0000, 1.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.0000, 0.0000, 1.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.0000, 0.0000, 0.0000, 1.0000, 0.0000, 0.0000
0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 1.0000, 0.0000

J:
0.0000, 0.0000, 0.0000, 0.0570, 0.0637, 0.0000, 0.4876
0.0091, 0.0000, 0.0001, 0.0000, 0.0000, 0.0003, 0.0108
0.1008, 0.0002, 0.0000, 0.0048, 0.0049, 0.0290, 0.0406
0.0278, 0.0068, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0772
0.0001, 0.0000, 0.0406, 0.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.0001, 0.2169, 0.0000, 0.0000, 0.0000, 0.0000
J Eigenvalues:
(0.3484+0.0000j)
(-0.1892+0.0000j)
(-0.1482+0.0000j)
(-0.0095+0.0000j)
(-0.0015+0.0000j)
(0.0000+0.0004j)
(0.0000+0.0004j)

################################ ECONET MODEL ################################

PN_phyto -> PN_phyto c=0.0;
PNN hetero -> PN_phyto c=0.0;
N_sed -> PN_phyto c=0.0;
DON -> PN_phyto c=5.7
;NOx -> PN_phyto c=63.7
;NH4 -> PN_phyto c=0.0
;PN_abiotic -> PN_phyto c=487.6;
PN_phyto -> PN_hetero c=9.1;
PN_hetero -> PN_hetero c=0.0;
N_sed -> PN_hetero c=0.1;
DON -> PN_hetero c=0.0;
NOx -> PN_hetero c=0.3;
NH4 -> PN_hetero c=9.1;
PN_abiotic -> PN_hetero c=10.8;
PN_phyto -> N_sed c=100.8;
PN_hetero -> N_sed c=0.2;
N_sed -> N_sed c=0.0;
DON -> N_sed c=4.8;
NOx -> N_sed c=4.9;
NH4 -> N_sed c=29.0;
PN_abiotic -> N_sed c=406.8;
PN_phyto -> DON c=27.8;
PN_hetero -> DON c=0.0;
N_sed -> DON c=6.8;
DON -> DON c=0.0;
NOx -> DON c=0.0;
NH4 -> DON c=0.0;
PN_abiotic -> DON c=0.0;
PNN hetero -> NOx c=0.0;
PNN hetero -> NOx c=0.0;
N_sed -> NOx c=0.0;
DON -> NOx c=0.0;
NOx -> NOx c=0.0;
NH4 -> NOx c=0.0;
PN_abiotic -> NOx c=77.2;
PN_phyto -> NH4 c=0.1;
PN_hetero -> NH4 c=0.0;
N_sed -> NH4 c=40.6;
DON -> NH4 c=0.0;
NOx -> NH4 c=0.0;
NH4 -> NH4 c=0.0;
PN_abiotic -> NH4 c=0.0;
PN_phyto -> PN_abiotic c=0.0;
PN_hetero -> PN_abiotic c=0.1;
N_sed -> PN_abiotic c=216.9;
DON -> PN_abiotic c=0.0;
NOx -> PN_abiotic c=0.0;
NH4 -> PN_abiotic c=0.0;
PN_abiotic -> PN_abiotic c=0.0;

# Initial State
* -> PN_phyto c=1
* -> PN_hetero c=4
* -> N_sed c=8
* -> DON c=27
* -> NOx c=64
* -> NH4 c=23
* -> PN_abiotic c=5

PN_phyto -> * c=0.25
PN_hetero -> * c=0
N_sed -> * c=0.06923
DON -> * c=0.3333
NOx -> * c=0.1429
NH4 -> * c=0.4
PN_abiotic -> * c=0.2917

# Initial values

PN_phyto = 24, PN_hetero = 22, N_sed = 1300
DON = 78, NOx = 7, NH4 = 5, PN_abiotic = 24

### ECONET RESULTS ###

TotalSystemThroughflow: 32301.3
FinnsCyclingIndex: 0.982063
IndirectEffectsIndex: 378.054
Ascendency: 27212.7
DevelopmentCapacity: 50863.5
AggradationIndex: 374.296
SynergismIndex: 4.28408
MutualismIndex: 2.0625
HomogenizationIndex: 2.02625

