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A Complex Systems Simulation Study for Increasing Adaptive-Capacity

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Abstract

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Dissertation Submitted in Partial Fulfillment

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Abstract

Examination of empirical research confirmed that climate change is a complex problem of anthropological origin and revealed the need for a management framework to facilitate strategic decisions aimed at mitigating a rise in global temperatures of 2°C linked to irresponsible and unsustainable business practices. The purpose of this simulation study was to develop a management framework of resilience, robustness, sustainability, and adaptive-capacity (RRSA) for organizations viewed as complex systems to address the current unsustainable state. As such, the evolutionary-RRSA prisoner's dilemma (PD) simulation was developed using an evolutionary game theory approach to agent based modeling and simulation, to generate data. Regression analyses tested the relationships between organizational resilience (x_1), robustness (x_2), and sustainability (x_3) as independent variables, and the dependent variable of adaptive capacity (y) for cooperative and defective strategies. The findings were that complex nonlinear relationships exist between resilience, robustness, sustainability, and adaptive-capacity, which is sensitive to initial conditions and may emerge and evolve from combinations of cooperative and defective decisions within the evolutionary RRSA PD management tool. This study resulted in the RRSA management framework, a cyclical 4-phased approach, which may be used by climate governance leaders, negotiators, and policy-makers to facilitate strategy to move global climate change policy forward by guiding bottom-up consumption and production of GHGs, thereby improving adaptive-capacity, while mitigating an increase in global temperatures of 2°C, which in turn would improve global socio-economic conditions.

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Dedication

For Paulo, who was always by my side providing unconditional love and support, patiently waiting for me to finish my work, and Fuji and Dickens, who were strong enough to make it to this point and who have taught me the true meaning of devotion.

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Chapter 1: Introduction to the Study

While Cartesian reductionism dominated scientific inquiry from its birth in the 1600s until the late 19th century, current tools offered by science are not adequate for understanding complex systems such as living organisms, diseases, the human brain and immune system, computational intelligence, and consciousness in their entirety (Midgley, 2003). Similarly, climate change falls within the ambit of complex systems not adequately explained via reductionism. Emergent in nature, the phenomenon of climate change is different from the sum of its parts, arising from a plethora of human activities. Not negating the natural contribution of carbon dioxide and other greenhouse gas (GHG) emissions, the anthropological contribution outweighs the latter; with up to 75% of emissions deriving from cities (Bulkeley, 2010), anthropogenic activities are considered the fundamental driver of climate change (Stocker, 2014; Tosun & Schoenefeld, 2017). From this perspective, it is pertinent and critical to understand the role of organizations as representing the pinnacle form of anthropological complexity and the role of governance as representing the pinnacle form of managerial leadership in mitigating the emergence of climate change and its deleterious consequences. Consequently, a much-needed framework for management and leadership was derived based on the hypothesis that a positive relationship exists between resilience, robustness, sustainability (RRS) and adaptive capacity for cooperative climate governance structures.

This chapter includes the background of the study, the problem, and purpose statements. Additionally, the research question and hypotheses are presented followed by the theoretical foundation. Thereafter the nature of the study is discussed, and definitions of variables, key terms, as well as the main assumptions of the study are presented. Consequently, the scope, delimitations, scope, and limitations are discussed. This chapter includes the significance of the study, and the study's significance to theory, practice, and social change, concluding a summary and transition to Chapter 2.

Background of the Study

Descartes developed the Cartesian coordinate system in the early 17th century, which informed the dominating scientific view of Cartesian reductionism, scientific reductionism, or hard science, an approach to understanding problems and/or systems in terms of their constituent parts, which served as the dominant paradigm of scientific inquiry from its inception until the late 19th century. Through the lens of reductionism, systems including the biological body are viewed as machines, with the mind being separate, constituting the Cartesian dualistic machine metaphor view of mind/body, which is still adopted by many today. While simple systems are adequately understood through the lens of Cartesian reductionism; for example, it is possible to understand how a clock works by examining its individual cogs, springs, and other parts, which when assembled enable the clock to function as a machine as expected; the clock does not exhibit any unexpected behavior. However, the same cannot be said for a frog. The parts of a frog do not explain why it may choose to sit on a lily pad one day and a rock on another day; the frog unlike the clock is unpredictable; there is something extra or emergent in the behavior of the said frog. The frog cannot be completely understood in terms of its parts, representing one of a multitude of complex problems unanswered by reductionism. The latter became less appealing as the dominant scientific paradigm in the

20th century as a result of its inadequacy to address complex problems and systems such as economies, insect colonies, climate change, the world wide web, adaptation by living organisms and diseases, the human brain and immune system, computational intelligence, and understanding consciousness. In response to this inadequacy, the counter-reductionist view that the whole is greater than or different from the sum of its parts, capable of adaptation, emerged with the advent of systems, chaos and network theories. Institutionally, the Santa Fe Institute was founded in 1984 for the study of complex systems, viewed as an interdisciplinary field of research.

Complex systems such as human civilizations and social insects exhibit common properties such as complex collective behavior, signal and information processing such as optic flow matching in bees (Klein, Cabirol, Devaud, Barron, & Lihoreau, 2017), and adaptation such as various species acquiring additional physical or behavioral traits better suited to their environments. Posed as a solution to the questions unanswered by reductionism, complexity science requires methods and means of quantitative measurement, in addition to the qualitative descriptions of complexity discussed above. Examination of the quantitative nature of complexity in the literature reveals that no single theory of complexity exists; instead, complexity might be quantitatively described using dynamical systems theory, chaos theory, information theory, and prediction (Mitchell, 2009).

Holland (1992) articulated that the common properties or universal features of complex systems were significant enough to group them collectively under the rubric of complex adaptive systems (CASs). Holland argued that the common principles of CASs, which are discussed in the theoretical foundation section of Chapter 2, provide a structural foundation for the development of computation-based models that could potentially inform decision-making to address critical leadership problems. Influentially, Holland’s work emphasized the role of computational models in understanding CASs and assisting experts, despite their potential lack of expertise in the field of computer science, to formulate decisions.

Manson, Sun, and Bonsal (2012) articulated that complexity theory provides a common language or rubric for examining complex systems, specifically with the use of agent-based modeling and simulation (ABMS). Thus, by complexity theory providing the necessary conceptual foundation for modeling and ABMS affording researchers the tools to represent complex systems in less rhetorical ways, the relationship between ABMS and complexity is mutually beneficial (Manson et al., 2012). Moreover, the intersection between complexity and ABMS is applicable to a wide range of disciplines including policy fields, natural sciences, and social sciences, enabling the shift between theoretical and empirical research over multiple scales, such as cells in a living organism to the movement of galaxies, the management of information systems within organizations, and beyond (Manson et al., 2012).

Dynamical systems theory provides tools and methods for quantitatively describing and predicting how CASs behave, work, and change over time in general terms (Levin et al., 2013; Weaver, 1948). The use of dynamical systems theory is not applicable to nonchaotic CASs. Dooley and Van de Ven (1999) and Guastello (2013) provided a complex systems dynamical perspective of organization, supporting the view that complex networked organizations might be sensitive to initial conditions.

Central to the study of CASs is network theory, which enables understanding structure and consequent function, ranging from how to control epidemics and manage large organizations to the preservation of endangered species. Resilience is a functional advantage of the scale-free network structure of CASs that display power law distributions (Barabasi, 2014). Hofstadter (as cited in Mitchell, 2009) discussed robustness, efficiency, and evolvability as advantages of the networked structure of CASs, the architecture of which is fine-grained, with the simple components of the system working together in a highly parallel manner, and providing the capability of parallel terraced scans or multiple simultaneous searches of several pathways as displayed by ant colonies (Rehling & Hofstadter, 1997). Redundancy is an important feature of fine-grained systems in that it allows for processing of statistical information in organizations as CASs and their consequential resilience to emergent perturbations such as climate change (Linnenluecke & Griffiths, 2012). Redundancy allows for the rendering of actions as consequential only when taken by numerous components, thereby guiding the design of robust systems in the form of degeneracy, which is the partial redundancy of functions or capabilities of components in a system (Whitacre & Bender, 2010).

Closely linked to complexity theory is evolutionary game theory, which as a key foundational tool of decision-sciences provides valuable sagacity into the emergence and sustainability of cooperation at various levels of organization (Axelrod, 1984). The N-

Person Prisoner's Dilemma Public Goods Game (NPD PGG) has specifically been discussed and studied at length in the literature following Axelrod's finding that the Tit-for-Tat (TfT) strategy outperformed all other strategies for achieving reciprocal altruism. The NPD as an archetypal PGG involves N number of players consisting of cooperators (C) and defectors (D). The cooperators contribute to the cost c of a public good, whereas the defectors do not. The NPD is played by giving all participants a chance to cooperate and contribute to c, and at the end of a round, the total contribution is divided equally among all players after being multiplied by an incentive factor I (Pacheco, Santos, Souza, & Skyrms, 2009). Hence, the free-riding problem emerges, which involves Ds benefiting from the efforts of Cs while simultaneously defecting (Bulkeley & Newell, 2015). In other words, if there were m number of contributors, then the defectors get the contribution mIc/N, whereas the contributors only get $mIc/N - c$. Ergo in heterogeneous groups the defectors always win. Thus, the NPD has significance as a means of understanding the decision dynamics associated with climate change negotiations, as climate change is viewed as a tragedy of the commons problem in the literature, which is approached using various types of PGG game theories, the most predominant being NPD (Bulkeley & Newell, 2015; Olson, 1965; Ostrom, 1990).

Synthesis of the literature on dynamical processes in CASs reveals that sociotechnical systems such as organizations display the information processing and computational optimization processes of dynamical systems (Vespignani, 2012). However, there is a need for a conceptual management framework, based on the models of evolutionary game theory and dynamical systems presented in the current literature that guides the prediction and control of organizational dynamical processes. I addressed this gap by demonstrating that organizations are sensitive to initial conditions, using evolutionary game theory characteristics to model agents as organizations (state, private, transnational, and community), and tested four types of climate governance structures using evolutionary PD. A management framework for resilience, robustness, and sustainability (RRS) was developed in this study.

Problem Statement

Empirical research clearly confirms that climate change and global warming are complex wicked problems of anthropological origin (Barnes et al., 2013). These problems consist of multiple levels of sociopolitical, socioeconomic (Berkhout, 2012), and socioecological subproblems linked to irresponsible and unsustainable business practices, industrialized farming, speciesism, extinction, and the use of fossil fuels for transportation and energy generation (Hall & Vredenburg, 2012) to name a few. As organizations constitute some of the largest complex human systems, the anthropological contribution of organizations to global warming and climate change must be examined and understood to develop solutions for the problems stemming from the lack of adaptive capacity to climate change (Moore, 2012). Furthermore, scholars have theorized that organizations constitute complex evolutionary and networked organisms (see Mitchell, 2009); however, scientific literature points to a lacuna or gap for a framework to understand the role of organizations, specifically within the context of information systems management, in mitigating climate change and global warming. Therefore, the specific problem was the lack of a management decision framework for increasing adaptive capacity to climate change via the mechanisms RRS, which facilitate the improvement of climate governance strategies.

Purpose of the Study

The purpose of this quantitative computational experimental study was to develop a management decision framework of resilience, robustness, sustainability, and adaptive capacity (RRSA) for climate governance organizations (state, private, transnational, and community) viewed as complex evolutionary systems to transcend the current unsustainable state. Thus, I tested the hypothesis that a positive relationship exists between organizational resilience, defined as the amplitude of organizational deviation tolerance possible, before returning to an expected output level. Robustness was defined as the measure of organizational deviation from an expected outcome due to perturbation; sustainability was defined as the length of time (number of time steps) the system is able to remain resilient; and adaptive capacity was defined as the quantitative increase in complicated dynamics, emergent self-organized behavior, and information processing ability for cooperative climate governance decisions, else for defective decisions, the relationship between the variables is negative for evolutionary-RRSA, evolutionary-TfT, cooperate, and defect PD games. The objective was to relate the evolutionary traits of resilience, robustness, and sustainability (independent variables) to the adaptive capacity (dependent variable) of organizations using an originally developed evolutionary PD simulation in Netlogo and statistical variable-based modeling in Excel. The evolutionary game theory rules of PD have been adapted for this study to understand the complex dynamics of RRSA embedded in climate change decision-making structures that either limit or facilitate adaptive capacity. The independent variables of resilience, robustness, and sustainability were defined in evolutionary game theory terms for the purpose of this study. The dependent variable of adaptive capacity was defined as the quantitative increase in adaptive behaviors agents in NetLogo, (i.e., a quantitative increase in complicated dynamics, emergent self-organized behavior, and information processing ability).

This study may provide insight into a lacuna in the current literature on understanding the relationship between organizational resilience, robustness, sustainability, and organizational adaptability, from a complex evolutionary systems perspective using a quantitative strategy of inquiry. Greater knowledge of this relationship may be used to facilitate strategic management and decision making in addition to moving policy forward in a positive socioeconomic manner. Furthermore, this study has implications for the objectives of the United Nations Framework Convention on Climate Change (UNFCCC) concerning the adaptation of developing countries to climate change and the devastating effects of noncompliance if global policy, as indeed a function of management and decision making does not move forward in a positive manner.

Research Question and Hypotheses

Research question: What is the relationship (linear, superlinear, sublinear, power law, or other) between organizational resilience (x_1), robustness (x_2), and sustainability (x_3) and adaptive capacity (X_{t+1}) for cooperative and defective climate governance strategies?

Null hypothesis (H_0): There is no relationship between the independent variables of organizational resilience, robustness, and sustainability as integral components of complex evolutionary systems, and adaptive capacity (dependent variable) for cooperative and defective climate governance decisions that constitute PD strategies.

Alternate hypothesis (H_1): A relationship exists between the independent variables of organizational resilience, robustness, and sustainability as integral components of complex evolutionary systems, and adaptive capacity (dependent variable) for cooperative strategies of climate governance involved in PD strategies.

Alternate hypothesis (H_2): A negative relationship exists between the independent variables of organizational resilience, robustness, and sustainability as integral components of complex evolutionary systems, and adaptive capacity (dependent variable) for defective decisions of climate governance involved in PD strategies.

Alternate hypothesis (H_3): Organizations represent dynamical complex adaptive systems that display sensitive dependence to initial conditions.

Using evolutionary game theory dynamics, I examined the relationship between organizational resilience, robustness, sustainability, and adaptive capacity. The boundary limitations for this model were set quantitatively by using agents to represent climate government organizations. Specifically, ABMS using an originally developed evolutionary PD simulation on the NetLogo platform in combination with statistical modeling in Excel was used.

Theoretical Foundation

Evolutionary game theory, specifically N-Person PD (Axelrod, 1984), network (Barabasi, 2014), complexity (Mitchell, 2009; Weaver, 1948), CAS, and dynamical systems (Lyon & Lyon, 1975) were applicable to this study, and are discussed in greater detail in Chapter 2. Recent applications of dynamical systems theory include bifurcation and stability analysis for studying complex adaptive systems (Ruelle, 2014). Anderies et al. (2013) stated the relevance of dynamical systems theory to the study of adaptation, decision making, and the alignment of resilience, robustness, and sustainability for moving global change forward.

Nature of the Study

Specifically, an evolutionary game theory approach to ABMS, using an originally developed evolutionary PD simulation on the NetLogo platform and statistical modeling in Excel tested the hypothesis that a positive relationship exists between resilience, robustness, and sustainability as independent variables, and the dependent variable of adaptive capacity. Stated another way, a simulation study was used to generate the data for testing the hypothesis that the evolutionary game theory rules governing the traits of resilience, robustness, and sustainability give rise to the emergent phenomenon of adaptive capacity for cooperative strategies of climate governance and reciprocal altruism (i.e., TfT); otherwise, adaptive capacity is compromised, (i.e., there is a decrease in emergent self-organized behavior of agents) for defective climate governance strategy scenarios, *D*. As such, in this quantitative computational experimental study, I employed a bimodal design using ABMS and statistical modeling for developing a framework for organizations viewed as complex evolutionary systems to transcend the current unsustainable state of organization.

Definitions

Agents: Organizations within the modified basic evolutionary PD simulation used for this study. The terms agents, players, and organizations are used synonymously in this study.

Chaos: A regime of behavior in a deterministic, nonlinear dynamical system, deterministic in the sense that chaotic systems are predictable in pattern (Dooley & Van de Ven, 1999), exhibiting sensitive dependence to initial conditions, infinite recurrence, boundedness, one or more Lyapunov exponents (Vaidyanathan, 2015; Wolf, Swift, Swinney & Vastano, 1985), and lower dimensionality than truly random systems that have high to infinite dimensionality (Dooley & Van de Ven).

Complicated dynamics: The collective outcomes of the components of CAs following simple rules (Mitchell, 2009).

Edge of chaos: Regions before and after the chaotic region that display long-lived localized structures and fall within Wolfram's Class 4, such as Rule 110 (Mitchell, 2009).

Emergence: Interesting, hard to predict, yet organized behavior (Crutchfield, 1994).

Entropy: The heat that is lost when energy is transformed from one state to another via work. Entropy is a way of characterizing disorder that assumes all microstates are equally probable defined by the equation $S = k \text{ Log } W$, where S is the macrostate, W is the corresponding number of microstates for that macrostate, and k is Boltzmann's constant. According to the second law of thermodynamics, entropy increases until it reaches a maximum value (Boyd & Crutchfield, 2016; Wolfram, 1983).

Fixed-point: State of behavior of cellular automata defined by a highly organized structure with low entropy (Dooley & Van de Ven, 1999).

Information processing: A type of emergent behavior characterized by the system gaining information about itself and its environment and the use of such information for making decisions about what actions to take (Linnenluecke & Griffiths, 2012).

Lyapunov exponent: The average exponential rate at which small perturbations grow in phase space (Wolf et al., 1985).

Macrostate: Collection or set of microstates (Ryan, 2007).

Microstate: Detailed configuration of system components (Ryan, 2007).

Nonlinearity: A necessary but not sufficient condition for emergence (Ryan, 2007).

Ordinary differential equation (ODE): A differential equation that expresses a set of constraints among the derivatives of an unknown function (Paliathanasis & Leach, 2016). For example, $\frac{d}{dt}x(\mathrm{t}) = ax(\mathrm{t})$,

(1)

which means that the derivative of the unknown function x(t), is equal to a times the unknown function itself. The differential $\frac{d}{dt}x(\mathrm{t})$ is often annotated as $\frac{dx}{dt}$, or simply as $\dot{x}$ or x', thus equation (1) becomes $\dot{x} = ax$.

Self-organization: Resultant patterns of an organization from localized interactions between the components of a system in the absence of central control, including such behaviors as flocking, schooling, clustering, decision-making, foraging, task allocation, and synchronization (Sayama, 2015).

Sensitive dependence to initial conditions: Small changes to the initial conditions of a dynamical chaotic system (Goldenfield & Kadanoff, 1999) result in large errors in predication due to reshuffling of the loops (Kadanoff, 1993).

Shannon information content: The adaptation of Boltzmann's concept of statistical mechanics to information measured or computed using the equation $H = -\sum_{i=1}^{M} piLog2\ pi$, where H is the message source measured in bits, and M is the possible number of messages with probability p (Bar-Yam & Yaneer, 1997).

Statistical mechanics: A general mathematical framework that shows how macroscopic properties emerge or arise from statistics of the mechanics of large numbers of microscopic components (Bar-Yam & Yaneer, add missing year here).

Statistical mechanics entropy: The number of possible microstates that lead to a macrostate (Mitchell, 2009).

Symbolic dynamics: The mapping of a set of numbers according to a specific rule (Wolfram, 1983).

Independent Variables

Organizational resilience (x_1): The amplitude of organizational deviation tolerance possible before returning to an expected output level (Wu et al., 2009).

Organizational robustness (x_2): The measure of organizational stability in fulfilling an expected outcome despite environmental perturbations (i.e., deviation from an expected outcome), according to Wu et al. (2009).

Organizational sustainability (x_3): The length of time (number of time steps) the system is able to remain resilient (Wu et al., 2009).

Dependent Variable

Adaptive capacity (x_{t+1}): The quantitative increase in complicated dynamics, emergent self-organized behavior, and information processing ability (Mitchell, 2009).

Assumptions

Organizations Viewed as Dynamical Systems

This study was developed on the assumption that organizations represent dynamical systems that display the properties of information processing and computational optimization therewith associated (Guastello, 2013). A chaotic system is one type of deterministic nonlinear dynamical system, which organizations may or may not be (Mitchell, 2009). Organizations as dynamical systems may only be characterized as chaotic if they satisfy three properties: sensitive dependence on initial conditions, infinite recurrence, and boundedness (Vaidyanathan, 2015). According to Wolf et al. (1985), a dynamical system may be classified as chaotic by demonstrating one or more positive Lyapunov exponents. The assumption that organizations can be treated as dynamical systems is mathematically relevant for this study to use the logistic map equation for modeling purposes.

Prisoner's Dilemma Adequately Represents Climate Governance Decision Dynamics

As previously discussed, climate change is a tragedy of the commons problem, which presents the risk of players (nations, states, organizations, and so on) unilaterally opting to be free-riders, by not cooperating while benefitting from the efforts of others, as evidenced by the International Panel on Climate Change (IPCC) negotiations (Bulkeley & Newell, 2015). One of the challenges associated with such N-Person PGG is the coordination of collective action into cooperation (Tosun & Schoenefeld, 2017). As discussed in the literature review, Hurlstone, Wang, Price, Leviston, and Walker (2017) further clarified the role of collective action in successful climate negotiations using a game theoretic perspective, underscored by the problems of free-riding and the tragedy of the commons, and elucidated the applicability of evolutionary game theory, specifically the PD, for understanding certain conditions of climate negotiation, resulting in either cooperation (i.e., collaborative governance) or defection, and opined that the only PD Nash equilibrium is defection. However, I posit an alternative approach for cooperation considering the hypothesis that a positive relationship exists between RRS and adaptive capacity for cooperative strategies, thereby providing an incentive for cooperation. In other words, an increase in RRS for individual players in an N-Person PGG using cooperative strategies implies an increase in self-interested objectives while meeting the collective public good target.

Self-Organizing Systems Capable of Processing Information

Biological self-organizing systems such as social insects demonstrate the capability of information processing through their behavior (Detrain, Deneubourg, & Pasteels, 1999; Shouse, 2002). Other biological self-organizing systems capable of processing information are brains, as evidenced by research into neural information processing (Serban, Sordoni, Bengio, Courville, & Pineau, 2016), bacteria, as evidenced by quorum sensing (Bassler, 2016), immune systems, plants, and slime molds (Mitchell, 2009). Viewing organizations as systems capable of self-organization, in the sense that effective processes, structures, and strategies emerge and evolve from teleological bottom-up processes comparative to biological self-organizing systems, has significant and far-reaching implications for applied management research, informing the role of managers (Anderson, 1999) and leaders in the creation of agile organizations.

Scope and Delimitations

Pertaining to scope, Bogdanov's tektology begins by treating the physical and psychical, or the world in its entirety, through the lens of organization (as cited in Biggart, Dudley, & King, 1998). In line with the current perspective on modeling complex problems using the tools offered by complexity theory, Bogdanov's tektology posits treating such problems as composed of complexes and interrelationships (as cited in Biggart et al., 1998). Applied to the research problem under examination through this study, the complexes are organizations and the interrelationships aggregate to produce the characteristics of RRS. This specific focus was chosen due to the sparseness of empirical research in the field of applied complexity theory to organizational studies, in addition to the fact that the characteristics of RRS are desirable for organizations experiencing perturbations from the threats of economic and environmental collapse within the adaptive cycle. Current literature validates the relevance and need for this study with an evident lacuna as presented in the literature review section.

This study was bounded by the need for a conceptual management framework, based on the models of evolutionary game theory and dynamical systems presented in the literature review that guides the prediction and control of organizational dynamical processes, shaped by the interrelationships between RRS, given that resilience is a functional advantage of the scale-free structural nature of CASs with a power law distribution (Barabasi, 2014). Thus, network theory constrains structure and function. This study is further constrained by defining the characteristics of RRS in evolutionary terms for modeling purposes.

Limitations

The use of an ABMS computational-based experimental quantitative methodology for studying real-world phenomena relies on abstraction and representation of specific real-world scenarios using models consisting of agents, agents' states, rules, and the environment in which agents are situated. Therefore, an associated limitation of ABMS is that a model, as an abstract representation of reality, is an idealized or simplified formalization of the researcher's perspective of a real-world scenario (Lustick & Miodownik, 2009). As researchers' perspectives are subject to their worldview, upon which the model is then built, the model is twice removed from reality (Lustick & Miodownik, 2009). Nevertheless, agents are encapsulated within well-defined boundaries, capable of autonomous, anticipatory, and flexible action within their environment, and meet their problem-solving objectives (Jennings, 2000). Therefore, the benefits of ABMS for decision-making and problem solving outweigh the limitations of abstraction and representation associated with this methodology.

The observing instrumentation of computational experiments in general introduces spurious information by using finite precision arithmetic, as depicted by truncation errors and roundoff errors. The accuracy of the ODE solvers is affected by parameters such as changes in time. Furthermore, threats to external generalizability associated with computational modeling are intractable problems and NP-hard problems (Boschetti & Gray, 2013), which have been mitigated in this study by virtue of setting finite boundary limitations. Consequently, an applied complexity empirical management framework for RRSA was developed.

Conceptually, applied complexity theory is viewed in the literature as the third way of doing science. In other words, in response to the limitations of deductive and inductive scientific inquiry, applied complexity theory proposes a generative method, which finds itself in the realm of postnormal science, and which takes uncertainty and value loading into account while considering multiple perspectives (Funtowicz & Ravetz, 2003). Generative postnormal science studies using ABMS are empirical and therefore highly generalizable for decision-making and problem solving (Epstein, 1999).

Significance of the Study

This study may provide insight into a lacuna in the current literature on understanding the relationship between organizational resilience, robustness, sustainability, and adaptation to climate change, from a complex evolutionary systems or applied complexity theory perspective using an empirical computational-based quantitative strategy of inquiry. Greater knowledge of this relationship may be used to facilitate managerial and leadership decision-making for moving policy forward in a positive and innovative socioeconomic/sociotechnical manner. Furthermore, this study has implications for the objectives of the UNFCCC concerning the adaptation of developing countries to climate change and the devastating effects of noncompliance if global policy does not move forward in a positive manner.

Significance to Theory

This is a pioneering study in the field of information systems management in the sense that the property of agency associated with ABMS enables the study of diverse and complex sociotechnical systems. Furthermore, organizations and livings beings are viewed as information processing systems (Mitchell, 2009), thus phenomena as diverse as ecosystems, biospheres, the stock market, and animal behavior are theorized to fall within the ambit of information systems management proper. Previous barriers to such a thorough view of information systems management arises from a combination of factors: (a) complexity theory, given its interdisciplinary nature, strong connection with complicated mathematics, and ABMS presents significant challenges for researchers; and (b) information systems management as a discipline is a nascent field. However, the latter provides an advantage for the trajectory of future information systems theory to be shaped by positive socioecological/technical goals and objectives.

The subdisciplines of complexity theory, namely dynamical systems theory, information theory, and complex adaptive systems science, are navigated in this study to test the hypotheses as stated in the research questions and hypotheses section. This empirical computational study illustrates the relationship between RRS and adaptive capacity in the field of information systems management, drawing on complexity and game theories in an applied manner, thereby adding value to both the application of complexity and game theories and the methodology of ABMS within the respective domain and discipline.

Significance to Practice

included the notion of agency as central to ABMS, from which perspective living beings are autonomous information processing systems, and that an evolutionary advantage can be gained via optimization of these processes (Ay, Der, & Prokopenko, 2012). If the contention that surviving climate change is an evolutionary advantage holds, then mitigation of climate change may be operationalized through optimization of the information processes relating to living beings. Past studies in the field of applied complexity science and information processing have used biological models of ant foraging and firefly synchronization to inspire optimization and synchronization in computer science, as evidenced by particle swarm optimization applications (Shi, Eberhart, & Chen, 1999). According to the literature, applications of ABMS range from modeling the behavior of agents in the stock market and supply chains and planning future health care management to anticipating the spread of epidemics and the success of marketing campaigns (Macal & North, 2014), thereby eluding to the potential efficacy of applied complexity theory to other technical areas such as the study of climate change decision dynamics, which this study addresses. Greater empirical knowledge of the relationship between RRS and adaptive capacity, and more specifically a conceptual management framework for RRSA, holds the potential to guide governmental decision making in determining the use and role of incentives and mandates associated with reducing GHGs, land-use regulation, zoning, urban sprawl, and federal law as it pertains to climate change, such as the clean air act, according to Canale (2012). Furthermore, quantification of the complexity of information systems as sociotechnical systems facilitates the guidance of diverse dynamical phenomena and the understanding of tipping points (Vespignani, 2012), which is viewed as critical to future leadership endeavors. The application or implementation of the derived management framework of RRSA further addresses the need for innovative policy responses and collective action (Hurlstone et al., 2017; Tosun & Schoenefeld, 2017) by illustrating networked collaborative climate governance (Johnston, Hicks, Nan, & Auer, 2011) and is significant to decision making, problem solving, and thus managerial practice within the field of information systems. By virtue of the fact that an increase in adaptive capacity is hypothesized to facilitate the mitigation of threats to the system's RRS for collective cooperative climate governance strategies, the resulting RRSA management framework thereby incentivizes decentralized, polycentric, bottom-up collective action initiatives.

Significance to Social Change

The application of an effective management framework for organizational resilience, robustness, and sustainability has positive implications for social change in the sense that the former variables are positively linked to reducing unsustainable business practices, reducing GHGs and thereby improving global conditions for mitigating climate change. Climate change during the anthropogenic period has resulted in increased oceanic acidity, which in turn threatens the oceanic coral reefs (Pendleton, Hoegh-Guldberg, Langdon, & Comte, 2016). Consequently, the geosphere as an open and integrated system, including human beings and all organic life forms, could benefit from the outcome of this study. The resulting RRS managerial framework provides insight into complex sociotechnical dynamics, as adaptive dynamics are also a property of complex socioecological systems (SES) and adaptive capacity is an important aspect of resilience (Cote & Nightingale, 2012). The provision of incentives using evolutionary traits such as captured in the RRSA framework for bottom-up collection action, which serves self-interested parties as well as contributing to the collective goal of mitigating the risk of global temperatures increasing by 2°C, adds value to the understanding of evolutionary game theory for future studies involving N-Person PPG dilemmas.

Summary and Transition

Climate governance organizations (state, private, transnational, and community) viewed as the pinnacle form of anthropogenic activity and as complex adaptive systems viewed through the lens of complexity theory have a critical role to play in efforts towards climate change mitigation. In this study, I aimed at understanding the role of these organizations in mitigating climate change through obtaining insight into the dynamics of RRSA viewed as evolutionary traits of agile climate governance organizations. This insight was obtained via a computational experimental research design or simulation study, using the strategies of an originally developed evolutionary PD simulation to represent climate governance structures with agents representing decision-making bodies, including governments, cities, international organizations, and bodies from the private sector such as private and civil society organizations and communities (Tosun & Schoenefeld, 2017).

In summary, this was a pioneer study in the field of information systems management aimed at providing insight into the decision dynamics of climate change for effective networked climate governance by understanding the relationship between organizational resilience, robustness, sustainability, and adaptation to climate change from a complex evolutionary system or applied complexity and game theoretical perspective using an empirical computational-based quantitative strategy of inquiry. The application or implementation of the derived management framework of RRSA is significant to managerial practice within the field of information systems by facilitating positive socioeconomic and socioecological change via the mitigation of threats to the system by increasing adaptive capacity. The literature underpinning this study is discussed in Chapter 2, and the methodology is covered in Chapter 3.

Chapter 2: Literature Review

The specific problem was the lack of a management decision framework for increasing adaptive capacity to climate change via the mechanisms of resilience, robustness, and sustainability because of improved climate governance structures or strategies. The purpose of this quantitative computational experimental study was to develop a management framework of RRSA for climate governance organizations viewed as complex evolutionary systems in order to transcend the current unsustainable state.

This chapter includes the literature search strategy used during formulation of the literature review and research process in general. Related to this, the most frequently searched terms used in search engines, influential library databases and major journals, types of literature including seminal and peer reviewed sources, and scope of the literature review in terms of years searched are discussed. Thereafter, the theoretical foundation for the study is presented followed by the literature review, summary, and conclusions.

Literature Search Strategy

The research process employed for this dissertation underwent several incarnations until becoming finely tuned and second nature. Deriving from the need to write annotated bibliographies during my PhD course work journey, spurred on by the finite time constraints of submission deadlines, method became a highly prioritized requirement of the research process, a fact asserted by Descartes (1960) in his emphasis of the importance of method in the articulation of the scientific method. However, the evolution of my dissertation topic included a discovery phase, during which the current area of investigation at the time catalyzed the search for references. These preliminary and foundational topics served as search terms and seeds for related search terms leading to the discovery and evolution of my current topic, thereby directly informing my literature search strategy.

A concise list of search terms used for this literature review were *complex adaptive systems, organizational complexity, organizations as complex adaptive systems, resilience, robustness, sustainability, cellular automaton, agent-based modeling and simulation, properties of complex adaptive systems, general systems theory, information theory, fractal dimension, dynamical systems theory*, *climate governance, networked climate governance, decision-making for climate governance*, *Lotka-Volterra models, application of Lotka-Volterra equations to cellular automata, N & L type collapses, macro dynamics of climate change, Game of Life, Prisoner's Dilemma, evolutionary game theory, ,* and *evolutionary game theory for understanding climate governance*. Journals that were often cited include *Simulation*, *Nature, Ecological Economics, Scientific American, Evolutionary Economics, Complexity*, and *Nature Climate Change.* While there are no dissertations that use a computational experimental design for analyzing organizational RRS in the Walden Library, the literature on complexity and its study using ABMS for CASs is extensive.

Theoretical Foundation

It is necessary to underscore the contribution of general systems theory (GST) to the theoretical underpinnings of this study from the perspective that the study and consequent understanding of SESs, socioeconomic, sociocultural, and sociotechnological systems is improved through the lens of complexity and complex systems analysis (Allen, 2012), which in turn is derived from GST (Midgley, 2003). Complexity theory provides the theoretical foundation for this study, the early underpinnings of which can be traced back to the Aristotelian notion of unity being greater than the sum of its parts, and more recently to GST and cybernetics (Manson et al., 2012). The study of complex systems is interdisciplinary, meaning that the types of phenomena and systems studied by complex systems scientists display common properties, which are better understood via individual core disciplines that are united under the rubric of complexity theory (Manson et al., 2012). A major proposition of complexity theory is that all complex systems are composed of simple agents or components that interact with each other in nonlinear ways, thereby demonstrating emergent behaviors, which cannot be easily understood by studying the behavior of the individual agents/components (Mitchell, 2009). Complexity theory embodies the notion that the whole is greater than or different from the sum of its parts because emergent behaviors such as flocking birds, changes in stock market prices, or the phenomenon of climate change are collective outcomes of the entire system and can only be understood at the system level and not at the individual level (Mitchell, 2009). Another proposition of complexity theory is that these nonlinear interactions resulting in self-organized emergence occur despite the lack of central control, implying that the system is self-organized via the cooperative behaviors of simple agents or components (Bar-Yam & Yaneer, 1997; Mitchell, 2009). Types of emergent behaviors proposed by complexity theory include hierarchical organization, information processing, complex dynamics or how system patterns change in space and time, and evolution and learning resulting in adaptation over time (Wilensky & Rand, 2015).

The general field of dynamics or the study of how systems change and behave over time is one of the core disciplines of complexity theory, including but not limited to the flow of fluids or fluid dynamics, the movement of planets or planetary dynamics, and climate dynamics and other dynamical systems (Bardi, 2011). Dynamical systems theory is the general field of mathematics that is used to understand dynamical systems via differential equations, calculus, and iterated maps among others (Boyd & Crutchfield, 2016). Poincaré pioneered modern dynamical systems theory and chaos theory (as cited in Verhulst, 2016), a central construct of the latter being sensitive dependence on initial conditions, the relevance of which to this study is discussed at greater length in the literature review below. Pertaining to the application of dynamical systems theory to the study of CASs, *chaos* is the semantically correct technical term used to describe dynamical systems that display sensitive dependence on initial conditions. The latter refers to the phenomenon of small perturbations in initial conditions resulting in massive errors in prediction, colloquially referred to as the butterfly effect, and mathematically conveyed by the model for population growth known as the logistic map equation: $X_{t+1} = rx_t(1-x_t)$, where r is the combined effect of birth rate and death rate into a single number, and x is the fraction of a system's carrying capacity (Li & Yorke, 1975; Mitchell, 2009), as shown in Figure A1. Varying the value of r produces different classes of attractors: fixed point, periodic, and chaotic or strange attractors. The behavior of a dynamical system sensitive to initial conditions is characterized by the type of attractor obtained by varying *r*, plotted on the x-axis in Figure A1 (Mitchell, add missing year here). Furthermore, unlike random systems, chaotic systems progress deterministically, and display universal features such as the period doubling route to chaos and Feigenbaum's constant, which is the value of 4.6692016 or the rate at which all unimodal maps converge to chaos (Rasband, 2015). From this perspective, although prediction might be difficult, the mathematical language of dynamical systems provides a means of describing universal properties and behaviors of chaotic systems.

Another core discipline of complexity theory is information theory derived mathematically from the laws of thermodynamics (Szilard, 1964), central to which is the concept of entropy used to characterize order and disorder in complex systems (Gell-Mann, 1995; Landauer, 1996). Furthermore, information theory or the study of representation, symbols, and communication has culminated in the physics of information (Bennett & Landauer, 1985), a nascent field of research within the discipline of information. Computation, or the study of how systems process information and then respond, to which the notion of universal computation is a central construct, is a pivotal founding discipline of complexity theory (Bar-Yam & Yaneer, 1997). Finally, evolution or the study of how systems adapt to change over time is an integral discipline of complexity theory (Bar-Yam & Yaneer, 1997). When united for studying complex systems, the disciplines of dynamics, information, communication, and evolution share common goals, such as the development of mathematical and computational tools that lead to cross-disciplinary insights.

A challenging aspect of defining complexity theory and an ongoing area of research is the problem of how to measure complexity. Weaver (1948) proposed that complex problems be divided into three categories based on (a) difficulty of description or problems of simplicity such as problems in physics that relate pressure to temperature consisting of few variables, (b) difficulty of creation or problems of disorganized complexity that involve trillions of variables, and (c) degree of organization or problems of organized complexity that involve a moderate number of variables; however, the variables display nonlinear interactions and cannot be averaged in order to understand the whole system as is the case with problems of simplicity. Current complex systems scientists are concerned predominantly with Weaver's last category of organized complexity. Lloyd (2001) originally published a list of 40 measures of complexity grouped according to the difficulty of description as measured in bits (e.g., entropy); difficulty of creation as measured in time, energy, pounds, and so on (e.g., logical and thermodynamic depth); and difficulty of organization of the system as measured according to the context (e.g., algorithmic information content, fractal dimension, hierarchical complexity, and statistical complexity, with the addition of Shannon information, and fractal dimension).

