Conflict and Cooperation as Social Responses to Ecological Change

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Abstract of the Dissertation

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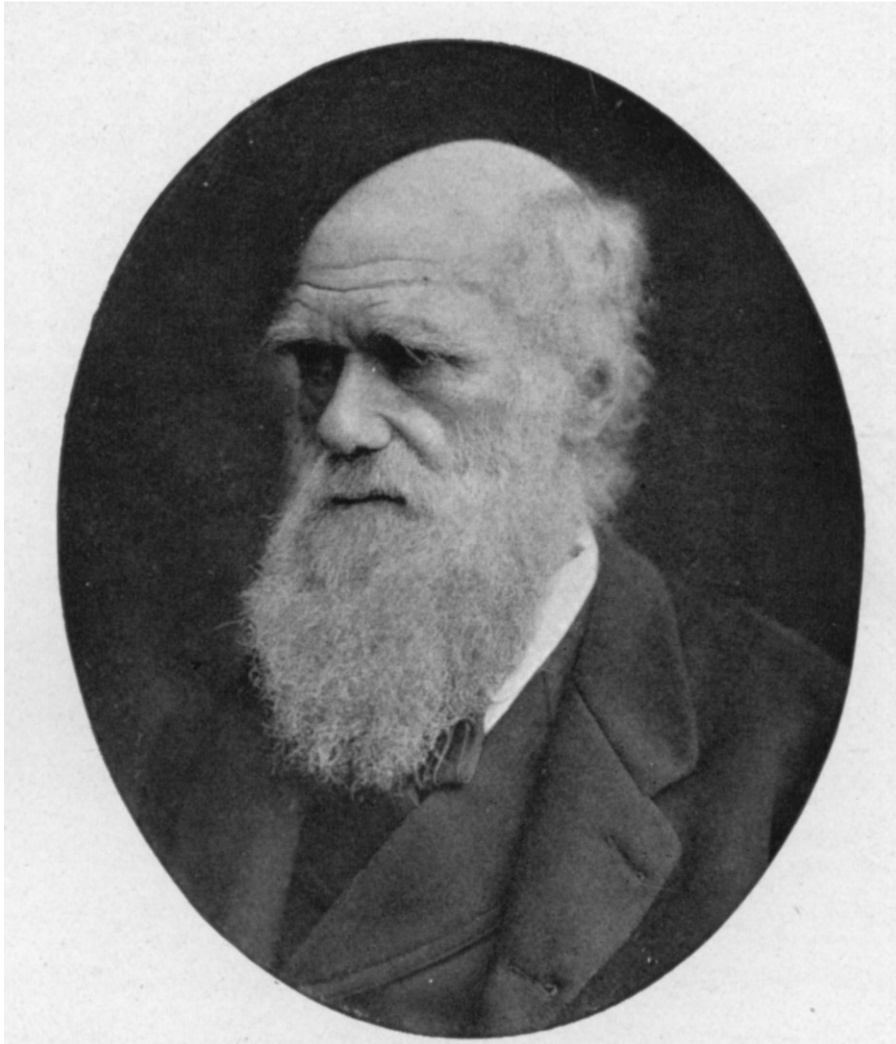
This dissertation examines ways the environment conditions individual incentives to participate in collective action. I hypothesize that as resources become scarce, individuals are more willing to participate in individually-costly collective action, including intragroup cooperation and intergroup hostility. The first and second of three studies establish a unit-of-selection based, game-theoretic foundation for intergroup conflict. The final study explores macro-level implications for the relationship between climate change and violence in Africa. For human beings and other highly social creatures, cooperation is the key adaptation with which we respond to environmental challenges. Faced with resource scarcity, group living becomes increasingly vital for individual survival. The logic of markets dictates that demand benefits of group living increase, so does the price. Hence, groups may demand greater contributions from individuals, which enhances the strength and cohesion of the group, enabling it to take on more ambitious collective action efforts. Changing ecological circumstances should result in shifting selective pressures on individuals, disposing them to pursue alternative social strategies. Accordingly, we should observe indirect effects on patterns of intergroup-level. If true, this dissertation could have implications for social responses to global climate change. I test this hypothesis using climate and event data from Africa 1989-2006. In order to overcome methodological problems challenging previous studies, I use a disaggregated, time-series data structure better suited to dynamic analysis.

Dedication Page

In many ways a doctoral degree can be a very selfish pursuit. The student is not nearly the only one who made sacrifices, but is the only one who volunteered and directly benefits. Yet so many have been there to support me through this, even as I was absent from their lives and unable to reciprocate. To all of the people who held me up long enough to make this happen and have suffered as a result of my choices, I owe a debt which can never be repaid. The best I can do is to promise to work diligently in the public interest, even if this should occasionally conflict with other incentives. It is for these magnanimous individuals that I dedicate this dissertation and all of my subsequent work.



Frontispiece

"A tribe including many members who, from possessing in high degree the spirit of patriotism, fidelity, obedience, courage, and sympathy, were always ready to aid one another, and to sacrifice themselves for the common good, would be victorious over most other tribes, and this would be natural selection."

- Charles Darwin, *Descent of Man* (1871)

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Preface

The details and processes of human sociality lie at the heart of political science and the social sciences generally. It might be said that the study of politics has never existed outside of some conception of human nature. The Greek philosopher and great teacher Plato held that most individuals were haplessly enthralled by corporeal desire, and cannot bear to spend the time necessary to reflect and seek knowledge of Justice and The Good. Accordingly, in his opus The Republic ($\sim$ 380 B.C.E) he presented a model of government and society centered on the dominion of the philosopher-kings, who would be removed from society at birth and trained as philosophers, for only a true philosopher could manage to escape the realm of belief and apprehend knowledge, as symbolized in the Allegory of the Cave. In 1651, Thomas Hobbes, who might be described as the first of the moderns, explained in The Leviathan that human beings were driven essentially mad by constant, never-ending agony, which he ascribed to the "pain of privation". That is, human beings, while not inherently good or evil, are helplessly driven to do evil in a fit of blind desperation to assuage the suffering of constant want for food, shelter, sex, and status. On this basis, Hobbes famously advocated that society's only chance for peace was to establish a Leviathan, or a paramount sovereign who is imbued with all the requisite authority and power to enforce civil, cooperative behavior on a populace incapable of doing so by their own designs.

From Hobbes' conception of human nature, he established the political-philosophical foundation underlying an ultimately normative conception of government, as well as a description of the consequences of anarchy that is, to this day, at the heart of the realist school of thought in domestic and international politics. Contrasting with Hobbes, rationalist intellectual John Locke agreed that while anarchy means a state of constant war, humans possessed a faculty for reason and were, in fact, capable of coming together and establishing a basis for cooperation in the form of a social contract. For Jean-Jacque Rousseau, human nature was inherently good, but could be corrupted by a poorly constructed social contract, or an unjust society; from inequality, arises negative feelings such as jealously and motivations for conspiracy. Within these perspectives, we find the political-philosophical bases for the Anglo-American and continental liberal traditions. Similarly, unique conceptions of human nature may be found at the intellectual foundations of Marxism, constructivism,[1] and rational-choice theory.[2]

As brilliant as these great minds' insights into the heart of human nature were, they were like most theories confined to the greater body of knowledge and ideas of their time. They were largely conceived prior to the discovery of biological evolution by natural selection (or at least during its infancy), at a time when it was comparatively easier to believe that humans were somehow apart, exceptional, from the rest of the animal kingdom. After the disastrous adventures in *Social Darwinism* of the late 19th and early 20th centuries, it was a long while before scholars would begin to revisit human nature from a post-Darwinian, biological perspective.

In 1985, 20th century intellectual giant Herbert Simon criticized the then-prevalent the tenets of the rational actor model of human decision-making as incompatible with the "characteristics of the choosing organism" (Simon 1985). Alternatively, he introduced the concept of *bounded-rationality* in order to anchor the rational actor model more firmly in plausible assumptions of human physical and mental architecture.

In 1994 at the annual meeting of the American Economic Association, evolutionary psy-

[1] Influenced by Rousseau, the 19th century giant Karl Marx agreed that humanity's manifest nature was generated in context, though not politico-institutional, but economic. In his Economic and Political Manuscripts of 1844, Marx describes the features of humanity's *species-being*, or *gattungswesen*. His conception was significant because it introduced to western thought the notion that human nature is not constant, but plastic and flexible, and is determined by the totality of all social and economic relations. During the 20th century, the Soviet Union and the People's Republic of China attempted to alter the condition of humanity by fundamentally restructuring the social and economic relationships between all members of their societies. As well, the contemporary school of thought known as constructivism can be described as having its roots in Marxian human nature (Paul et al. 1998).