Run: 123
Original Matrix:
0.0000,0.0000,0.0000,0.0057,0.0637,0.4876,0.0000
0.1008,0.0000,0.0002,0.0048,0.0049,0.4068,0.0290
0.0091,0.0001,0.0000,0.0000,0.0003,0.0108,0.0091
0.0278,0.0068,0.0000,0.0000,0.0000,0.0000,0.0000
0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0772
0.0000,0.2169,0.0001,0.0000,0.0000,0.0000,0.0000
0.0001,0.0406,0.0000,0.0000,0.0000,0.0000,0.0000

Original Eigenvalues:
(0.3484+0.0000j)
(-0.1892+0.0000j)
(-0.1482+0.0000j)
(-0.0095+0.0000j)
(-0.0015+0.0000j)
(0.0000+0.0004j)
(0.0000+0.0004j)

R:
1.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.0000,0.0000,1.0000,0.0000,0.0000,0.0000,0.0000
0.0000,1.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.0000,0.0000,0.0000,1.0000,0.0000,0.0000,0.0000
0.0000,0.0000,0.0000,0.0000,1.0000,0.0000,0.0000
0.0000,0.0000,0.0000,0.0000,0.0000,1.0000
0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,1.0000

J:
0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.0091,0.0000,0.0001,0.0000,0.0108,0.0003,0.0091
0.1008,0.0002,0.0000,0.0048,0.4068,0.0049,0.0290
0.0278,0.0000,0.0068,0.0000,0.0000,0.0000,0.0000
0.0000,0.0001,0.2169,0.0000,0.0000,0.0000,0.0000
0.0000,0.0000,0.0000,0.0000,0.0772,0.0000,0.0000
0.0001,0.0000,0.0406,0.0000,0.0000,0.0000,0.0000
J Eigenvalues:
(0.3484+0.0000j)
(-0.1892+0.0000j)
(-0.1482+0.0000j)
(-0.0095+0.0000j)
(-0.0015+0.0000j)
(0.0000+0.0004j)
(0.0000+0.0004j)

############################ ECONET MODEL ############################

PNPHYTO -> PNPHYTO c=0.0;
PNHETERO -> PNPHYTO c=0.0;
NSED  -> PNPHYTO c=0.0;
DON   -> PNPHYTO c=5.7;
NOX   -> PNPHYTO c=487.6;
NH4   -> PNPHYTO c=63.7;
PNABIOTIC -> PNPHYTO c=0.0;
PNPHYTO  -> PNHETERO c=9.1;
PNHETERO -> PNHETERO c=0.0;
NSED   -> PNHETERO c=0.1;
DON   -> PNHETERO c=0.0;
NOX   -> PNHETERO c=10.8;
NH4   -> PNHETERO c=0.3;
PNABIOTIC -> PNHETERO c=9.1;
PNPHYTO  -> NSED  c=100.8;
PNHETERO -> NSED  c=0.2;
NSED   -> NSED  c=0.0;
DON   -> NSED  c=4.8;
NOX   -> NSED  c=406.8;
NH4   -> NSED  c=4.9;
PNABIOTIC -> NSED  c=29.0;
PNPHYTO  -> DON  c=27.8;
PNHETERO -> DON  c=0.0;
NSED   -> DON  c=6.8;
DON   -> DON  c=0.0;
NOX   -> DON  c=0.0;
NH4   -> DON  c=0.0;
PNABIOTIC -> DON  c=0.0;
PNPHYTO  -> NOX  c=0.0;
PNHETERO -> NOX  c=0.1;
NSED   -> NOX  c=216.9;
DON   -> NOX  c=0.0;
NOX   -> NOX  c=0.0;
NH4 -> NOx c=0.0;
PN_abiotic -> NOx c=0.0;
PN_phyto -> NH4 c=0.0;
PN_hetero -> NH4 c=0.0;
N_sed -> NH4 c=0.0;
DON -> NH4 c=0.0;
NOx -> NH4 c=77.2;
NH4 -> NH4 c=0.0;
PN_abiotic -> NH4 c=0.0;
PN_phyto -> PN_abiotic c=0.1;
PN_hetero -> PN_abiotic c=0.0;
N_sed -> PN_abiotic c=40.6;
DON -> PN_abiotic c=0.0;
NOx -> PN_abiotic c=0.0;
NH4 -> PN_abiotic c=0.0;
PN_abiotic -> PN_abiotic c=0.0;