From a methodological perspective, complexity theorists rely greatly on computer based modeling and simulation designs. Axelrod (1997), a seminal thinker and practitioner in the computational experimental field using ABMS, advocated parsimonious design for simulation models with the keep it simple stupid principle, a notion previously expounded by Einstein in that a model should be as simple as possible but not simpler. The choice of a computational experimental research methodology was guided by the fact that complexity theory, as the theoretical foundation for this study, is complimented at several points of contact, such as the scale of complex systems and decision making in complex environments, by ABM (Manson et al., 2012).

Referring to the application of complexity theory, the physics of information has been applied to electronics for charging and recharging a closed-loop battery by means of an electronic Maxwell's demon in a box (Schaller, Emary, Kiesslich, & Brandes, 2011) and biology via the proposition that creation of synthetic biological constructs would be possible by harnessing biological Maxwell's demon (Binder & Danchin, 2011). More specifically, within the scope of information systems management, Valente (2013) applied complexity and evolutionary theories to organizational processes using an NK-like model for complexity to demonstrate how the refinement of exploitation over exploration as processes of adaptation are beneficial in the short term but destructive in the long term, in addition to the ineffectiveness of greedy strategies for organizational adaptation in the long term.

Similarly, CASs share common properties and constructs, such as observer dependence, system nestedness, path dependence, adaptivity, chaos, randomness and instability, diversity and self-similarity, robustness and resilience, evolution, and network theory, with emergence being the most cited characteristic (Davis & Nikolic, 2014). Additionally, CASs are modeled using generative bottom-up ABMS (Davis & Nikolic, 2014). Using these tools, it is possible to view organizations as CASs, with systems embedded or nested within other self-similar systems, in order to study and develop greater understanding of system level emergent behavior or epiphenomena such as climate change (Emmeche, Køppe, & Stjernfelt, 2000).

The domain of artificial life encompasses the theoretical areas discussed above, is relevant to simulation studies, and more specifically applies to the use of agents in Netlogo as representations of complex adaptive and dynamical systems (Langton, 1997). Ergo the rationale for each agent in the evolutionary PD simulation to represent climate change governing bodies for addressing the research questions of this simulation study, with the addition of network theory for the guidance of networked governance structure (Tosun & Schoenefeld, 2017) is theoretically substantiated in a comprehensive manner. Barabasi (2014) contributed prominently to network theory having discovered scale-free networks, which follow power law distributions. Scale-free networks range in diversity from natural biological networks such as viral epidemics, and protein interactions, to the World Wide Web being the largest man-made scale-free network. For this reason, the scale-free property is considered a universal network characteristic (Barabasi, 2014). Applications of the principles of network theory include discovering the factors that influence the spread of positive network traits and those that limit the weaknesses and vulnerabilities associated with interconnectivity, such as blackouts and the spread of information, memes, business practices, power, and energy respectively (Barabasi, 2014).

In current literature, Ostrom (as cited in Tosun & Schoenefeld, 2017) hypothesized that organizations can self-organize sustainable management systems using institutional design principles partially derived from CASs theory, (i.e., are composed of simple components, have clear boundaries, and display collective behaviors). However, Ostrom included the principle of monitoring, an exception to CASs theory, which expounds self-organization despite the absence of external monitoring and central control.

In addition to complexity theory, evolutionary game theory, which is considered foundational to decision-sciences, provides theoretical insight for this study. While historically, game theory can be retrospectively applied to human social behavior from the time of hunter-gatherers, game theory was introduced academically into the literature by von Neumann and Morgenstern (1944), who proposed that a solution exists for all zero-sum games. Game theory provides the foundational tools for microeconomics, areas of artificial intelligence, and decision-making within multiple disciplines. Ostrom (1990) discussed three formative game theory models often employed institutionally for developing market or state solutions for governing CPRs, namely Hardin's (1968) *Tragedy of the Commons*, Dawes's (1973; 1974) *Prisoners' Dilemma* (PD), and Olson's (1965) *Logic of Collective Action*, using an extensive collection of existing case studies involving both successful and failed examples of CPR self-governance, by examining how those institutions affected the performance of their respective political and economic systems, and how self-governance in those cases evolved via individual choices, incentives, and strategies. Furthermore, Hurlstone, Wang, Price, Leviston, and Walker (2017) elucidated the applicability of evolutionary game theory, specifically the Prisoner's Dilemma (PD) for understanding certain conditions of climate negotiation resulting in either cooperation (i.e., collaborative governance, or defection), and noted that the only PD Nash equilibrium is defection.

Concerning the governance of climate change, the theory of *collective climate action*, referring to actions taken by individuals that are aimed at benefiting the collective, is derived from environmental and social psychology, and is pertinent to this study (Tosun & Schoenefeld, 2017). In current literature, collective climate action was applied to the study of networked climate governance (Tosun & Schoenefeld). Recent literature further indicated that a networked model of decentralized climate governance, punctuates traditional hierarchical climate governance structures (Jordan et al., 2015), thereby forming the new global climate governance architecture (Widerberg & Pattberg, 2015), underpinned by both network theory and the policy change theory of polycentric governance.

Finally, the theory of polycentric governance is a prominent political science theory of policy change that informs this simulation study as an approach to climate policy governance. In contrast to a monocentric political hierarchy, a central tenant of the polycentric approach is that learning and adaptation are encouraged and improved via decentralized cooperation and communication across all levels of social organization (Cole, 2015). Thus, collective climate action, aimed at solving social and combined socio-ecological problems, was suffused by the theory of polycentric governance (Cole).

Critical analysis of the current literature reveals that the application of evolutionary game theory and complexity theory, including dynamical systems, information, and network theories for addressing the research question of this simulation study is well grounded in existing interdisciplinary studies. Synthesis of the relevant literature revealed that ABMS is complimented by complexity theory and its subtheories for understanding the relationship between RRS and adaptive capacity, which combined with the polycentric approach to governance, illustrates the decision dynamics of climate change for application in the field of decision sciences and information systems management.

Literature Review

Synthesis of the literature relevant to the study of the relationship between organizational RRS and adaptive capacity within the scope of information systems management reveals that the constructs of interest for this study are *resilience* and *adaptive capacity; robustness* linked to *self-organization* and *guided self-organization (GSO); sustainability* as applicable to the aforementioned constructs: *climate change governance* and *decision dynamics of climate change*; *collapse* as it pertains to *climate change*, *sensitive dependence on initial conditions*, *nonlinearity*, *emergence*, *complicated dynamics*, and *information processing*. What follows is an exhaustive review of the current literature describing studies relevant to the constructs of interest, the ABMS methodology, and ways in which researchers within the field of information systems management and decision sciences have approached studies closely related to the research problem, including the limitations and affordances inherent in their approaches. I will further draw on the literature to substantiate my rationale for choosing the independent variables of resilience, robustness, and sustainability, and the dependent variable of adaptive capacity. In addition to the other constructs mentioned above, this literature review illustrates what is already understood about the variables in current literature, including controversies, and opportunities for further research.

Resilience

On the construct of resilience, the literature points to several attempts at defining resilience within different contexts; however, this stimulation study uses a highly integrated approach to social, economic, ecological, and technological systems, the intersection of which are socio-economic systems, socio-ecological systems (SESs) and socio-technological systems (STSs) respectively. This integrated approach aligns with the approach of *Disturbance as Opportunity* (Folke, 2006) for the purpose of defining factors and their interaction when modeling SESs and organizational resilience to climate change, and stresses the integration of five types of capital namely social, economic, human, physical, and natural capital to the resilience of SESs (Mayunga, 2007) requiring a cross-scalar perspective including social norms, values such as trust, networks, air, water, and soil (Bahadur, Ibrahim, & Tanner, 2010).

The construct of resilience originally derives from ecological studies in the 1960s and early 1970s on predator-prey dynamics in relation to ecological stability theory (Holling, 1961; Holling, 1973). In recent literature, Oliver et al. (2015) defined ecological resilience in terms of a system's ability to recover after a disturbance and maintain its adaptive capacity by resisting regime shifts. However certain ecosystems such as tundra, boreal forest, mountains, Mediterranean-type ecosystems, mangroves and salt marshes, coral reefs and the sea-ice biomes are particularly vulnerable to an increase in temperatures of 2-3%, as indicated by statistics related to degradation and extinction of species, thereby supporting the argument for ecosystem management as a resilience tool for mitigation against climate change impacts and complete collapse of the global ecosystem (Munang, Thiaw, Alverson, Liu, & Han, 2013). Munang et al. aimed to clarify the central role of ecosystem management as a resilience tool in climate change adaptation and disaster risk reduction, discussed ad hoc initiatives driven by ecosystem-based adaptation strategies, the need for greater effort and collaboration concerning ecosystem management, and presented several benefits and advantages pertaining to the use of ecosystem-based adaptation strategies. Munang et al. concluded that the benefits and advantages of ecosystem management met the needs associated with UNFCCC priorities and the Hyogo Framework for Action, albeit requiring appropriate policy and action.

Socioecological resilience. Cote and Nightingale (2012) extended resilience in ecology for understanding and analyzing human-environment dynamics and recommended that insights into resilience be treated as a heuristic for thinking about environmental-social dynamics. Cote and Nightingale discussed the potential for a coupled SES approach to facilitate unpredictable change, yet criticized resilience thinking as an SES approach, flawed due to the lack of allowances for political economic factors, lacking the tools to address adaptive governance. The goal to address the lack of adaptive capacity or vulnerability of developing countries to climate change requires adequate governance informed by an appropriate approach. Effective governance of funds such as the adaptation fund for moving global change forward requires adaptive governance. Cote and Nightingale noted that these capabilities are beyond the scope of resilience for SES, calling for a situated approach or resilience in context approach, which questions whether resilience to some implies vulnerability to others.

Social resilience. Within the context of social resilience, the recent literature expounds a need for human livelihood resilience, as the world's most economically vulnerable communities lack adaptability strategies, and are likely to suffer the worst consequences of climate change (Tanner et al., 2014). Linked to the work of Baggio, Brown, and Hellebrandt (2013), Tanner et al. noted that livelihood resilience might serve as a boundary object for improved cross-disciplinary communication, coherence, and cooperation with anti-poverty climate and development policy serving as the common object. Baggio et al. conducted a bibliometric analysis to understand whether resilience serves as a boundary object or bridging concept in the literature, concluding that resilience has a limited bridging function, mainly for understanding SESs, otherwise serves as a boundary object for scientific, policy, and social research.

Organizational resilience. Riolli and Savicki (2003) aimed at understanding organizational resilience within the field of information systems by developing an integrated theoretical model for individual and organizational resilience using literature pertaining to the characteristics of the information system work environment on both levels, however it was unclear whether the factors for resilience at the organizational level may be used *in silico*, presenting an opportunity for further research. Riolli and Savicki extended the theoretical contributions of Thong and Yap (2000) on occupational stress to organizational resilience, and recommended GST for understanding how resilience is developed at the organizational level. Riolli and Savicki concluded that the seven streams of resilience developed by Home and Orr (1998) are advantageous to information systems organizations at both the individual and organizational level, and considered nine key characteristics as integral to their model.

Economic resilience. Pertaining to economic resilience, Röhn, Sánchez, Hermansen, and Rasmussen (2015) discussed the high cost of economic crises and the need for an economic framework, as part of an ongoing body of work, that assesses resilience for Organization for Economic Cooperation and Development (OECD) countries, and expounded several indicators of vulnerabilities for early detection and mitigation of costly economic crises in OECD countries. Pertaining to the relationship between economic and ecological resilience, Fiksel (2006) used several pertinent cases to succinctly illustrate the paradoxical rebound-effect of greater efficiency in energy use leading to faster economic growth, resulting in a net increase in the ecological footprint of society, and pointed out that global economic growth would not be offset by incremental environmental organizational improvements, with the growth of China and India contributing to the problem. As such Fiksel highlighted the urgent need for urban system resilience, and the relevance of the industrial ecology approach toward sustainability involving a shift from linear models to closed loop models. Fiksel remarked that industrial ecology research has thus far focused on reducing unsustainability instead of fortifying the systemic underpinnings of sustainability. Fiksel's elucidation that the field of biocomplexity is relevant for understanding sustainable systems was of interest for further research. Additionally, ecological footprint analysis was used contextually, revealing the ecological overshoot of mankind's demand having exceeded nature's supply, and therefore relevant to the study of enhancing the resilience of complex adaptive systems such as organizations (Fiksel). Of the six integrated approaches presented for systems modeling and management, thermodynamic life cycle analysis (LCA) is of relevance to the problem of measuring complexity. Fiksel's observation that agent-based modeling underpins the cutting-edge efforts to incorporate sustainable systems thinking into the design and development of energy and mobility solutions further substantiates my choice of research design for the specific research question.

Martin, Sunley, Gardiner, and Tyler (2015) extended the construct of economic resilience for understanding how UK geographic regions have reacted to the last four cycles of economic recession, underpinned by the *North-South Divide*, and the unsustainable and unstable recessionary contraction of 2008, the worst economic contraction since the Great Depression in the early 1930s. However, the statistical quantitative methodology employed by Martin et al. is generalizable to other geographic contexts. Martin et al. concluded that different resilience responses to recessionary cycles across regions might not only be the result of economic structure, (i.e., that long-term economic growth is defined as contractions/shocks followed by expansions/recovery within the business cycle with peaks and troughs as turning points), but also the result of interactions and linkages of industries between and across regions, and cited several region specific factors, linked to the economic conditions in each region, that contribute to the differences in resilience between them. Furthermore, Martin and Sunley (2015) defined economic resilience, in addition to the usefulness of the construct for understanding response to shock, by using four recursive steps, namely the *risk* of a region's institutions and employees to shocks, the *resistance* of those institutions and workers to the effect of shocks, their ability to adapt (*adaptability*) to resume core functions, and their *recoverability*. Martin, Sunley, Gardiner, and Tyler (2015) borrowed the term *adaptive robustness* from complex biological, organizational, and physical systems studies to describe an economy's ability to undergo changes because of shocks and maintain or restore core functionalities. From this perspective, the construct of resilience in economic literature (Martin & Sunley, 2015; Martin et al.) was found to be conceptually consistent with its application in ecological, social, and information systems management literature, and their intersections.

Characteristics of resilience. Bahadur, Ibrahim, and Tanner (2010) provided a multidisciplinary perspective, discussed a comprehensive list of approaches and models, and outlined 16 overlapping conceptualizations of resilience, including key characteristics and indicators, thereby providing a thorough theoretical background to the subject of resilience. Bahadur et al. highlighted the need for robust studies aimed at clarifying both the operationalization of resilience and the relationship between adaptation, adaptive capacity, and resilience. The 10 main characteristics of resilience were found to be (a) a high level of diversity in groups performing functions in an ecosystem; (b) enhanced community cohesion through effective governance and institutions; (c) acceptance of change and uncertainty; (d) community involvement and use of local knowledge for resilience-building projects; (e) activities in preparation of change; (f) systems are characterized by a high degree of social and economic equity; (g) emphasis on social values and structures; (h) acknowledgement of the nonequilibrium dynamics of a system; (i) continual and effective learning; and (j) cross-scalar perspective of events and occurrences adopted by resilient systems (Bahadur et al.). According to Bahadur et al., resilience at the organizational scale may share some of the characteristics of resilience at the systems-level; however, other characteristics may not necessarily translate well methodologically for assessing organizational resilience (Bahadur et al.). Bahadur et al. observed that the lexicon for climate change adaptation derived from the efforts of the Intergovernmental Panel on Climate Change (IPCC) and the Global Assessment Report, and international policy processes of the UN Framework Convention on Climate Change (UNFCCC) and Hyogo Framework for Action are applicable across multiple disciplines.

Sociotechnical resilience. Bhamra, Dani, and Burnard (2011) included the intersection of technological systems with social and ecological systems for defining interconnected organizations and examined their resilience to disasters such as tsunamis, earthquakes, volcanic eruptions, financial crises, and economic recessions with an emphasis on the importance of making small to medium sized enterprises (SMEs) robust and resilient to disasters. Related to this is the relevance of scale to research on resilience as it applies to SESs. Engle (2011) discussed the incompatibility of scales used for policymaking and the ecological boundaries of a system, attributable to the lack of operationalization and generalization of adaptive capacity concepts, emphasizing the need for clearly defined system boundaries, and greater understanding of how to measure resilience and the five types of capital (Bahadur et al., Mayunga, 2007).

Measuring resilience. Cutter, Burton, and Emrich (2010) addressed the need for metrics and a standard for measuring resilience, with the aim of providing a methodology and set of indicators to measure the present conditions influencing disaster resilience within communities in the Southeastern U.S. Cutter et al. presented divergent views on community resilience in order to derive the baseline indicators, and used the disaster resilience of place (DROP) model as the conceptual basis for their study, employing an empirical strategy of enquiry. Additionally, composite indicators, referring to an aggregate measure of disaster resilience via the manipulation of individual variables, were discussed as useful tools for policymaking and public communication (Cutter et al.).

On the other hand, Lee, Vargo, and Seville (2013) aimed to develop a tool to measure and compare organizational resilience by expanding on the relative overall resilience (ROR) model developed by McManus (2008). However, Lee et al. used a quantitative strategy of inquiry and factor analysis to deduce that the original 4-factor ROR model was not supported, and developed a new 2-factor model of organizational resilience with planning and adaptive capacity serving as the factors by using the theory of situational awareness. Furthermore, Lee et al. justified the reliability and validity of their findings using Cronbach's alpha. The sample size for the study conducted by Lee et al. was 1009 organizations, and a survey for organizational resilience based on McManus's work using a 4-point Likert scale, was the instrument. Lee et al. concluded that further research was needed using regression and structural equation modeling to understand how the indicators identified combine to produce resilience, and the corresponding weights of their contribution. Ergo, deductively ABMS might be used to achieve the same ends.

Resilience management. On resilience management, Folke, Hahn, Olsson, and Norberg (2005) noted that the costs of collaboration and conflict resolution might be lowered via the emergence of *bridging organizations*. Thus, the latter supports self-organization by enabling legislation and governmental policies for co-management of adaptive capacity efforts. Theoretically, the authors used a SESs approach based on the move from assessments using the maximum sustainable yield of individual species, to the management of ecological processes. The work of Folke et al. resonated with that of Lemos, Agrawal, Eakin, Nelson, Engle, and Johns (2013) in that the authors observed the counter-productive effects of specific adaptive capacity efforts on the generic adaptive capacity of a system by using the mobilization of Belizian coastal fisherman as an example. The operationalization of adaptive governance was therefore proposed through adaptive co-management of systems, for which four essential features of SESs were presented (Folke et al.). Ergo adaptive management, in contrast to conventional management, is the conceptualization that policies be treated as hypotheses and management actions are the experiments that test those hypotheses (Folke et al.) This approach to adaptive management is both practical and methodological, serving as a topic for further examination within the field of organizational resilience, and draws attention to the intersection between resilience and adaptive capacity.

Similarly, a sustain-centric management paradigm presents several significant operationalization challenges to organizations. As the literature points out that an open systems view of resilience is empirically untapped, a lacuna exists for a consistent conceptualization of organizational resilience for practical and research purposes

(Linnenluecke & Griffiths, 2010). In response to this gap, Linnenluecke and Griffiths outlined the main aspects of organizational resilience, discussing resilience and adaptive cycles. A valid contribution to the intersection between resilience and adaptive capacity was the insight that organizational requirements for coping with major disturbances exceed those for overcoming minor ones, thereby exceeding the thresholds for adaptation (Linnenluecke & Griffiths). The authors observed that the coping range of an organization might be important for statistically or objectively understanding the extremities of resilience.

Linnenluecke and Griffiths (2010) discussed climate change, extreme weather conditions and the disastrous consequences therewith associated, provided examples using real cases, and developed a resilience framework for the study of organizational adaptation to climate change, because an approach of economic factors of competition to the former lacks the necessary tools to provide thorough understanding. Because of the economic factors approach, past methods of coping with sudden changes have included risk and crisis adaptation mechanisms. These mechanisms aimed at mitigating the consequences of disruptions such as strikes, changes in demand and competition, accidents. However, the uncertainty and potential disastrous consequences associated with climate change and extreme weather conditions is unprecedented. Therefore, the goal of the resilience framework is to facilitate organizational development of resources and capabilities that mitigate the disastrous consequence of organizational collapse because of climate change and weather extremes (Linnenluecke & Griffiths).

Adaptive Capacity

As previously mentioned, closely linked to the construct of resilience is the construct of adaptive capacity. Nelson, Adger, and Brown (2007) framed the resilience approach as being systems oriented, with adaptive capacity serving as a core feature of social-ecologically resilient systems. Nelson et al. highlighted the role of robustness and adaptation in the conceptualization of resilience, and the usefulness of resilience as a framework for analyzing adaptation processes and identification of appropriate policy responses. Additionally, the inherent characteristics of resilience were deemed to be consistent, and capable of absorbing disturbances across scales (Nelson et al.). As such Nelson et al. distinguished between adaptation in the environmental change literature and adaptation within a resilience framework context, discussing the components of adaptation in detail. Nelson et al.'s description of adaptive capacity as a core precondition for a system to be able to adapt to perturbations feeds into my research and is supportive of the conceptual framework used for my model. The detail provided on the relationship between the characteristics, processes, and outcomes of an adaptive system is further useful for the purposes of modeling resilience. The contributions of Nelson et al.'s resilience framework are of particular relevance to my study, including descriptions of states, thresholds, surprise, and tradeoffs in resilience and adaptedness.

Engle (2011) addressed the role of adaptive capacity and how it relates to literature in the fields of resilience, vulnerability, sustainability, and the management thereof, articulating that there are few efforts concerned with the evaluation of adaptive capacity across resilience and vulnerability frameworks. As such adaptive capacity was defined as a prerequisite for leadership and organizational success in addition to the recommendations presented by the IPCCC (Engle). Furthermore, Engle distinguished between different types of adaptation, clarifying the point that the complexity of adaptation is illustrated through maladaptation. In other words, adaptation is not linearly positive. Engle clarified the usefulness of adopting coupled SES as the unit of analysis in resilience research, to understand the way mechanisms fit together, within, and across systems, which relates to interactions and emergence. Engle clarified the caveat for translating the construct of resilience into practice by discussing the role of adaptive capacity in resilience literature and how the former relates to vulnerability.

Adaptive management and governance. Of value to a discussion going forward on organizational adaptive capacity was the insight provided by Engle (2011) on the important role of institutions, governance, and management in determining a system's ability to adapt to climate change. As such, the former bodies play a vital role in redistribution of power and contributing to solving the justice issues intrinsic to the climate change debate, pointing to recent emphasis in the literature on adaptive management (AM) and adaptive governance (AG) research, which stresses realignment of decision making to the ecological scale. A key take away from Engle's work was the insight that the building of adaptive capacity is rooted in organizational theory, but better suited for policy application through the coupled SES paradigm, appropriately viewed through the lenses of resilience and vulnerability.

Reeves and Deimler (2011) framed adaptability as a competitive advantage for organizations and outlined four organizational capabilities that facilitate adaptation.

Reeves and Deimler opined that traditional approaches to strategy only apply to stable environments and that a rapidly changing and unpredictable world requires a different set of capabilities. According to Reeves and Deimler these *second order* capabilities foster rapid adaptation resulting in sustainable competitive advantage.

The role of technology. Reeves and Deimler (2011) discussed the role of technology in acquiring adaptability, specifically for experimental purposes within the context of testing services and products. The authors claimed that adaptable companies use experimentation to a greater degree than their competitors. Additionally, strategy follows organization in adaptive companies, which were conceived to withstand failure than those that are not adaptive (Reeves & Deimler). In other words, adaptive companies were found to be more robust to failure than their competitors because of dispersed and decentralized decision-making, following a bottom-up rather than top-down approach (Reeves & Deimler). Reeves and Deimler's perspective that organizational adaptation to the environment, specifically to climate change, requires robustness is relevant to this study and directly informs the choice of robustness as an independent variable for modeling adaptive capacity.

Lemos, Agrawal, Eakin, Nelson, Engle, and Johns (2013) argued that improved asset development, institutional access, and an awareness of institutional inequalities reduce vulnerability through a combination of policies and interventions thereby building adaptive capacity. Lemos et al. reviewed the literature pertaining to adaptive capacity, using the IPCCs categorization of the determinants of adaptive capacity as the basis of their paper, aimed at understanding the factors that make human, social and political systems less vulnerable to climate-related phenomena, using a conceptual foundation of adaptive capacity as generic on the one hand and specific on the other. Lemos et al. cited two cases, namely disaster risk reduction in Bangladesh and the governance and adaptive capacity of the Brazilian water sector. The second case aptly illustrated how stakeholder participation and integration can result in deleterious effects by reducing adaptive capacity, ergo indicating that specific and generic adaptive capacity efforts are not always positively related (Lemos et al.). Lemos et al. drew attention to the differentiation between specific and generic adaptive capacity, specifically their non-linear relationship highlighted the inherent complexity of adaptive capacity. Nevertheless, an empirical analysis of this relationship was lacking in the literature, and serves as an area for further research.

Adaptive capacity and climate change. McEvoy, Fünfgeld, and Bosomworth (2013) used a conceptual framework derived from studies on adaptation that are framed by the construct of resilience, and included the effects of climate change and the difference in temporal and spatial scales of its problems in their discussion. McEvoy et al. opined that climate change is still in an embryonic stage of development, thus emphasizing the importance of *framing* the research, and distinguished between meta, conceptual, and operational types of frames for this purpose. McEvoy et al. proposed that the social framing of adaptation is necessary for collaborative processes, highlighting that differences in opinions might complicate decision-making. Thus, the implications of resilience as a frame for climate change adaptation were discussed for policy and practice (McEvoy et al.). Although resilience was an emergent frame for climate change adaptation, combining the use of both top-down and bottom-up approaches within an Australian context, the concepts associated with climate change and resilience can be thought of as universal, and therefore the conclusion that resilience is important for policy development in Australia, particularly relating to sustainable communities, is thought to be generalizable to all SESs within the literature.

Robustness

The construct of resilience as it applies to networks within the field of information systems management directly informs this simulation study, and is closely related to the construct of robustness in the literature. Watts' (2014) conceptualization of organizational robustness affirms the notion that authors use the terms robustness and resilience interchangeably, albeit incorrectly. The need to define the term robustness for constructing a simulation model, calls for close inspection of the parameters, if any, and theories that apply (Watts). Watts opined that an organization's robustness, which involves the ability to allocate resources, innovate, adapt, and solve problems, is related to its organizational structure. The finding that robustness is a feature of complex organization, operationalized by the prevention of failure on the one hand, and preparation for its inevitability on the other (Watts) directly informed my choice of robustness as an independent variable for this study, and lead to the derivation of my hypothesis that robustness is required of organizations in order to adapt to climate change strategic objectives, supported by the pertinent example of the Internet, which is a networked system requiring robustness in order to survive unpredictable breakdowns (Watts).

Guided self-organization (GSO) pertains to the construct of robustness as it applies to network structure (Ay, Der, & Prokopenko, 2012). Ay et al. defined self-organization as the transition of a system into an organized form in the absence of centralized control or an external agent, drawing attention to the seemingly paradoxical nature of the term, *guided self-organization* (GSO), and addressed this contradiction using optimal path formation within artificial ant colonies. Ay et al. highlighted the emergence of organized behavior because of interactions between agents and their environment, in the absence of an overarching blueprint or design, and clarified the difference between an explicit effect, (i.e., change in the agent's decision-making mechanism), and an implicit effect (i.e., change to the environment).

Perception-action loops of embodied systems relating to GSO may be of value to my dissertation. Viewing organizational resilience, robustness and sustainability (RRS) through the lens of GSO provides a novel approach for modeling organizational RRS and the potential emergent behaviors that may result (Ay, Der, & Prokopenko, 2012). Furthermore, the optimization principle mentioned by Ay et al. suggested that exploration emerges because of optimizing information gain, rather than because of behavior randomization modeling. Thus, the cognitive aspect, or embodied cognition among multiple agents, of modeling emergence was emphasized and should be examined for further research. Of relevance was the perspective that living beings are information-processing systems, and that an evolutionary advantage can be gained via optimization of these processes. If the contention that surviving climate change is an evolutionary advantage holds, then mitigation of climate change may be operationalized through optimization of the information processes relating to living beings. The authors discussed application of this method using the dynamical systems approach to robot control, stating that the learning rules derived from maximum PI may be used as a tool for self-organization of behavior in complex robotic systems, ergo may be used to guide the behavior of agents in this simulation study.

Gershenson (2011) discussed random Boolean networks (RBNs) as self-organizing systems, to examine how the changes in nodes and connections affect the global network dynamics, and discussed eight different methods for guiding the self-organization of RBNs, with emphasis on guiding the RBN toward the critical dynamical regime. In slight contrast to the principles of GSO, a self-organizing system is described as one in which the elements interact, thereby dynamically producing a global pattern or behavior (Gershenson). In other words, a global pattern in produced from local interactions. Furthermore, Gershenson mentioned that any system, can in principle, be described as self-organizing, thereby prompting the question of when does it become useful to describe a system as self-organizing. Gershenson adequately answered this question by clarifying that self-organization becomes useful when there are at least two levels of description present (e.g., behaviors and individuals, teams and organization).

Gershenson's (2011) work is relevant to further research on modeling organizational resilience, robustness, and sustainability (RRS) from the perspective that the properties and advantages of the critical regime, which is the phase transition between the ordered and dynamical phases, apply to life, computation, adaptability, evolvability, and robustness. Gershenson further recommended the application of the guidance methods of RBNs to engineering systems with features of the critical regime, as well as the study of how living systems evolved via natural selection. For my dissertation, I have conceived the organization as an embodied system, the properties of which can be easily interpreted through information dynamics, ergo organizational adaptability to climate change because of RRS can be viewed as an embodied engineering system.

Emergence and self-organization for robust systems. Related to the work of Gershenson (2013) about describing science using a non-reductionist language, albeit for the purposes of GSO, Polani, Prokopenko, and Yaeger (2013) elucidated the difference between emergence and self-organization using information theory and graph theory, and an example of particles self-organizing devoid of any emergent pattern-like. Polani et al. framed GSO as a set of principles that apply to the process of organization across scales and contexts using the examples of a slime mold approach to the bio-development of motorways in the Netherlands, and ant-based algorithms with local optimization for community detection in large-scale networks, which shed light on the use of biological analogues for modeling networks, thereby substantiating the choice of cellular automata for this simulation study.

Evolutionary robust systems. Whitacre and Bender (2010) clarified the link between robustness and fitness of a system by discussing robustness within the context of evolution. Whitacre and Bender postulated that living systems display two desirable characteristics, namely, robustness and innovation; borrowing from biological taxonomy, the definition of phenotypic variability serves as a proxy for evolvability of a system. Whitacre and Bender noted the limitations of Darwin's principles of evolution for systems of unbounded complexity, with the goal of developing a modern theory for the evolvability of unbounded complex systems based on the requirement of robustness using degeneracy, which is the partial redundancy of functions or capabilities of components in a system.

Whitacre and Bender (2010) applied biological taxonomy to computational requirements for modeling systems, evidenced by the phenotype attractor, and used a protein model consisting of genetically specified proteins to illustrate the concept of degeneracy as applied to modeling. Further discussion of the fitness landscape, neutral network, 1-neighborhood and evolvability, robustness, and the fitness landscape exploration, elucidated the degree to which design principles affect system evolvability (Whitacre & Bender). Whitacre and Bender clarified the link between robustness and evolvability of a system, ergo applied to this simulation study, an organization that is robust to climate change, or demonstrates a high degree of adaptability, must also be evolvable. These concepts have computational implications for modeling which, when interpreted using information dynamics, are relevant and necessary for modeling RRS.

Sustainability

Thus, the constructs of resilience, adaptive capacity, and robustness have been discussed within the contexts of social, ecological, technological, and their intersecting systems, and may be applied to the phenomenon of climate change across all contexts, underpinned by the fact that industrial, social, and ecological systems are closely intertwined, calling for a comprehensive systems approach for effective decision-making regarding global sustainability (Fiksel, 2006). Fiksel explored several questions aimed at providing guidance for future research and initiatives towards sustainability using a qualitative multi-case study approach, and acknowledged the use of dynamic modeling techniques such as biocomplexity, system dynamics, and thermodynamic analysis by researchers to study the effects of climate change on ecological and human systems. Furthermore, resilience was discussed as a necessary quality of complex adaptive systems, with the U.S. Environmental Protection Agency (EPS) incorporating the design of sustainable systems into their strategy (Fiksel).

While the construct of sustainability is interwoven in the literature on constructs already reviewed, it is necessary to include the Triple-Bottom-Line (TBL) and triple value models as innovative frameworks that capture the nuances of sustainable systems, involving the flows between industrial, societal and environmental systems (Elkington, 1994; Fiksel, Bruins, Gatchett, Gilliland, & ten Brink, 2014; Slaper & Hall, 2011). Slaper and Hall discussed Elkington's TBL model, which extended the traditional measurements of profits (i.e., return on investment and shareholder value, to include environmental and social imperatives). Thus, the TBL model constitutes people, the planet and profit as bottom line contributors, thereby also referred to as the 3Ps. Slaper and Hall reviewed the TBL concept and its application for business, policy-makers and economic development practitioners, and elucidated that defining the TBL is not where the difficulty lies, but rather in measuring it. As such, the TBL was developed in response to the struggle involved with measuring sustainability and the 3Ps, ergo an associated strength of the TBL is that no universal index or standard measures exist, instead a general framework may be applied to different entities based on various needs (Slaper & Hall). As stakeholders determine TBL measures, depending on the level of entity, type of project and geographic scope, the TBL framework may be adapted to either narrow or broad scopes (Slaper & Hall). Slaper and Hall presented several traditional TBL economic, environmental and social measures, discussed variations of TBL measurement, and dissected how businesses, nonprofits and government entities might use the TBL with regards to each of the 3Ps or the economic, social and environmental dimensions, including the importance of ecological stewardship.

Similarly, the triple value model involves identification of the value pathways in three types of capital assets, namely industrial economic capital, social and human capital, and natural capital, which are described and discussed in terms of motivations for adopting the approach and the results of its application (Fiksel, Bruins, Gatchett, Gilliland, & ten Brink, 2014). However, the relation of this approach to the triple bottom line approach, at least from a theoretical perspective was not mentioned. Application of the RRS model from this simulation study might be facilitated via the use of a triple bottom line or triple value model.

Relating the construct of sustainability to policy and decision-making within a Sub-Saharan context, Götz and Schäffler (2015) described ecological challenges facing the Gauteng city-region, symptomatic of past political decisions to externalize environmental costs to future generations. Götz and Schäffler drew attention to the weak implementation of green economy strategies such as the Developmental Green Economy Strategy (2010) and the Green Strategic Programme (2011) in favor of continued industrial-policy style decision-making and the consequences thereof, and discussed the

Gauteng Green Strategic Programme (GGSP) within the Gauteng City-Region (GCR), outlining the major ecological issues of the GCR, such as acid mine drainage (AMD), variable rainfall patterns, high GHG emissions, poor air quality and high resource consumption in addition to socio-economic challenges such as urban sprawl resulting from apartheid geographies, and the dependence of industries on cheap coal-fired electricity. Götz and Schäffler elucidated that the GGSP was developed in response to a massive economic downturn involving the loss of 250 000 jobs (6% of employment) between 2008 and 2010. The lack of implementation of GGSP objectives and goals, clearly demonstrates the importance of political decision-making, governance, institutional support and organizational capacity to operationalize strategy. Despite a well-defined mandate and existing programs for supporting green economic efforts, no progress has been made. Götz and Schäffler attributed this lack of progress to a common policy implementation problem, embedded in cross-departmental cooperation challenges and a set of governmental conundrums, which they discussed in detail.

The work of Anderies, Folke, Walker, and Ostrom (2013) is of relevance to affecting sustainable global change. Anderies et al. noted that sustainability has become an accepted concern for organizational executives who do not possess the necessary tools or knowledge for its successful initiation. Additionally, the distinction between resilience, robustness, and sustainability was discussed in terms of their alignment for global change (Anderies et al.), thus substantiating the use of sustainability as an independent variable for this simulation study. Several pertinent examples were provided in support of the plausibility of sustainable actions at the individual level, be it firm, organizational or other entity, derailing sustainability at the global level, or at the system level (Anderies et al.). Therefore, a key element for this study, derived from the work of Anderies et al., is the necessary distinction between the individual level of sustainable action and the global or systemic level thereof.

Sustainable technology. Amemiya-Ramírez (2014) clarified the use and definition of sustainable technology; having no negative effect on the environment, society, the economy, or other technological systems, and carried out an assessment of sustainable technologies using hard and soft system analyses, both quantitative and qualitative in nature respectively. Amemiya-Ramírez used a system dynamics modeling methodology and information on shale gas extraction as an alternate solution to the energy crisis of the 1970s to assess whether shale gas is a sustainable energy source, and consequently provided a definition of sustainable societies, economies, environments, and technologies, explaining that aspects of the definition of sustainability are quantitative or measurable while other aspects are qualitative. Amemiya-Ramírez concluded that the production and use of shale gas contributes significantly to greenhouse gas (GHG) emissions, with high water consumption involved in the extraction process, ergo shale gas was found to be an unsustainable energy source using system dynamics and simple modeling techniques.

Sustainability management. The construct of sustainability as it applies to management is often framed in the literature within the context of social responsibility. For example, the ISO26000 standard formalizes the need for guidance on social responsibility and states, “An organization’s performance in relation to the society in which it operates and to its impact on the environment has become a critical part of measuring its overall performance and its ability to continue operating effectively" (ASQ & Manpower Professional, 2010). Furthermore, ISO26000 was articulated as a mindset, to be applied at all levels of organization, i.e. planning, execution, and stakeholder interaction for right action, including the seven principles of social responsibility and their application to core subjects (ASQ & Manpower Professional).

ASQ and Manpower Professional (2010) noted that society's consumption outstrips the world's biocapacity to regenerate by approximately 30%, thereby requiring organizational attention, and further revealed in a study conducted in 2008 that social responsibility constituted the second leading force of change in quality. ASQ & Manpower Professional conceptualized organizational success as the dual objective of achieving sustainability through social impact and bottom-line growth. Furthermore, an integral characteristic of social responsibility was the willingness to include environmental and social considerations into decision-making, and the accountability thereof (ASQ & Manpower Professional).