[2] Even the "rational choice" model human decision-making is based on a certain understanding of human nature, at least by assumption. Principally, the rational choice model assumes a kind of godlike purity of thought, in way that is unconstrained by what Herbert Simon (1985) called the "characteristics of the choosing organism" (Simon 1985).

chologists Leda Cosmides and John Tooby introduced the economics world to the notion of "rationality in design" (Cosmides and Tooby 1994). This is the idea that economic behavior is discharged by specific, physical mechanisms in the brain shaped by natural selection in a way that maximizes utility across a broad array of adaptive problems for our early human ancestors. Among these adaptive problems were the opportunities and perils of social living. Political psychologist Marilynn Brewer sought to rethink human social behavior from the ground up, starting with the explicit premise that "human beings are adapted for group living" (Brewer and Caporael 2006). In support of this premise, she writes:

> *"Even a cursory review of the physical endowments of our species—weak, hairless, and extended infancy—makes it clear that we are not suited for survival as lone individuals, or even as small family units. Many of the evolved characteristics that have permitted humans to adapt to a wide range of physical environments, such as omnivorousness and toolmaking, create dependence on collective knowledge and cooperative information sharing. As a consequence, human beings are characterized by obligatory interdependence, and our evolutionary history is a story of coevolution of genetic endowment, social structure, and culture."*

Accordingly, she reasons that with coordinated group living as a primary survival strategy of the human species, it is principally through, or as a part of, the social group that individuals respond to the exigencies of the physical environment.

It is from this point that this dissertation began its voyage, on a mission to press further and deeper into humanity's social nature. I believe this effort is worthwhile, for a fully elaborated theory connecting strategic, or intergroup-level behavior to individual-level motives stands to generate powerful new insights on politics and the world. Equipped with a more accurate conception of human nature, both in terms of our capacities and our limitations, we are in that much greater of a position to resolve the daunting challenges that lie in store for us this century.

And I believe this research was profitable. Brewer describes the default condition of human being as as "obligatory interdependence." We gleamed new insight into a possible explanation *why* our evolutionary history has lead us here, and importantly *how* we go about building the social structures. That is, we have begun to theorize about the organizing protocol of human sociality encoded that may be encoded in our genetic make up.

Equipped with this insight, we might resolve one of the long lasting paradoxes of human nature: While we praise as "humanistic" or "humane" behaviors associated with cooperation like love, altruism, forgiveness, sacrifice, loyalty, and empathy, we are time and time again forced to reconcile these "virtues" with an apparent dark side. In the year 2014, war is still a fact of life. Politics divides us at the same time it unites us. So-called "vicious" dispositions such as racism, hate, denigrative *othering* and intolerance characterize shape our mental landscapes of our social environments arguably as much as do the aforementioned virtues. Naturally, we would tend not to acknowledge these aspects of our souls as openly. Certainly, no one is likely to claim them 'humanistic'. In fact, it seems common that we externalize these sentiments, attributing them to devils and beasts; ironically, our penchant for disproportionately seeing such *inhuman* influences acting upon our enemies may make it easier for us to exterminate them (Smith 2011).[3] Yet these moral judgments—virtue and vice—may very well correspond to the two sides of the very same coin; both may correspond to fundamental dynamics of human cooperation. Indeed, the present research would suggest that intergroup conflict is not only enabled by cooperation, but may in fact be its purpose.

[3] Philosopher and evolutionary theorist David Livingstone Smith has written extensively on the role of denigrating and demeaning others as a psychological mechanism for suppressing empathic concern and enabling violence. Also see Smith (2007, 2009).

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I wish to thank, first and foremost, my adviser and mentor Oleg Smirnov. Without his guidance and truly expert tutelage this thesis would have remained a dream. I want to thank Chuck Taber, for without his inspiration and support it would have been a dream cut short.

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I am indebted to the many teachers, friends and colleagues who supported me along this long road, a road which began in 1996 in introductory philosophy course at Mesa College in San Diego, CA. That course was taught by a very special teacher, a true philosopher and the first adult I ever wanted to be like. Thank you, Dr. Michael Mussachia. If Dr. Mussachia gave me a vision of what I could become, Dr. Nicholas Dungey inspired within me the passion to realize it. I owe my deepest gratitude to Adam Gendelman, my best friend and companion along the journey from ignorance to wisdom. *Eheu, fugaces labuntur anni!* I want to thank the brilliant mathematician Yury Sobolev, my trusted friend and programming teacher. I also wish to thank Mohammed Osman for his unwavering friendship, his music, and his ideas. Immense appreciation for my good friend and gifted statistics teacher Dr. Joshua Johnson, and Dr. April Johnson for her friendship and counsel. Amir Bahkshaie and Yuji Okamura, who have each in their own diametrically opposite, yet complimentary ways helped me keep my eyes on the prize. Casey Wilson, who on one warm summer day on a grassy field in Vermont made me promise to pursue my doctorate, no matter what. Kitwai Wong, who once when I was feeling frustrated and unable to compose a Statement of Purpose, stayed up half the night to help me re-write it. Of course I did not use that statement, but it meant a lot that she believed in me. Special thanks to Rachel Phillips, my digital confidant and favorite song soul-mate, and Emily Lam, for her support even when it was at great personal cost.

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Publications

- Seltzer, Nicholas A., April Strickland, and Karyn Amira. (2013). On the Social Nature of Attitudes: A Multi-agent Based Simulation of the Social Diffusion of Political Attitudes. *International Journal of Politics, Culture, and Society.* Vol. 26; Num. 3.
- Seltzer, Nicholas A. and Matthew Weinberg. A Case Study for Behavioral Signature Analysis: The Federally Administered Tribal Areas of Pakistan. Published by Evidence Based Research, Inc. for the United States Department of Defense. Mclean, VA. May 2008.

Under Review

- Seltzer, Nicholas A. and Oleg Smirnov. Degrees of Separation, Social Learning, and the Evolution of Cooperation in the Modern Society. Under review at the *Journal of Theoretical Politics.*

Conference Papers

- Seltzer, Nicholas A., Reuben Kline, Yvgenia Lukinova, and Autumn Bynum. Asymmetric Responsibility Ownership in a Collective-Risk Social Dilemma Model of Climate Change. Presented at the Annual Meeting of the Midwest Political Science Association, April 2014.
- Seltzer, Nicholas A., Yamil Velez, and Patrick Lown. Authoritarianism: Its Origins and Effects. Presented at the Annual Meeting of the Midwest Political Science Association, April 2013.
- Seltzer, Nicholas A., Oleg Smirnov. Why We Care About Others: The Evolution of Cooperation on a Social Network as a Function of Degrees of Separation. Presented at the Annual Meeting of the Midwest Political Science Association, April 2013.

Dataset

Gridded Environmental Conflict in Africa Dataset, or *GECAD*. Organizes and structures diverse human and remotely sensed datasets in order to assess causal pathways between ecological variables and political instability in Africa. Using disaggregation techniques in GIS, the GECAD allows for high resolution spatial and time series analysis using variables from the World Bank African Development Indicators, NASA, the Global Database of Events, Language, and Tone (GDELT), and Climate Research Unit of East Anglia University.

Courses Taught

- *World Politics* (Spring 2012, Fall 2012, Spring 2012). Analysis of the basic concepts and issues of international relations in the contemporary international system. Students learn several prominent theories of international politics, with an emphasis on the historical context of their development.

- *Mass Media in American Politics* (Fall 2011). An upper-division exploration of the nature of mass media communication in society, the institutional structure of the media, and the role of the media in American political and economic life past and present.
- *Public Policy and Evaluation, TA* (Fall 2009, Fall 2010). This is a required course in Stony Brook's Masters in Public Policy program. Provides an introduction to the concepts, political and philosophical foundations, and operational methods used in public policy decision-making and implementation.
- *Introduction to Sociology, TA* (Spring 2010). The foundational course in the undergraduate sociology program at Stony Brook. Students are given a broad introduction to the problems, perspectives, and methods of the sociology discipline.

1 Introduction

1.1 Cooperation and 'Us'

On November 23, 2013 in New Haven, Connecticut, bleachers were filled to capacity for the annual Harvard-Yale football game. On each side of the gridiron a crimson or blue sea of feverous loyalists flying the colors of their *alma mater*. Between them their champions meet in a dramatic, yet unscripted reenactment of primitive tribal struggles for strategic dominance over ancient adversaries. "Spirit leaders"—costumed caricatures of forebears (John Harvard) and sacred animals (the Yale Bulldog)—lead their constituencies in revelatory songs glorifying the virtue of their respective tribes, as evident in past victories and superior creeds. At no time of the year do these two populations feel more distinct from one another than on this chill day in the late, New England Fall.

But demographically, one would be hard pressed to find two groups with more in common than these two. In terms of virtually any salient socioeconomic category, these populations are essentially indiscernible from one other. That is, these two groups of people are the *same* people. They are the cream of America's Ivy League, centers of America's intellectual, political, and economic elite. Indeed, the demographic breakdown of those attending these institutions in 2014 are mirror images of the other, as if they were randomly assigned from the same population (see Table 1).

Red or blue? Sidanius and Pratto describe this seemingly imagined social distinction, which seem so intense during that November game—as *arbitrary sets*. No doubt many people are likely to take offense at the notion that such essentially elements of our identities are somehow "arbitrary". Why are such arbitrarily defined categories so important to us personally? Why should we yield such incredible power to influence our feelings, or actions, and our ideas? The shorter, more proximate answer to this question might be that we just love to do it. It feels great. We *literally* revel in our identities. They fill us with the joy and comfort that comes with a sense of belonging, of having unloaded the great, but unspoken

Table 1: Racial and ethnic demographics of among undergraduate at Harvard and Yale Universities.