# Initial State
* -> PN_phyto c=1
* -> PN_hetero c=4
* -> N_sed c=8
* -> DON c=27
* -> NOx c=64
* -> NH4 c=23
* -> PN_abiotic c=5

PN_phyto -> * c=0.25
PN_hetero -> * c=0
N_sed -> * c=0.06923
DON -> * c=0.3333
NOx -> * c=0.1429
NH4 -> * c=0.4
PN_abiotic -> * c=0.2917

# Initial values
PN_phyto = 24, PN_hetero = 22, N_sed = 1300
DON = 78, NOx = 7, NH4 = 5, PN_abiotic = 24

### ECONET RESULTS ###

TotalSystemThroughflow: 32998.8
FinnsCyclingIndex: 0.982913
Indirect Effects Index: 394.538
Ascendency: 27630.0
Development Capacity: 51806.8
Aggradation Index: 391.281
Synergism Index: 4.29962
Mutualism Index: 2.0625
Homogenization Index: 2.02536

Run: 124
Original Matrix:
0.0000, 0.0000, 0.0000, 0.0000, 0.0057, 0.0637, 0.4876, 0.0000
0.1008, 0.0000, 0.0000, 0.0002, 0.0048, 0.0049, 0.4068, 0.0290
0.0091, 0.0001, 1.0000, 0.0000, 0.0000, 0.0003, 0.0108, 0.0091
0.0278, 0.0068, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.2169, 0.0001, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000
0.0001, 0.0406, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000

Original Eigenvalues:
(0.3484+0.0000j)
(-0.1892+0.0000j)
(-0.1482+0.0000j)
(-0.0095+0.0000j)
(-0.0015+0.0000j)
(0.0000+0.0004j)
(0.0000+-0.0004j)

R:
1.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.0000, 1.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000
0.0000, 1.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.0000, 0.0000, 1.0000, 0.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 1.0000, 0.0000, 0.0000
0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 1.0000, 0.0000
0.0000, 0.0000, 0.0000, 0.0000, 1.0000, 0.0000, 0.0000, 0.0000

J:
0.0000, 0.0000, 0.0000, 0.0000, 0.0057, 0.4876, 0.0000, 0.0637
0.0091, 0.0000, 0.0001, 0.0000, 0.0108, 0.0091, 0.0003
0.1008, 0.0002, 0.0000, 0.0048, 0.4068, 0.0290, 0.0049
0.0278, 0.0068, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.0001, 0.2169, 0.0000, 0.0000, 0.0000, 0.0000
0.0001, 0.0406, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000
0.0000, 0.0000, 0.0000, 0.0000, 0.0772, 0.0000, 0.0000
J Eigenvalues:
(0.3484+0.0000j)
(-0.1892+0.0000j)
(-0.1482+0.0000j)
(-0.0095+0.0000j)
(-0.0015+0.0000j)
(0.0000+0.0004j)
(0.0000+0.0000j)

############################ ECONET MODEL ##################################

PN_phyto -> PN_phyto c=0.0;
PN_hetero -> PN_phyto c=0.0;
N_sed -> PN_phyto c=0.0;
DON -> PN_phyto c=5.7
;NOx -> PN_phyto c=487.6
;NH4 -> PN_phyto c=0.0
;PN_abiotic -> PN_phyto c=63.7;
PN_phyto -> PN_hetero c=9.1;
PN_hetero -> PN_hetero c=0.0;
N_sed -> PN_hetero c=0.1;
DON -> PN_hetero c=0.0;
NOx -> PN_hetero c=10.8;
NH4 -> PN_hetero c=9.1;
PN_abiotic -> PN_hetero c=0.3;
PN_phyto -> N_sed c=100.8;
PN_hetero -> N_sed c=0.2;
N_sed -> N_sed c=0.0;
DON -> N_sed c=4.8;
NOx -> N_sed c=406.8;
NH4 -> N_sed c=29.0;
PN_abiotic -> N_sed c=4.9;
PN_phyto -> DON c=27.8;
PN_hetero -> DON c=0.0;
N_sed -> DON c=6.8;
DON -> DON c=0.0;
NOx -> DON c=0.0;
NH4 -> DON c=0.0;
PN_abiotic -> DON c=0.0;
PN_phyto -> NOx c=0.0;
PN_hetero -> NOx c=0.1;
N_sed -> NOx c=216.9;
DON -> NOx c=0.0;
NOx -> NOx c=0.0;
NH4 -> NOx c=0.0;
PN_abiotic -> NOx c=0.0;
PN_phyto -> NH4 c=0.1;
PN_hetero -> NH4 c=0.0;
N_sed -> NH4 c=40.6;
DON -> NH4 c=0.0;
NOx -> NH4 c=0.0;
NH4 -> NH4 c=0.0;
PN_abiotic -> NH4 c=0.0;
PN_phyto -> PN_abiotic c=0.0;
PN_hetero -> PN_abiotic c=0.0;
N_sed -> PN_abiotic c=0.0;
DON -> PN_abiotic c=0.0;
NOx -> PN_abiotic c=77.2;
NH4 -> PN_abiotic c=0.0;
PN_abiotic -> PN_abiotic c=0.0;