Catastrophes, disasters, and system collapses. The constructs of resilience, adaptive capacity, robustness, sustainability, and climate change are often discussed in the literature within the context of predicting and/or preventing catastrophes, disasters, and system collapses. Mrotzek and Ossimitz (2008) acknowledged the contribution of climate change to catastrophes and employed a systems dynamics theoretical framework to model and understand common systemic structures and behaviors of catastrophes, using the Integrated Modeling Environment program at the International Institute for

Applied Systems Analysis (IIASA), which served as the theoretical paradigm for the view that catastrophes comprise extreme events. Furthermore, Mrotzek and Ossimitz described several cross-disciplinary catastrophe theories including the integrated systemic theory of catastrophes (ISTC) based on Senge's general system archetypes. Their discussion on ISTC included applicability of catastrophe archetypes, identifying and modeling of catastrophe archetypes and finally presentation of a set of catastrophe archetypes. Mrotzek and Ossimitz concluded that the ISTC enables identification of systemic patterns in the field of catastrophe research, informing basic patterns of modeling catastrophes. Of the six catastrophe types presented by Mrotzek and Ossimitz, overload catastrophe, overshot catastrophe and tragedy of the commons, and creeping catastrophe might be of theoretical value to the study of organizational RRS and consideration is given to the recommendation that catastrophe archetypes be used for inclusion of catastrophe aspects into existing models.

Organizational collapse. Linnenluecke and Griffiths (2010) aimed at facilitating organizational development of resources and capabilities that mitigate the disastrous consequence of organizational collapse because of climate change and weather extremes using a resilience framework, because an economic factors of competition approach to the former lacks the necessary tools to provide thorough understanding. Because of the economic factors approach, past methods of coping with sudden changes have included risk and crisis adaptation mechanisms. These mechanisms aimed at mitigating the consequences of disruptions such as strikes, changes in demand and competition, and accidents. However, the uncertainty and potential disastrous consequences associated with climate change and extreme weather conditions is unprecedented.

Limits to growth. Turner (2012) posed the question of whether the scenarios of the original collapse as articulated in Limits to Growth (LtG) simulation models and text of Meadows D. H., Meadows D. L., Randers, and Behren (1972) were present in the events leading to the global financial crisis (GFC). In other words, if the former hypothesis is true, then the GFC could be a predictor of the collapse presented in the LtG standard Run scenario. Turner (2012) thus tested his hypotheses and conducted the study using observed data over a 40-year period from 1970 to 2010, for comparative purposes, to the *World3* model for three key scenarios simulated in the LtG model. Turner concluded that the observed data was in line with the standard Run scenario simulated by the LtG, resulting in global collapse beginning in 2015. Furthermore, Turner's presentation and discussion of the standard Run, comprehensive technology, and stabilized world scenarios from the LtG simulations shed light on the relevance of the LtG for simulation modeling work.

The observed data presented by Turner (2012) was enlightening when viewed in comparison to the graphed LtG scenarios. For *population* and *crude birth rates*, the observed data matched the LtG *comprehensive technology* scenario closely. However, the observed data for *crude death rates* followed a trajectory closer to the *stabilized world* scenario. In contrast, the observed data for *industrial output per capita*, *food per capita* and *services per capita* were closer to the standard Run scenarios, which resulted in collapse in the LtG simulations. Finally, the author's conclusions including the fact that focus by the scientific community on climate change detracts from imminent global economic collapse, attributable to declining resources, particularly oil, is a point for further consideration.

Eastin, Grundmann, and Prakash (2011) discussed the current global warming debate in relation to the LtG discourse, relating the work of Turner (2012) on Gaia to the scenarios presented in the Limits to Growth (LtG) model by comparing the observed data. However, in contrast to the opinion held by Turner, Eastin et al. opined that the two cases differ fundamentally, albeit share a technocratic approach to public policy. Nevertheless, Eastin et al. agreed that the standard Run simulation of the LtG model is an accurate depiction of the future, and clarified a key theoretical point by contrasting the problematic greater growth paradigm with the view that developing countries are the main challenge. Eastin et al. stated that this difference fundamentally narrows down to a difference in perspective, (i.e., the LtG school of thought views the overarching growth paradigm as the challenge), whereas the neo-Malthusians consider the developing countries crisis to be the focus (Eastin et al.). Furthermore, sustainable development replaced the LtG paradigm in the 1980s, positing the optimistic possibility of economic growth as compatible with environmental protection and resource conservation, whereas the LtG paradigm considered growth as inimical to environmental protection (Eastin et al.).

Climate Change

Climate change serves as a mitigating construct for this simulation study. Specifically relating to the field of information systems management and decision-making, Miles, Snover, Binder, Sarachik, and Mantua (2006) articulated the need for a national climate service (NCS), in response to the lack of climate information being used for planning, despite the advances made in the field of climate science, ergo an NCS was conceptualized to bridge the gap between climate science and decision-making thereby improving adaptive capacity through planning for climate changes. Miles et al. proposed five research questions relating to the development of an NCS conceptual framework, each of which were discussed within the context of observation, modeling, and research as the three legs of the NCS institutional structure, and discussed challenges facing the creation of an NCA such as institutional barriers and organizational infrastructures.

Shull (2011) focused on the use of software to support climate studies, opining that the field would benefit from the collaboration of experts from multiple disciplines. Shull specifically aimed at understanding the experiences of climate modeling software developers in light of the complex political controversies surrounding climate change, thus interviewed Jacob, a computational climate scientist in the mathematics and computer science division of Argonne National Laboratory; and Schmidt, a climatologist and modeler at the NASA Goddard Institute for Space Studies, discussing various aspects of the climate modeling process, with specific emphasis on validating model results covering topics such as testing the code, comparing model outputs to analytically derived answers, divide-and-conquer strategies, and benchmarking. Shull provided the insight that models are not validated via comparison to real-world data, but rather to thought experiment conditions for which scientists have the answers. However, this point does not apply to validation of the LtG scenarios discussed further on in this literature review, which were tested according to actual real-world data. Therefore, despite the impressive qualifications of the interviewees, the conclusions of this article were not supported in the literature regarding the validation of the LtG model, which is a milestone in the modeling literature.

The UNFCCC (2014) employed a pragmatic approach to provide guiding principles and criteria for practical establishment of the climate technology network (CTN), and outlined the requirements for CTN membership, which included the requirement for members to follow specific institutional structures that are clearly outlined within the document, and responsibility of all members. The UNFCCC assumed that establishment of a CTN would enhance or contribute to their overall goals and objectives, with developing country Party National Designated Entities (NDEs) represented via members of the CTN. The CTCN initiative falls within the technological portal of the UNFCCC as a technological mechanism, with the *guiding principles and criteria for the establishment of the climate technology network* report, approved by the Advisory Board of the Climate Technology Center and Network on 9-11 September 2013 in Bonn, Germany, and serves an important role in the establishment of a network for mitigating climate change, albeit fair representation of developing countries is of concern.

Canale (2012) framed a solution to climate change as consisting of a combination of incentives and mandates governed by cooperative federalism, aimed at reducing the amount of greenhouse gas (GHG) emissions. Canale described the climate change problem, land-use regulation, zoning, urban sprawl, and federal law as it pertains to climate change, such as the clean air act (CAA). However, Canale did not test his hypothesis that land-use planning holds the potential to slow global climate change. Similarly, reduction of GHGs through Smart Growth was discussed conceptually, however not examined quantitatively or explored qualitatively (Canale). Nevertheless, Canale's recommendation that federal government should mix incentives with mandates, as was exemplified by the Georgia Regional Transportation Authority (GRTA), is relevant and significant to reducing GHGs, and spoke to the need for policy to drive global change forward and is relevant at the organizational level.

On the other hand, based on the premise that good local development plans promote sustainable urban land use, provide environmental protection and reduce risks by managing threats from natural hazards, Grover (2010) aimed to assess whether local planning policies influenced local greenhouse gas emissions (GHGs), and if so what was the effect? Grover addressed this research question using a quantitative strategy of inquiry, and a pretest-posttest nonequivalent groups quasi-experimental research design, and estimated emissions in a geographic information systems (GIS) software environment. Grover's conceptual framework involved viewing the urban environment as consisting of three areas, the human environment, the biophysical environment, and the local policy environment.

Grover (2010) raised the pertinent point that certain mitigation strategies might lower the adaptive capacity of individuals using the A1T, A1B, A1F1, A2, B1, and B2 scenarios contained in the fourth intergovernmental panel on climate change (IPCC) assessment report. This point shed light on the challenges of integrating mitigation and adaptive activities, which arise primarily from the differences in scale (international versus local and regional) and time (immediate versus long term) of each activity. Grover's research methodology, design and use of statistics further substantiated the perspective that agent-based modeling and simulation offers an unparalleled thoroughness for studying complex systems, such as climate change within the organizational context.

The opinion held by Munang, Thiaw, Alverson, Liu, and Han (2013) that climate change has the potential to trigger a positive shift to a sustainable global civilization is optimistic considering the relevant scientific literature and simulations of global scenarios such as those proposed in the LtG model. Nevertheless, the black swan outcome scenario proposed by the authors, although improbable is still possible, as evidenced by other black swan (highly improbable but possible) game changing events that have occurred throughout history. The perspective held by Munang et al. is one to consider for modeling the potential outcomes of climate change and more importantly, consideration of weights for outcome scenarios, such as a sustainable global civilization as an extreme outlier scenario.

Climate Governance

This simulation study is aimed at understanding the dynamics of climate change decision-making, to which the construct of climate governance is central and determines the agent types within the simulation model. Ostrom's (1990) work is considered foundational to the construct of climate governance in the literature, as it pertains to the governance of common pool resources (CPRs), and understanding how to avoid their exploitation and manage associated administrative costs. Ostrom overviewed three formative game theory models often employed institutionally for developing market or state solutions for governing CPRs, namely Hardin's (1968) *Tragedy of the Commons*, Dawes's (1973; 1974) *Prisoners' Dilemma* (PD), and Olson's (1965) *Logic of Collective Action*, using an extensive collection of existing case studies involving both successful and failed examples of CPR self-governance, by examining how those institutions affected the performance of their respective political and economic systems, and how self-governance in those cases evolved via individual choices, incentives, and strategies.

Eastin, Grundmann, and Prakash (2011) noted the technocratic paradox inherent in climate change policy. In other words, the UNFCCC has put forth recommendations for policy in developing countries pertaining to climate change and adaptive capacity; however, climate change poses challenges and problems, which only the technically skilled elite are suited to tackle. Thus, the technocratic approach to public policy required for climate change is in and of itself symptomatic of the justice issues embedded in the climate change debate.

Moore (2012) discussed climate change policy in terms of adaptation negotiations, clarifying adaptation as a separate policy area, as developed by the UNFCCC to include the needs of the poorest communities, resulting in the institutionalization of policy. As such Moore framed the problem of climate change in terms of being driven by activities in first world countries albeit affecting those most vulnerable in third and developing world countries, as well as other animal species, and future generations the most. Moore's work thus drew attention to the relationship between adaptation and vulnerability; clarifying the *adaptation debt* of developed/industrialized countries owed to developing and vulnerable nations, (i.e. that funds sourced from rich countries should be channeled to poor countries) for development purposes guided by the norm of *obligatory compensation* known as *adaptation restitution*, which does not concern the nature of projects funded, viewing the financial transfer itself as facilitating adaptation. However, the construct of *adaptation debt* also includes the norm of *adaptation development*, which does concern *how* the funds are used within a country, taking climate change adaptation into consideration (Moore). From this perspective, Moore opined that *adaptation debt,* framed by the competing norms of *adaptation restitution* and *adaptation development*, is robust albeit the conflicting source of consensus and controversy in UNFCCC adaptation negotiations, yet underscores the US $100 billions of climate financing pledged in Copenhagen (COP15) expiring in 2020.

Barnes et al. (2013) clarified that the need for policy responses to climate change substantiates the already well-developed scientific understanding the anthropological contributions or human systems that generate climate change. Ergo Barnes et al. proposed questions via which anthropological studies might contribute methodologically and analytically to the study of climate change; its mitigation and adaptation. In support of the research presented by Moore (2012) and Barnes et al. (2013) on the disproportion of power between developing and developed countries, Berkhout (2012) added that organizational adaptation processes should consider the needs of climate change vulnerability. The perspective provided by Berkhout included households, private and public sector organizations and civil society as examples of organizations. From this perspective, the Adaptation Fund for climate change represents an organization, which takes the needs of previously marginalized countries into consideration, thereby representing an innovation to previous organizational structures (Moore).

Networked climate governance. Tosun and Schoenefeld (2017) discussed the phenomenon of networked decentralized climate governance, using Bäckstrand's (2008) conceptualization involving three types of transnational climate partnerships, namely governmental, private-to-private, and the hybrid public-to-private, including bodies such as civil society organizations, communities, national governments, cities, international organizations, and corporations. Tosun and Schoenefeld argued that the disparate portrayal of the notion of collective climate action with networked climate governance in the literature can be reconciled by framing networked climate governance as an opportunity structure for collective climate action, underpinned by the need for a new climate governance system because of the impasse in international climate negotiations, and challenges with the pace of policy change. According to Tosun and Schoenefeld, far-reaching social change involving transformations to individual production and consumption patterns, and more substantial involvement from citizens at the subnational level constitutes collective climate action, which can be diffused to larger international areas, exemplified by the Transition Towns movement case. Ergo Tosun and Schoenefeld discussed the motivations needed for collective action with the aim of understanding the underlying factors that contribute to individual willingness to participate or contribute to localized climate initiatives such as renewable energy cooperatives in order to facilitate and govern citizen involvement such as modification of consumption behavior, signing petitions, boycotts, demonstrations, and other forms of political activism, and highlighted the social dilemma of *free-riding,* occurring at both the individual and state levels, as a barrier to successful collective action initiatives. Tosun and Schoenefeld's articulation of three governance functions, namely information sharing, capacity building, and rule-setting are relevant for modeling governance functions. Their work drew attention to the research question of how grassroots organizations might positively affect networked governance, and vice versa, as areas for future research.

Cole (2015) discussed the advantages of a bottom-up polycentric approach to climate change policy in contrast to a monocentric hierarchical approach characterized by top-down decision-making framed by the lack of progress thus far made by the UNFCCC; a problem, which Ostrom (1990) partly attributed to the lack of time needed for mutual trust to develop between individuals for mutually beneficial transactions such as climate change negotiations. Cole highlighted the role of private actors in polycentric governance initiatives, citing the formation of the World Business Council for Sustainable Development (WBCSD) in 1992 as an example. The WBCSDs collaboration with CEOs of private organizations and scientists from the Stockholm Resilience Centre for the creation of the ACTION2020 programme, the aim of which is to develop business solutions that contribute to mitigating a 2° C rise in global temperatures by 2050, is an example of successful polycentric climate change governance (Cole).

Bulkeley and Newell (2015) discussed climate change governance, and opined that the *multiple scales of political decision making*; *fragmented and blurred roles of* *state and non-state actors*; and the GHG producing processes engrained in everyday production and consumption patterns all contribute to the complexity of climate change governance. Bulkeley and Newell questioned the role of nation-states in solving the climate change problem, which she considered to be not solely a global issue, proposing that a framework for understanding how climate change is governed must include an understanding of the multitude of actors involved in its governance. Bulkeley and Newell proposed that treating climate change as an international or global problem evokes the tragedy of the commons problem in which no actor or institution has control of the atmosphere as a common resource. Bulkeley and Newell discussed the importance of understanding the role of regimes in the governance of climate change, and pointed out that the survival of the Kyoto Protocol, despite the non-cooperation and free-riding hegemonies, substantiates that the institutional whole is greater than the sum of its parts.

Climate governance and game theory. Hurlstone, Wang, Price, Leviston, and Walker (2017) further clarified the role of collective action in successful climate negotiations using a game theoretic perspective, underscored by the problems of *free-riding* and the *tragedy of the commons*, as previously discussed. Hurlstone et al. reiterated Milinski, Sommerfeld, Krambeck, Reed, and Marotzke's (2008) finding that high-risk perception has a positive effect on facilitating cooperation or collaboration for simulated catastrophe avoidance. Milinski et al. came to this conclusion by using a simulation game to test the Nash equilibria of various scenarios for free riders, fair-sharers, and maximum contributors for the purpose of mitigating the disastrous consequences of climate change, ergo Hurlstone et al. elucidated the applicability of evolutionary game theory, specifically the *Prisoner's Dilemma* (PD) for understanding certain conditions of climate negotiation resulting in either cooperation (i.e., collaborative governance, or defection, and opined that the only PD Nash equilibrium is defection). According to Johnston, Hicks, Nan, and Auer (2011) successful collaborative governance, as a type of democratic governance, is fostered by *shared commitment*, *mutual accountability*, and a *willingness to share risk*, thereby calling for the *inclusion* of all stakeholders affected by the problem. Johnston et al. framed the *contingency model* of collaborative governance created by Ansell and Gash (2008) as highly influential in the literature. Ansell and Gash found the process of collaboration to be of a complex nature, exhibiting characteristics of complexity theory such as path dependence and sensitive dependence on initial conditions. However, Johnston et al. used ABMS, specifically Netlogo, and a chain-building game theoretic approach to test the strategic choices, dilemmas, and situations involved in collaboration. Johnston et al. acknowledged the relevance of the PD game theoretic for understanding the dynamics of collaborative governance, ergo their work substantiates my choice of research design and instrument. Additionally, Nowak and Sigmund (1993) presented Pavlov, the win-stay lose-shift strategy with probabilities $(p_1, p_2, p_3, p_4) = (1, 0, 0, 1)$, which they found outperformed both tit-for-tat (TfT) with probabilities $(p_1, p_2, p_3, p_4) = (1, 0, 1, 0)$ and generous TfT (GTfT) strategies, in the Prisoner's Dilemma game, using an evolutionary simulation, in which they observed each Run for 10^7 generations, with a total of 10^5 mutant strategies generated. TfT is the strategy, which involves a player cooperating if their opponent cooperated in the previous round, and defecting if their opponent defected in the previous round. TfT was found to be the optimal strategy for reciprocal altruism (Axelrod, 1984). The GTfT strategy involves a player cooperating after an opponent's play of cooperation in the previous round, but also cooperating, with a probability p_i, after the opponent's play of defection in a previous round, which Axelrod referred to as TfT with forgiveness.

Adami, Schossau, and Hintze (2016) articulated the *paradox of cooperation*, which derives from the Nash equilibrium strategy of PD being defection, as also stated by Hurlstone, Wang, Price, Leviston, and Walker (2017). Adami et al. presented the replicator equation, an ODE used in this simulation study to determine the fraction of cooperators from the entire population consisting of cooperators (*C*) and defectors (*D*), as well as the density of *D*s. Additionally, the work of Adami et al. elucidated the validity of N-person PD simulations involving infinite populations, and the limitations of finite populations, including the fact that the outcome for the replicator equation was approached accurately with finite populations.

Methodology

On methodology, the lack of historical information regarding the scenarios leading up to organizational resilience to climate change pointed to a lacuna in the literature for the development of managerial methodological approaches for resilience. Linnenluecke and Griffiths (2012) addressed this gap, with the authors recommending methodological pathways to organizational managers for resilience assessments. However, this work is also pertinent to researchers in the field of modeling organizational resilience to climate change as approaches for identifying factors that facilitate organizational resilience were presented. Linnenluecke and Griffiths addressed the research question of whether and how recognizing and isolating the contributing factors can predict future organizational resilience to climate change and extreme weather conditions. Furthermore Linnenluecke and Griffiths clarified that retrospective analyses of past cases have been the prominent empirical approach for assessing organizational resilience, albeit have not uncovered the full range of factors leading to resilience, thereby substantiating the additional approaches presented for this purpose, namely climate projections, analogues, high impact studies, identification of factors promoting organizational resilience, business loss estimation models, resilience indicators, scenarios, and identification of thresholds.

Linnenluecke and Griffiths (2012) defined the *coping range* for organizations as a range of circumstances defined by one or more climate-related variables, that an organization is capable of withstanding without experiencing adverse consequences. Reminiscent of the *edge-of chaos* in guided self-organization (GSO) literature, are the edges of the coping-range, towards which conditions become increasing more challenging, but still tolerable. Beyond these boundaries, adverse reactions to climate change become significant. From this perspective, adaptation is viewed as the ability of an organization to widen its coping-range, albeit requiring time for implementation (Linnenluecke & Griffiths). The authors further clarified that some researchers view resilient organizations as possessing sufficiently wide coping-ranges to deal with variability in climatic conditions, while others postulated that resilience is needed by vulnerable organizations to rebound once the coping-range boundaries have been exceeded. From this perspective, a resilient response was defined by the rapidity and/or amount of recovery to a pre-disturbance or even an improved state, with *impact resistance* and *rapidity* as key organizational performance indicators ranging from 0%-100% (Linnenluecke & Griffiths).

The work of Linnenluecke and Griffths (2012) provided insight into methods of assessing organizational resilience to climate change and weather conditions, and the complexities therein involved. The authors aptly raised the question of how information concerning future climate and weather extremes can be derived on an organizationally relevant scale, in addition to the relevant question of what leads to organizational resilience and which variables should be measured in a study to determine future organizational resilience. As key performance indicators of resilience, *impact resistance* was shown to be facilitated by the variables of decentralization, diversity and redundancy of organizational resources and structure, while *rapidity* by variables of the processes that identify problems, establish priorities, and mobilize and deploy resources.

Agent–based modeling and simulation (ABMS). Hughes, Clegg, Robinson, and Crowder (2012) substantiated the fact that there is a gap and need in organizational literature for simulation modeling, the problems of which are well suited to the method, by stating that they could find only a single simulation model in the *Journal of Occupational and Organizational Psychology.* As such, Hughes et al. examined agent-based modeling and simulation (ABMS); its uses; functionality; advantages and opportunities; and clarified the thoroughness involved in the use simulation modeling in answering questions in contrast to other traditional methods. For example, researchers must explicitly explore all assumptions and aspects of a process to develop a model.

Some of the questions researchers must ask to develop an effective simulation model are: *what are the variables, agents and characteristics of the model? What is the sequence of events? Are there feedback loops, and what triggers them?* (Hughes et al.) The model then tests these assumptions, which can be modified until an adequate solution is found. Researchers must understand a scenario completely to make assumptions about the tasks, goals, rules, states, processes and plans of a system. Ergo in contrast to traditional models, ABMS provides a sophisticated level of granularity. Another key difference between ABMS and other approaches such as hierarchical task analysis (HTA) is that simulation modeling *generates* rather than *deduces* solutions to problems, based on real-world scenarios. Thus, the resulting system is generated in an elegant emergent manner that takes the interactions between agents and their environment into consideration (Hughes et al.). An important difference between statistical methods such as regression and structural equation modeling and ABMS is that these methods are discrete, capable of measuring only snapshots, whereas ABMS captures continuous dynamism (Hughes et al.). Hughes et al. clearly articulated reasons for the use of ABMS to study complex scenarios, as a complementary approach to statistical modeling, since ABMS do not test the strength of relationships between variables, nor do they examine cause and effect relationships. A bi-model design using ABMS and statistical modeling was the optimal approach to understand the relationship between organizational resilience, robustness, sustainability (RRS) and climate change adaptation.

Macal and North (2014) clarified the importance of agent-based modeling and simulation (ABMS) for organizational decision-making, and cited the models that have been developed in this regard. Macal and North stated the relevance of ABMS to complex adaptive systems, and their discussion of sustainable, self-organizing patterns and emergent organization as properties of ABMS was of relevance to the study of organizational RRS and its relationship to climate change adaptation. Fioretti (2013) described a lacuna in social science research, requiring simulation-modeling techniques, particularly organization science, and clarified that organizational problems involving micro-interactions and macro-behaviors are well suited to ABM.

ABMS platforms. Gilbert (2008) briefly discussed the differences between Swarm, Repast, Mason, and Netlogo as platforms for ABMS, providing a useful table of comparative features; however, focused on Netlogo, which is the platform used in this simulation study for understanding the relationship between organizational RRS and adaptive capacity. As such Gilbert provided code for simple practical model development in a tutorial-style, including several screenshots from Netlogo to illustrate the use of Netlogo for model building, and clarified that the first step in building a model involves making fundamental decisions regarding the agents and the environment. Furthermore as systems modeled using ABM can be of any scale comprising discrete entities, in addition to defining system boundaries, a crucial step in modeling complex systems involves capturing the characteristics of entities and their interactions (Manson, Sun, & Bonsal, 2012). As such, self-organization as a characteristic of complex systems, and emergence as a characteristic of CASs results from the interaction between entities at lower levels giving rise to larger entities and emergent behaviors (Manson et al.).

Helbing and Balietti (2011) discussed ABMS at great length and included a discussion on the usefulness of simulation studies for socio-economic sciences in addition to the advantages of ABMS, including the affordance of understanding self-organization and emergence. Helbing and Balietti provided several examples of ABS and discussed the principles of the methodology. The work of Helbing and Balietti supports the choice of ABMS as a methodology for this simulation study.

Addressing complexity with ABMS. Pertaining to ABMS as a methodology and the constructs associated with the theory of complexity, Manson, Sun, and Bonsal (2012), opined that the constructs of *sensitive dependence on initial conditions*, *nonlinearity*, *self-organization*, *emergence*, *complicated dynamics*, and *information processing*, deriving from complexity and evolutionary game theories are mutually complemented by a computational experimental research design using ABMS. In fact, Manson et al. opined that complexity theory and complex systems provide the theoretical foundation for ABM in general. Manson et al. elucidated the relevance of complexity constructs to a computational experimental methodology using ABM within the scope of social science studies and policy fields. Manson et al. identified three types of complexity research: algorithmic complexity for understanding and replicating systems using heuristic, mathematical and/or computational terms; deterministic complexity envisioned through the lens of nonlinear dynamics and chaos theory, using sets of mathematical terms for determining the trajectory of complex systems; and aggregate complexity for understanding how complex systems emerge through interactions, each contributing to the overall understanding of a system of almost any scale, and its connection to the external environment.

ABMS for studying organizational adaptation, robustness, and sustainability. Wu, Hu, Zhang, Spence, Hall, and Carley (2009) used ABMS to explore organizational adaptation on the Netlogo platform. Wu et al. used *agility, robustness*, *resilience*, and *survivability* as their independent variables, and *organizational adaptation* as their dependent variable. From this perspective, the study by Wu et al. was relevant for this simulation study for illustrating how to define the independent variables of *resilience*, *robustness*, and *sustainability;* and *adaptive capacity* as the dependent variable. Mitchell's (2009) discussion of complex systems substantiates the applicability and usefulness of ABMS for understanding how behaviors at lower levels give rise to behaviors at higher levels in complex systems as diverse as the human immune system, the brain, ant colonies, and organizations.

Humanity is facing serious challenges in the form of financial crises, international wars, and global terror, the spreading of diseases; cyber-crime; and demographic, technological, and environmental change requiring innovative approaches to complex systems and emerging phenomena (Helbing, Bishop, Conte, Lukowicz, & McCarthy, 2012). Moving away from a component-oriented view of the world to an interaction-oriented view of the world is an example of the directive perspective required, or a paradigm shift that calls attention to the interaction between components rather than the components themselves (Helbing et al.), which is useful for testing the resilience, robustness, and sustainability, or dynamics of climate change governance for the purpose of improving adaptive capacity.

Summary and Conclusions

The constructs of RRSA have been framed in current literature within the context of information systems management and their efficacy for understanding and mitigating climate change via the dynamics of climate governance. More specifically using a multidisciplinary, cross-scalar, integrated approach to various forms of resilience, including *economic resilience*, *ecological resilience*; *social resilience*, *organizational resilience*, *resilience management*, *models of resilience*, *resilience measures*, and their intersections, serving as an independent variable; interwoven with the construct of *adaptive capacity*, serving as the dependent variable; and the constructs of *robustness*, and *sustainability*, serving as independent variables. Furthermore, the constructs of *disaster management* and *collapse* were discussed in relation to *climate change studies* (Canales, 2012; Grover, 2010; Shull, 2011; UNFCCC, 2014) and *climate governance* (Bäckstrand, 2008; Berkhout, 2012; Bulkeley & Newell, 2015; Hardin, 1968; Olson, 1065; Ostrom, 1990; Tosun & Schoenefeld, 2017; UNFCCC, 2014) using an ABMS methodology (Hurlstone, Wang, Leviston & Walker, 2017; Linnenluecke & Griffiths, 2012; Macal & North, 2014). While the constructs are independently well grounded in the literature and intertwined, no single study exists for understanding the dynamics of climate governance through the lens of complexity using resilience, robustness, sustainability, and adaptive capacity to test the efficacy of collaborative or cooperative governance structures using the PD game theoretic, thereby indicating a lacuna for this simulation study.

Chapter 3: Research Method

The purpose of this quantitative computational experimental study was to develop a management decision framework of RRSA for climate governance organizations (state, private, transnational, and community) viewed as complex evolutionary systems to transcend the current unsustainable state. I tested the hypothesis that a positive relationship exists between organizational resilience defined as the amplitude of organizational deviation tolerance possible before returning to an expected output level. Robustness was defined as the measure of organizational stability in fulfilling an expected outcome despite environmental perturbations; sustainability was defined as the length of time (number of time steps) the system is able to remain resilient; and adaptive capacity was defined as the quantitative increase in complicated dynamics, emergent self-organized behavior, and information processing ability for cooperative decisions and negative for defective decisions associated with climate governance strategies of types evolutionary-RRSA, evolutionary-tit-for-tat, repeated-cooperate, and repeated-defect. The objective was to relate the evolutionary traits of resilience, robustness, and sustainability (independent variables) to the adaptive capacity (dependent variable) of organizations using an originally developed evolutionary PD simulation in Netlogo and statistical modeling in Excel. The evolutionary game theory rules of PD have been adapted for this study to understand the complex dynamics of RRSA embedded in climate change decision-making structures that either limit or facilitate adaptive capacity. The independent variables of resilience, robustness, and sustainability were defined in evolutionary game theory terms for this study. The dependent variable of adaptive capacity was defined as the quantitative increase in adaptive behaviors of agents in NetLogo (i.e., a quantitative increase in complicated dynamics, emergent self-organized behavior, and information processing ability).

This chapter includes a discussion on why mixed methods, qualitative methods, and nonexperimental, and quasi-experimental research designs were not chosen for this study. Consequently, the appropriateness of the computational experimental research design, specifically ABMS and statistical modeling to the specific research question, is discussed, outlining how the chosen research design informs and advances knowledge within the scope of information systems management. Time and resource constraints consistent with the research design are also presented.

Research Design and Rationale

As there is a need to test hypotheses for examining the relationship between variables, a qualitative strategy of inquiry was not appropriate, of which neither the associated worldviews or strategies of data collection and analysis are of relevance to this study. Similarly, a mixed methods approach was not necessary as there was no need for in-depth inductive understanding in tandem with deductive reasoning for this study. Moreover, as surveys were not an aspect of the research design, as and the population consists of organizations that were not selected using systematic bias, neither nonexperimental nor quasi-experimental types of quantitative designs were applicable to this study. A bimodal computational-based experimental quantitative research design, or simulation study in combination with statistical modeling, was chosen to test the hypotheses due to it being a well-recognized method for studying complex systems

(Mitchell, 2009). Agent-based modeling underpins cutting-edge efforts to incorporate sustainable systems thinking into the design and development of systems within the scope of information systems management (Fiksel, 2006). Hughes et al. (2012) substantiated the fact that there is a gap and need in organizational literature for simulation modeling, the problems of which are well suited to the method. Similarly, Fioretti (2013), and Macal and North (2014) substantiated the choice of ABMS for studying complex adaptive systems such as organizations, specifically regarding sustainable, self-organizing patterns and emergent organization, such as the dynamics of cooperation, as properties of ABMS.

The objective was to address the research question, which was to understand the relationship (linear, superlinear, sublinear, power law, or other) between organizational resilience (x_1), robustness (x_2), and sustainability (x_3) and adaptive capacity (Y) for cooperative and defective climate governance strategies. As such, I tested the hypothesis that a positive relationship exists between the evolutionary traits of resilience, robustness, sustainability (independent variables) and adaptive capacity (dependent variable) of organizations (state, private, transnational, and community) that operate within cooperative or collaborative governance structures (Johnston et al., 2011). In other words, the objective was to test that the agents in the simulation display evolutionary traits of resilience, robustness, and sustainability with increased adaptive capacity for cooperative decisions. The alternate hypothesis, that the relationship between the independent and dependent variables was negative for defective decisions, was also tested.

While Wu et al. (2009) used ABMS to explore organizational adaptation on the Netlogo platform with agility, robustness, resilience, and survivability as their independent variables, and organizational adaptation as their dependent variable, their work was not related to climate change and did not address the efficacy of climate governance structures using PD strategies. The constructs of RRSA were framed separately and partially connected in the literature to facilitate organizational development of resources and capabilities that mitigate the disastrous consequence of organizational collapse as a result of climate change; ergo this simulation study consolidates the gaps between the constructs for achieving this purpose.

Methodology

Testing the relationship between RRS and adaptive capacity is well suited to a computational-based experimental quantitative method of inquiry. Simulation modeling generates data, which are then used for deducing solutions to problems based on real-world scenarios in contrast to other approaches such as hierarchical task analysis, according to Hughes et al. (2012). Thus, the resulting system is generated in an elegant emergent manner that takes the interactions between agents and their environment into consideration.

As this was a simulation study, data were generated and not collected. More specifically, an ABM using PD evolutionary game theory was used to simulate the decision dynamics of climate governance structures, using the constructs of RRS to test the efficacy of the governance structures based on the hypothesis that a positive relationship exists between RRS and adaptive-capacity to climate change, quantified as an increase in complicated dynamics, emergent self-organized behavior, and information processing ability of agents, for cooperative or collaborative strategies (Johnston et al., 2011) for governing the commons by adhering to a specific emission target. Therefore, I tested the relationship between RRS and A for the evolutionary-RRSA PD strategy, in which agents were bred as either cooperators or defectors and played their respective inherited strategies, either cooperate or defect, against each other; the evolutionary-TfT strategy, which included actions of both cooperation and defection; as well as repeated-cooperate as a strategy consisting of only cooperative decisions; and repeated-defect as a strategy consisting only of defective decisions. In the evolutionary-TfT PD game, the inherited phenotype was overridden, and players instead chose the strategy taken by their opponent in the previous round. In other words, if the opponent cooperated in the previous round, then the player cooperates in the current round, and similarly if their opponent defected in the previous round, then the player defects in the current round, irrespective of their breed, and a GA is used to optimize their decision scores at the end of each round. For the repeated-cooperate PD strategy type, both cooperators and defectors chose to cooperate in both previous and current rounds despite what the opponent had decided. Similarly, for the repeated-defect PD strategy type, both cooperators and defectors chose to defect in both previous and current rounds despite what the opponent had decided. Lastly, the evolutionary-RRSA PD game is the only game in which players used their hard-wired phenotype to play against each other. The relationship between RRS and adaptive-capacity for the actions of cooperation and defection was assessed by analyzing the generated data of oscillatory decision dynamics from agents in the simulation.

The simulation was set up as follows: Each agent was given an emissions allowance at the beginning of the simulation, and the game ran with emissions rewards for cooperation and emissions penalties for defection. The emissions rewards and penalties can be set using a slider on a scale from 0 to 100. At the end of each round, the emissions score retained by the agent was indicative of whether the agent had used their emissions allowance. The agents that exceeded the emissions target were removed at each time step if the eliminate-organizations switch was on. If either the sum of all agents' emissions scores was greater than the emissions target, less than zero or sustainably less than the emissions target, the simulation stopped due to organizational collapse, or reached a stable sustainable state with emissions below the target or below zero and the message "organizational collapse—emissions target exceeded or sustainable resilient state achieved" was printed in the observer window respectively.

Each strategy was described using conditional probabilities of the opponent's move in the previous round denoted by

$\vec{P} = (p(\mathrm{C|CC}), p(\mathrm{C|CD}), p(\mathrm{C|DC}), p(\mathrm{C|DD})) \equiv (p1, p2, p3, p4)$ for cooperation,

where the character to the left of the vertical line denotes the probability of the agent to cooperate, the vertical line denotes the given condition, with the first character after the vertical line denoting the action taken by the agent in the previous round, and the second character to the right of the vertical line denoting the action taken by the opponent in the previous round. For example, $p(\mathrm{C|CC})$ is the probability that the agent will cooperate given that the agent cooperated in the previous round and their opponent also cooperated in the previous round, which is equivalent to p_1 and so on. And

$p(D|DC) = 1 - p(C|DC)$ for defection.

The probabilities within the context of ABMS represent genes, which are evolved using a GA (Adami et al., 2016). According to Adami et al. (2016), the TfT PD game in which players consider the opponents' previous action requires *2k* genes, or probabilities, where *k* is the number of players. The relative fitness of generations is then considered and a random fraction $Q = 1/N$ of the population is removed. Q is an important quantity for the population dynamics of the simulation as the ratio $1/Q$ also determines the average number of games played by each agent (Adami et al., 2016).

An important distinction exists between the payoffs to players (*T, R, P, S*), which are considered to be some gain or loss (fiscal, production, or other) from their carbon emitting activities and their emissions scores. Payoffs and emissions scores are considered to be inversely proportional in the absence of emissions penalties and cooperation rewards. According to Epstein (1998), a typical payoff matrix for NPD assumes the form of

$$\begin{array}{cc} & \begin{array}{cc} C & D \end{array} \\ \begin{array}{c} C \\ D \end{array} & \begin{pmatrix} (R,R) & (S,T) \\ (T,S) & (P,P) \end{pmatrix} \end{array}$$

where if both players cooperate, they receive the payoff (*R, R)*; if one cooperates and the other defects, the payoff is *S* to the cooperator and *T* to the defector; and if both defect, each player receives a payoff of *T*, such that $T > R > P > S$ (Axelrod, 1984). In other words, the highest payoff *T* goes to the player who defects against a cooperator. The second highest payoff *R* results from mutual cooperation, cooperating against a cooperator. The second lowest payoff *P* results from mutual defection, defecting against a defector, and the smallest payoff *S* goes to the player that cooperates against a defector.

Population

The population for this simulation study consisted of heterogeneous climate governance organizations, specifically of the types state, private, transnational, and community, as specified by the research conducted by Bulkeley and Newell (2015), Ostrom (1990), and Tosun and Schoenefeld (2017). As this was an N-Person PGG PD simulation study, an infinite, well-mixed heterogeneous population was assumed, with a fraction *xC(t)* of *N* constituting *Cs*, and the remaining population *1- xC(t)* of *N* constituting *Ds*, denoted determined by the sampling strategy discussed below and constituted the governance population in its entirety, leading to richer dynamics (Pacheco et al., 2009). The size of the population of initial cooperators at each Run can be set by the user, by means of a slider, as a percentage of the total population.