	Harvard	**Yale**
American Indian or Alaskan native	0.29%	0.5%
Asian/Native Hawaiian/Pacific Islander	15.24%	15.27%
Black or African American	6.13%	6.28%
Hispanic/Latino	8.26%	9.74%
White	48.58%	47.3%
Two or More Races	4.3%	5.18%
Race/Ethnicity Unknown	6.82%	5.18%
Non-Resident Alien	10.38%	10.15%

Source: Forbes (2014)

burden of *self*, of knowing that you are not alone. Attachment to others is a fundamental psychological need for humans. Tellingly, it is often our habit to regard those who are either unable or unwilling to entangle themselves in the tendrils of social connections as "ill", having a "disability", or worse.[4] Whether it is through attachment to sports teams, schools, brands, religions, music styles, lifestyles, or even lettuce preferences[5], we are constantly (and largely unconsciously creating), seeking-out symbols with which we may signify to the world *who* we are. Not as individuals, but rather in terms of the social categories to which we appertain. Such symbols are a broadcasting of individual identity through group identification, a call out into the wilderness like minded persons will recognize us and invite us to join them.[6] Such symbols are the tangible objects to which we fix all of the intangible but critically important elements of our identities. They suggest connections based on shared sets of myths, beliefs, origins, or practices, which may in part substitute, and provide the context

[4]This is most directly a reference to diagnoses such as autism or Asperger's syndrome, which are purported to inhibit individuals from forming "ordinary" social ties. However, the connotation of mental illness may also be read from a Foucaultian perspective on "madness".

[5]According to the scholarly sociological text the *Encyclopedia of Food & Culture* (Katz and Weaver 2003), "Food as symbol can represent differences between groups, with foods considered inedible or unsavory by one group used to show the other as less civilized or even less human." Though possibly apocryphal, non-academic studies (Kelly Ford), journalists (National Public Radio), political commentators (Rush Limbaugh), and numerous other popular web sources have suggested that liberals prefer bitter lettuces like arugula while conservatives prefer the more bland iceberg variety. Other food preferences correlating to ideology such as dining-out preferences have been noted in the *Wall Street Journal* (Epstein 2014)

[6]For a thorough discussion on the evolution of *ethnic markers*, see Boyd and Richerson (1987).

for, actual rapport.

The longer, more complete answer to the above question, “Why do we so value, and so devote ourselves to these associations,” is as astrophysicist Neil deGrasse Tyson eloquently put it “the greatest story science ever told”; the evolutionary history of *us*.

1.2 Evolutionary origins of sociality

Why are humans the tribe-minded, massive-brained socializing wizards of the animal kingdom? This is one of the most ancient, unanswered questions in social science. It has central implications for virtually all that we study. In the simplest explanation, we can be reasonably certain that cooperation was advantageous for our ancestors. This behavior—and all the genes encoding for the neural and physiological hardware supporting it—enabled those individuals with the capacity to join forces with other individuals to multiply faster and be more fruitful than those who could not. Those genes are our inheritance, passed on, added to, and passed on again and again from generation to generation over millions of years. But if cooperation is such a powerful tool, why is it not the rule of nature? In fact, it is more accurate to say that it is the exception that breaks the rule. In the traditional Darwinian sense, the manifestation of any cooperation whatsoever constitutes a conundrum. Why should essentially egoistic, self-serving agents ever contribute some of their precious resources (food, time, protection) toward the well-being of another? Any conferral of assistance to another individual, especially a conspecific, should equate to a detrimental change to the relative fitness of the provider. Thus, we would expect any individual displaying this behavior to die out along with whichever genes may underly it, never to be heard from again. Sure, a mutually cooperative relationship could be beneficial to both parties, assuming they each keep up their own end of the bargain. But how can I, as a prospective cooperator, know that my act of good will will not be met with betrayal? This, in the jargon of those who study the mystery of cooperation, is the problem of *defection*. An act of individually costly benevolence met with betrayal can potentially be—and presumably often was to our distant ancestors—extremely hazardous when survival is already challenging due to limited resources and harsh environments.

A prevailing perspective is that certain external conditions can help to mitigate the risk of defection for would-be cooperators. Given the opportunities inherent in cooperation, theorists suppose certain circumstances can increases individuals' confidence that their partner will cooperate back if they do. This in turn diminishes the risk of defection and opens the evolutionary door to cooperation, society, and eventually cities and counties. One such condition is the notion of repeated encounters. Given some rudimentary faculties of memory and individual recognition, Trivers (1971) demonstrated that cooperation can evolve on the principle of *direct reciprocity*[7], i.e., "if I cooperate now, you may cooperate later." Epstein (2006) and Ohtsuki, Hauert, Lieberman and Nowak (2006) have described how *population structures* may achieve a similar effect. Where repeated interaction is infrequent or unlikely, a number of mechanisms have been proposed that accomplish the same result. For example, Nowak and Sigmund (2005) describes the evolution of cooperation on the condition of individual-level reputation building, or so-called *indirect reciprocity* mechanisms; that is, "if you see me cooperate with others right now, you may cooperate with me later".[8] Elinor Ostrom (1990) reasoned that cultural *institutions* serve to increase certainty over others' future behavior, thereby assuaging others individuals' concerns they will be put at a disadvantage by cooperating. In particular, institutions which provide a routine and reliable means of punishment can dramatically affect expectations of behavior (Fehr and Gächter 2000, 2002; Bowles and Gintis 2002; Fowler 2005; Smirnov 2007; Rustagi et al. 2010). Other conditional explanations include *fitness-based cues* (Johnson and Smirnov 2012), spatial conditionality (Seltzer and Smirnov 2013), and cooperation based on *arbitrary tags* such as observable traits (e.g. a "green beard") which serve to distinguish cooperators from defectors (Hamilton 1964, 1975).

It is not difficult to see these mechanisms at work in the respective crowds at the Harvard-Yale game. The loud proclamations (Go Crimson!) and garish display of colors, emblems,

[7] Also see Axelrod and Hamilton (1981).

[8] Also see Riolo, Cohen and Axelrod (2001).

and banners communicate to others an individual's allegiance, what they believe, and even how they may be expected to act. All of these symbols carry information about reputations, associations, and shared values. In a glance, they tell others who they are—not as individuals, of course, but socially. And from their social linkages, individual behavior may be inferred. In this sea of individuals largely unknown to each other individually, there is not one "stranger" among them.

But there are no strangers to be found in the opposition's bleachers either. They are also known quantities. Previous literature on the evolution of cooperation has frequently neglected this darker side of cooperation: within group cooperation to facilitate *intergroup conflict*. By their colors and their songs, our two groups are recognized as "rivals". Human cooperation is not universal. Cooperation is necessarily bounded. Each of the above mechanisms for the evolution of cooperation imply a finite, knowable social space. Individuals must be recognizable either individually or by category. Relatively stable structures of relationships must exist. Cultural markers must be recognized and traceable to known identities. The jurisdiction of institutions, whether or social or political, are confined in space and time and are therefore inherently exclusive.

Thus, the emergence of cooperation does not occur uniformly. Rather, it emerges in largely independent clusters within which rules, mores, and customs are commonly known, and where individuals or the social positions they occupy are recognized. Social connective pathways must be apprehensible for reputational mechanisms to operate when direct observation is not possible. If only direct observation is possible, then interactions must be confined spatially and temporally. Without such prerequisites, it is impossible to convey new information about a given individual's propensity to cooperate, and therefore cannot increase assurance of mutual cooperation. This is an important insight because it while internally cooperative clusters may emerge, there is no reason to expect them to be cooperative with each other, since it is impossible for information about each group's behavior to be communicated to the other group without a common language of norms, symbols, and so on.[9]

Political psychologist and conflict theorist Marilynn Brewer argues that within group attachment does not necessarily imply outgroup denigration or antagonism (Brewer 2000; Brewer and Caporael 2006). This is reasonable since antagonism will carry an inherent cost, as does benevolence. However, the existence of multiple clusters of internally cooperating individuals establishes the groundwork for intergroup conflict or cooperation. Even if within group cooperation is robust, this does not mean that a group consists of peaceful beings; it only means that they are cooperative with each other, internally bound by some set of social-behavioral obligations. This primitive "morality" is inherently parochial, governing interactions within the tribe only. Whether some "universal morality", or universal protocol for interpersonal obligation is established, defection as cheating or violence is only opportunistically determined. In other words, when the collective interests of groups are at odds, there is no reason to assume that their successful mastery of internal cooperation extends to other groups or individuals from other groups. On the contrary, when internal cooperation can be brought to bear to advance one group's collective interests at the expense of other internally cooperating groups, we can expect them to do so. It stands to reason that the presence of such competition could act as a "trigger", amplifying ingroup attachment while simultaneously motivating outgroup denigration.