# Initial State
* -> PN_phyto c=1
* -> PN_hetero c=4
* -> N_sed c=8
* -> DON c=27
* -> NOx c=64
* -> NH4 c=23
* -> PN_abiotic c=5

PN_phyto -> * c=0.25
PN_hetero -> * c=0
N_sed -> * c=0.06923
DON -> * c=0.3333
NOx -> * c=0.1429
NH4 -> * c=0.4
PN_abiotic -> * c=0.2917

# Initial values
PN_phyto = 24, PN_hetero = 22, N_sed = 1300
DON = 78, NOx = 7, NH4 = 5, PN_abiotic = 24

### ECONET RESULTS ###

TotalSystemThroughflow: 32326.2
FinnsCyclingIndex: 0.982188
IndirectEffectsIndex: 377.323
Ascendency: 27050.0
DevelopmentCapacity: 50753.2
AggradationIndex: 374.494
SynergismIndex: 4.29792
MutualismIndex: 2.0625
HomogenizationIndex: 2.02587

Run: 125
Original Matrix:
0.0000,0.0000,0.0000,0.0057,0.0637,0.4876,0.0000
0.1008,0.0000,0.0000,0.0048,0.0049,0.4068,0.0290
0.0091,0.0001,0.0000,0.0000,0.0003,0.0108,0.0091
0.0278,0.0068,0.0000,0.0000,0.0000,0.0000,0.0000
0.0000,0.0000,0.0000,0.0000,0.0000,0.0772,0.0000
0.0000,0.2169,0.0001,0.0000,0.0000,0.0000,0.0000
0.0001,0.0406,0.0000,0.0000,0.0000,0.0000,0.0000

Original Eigenvalues:
(0.3484+0.0000j)
(-0.1892+0.0000j)
(-0.1482+0.0000j)
(-0.0095+0.0000j)
(-0.0015+0.0000j)
(0.0000+0.0004j)
(0.0000+-0.0004j)

R:
1.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.0000,0.0000,1.0000,0.0000,0.0000,0.0000,0.0000
0.0000,1.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.0000,0.0000,0.0000,1.0000,0.0000,0.0000,0.0000
0.0000,0.0000,0.0000,0.0000,0.0000,1.0000,0.0000
0.0000,0.0000,0.0000,0.0000,1.0000,0.0000,0.0000
0.0000,0.0000,0.0000,0.0000,1.0000,0.0000,0.0000

J:
0.0000,0.0000,0.0000,0.0057,0.0000,0.0637,0.4876
0.0091,0.0000,0.0001,0.0000,0.0091,0.0003,0.0108
0.1008,0.0002,0.0000,0.0048,0.0290,0.0049,0.4068
0.0278,0.0000,0.0068,0.0000,0.0000,0.0000,0.0000
0.0001,0.0000,0.0406,0.0000,0.0000,0.0000,0.0000
0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0772
0.0000,0.0001,0.2169,0.0000,0.0000,0.0000,0.0000
J Eigenvalues:
(0.3484+0.0000j)
(-0.1892+0.0000j)
(-0.1482+0.0000j)
(-0.0095+0.0000j)
(-0.0015+0.0000j)
(0.0000+0.0004j)
(0.0000+0.0004j)