Sampling and Sampling Procedures

Random sampling of organizations within a well-mixed heterogeneous infinite population *N* for NPD produces evolutionary dynamics and leads to groups that follow a binomial distribution and the formation of the average fitness of Cs (f_C) and Ds (f_D) (Pacheco et al., 2009). According to Adami et al. (2016), the infinite population would be sampled within the simulation, with the fraction of the population consisting of Cs determined by the ODE:

$\dot{x}C(t) = xC(t) * (1 - xC(t))\ [-(b + a)xC(t) + a]$ assuming two strategies *a* and *b* are played and a fraction of the population is removed at each time step; consequently, the fraction of the population consisting of Ds was sampled using the ODE:

$xD(t) = 1 - xC(t)$

Within the context of the model N = n-organizations, which is a slider and *xC(t),* the number of cooperators, is denoted by the code create-cooperators round ((init-cooperation / 100) * n-organizations), while *xD(t)*, the number of defectors is denoted by the code create-defectors round (n-organizations - ((init-cooperation / 100) * n-organizations))

Instrumentation and Operationalization of Constructs

The PD model for adaptive capacity is based on the original PD game theory formulated by Dawes (1973; 1974) and was discussed at length by Ostrom (1990) in relation to climate governance. The PD has further been used in recent studies for understanding climate governance structures, incentive, mandates, and other strategies for decision making to mitigate the disastrous consequences of climate change as evidenced by the work of Cole (2015), Doncaster, Tavoni, and Dyke (2017), Hurlstone et al. (2017), and Milinski et al. (2008), thus substantiating the use of the PD for this simulation study.

The PD model has been used extensively in existing literature related to evolutionary game theory for the testing and exploration of cooperative and defective strategies. Originally, Axelrod (1984) found that the TfT strategy outperformed all others in games of reciprocal altruism using the PD model. Nowak and Sigmund (1993) built upon the findings of Axelrod, and presented the Pavlov strategy, which they found outperformed TfT using the PD model. Furthermore, O'Gorman, Henrich, and Van Vugt (2009) used an iterated PD model to posit strategies that constrain free-riding, which involves *D*s benefiting from the efforts of *C*s while simultaneously defecting (Bulkeley & Newell, 2015). In other words, if there were *m* number of contributors, then the defectors get the contribution mIc/N, whereas the contributors only get $mIc/N - c$. Ergo in heterogeneous groups, the defectors always win. Thus, the NPD has significance as a means of understanding the decision dynamics associated with climate change negotiations as climate change is viewed as a tragedy of the commons problem in the literature, which is approached using various types of PGG game theories, the most predominant being NPD (Bulkeley & Newell, 2015; Olson, 1965; Ostrom, 1990).

Intervention Studies or Those Involving Manipulation of an Independent Variable

This study does not involve intervention studies, or the manipulation of an independent study. The independent variables are operationalized as follows:

Organizational resilience (x_1) is the amplitude of organizational deviation tolerance possible before returning to an expected output level (Wu, Hu, Zhang, Spence, Hall, & Carley, 2009);

Organizational robustness (x_2) is the measure of organizational stability in meeting the emissions target despite environmental perturbations, (i.e., the lower the deviation from the expected outcome the higher the robustness) according to Wu et al.

Organizational sustainability (x_3) is the length of time (number of time steps) the system remains resilient or $x_3 = \mathrm{t}(x_2)$ according to Wu et al.

Data Analysis Plan

The generated data from simulation was analyzed within the Netlogo environment by plotting each dependent variable against the independent variable on separate graphs to inspect the evolutionary dynamics between RRS and adaptive capacity. In other words, there are three graphs: (a) y = organizational adaptive capacity defined as the quantitative increase in complicated dynamics, emergent self-organized behavior, and information processing ability, and x_1 = organizational resilience defined as the amplitude of organizational deviation tolerance possible before returning to an expected output level (Wu, Hu, Zhang, Spence, Hall, & Carley, 2009); (b) y = organizational adaptive capacity as defined in (a) and x_2 = organizational robustness defined as the measure of organizational stability in fulfilling an expected outcome despite environmental perturbations, (i.e., deviation from an expected outcome) according to Wu et al. (2009); and (c) y = organizational adaptive capacity as defined in (a) and (b), and x_3 = organizational sustainability defined as the length of time (number of time steps) the system is able to remain resilient. The graph for (c) is hypothesized to be defined by the relationship $y = x_3(1\text{-}x_3)\ (f_C - f_D)$, where f_C is the average fitness for cooperators, and f_D is the average fitness for defectors. This relationship is defined as the time evolution for the fraction of cooperators in current literature (Pacheco, Santos, Souza, & Skyrms, 2009). The average fitness of agents after each Run determines the next generation of chromosomes (i.e., probabilities) in the genetic algorithm (GA) for the evolutionary demographic game. At the end of each Run, an aggregation of the data is performed and the conclusion of that Run is printed in the observer window, which is a feature within the Netlogo simulation platform that enables direct programming of agents and patches, as well as observation of printed output.

As data was generated from simulation experiments, there were no human subjects implying that there were no confidentiality restrictions or permissions associated with data use and dissemination. IRB approval (number 05-22-17-04320) was attained based on the specifications articulated in the IRB application for this simulation study. The data generated from simulations in Netlogo was exported to Excel for statistical analysis. The data was cleaned by removing all non-essential information such as syntax and missing data was treated as missing. A Langrange multiplier technique was used to treat data before analyses to avoid violating the assumptions of normality, homoscedasticity, and serial independence (Jarque & Bera, 1980). Regression analyses was then performed in Excel at a confidence interval of 95% to test the relationship between variables. Validity and significance of relationships was determined using p-values < 0.01 for all independent variables and F-statistics > 5 for each analysis.

Threats to Validity

External Validity

The definitions, quantifications, and boundary conditions for the independent variables for this study were derived from current literature. *Organizational resilience (x_1)* is the amplitude of organizational deviation tolerance possible before returning to an expected output level (Wu et al., 2009); *organizational robustness (x_2)* is the measure of organizational stability in meeting the emissions target despite environmental perturbations; and *organizational sustainability (x_3)* is the length of time (number of time steps) the system is able to remain resilient or $x_3 = t(x_2)$. The definition and quantification of the dependent variable adaptive capacity *y* as the quantitative increase in complicated dynamics, emergent self-organized behavior, and information processing ability is well grounded in the literature (Mitchell, 2009). Thus, measurement of the variables accurately reflects the theoretical underpinnings of complex adaptive systems and evolutionary game theory.

Regarding conclusion and external validity, as this was an N-Person PD, the population of agents can be set to replicate the actual population of organizations involved in climate governance, using the *n-organizations* and *init-cooperation* sliders for sampling of *C*s and *D*s at each Run, thereby providing accurate statistical power. Moreover, at any given Run the well-mixed heterogeneous random sampling of the entire population to represent groups eliminates systematic bias and ensures high external validity. This study was not time bounded and the findings from ABMS are highly generalizable. Generative post-normal science studies using ABMS are empirical and therefore highly generalizable for decision-making and problem solving (Epstein, 1999).

Internal Validity

Regarding the internal validity of ABMS studies using game theory, finite populations render the replicator equation approach for outcomes inaccurate (Adami, Schossau, & Hintze, 2016). However, due to the stochastic nature of this study, and N-person population using ODE sampling, the threats of selection bias and attrition are eliminated. Moreover, in line with decisions made in the real world, individuals are unlikely to behave completely deterministically, thus the probabilities assigned to agents within the simulation stochastically capture real world decision dynamics (Adami et al.).

The design decisions for ABMS studies are crucial and will ultimately affect the population dynamics. For example, setting the probabilities as discrete or continuous variables will have significantly different outcomes. However, due to the quantification and boundary limitations of variables, the threat of ambiguous temporal precedence is mitigated. Additionally, as there is not intervention or treatment involved in testing the relationship between RRS and A for cooperative strategies the historical internal threat and threat of regression artifacts are mitigated, and the removal of individuals by the random fraction $Q = 1/N$ eliminates the threat of maturation. Finally, the evolutionary PD is a stable and well-tested instrument thereby eliminating unwanted changes in measurement.

Construct Validity

Construct validity concerns the recognition and measurement of the relationship between variables using the measuring instrument. As discussed extensively in the literature review, the variables of resilience, robustness, sustainability, and adaptive capacity have been studied quantitatively using ABMS at various levels of organization (Davis & Nikolic, 2014; Epstein, 1999; Manson, Sun, & Bonsal, 2012). The measurement of the relationship between variables was conducted using generated data from the simulation (Epstein, 1999), and analyzed using regressions analysis, which is an established method for testing hypotheses concerning the relationship between variables.

Summary

This was a computational experimental quantitative research design, specifically a simulation study using agent-based modeling and the evolutionary PD model derived from game theory (Adami, Schossau, & Hintze, 2016; Axelrod, 1984; von Neumann & Morgenstern, 1944) for testing the hypothesis that a positive relationship exists between the independent variables of *organizational resilience* (x_1), *organizational robustness* (x_2), *organizational sustainability* (x_3); and the dependent variable of adaptive capacity y. The independent variables are defined as follows, *organizational resilience* (x_1) is the amplitude of organizational deviation tolerance possible before returning to the expected emissions target (Wu et al., 2009); *organizational robustness* (x_2) is the measure of organizational stability in meeting the emissions target despite environmental perturbations; and *organizational sustainability* (x_3) is the length of time (number of time steps) the system is able to remain resilient or $x_3 = \mathrm{t}(x_2)$. The dependent variable of adaptive capacity y is defined as the quantitative increase in complicated dynamics, emergent self-organized behavior, and information processing ability (Mitchell, 2009). The relationship between the dependent variable and each of the independent variables is hypothesized to be positive for decisions of cooperation, else negative for defection in all evolutionary-RRSA, evolutionary-TfT, repeated-cooperate, and repeated-defect PD games. Regression analysis was used to test the relationship using generated data from the simulation study. Internal, external, and construct validity for this study are high given that systematic bias was eliminated, and that post-normal generative ABMS are highly generalizable (Epstein, 1999). Data collection and results of the simulation study are discussed in Chapter 4.

Chapter 4: Results

In review, the purpose of this simulation study was to develop a management framework of RRSA for organizational regimes involved in climate governance viewed as complex systems to transcend the current unsustainable state. An evolutionary game theory approach to ABMS, specifically using the PD model addressed the research question of what the relationship (linear, superlinear, sublinear, power law, or other) between organizational resilience (x_1), robustness (x_2), and sustainability (x_3) and adaptive capacity (X_{t+1}) for cooperative and defective climate governance stratagems was, and I tested the hypothesis that a positive relationship exists between organizational RRS as independent variables and the dependent variable of adaptive capacity for cooperative stratagems. Greater knowledge of this relationship may be used to facilitate decision making to move global climate change policy forward in a positive socioeconomic manner.

This chapter includes the timeframe for model creation and data collection and any discrepancies between the actual data collection methods and those described in Chapter 3. The results of the study are presented in the following section, including statistics and assumptions. In the conclusion, the contents of this chapter are summarized.

Data Collection

In Chapter 3, I discussed my intended use of the basic evolutionary PD model; however, in practice, the as-is parameters of the existing basic evolutionary PD model did not sufficiently capture the decision dynamics needed for this study. As such, a new model, namely the evolutionary-RRSA PD*,* using PD PGG theory was developed, which captures the dynamics of decision making and is representative of the variables of interest. It is important to mention that the new model does not compromise validity as discussed in Chapter 3, as the game theory rules associated with the PD PGG remain as the basis of the simulation. As data were generated from simulations for collection, and this chapter addresses discrepancies in data collection between methods discussed in Chapter 3 and actual data collection, actual model setup must be described in contrast to that which was theoretically proposed in Chapter 3. There are several discrepancies from Chapter 3 in terms of setting up the model, discussed below and summarized in Table A1.

In Chapter 3, before model development had begun, the plan was to use an infinite well-mixed heterogeneous population, with the fraction of the population consisting of Cs determined by the ODE (Adami et al., 2016):

$\dot{x}C(t) = xC(t) * (1 - xC(t)) [-(b + a)xC(t) + a]$ assuming two strategies *a* and *b* are played and a fraction of the population is removed at each time step; consequently, the fraction of the population consisting of Ds would be sampled using the ODE:

$xD(t) = 1 - xC(t)$

In practice, a finite well-mixed heterogeneous population (Epstein, 1998, 2006) was required to test the relationship between variables, with *xC(t)*, or the number of cooperators denoted by the code

create-cooperators round ((init-cooperation / 100) * n-organizations)

and *xD(t),* or the number of defectors denoted by the code create-defectors round (n-organizations - ((init-cooperation / 100) * n-organizations))

In other words, the population consisted of two types of players or breeds, either cooperator or defector, who inherited a fixed strategy or phenotype on model setup as a result of their breed. Cooperators and defectors were indistinguishable to each other but were coded as blue and red respectively and were paired at random to execute a specific strategy type, as described in Table A2. The sample of cooperators and defectors was representative of the population of interest, namely climate governance organizations, in that this study addresses the decision dynamics of the population, which consist solely of the decision types cooperate and defect. Sample size can be adjusted in the model to be as large or as small as required, with a minimum of two agents. There were no upper bounds to the size of the sample population other than computing speed and time, as the more agents that are added, the longer the processing time of each time step. As the sampled population is finite, the ODE replicator equation approach for sampling discussed in Chapter 3 was no longer valid; however, the threats of attrition and selection bias were mitigated via random sampling.

As shown in Table A2, cooperators and defectors were only hard-wired to perform their respective fixed strategies for the evolutionary-RRSA PD game. For the evolutionary-TfT PD, both cooperators and defectors executed the strategy their partner played in the previous round; in other words, if their partner defected in the last round, they also defected in the current round. Likewise, if their partner cooperated in the previous round, they cooperated in the current round, regardless of their breed, and genes were optimized at each round via a GA, thus representing a repeated game with Memory 1. The repeated-cooperate PD and repeated-defect PD simulations forced both cooperators and defectors to play the cooperate strategy and defect strategy respectively repeatedly until the simulation ended. An eliminate-organizations chooser provided the option of eliminating organizations with the lowest fitness, determined by whether their emissions-score had exceeded the emissions-target or not at each time step, in contrast to the random quantity $Q = 1/N$ described in Chapter 3. The risk of maturation was nevertheless mitigated due to new agent sets with zero memory populating the phase space at each new Run of the simulation.

The timeframe for data collection was calculated from the start of model creation, as Runs were performed and data were reviewed during model development to assess whether the variables of interest were captured and PD game theory rules applied. The timeframe from the start of coding to the end of data generation for collection and analyses spanned 4 months. The resulting univariate analyses from the graphs $y = f(x_1)$, $y = f(x_2)$, and $y = f(x_3)$, where y is the dependent variable adaptive capacity, x_1 is resilience, x_2 is robustness, and x_3 is sustainability showed that the hypothesized relationships between the dependent variable and each of the covariates for defective and cooperative decision types were valid and justified the inclusion of these covariates in the model. Study results are discussed in detail in the next section.

Study Results

This chapter addresses the statistical measures of the mean, median, mode, range, minimum, maximum, and standard deviation, their associated assumptions, confidence intervals, effect sizes as appropriate, and write-up of statistical results arranged according to the research question and hypotheses. Specifically, I include the output tables and graphs for the statistics of the metric variables x_1 = resilience, x_2 = robustness, x_3 = sustainability, and y = adaptive capacity, per simulation per Run respectively in the appendix. The data output files were generated in Netlogo using BehaviorSpace to Run each experiment and were exported to Microsoft Excel where the descriptive statistics tables were formatted. Statistical analyses were conducted in Excel to analyze the data generated in Netlogo for testing the relationship between variables. All graphs were generated in Netlogo. The PD payoff matrices are reported in tons of emissions; therefore, smaller values are preferred for calculating the NE.

Statistical Assumptions

1. The input data were not weighted for all metric variable descriptive statistics tests.
2. Missing values were treated as missing for all metric variable descriptive statistics tests.
3. All nonmissing data were used for all metric variable descriptive statistics tests.
4. No assumptions were made regarding the distribution of the scores for the untreated data.
5. The cases represented a random sample of the population, and the scores are independent of each other.

6. The assumptions of normality, homoscedasticity, and serial independence were not violated by application of the Lagrange multiplier technique (Jarque & Bera, 1980).
7. The four payoffs, defect-against-cooperator (T), cooperate-against-cooperator (R), defect-against-defector (P), and cooperate-against-defector (S), were ordered according to the PD definition (i.e., T > R > P > S).

Statistical Results

Evolutionary-RRSA PD simulation experiment. Table A3 exhibits the statistical results for Run 1 of the evolutionary-RRSA PD experiment. The sample size for the entire Run was 35, indicating the total population of organizations, 17 of which were bred as defectors and 18 were cooperators, as initial-cooperation was set to 50%. The emissions-penalty and cooperation-reward sliders were set to zero, and the eliminate-organizations chooser was set to false. Run 1 ran for 50 time steps. All descriptive statistics for the covariates resilience, robustness, sustainability, and the dependent variable adaptive-capacity are reported below as found in Table A3. The model stopped at net emissions of -16 tons, indicating an emissions credit, resulting in a robust state. The emissions target was 5196 tons.

The PD payoff-matrix was

	D	C
D	-6, -6	206, -94
C	-94, 206	56, 56

The Nash equilibrium analysis was as follows:

(D, D) = (-6, -6) ≠ NE; Player 1 has an incentive to change his or her strategy to cooperate, for a better payoff of -94, and Player 2 has incentive to change his or her strategy to cooperate for a better payoff of -94.

(D, C) = (206, -94) ≠ NE; Player 1 has an incentive to change his or her strategy to cooperate for a better payoff of 56. Player 2 has no incentive to change his or her strategy.

(C, D) = (-94, 206) ≠ NE; Player 2 has an incentive to change his or her strategy to cooperate for a better payoff of 56, while Player 1 has no incentive to change his or her strategy.

(C, C) = (56, 56) = NE; Player 1 has no incentive to change his or her strategy, and Player 2 has no incentive to change his or her strategy.

Using regression analysis performed in Excel, the following relationship for defection was deduced:

$Y = 4.492 - \sqrt[3]{\mathrm{Ln}(x1)\text{^}2} + 5.34x_2 + 0.182x_3$;

where x_1 = resilience; x_2 = robustness; and x_3 = sustainability.

At a confidence interval of 95%, the *p* values for all covariates were less than 0.05 with an *F* statistic of 55.066, which indicated that the null hypothesis was rejected, and the covariate resilience was exponentially negatively correlated with adaptive-capacity for defection, while robustness and sustainability were positively correlated with adaptive-capacity for defection within the evolutionary-RRSA PD scenario for population size of 35, when emission-penalties and cooperation-rewards are set to zero. The R^2 statistic, or coefficient of determination was 0.785, which indicated that the data fit the regression model for the evolutionary-RRSA PD for defection with the constraints specified for this Run and explained 78.5% of the variance, as shown in Figures A2, A3, A4, and A5.

For cooperation, the relationship was

$Y = 27.379 + 0.155x_1 - 0.074\text{Ln}(x_3 - x_2)$

where x_1 = resilience; x_2 = robustness; and x_3 = sustainability.

At a confidence interval of 95%, the *p* values for all covariates were less than 0.05 with an *F* statistic of 1404.69, which indicated that the null hypothesis was rejected and that resilience was positively correlated with adaptive capacity for cooperation in contrast to the exponential negative correlation of resilience with adaptive-capacity for defection. Robustness and sustainability were negatively correlated with adaptive-capacity for cooperation within the evolutionary-RRSA PD scenario for a population size of 35, when emission-penalties and cooperation-rewards are set to zero. The R^2 statistic, or coefficient of determination was 0.984, indicating that the data fit the regression model for all covariates for cooperation within the evolutionary-RRSA PD and explained 98.4% of the variance around the mean with the constraints specified for this Run.

For the covariate resilience, defined as the amplitude of organizational deviation tolerance possible before returning to the expected emissions target and measured in tons, for defection within the evolutionary-RRSA PD simulation (Run 1) the range, which is the difference between the maximum (max) statistic of -25.294 and the minimum (min) statistic of -60.399, is 35.106. as exhibited in Table A3. The defection mean for the covariate resilience located in Table A3 of -42.847 represents the average of all score values calculated using the formula: $(\sum X)/\mathrm{N}$, where sigma is the sum of X or raw scores, all divided by *N* or the sample size of 35. Table A3 shows the standard deviation of 24.824, which is calculated using the formula s=$\sqrt{\sum SS}$, where *s* is the standard deviation and $\sqrt{\sum SS}$ is the square root of the sum of squares. The median is a statistic of central tendency that divides the sample into exactly half (Bryman, 2012), the value of which is -42.847 for this variable. Furthermore, the mode is a statistic of central tendency that represents the value of a score or scores that present in the sample with the greatest frequency (Lomax & Hahs-Vaughn, 2013). For the metric variable resilience*,* the modes for defection exhibited in Table A3 were -60.399 and -25.294. In contrast, the max, min, and range statistics for cooperation were 8,200, 7,800, and 400 respectively, with a mean of 8,000, standard deviation of 282.843, and modes of 2,800 and 8,200, indicating significantly greater resilience for cooperation than defection for the covariate resilience as a function of adaptive-capacity within the evolutionary-RRSA PD simulation for Run 1. The mean for overall system resilience for the evolutionary-RRSA PD simulation was 3978.577 for Run 1.

For the covariate robustness, defined as the measure of organizational stability in meeting the emissions target despite environmental perturbations, measured on a sliding scale from 0 (*not robust*) to 1 (*fully robust*), the max, min, range, and mean for defection within the evolutionary-RRSA PD simulation for Run 1 are 0.797, 0.594, 0.247, and 0.673 respectively, with a median of 0.673 as shown in Table A3, in contrast to the former statistics for cooperation being 1, 1, 0, 1, and 1, indicating that the cooperation stratagem is fully robust compared to the defection stratagem, which achieves only partial robustness for Run 1. The mean for overall system robustness for the evolutionary-RRSA PD simulation was 0.837 for Run 1.

For the covariate sustainability, defined as the length of time the system can remain resilient, measured in time steps the max, min, range, and mean for defection and cooperation within the evolutionary-RRSA PD simulation for Run 1 are 27, 26, 1, and 26.5 respectively, with a median of 26.5 as shown in Table A3. The mean for overall system sustainability for the evolutionary-RRSA PD simulation was 26.5 for Run 1.

For the dependent variable adaptive-capacity, defined as the quantitative increase in complicated dynamics, emergent self-organized behavior, and information processing ability, measured on a sliding scale from 0 (*not robust*) to 1 (*fully robust*), the max, min, range, and mean for defection within the evolutionary-RRSA PD simulation for Run 1 are 84, 79, 5, and 8 respectively with a median of 81.5 as shown in Table A3, in contrast to the former statistics for cooperation being 182, 178, 4, 180 and 180, indicating that the cooperation stratagem results in greater adaptive-capacity compared to the defection stratagem. The mean for overall system adaptive-capacity for the evolutionary-RRSA PD simulation was 130.75 for Run 1.

Table A4 includes the statistical results for Run 2 of the evolutionary-RRSA experiment. The sample size for the entire Run was 100, indicating the total population of organizations, 50 of which were bred as defectors and 50 were cooperators, as initial-cooperation was set to 50%. The emissions-penalty and cooperation-reward sliders were set to zero, and the eliminate-organizations chooser was set to false. Run 2 of the evolutionary-RRSA simulation ran for 17 time steps.

The PD payoff-matrix was:

	D	C
D	20, 20	155, -96
C	-96, 155	54, 54

Nash equilibrium analysis

(D, D) = (20, 20) ≠ NE; Player 1 has an incentive to change their strategy to cooperate, for a better payoff of -96, and Player 2 has incentive to change their strategy to cooperate for a better payoff of -96.

(D, C) = (155, -96) ≠ NE; Player 1 has an incentive to change their strategy to cooperate for a better payoff of 54. Player 2 has no incentive to change their strategy.

(C, D) = (-96, 155) ≠ NE; Player 2 has an incentive to change their strategy to cooperate for a better payoff of 54, while Player 1 has no incentive to change their strategy.

(C, C) = (54, 54) = NE; Player 1 has no incentive to change their strategy, and player 2 has no incentive to change their strategy.

Using regression analysis performed in Excel the following relationship for defection was deduced:

$Y = 0.07 + 0.069x_1^3 + 5.12x_2 + 0.323x_3$;

where x_1 = resilience; x_2 = robustness; and x_3 = sustainability.

At a confidence interval of 95%, the p-values for all covariates were less than 0.05 with an F-statistic of 186.04, which indicated that the null hypothesis was rejected and that all covariates were positively correlated with adaptive capacity for defection when population size was increased to 100 within the evolutionary-RRSA PD scenario with zero emission-penalties. The R^2 statistic, or coefficient of determination was 0.925, which indicated that the data fit the regression model for all covariates for defection within the evolutionary-RRSA PD and explained 92.5% of the variance around the mean with the constraints specified for this Run.

The relationship for cooperation for Run 2 of the evolutionary-RRSA PD was:

$Ln(Y) = 2.236 + \sqrt[3]{0.324x1} - 3.768Ln((x_3 - x_2)^2)$;

At a confidence interval of 95%, the p-values for all covariates were less than 0.05 with an F-statistic of 186.04, which indicated that the null hypothesis was rejected and that resilience was positively correlated with adaptive capacity, whereas robustness and sustainability were negatively correlated with the latter for cooperation when population size was increased to 100 within the evolutionary-RRSA PD scenario with zero emission-penalties. The R^2 statistic, or coefficient of determination was 0.778, which indicated that the data fit the regression model for all covariates for cooperation within the evolutionary-RRSA PD and explained 77.8% of the variance around the mean with the constraints specified for this Run.

Resilience (x_1) Run 2. For the covariate *resilience*, the max, min, range, and mean for *defection* within the evolutionary-RRSA PD simulation for Run 2 are -10.502, -20.116, 9.614, and -15.309 respectively with a median of -15.309 as shown in Table A4, in contrast to the former statistics for *cooperation* being 6700, 6700, 0, 6700 and 6700, indicating significantly greater resilience for *cooperation* than *defection* for the covariate *resilience* as a function of *adaptive-capacity* within the evolutionary-RRSA PD simulation. The mean for overall system *resilience* for the evolutionary-RRSA PD simulation was 3342.346 for Run 2.

Robustness (x_2) Run 2. For the covariate *robustness*, the max, min, range, and mean for *defection* within the evolutionary-RRSA PD simulation for Run 2 are 0.651, 0.357, 0.293, and 0.504 respectively with a median of 0.504 as shown in Table A4, in contrast to the former statistics for *cooperation* being 1, 1, 0, 1 and 1, indicating that the *cooperation* stratagem is fully robust compared to the defection stratagem which achieves only partial robustness in Run 2. The mean for overall system *robustness* for the evolutionary-RRSA PD simulation was 0.752 or 75.2% for Run 2.

Sustainability (x_3) Run 2. For the covariate *sustainability*, the max, min, range, and mean for *defection* within the evolutionary-RRSA PD simulation for Run 2 are 17, 16, 1, and 16.5 respectively with a median of 16.5 as shown in Table A4, in contrast to the former statistics for cooperation being 17, 17, 0, and 17 respectively with a median of 17 indicating that the system sustainability was increased by one time step as a result of the *cooperation* stratagem. The mean for overall system sustainability for the evolutionary-RRSA PD simulation was 16.75 for Run 2.

Adaptive-capacity (y) Run 2. For the dependent variable, *adaptive-capacity*, the max, min, range, and mean for *defection* within the evolutionary-RRSA PD simulation for Run 2 are 89, 81, 8, and 85 respectively with a median of 85 as shown in Table 4, in contrast to the former statistics for *cooperation* being 167, 167, 0, 167 and 167, indicating that the *cooperation* stratagem results in greater and consistent *adaptive-capacity* compared to the defection stratagem. The mean for overall system adaptive-capacity for the evolutionary-RRSA PD simulation was 126 for Run 2.

Run 3. Table A5 exhibits the statistical results for Run 3 of the *evolutionary-RRSA* experiment. The sample size for the entire Run was 100, indicating the total population of organizations, 50 of which were bred as defectors and 50 were cooperators, as initial-cooperation was set to 50%. The *emissions-penalty* and *cooperation-reward* sliders were set to 20 and zero respectively; and the *eliminate-organizations* chooser was set to *false*. Run 3 of the evolutionary-RRSA simulation ran for 50 time steps. The PD payoff-matrix was

	D	C
D	13, 13	0, -98
C	-98, 0	52, 52

Nash equilibrium analysis

(D, D) = (13, 13) ≠ NE; Player 1 has an incentive to change their strategy to cooperate, for a better payoff of -98, and Player 2 has incentive to change their strategy to cooperate for a better payoff of -98.

(D, C) = (0, -98) = NE; neither players have an incentive to change their strategies.

(C, D) = (-98, 0) = NE; neither players have an incentive to change their strategies.

(C, C) = (52, 52) ≠ NE; Player 1 has an incentive to change their strategy to defect for a better payoff of 0, and Player 2 has an incentive to change their strategy to defect for a better payoff of 0.

Regression analysis was performed in Excel for the application of an emissions-penalty to the simulation holding all other parameters constant, and the following relationship for defection was deduced:

$\text{Ln}(Y) = 1.339 - \sqrt[3]{0.861x1} + 0.289\text{Ln}(x_3 - x_2)$;

where x_1 = resilience; x_2 = robustness; and x_3 = sustainability.

At a confidence interval of 95%, the p-values for all covariates were less than 0.05 with an F-statistic of 59.755, which indicated that the null hypothesis was rejected and that resilience was negatively correlated with adaptive capacity for defection when emissions-penalty was applied, whereas robustness and sustainability were positively correlated with adaptive-capacity because of the emissions-penalty for defection within the evolutionary-RRSA PD scenario. The R^2 statistic, or coefficient of determination was 0.804, which indicated that the data fit the regression model for all covariates for defection within the evolutionary-RRSA PD and explained 80.4% of the variance around the mean with the constraints specified for this Run.

The relationship for cooperation for Run 3 of the evolutionary-RRSA PD was:

$Y = 13.872 + 10.329\text{Ln}(x_1) + 2.723\text{Ln}(x_3 - x_2)$;

At a confidence interval of 95%, the p-values for all covariates were less than 0.05 with an F-statistic of 1168.764, which indicated that the null hypothesis was rejected and that all covariates were positively correlated with adaptive capacity for cooperation when the emissions-penalty was applied, within the evolutionary-RRSA PD scenario. The R^2 statistic, or coefficient of determination was 0.987, which indicated that the data fit the regression model for all covariates for cooperation within the evolutionary-RRSA PD and explained 98.7% of the variance around the mean with the constraints specified for this Run.

Resilience (x_1) Run 3. For the covariate *resilience*, the max, min, range, and mean for *defection* within the evolutionary-RRSA PD simulation for Run 3 are -19.878, -28.274, 8.396, and -24.076 respectively with a median of -24.077 as shown in Table A5, in contrast to the former statistics for *cooperation* being 5400, 5400, 0, 5400 and 5400, indicating significantly greater and consistent resilience for *cooperation* than *defection* for the covariate *resilience* as a function of *adaptive-capacity* within the evolutionary-RRSA PD simulation Run 3. The mean for overall system resilience for the evolutionary-RRSA PD simulation was 2687.962 for Run 3.

Robustness (x_2) Run 3. For the covariate *robustness*, the max, min, range, and mean for *defection* within the evolutionary-RRSA PD simulation for Run 3 are 0.271, 0.162, 0.109, and 0.217 respectively with a median of 0.217 as shown in Table A5, in contrast to the former statistics for *cooperation* being 1, 1, 0, 1, and 1, indicating that the *cooperation* stratagem is fully robust compared to the defection stratagem which achieves only partial robustness in Run 3. The mean for overall system robustness for the evolutionary-RRSA PD simulation was 0.608 for Run 3.

Sustainability (x_3) Run 3. For the covariate *sustainability*, the max, min, range, and mean for *defection* within the evolutionary-RRSA PD simulation for Run 3 were 49, 37, 12, and 43 respectively with a median of 43 as shown in Table A5, in contrast to the former statistics for cooperation being 49, 49, 0, and 49 respectively with a median of 49 indicating that system sustainability was increased by 3 time steps because of the *cooperation* stratagem. The mean for overall system sustainability for the evolutionary-RRSA PD simulation was 46 for Run 3.

Adaptive-capacity (y) Run 3. For the dependent variable, *adaptive-capacity*, the max, min, range, and mean for *defection* within the evolutionary-RRSA PD simulation for Run 3 are 24, -3, 27, and 10.5 respectively with a median of 10.5 as shown in Table A5, in contrast to the former statistics for *cooperation* being 154, 154, 0, 154, and 154, indicating that the *cooperation* stratagem results in greater and consistent *adaptive-capacity* compared to the defection stratagem. The mean for overall system adaptive-capacity for the evolutionary-RRSA PD simulation was 82.25 for Run 3.

Evolutionary-Tit-for-Tat PD Simulation Experiment

Run 1. Table A7 exhibits the statistical results for Run 1 of the *evolutionary-TfT* experiment. The sample size for the entire Run was 35, indicating the total population of organizations, 17 of which were bred as defectors and 18 were cooperators, as initial-cooperation was set to 50%. The *emissions-penalty* and *cooperation-reward* sliders were set to 0 and 0 respectively; and the *eliminate-organizations* chooser was set to *false*. Run 1 of the evolutionary-TfT simulation ran for 50 time steps with net emissions of 62545 tons exceeding the emissions target of 5183 tons, resulting in organizational collapse. The PD payoff-matrix was

	D	C
D	796, 796	N/A
C	N/A	2582, 2582

Nash equilibrium analysis

(D, D) = (796, 769) = NE; neither player can change their strategy.

(D, C) = (N/A, N/A) ≠ NE; this is not a valid option as Player 1 cannot chose to defect against a cooperator, and similarly for Player 2.

(C, D) = (N/A, N/A) ≠ NE; this is not a valid option as Player 1 cannot chose to cooperate against a defector, and similarly for Player 2.

(C, C) = (2582, 2582) = NE; neither player can change their strategy.

Using regression analysis performed in Excel the following relationship for defection was deduced:

$Y = -20984 + 7.858x_1 + 1494.064x_2 - 28.097x_{3;}$

where x_1 = resilience; x_2 = robustness; and x_3 = sustainability.

At a confidence interval of 95%, the p-values for all covariates were less than 0.05 with an F-statistic of 241.036, which indicated that the null hypothesis was rejected and the covariates resilience and robustness were positively correlated with adaptive-capacity for defection, while sustainability was negatively correlated with adaptive-capacity for defection within the evolutionary-TFT PD scenario for population size of 35, when emission-penalties and cooperation-rewards are set to zero. The R^2 statistic, or coefficient of determination was 0.957, which indicated that the data fit the regression model for the evolutionary-TFT PD for defection with the constraints specified for this Run, and explained 95.7% of the variance, as shown in Figures A18, A19, A20, and A21.

For cooperation, the relationship was

$$Y = 3.046 + 2.303x_1 + 0.015x_1^2 + 1392.312x_2^4 + 33.261x_3$$

where x_1 = resilience; x_2 = robustness; and x_3 = sustainability.

At a confidence interval of 95%, the p-values for all covariates were less than 0.05 with an F-statistic of 10504.81, which indicated that the null hypothesis was rejected and that resilience and robustness are exponentially positively correlated with adaptive capacity for cooperation in contrast to the linear correlation of resilience and robustness with adaptive-capacity for defection, and sustainability was positively correlated with adaptive-capacity for cooperation within the evolutionary-TFT PD scenario for population size of 35, when emission-penalties and cooperation-rewards are set to zero, as seen in Figures A18, A19, A20, and A21. The R^2 statistic, or coefficient of determination was 0.998, indicating that the data fit the regression model for all covariates for cooperation within the evolutionary-TFT PD and explained 99.8% of the variance around the mean with the constraints specified for this Run.

Resilience (x_1) Run 1. For the covariate *resilience*, the max, min, range, and mean for *defection* within the evolutionary-TfT PD simulation for Run 1 are -11.275, -99.528, 88.253, and -70.597 respectively with a median of -99.496 as shown in Table A7, in contrast to the former statistics for *cooperation* being 12800, 11300, 1500, 11984.615, and 11900, indicating significantly greater resilience for *cooperation* than *defection* for the covariate *resilience* as a function of *adaptive-capacity* within the evolutionary-TfT

PD simulation Run 1. The mean for overall system resilience for the evolutionary-TfT PD simulation was 5840.845 for Run 1.

Robustness (x_2) Run 1. For the covariate *robustness*, the max, min, range, and mean for *defection* within the evolutionary-TfT PD simulation for Run 1 are 0.338, 0.054, 0.284, and 0.243 respectively with a median of 0.325 as shown in Table A7, in contrast to the former statistics for *cooperation* being 1, 1, 0, 1, and 1, indicating that the *cooperation* stratagem is fully robust compared to the *defection* stratagem which achieves only partial robustness in Run 1. The mean for overall system robustness for the evolutionary-TfT PD simulation was 0.611 for Run 1.

Sustainability (x_3) Run 1. For the covariate *sustainability*, the max, min, range, and mean for *defection* and *cooperation* within the evolutionary-TfT PD simulation for Run 1 were 6, 6, 0, and 6 respectively with a median of 6 as shown in Table A7. The mean for overall system sustainability for the evolutionary-TfT PD simulation was 6 for Run 1.

Adaptive-capacity (x_4) Run 1. For the dependent variable, *adaptive-capacity*, the max, min, range, and mean for *defection* within the evolutionary-TfT PD simulation for Run 1 are -96, -113, 17, and -104.5 respectively with a median of -104.5 as shown in Table A7, in contrast to the former statistics for *cooperation* being 228, 213, 15, 219.846, and 219, indicating that the *cooperation* stratagem results in greater *adaptive-capacity* compared to the defection stratagem. The mean for overall system adaptive-capacity for the evolutionary-TfT PD simulation was 53.6 for Run 1.

Run 2. Table A8 exhibits the statistical results for Run 2 of the *evolutionary-TfT* experiment. The sample size for the entire Run was 100, indicating the total population of organizations, 50 of which were bred as defectors and 50 were cooperators, as initial-cooperation was set to 50%. The *emissions-penalty* and *cooperation-reward* sliders were set to 0 and 0 respectively; and the *eliminate-organizations* chooser was set to *false*. Run 2 of the evolutionary-TfT PD simulation ran for 50 time steps. The model stopped when the net emissions of 494950 tons exceeded the emissions target of 15134 tons, resulting in organizational collapse. The PD payoff-matrix was

	D	C
D	2640, 2640	N/A
C	N/A	7640, 7640

Nash equilibrium analysis:

(D, D) = (2640, 2640) = NE; neither player can change their strategy.