The Harvard-Yale game describes two populations of individuals who are as alike as any two populations of comparable size can be. They may very well work at the same places and have very similar lifestyles and daily experiences. The situation before them, however, casts the blue and crimson as adversaries in competition for an indivisible prize. And for one cold day in November whatever imagined, ideational differences have bound them together

[9] Often due to their simplicity, previous models of cooperation have tended to assume that cooperators cooperate with all other cooperators equally. As a practical matter, this is usually implicit because agents (as modeled) only possess the ability to discriminate cooperators from defectors. The clustered nature of cooperation implies that this ability has a limited range in terms of space and social distance. As distance increases, their ability to recognize other cooperators atrophies. Consequently, little is known about how disparate groups of cooperators are disposed toward one another. If human socio-cultural history is to be relied upon, we would reasonably expect groups of cooperators to regard other groups as hostile until otherwise revealed.

in their struggles for victory are all encompassing.

1.3 A Critical Gap

That in one context a given group attachment can be suddenly elevated in salience, but dismissed in others reveals a critical gap exists in our understanding of cooperation. Politics may be defined as the set of formal or informal institutions, processes, and relationships that determine the course of collective action and the division of the outcomes. Even in small-scale societies, this is rarely a game of individuals; it is characteristically a game of factions. Factions may be comprised of individuals bound by virtually any unifying principle, whether it be moral-philosophical, doctrinal, attachment to ethnic, religious, or linguistic kin, regionality, statehood or even arbitrary assignment.[10] In virtually all but the most controlled interactions within an experimental laboratory, the unit of analysis of a political scientific question is a group of some relevant level of social aggregation or another. To treat a group as a single, discrete unit is to necessarily assume that groups are primary and irreducible; they are so-called "unitary actors". In fact, thinking about or discussing politics can be extremely unwieldy without this assumption. For example, we would not be able to issue assessments of global strategic concerns as "America wants an Internet 'kill switch' ", "Russia wants to occupy Eastern Ukraine as a strategic buffer separating it from NATO." or "Shiites want to marginalize Sunnis in Iraq." Without this assumption, we would not be able to talk about "What the Tea Party wants", or for that matter the rich, the liberals, the conservatives, the Christians or the millenials. Treating such *categories* of individuals as unitary actors often produces sound, actionable predictions about how events are likely to play out and illuminating explanations of past events. This is, of course, is not in small part because these assumptions often hold. In other words, it is often the case that collectives

[10] Experiments by Henri Tajfel in the 1960s and 70s determined that individuals randomly assigned to groups would exhibit discriminatory behavior between ingroup and outgroup members if told their groups were defined according to meaningless, arbitrary rules. For example, groups (randomly assigned) would exhibit discriminatory behavior if told their groups were based shirt-color, guessing over or under the number of dots on a screen, or having received similar scores on a trivial computer task (Tajfel 1970; Tajfel, Billig, Bundy and Flament 1971).

of individuals really do begin to behave like unitary actors, and may in a real sense be considered as such.

But while the unitary actor assumption is often productive, it has not proved equally accurate in all situations. In other words, the 'unitariness' of a group is subject to variation. Further, this variation has remained unexplained in the political science literature. The level of 'unitariness' clearly exists on a graded scale. Some individuals, like the cells within a multi-celled organism, are so unitary that they are, for virtually all intents and purposes, a single individual. On the opposite end of the spectrum you might have very loose, ephemeral coalitions of individuals momentarily engaging in some kind of concerted action and then returning to disparate modes of behavior. Where do nation-states lie on this spectrum? How about labor unions? Political parties? What sorts of pressures cause individuals to sacrifice ever greater amounts of their own autonomy and submit to more group-centric decision-making processes, and why?

As groups become more cohesive and integrated, they become 'individuals' themselves; they act more like a unitary actor. The default relationship between individuals in nature, of course, is competition. The evolution of cooperation literature more broadly attempts to explain how we go from this default state of competition to cooperation and mutualism. Human groups are not perfectly unitary. There is a great deal of variation from group to group and for reasons that are not well-explored. This dissertation investigates the dynamics of group formation, the incentives that bring disparate individuals together to think and act as a unitary actor, and the factors that influence the degree to which indvidiuals behave uniformly within those groups. But to truly answer this question would require an individual-level theory of intergroup relations—not based on the interests of groups, but on the interests of the individuals who constitute them. Only then will we really understand the nature of groups as categories and as agents of change themselves.

In the next section I will outline the basis for a market-based theory of individual investment in group attachment.

1.4 Theory

Ecology is the economics of nature. Like the modern industrial economy, ecosystems are composed of countless actors—organisms and the communities they make up—dynamically interacting with each other and with the non-living elements of their environment. Ecosystems are defined by hierarchical processes, with organisms engaged in the extraction of minerals, salts, and sunlight, and the primary production of photosynthetic and chemosynthetic organic compounds to be consumed for every unimaginable purpose, but with the same goal in mind. Like firms, life forms are inherently economical. They seek to maximize their outputs relative to their inputs—breathing, building, moving, hardening, expanding, wasting—and so goods and services are exchanged and circulated through a vast network of interconnected beings. Just like firms, they do all this in the hopes of earning a little bit of profit, but not in the form of dollars, but in the ultimate currency of all life—evolutionary fitness. Firms are born into the marketplace, the crucible wherein they are tried and tested, where only those most responsive to the realities of the marketplace are allowed to survive. And so the ecological circumstances in which organisms find themselves test them, compel them to adapt, to become more efficient, to be more productive than their competitors. This is evolution.

Like market success, evolutionary success is not only about scraping by for the day; it is also about what competitors are doing. Organisms must struggle to stay ahead of the innovation curve. Investment in cooperative structures is investment in a kind of infrastructure; it is a capital good. In economics and sociology this is called “social capital”, and is considered a productive factor. In biology, this is called sociality. As with traditional economic factors, returns on cooperation are subject to fluctuations of supply and demand relative to other factors. Neither the supply nor demand for cooperation is constant. It must be traded for at a momentary price that maximizes the expected utilities of interacting in consideration of forgone opportunities. Consequently, cooperative structures exist heterogeneously in nature over time and space.

What are the determinants of biological spending on cooperative structures, or social capital? Traditional economic thinking argues firms trade in goods that rely heavily upon their relatively abundant, or cheapest factor (Heckscher 1919; Ohlin 1933; Ethier 1974). In the simplest, two-factor model of production, there exists only *capital* and *labor*. Either factor may be substituted for the other in the production of a good or service for a price. What is the price of cooperation? The price of cooperation is paid in units of its alternative, which in philosophy and biology, is conceived variously as autonomy, individualism, or liberty (henceforth 'individualism'). Thus, the price of cooperation may be thought of as a negotiated set of constraints on an actor's choices; it is a penalty, or cost, in terms of an agent's liberty to pursue any behavior it deems to be favorable without regard to any external influences or outcomes.

Investing in individualism may carry its own costs, as well. This essential trade-off is a central precept in even very divergent Western political philosophy. The thought of Thomas Hobbes, John Locke, and Jean-Jacques Rousseau begin at the *State of Nature*, or the putative primordial condition in which human beings existed prior to the advent of society. In the State of Nature, humans are born existentially free of any moral or legal imperatives. For each of these philosophers, it is assumed that they conditions of such an existence were horrifically intolerable.[11] And in all cases they argued that a certain amount of every individual's innate liberty be forfeited to a *common power* vested with the authority to impose *regulation* on the most egregious consequences of unrestrained individualism. From this point of view, the most relevant disagreements among these thinkers pertain to the terms of the sale, as codified (figuratively) in the social contract. Hobbes appeared to advocate for the wholesale usurpation of all individual liberty by the state, much in the same way some manifestations of *communism* sought to usurp all wealth (and in some cases liberty as well). Locke, on the other hand, might be more aptly described as a proponent of less restrictive "regulations" on individualism in the form of institutions.

[11]Rousseau's views on the state of nature differ most here, but the subtleties of his views are not relevant for our purposes.

We may postulate that organisms invest an amount of their fitness assets in a portfolio of individualism and cooperative structures that maximizes their expected evolutionary returns. In traditional theoretical models of the evolution of cooperation, the returns to cooperation are known, exogenous variables. Typically, they are highly abstract catch-all parameters that summarize the entirety of an ecological marketplace for cooperation as a ratio of the benefits of cooperation to the behavior's associated costs, or $\frac{b}{c}$. But how is this value determined in the real world? A second postulate is that the demand for cooperation is situational; i.e., the price will depend on both the supply of and demand for cooperation in the marketplace of actors. From this perspective, the ratio $\frac{b}{c}$ only makes sense as a spot estimate of the rate of exchange, since increasing returns to cooperation will correspond to higher demand and thus higher costs commensurate with supply.