################################ ECONET MODEL ################################

PN_phyto -> PN_phyto c=0.0;
PN_hetero -> PN_phyto c=0.0;
N_sed -> PN_phyto c=0.0;
DON -> PN_phyto c=5.7
;NOx -> PN_phyto c=0.0
;NH4 -> PN_phyto c=63.7
;PN_abiotic -> PN_phyto c=487.6;
PN_phyto -> PN_hetero c=9.1;
PN_hetero -> PN_hetero c=0.0;
N_sed -> PN_hetero c=0.1;
DON -> PN_hetero c=0.0;
NOx -> PN_hetero c=9.1;
NH4 -> PN_hetero c=0.3;
PN_abiotic -> PN_hetero c=10.8;
PN_phyto -> N_sed c=100.8;
PN_hetero -> N_sed c=0.2;
N_sed -> N_sed c=0.0;
DON -> N_sed c=4.8;
NOx -> N_sed c=29.0;
NH4 -> N_sed c=4.9;
PN_abiotic -> N_sed c=406.8;
PN_phyto -> DON c=27.8;
PN_hetero -> DON c=0.0;
N_sed -> DON c=6.8;
DON -> DON c=0.0;
NOx -> DON c=0.0;
NH4 -> DON c=0.0;
PN_abiotic -> DON c=0.0;
PN_phyto -> NOx c=0.1;
PN_hetero -> NOx c=0.0;
N_sed -> NOx c=40.6;
DON -> NOx c=0.0;
NOx -> NOx c=0.0;
NH4 -> NOx c=0.0;
PN_abiotic -> NOx c=0.0;
PN_phyto -> NH4 c=0.0;
PN_hetero -> NH4 c=0.0;
N_sed -> NH4 c=0.0;
DON -> NH4 c=0.0;
NOx -> NH4 c=0.0;
NH4 -> NH4 c=0.0;
PN_abiotic -> NH4 c=77.2;
PN_phyto -> PN_abiotic c=0.0;
PN_hetero -> PN_abiotic c=0.1;
N_sed -> PN_abiotic c=216.9;
DON -> PN_abiotic c=0.0;
NOx -> PN_abiotic c=0.0;
NH4 -> PN_abiotic c=0.0;
PN_abiotic -> PN_abiotic c=0.0;

# Initial State
* -> PN_phyto c=1
* -> PN_hetero c=4
* -> N_sed c=8
* -> DON c=27
* -> NOx c=64
* -> NH4 c=23
* -> PN_abiotic c=5

PN_phyto -> * c=0.25
PN_hetero -> * c=0
N_sed -> * c=0.06923
DON -> * c=0.3333
NOx -> * c=0.1429
NH4 -> * c=0.4
PN_abiotic -> * c=0.2917

# Initial values
PN_phyto = 24, PN_hetero = 22, N_sed = 1300
DON = 78, NOx = 7, NH4 = 5, PN_abiotic = 24

### ECONET RESULTS ###

TotalSystemThroughflow: 33733.3
FinnsCyclingIndex: 0.98393
Indirect Effects Index: 422.047
Ascendency: 28360.7
Development Capacity: 53035.9
Aggradation Index: 418.317
Synergism Index: 4.28248
Mutualism Index: 2.0625
Homogenization Index: 2.02502

Run: 126
Original Matrix:

0.0000,0.0000,0.0000,0.0000,0.0007,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.1008,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.0991,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.0278,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.0000,0.2169,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.0000,0.0406,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000

Original Eigenvalues:

(0.3484+0.0000j)
(-0.1892+0.0000j)
(-0.1482+0.0000j)
(-0.0095+0.0000j)
(-0.0015+0.0000j)
(0.0000+0.0004j)
(0.0000+-0.0004j)

R:
1.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000

J:
0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.0991,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.1008,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.0278,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.0001,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000
J Eigenvalues:
(0.3484+0.0000j)
(-0.1892+0.0000j)
(-0.1482+0.0000j)
(-0.0095+0.0000j)
(-0.0015+0.0000j)
(0.0000+0.0004j)
(0.0000+0.0004j)