(D, C) = (N/A, N/A) ≠ NE; this is not a valid option as Player 1 cannot chose to defect against a cooperator, and similarly for Player 2.

(C, D) = (N/A, N/A) ≠ NE; this is not a valid option as Player 1 cannot chose to cooperate against a defector, and similarly for Player 2.

(C, C) = (7640, 7640) = NE; neither player can change their strategy.

Regression analysis performed in Excel revealed the following relationship for defection:

$$Y = -265.228 + 0.818x_1 + 17.794x_2^3 + 0.148x_3^3$$

where x_1 = resilience; x_2 = robustness; and x_3 = sustainability.

At a confidence interval of 95%, the p-values for all covariates were less than 0.05 with an F-statistic of 728.796, which indicated that the null hypothesis was rejected and all covariates were positively correlated with adaptive-capacity for defection, as a result of the population size increasing to 100 from 35 in the previous Run within the evolutionary-TFT PD, when emission-penalties and cooperation-rewards are set to zero. The R^2 statistic, or coefficient of determination was 0.979, which indicated that the data fit the regression model for the evolutionary-TFT PD for defection with the constraints specified for this Run, and explained 97.9% of the variance, as shown in Figures A20, A21, A22, and A23.

For cooperation, the relationship was

$$Y = -1.064 + 1.039x_1 - 1.276\mathrm{Ln}((x_3 - x_2)^5)$$

where x_1 = resilience; x_2 = robustness; and x_3 = sustainability.

At a confidence interval of 95%, the p-values for all covariates were less than 0.05 with an F-statistic of 1530.037, which indicated that the null hypothesis was rejected and that resilience was positively correlated with adaptive capacity for cooperation, while robustness, and sustainability were exponentially negatively correlated with adaptive-capacity with population size increased from 35 to 100 for cooperation within the evolutionary-TFT PD scenario when emission-penalties and cooperation-rewards are set to zero, as seen in Figures A20, A21, A22, and A23. The R^2 statistic, or coefficient of determination was 0.985, indicating that the data fit the regression model for all covariates for cooperation within the evolutionary-TFT PD and explained 98.5% of the variance around the mean with the constraints specified for this Run.

Resilience (x_1) Run 2. For the covariate *resilience*, the max, min, range, and mean for *defection* within the evolutionary-TfT PD simulation for Run 2 are -21.635, -99.502, 77.867, and -77.037 respectively with a median of -99.444 as shown in Table A8, in contrast to the former statistics for *cooperation* being 19900, 12900, 7000, 16443.636, and 16500, indicating significantly greater resilience for *cooperation* than *defection* for the covariate *resilience* as a function of *adaptive-capacity* within the evolutionary-TfT PD simulation Run 2. The mean for overall system resilience for the evolutionary-TfT PD simulation was 11878.199 for Run 2.

Robustness (x_2) Run 2. For the covariate *robustness*, the max, min, range, and mean for *defection* within the evolutionary-TfT PD simulation for Run 2 are 0.364, 0.099, 0.265, and 0.281 respectively with a median of 0.340 as shown in Table A8, in contrast to the former statistics for *cooperation* being 1, 1, 0, 1, and 1, indicating that the *cooperation* stratagem is fully robust compared to the *defection* stratagem which achieves only partial robustness in Run 2. The mean for overall system robustness for the evolutionary-TfT PD simulation was 0.806 for Run 2.

Sustainability (x_3) Run 2. For the covariate *sustainability*, the max, min, range, and mean for *defection* and *cooperation* within the evolutionary-TfT PD simulation for Run 2 are 2, 2, 0, and 2 respectively with a median of 2 as shown in Table A8. The mean for overall system sustainability for the evolutionary-TfT PD simulation was 2 for Run 2.

Adaptive-capacity (x_4) Run 2. For the dependent variable, *adaptive-capacity*, the max, min, range, and mean for *defection* within the evolutionary-TfT PD simulation for Run 2 are -74, -100, 26, and -87 respectively with a median of -87 as shown in Table A8, in contrast to the former statistics for *cooperation* being 229, 229, 70, 264.436, and 265, indicating that the *cooperation* stratagem results in greater *adaptive-capacity* compared to the defection stratagem. The mean for overall system adaptive-capacity for the evolutionary-TfT PD simulation was 168.5 for Run 2.

Run 3. Table A9 exhibits the statistical results for Run 3 of the *evolutionary-TfT* experiment. The sample size for the entire Run was 100, indicating the total population of organizations, 50 of which were bred as defectors and 50 were cooperators, as initial-cooperation was set to 50%. The *emissions-penalty* and *cooperation-reward* sliders were set to 20 and 0 respectively; and the *eliminate-organizations* chooser was set to *false*. Run 3 of the evolutionary-TfT PD simulation ran for 50 time steps. The model stopped when net emissions of 9708900 tons exceeded the emissions-target of 14912 tons resulting in organizational collapse. The PD payoff-matrix was

	D	C
D	476, 476	N/A
C	N/A	7476, 7476

Nash equilibrium analysis:

(D, D) = (476, 476) = NE; neither player can change their strategy.

(D, C) = (N/A, N/A) ≠ NE; this is not a valid option as Player 1 cannot chose to defect against a cooperator, and similarly for Player 2.

(C, D) = (N/A, N/A) ≠ NE; this is not a valid option as Player 1 cannot chose to cooperate against a defector, and similarly for Player 2.

(C, C) = (7476, 7476) = NE; neither player can change their strategy.

Using regression analysis performed in Excel, the following relationship was deduced for defection:

$Y = -3624.586 + 1.335x_1 - 107.749x_2^3 + 0.323x_3^3$;

where x_1 = resilience; x_2 = robustness; and x_3 = sustainability.

At a confidence interval of 95%, the p-values for all covariates were less than 0.05 with an F-statistic of 604.567, which indicated that the null hypothesis was rejected and that resilience, and sustainability were positively correlated with adaptive-capacity, while robustness was exponentially negatively correlated with the latter as a result of the emissions-penalty for defection within the evolutionary-TFT PD scenario for population size of 100, when emission-penalties were set to 20 and cooperation-rewards were set to zero. The R^2 statistic, or coefficient of determination was 0.988, indicating that the data fit the multiple regression model for all covariates, and explained 98.8% of the variability around the mean for defection within the evolutionary-TFT PD with the constraints specified for this Run, as shown in Figures A24, A25, A26, and A27.

The relationship for cooperation was

$Y = -2180.815 + 1.182x_1 + 46322.029x_2 + 0.345x_3^3$;

where x_1 = resilience; x_2 = robustness; and x_3 = sustainability.

At a confidence interval of 95%, the p-values for all covariates were less than 0.05 with an F-statistic of 500.819, which indicated that the null hypothesis was rejected and all covariates were positively correlated with adaptive-capacity for cooperation as a result of the emissions-penalty leaving all other parameters constant for the evolutionary-TFT PD scenario for population size of 100, when emission-penalties are set to 20 and cooperation-rewards are set to zero. The R^2 statistic, or coefficient of determination was 0.970, indicating the data fit the regression model for all covariates, and explained 97% of the variability around the means for the evolutionary-TFT PD with the constraints specified for this Run, as shown in Figures A24, A25, A26, and A27.

Resilience (x_1) Run 3. For the covariate *resilience*, the max, min, range, and mean for *defection* within the evolutionary-TfT PD simulation for Run 3 are -37.918, -100.721, 62.803, and -76.703 respectively with a median of -90.497 as shown in Table A9, in contrast to the former statistics for *cooperation* being 200, 100, 200, 188, and 200, indicating significantly greater resilience for *cooperation* than *defection* for the covariate *resilience* as a function of *adaptive-capacity* within the evolutionary-TfT PD simulation Run 3. The mean for overall system resilience for the evolutionary-TfT PD simulation was 49.115 for Run 3.

Robustness (x_2) Run 3. For the covariate *robustness*, the max, min, range, and mean for *defection* within the evolutionary-TfT PD simulation for Run 3 are 0.079, 0.023, 0.056, and 0.048 respectively with a median of 0.046 as shown in Table A9, in contrast to the former statistics for *cooperation* being 1, 1, 0, 1, and 1, indicating that the *cooperation* stratagem is fully robust compared to the *defection* stratagem which achieves only partial robustness in Run 3. The mean for overall system robustness for the evolutionary-TfT PD simulation was 0.505 for Run 3.

Sustainability (x_3) Run 3. For the covariate *sustainability*, the max, min, range, and mean for *defection* and *cooperation* within the evolutionary-TfT PD simulation for Run 3 are -1, -1, 0, and -1 respectively with a median of -1 as shown in Table A9. The mean for overall system sustainability for the evolutionary-TfT PD simulation was -1 for Run 3.

Adaptive-capacity (x_4) Run 3. For the dependent variable, *adaptive-capacity*, the max, min, range, and mean for *defection* within the evolutionary-TfT PD simulation for Run 3 are -979, -1999, 1020, and -1489 respectively with a median of -1489 as shown in Table A9, in contrast to the former statistics for *cooperation* being 102, 101, 1, 101.88, and 102, indicating that the *cooperation* stratagem results in greater *adaptive-capacity* compared to the defection stratagem. The mean for overall system adaptive-capacity for the evolutionary-TfT PD simulation was -725.39 for Run 3.

Repeated-cooperate PD Simulation Experiment

Run 1. Table A11 exhibits the statistical results for Run 1 of the *repeated-cooperate PD* experiment. The sample size for the entire Run was 35, indicating the total population of organizations, 17 of which were bred as defectors and 18 were cooperators, as initial-cooperation was set to 50% The *emissions-penalty* and *cooperation-reward* sliders were set to 0 and 0 respectively; and the *eliminate-organizations* chooser was set to *false*. Run 1 of the repeated-cooperate PD simulation ran for 50 time steps. The model stopped at net emissions of -102 tons. The emissions-target was 5027 tons, resulting in an emissions credit. The PD payoff-matrix was

	D	C
D	N/A, N/A	N/A, -111
C	-111, N/A	2488, 2488

Nash equilibrium analysis:

(D, D) = (N/A, N/A) ≠ NE; this is not a valid combination as defection is not an option in this Run.

(D, C) = (N/A, -111) ≠ NE; this is not a valid combination as defection is not an option in this Run.

(C, D) = (-111, N/A) ≠ NE; this is not a valid combination as defection is not an option in this Run.

(C, C) = (2488, 2488) = NE; neither player can change their strategy.

Using regression analysis performed in Excel, the following relationship for cooperation was deduced:

$Ln(Y) = 4.151 + \sqrt[3]{0.35x1} + 0.05Ln((x_3 - x_2)^2)$;

where x_1 = resilience; x_2 = robustness; and x_3 = sustainability.

At a confidence interval of 95%, the p-values for all covariates were less than 0.05 with an F-statistic of 370.985, which indicated that the null hypothesis was rejected and all covariates were positively correlated with adaptive-capacity as seen in Figures A34, A35, A36, and A37 for cooperation within the repeated-cooperate PD scenario for population size of 35, when emission-penalties and cooperation-reward were set to 0. The R^2 statistic, or coefficient of determination was 0.940, which indicated that the data fit the regression model for all covariates and explained 94.0% of the variability around the means for the repeated-cooperate PD with the constraints specified for this Run.

Resilience (x_1) Run 1. For the covariate *resilience*, the max, min, range, and mean for *cooperation* within the repeated-cooperate PD simulation for Run 1 are 167.499, -74.311, 241.81, and 22.983 respectively with a median of 4.17 as shown in Table A11.

Robustness (x_2) Run 1. For the covariate *robustness*, the max, min, range, and mean for *cooperation* within the repeated-cooperate PD simulation for Run 1 are 0.913, 0.432, 0.284, and 0.243 respectively with a median of 0.481 as shown in Table A11.

Sustainability (x_3) Run 1. For the covariate *sustainability*, the max, min, range, and mean for *cooperation* within the repeated-cooperate PD simulation for Run 1 are 49, 49, 0, and 49 respectively with a median of 49 as shown in Table A11.

Adaptive-capacity (x_4) Run 1. For the dependent variable, *adaptive-capacity*, the max, min, range, and mean for *cooperation* within the repeated-cooperate PD simulation for Run 1 are 138, 51, 87, and 100.2 respectively with a median of 102 as shown in Table A11, meaning that adaptive-capacity was higher for cooperation than for defection, as reported below for the repeated-defect PD Run 1.

Run 2. Table A12 exhibits the statistical results for Run 2 of the *repeated-cooperate PD* experiment. The sample size for the entire Run was 100, indicating the total population of organizations, 50 of which were bred as defectors and 50 were cooperators, as initial-cooperation was set to 50% The *emissions-penalty* and *cooperation-reward* sliders were set to 0 and 0 respectively; and the *eliminate-organizations* chooser was set to *false*. Run 2 of the repeated-cooperate PD simulation ran for 50 time steps. The model stopped at net emissions of 804 tons. The emissions-target was 15700 tons, resulting in a stable sustainable state. The PD payoff-matrix was

	D	C
D	N/A, N/A	N/A, 75
C	75, N/A	8204, 8204

Nash equilibrium analysis

(D, D) = (N/A, N/A) ≠ NE; this is not a valid combination as defection is not an option in this Run.

(D, C) = (N/A, 75) ≠ NE; this is not a valid combination as defection is not an option in this Run.

(C, D) = (75, N/A) ≠ NE; this is not a valid combination as defection is not an option in this Run.

(C, C) = (8204, 8204) = NE; neither player can change their strategy.

Using regression analysis performed in Excel, the following relationship for cooperation was deduced with an increased population size:

$\mathrm{Ln}(Y) = 3.971 + \sqrt[3]{0.038x1} + 0.039\mathrm{Ln}((x_3 - x_2)^2)$;

where x_1 = resilience; x_2 = robustness; and x_3 = sustainability.

At a confidence interval of 95%, the p-values for all covariates were less than 0.05 with an F-statistic of 642.057, which indicated that the null hypothesis was rejected and an increase in population had no effect on the positive correlation between all covariates with adaptive-capacity as deduced in Run 1 as seen in Figures A38, A39, A40, and A41 for cooperation within the repeated-cooperate PD scenario for population size of 100, when emission-penalties and cooperation-reward were set to 0. The R^2 statistic, or coefficient of determination was 0.965, which indicated that the data fit the regression model for all covariates and explained 96.5% of the variability around the means for the repeated-cooperate PD with the constraints specified for this Run.

Resilience (x_1) Run 2. For the covariate *resilience*, the max, min, range, and mean for *cooperation* within the repeated-cooperate PD simulation for Run 2 were 4600, -102.345, 4702.345, and 75.078 respectively with a median of 8.453 as shown in Table A12.

Robustness (x_2) Run 2. For the covariate *robustness*, the max, min, range, and mean for *cooperation* within the repeated-cooperate PD simulation for Run 2 were 1, 0.421, 0.579, and 0.658 respectively with a median of 0.658 as shown in Table A12.

Sustainability (x_3) Run 2. For the covariate *sustainability*, the max, min, range, and mean for *cooperation* within the repeated-cooperate PD simulation for Run 2 were 45, 45, 0, and 45 respectively with a median of 45 as shown in Table A12.

Adaptive-capacity (x_4) Run 2. For the dependent variable, *adaptive-capacity*, the max, min, range, and mean for *cooperation* within the repeated-cooperate PD simulation for Run 2 are 146, 47, 99, and 101.94 respectively with a median of 96 as shown in Table A12.

Run 3. Table A13 exhibits the statistical results for Run 3 of the *repeated-cooperate PD* experiment. The sample size for the entire Run was 100, indicating the total population of organizations, 50 of which were bred as defectors and 50 were cooperators, as initial-cooperation was set to 50% The *emissions-penalty* and *cooperation-reward* sliders were set to 20 and 0 respectively; and the *eliminate-organizations* chooser was set to *false*. Run 3 of the repeated-cooperate PD simulation ran for 50 time steps. Run 3 yielded similar results to Run 2 of the repeated-cooperate PD as the emissions-penalty applies only to defection. The model stopped at -41 tons of emissions, and the emissions-target was 14765 tons, resulting in an emissions credit of 41 tons. The PD payoff-matrix was:

	D	C
D	N/A, N/A	N/A, 153
C	153, N/A	7359, 7359

Nash equilibrium analysis

(D, D) = (N/A, N/A) ≠ NE; this is not a valid combination as defection is not an option in this Run.

(D, C) = (N/A, 153) ≠ NE; this is not a valid combination as defection is not an option in this Run.

(C, D) = (153, N/A) ≠ NE; this is not a valid combination as defection is not an option in this Run.

(C, C) = (7359, 7359) = NE; neither player can change their strategy.

Using regression analysis performed in Excel, the following relationship for applying an emissions-penalty to cooperative stratagems was deduced:

$\mathrm{Ln}(Y) = 4.109 + \sqrt[3]{0.037x1} + 0.054\mathrm{Ln}((x_3 - x_2)^2)$;

where x_1 = resilience; x_2 = robustness; and x_3 = sustainability.

At a confidence interval of 95%, the p-values for all covariates were less than 0.05 with an F-statistic of 361.082, which indicated that the null hypothesis was rejected. All covariates were positively correlated with adaptive capacity and the emissions-penalty had no effect on the positive correlation deduced in Runs 1 and 2 above as seen in Figures A42, A43, A44, and A45 for cooperation within the repeated-cooperate PD scenario for population size of 100, when emission-penalties and cooperation-reward were set to 0. The R^2 statistic, or coefficient of determination was 0.938, which indicated that the data fit the regression model for all covariates and explained 93.8% of the variability around the means for the repeated-cooperate PD with the constraints specified for this Run.

Resilience (x_1) Run 3. For the covariate *resilience*, the max, min, range, and mean for *cooperation* within the repeated-cooperate PD simulation for Run 3 were 271.922, -107.594, 379.516, and 11.1 respectively with a median of -0.623 as shown in Table A13.

Robustness (x_2) Run 3. For the covariate *robustness*, the max, min, range, and mean for *cooperation* within the repeated-cooperate PD simulation for Run 3 were 0.924, 0.401, 0.523, and 0.638 respectively with a median of 0.642 as shown in Table A13.

Sustainability (x_3) Run 3. For the covariate *sustainability*, the max, min, range, and mean for *cooperation* within the repeated-cooperate PD simulation for Run 3 were 49, 49, 0, and 49 respectively with a median of 49 as shown in Table A13.

Adaptive-capacity (x_4) Run 3. For the dependent variable, *adaptive-capacity*, the max, min, range, and mean for *cooperation* within the repeated-cooperate PD simulation for Run 3 were 149, 51, 98, and 99.11 respectively with a median of 99.5 as shown in Table A13.

Repeated-defect PD Simulation Experiment

Run 1. Table A15 exhibits the statistical results for Run 1 of the *repeated-defect PD* experiment. The sample size for the entire Run was 35, indicating the total population of organizations, 17 of which were bred as defectors and 18 were cooperators, as initial-cooperation was set to 50% The *emissions-penalty* and *cooperation-reward* sliders were set to 0 and 0 respectively; and the *eliminate-organizations* chooser was set to *false*. Run 1 of the repeated-cooperate PD simulation ran for 50 time steps. Although the emissions-target was 4973 tons, the model stopped at 3222 tons of emissions, due to the step constraint of 50. The PD payoff-matrix was

	D	C
D	805, 805	832, N/A
C	N/A, 832	N/A

Nash equilibrium analysis:

(D, D) = (805, 805) = NE; neither player can change their strategy.

(D, C) = (832, N/A) ≠ NE; this is not a valid combination as cooperation is not an option in this Run.

(C, D) = (N/A, 832) ≠ NE; this is not a valid combination as cooperation is not an option in this Run.

(C, C) = (N/A, N/A) ≠ NE; this is not a valid combination as cooperation is not an option in this Run.

Using regression analysis performed in Excel the following relationship for defection was discovered for Run 1:

$\mathrm{Ln}(Y) = 5.464 - 0.034x_1 - 6.591x_2 - 0.078x_3$;

where x_1 = resilience; x_2 = robustness; and x_3 = sustainability.

At a confidence interval of 95%, the p-values for all covariates were less than 0.05 with an F-statistic of 210.941, which indicated that the null hypothesis was rejected and all covariates were negatively correlated with adaptive-capacity as seen in Figures A50, A51, A52, and A53 for defection within the repeated-defect PD scenario for population size of 35, when emission-penalties and cooperation-reward were set to 0. The R^2 statistic, or coefficient of determination was 0.932, which indicated that the data fit the regression model for all covariates and explained 93.2% of the variability around the means for the repeated-defect PD with the constraints specified for this Run.

Resilience (x_1) Run 1. For the covariate *resilience*, the max, min, range, and mean for *defection* within the repeated-defect PD simulation for Run 1 were -2.406, -3.943, 1.537, and -2.931 respectively with a median of -2.764 as shown in Table A15.

Robustness (x_2) Run 1. For the covariate *robustness*, the max, min, range, and mean for *defection* within the repeated-defect PD simulation for Run 1 were 0.072, 0.017, 0.055, and 0.036 respectively with a median of 0.028 as shown in Table A15.

Sustainability (x_3) Run 1. For the covariate *sustainability*, the max, min, range, and mean for *defection* within the repeated-defect PD simulation for Run 1 were 49, 49, 0, and 49 respectively with a median of 49 as shown in Table A15.

Adaptive-capacity (x_4) Run 1. For the dependent variable, *adaptive-capacity*, the max, min, range, and mean for *defection* within the repeated-defect PD simulation for Run 1 were 49, -43, 92, and 6.914 respectively with a median of 6 as shown in Table A15.

Run 2. Table A16 exhibits the statistical results for Run 2 of the *repeated-defect PD* experiment. The sample size for the entire Run was 100, indicating the total population of organizations, 50 of which were bred as defectors and 50 were cooperators, as initial-cooperation was set to 50% The *emissions-penalty* and *cooperation-reward* sliders were set to 0 and 0 respectively; and the *eliminate-organizations* chooser was set to *false*. Run 2 of the repeated-defect PD simulation ran for 50 time steps. Although the emissions-target was 14780 tons, the model stopped at 9740 tons of emissions, due to the step constraint of 50. The PD payoff-matrix was

	D	C
D	2340, 2340	2224, N/A
C	N/A, 2224	N/A, N/A

Nash equilibrium analysis:

(D, D) = (2340, 2340) = NE; neither player can change their strategy.

(D, C) = (2225, N/A) ≠ NE; this is not a valid combination as cooperation is not an option in this Run.

(C, D) = (N/A, 2224) ≠ NE; this is not a valid combination as cooperation is not an option in this Run.

(C, C) = (N/A, N/A) ≠ NE; this is not a valid combination as cooperation is not an option in this Run.

Using regression analysis performed in Excel the following relationship for defection was discovered:

$Ln(Y) = 5.477 – 0.019x_1 – 5.12x_2 – 0.079x_{3;}$

where x_1 = resilience; x_2 = robustness; and x_3 = sustainability.

At a confidence interval of 95%, the p-values for all covariates were less than 0.05 with an F-statistic of 191.505, which indicated that null hypothesis was rejected and all covariates were negatively correlated with adaptive-capacity for defection within the repeated-defect PD scenario for population size of 100, when emission-penalties and cooperation-reward were set to 0, as shown in Figures 54, 55, 56, and 57. The increase in population size from 35 in Run 1 to 100 in Run 2 had no effect on the relationship between variables. The R^2 statistic, or coefficient of determination was 0.925, which indicated that the data fit the regression model for all covariates and explained 92.5% of the variability around the means for the repeated-defect PD with the constraints specified for this Run.

Resilience (x_1) Run 2. For the covariate *resilience*, the max, min, range, and mean for *defection* within the repeated-defect PD simulation for Run 2 were -2.396, -3.819, 1.423, and -2.85 respectively with a median of -2.733 as shown in Table A16.

Robustness (x_2) Run 2. For the covariate *robustness*, the max, min, range, and mean for *defection* within the repeated-defect PD simulation for Run 2 were 0.068, 0.017, 0.051, and 0.032 respectively with a median of 0.027 as shown in Table A16.

Sustainability (x_3) Run 2. For the covariate *sustainability*, the max, min, range, and mean for *defection* within the repeated-defect PD simulation for Run 2 were 49, 49, 0, and 49 respectively with a median of 49 as shown in Table A16.

Adaptive-capacity (x_4) Run 2. For the dependent variable, *adaptive-capacity*, the max, min, range, and mean for *defection* within the repeated-defect PD simulation for Run 2 were 48, -48, 96, and 1.6 respectively with a median of 2.5 as shown in Table A16.

Run 3. Table A17 exhibits the statistical results for Run 3 of the *repeated-defect PD* experiment. The sample size for the entire was 100, indicating the total population of organizations, 50 of which were bred as defectors and 50 were cooperators, as initial-cooperation was set to 50% The *emissions-penalty* and *cooperation-reward* sliders were set to 20 and 0 respectively; and the *eliminate-organizations* chooser was set to *false*. Run 3 of the repeated-cooperate PD simulation ran for 50 time steps. The model stopped at 103007 tons of emissions, which exceeded the emissions target of 14981 resulting in organizational collapse. The PD payoff-matrix was

	D	C
D	507, 507	3010, N/A
C	N/A, 3010	N/A, N/A

Nash equilibrium analysis:

(D, D) = (507, 507) = NE; neither player can change their strategy.

(D, C) = (3010, N/A) ≠ NE; this is not a valid combination as cooperation is not an option in this Run.

(C, D) = (N/A, 3010) ≠ NE; this is not a valid combination as cooperation is not an option in this Run.

(C, C) = (N/A, N/A) ≠ NE; this is not a valid combination as cooperation is not an option in this Run.

Using regression analysis performed in Excel the following relationship was found for defection when an emissions-penalty was applied:

$Y = -184.998 + 0.029x_1^3 + 20.392.x_2^3 + 0.08x_3^3$;

where x_1 = resilience; x_2 = robustness; and x_3 = sustainability.

At a confidence interval of 95%, the p-values for all covariates were less than 0.05 with an F-statistic of 912.56, which indicated that null hypothesis was rejected and all covariates were positively correlated with adaptive-capacity for defection within the repeated-defect PD scenario for population size of 100, when emission-penalties was set to 20 and cooperation-reward was set to 0, as shown in Figures A58, A59, A60, and A61. The emissions-penalty affected the negative relationship between covariates and adaptive-capacity from Runs 1 and 2, which were positively correlated in Run 3. The R^2 statistic, or coefficient of determination was 0.983, which indicated that the data fit the regression model for all covariates and explained 98.3% of the variability around the means for the repeated-defect PD with the constraints specified for this Run.

Resilience (x_1) Run 3. For the covariate *resilience*, the max, min, range, and mean for *defection* within the repeated-defect PD simulation for Run 3 were -20.909, -31.563, 10.654, and -23.935 respectively with a median of -23.553 as shown in Table A17.

Robustness (x_2) Run 3. For the covariate *robustness*, the max, min, range, and mean for *defection* within the repeated-defect PD simulation for Run 3 were 0.205, 0.091, 0.114, and 0.127 respectively with a median of 0.119 as shown in Table A17.

Sustainability (x_3) Run 3. For the covariate *sustainability*, the max, min, range, and mean for *defection* within the repeated-defect PD simulation for Run 3 were -5, -5, 0, and -5 respectively with a median of -5 as shown in Table A17.

Adaptive-capacity (x_4) Run 3. For the dependent variable, *adaptive-capacity*, the max, min, range, and mean for *defection* within the repeated-defect PD simulation for

Run 3 were -20, -119, 99, and -69.81 respectively with a median of -73 as shown in Table A17.

Summary

The null hypothesis was rejected for all Runs of the evolutionary-RRSA PD, evolutionary-TfT PD, repeated-cooperate PD and repeated-defect PD. Resilience was negatively correlated with adaptive-capacity for defection, and positively correlated with the latter for cooperation in Run 1 of the evolutionary-RRSA PD. Within the same Run, robustness and sustainability were positively correlated with adaptive-capacity for defection, and negatively correlated with the latter for cooperation. For Run 2 of evolutionary-RRSA PD simulation an increase in population size from 35 to 100 organizations resulted in all covariates being positively correlated with adaptive-capacity for defection, while the relationship between variables remained the same as Run 1 for cooperation. Application of the emissions-penalty, keeping all other parameters constant in Run 3 of the evolutionary-RRSA PD simulation, kept correlation between variables for defection as negative, whereas for cooperation all covariates became positively correlated with adaptive-capacity.

For Run 1 of the evolutionary-TfT PD resilience and robustness were positively correlated with adaptive-capacity for defection, while sustainability was negatively correlated with adaptive-capacity for defection, in contrast to all covariates being positively polynomially correlated with adaptive-capacity for cooperation. Population increase in Run 2 resulted in positive correlation between all covariates and adaptive-capacity for defection while, robustness, and sustainability were exponentially negatively correlated with adaptive-capacity for cooperation in Run 2 of the Evolutionary-TfT PD. For Run 3 of the evolutionary-TfT PD simulation the emissions-penalty had the effect of negatively correlating robustness with adaptive-capacity for defection and positively correlating all covariates with adaptive-capacity for cooperation.

For Runs 1, and 2 of the repeated-defect PD simulation, the covariates were negatively correlated with adaptive-capacity. Application of an emissions-penalty to the repeated-defect PD simulation resulted in the positive correlation between all covariates and adaptive-capacity in Run 3. For the repeated-cooperate PD simulation all covariates were positively correlated with adaptive-capacity for all Runs. With respect to the NE analyses, for the evolutionary-RRSA PD, the NE for Runs 1 and 2 were mutual cooperation, whereas for Run 3, 2 NE were found; defect-against-cooperator and cooperate-against-defector (4 NE in total for this strategy). For the evolutionary-TfT PD, 2 NE were found per Run (6 NE in total for this strategy), these being mutual defection and mutual cooperation. For the repeated-cooperate PD the NE for all Runs was mutual cooperation (3 NE in total for this strategy), and for the repeated-defect PD the NE was mutual defection for all Runs (3 NE in total for this strategy). The evolutionary-TfT PD produced the highest net emissions per Run, followed by the repeated-defect PD. The evolutionary-RRSA PD produced the lowest net emissions followed by the repeated-cooperate PD. These findings are discussed in relation to the nature, purpose, and reason for conducting the study in the following chapter.

Chapter 5: Discussion, Conclusions, and Recommendations

The purpose of this simulation study was to develop a management framework of RRSA for organizational regimes involved in climate governance viewed as complex systems to transcend the current unsustainable state, using a quantitative computational simulation approach. An evolutionary game theory approach to ABMS, using an originally developed evolutionary PD simulation on the NetLogo platform to generate the data and statistical modeling in Excel tested the hypothesis that a positive relationship exists between resilience, robustness, and sustainability as independent variables and the dependent variable of adaptive capacity.

The data generated in Netlogo were analyzed in Excel using regression analysis, with the goal of optimizing the R^2 and F statistics, while minimizing p values of all covariates. The null hypothesis was rejected; thus, the covariates resilience, robustness, and sustainability were positively correlated with adaptive-capacity for iterated consecutive cooperative stratagems (repeated-cooperate PD), while the former covariates were negatively correlated with adaptive-capacity for iterated consecutive defective stratagems (repeated-defect PD) in the absence of an emissions-penalty. Application of an emissions-penalty to iterated consecutive defective stratagems resulted in positive correlation between covariates and adaptive-capacity. All covariates were positively correlated with adaptive-capacity in Run 3 of the evolutionary-RRSA PD for both cooperation and defection, while for the evolutionary-TfT PD all covariates were only positively correlated with adaptive-capacity in Run 3 for cooperation. In terms of game theory, several PD NE were found. These findings were used to formulate the recommended RRSA framework discussed below.

Interpretation of Findings

Axelrod (1984) found that the TfT PD outperformed all other strategies for reciprocal altruism, using the scoring method for payoffs described in Chapter 4. While the objective of this study was not to test the efficacy of strategies for reciprocal altruism, a secondary finding, based on analysis of both payoffs and net emissions as indicators of reciprocal altruism, was that the evolutionary-RRSA PD outperformed all other strategies, including the evolutionary-TfT PD for reciprocal altruism. Axelrod used a discount parameter in his experiments, which is comparable to the emissions-penalty used in this study. Axelrod further stated that continued interaction, depending on the magnitude of his discount parameter*,* was a necessary but not sufficient condition for cooperation to emerge. The finding that the covariates robustness and sustainability were negatively correlated with adaptive capacity in Run 2 of the evolutionary-TfT PD simulation but became positively correlated with adaptive-capacity in Run 3 corroborates Axelrod's latter finding, as Run 3 included the emissions-penalty. Both Runs 2 and 3 ran for 50 time steps, which substantiated that extended interaction is not sufficient for cooperation to emerge; however, the combination of the emissions-penalty with extended interaction in Run 3 provided the necessary initial conditions for cooperation to emerge. While Axelrod's experiments on the theory of cooperation using computer simulated PD strategies were based on game theory, he did not discuss the NE of any of the games played in his tournaments. As NE is integral to game theory, in this study, I expanded on the work of Axelrod by including analyses of the NE for each Run.

In current literature, as discussed in Chapter 2, Tosun and Schoenefeld (2017) discussed that coordination of collective action into cooperation was one of the challenges of PD PGGs, which I both confirmed and extended upon. While defection served as a fixed-point attractor for most Runs of all PD simulations except the iterated consecutive cooperation PD, application of an emissions-penalty to all strategy types (evolutionary-RRSA PD, evolutionary-TfT PD, repeated-defect PD, and repeated-cooperate PD), the latter being the exception, resulted in coordination of collective action, consisting of both cooperative and defective decision types, towards increased adaptive-capacity.

Hurlstone et al. (2017) further substantiated the role of collective action in successful climate negotiations, for mitigating the problems of free-riding and the tragedy of the commons associated with PGGs and opined that the only PD Nash equilibrium was mutual defection, known as the paradox of cooperation (Adami et al., 2016). The NE analyses presented in Chapter 4 for each Run indicated that mutual cooperation was a NE for the Evolutionary-RRSA PD in Runs 1 and 2, while defection against a cooperator and cooperation against a defector were the NEs for Run 3 of the Evolutionary-RRSA PD. For the evolutionary-TfT PD, both mutual defection and mutual cooperation were NEs, whereas mutual cooperation was the only NE for the iterated consecutive cooperate PD, and mutual defection was the only NE for the iterated consecutive defect PD. Interpreted through the lenses of complexity theory and game theory, these findings imply that the problems of free-riding and the tragedy of the commons can be mitigated in the absence of central control, given that the parameters, which can be thought of as fostering adaptive-capacity, serve as the initial conditions, which then give rise to the emergence and evolution of strategies that maximize payoffs with respect to adaptive-capacity. While Adami et al. (2016), and Hurlstone et al. (2017) emphasized the importance of the coordination of collective action into cooperation, it might be too naïve and idealistic a goal, as defection is inherent in all PD PGG strategies and constitutes the NE for many types of PD PGGs.

The evolutionary-RRSA PD showed that the goal of steering global temperatures away from a 2°C increase by 2050 (Cole, 2015) can be facilitated through combinations of cooperative and defective actions given the appropriate initial conditions, which herein after will be referred to as RRSA climate negotiations. The following primary deductions from this study were used to generate the evolutionary RRSA management framework, as shown in Figure A50, which may be used by climate governance leaders, negotiators, and policy-makers to facilitate improved organizational adaptive-capacity, through the mechanisms of RRS: (a) adaptive-capacity is sensitive to initial conditions, emerging and evolving from cooperative and defective strategic decisions in the evolutionary- RRSA PD; (b) RRSA as an effective framework for climate negotiations does not substitute top-down decision making with a polycentric bottom-up approach, but rather facilitates bottom-up processes using top-down implementation with a distinction between the latter and central control; (c) defection and improved adaptive-capacity within the context of climate change are not mutually exclusive; (d) RRSA climate negotiations and defection are not mutually exclusive; (e) RRSA climate negotiations are sensitive to initial conditions; (f) improved RRSA does not necessarily involve collective coordination or control but rather emerges and evolves as a result of the initial conditions specified for the evolutionary-RRSA PD; and (g) RRSA climate negotiations consisting of combinations of mutual-cooperation (C, C) with defection against a cooperator (D, C), and cooperation against a defector (C, D) can lead to maximization of payoffs to self-interested parties while maintaining the goal of increasing adaptive-capacity to climate change using the evolutionary-RRSA PD.

Evolutionary RRSA Management Framework

Using the seven deductions discussed above, the cyclical 4-phased RRSA management framework was developed, as shown in Figure A50. Beginning at Phase 1, the evolutionary RRSA management framework uses the outputs from Phase 1 as inputs to Phase 2, followed by top-down implementation of the outputs of Phase 2, evaluation, and a return to Phase 1. The evolutionary RRSA management framework cycles through all 4 Phases incrementally thereby increasing adaptive-capacity with each cycle.

Phase 1. Phase 1 of the RRSA management framework constitutes an emissions audit. Analysis of organizational consumption and production patterns should be conducted to ascertain as-is parameters. The key performance indicator from Phase 1 is the emissions-score consisting of the sum of GHG consumption and production emissions.

Phase 2. Phase 2 calls for the use of the RRSA management framework simulation tool. The emissions-score from the audit conducted in Phase 1 serves as the initial-emissions-score, should be plugged into the simulation, using the evolutionary-RRSA simulation tool to calibrate to-be parameters. Managers, leaders, and policy developers are encouraged to use the tool to test initial conditions until desired outcomes are simulated. The calibration of to-be parameters will produce the emissions-target, emissions-penalty, fitness, and emissions-allowance. Organizational adaptive-capacity is calibrated in Phase 2 via the mechanisms of resilience, robustness, and sustainability.

Phase 3. Phase 3 of the RRSA management framework involves top-down implementation of the initial conditions produced from Phase 2. In other words, Phase 3 involves ensuring that the emissions-target, emissions-penalty, and emissions-allowance are set and clearly communicated to the rest of the organization or bodies under governance. Key performance indicators for this phase, including adaptive-capacity, resilience, robustness, and sustainability, should be benchmarked against the to-be simulation parameters acquired in Phase 2.

Phase 4. Phase 4 involves evaluation of the current emissions-score. As such Phase 4 triggers a return to Phase 1, in which an emissions audit is conducted. The 4-phase RRSA framework should be viewed as a cyclical management approach to reducing consumption and production of GHGs by implementing appropriate initial conditions through the use of the simulation tool.

Limitations of the Study

In Chapter 1, I referred to the abstract nature of ABMS as a limitation of this study; however, experimental execution proved that the abstraction of ABMS allowed for the refinement of those parameters that were necessary for generating relevant and necessary data while tuning out the noise. The NP-hard and intractable threats to generalizability associated with ABMS were mitigated by setting stop conditions in the model and in the experiments run in BehaviorSpace. Generative postnormal science studies using ABMS are empirical and therefore highly generalizable for decision-making and problem solving (Epstein, 1999).