The major theoretical goal of this dissertation is to begin to develop a framework for describing this cooperation marketplace. At the core of this project is the goal to move away from the catch-all benefit-to-cost ratio model of cooperation and start thinking about the ecological conditions that determine the supply of and demand for cooperation. Concepts this dissertation investigates include the potential influence of ecological energy density, how the resources individuals need to survive are distributed in a space, and the presence of a common external threat. Critically, a truly individual-centric, "market-oriented" model of cooperation must also endogenize, or take into account, *what an individual's competitors are doing.* All evolutionary models do this in some sense through imitation, replicator dynamics, or other hereditary trait replication procedures. However, I argue that ecosystems delivering large returns on cooperation do not result in uniform distributions of cooperation. Rather, cooperation will emerge in structures. To be sure, numerous models have described the positive effects of *cooperative clustering*, but what they tend to assume is that all cooperators are indiscriminately cooperating with other cooperators (Ohtsuki et al. 2006). In other words, they make the assumption that such clusters of cooperators individuals are not competing with each other, and further that the state of competition that exists between those clusters is not driving the high rates of cooperation within them. This potentiality may only be taken into account in the context of a true, *multi-level selection* model of cooperation. The implication of this is that such clusters may represent primitive "groups", in the sociological sense. Competition between them for resources might render prospects for survival on one's own increasingly precarious. Thus, individuals may be compelled by their impoverishment into accepting significantly higher costs of cooperation, in terms of their liberty, in order to secure the precious benefits of cooperation and social living.

The central motivation of the present research is to establish a basis for a theory of inter-group conflict that is reducible to individual-level, evolutionarily adaptive processes. Such a theory would facilitate further study of cooperation as it manifests in the real world in all of its diverse applications more rigorously, and to generate more accurate predictions political outcomes. The principles of such a theory should be scalable to virtually any level of biological or social aggregation. Such a tool would also enable better understanding of the complex dynamics of pressing political and social responses to major ecological changes, whether environmental (e.g., climate change) or institutional like new constitutions or campaign finance reforms. Such a theory could be used to illuminate the dynamics of global politics and diplomacy, subnational dynammics such as ethnic and religious conflict, as well as domestic political contests between interest groups competing for shares of government resources, or even political parties competing for votes.

1.5 Research Outline

This dissertation tackles this question on multiple levels of analysis with three distinct, but related studies. While each study addresses this central theme, they are sufficiently distinct to warrant their own in-depth literature reviews. With each study, we progress from a strictly individual-level analysis (chapter 2) to the group-level (chapter 4). These studies and their inter-connections are discussed next.

Chapter 2: Coevolution of Cooperation and Social Networks

This study is the continuation of a pilot study initially conducted by Oleg Smirnov exploring the evolution of social preferences in a multi-agent based computational model. His preliminary results suggested that agents may evolve altruistic propensities to contribute resources to others even when the agent needs those resources for personal survival. Smirnov's explanation was based on the notion that under circumstances where individuals are mutually dependent on each other for survival, there is an evolutionary payoff for helping others survive in order to overcome environmental challenges together. This chapter expands on a growing literature exploring the evolution of cooperation on social network models that more accurately reflect the structures of human social relations. In particular, it aims to resolve a limitation of existing models of the evolution of cooperation is that they tend to treat network graph topology as exogenous. This assumption is problematic because the structures of relationships that define a society are themselves a product of cooperation. Alternatively, I advance the hypothesis that cooperation and network structure are co-evolved, such that network structure will reflect the particular set of natural selective pressures favoring cooperation.

To test this hypothesis, I evaluate an evolutionary model that endogenizes network topology and exogenizes factors of the environment. I find that network topology and the evolution of cooperation are indeed highly endogenous, shaped in conversation with each other in response to continually changing environmental circumstances. Further, I find that the management of the risk of defection for cooperators appeared to be a fundamental design principle of social network architecture. These findings suggests the broader notion that every social network is a unique, socially-generated solution to a complex ecological problem space. The apparent "default" individual logic in forming social ties appeared to lean toward participation in smaller networks constituted of fewer, but more trusted relationships. As ecological hardship increased, however, agents became increasingly willing to expand the number of their connections even if as it increased their exposure to risk. Interestingly, the richest environments tended to produce the largest, yet least cooperative populations.

Chapter 3: A Multi-level Selection and Malthusian Conflict Among Pastoralist Societies

The second study uses multi-agent simulation to evaluate cooperation and conflict between groups rooted in individual-level decision-making processes. But where Study 1 looked at individual behavior and migration to cooperative behavior, Study 2 models cooperation and conflict between communities as a function of individual-level interests. To summarize the computational model, I simulate the lives of and interactions between n individuals from k tribes. A simple climate and soil model inspired by Kuznar and Sedlmeyer (2005) determines the productivity of the environment and water availability. Scarce resources compel agents to make choices between selfishness and tribe-based altruism. The tribes benefiting from the preponderance of patriotism, camaraderie, obedience, courage, and mutual sympathy are better equipped to engage in collective action against other tribes. Thus, the frequency of intergroup conflict is a key dependent variable in this study. The theoretical focus of this study is to evaluate whether cooperation with discrete groups is a successful human adaptation for overcoming ecological challenges, including resource scarcity and competition from other groups. In other words, this model evaluates how the presence of intergroup competition shifts evolutionary rewards to individuals who engage in individually costly, but group-beneficial behavior. Design elements are abstracted from the arid and semi-arid regions of east Africa.

This study reveals new insight into the emergence of primitive social identities and their curious entanglement with intergroup conflict. These data affirm the hypothesis that co-operation within groups *does not* imply cooperation between groups. Far from it. The presence of other internally cooperating groups constituted a revolutionary new weapon in the battle for access to limited resources. Agents in this simulation were often compelled to either adopted social living themselves or perished alone. But this was not always the case. In fact, it appeared to significantly depend on how the resources individuals needed to survive and prosper were distributed spatially. Individuals were likely to fight over resources that were clustered together rather than widely distributed. Further, social conflict emerged when land quality was unequal. In sum, these to results emphasize the finding that when the successful progress of violent conflict can afford a group premium access to the highest quality resources at the exclusion of others, its members are more willing to submit their autonomy to the group in order to enhance its combat potential.

Chapter 4:Using Time-Series Analysis and Geographic Information Systems to Study the Relationship between Climate Change and Violent Conflict in Africa

Combining recently developed techniques in time-series analysis and Geographic Information Systems (GIS), I connect the theoretical insights developed in the previous studies to a small, but rapidly growing literature on the relationship between climate change and violent conflict in Africa (Burke and Miguel 2009; Lobell and Burke 2010; Dell, Jones and Olken 2008). This study establishes the most comprehensive and sophisticated dataset of its kind, capable of offering greater insight into the macro-level, socioeconomic and geographic moderators of the effects of climate change on violent conflict.

Following Buhaug and Lujala (2005), I disaggregate data from the state-level and re-aggregate based on new, arbitrary geographical units. These units house variables from diverse datasets including georeferenced event data (Uppsala University Department of Peace and Conflict Research Georeferenced Event Dataset; GED), gridded precipitation and temperature data (Matsuura and Willmott 2009), satellite imagery (vegetative index and population density), ethnographic maps, land characteristics and the distribution of strategic resources. The disaggregation algorithm allows me to incorporate data collected at the nation-state level, such as World Bank African Development Indicators, and distribute it over more finely measured covariates. Consequently, I am not only able to test hypotheses concerning links between climate change and conflict, but I can also explore the moderating effects of governmental responses and the impact of aid. Each data point is located in a 3-dimensional data matrix by X and Y coordinates corresponding to 1 degree by 1 degree land surfaces on the continent of Africa, and Z coordinate corresponding to one month intervals from January 1989 to December 2008. Values represent monthly averages. This data structure enables me to use specialized statistical methods for modeling dynamic trends and modeling individual-specific effects.

Whereas thee studies presented in Chapters 2 and 3 sought to establish a theoretical basis for understanding groups, qua unitary actors, as emergent phenomena arising from the many countless decisions of individuals interacting with each other and with their environment. If true, this would lead us to hypothesize that a significant role of group identity as a moderator of realistic conflict. As a chief explanatory variable, temperature extremity showed to be a significant driver of conflict. Consistent with expectations, this effect appeared to be substantially moderated by ethnic fractionalization. While the mechanism at work could not be ascertained, this finding does demonstrate the fundamental premise that ethnic identities are flexibly salient in response to environmental variables. These data also affirm previous findings that extreme precipitation is associated with conflict, as well as reveal significant effects for a wide variety of environmental variables.

Thus, this dissertation examines the ways in which ecological conditions alter individual incentives to participate in groups; i.e., to rely upon collective action such as cooperation and intergroup conflict in order to resolve individual adaptive challenges. It describes a theory of how the behavior of groups, as actors, change as a function of ecological challenges facing the individuals who constitute them. In the simplest conception, as individuals become more committed to group-based strategies, submitting individual decision sovereignty to social processes, groups themselves become more like decision-making units of analysis: groups exist to the extent they are cohesive, and they are cohesive to the extent that we submit to their rules and maintain our commitments. To flesh this out in greater detail, this research begins with a basic supposition of evolutionary theory: ecological circumstances shape natural selective pressures on individuals. For human beings and other highly social creatures, cooperation is the key adaptation with which we respond to environmental challenges. It follows thus, that changing ecological circumstances result in shifting selective pressures on individuals, disposing them to pursue alternative social strategies with indirect effects on patterns of behavior and interaction at the intergroup-level. For example, a population facing acute resource scarcity might find that cooperation yields productive efficiencies yield greater stability in the resources individuals need to survive. The logic of markets dictates that as the benefits of group living increase, so does the price. Hence, groups may demand greater contributions from individuals, which enhances the strength and cohesion of the group, enabling it to take on more ambitious collective action efforts. Changing ecological circumstances should result in shifting selective pressures on individuals, disposing them to pursue alternative social strategies. Accordingly, we should observe indirect effects on patterns of intergroup-level.