################################ ECONET MODEL ################################

PN_phyto -> PN_phyto c=0.0;
PN_hetero -> PN_phyto c=0.0;
N_sed -> PN_phyto c=0.0;
DON -> PN_phyto c=5.7
;NOx -> PN_phyto c=0.0
;NH4 -> PN_phyto c=487.6
;PN_abiotic -> PN_phyto c=63.7;
PN_phyto -> PN_hetero c=9.1;
PN_hetero -> PN_hetero c=0.0;
N_sed -> PN_hetero c=0.1;
DON -> PN_hetero c=0.0;
NOx -> PN_hetero c=9.1;
NH4 -> PN_hetero c=10.8;
PN_abiotic -> PN_hetero c=0.3;
PN_phyto -> N_sed c=100.8;
PN_hetero -> N_sed c=0.2;
N_sed -> N_sed c=0.0;
DON -> N_sed c=4.8;
NOx -> N_sed c=29.0;
NH4 -> N_sed c=406.8;
PN_abiotic -> N_sed c=4.9;
PN_phyto -> DON c=27.8;
PN_hetero -> DON c=0.0;
N_sed -> DON c=6.8;
DON -> DON c=0.0;
NOx -> DON c=0.0;
NH4 -> DON c=0.0;
PN_abiotic -> DON c=0.0;
PN_phyto -> NOx c=0.1;
PN_hetero -> NOx c=0.0;
N_sed -> NOx c=40.6;
DON -> NOx c=0.0;
NOx -> NOx c=0.0;
NH4 -> NOx c=0.0;
PN_abiotic -> NOx c=0.0;
PN_phyto -> NH4 c=0.0;
PN_hetero -> NH4 c=0.1;
N_sed -> NH4 c=216.9;
DON -> NH4 c=0.0;
NOx -> NH4 c=0.0;
NH4 -> NH4 c=0.0;
PN_abiotic -> NH4 c=0.0;
PN_phyto -> PN_abiotic c=0.0;
PN_hetero -> PN_abiotic c=0.0;
N_sed -> PN_abiotic c=0.0;
DON -> PN_abiotic c=0.0;
NOx -> PN_abiotic c=0.0;
NH4 -> PN_abiotic c=77.2;
PN_abiotic -> PN_abiotic c=0.0;

# Initial State
* -> PN_phyto c=1
* -> PN_hetero c=4
* -> N_sed c=8
* -> DON c=27
* -> NOx c=64
* -> NH4 c=23
* -> PN_abiotic c=5

PN_phyto -> * c=0.25
PN_hetero -> * c=0
N_sed -> * c=0.06923
DON -> * c=0.3333
NOx -> * c=0.1429
NH4 -> * c=0.4
PN_abiotic -> * c=0.2917

# Initial values
PN_phyto = 24, PN_hetero = 22, N_sed = 1300
DON = 78, NOx = 7, NH4 = 5, PN_abiotic = 24

### ECONET RESULTS ###

TotalSystemThroughflow: 33785.6
FinnsCyclingIndex: 0.984
IndirectEffectsIndex: 422.688
Ascendency: 28345.0
DevelopmentCapacity: 53070.7
AggradationIndex: 419.656
SynergismIndex: 4.28445
MutualismIndex: 2.0625
HomogenizationIndex: 2.02529

Run: 127
Original Matrix:
0.0000,0.0000,0.0000,0.0057,0.0637,0.4876,0.0000
0.1008,0.0000,0.0002,0.0048,0.0049,0.4068,0.0290
0.0091,0.0001,0.0000,0.0000,0.0003,0.0108,0.0091
0.0278,0.0068,0.0000,0.0000,0.0000,0.0000,0.0000
0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0772,0.0000
0.0000,0.2169,0.0001,0.0000,0.0000,0.0000,0.0000,0.0000
0.0001,0.0406,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000

Original Eigenvalues:
(0.3484+0.0000j)
(-0.1892+0.0000j)
(-0.1482+0.0000j)
(-0.0095+0.0000j)
(-0.0015+0.0000j)
(0.0000+0.0004j)
(0.0000+-0.0004j)

R:
1.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.0000,0.0000,1.0000,0.0000,0.0000,0.0000,0.0000
0.0000,1.0000,0.0000,0.0000,0.0000,0.0000,0.0000
0.0000,0.0000,0.0000,0.0000,1.0000,0.0000,0.0000
0.0000,0.0000,0.0000,0.0000,0.0000,1.0000,0.0000
0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,1.0000
0.0000,0.0000,0.0000,0.0000,0.0000,0.0000,0.0000