Grounding the quantitative definitions of all variables in the relevant game theory and complexity theory literatures ensured external validity. Regarding conclusion validity, all statistical analyses were conducted using a 95% confidence interval with the goal of maximizing the R^2 and F statistics, while minimizing the p values of all covariates, thereby providing accurate and reliable statistical power. The generated data were tested for violation of normality, homoscedasticity, and serial independence using optimization of the SSR statistic for the best-fit curve and application of a Lagrange multiplier technique (Jarque & Bera, 1980). Moreover, at any given Run, the well-mixed heterogeneous random sampling of the entire population to represent groups eliminates systematic bias and ensures high external validity. This study was not time bounded, and the findings from ABMS are highly generalizable.

Recommendations

The data generated for this study from Runs 1, 2, and 3 for all types of strategies did not include the effect of a cooperation reward. Further research is required to test the relationship between RRS and adaptive-capacity with the application of a cooperation-reward. The hypothesis was that the cooperation-reward will result in greater positive correlation between the covariates and adaptive-capacity. A future study using the model developed for this study with the cooperation-reward parameter included, in combination with statistical modeling to test the relationship between variables, is recommended for further research in the field of information systems.

Potential for further research in the field of applied complexity using the model created for this study is possible by examining the behavior between agents and analyzing the complexity of their interactions and information processing abilities. The model is currently written to simulate strategies using PD PGG for climate governance; however, the parameters may be modified to test the strategies for other types of PGG problems, such arms races, nuclear power contractual agreements, water restrictions, and so forth. Having developed the methodology for this study, modification of parameters in the model to facilitate the research questions associated with the PD PGG scenarios herein mentioned would carry with it the strengths of the current study.

Implications

In current literature, the lack of progress thus far made in climate negotiations was attributed to a need for a bottom-up polycentric approach to climate change policy in lieu of monocentric top-down decision-making (Cole, 2015). The RRSA framework for climate negotiations developed in this study facilitates the bottom-up processes using top-down implementation by climate governance leaders and decision-makers, thereby emphasizing the distinctions between central control or coordination of cooperation and top-down implementation of the evolutionary RRSA management framework, as shown in Figure A50, which is devoid of central control but facilitates the emergence of increased adaptive-capacity to climate change. Ostrom (1990) attributed the shortfall of progress in climate negotiations to the lack of time needed for mutual trust to develop between individuals for mutually beneficial transactions such as climate change negotiations. However, the ABMS methodology used in this study employed the use of autonomous agents in the absence of trust or friendship, which emphasized instead the need for extended interaction to solidify positive and beneficial negotiations between players. Trust is not a requirement for mutual altruism in game theory (Axelrod, 1984) nor is it a requirement for increased adaptive-capacity to emerge using the evolutionary-RRSA PD, which has implications for the responsible use of the US $100 billion of climate financing pledged in Copenhagen (COP15) expiring in 2020, which is a conflicting source of consensus and controversy in UNFCCC adaptation negotiations underscored by the adaptation debt, framed by the competing norms of adaptation restitution and adaptation development.

While Cole (2015) highlighted the role of private actors in polycentric governance initiatives, citing the formation of the WBCSD in 1992 as an example, the evolutionary-RRSA PD showed that increased adaptive-capacity emerges from bottom-up processes or exchanges in negotiations. These negotiations might occur at any level of organization, including leaders, and business, private, transnational, or governmental decision-makers and players. Thus, the RRSA framework for climate negotiations herein developed can be used to develop business solutions that contribute to mitigating a 2° C rise in global temperatures by 2050.

While Bulkeley and Newell (2015) proposed that treating climate change as an international or global problem evokes the tragedy of the commons problem in which no actor or institution has control of the atmosphere as a common resource, the RRSA framework for climate negotiations emphasizes the distinction between top-down implementation and central control. The GHG producing processes engrained in everyday production and consumption patterns constitute the bottom-up processes that underscore the emissions-score, emissions-target, and net emissions of agents in the evolutionary-RRSA PD, which evolve to produce increased adaptive-capacity despite the lack of central control. The question raised by Bulkeley and Newell as to what the role of nation-states are in solving the climate change problem was herein addressed as the role of implementation of the RRSA framework for climate negotiations to provide the necessary initial conditions for increased adaptive-capacity to emerge.

Conclusions

Climate change leaders, negotiators, decision-makers, and participants are advised to understand the distinction between top-down implementation of the cyclical 4-Phase evolutionary RRSA management framework, as shown in Figure A50 herein developed, and central control. The evolutionary RRSA management framework for climate negotiations uses the evolutionary-RRSA PD as a management tool, which is devoid of central control, but when implemented by leaders, provides an incubator for the initial-conditions necessary for increased adaptive-capacity to climate change as a result of bottom-up processes. In conclusion, the cyclical 4-Phase evolutionary RRSA management framework for climate negotiations, consisting of the 4 Phases presented above, provides climate governing bodies with the tools to create the necessary initial conditions for PGG participants, while acting for their own self-interests, to participate in the greatest and most complex of all public goods games with the highest stakes, which leads to emergence and evolution of resilience, robustness, sustainability, and increased adaptive-capacity to mitigate the catastrophes and disasters of climate change discussed in Chapter 2, by using the evolutionary-RRSA PD management tool that includes both cooperation and defection, because their payoffs will be maximized.

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Appendix A: Tables and Figures

Table A1

Discrepancies Between Planned Model and Actual Model

Planned model	Actual model
Existing basic evolutionary PD model	New evolutionary PD model for adaptive capacity
Infinite sample size, sampled randomly using ODE approach to determine proportion of breeds.	Finite sample size, sampled using random sampling and sliding proportion of breeds.
Random proportion Q = 1/ N removed from the population at each time step.	Organizations eliminated using a GA, based on fitness.

Table A2

Types of Strategies Played by Agent Breeds for PD Simulation Games

Agent-type / strategy-type	**Evolutionary-demographic PD**	**Evolutionary Tit-for-tat PD**	**Repeated-cooperate PD**	**Repeated-defect PD**
Cooperators	Plays phenotype cooperate (Payoff *T* /*R* / *P* / *S*)	Plays cooperate if partner cooperated (payoff *R*) / defect if partner defected (payoff *P*)	Plays cooperate against defector (payoff *S*) / cooperate against cooperator (payoff *R*)	Plays defect against defector (payoff *P*) / defect against cooperator (payoff *T*)
Defectors	Plays phenotype defect (Payoff *T* /*R* / *P* / *S*)	Plays cooperate if partner cooperated (payoff *R*) / defect if partner defected (payoff *P*)	Plays cooperate against defector (payoff *S*) / cooperate against cooperator (payoff *R*)	Plays defect against defector (payoff *P*) / defect against cooperator (payoff *T*)

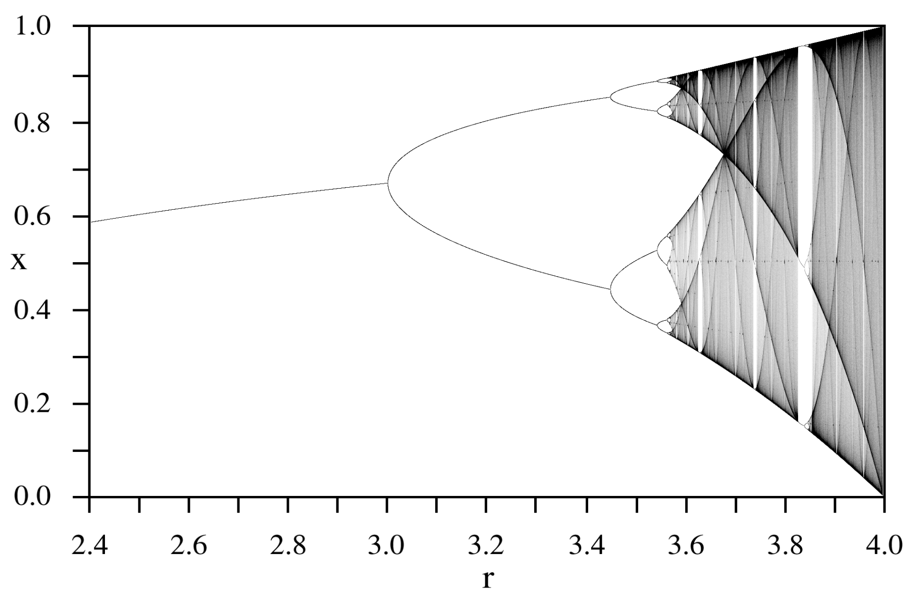

Figure A1. Graph of the logistic map with X = fraction of carrying capacity, and r = combined effect of birth rate and death rate. Retrieved from Mitchell (2009).

Table A3

Evolutionary-RRSA PD Experiment for RRS - Run 1

	population size	emissions-penalty	cooperation-reward	min	max	range	mean	median	modes	standard deviation
Resilience / Defection	17	0	0	-60.399	-25.294	35.106	-42.847	-42.847	[-60.399 -25.294]	24.824
Resilience / Cooperation	18	0	0	7800	8200	400	8000	8000	[7800 8200]	282.843
System Resilience	35	0	0	-60.399	8200	8260.399	3978.577	3887.353	[-60.399 8200 7800 -25.294]	4646.432
Robustness / Defection	17	0	0	0.549	0.797	0.247	0.673	0.673	[0.797 0.549]	0.175
Robustness / Cooperation	18	0	0	1	1	0	1	1	[1]	0
System Robustness	35	0	0	0.549	1	0.451	0.837	0.898	[1]	0.214
Sustainability / Defection	17	0	0	26	27	1	26.5	26.5	[27 26]	0.707
Sustainability / Cooperation	18	0	0	26	27	1	26.5	26.5	[26 27]	0.707
System Sustainability	35	0	0	26	27	1	26.5	26.5	[27 26]	0.577
Adaptive-capacity / Defection	17	0	0	79	84	5	81.5	81.5	[84 79]	3.536
Adaptive-capacity / Cooperation	18	0	0	178	182	4	180	180	[178 182]	2.828
System Adaptive-capacity	35	0	0	79	182	103	130.75	131	[84 182 178 79]	56.929

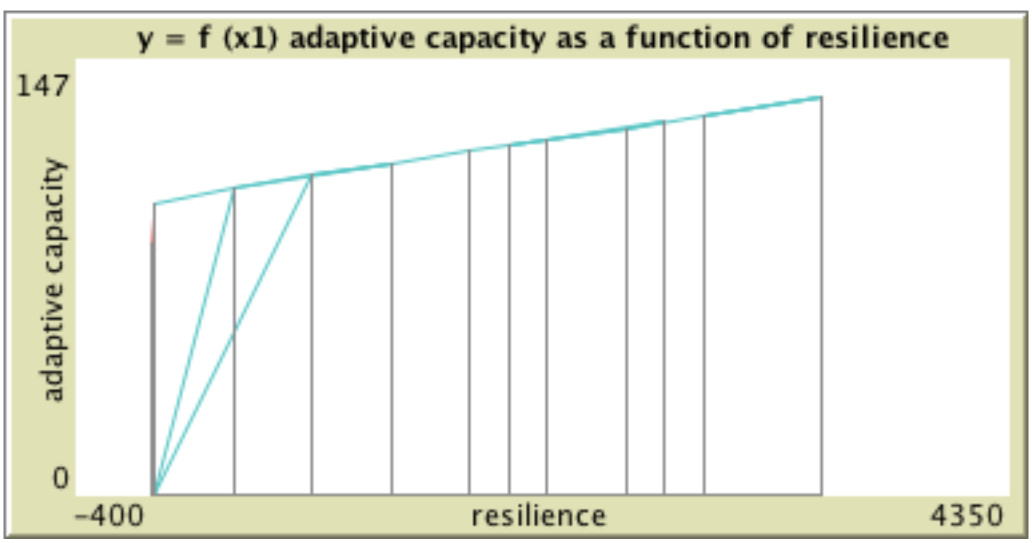

Figure A2. y = f (x_1) – Run 1

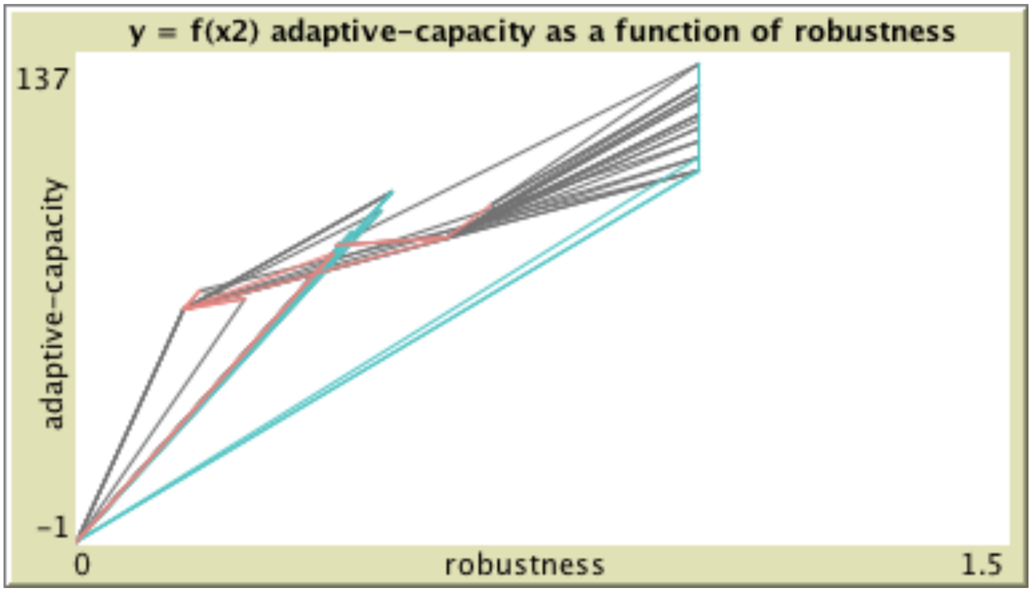

Figure A3. y = f (x_2) – Run 1

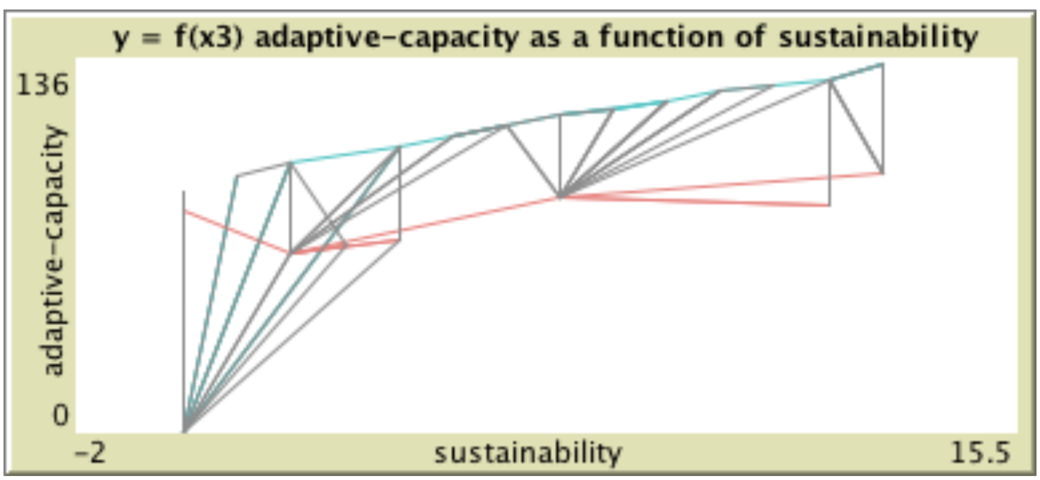

Figure A4. y = f (x_3) – Run 1

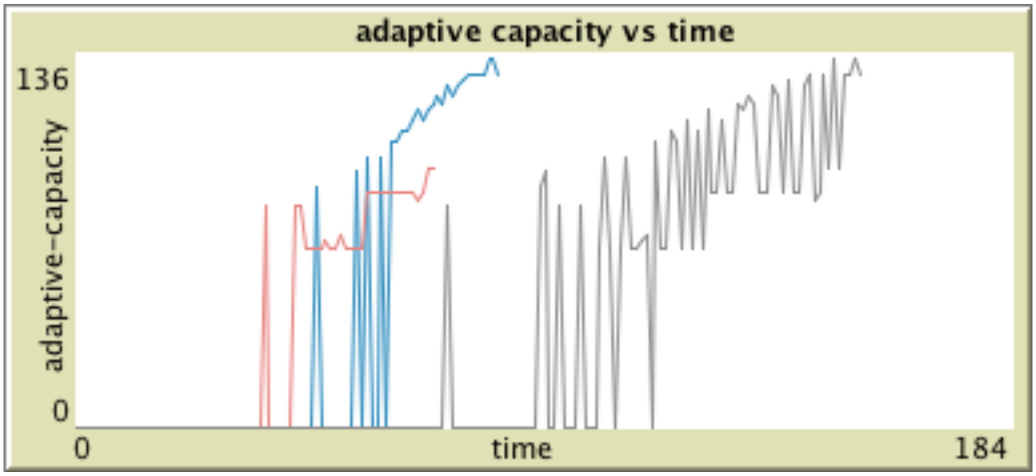

Figure A5. Adaptive-capacity vs time for the evolutionary-RRSA PD – Run 1

Table A4

Evolutionary-RRSA PD Experiment for RRS –Run 2

	population size	emissions-penalty	cooperation-reward	min	max	range	mean	median	modes	standard deviation
Resilience / Defection	50	0	0	-20.116	-10.502	9.614	-15.309	-15.309	[-20.116 -10.502]	6.798
Resilience / Cooperation	50	0	0	6700	6700	0	6700	6700	[6700]	0
System Resilience	100	0	0	-20.116	6700	6720.116	3342.346	3344.749	[6700]	3877.087
Robustness / Defection	50	0	0	0.357	0.651	0.293	0.504	0.504	[0.651 0.357]	0.208
Robustness / Cooperation	50	0	0	1	1	0	1	1	[1]	0
System Robustness	100	0	0	0.357	1	0.643	0.752	0.826	[1]	0.310
Sustainability / Defection	50	0	0	16	17	1	16.5	16.5	[17 16]	0.708
Sustainability / Cooperation	50	0	0	17	17	0	17	17	[17]	0
System Sustainability	100	0	0	16	17	1	16.75	17	[17]	0.5
Adaptive-capacity / Defection	50	0	0	81	89	8	85	85	[89 81]	5.657
Adaptive-capacity / Cooperation	50	0	0	167	167	0	167	167	[167]	0
System Adaptive-capacity	100	0	0	81	167	86	126	128	[167]	47.455

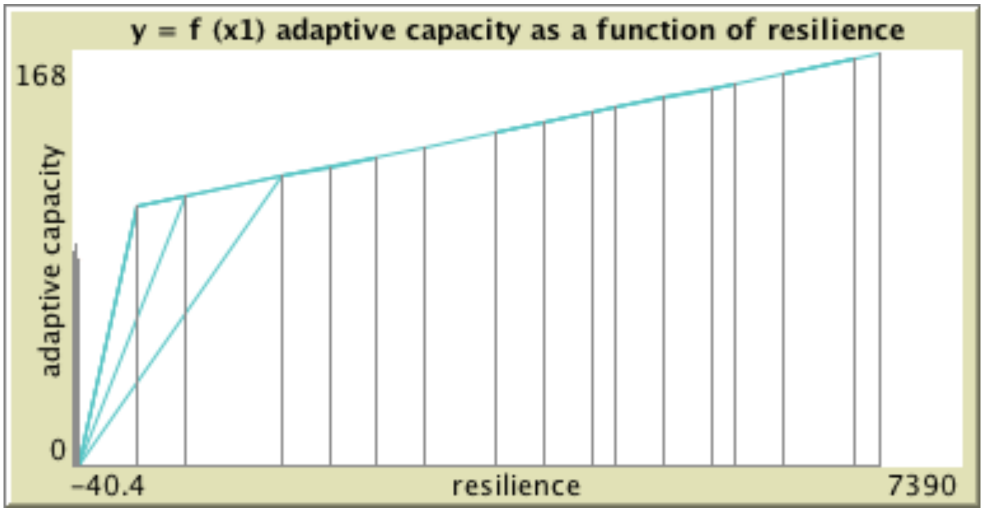

Figure A6. y = f (x_1) - Run 2

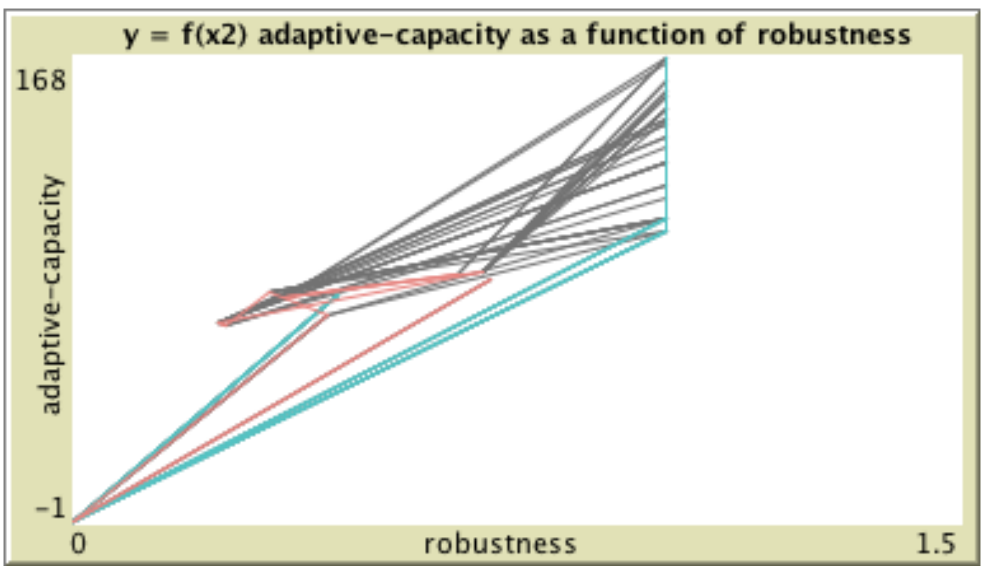

Figure A7. y = f (x_2) - Run 2

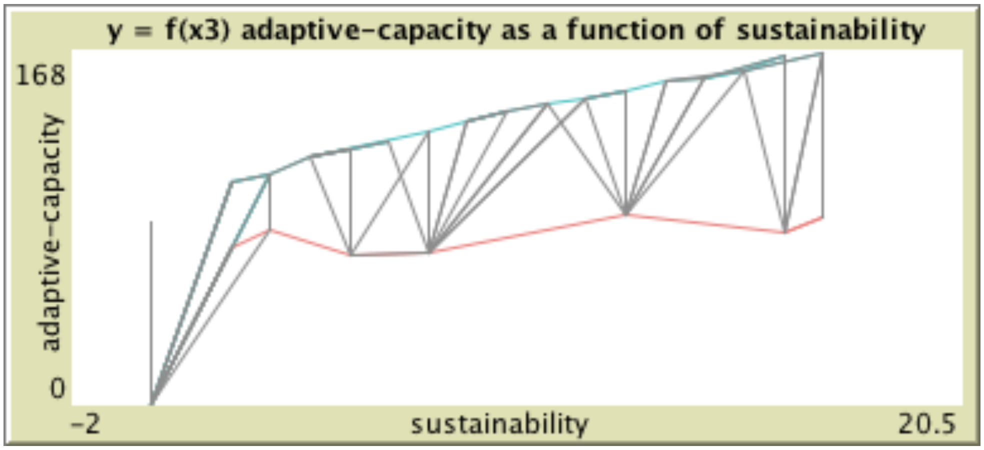

Figure A8. y = f (x_3) - Run 2

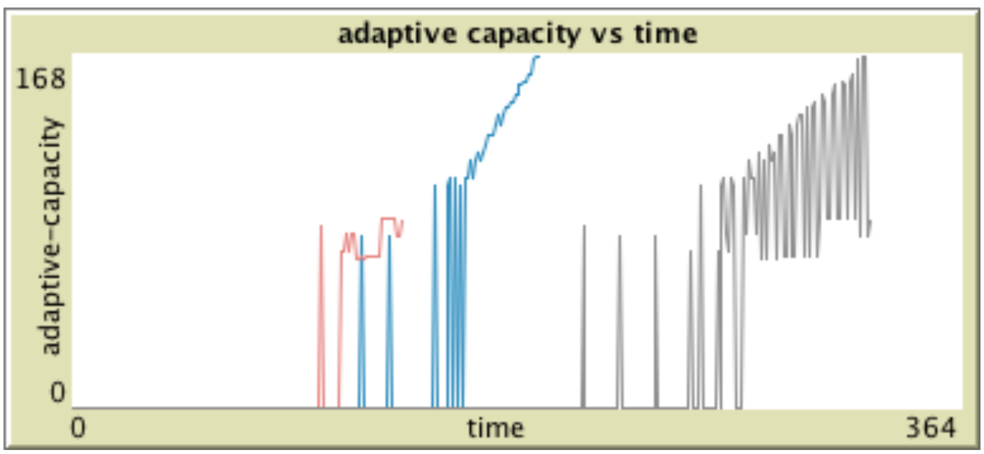

Figure A9. Adaptive-capacity vs time - Run 2

Table A5

Evolutionary-RRSA PD Experiment for RRS –Run 3

	population size	emissions-penalty	cooperation-reward	min	max	range	mean	median	modes	standard deviation
Resilience / Defection	50	20	0	-28.274	-19.878	8.396	-24.076	-24.077	[-19.878 -28.274]	5.937
Resilience / Cooperation	50	20	0	5400	5400	0	5400	5400	[5400]	0
System Resilience	100	20	0	-28.274	5400	5428.274	2687.962	2690.061	[5400]	3131.594
Robustness / Defection	50	20	0	0.162	0.271	0.109	0.217	0.217	[0.162 0.272]	0.078
Robustness / Cooperation	50	20	0	1	1	0	1	1	[1]	0
System Robustness	100	20	0	0.162	1	0.838	0.608	0.636	[1]	0.454
Sustainability / Defection	50	20	0	37	49	12	43	43	[49 37]	8.485
Sustainability / Cooperation	50	20	0	49	49	0	49	49	[49]	0
System Sustainability	100	20	0	37	49	12	46	49	[49]	6
Adaptive-capacity / Defection	50	20	0	-3	24	27	10.5	10.5	[-3 24]	19.092
Adaptive-capacity / Cooperation	50	20	0	154	154	0	154	154	[154]	0
System Adaptive-capacity	100	20	0	-3	154	157	82.25	89	[154]	83.579

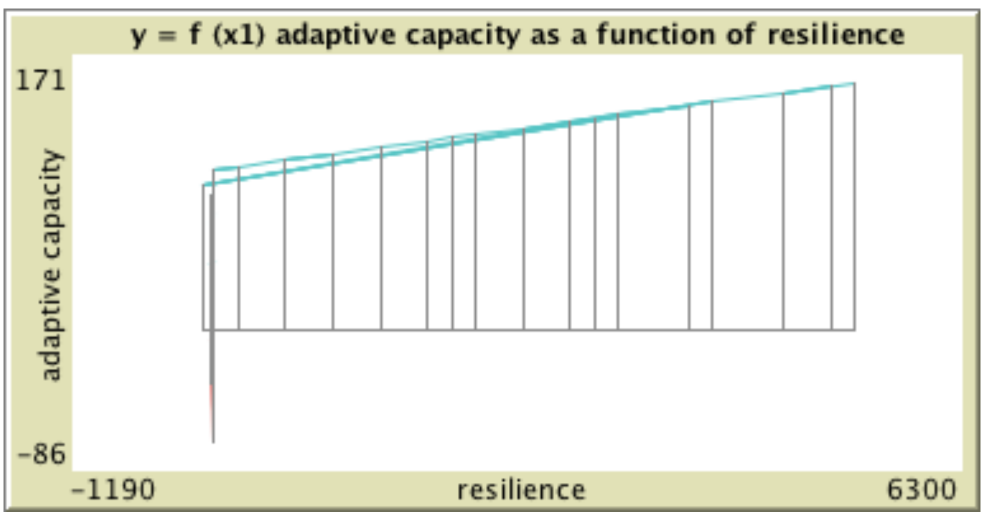

Figure A10. y = f (x_1) - Run 3

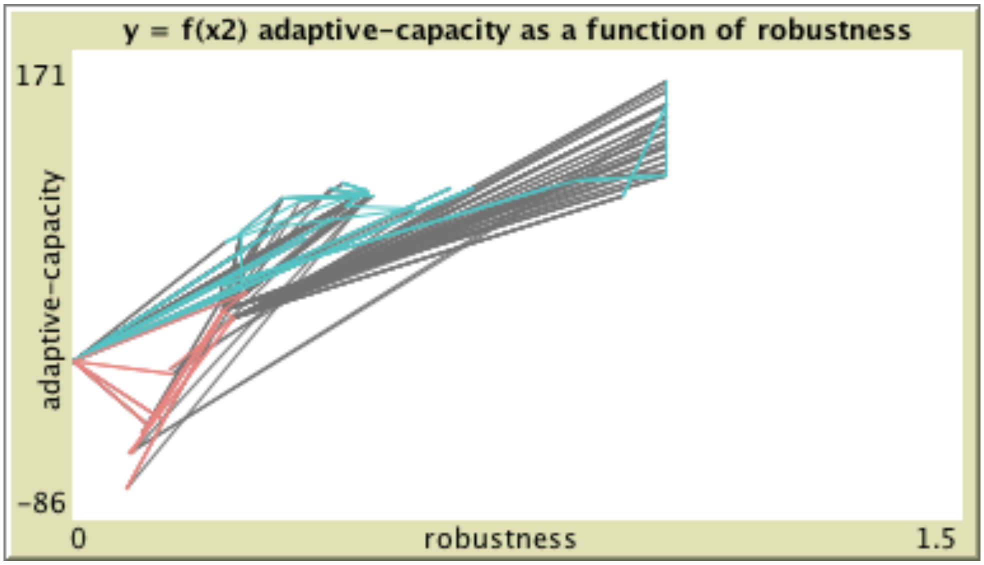

Figure A11. y = f (x_2);Run 3

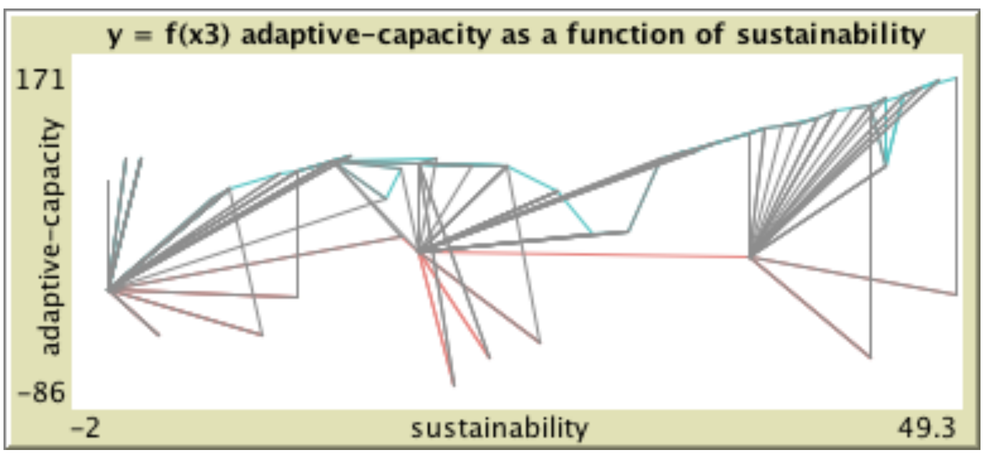

Figure A12. $y = f(x_3)$ - Run 3

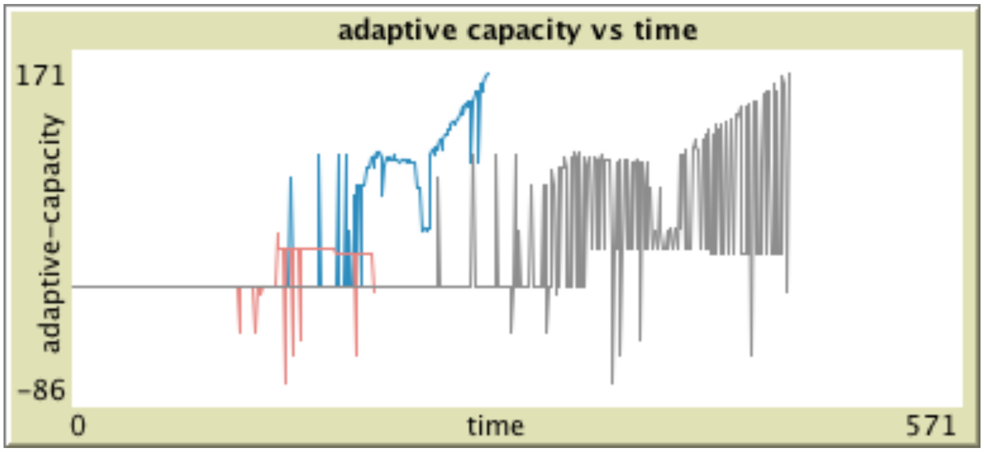

Figure A13. Adaptive-capacity vs time - Run 3

Table A6

Evolutionary-TfT PD Experiment for RRS –Run 1

	population size	emissions-penalty	cooperation-reward	min	max	range	mean	median	modes	standard deviation
Resilience / Defection	17	0	0	-99.528	-11.275	88.253	-70.579	-99.496	[-11.275 -13.0407 -99.512 -99.509 -99.495 -99.528 -35.216 -99.505 -99.507 -22.210 -99.526 -99.492 -35.495 -36.163 -99.517 -99.502 -22.425 -99.497]	37.853
Resilience / Cooperation	18	0	0	11300	12800	1500	11984.615	11900	[12500 11300 12100 11900 12600 12200 11700 11600 12400 11800 11400 11500 12800]	487.931
System Resilience	35	0	0	-99.528	12900	12999.528	5840.845	-11.275	[12800 -99.509 12900 -99.505 -11.275 11400 -99.512 12200 -99.492 12600 11900 -99.527 -22.425 -99.507 11500 11600 12400 12100 12700 11300 12300 12500 -99.528 -36.163 -35.495 -35.216 -99.495 -99.517 -99.497 -13.0407 11800 -22.210 12000 -99.502 11700]	6181.382
Robustness / Defection	17	0	0	0.0536	0.338	0.284	0.243	0.325	[0.0536 0.059 0.329 0.330 0.337 0.322 0.143 0.332 0.331 0.0969 0.322 0.338 0.146 0.145 0.327 0.334 0.0969 0.336]	0.115
Robustness / Cooperation	18	0	0	1	1	0	1	1	[1]	0
System Robustness	35	0	0	0.0536	1	0.946	0.611	0.338	[1]	0.392
Sustainability / Defection	17	0	0	6	6	0	6	6	[6]	0
Sustainability / Cooperation	18	0	0	6	6	0	6	6	[6]	0
System Sustainability	35	0	0	6	6	0	6	6	[6]	0
Adaptive-capacity / Defection	17	0	0	-113	-96	17	-104.5	-104.5	[-99 -105 -104 -103 -97 -111 -112 -101 -102 -107 -110 -96 -108 -113 -106 -100 -109 -98]	5.338
Adaptive-capacity / Cooperation	18	0	0	213	228	15	219.846	219	[225 213 221 219 226 222 217 216 224 218 214 215 228]	4.879
System Adaptive-capacity	35	0	0	-113	229	342	53.6	-96	[228 -103 229 -101 -99 214 -104 222 -96 226 219 -110 -109 -102 215 216 224 221 227 213 223 225 -111 -113 -108 -112 -97 -106 -98 -105 218 -107 220 -100 217]	165.138