2 Coevolution of Cooperation and Social Networks

This study is the continuation of a pilot study initially conducted by Oleg Smirnov exploring the evolution of social preferences in a multi-agent based computational model. His preliminary results suggested that agents may evolve altruistic propensities to contribute resources to others even when the agent needs those resources for personal survival. Smirnov's explanation was based on the notion that under circumstances where individuals are mutually dependent on each other for survival, there is an evolutionary payoff for helping others survive in order to overcome environmental challenges together. The present research also contributes to the growing literature exploring the evolution of cooperation on social network models that more accurately reflect the structures of human social relations. One potential limitation of existing models of the evolution of cooperation is that they tend to treat network graph topology as exogenous. I argue that this assumption is problematic because the structures of relationships that define a society are themselves a product of cooperation. Alternatively, I advance the hypothesis that cooperation and network structure are co-evolved, such that network structure will reflect the particular set of natural selective pressures favoring cooperation. In this chapter, I develop an evolutionary simulation that endogenizes network topology and exogenizes factors of the environment in which the simulation takes place. I find that network topology and the evolution of cooperation are indeed highly endogenous. Finally, I will discuss implications for how we think about the role of population and population structure in the context of collective action.

Since Charles Darwin first proposed his revolutionary theory of evolution by natural selection, scholars (including Darwin himself) have speculated on implications for our own human nature. One of the most challenging puzzles embedded in this question is the evolutionary origin of cooperation. West, Griffin and Gardner (2007*a*,*b*) defines cooperation as "A behaviour which provides a benefit to another individual (recipient), and which is selected for because of its beneficial effect on the recipient". The evolutionary problem, of course, is why should an individual fundamentally preoccupied with its own adaptive success perform a costly behavior benefiting other individuals? In other words how can a behavior that appears to reduce an individual's fitness relative to others possibly be selected for? Contrary to this intuition, cooperation is a recurring pattern at every level of biological organization. Biologists, zoologists, and social scientists have described and cataloged the structures of relations in which cooperation takes place in exquisite detail. Genes, as the molecular unit of selection, cooperate in the form of a genome. Once free-living prokaryotic organisms engulfed others—an act which had in extremely rare cases proved so prodigiously successful for both organisms that this *endosymbiotic* relationship would in time evolve into the first eukaryotic cells (Margulis 1970). Free-living cells would cooperate in the form of multicellular life. Within multicellular organisms, the work of life is divided up among such specialized cellular divisions that we may say the entirety of them constitute a logical unit, or *vehicle* of selection. Many animals are organized into herds, flocks, and schools for cooperative defense and mobility. Packs, prides, families, and bands help each other hunt, forage, and breed. *Eusocial* beings such as ants, termites, wasps, and humans build societies. Human societies are themselves constituted from myriad intersecting structures embedded within formal and informal institutions, such as markets, polities, economies, languages, religions, and cultures.

Until recently, the structures of cooperation have generally been of only secondary interests to theorists of the evolution of cooperation. Structure is treated like any other exogenous variable in the model. This is a different question than asking why relationships are structured in such a way. For example, Trivers (1971) discovered that the so-called *tit-for-tat* cooperative strategy was remarkably successful in the *repeated prisoner's dilemma* game. Even this simple model makes some primitive demands on the structure of the population; specifically, the model assumes a population is situated with regard to one another such that any two individuals at all times are equally likely to interact. Reputational mechanisms similarly assume a population of individuals is distributed such that it is possible to observe interactions between others (Wedekind and Milinski 2000).

Models with structure explicitly defined include models based on *kin selection* (Hamilton 1964) and *social networks*. In kin selection, probabilities of interaction are relatively unimportant compared to the probability of shared genetic profiles. As implied in JBS Haldane's famous proclamation that he would happily "jump into the river to save two brothers or eight cousins", kin selection assumes individuals receive some kind of direct genetic payoff by helping others who probabilistically share their genes. In terms of the underlying mathematics, kin selection models are similar to network models, only substituting proportions of genetic relatedness for probabilities of interaction. Network models explicitly do away with the assumption of well-mixed populations, imposing strict order on who interacts with whom, and how often. In the simplest conception of a *homogenous* network is the 2-lattice spatial grid, individuals interact only with those who they are directly "connected" to, or neighbors.

More recently, scholars have sought to model the evolution of cooperation on more complex, realistic random graphs such as the Watts-Strogatz small-world, and the Barabási-Albert scale-free network . Abramson and Kuperman (2001) were the first authors (to this author's knowledge) to explore this concept. Being first they enjoyed the opportunity to test the most parsimonious model, consisting simply of a repeated prisoner's dilemma with imitation played on a basic Small-World random graph. They find that changes in both of the Small-World's parameters (rewiring probability and number of connections per node) significantly impacted behavioral outcomes. Deng, Liu and Chen (2010) later on showed that using a modified form of the small-world random graph allowing for nodes to have different numbers of connections (Newman-Watts network), degree heterogeneity positively affected the amount of cooperation in the system (Newman and Watts 1999). Santos and Pacheco (2005); Santos, Rodrigues and Pacheco (2006) execute prisoner's dilemma and snowdrift games on a scale-free network. They find that in both cases when an individuals' *network of contacts*, or the set of neighbors with which they interact, are generated via growth and preferential attachment, early cooperators are able to connect and cooperatively endure the periodic arrival of defectors. Du, Cao, Zhao and Hu (2009) replicated this finding in a similar model.

While these research efforts have produced profound new insights into the dynamics of cooperation on realistically modeled social networks, the network models employed are themselves static. This may be problematic because, insofar as the social networks represent real human networks, they are themselves likely to be a *consequence* of cooperation, as well as a *cause*. Does it make sense that a small-world network would accurately reflect the organizations of species before the advent of cooperation altogether? It is not surprising that network models should promote cooperation because the structure might itself be a form of cooperation, or at least coevolved with cooperation? This places considerable limitations on what we may infer from these results about the emergence of cooperation from a primordial state wherein no such structure existed.

In an innovative study comparing the relative covariances of traits within monozygotic and dizygotic twins, Fowler, Dawes and Christakis (2009) conclude that behavioral traits associated with network in-degree, transitivity, and centrality have a genetic basis. It follows then that key traits determining an individual's social network activity are heritable with potential consequences for human evolution. As Nature selected for cooperation within humans, was she simultaneously selecting on individuals who managed to situate themselves the most advantageously within their network of contacts? If so, then the evolutionary histories of cooperation and social network topology are likely endogenous.

Few studies have sought to investigate this directly. This is likely in part because the implementation can be rather tricky. In a pioneering effort, Zimmermann and Eguíluz (2005) advance a model where individuals playing an iterated prisoner's dilemma with a network of contacts are allowed to sever poorly performing relationships. Dismissed contacts are replaced randomly with new ones, allowing the network to evolve over time in sync with player decisions. Unfortunately, the authors' research goals were mainly to do with the evolution of cooperation, and so stopped short of providing comprehensive descriptions of the resulting networks in terms of standard social network metrics. Two years later, Fu, Chen, Liu and Wang (2007) run a very similar model and do supply some basic descriptions of the resultant networks. They find that cooperation was linked to heterogeneity in degree distributions, as well as average degree. Tanimoto (2009) also adopts the same basic model configuration but substitute the random attachment for a preferential attachment rule for new connections. He finds behavioral strategies in the prisoner's dilemma to be strongly influenced by the amount of the degree of preference bias, clustering, assortivity. Qin, Zhang and Chen (2009) presents a model which may be described as the first major departure from the approach pioneered by Zimmermann and Eguíluz. The authors start with a ring network with four connections ($k = 4$) per node that cannot be severed or reassigned. In addition to these basic connections, however, each node is granted an additional "adjustable link", which it may sever and probabilistically reassign according to a preferential attachment rule. They find that a disproportionate number of outlinks go to the richest individuals, which appeared to have the counter-intuitive effect of promoting the overall prevalence of cooperation. Lastly, in a handsome demonstration of what is possible with actual human subjects in a controlled laboratory, Fehl, van der Post and Semmann (2011) compare sets of multiple repeated prisoner's dilemma games between participants in static and dynamic networks. In the dynamic condition, players may break connections with players if they dislike their outcome and receive a new partner. After 10 rounds, cooperation was substantially higher in the dynamic condition. The authors attributed this outcome to clustering among cooperators.

2.1 Theory

In the four or so decades since biologists and social scientist have taken up the question of the evolution of cooperation, we have identified numerous possible pathways. This research has treated cooperation primarily as a decontextualized behavioral propensity, but cooperation is also context. Cooperation occurs within structures of relations, or social structures. Such structures are found in nature in many diverse forms, but we do not really know why. In sum, we now have good ideas about how cooperation emerges in a general sense, but comparatively little about how it may emerge in a specific sense. Why is cooperation structured *this way* and not *that way*? Previous efforts to explain cooperation have for the most part sought to exclude as many extraneous influences from the model for the sake of parsimony. Now we are increasingly confident that the cooperation is, as Fu et al. (2007) put it, "attributed to the entangled evolution of individual strategy and network structure".