J:
0.0000,0.0000,0.0000,0.0637,0.0057,0.4876,0.0000
0.0091,0.0000,0.0001,0.0003,0.0000,0.0108,0.0091
0.1008,0.0002,0.0000,0.0049,0.0048,0.4068,0.0290
0.0000,0.0000,0.0000,0.0000,0.0000,0.0772,0.0000
0.0278,0.0000,0.0068,0.0000,0.0000,0.0000,0.0000
0.0000,0.0001,0.2169,0.0000,0.0000,0.0000,0.0000
0.0001,0.0406,0.0000,0.0000,0.0000,0.0000,0.0000

308
J Eigenvalues:
(0.3484+0.0000j)
(-0.1892+0.0000j)
(-0.1482+0.0000j)
(-0.0095+0.0000j)
(-0.0015+0.0000j)
(0.0000+0.0004j)
(0.0000+0.0004j)

################################ ECONET MODEL ################################

PN_phyto -> PN_phyto c=0.0;
PN_hetero -> PN_phyto c=0.0;
N_sed -> PN_phyto c=0.0;
DON -> PN_phyto c=63.7
:NOx -> PN_phyto c=5.7
;NH4 -> PN_phyto c=487.6
;PN_abiotic -> PN_phyto c=0.0;
PN_phyto -> PN_hetero c=9.1;
PN_hetero -> PN_hetero c=0.0;
N_sed -> PN_hetero c=0.1;
DON -> PN_hetero c=0.3;
NOx -> PN_hetero c=0.0;
NH4 -> PN_hetero c=10.8;
PN_abiotic -> PN_hetero c=9.1;
PN_phyto -> N_sed c=100.8;
PN_hetero -> N_sed c=0.2;
N_sed -> N_sed c=0.0;
DON -> N_sed c=4.9;
NOx -> N_sed c=4.8;
NH4 -> N_sed c=406.8;
PN_abiotic -> N_sed c=29.0;
PN_phyto -> DON c=0.0;
PN_hetero -> DON c=0.0;
N_sed -> DON c=0.0;
DON -> DON c=0.0;
NOx -> DON c=0.0;
NH4 -> DON c=77.2;
PN_abiotic -> DON c=0.0;
PN_phyto -> NOx c=27.8;
PN_hetero -> NOx c=0.0;
N_sed -> NOx c=6.8;
DON -> NOx c=0.0;
NOx -> NOx c=0.0;
NH4 -> NOx c=0.0;
PN_abiotic -> NOx c=0.0;
PN_phyto -> NH4 c=0.0;
PN_hetero -> NH4 c=0.1;
N_sed -> NH4 c=216.9;
DON -> NH4 c=0.0;
NOx -> NH4 c=0.0;
NH4 -> NH4 c=0.0;
PN_abiotic -> NH4 c=0.0;
PN_phyto -> PN_abiotic c=0.1;
PN_hetero -> PN_abiotic c=0.0;
N_sed -> PN_abiotic c=40.6;
DON -> PN_abiotic c=0.0;
NOx -> PN_abiotic c=0.0;
NH4 -> PN_abiotic c=0.0;
PN_abiotic -> PN_abiotic c=0.0;

# Initial State
* -> PN_phyto c=1
* -> PN_hetero c=4
* -> N_sed c=8
* -> DON c=27
* -> NOx c=64
* -> NH4 c=23
* -> PN_abiotic c=5

PN_phyto -> * c=0.25
PN_hetero -> * c=0
N_sed -> * c=0.06923
DON -> * c=0.3333
NOx -> * c=0.1429
NH4 -> * c=0.4
PN_abiotic -> * c=0.2917

# Initial values

PN_phyto = 24, PN_hetero = 22, N_sed = 1300
DON = 78, NOx = 7, NH4 = 5, PN_abiotic = 24

### ECONET RESULTS ###

TotalSystemThroughflow: 37930.6
FinnsCyclingIndex: 0.988091
IndirectEffectsIndex: 572.847
Ascendency: 31768.6
DevelopmentCapacity: 59475.1
AggradationIndex: 565.438
SynergismIndex: 4.28311
MutualismIndex: 2.0625
HomogenizationIndex: 2.02288