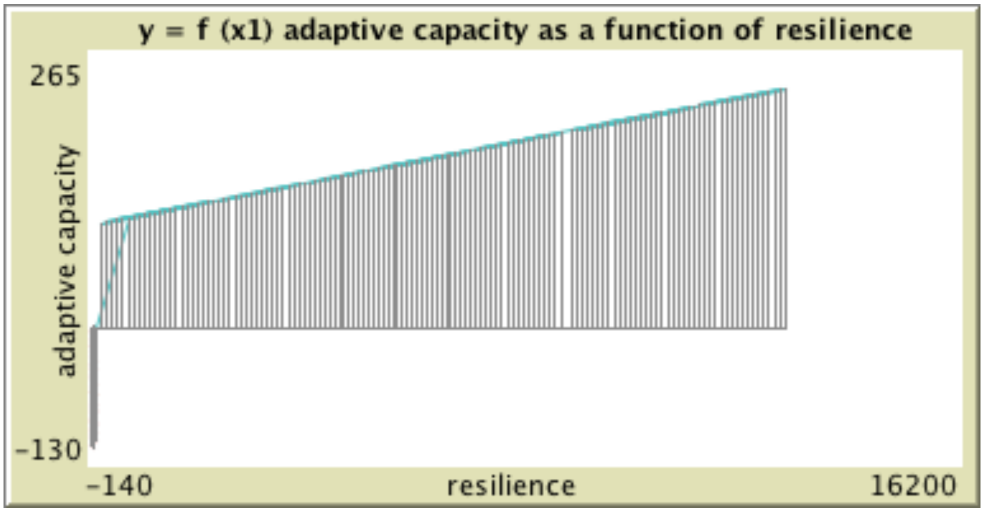

Figure A14. y = f (x_1) - Run 1

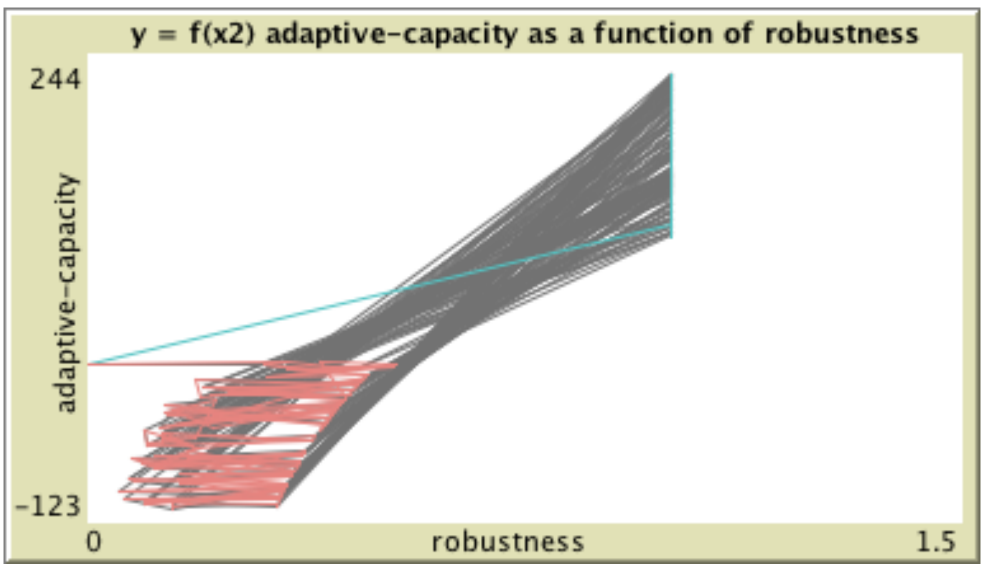

Figure A15. y = f (x_2) - Run 1

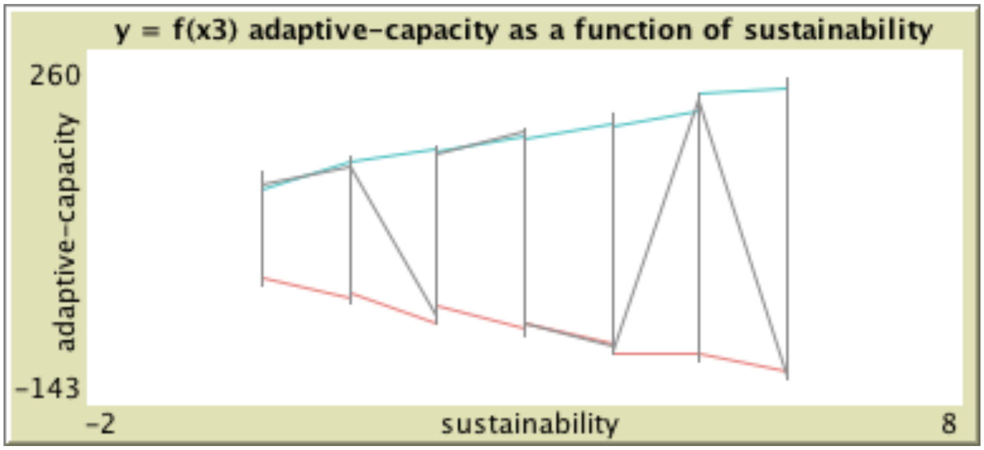

Figure A16. y = f (x_3) - Run 1

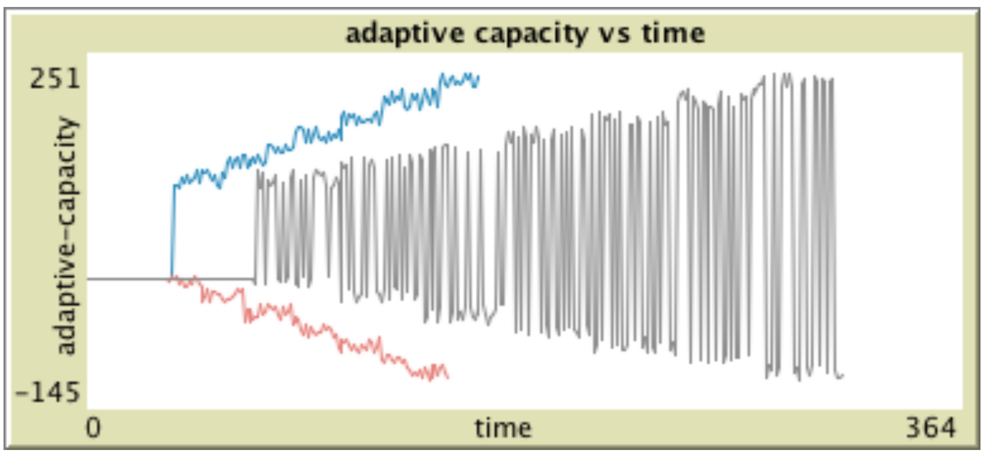

Figure A17. Adaptive-capacity vs time - Run 1

Table A7

Evolutionary-TfT PD Experiment for RRS –Run 2

	population size	emissions-penalty	cooperation-reward	min	max	range	mean	median	modes	standard deviation
Resilience / Defection	50	0	0	-99.502	-21.635	77.867	-77.037	-99.444	['-99.487 '-37.196 '-99.438 '-21.635 '-99.450 '-99.431 '-99.468 '-99.435 '-36.381 '-99.445 '-34.221 '-99.465 '-99.482 '-99.474 '-37.021 '-99.489 '-99.484 '-24.827 '-99.462 '-37.296 '-99.441 '-99.492 '-22.974 '-38.046 '-99.497 '-99.502 '-99.459]	32.551
Resilience / Cooperation	50	0	0	12900	19900	7000	16443.636	16500	[14600 18300 14700 17700 15300 14800 19900 18200 16400 19000 17600 16100 15900 14500 18000 19200 16200 19400 19600 19500 16500 18600 17900 16000 17800 18500 13800 16600 18400 17400 17100 13700 15100 14000 15000 12900 13100 15600 14900 17000 19700 17500 18700 18100 16300 14100 16800 14400 16900 17200 15200 13000 14300 13900 13500]	1989.488
System Resilience	100	0	0	-99.502	19900	19999.502	11878.199	14950	[17900 12800 -34.221 -37.2951 15900 13400 19000 18500 19600 -99.465 19300 -99.438 17700 13500 19800 14400 19400 14600 17300 -24.827 18700 -21.635 -99.432 17000 -99.487 15300 1 9100 15400 17100 -99.468 16600 -99.482 17600 -99.435 18400 -99.485 18300 15200 12700 -99.503 14000 -99.498 15000 16900 -38.0457 13800 13600 14700 -99.451 15700 15100 -99.489 13100 18000 -99.462 16000 19500 13900 16800 17500 14800 17800 -99.459 13000 12900 13200 -99.441 19700 -37.021 13300 18100 -99.474 13700 16200 -36.381 15500 14300 16400 16100 14900 19900 18600 -37.196 14100 14500 16700 17200 18200 18900 19200 -99.445 15600 16300 18800 16500 -99.492 17400 14200 15800 -22.974]	7528.072
Robustness / Defection	50	0	0	0.099	0.364	0.265	0.281	0.340	[0.340 0.1578 0.361 0.0991 0.356 0.364 0.348 0.362 0.160 0.358 0.159 0.349 0.342 0.346 0.176 0.338 0.341 0.117 0.351 0.170 0.359 0.338 0.108 0.172 0.336 0.334 0.352]	0.098
Robustness / Cooperation	50	0	0	1	1	0	1	1	[1]	0
System Robustness	100	0	0	0.099	1	0.901	0.806	1	[1]	0.325
Sustainability / Defection	50	0	0	2	2	0	2	2	[2]	0
Sustainability / Cooperation	50	0	0	2	2	0	2	2	[2]	0
System Sustainability	100	0	0	2	2	0	2	2	[2]	0
Adaptive-capacity / Defection	50	0	0	-100	-74	26	-87	-87	[-94 -99 -77 -97 -81 - 75 -87 -76 -91 -79 -80 -86 -92 -89 -74 -95 -93 -88 -85 -82 -78 -96 -90 -83 -98 -100 -84]	7.937
Adaptive-capacity / Cooperation	50	0	0	229	299	70	264.436363 63636364	265	[246 283 247 277 253 248 299 282 264 290 276 261 259 245 280 292 262 294 296 295 265 286 279 260 278 285 238 266 284 274 271 237 251 240 250 229 231 256 249 270 297 275 287 281 263 241 268 244 269 272 252 230 243 239 235]	19.895
System Adaptive-capacity	100	0	0	-100	299	399	168.5	249.5	[279 228 - 80 -82 259 234 290 285 296 -86 293 -77 277 235 298 244 294 246 273 -88 287 -97 -75 270 -94 253 291 254 271 -87 266 -92 276 -76 284 -93 283 252 227 -100 240 -98 250 269 -83 238 236 247 -81 257 251 -95 231 280 -85 260 295 239 268 275 248 278 -84 230 229 232 -78 297 -74 233 281 -89 237 262 -91 255 243 264 261 249 299 286 -99 241 245 267 272 282 289 292 -79 256 263 288 265 -96 274 242 258 -90]	157.266

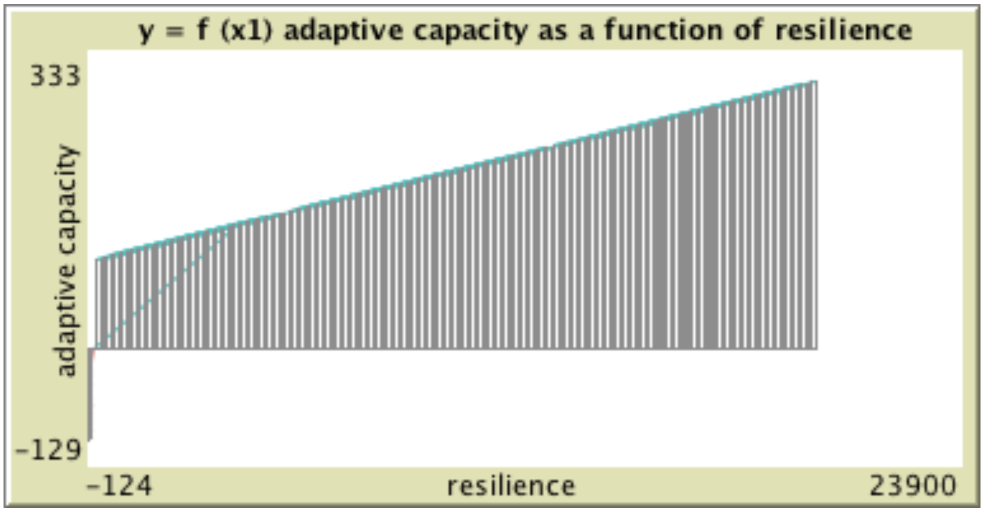

Figure A18. y = f (x_1) - Run 2

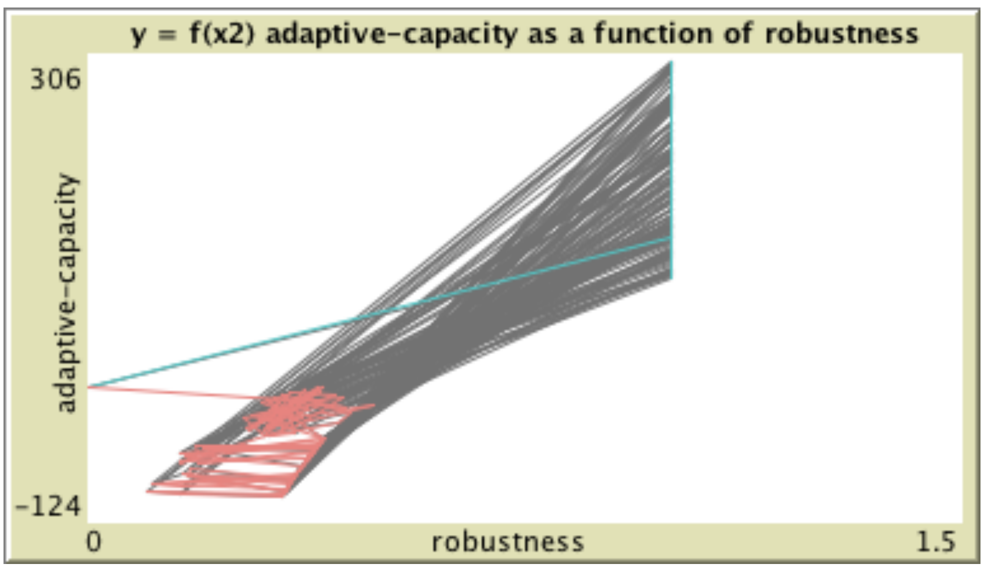

Figure A19. y = f (x_2) - Run 2

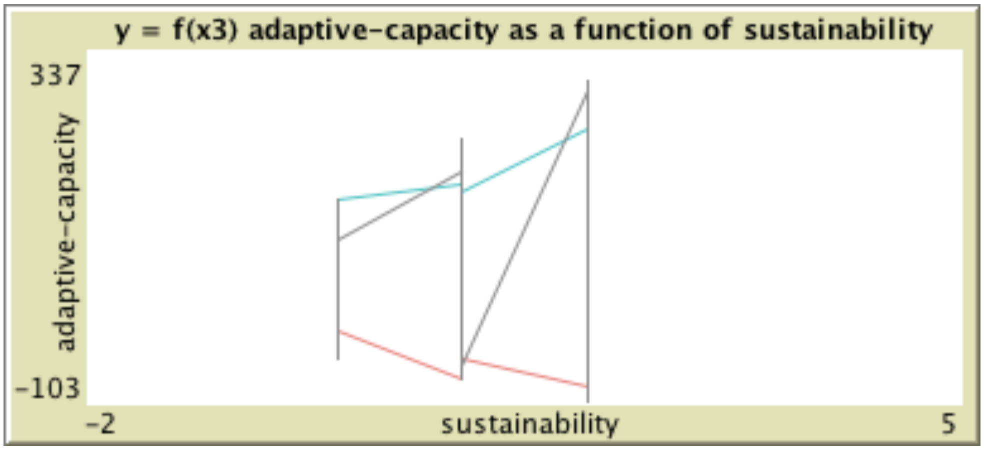

Figure A20. y = f (x_3) - Run 2

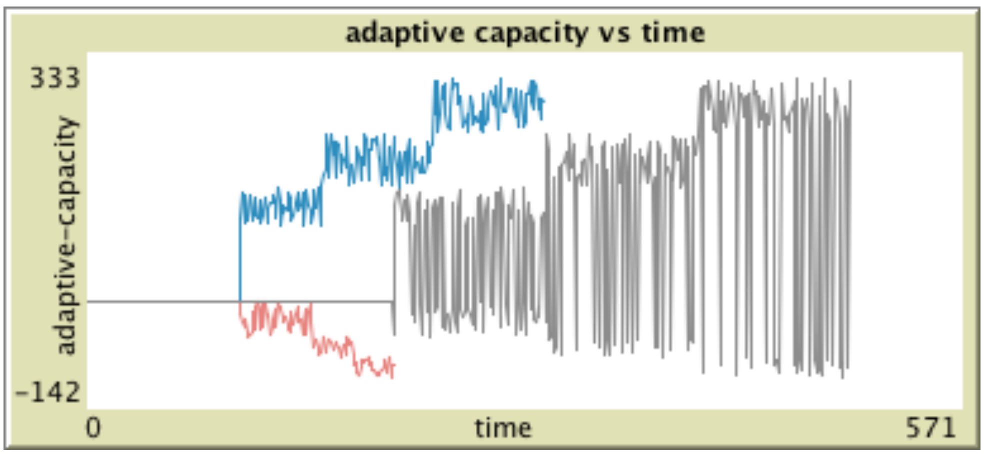

Figure A21. Adaptive-capacity vs time - Run 2

Table A8

Evolutionary-TfT PD Experiment for RRS –Run 3

	population size	emissions-penalty	cooperation-reward	min	max	range	mean	median	modes	standard deviation
Resilience / Defection	50	20	0	-100.721	-37.918	62.803	-76.703	-90.497	[-97.797 -60.933 -61.235 -94.436 -49.877 -89.241 -94.078 -78.517 -97.783 -40.954 -54.522 -98.408 -96.153 -98.378 -60.531 -93.115 -58.017 -94.821 -93.663 -95.45 -91.753 -49.738 -82.843 -53.52 -97.003 -71.714 -48.982 -59.339 -96.698 -96.658 -97.316 -92.928 -55.038 -43.817 -97.919 -53.037 -58.164 -98.57 -37.918 -91.766 -51.797 -100.721 -64.3 -52.705 -95.512 -96.213 -49.067 -43.172 -94.513 -99.154 -98.55 -60.203]	21.496
Resilience / Cooperation	50	20	0	100	200	100	188	200	[200]	33.166
System Resilience	100	20	0	-100.721	200	300.721	49.115	-42.063	[200]	134.775
Robustness / Defection	50	20	0	0.023	0.079	0.056	0.048	0.046	[0.046 0.027 0.032]	0.0159
Robustness / Cooperation	50	20	0	1	1	0	1	1	[1]	0
System Robustness	100	20	0	0.023	1	0.977	0.505	0.077	[1]	0.478
Sustainability / Defection	50	20	0	-1	-1	0	-1	-1	[-1]	0
Sustainability / Cooperation	50	20	0	-1	-1	0	-1	-1	[-1]	0
System Sustainability	100	20	0	-1	-1	0	-1	-1	[-1]	0
Adaptive-capacity / Defection	50	20	0	-1999	-979	1020	-1489	-1489	[-1559 -1239 -1219 -1859 -1779 -1099 -1639 -1579 -1379 -1019 -1179 -1439 -1159 -1939 -1419 -1119 -1999 -1299 -999 -1899 -979 -1839 -1399 -1759 -1599 -1979 -1039 -1919 -1699 -1659 -1079 -1739 -1879 -1339 -1459 -1359 -1199 -1279 -1059 -1139 -1679 -1499 -1819 -1519 -1619 -1719 -1959 -1479 -1539 -1319 -1259 -1799]	303.095
Adaptive-capacity / Cooperation	50	20	0	101	102	1	101.88	102	[102]	0.332
System Adaptive-capacity	100	20	0	-1999	102	2101	-725.39	-1009	[102]	827.888

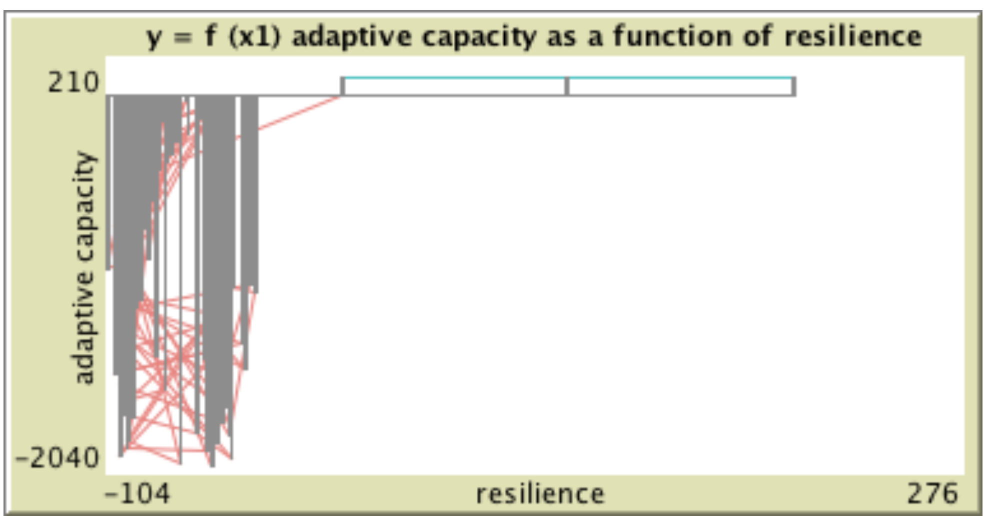

Figure A22. y = f (x_1) - Run 3

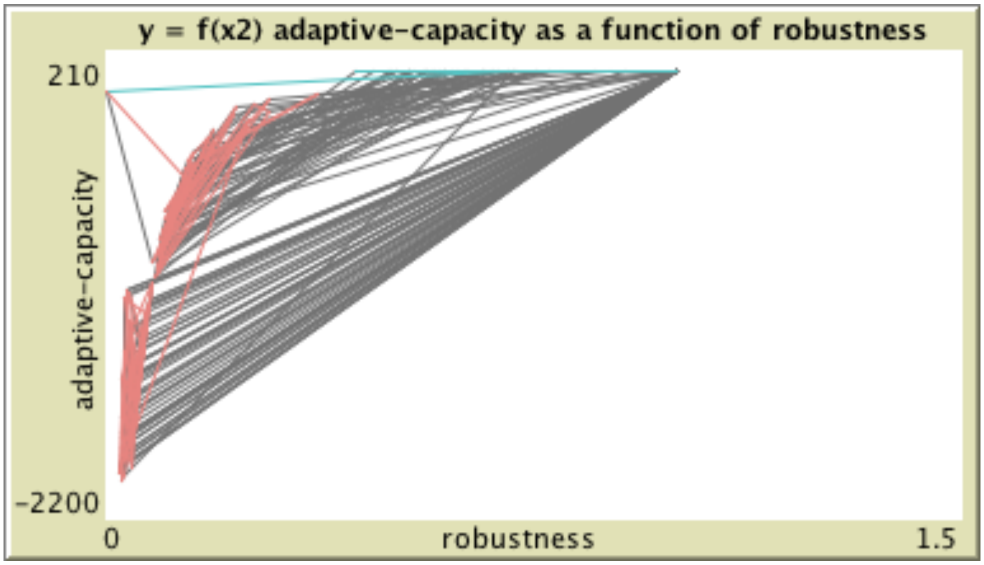

Figure A23. y = f (x_2) - Run 3

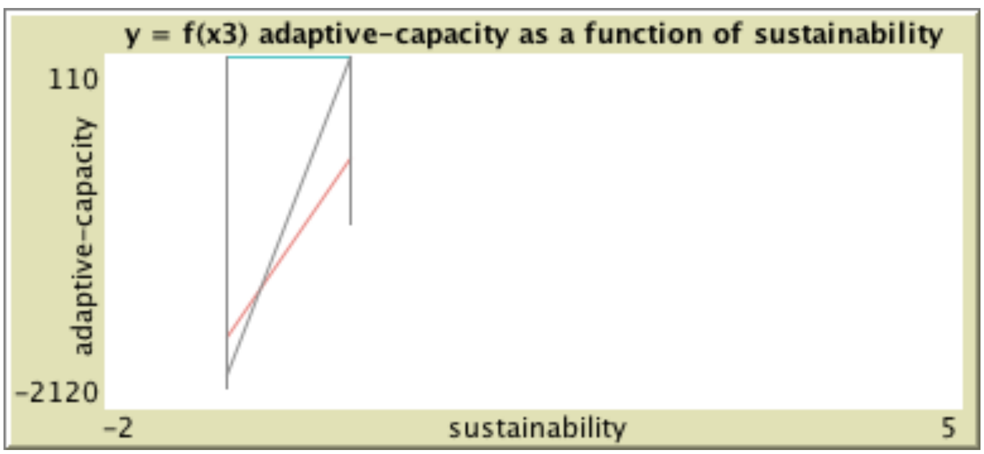

Figure A24. y = f (x_3) - Run 3

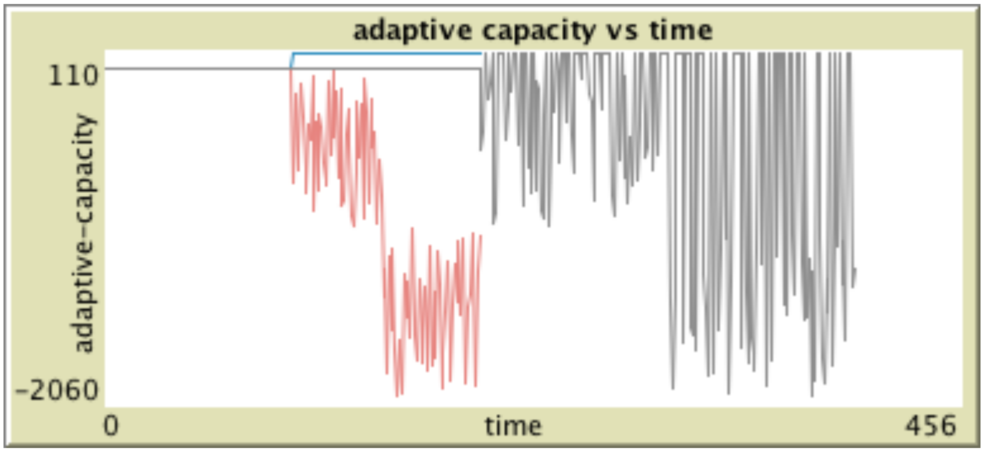

Figure A25. Adaptive-capacity vs time - Run 3

Table A9

Repeated-Cooperate PD Experiment for RRS –Run 1

	population size	emissions-penalty	cooperation-reward	min	max	range	mean	median	modes	standard deviation
Resilience / Cooperation	35	0	0	-74.311	167.499	241.81	22.983	4.17	[-3.814 2.558 124.881 -16.718 -74.311 -26.267 76.797 -15.367 -37.316 24.662 55.629 55.919 4.17 29.396 167.499 -26.47 -18.951 -15.779 26.07 -36.37 -18.882 0 62.843 57.125 85.847 19.046 97.789 -32.871 156.222 77.054 77.973 -22.122 40.135 -48.374 -43.608]	59.145
Robustness / Cooperation	35	0	0	0.432	0.913	0.481	0.659	0.663	[0.863 0.73 0.587]	0.133
Sustainability / Cooperation	35	0	0	49	49	0	49	49	[49]	0
Adaptive-capacity / Cooperation	35	0	0	51	138	87	100.2	102	[121 83]	24.883

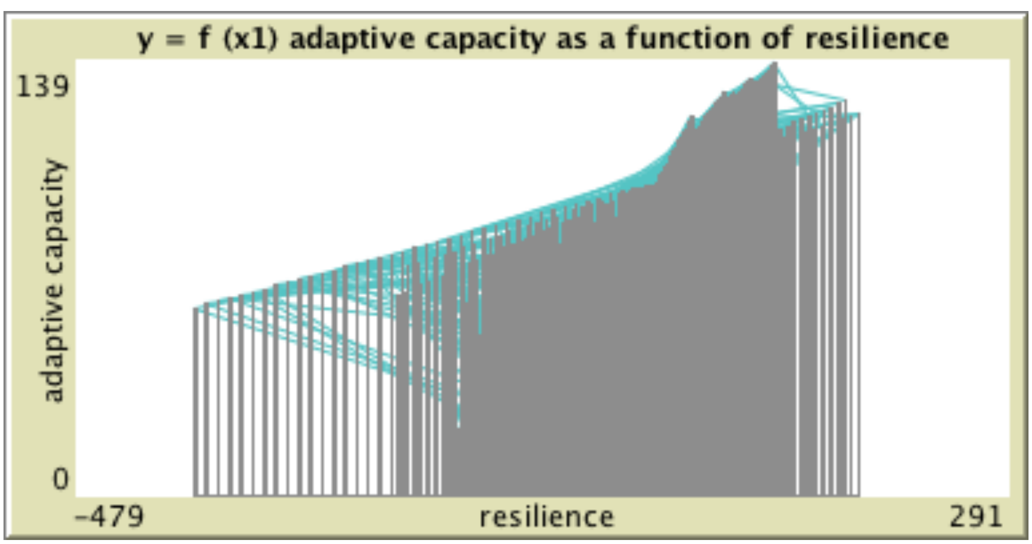

Figure A26. y = f (x_1) - Run 1

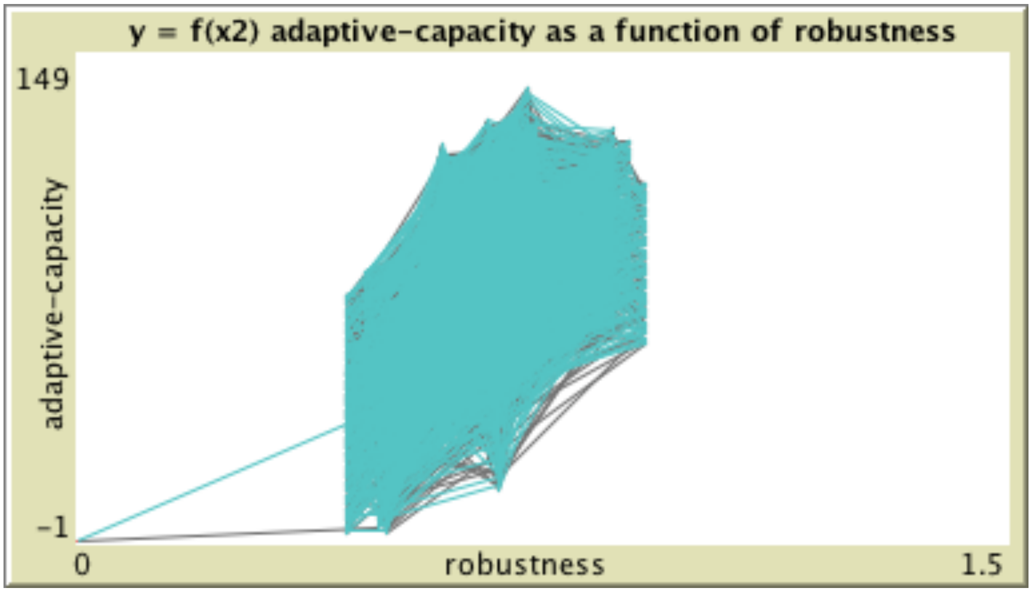

Figure A27. y = f (x_2) - Run 1

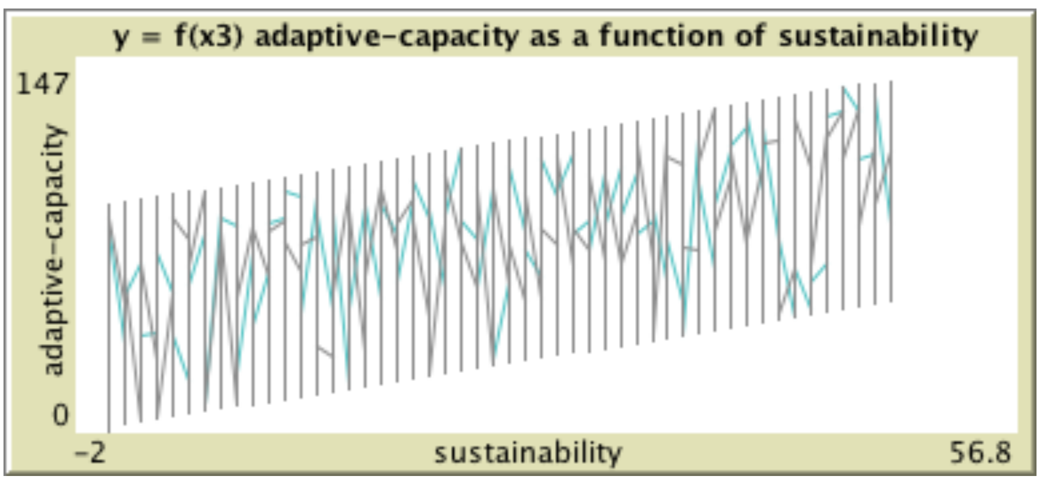

Figure A28. y = f (x_3) - Run 1

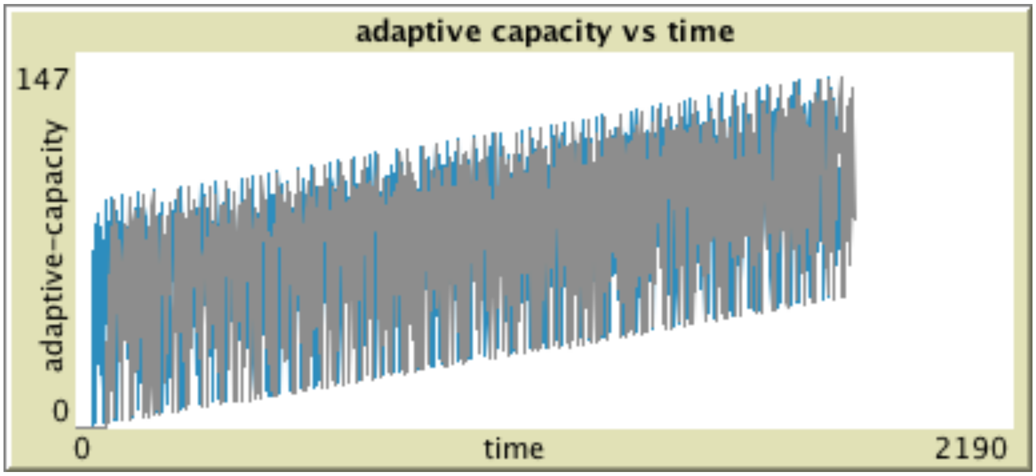

Figure A29. Adaptive-capacity vs time - Run 1

Table A10

Repeated-Cooperate PD Experiment for RRS –Run 2

	population size	emissions-penalty	cooperation-reward	min	max	range	mean	median	modes	standard deviation
Resilience / Cooperation	100	0	0	-102.345	4600	4702.345	75.078	8.4525	[1.041 40.41 -39.456 -64.228 -33.006 -37.426 -17.981 158.909 -61.411 15.699 -77.515 491.993 -76.98 -33.225 -19.961 75.072 -60.16 23.774 74.491 42.309 -32.022 18.778 300.168 -37.888 57.685 -9.436 105.281 156.188 -17.859 -54.814 39.285 64.314 69.363 120.066 43.157 44.811 4600 -39.117 -43.966 101.421 9.688 -44.815 296.777 -73.713 -38.862 -2.576 56.633 -7.726 -3.385 4.707 35.134 6.357 -7.737 -50.416 105.523 -16.192 47.548 104.335 7.217 35.938 -46.54 109.146 71.867 -13.41 -35.069 157.163 -20.177 30.036 -29.808 -29.18 -12.142 247.028 29.213 39.056 100.162 -10.114 5.732 74.278 -55.021 20.32 -102.345 108.265 44.208 -32.169 94.317 -12.053 72.946 73.553 6.211 -44.573 36.763 59.785 28.891 0 48.866 48.177 173.417 -41.436 -23.262 -16.459]	465.338
Robustness / Cooperation	100	0	0	0.421	1	0.5789	0.658	0.648	[0.725 0.675 0.537 0.578 0.758 0.813 0.804 0.648]	0.126
Sustainability / Cooperation	100	0	0	45	45	0	45	45	[45]	0
Adaptive-capacity / Cooperation	100	0	0	47	146	99	101.94	106	[116 118]	28.885

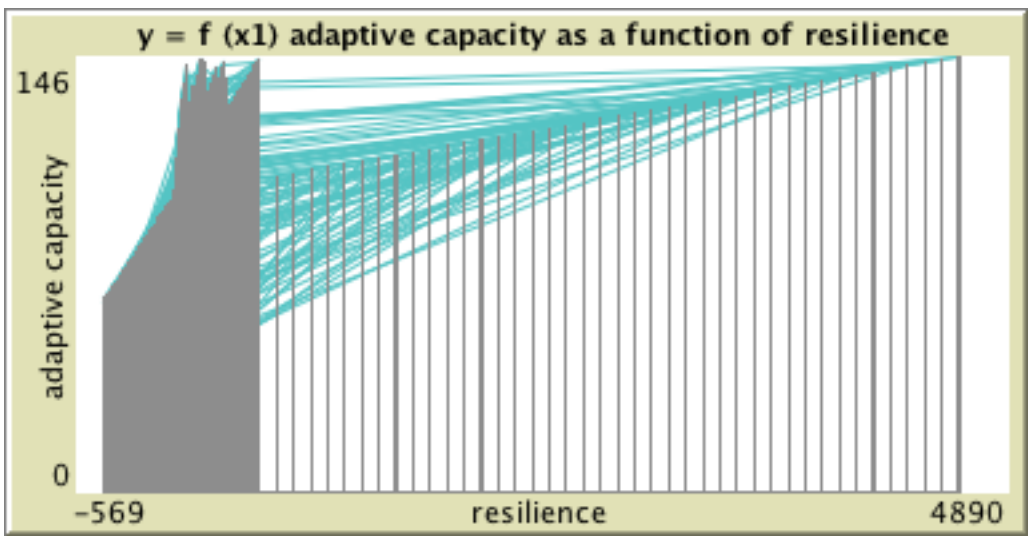

Figure A30. y = f (x_1) - Run 2

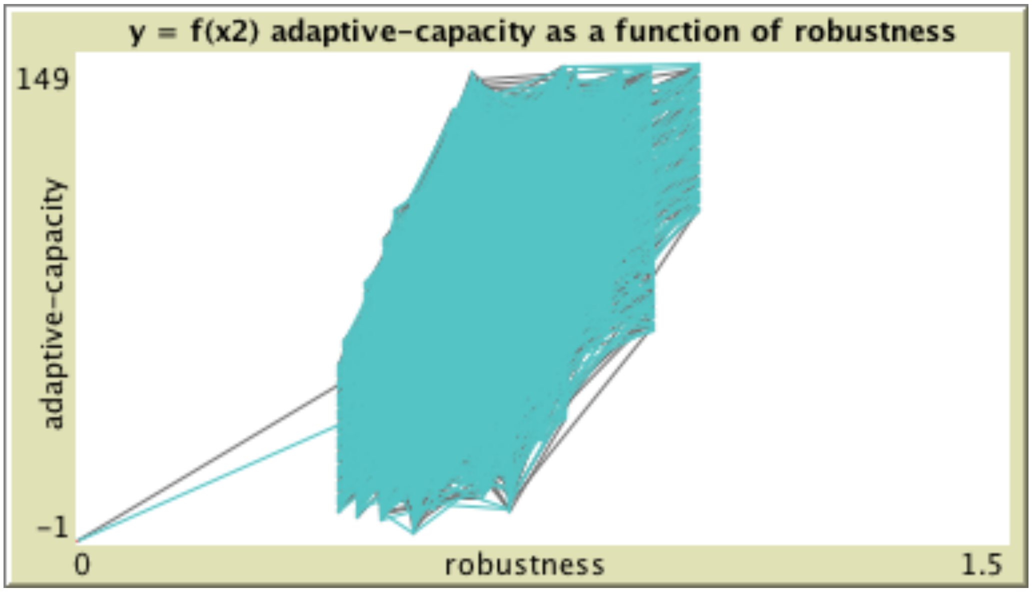

Figure A31. y = f (x_2) - Run 2

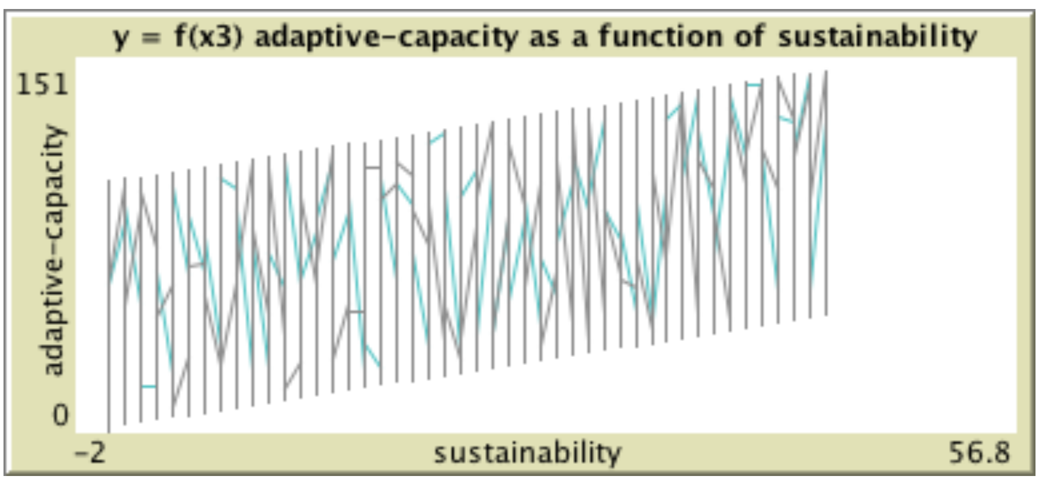

Figure A32. y = f (x_3) - Run 2

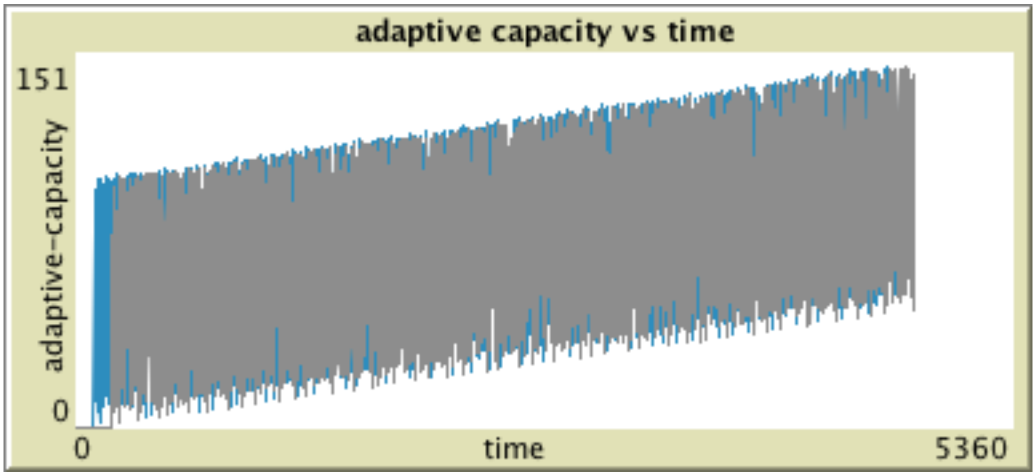

Figure A33. Adaptive-capacity vs time - Run 2

Table A11

Repeated-Cooperate PD Experiment for RRS –Run 3

	population size	emissions-penalty	cooperation-reward	min	max	range	mean	median	modes	standard deviation
Resilience / Cooperation	100	20	0	-107.594	271.922	379.516	11.1	-0.623	[0 -42.276 -91.672 65.694 34.925 -23.412 -41.265 111.793 -1.246 65.218 -21.627 35.145 -9.254 -12.458 49.247 13.954 -19.189 -28.647 -34.766 -5.174 -41.54 -39.48 33.074 -35.903 -72.709 -13.088 -28.364 91.102 43.841 -24.541 -13.739 47.957 -27.45 131.335 24.881 95.835 -40.953 9.451 -9.251 50.163 -20.027 113.965 91.238 15.986 67.322 63.884 -56.584 6.059 -35.983 78.433 60.889 52.205 25.569 -35.819 2.715 72.699 -23.648 15.876 3.027 -100.231 -42.875 157.747 8.066 -92.519 46.5 -5.637 -29.323 92.252 -28.209 8.244 82.18 1.046 -58.759 271.922 65.896 120.274 106.051 -39.013 16.731 64.471 -15.314 -32.098 32.629 41.194 -26.392 -54.188 -47.862 -36.293 -107.594 53.42 -32.276 -31.267 -29.517 -10.927 53.038 -25.109 -57.911 21.672 -8.037 54.567]	60.266
Robustness / Cooperation	100	20	0	0.401	0.924	0.523	0.638	0.642	[0.582 0.573 0.586 0.474 0.777 0.606 0.755 0.673 0.568 0.514]	0.111
Sustainability / Cooperation	100	20	0	49	49	0	49	49	[49]	0
Adaptive-capacity / Cooperation	100	20	0	51	149	98	99.11	99.5	[72]	26.988