West et al (2007) *formally* defines cooperation as "a behaviour which provides a benefit to another individual (recipient), and which is selected for because of its beneficial effect on the recipient". In terms of formal modeling, this is an excellent definition and has led to remarkable theoretical progress. However, to move forward it may be worthwhile to step back for a moment and rethink about what cooperation is—not in a definitional sense—but in a broader functional sense. By analogy, the anatomical jaw is from a technical standpoint a simple *Class-3 lever* that concentrates force through mechanical advantage. But what does that mean to a wolf? For it, a jaw is a means of survival: a tool that disables prey, severs flesh, and crushes bone. So what then is the function of cooperation to a cooperating organism? I argue that cooperation is, like powerful jaws, an adaptation with which social organisms respond to challenges and opportunities in its environment. And just as the particular form of a jaw will vary from species to species depending on the particular adaptive challenges it faces, so will the structure of cooperation. Accordingly, an evolutionary explanation for the emergence of cooperation must ultimately have strong theoretical links to the environment. *Fitness* does not make sense otherwise. Often confused with health, or physical fitness, fitness describes an organism's adaptive "fit" to the particular set of conditions it happens to find itself in. Previous models removed the environment from the equation in order to show that, under the right conditions, cooperation could evolve. These models are limited, however, in that they cannot tell us what those conditions might be, or what form cooperation might take.

2.2 Model

In this section, I present an agent-based coevolutionary model of cooperation and network topology in a simple environmental context. This model does not rely on any particular random graph algorithm, but rather is designed to allow agents the greatest freedom to flexility respond to environmental challenges. One key difference between this research and prior efforts is that social network metrics are the primary model outputs, or dependent variables, rather than inputs. The explanatory variables, in turn, are primarily parameters of the environment. I expect that characteristics of the environment will shape whether, and importantly *how*, cooperation emerges as an evolutionary stable strategy.

The initial state of the model is a non-spatial social network of N nodes with 0 edges. In each of T generations, agents, or nodes, probabilistically form non-directional edges to other agents. The global, base probability of any $agent_i$ forming a connection to any $agent_j$ in time period t is P. However, agents differ individually degree they favor establishing connections to more popular, highly connected agents. This *preference bias* e is initially distributed uniformly in $[0, 1]$. Agent popularity is calculated according to the Barabási-Albert formula $\frac{k_j}{\sum_j k_j}$, where k_j is j's degree, and scaled by P. Therefore, in each round $agent_i$ forms a connection to $agent_j$ with probability:

$$P + \frac{Pk_j}{\sum_j k_j} \tag{1}$$

It is necessary to include the additive P term because the probability of linking to an agent must never be 0.

Survival is the core principle of the ecological model. In order to survive, agents must satisfy their metabolic needs, *mcost*, which must be paid out of their endowment SF. SF is a global parameter, assumed to be equal to the total quantity of resources an agent "gathers" in a time period. The ratio of SF to *mcost* characterizes the notional nutritional, or energy, density of the resources. When the ratio is low, agents must consume more resources to satisfy their metabolic requirements, and therefore live a more precarious existence.

Agents who are not connected to any other nodes, or have a degree of 0, "go it alone". Meaning they must survive on what resources they must survive on their endowment alone. This is not initially a problem for agents, but could pose as challenge if the population increases and the available resources become increasingly picked over. While cooperation may result in a more efficient usage of resources, the final resource volume of the environment is fixed at $maxR$. Agents who are connected to other agents engage in up to R games of a 2-player prisoner's dilemma (PD) per time period with other agents in their social network, such that:

	Cooperate	Defect
Cooperate	B-C, B-C	-C, B
Defect	B, -C	0, 0

where C is the cost of cooperation and B is the benefit of cooperation. The ratios of C to SF and B to C characterize the possibility space for cooperation in a given environment. When the cost of cooperation is high relative to SF cooperation carries with it substantially greater risk because a response of defection is potentially debilitating. At lower relative costs, outcomes are more like the less harsh "Snowdrift" game, which some research has suggested is more characteristic of the social situations humans commonly face (Kümmerli, Colliard, Fiechter, Petitpierre, Russier and Keller 2007). The ratio of B to C characterizes the rate at which cooperation between individuals generates social value. The possibility space for cooperation in an environment is also characterized by R, which corresponds to the *velocity of interaction.* In low R environments, cooperation with others is relatively time consuming giving agents less time to interact with a wider society of partners or to "bet it all" on a single partner. Accordingly, in any given game cooperators wager $\frac{C}{R}$ to potentially receive $\frac{B}{R}$, since their investments are spread across multiple games with up to R individuals.

This model innovates upon previous social network models of cooperation by allowing agents to interact not only with agents they are *directly* connected to, but also those they are *indirectly* connected to at up to D degrees of separation. For example, if $D = 2$ agents may interact with agents they know personally as well as agents their personal relations know personally. Further, agents are able to make categorical distinctions between agents at each order of social distance and need not regard them the same. An individual A's strategy profile is $[A_1, A_2, ..., A_D$, where $A_d \in [0, 1]$ is the probability A cooperates with others of social distance d and D is the total number of types. Agents' strategy profiles, therefore, may be said to be heterogenous.

In each time period agents initiate interactions with other agents in their social network, choosing on average $\frac{R}{D}$ partners (at random) from each order of social distance. It is a characteristic of heterogenous social networks that the number of individuals is increasing in social distance. Thus, agents interact on average more often with those who are socially closer to them since there are fewer of them.[12] Since no agent may interact more than R times in a single time period, some may have an opportunity to interact with others more times per time period if they move first. In order to account for serial dependence, the order in which agents initiate interactions is randomized every time period. The system is also smart enough to disallow any agents from interacting greater than R times per time period, even if they have had an opportunity to initiate an interaction themselves (i.e., other agents chose them R times).

After all interactions are complete, agents must assess which connections are advantageous to them. Since they cannot sever indirect connections, they can only take into account their utility as consequences of their direct connection, which they do have control over. Accordingly, agents calculate their net payoffs by direct connection, taking into account interactions with higher order connections. For example, if A is directly connected to B, and B is connected to C, and C is connected to D, then

[12] If there are 2 neighbors in distance 1, 3 neighbors at distance 2 and 4 neighbors at distance 4, the probabilities of an agent interacting with any neighbor at those distances will be 1/2, 1/3, and 1/4 respectively, the probabilities of choosing any category are equal.

$$\Pi(connectiontoB) = \Pi(B) + \Pi(C) + \Pi(D) \tag{2}$$

If $\Pi(connectiontoB)$, including whatever value is generated or lost through interactions with B's social network, is positive then the edge is maintained. If it is negative, then A dissolves the edge.

As mentioned above, the requirement that every time period agents are compelled to pay an additional metabolic cost *mcost* in order to stay alive is the link that ties individual behavior to the realities of their environment. It is the core of the ecological model. If at the end of the time period agents possess insufficient resources to pay their metabolic cost, they will begin to "starve". When starving agents to not necessarily die immediately. Rather, they die probabilistically, where the probability of death is increasing in time. This function is given by,

$$Pr(Death_i) = 1 - \frac{1}{Starved^{SR}} \tag{3}$$

where,

Starved is the number of time periods $Agent_i$ is starving and SR is a global, exogenous parameter representing a "rate of exhaustion". At higher values of SR, they are less robust to temporary privation.

Death and birth are the engines of the evolutionary subroutine. The evolutionary mechanism is entirely based on deaths, births (with heredity), and mutation. All agents surviving at the end of a time period have a chance to reproduce, where each agent's probability of reproducing is a function of its relative fitness. The probability of reproduction is given by,

$$Pr(Reproduction_i) = \frac{Fitness_i^{Rskew}}{\sum_{i=0}^{n} Fitness_i} \tag{4}$$

where,

Reproductive skew (*rskew*) is a global parameter describing the rate at which adaptive advantage is conferred upon higher fitness agents. This is analogous to the intensity of mate selection. At high levels of $rskew$, only the highest fitness agents are likely to reproduce. One advantage of carrying out reproduction in this way is that it implies the rate of population growth remains level even as the population increases. Ordinarily, arbitrary limitations on population size, how many connections, or any other exogenous constraint on network topology would bias results. However this mechanism should be able to limit population sizes to computationally feasible sizes without doing so. Offspring, of course, inherit their strategy profiles and preferential attachment biases from the parent. Lastly, in order to ensure evolutionary dynamism agents are subject to random mutation of their behavioral attributes with probability mut.

In sum, this model tests the responsiveness of social network and cooperation metrics to a wide variety of exogenous parameters characterizing the environment. Flexible terms in the prisoner's dilemma allow a greater representation of the possible ways cooperation may or may not be suited to the particular environmental challenges individual agents face. Inputs and outputs are enumerated below.