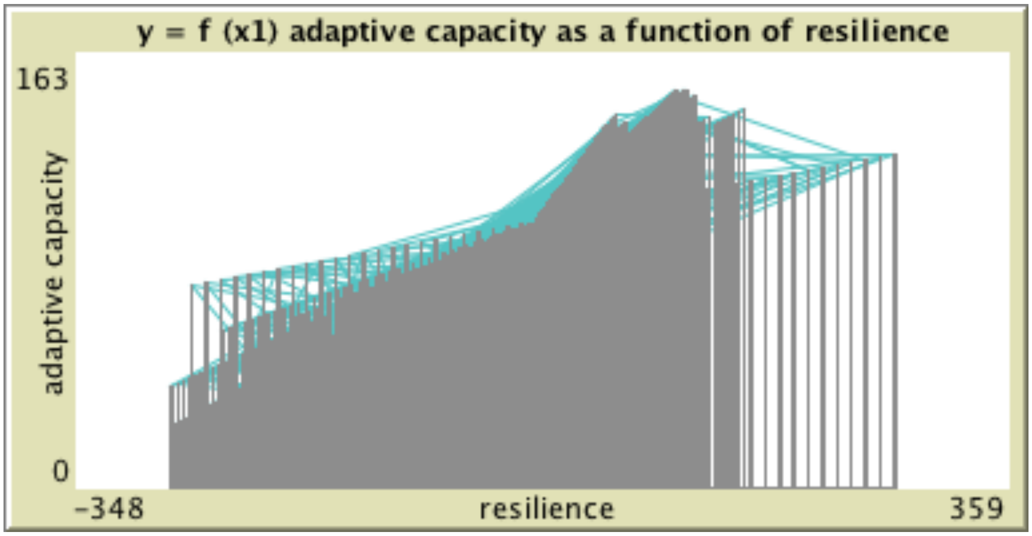

Figure A34. y = f (x_1) - Run 3

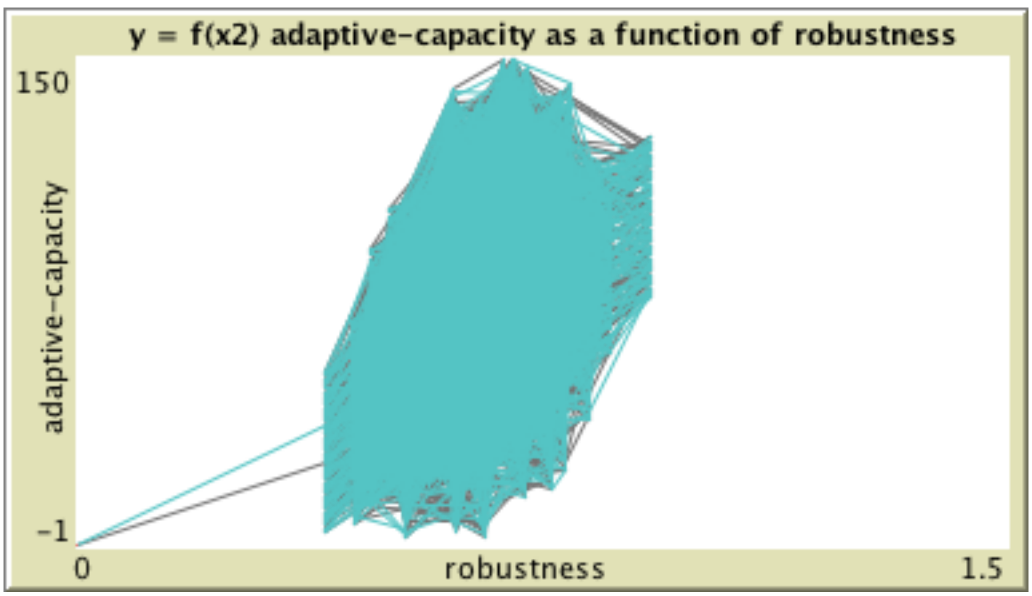

Figure A35. y = f (x_2) - Run 3

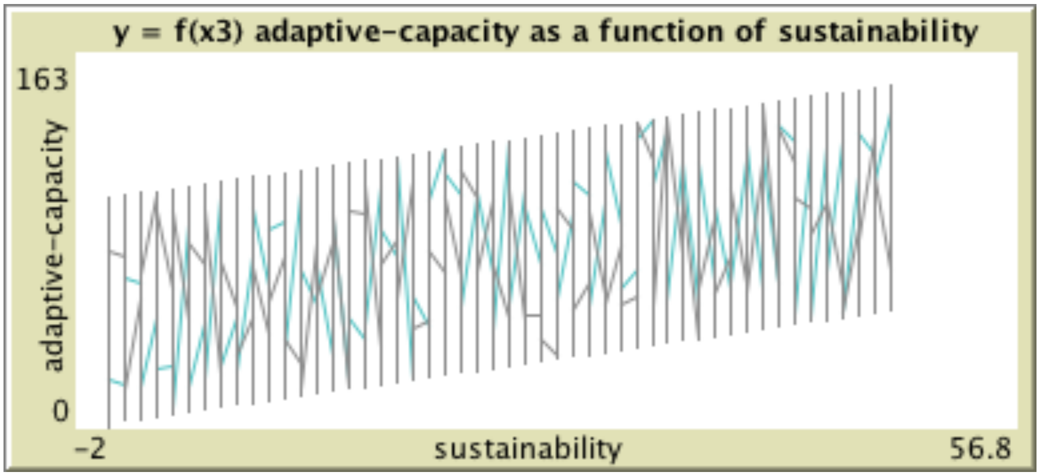

Figure A36. y = f (x_3) - Run 3

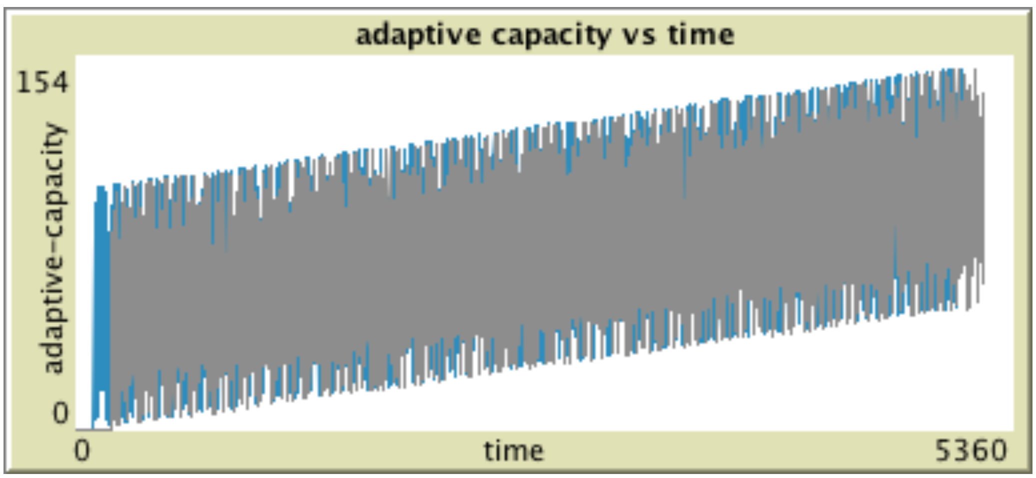

Figure A37. Adaptive-capacity vs time - Run 3

Table A12

Repeated-Defect PD Experiment for RRS –Run 1

	population size	emissions-penalty	cooperation-reward	min	max	range	mean	median	modes	standard deviation
Resilience / Defection	35	0	0	-3.943	-2.406	1.537	-2.931	-2.764	[-2.636 -2.507 -2.515 -2.806 -2.764 -2.568 -2.964 -3.943 -2.452 -3.025 -3.474 -3.382 -3.496 -2.449 -2.528 -2.859 -3.309 -3.55 -2.413 -2.608 -2.699 -3.329 -2.579 -2.493 -3.021 -2.508 -2.577 -3.188 -2.462 -2.406 -3.557 -2.491 -3.818 -3.796 -3.409]	0.477
Robustness / Defection	35	0	0	0.017	0.072	0.055	0.036	0.028	[0.02]	0.018
Sustainability / Defection	35	0	0	49	49	0	49	49	[49]	0
Adaptive-capacity / Defection	35	0	0	-43	49	92	6.914	6	[-8 42 37 41 44 -43 -23]	31.225

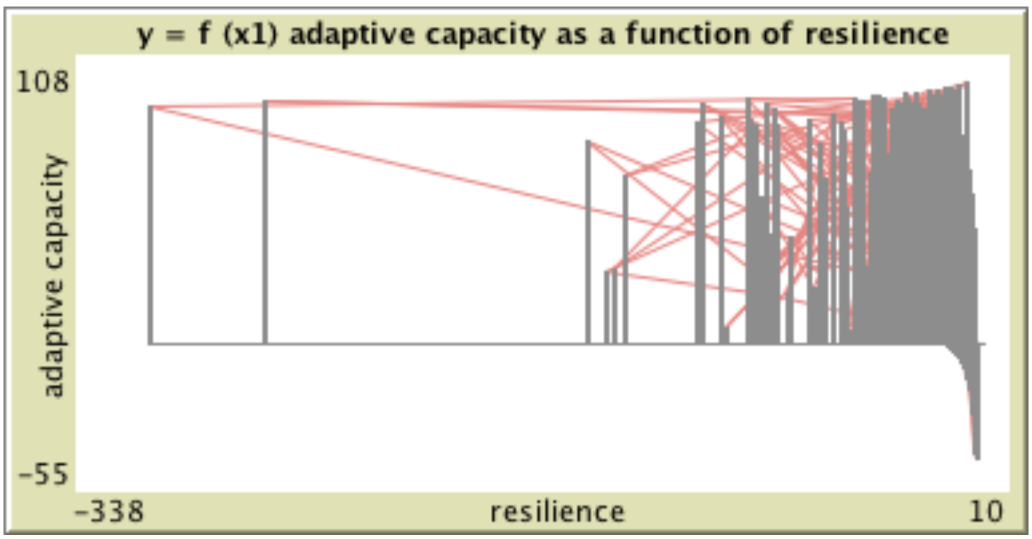

Figure A38. y = f (x_1) - Run 1

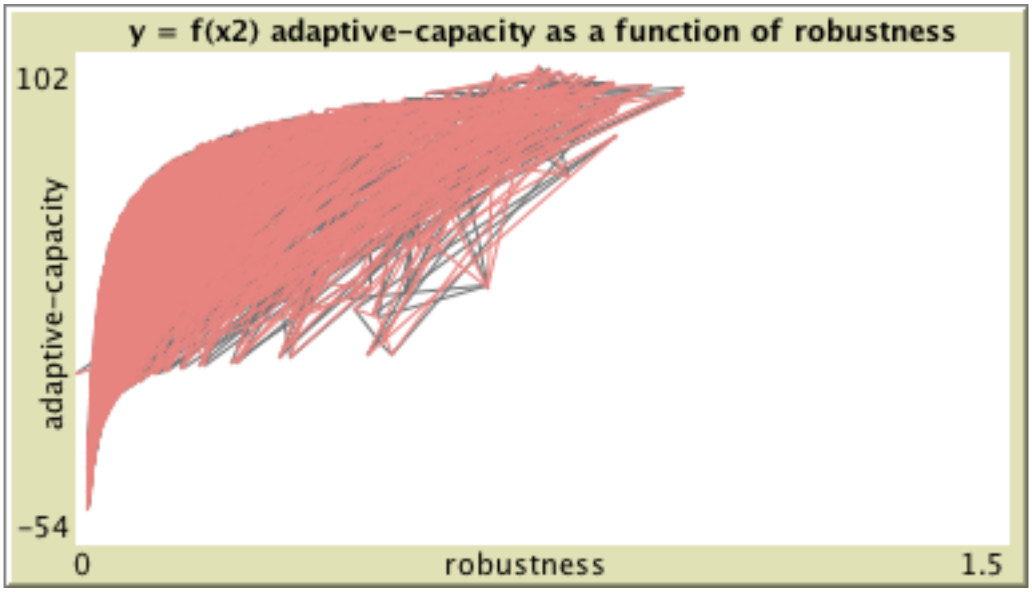

Figure A39. y = f (x_2) - Run 1

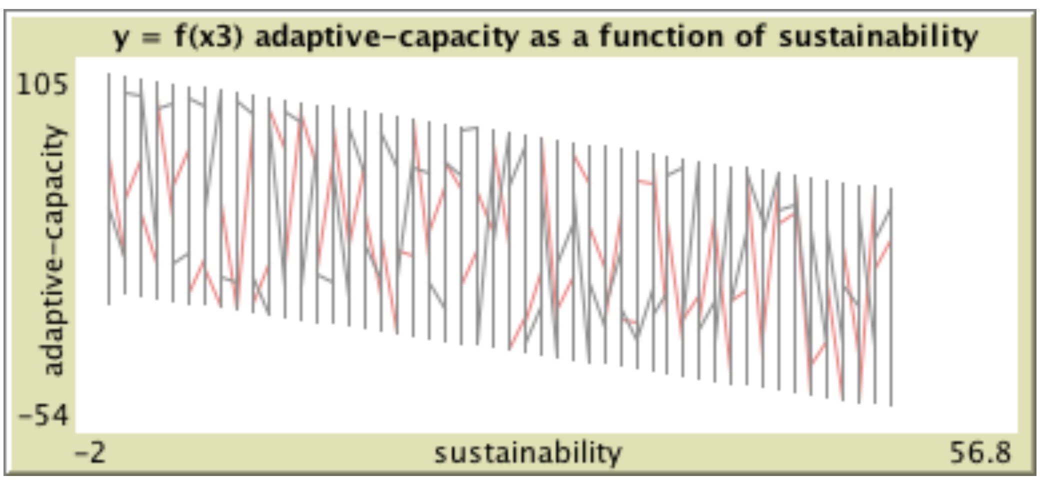

Figure A40. y = f (x_3) - Run 1

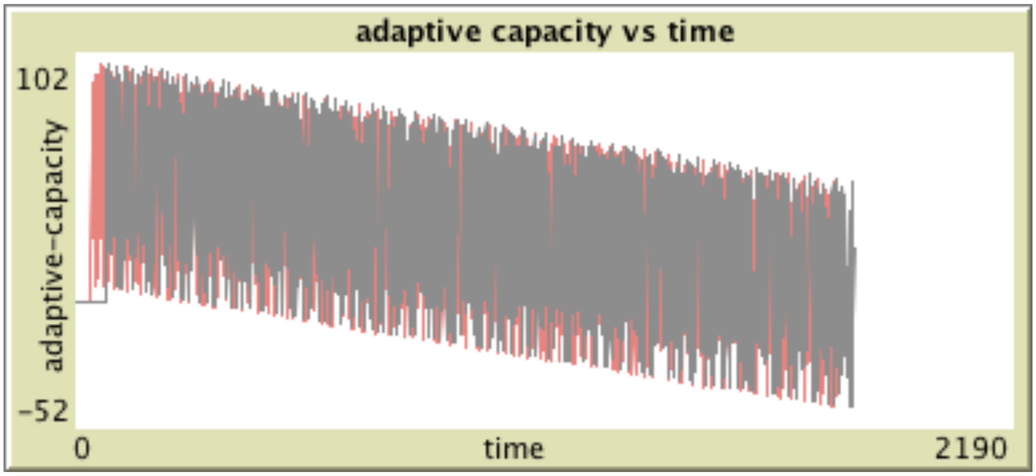

Figure A41. Adaptive-capacity vs time - Run 1

Table A13

Repeated-defect PD Experiment for RRS –Run 2

	population size	emissions-penalty	cooperation-reward	min	max	range	mean	median	modes	standard deviation
Resilience / Defection	100	0	0	-3.819	-2.396	1.423	-2.85	-2.7325	[-2.816 -2.65 -2.651 -2.614]	0.363
Robustness / Defection	100	0	0	0.017	0.068	0.051	0.032	0.027	[0.022]	0.014
Sustainability / Defection	100	0	0	49	49	0	49	49	[49]	0
Adaptive-capacity / Defection	100	0	0	-48	48	96	1.6	2.5	[0 37]	28.248

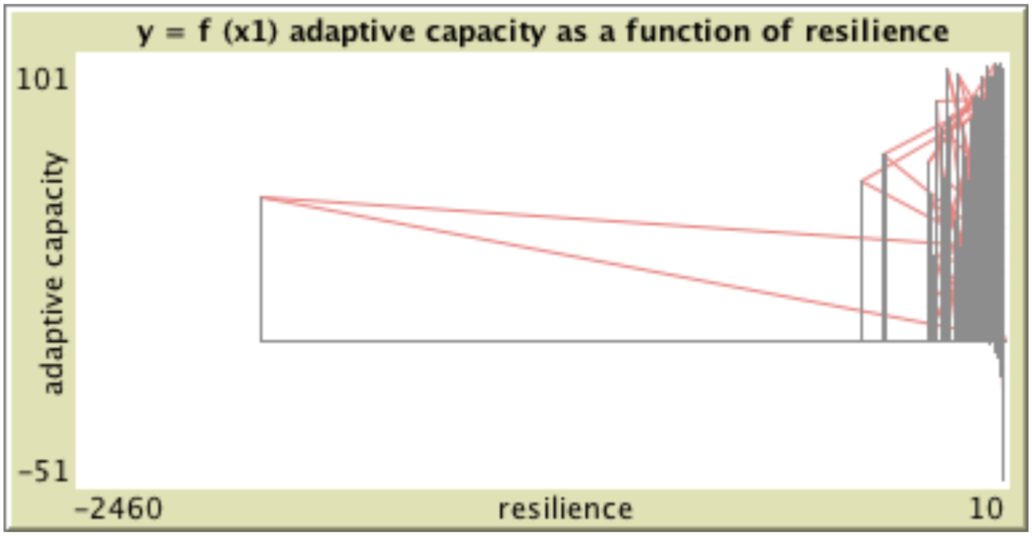

Figure A42. y = f (x_1) - Run 2

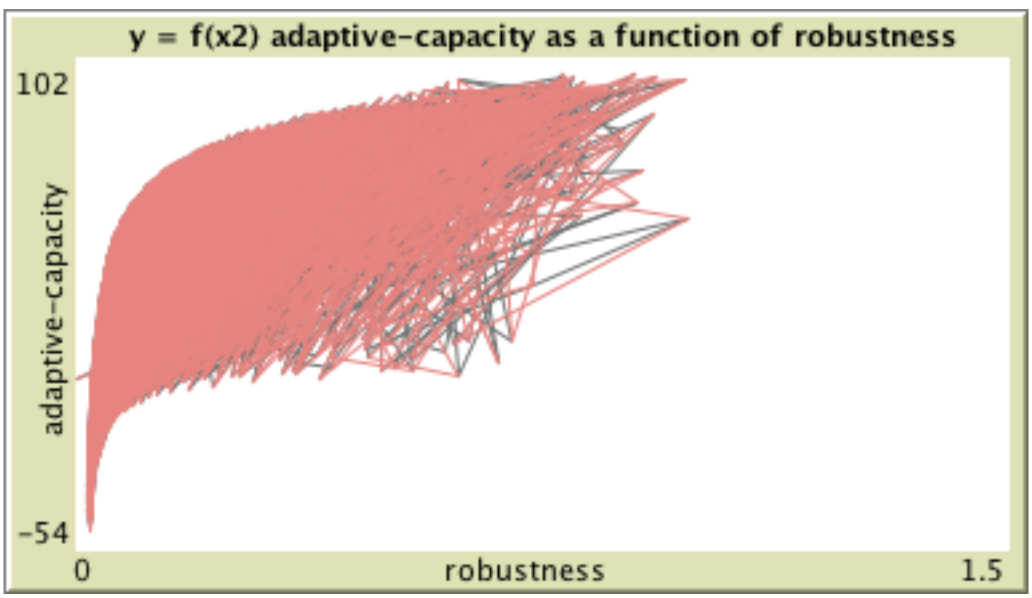

Figure A43. y = f (x_2) - Run 2

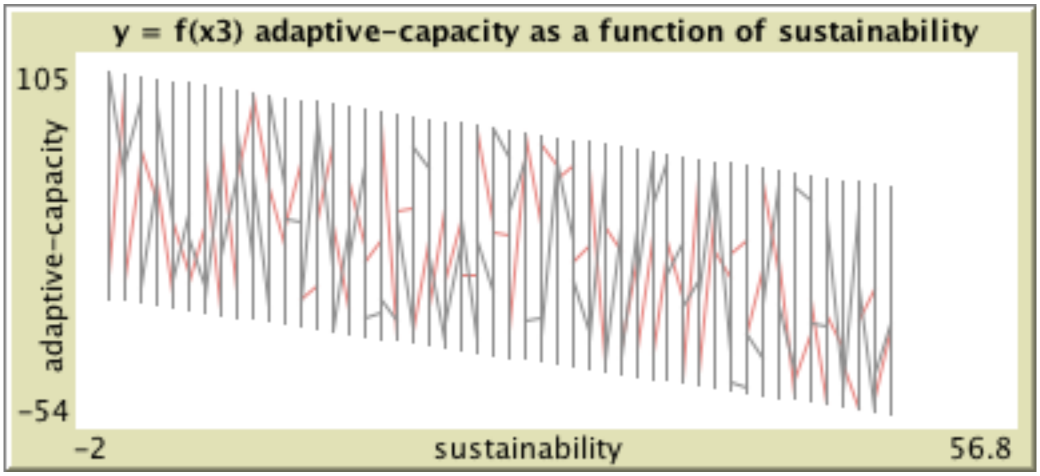

Figure A44. y = f (x_3) - Run 2

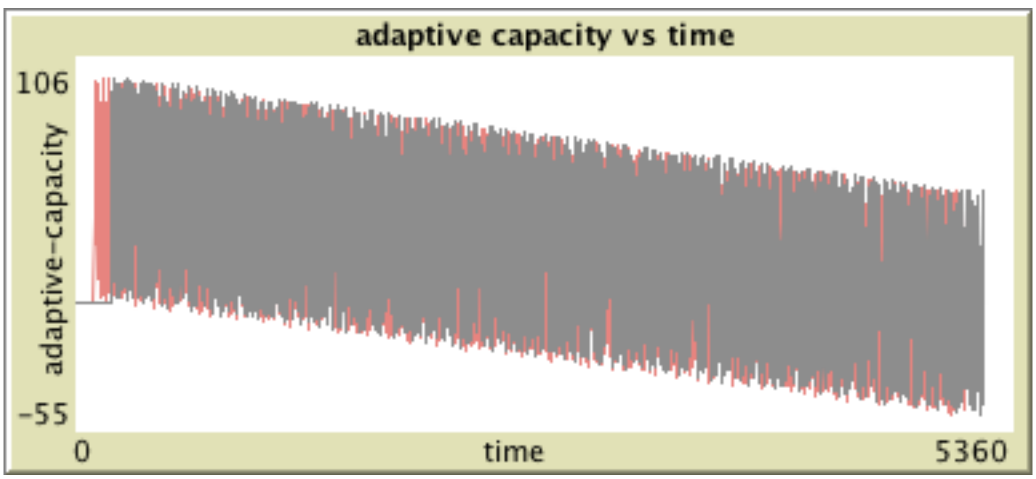

Figure A45. Adaptive-capacity vs time - Run 2

Table A14

Repeated-Defect PD Experiment for RRS –Run 3

	population size	emissions-penalty	cooperation-reward	min	max	range	mean	median	modes	standard deviation
Resilience / Defection	100	20	0	-31.563	-20.909	10.654	-23.935	-23.553	[-23.936 -21.994 -25.383]	2.124
Robustness / Defection	100	20	0	0.091	0.205	0.114	0.127	0.119	[0.114 0.093 0.117 0.109]	0.029
Sustainability / Defection	100	20	0	-5	-5	0	-5	-5	[-5]	0
Adaptive-capacity / Defection	100	20	0	-119	-20	99	-69.81	-73	[-109 -99 -78]	27.814

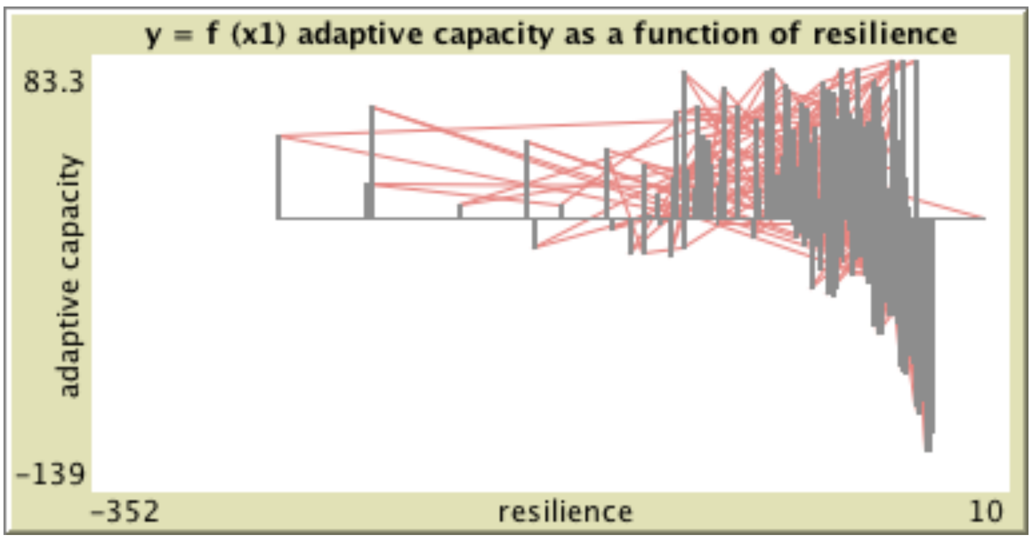

Figure A46. y = f (x_1) - Run 3

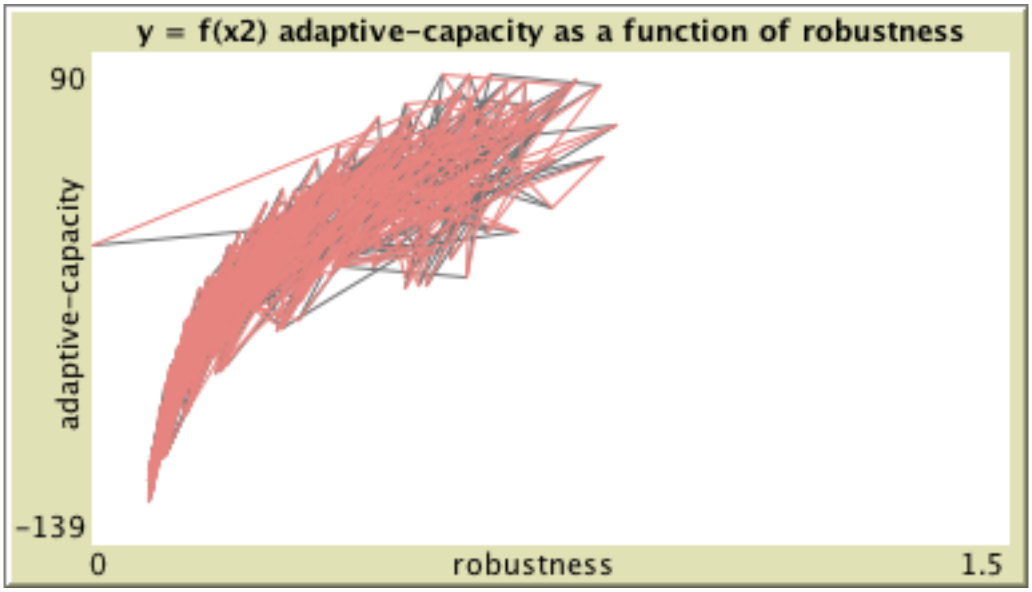

Figure A47. y = f (x_2) - Run 3

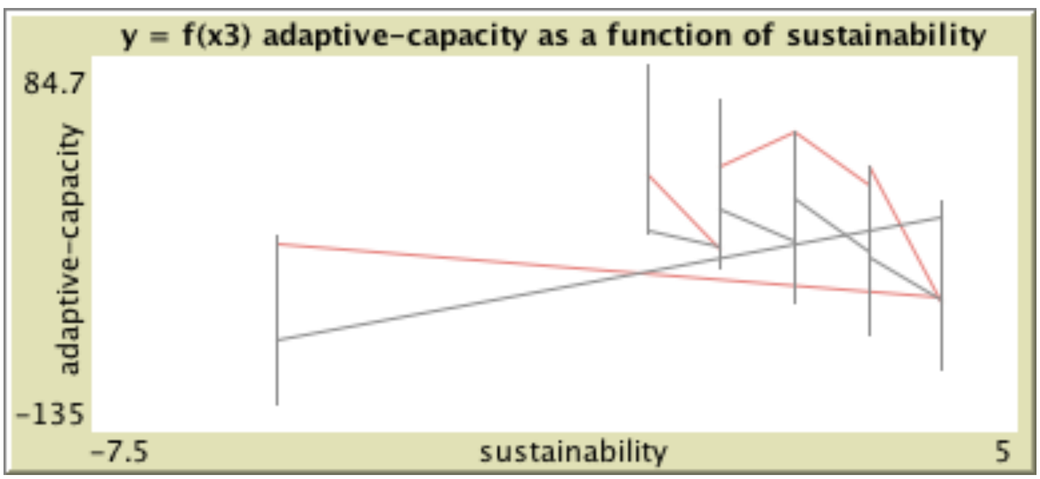

Figure A48. y = f (x_3) - Run 3

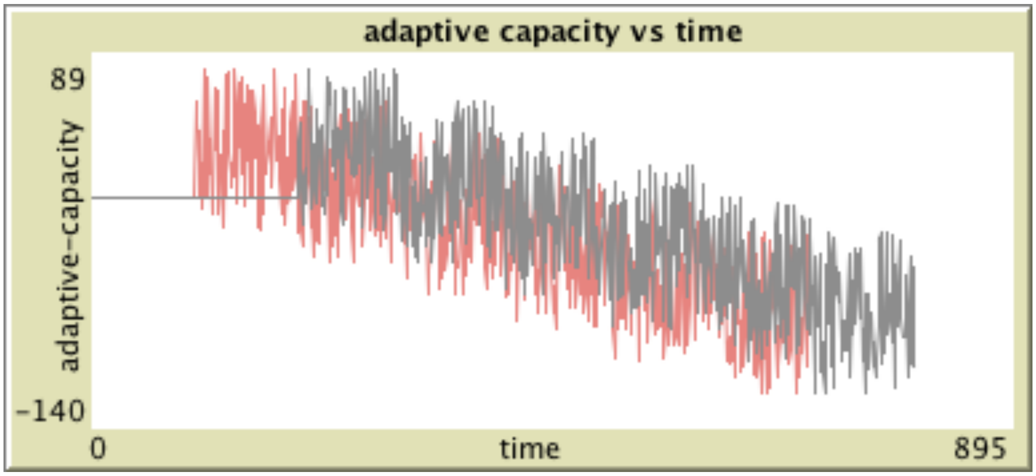

Figure A49. Adaptive-capacity vs time - Run 3

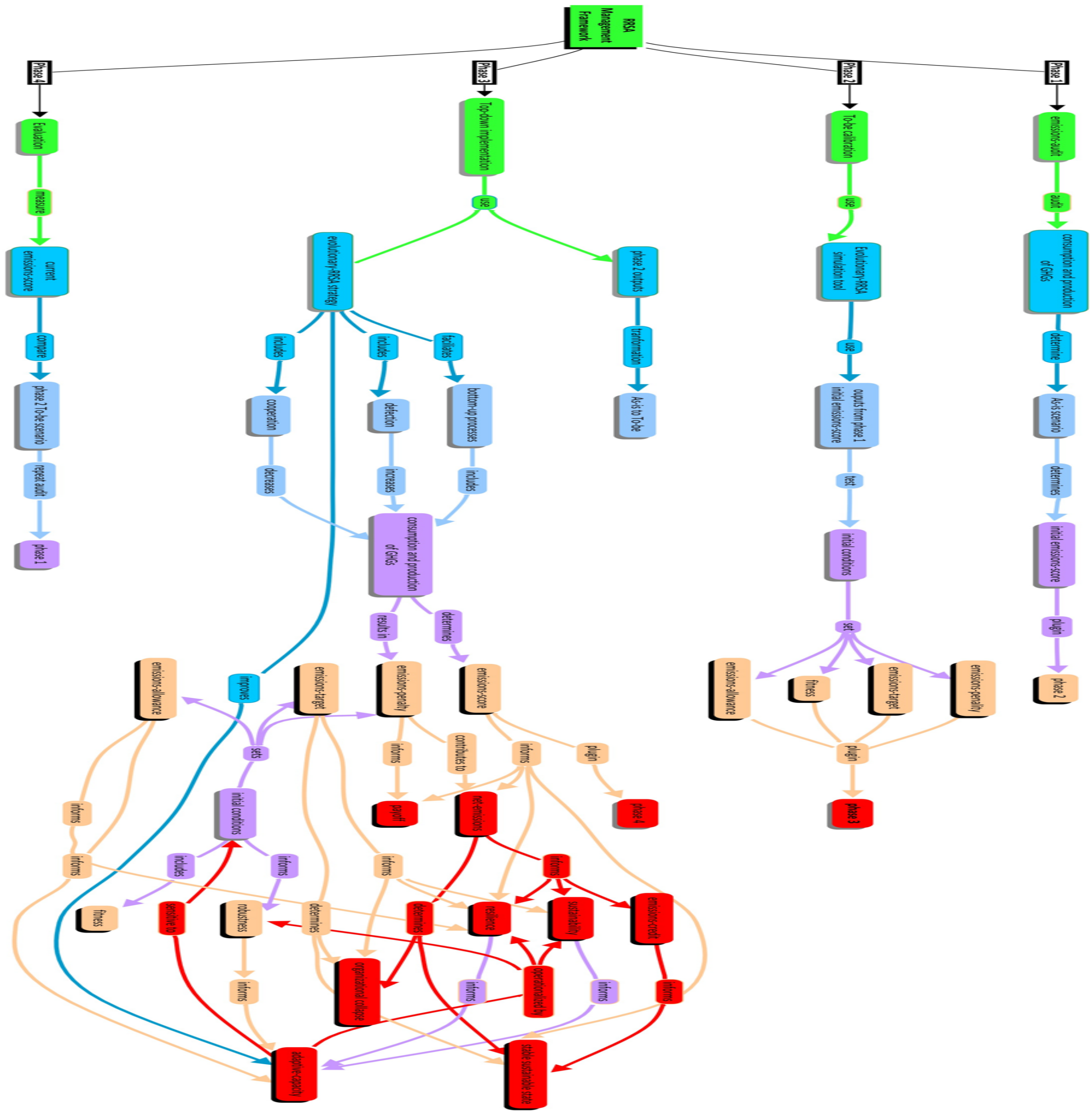

Figure A50. Evolutionary-RRSA Management Framework