1. Model inputs

   (a) Initial population size

   (b) Base probability of connecting

   (c) Interactions per/time period

   (d) Starting fitness

   (e) Metabolic cost

   (f) Resource volume

   (g) Degrees of interaction

   (h) Energy density

   (i) Cost of cooperation

(j) Benefit of cooperation

(k) Mutation rate

(l) Rate of exhaustion exponent

(m) Intensity of mate competition2

2. Model outputs

   (a) Cooperation, degree 1

   (b) Cooperation, degree 2

   (c) Cooperation, degree 3

   (d) Avg. fitness

   (e) Preference bias (Barabási-Albert parameter)

   (f) Connected graph (0/1)

   (g) Num. of connected components

   (h) Size of giant component

   (i) Average connected component size

   (j) Gini-coefficient (on fitness)

   (k) Population size

   (l) Eigenvector centrality

   (m) Closeness centrality

   (n) Betweenness centrality

   (o) Degree centrality

   (p) Degree distribution

   (q) Avg. degree

   (r) Avg. clustering

(s) Avg. transitivity

(t) Avg. starvation

(u) Avg. age

2.3 Data

2.3.1 Monte Carlo Simulation

The first set of data is generated using Monte Carlo simulation. Monte Carlo simulation allows the exploration of the parameter space across many observations of the simulation. As Randal Olson points out, “evolution isn't over until you click stop” (Olson 2013). Stopping the simulation too soon can lead to false conclusions. The death-birth cycle of heredity is slow and may take many more generations to converge than other replication algorithms, such as social learning. It was therefore important to run the simulation for as many “generations”, or time periods, as possible. In simulation pre-tests, I run simulations out to 10,000 time periods and find that for all tested parameter configurations output parameter means have stabilized in about 2000 time periods. While parameters are mean-stable, there still appeared to be considerable homoskedastic variance (with respect to time). In order to account for this, model outputs are averaged over the final 200 generations. Values for input variables are selected at the start of each simulation with equal probability from a range of possible values. These values are depicted in Table 2. To maximize the number of simulations given computational and time limitations, the simulation was run 415 times for 2000 time periods (N = 415).[13] Summary statistics of output variables are depicted in Table 3.

Based on the summary statistics in Table 3 there was substantial variation in the model outputs across the 415 simulations. Table 4 depicts correlations matrices for each of the major network metrics variables with model inputs and outputs. While this results cannot suggest causal relationships, they show that the model “worked” in the sense that outcomes are functionally related to inputs and can provide a useful guide for subsequent analysis. The

[13] 415 was the maximum number of simulations I was able to conduct in the time available.

Table 2: Means and ranges of model input parameters, N = 415

Input	**Mean**	**Minimum**	**Maximum**
Initial size (n)	32.176	25.000	39.000
Base prob of connection (p)	0.002	0.001	0.004
Interactions per period (r)	4.836	1.000	9.000
Maximum resources (res)	176.819	120.000	240.000
Nutrition density (sf/mcost)	1.375	1.001	2.600
Degrees of interaction (d)	1.010	0.000	2.000
Benefit of cooperation (c/b)	1.300	1.101	1.498
Mutation rate (mu)	0.00249	0.00002	0.00495
Rate of exhaustion (sr)	1.762	1.007	2.498
Reproductive skew (rskew)	1.738	1.008	2.496

highlighted values in this table indicate which pairs of network metrics and model parameters bear substantial correlation, given that no significant correlation exists for cooperation and the same model parameters.

To recapitulate the major supposition of this research, I argue social network topology and cooperation are co-evolved in the context of a particular constellation of ecological variables. This notion extends ongoing research efforts to understand the emergence of the structures of cooperation we observe in nature by divesting the assumption that structures are static. While this idea may be simple enough to describe in prose, describing it quantitatively with sufficient nuance to test an empirical model is challenging. This analysis relies on three key quantitative descriptions of the social network structures which emerged as a result of agent interactions during the simulation: Average node degree, network size, and the size of the networks largest connected component (giant component) relative to the size of the network. Other standard descriptive measures of social networks include the clustering coefficient and transitivity. However, both of these measures are both (very) highly correlated to average node degree (see Table 5).

From a theoretical standpoint each of these three measures represent distinct concepts. I choose to focus on the average node degree because it tends to imply clustering and transitivity, but is also typically taken to be an input parameter for several random network gen-

Table 3: Average values of model outputs over last 200 of total 2,000 generations, N = 415

Output	**Mean**	**Std. Dev.**	**Minimum**	**Maximum**
Propensity to cooperate	0.065	0.034	0.016	0.217
Fitness	0.669	0.473	0.032	2.550
Preference bias	0.479	0.263	0.009	0.953
Age	38.663	14.654	15.308	89.656
Starvation	0.991	0.010	0.962	1.029
Avg. degree	1.884	2.874	0.052	22.895
Clustering Coef.	0.038	0.061	0.000	0.334
Transitivity	0.060	0.071	0.000	0.380
Connected graph (0/1)	0.003	0.014	0.000	0.125
Gini coefficient	0.380	1.347	-0.554	27.059
Network size	44.779	15.063	20.905	96.880
Giant component	18.833	20.451	1.645	93.200
Giant Comp. (norm)	0.374	0.325	0.040	0.962
Num. of components	21.741	12.853	3.445	70.010
Num. of comps. (norm)	0.528	0.275	0.038	0.947

eration models, such as the Watts-Strogatz and in some sense the Barabási-Albert scale-free network. Whereas the other two are purely descriptions of network outcomes, information about average node degree resulting from the present research may then offer some additional usefulness as a model input in subsequent research.

Importantly, the present research proposes that these network measures are likely to be endogenously related to a measure of cooperation, which I hypothesize may be a function of any of these metrics, as well as other exogenous ecological variables. To assess whether this is the case, I employ Durbin-Wu-Hausman augmented regression tests for endogeneity (Davidson and MacKinnon 1993). This consists of four separate regressions on cooperation, including models with each individually instrumented endogenous variable and a combined model with corresponding F-tests. The highlighted relationships in Table 4 are used for instrumentation. Table 6 depicts these results in detail. The Durbin-Wu-Hausman test statistics in each case and the joint test are significant, affirming the hypothesis of bidirectional effects. Still, we should be careful not to jump to conclusions since these network metrics often load on the same truly exogenous model parameters. This implies that substantial

Table 4: Correlations for cooperation and major network metrics and model parameters. Relationships for which a substantial correlation between model parameters and network metrics, but not cooperation, are highlighted.

Covariate	Coop 1	Avg. Degree	Giant Comp	Net. Size
Initial pop	-0.02	0.02	0.08	0.00
Base pr(conn)	0.11	0.22	0.17	-0.15
Pace of interaction	-0.06	-0.10	-0.19	0.15
Carrying cap	0.05	0.23	0.14	0.52
Nut. Density	-0.01	0.44	0.27	0.74
Degs. Of interation	0.32	-0.44	-0.66	-0.22
Mutation rate	-0.07	0.19	0.14	0.12
Exhaustion rate	0.04	0.02	-0.04	-0.01
Repro. Skew	-0.10	0.03	0.02	0.02
Gini coef.	-0.01	-0.04	-0.06	-0.07
Coop benefit	0.06	-0.10	-0.05	-0.09
Simulation time	-0.25	0.83	0.40	0.56
Fitness	0.18	0.07	0.06	0.42
Pref. bias	-0.04	-0.04	-0.02	-0.02
Age	-0.18	0.48	0.34	0.95
Starvation	-0.08	0.10	0.09	0.41
Clustering	-0.45	0.95	0.84	0.50
Transitivity	-0.48	0.91	0.86	0.46

correlation exists between the network metrics as instrumented and it is therefore difficult to ascertain the size of each variables unique relationship to cooperation. In other words, since the three network metrics often load on the same exogenous ecological parameters, it can be difficult to ascertain how each network attribute uniquely structures cooperation in response to the environment.

Table 5: Correlation matrix of three like network descriptions

	Avg. node degree	Transitivity	Clust coef.
Avg. node degree	1		
Transitivity	0.9107	1	
Clustering coefficient	0.9465	0.9811	1

To get a better handle on this question, it is useful to adopt analytical tools better suited to describing the broader structure of relationships between exogenous ecological

Table 6: Augmented regressions on cooperation (first degree) with major endogenous network metrics

DV = Cooperation	**Avg. Degree**	**Net. Size**	**Giant Comp.**	**Combined**
Base pr(conn)	10.98***	11.11***	10.97***	11.14***
	(1.840)	(1.826)	(1.839)	(1.828)
Pace of interaction	-0.00235***	-0.00238***	-0.00233***	-0.00238***
	(0.000515)	(0.000515)	(0.000517)	(0.000518)
Degs. Of interation	-0.00704**	-0.00701**	-0.00678**	-0.00688**
	(0.00305)	(0.00307)	(0.00308)	(0.00306)
Exhaustion rate	0.0145***	0.0175***	0.0161***	0.0191***
	(0.00538)	(0.00556)	(0.00555)	(0.00634)
Mutation rate	1.749	1.767	1.651	1.726
	(1.131)	(1.135)	(1.139)	(1.136)
Repro. Skew	-0.00571*	-0.00560*	-0.00592*	-0.00567*
	(0.00331)	(0.00327)	(0.00332)	(0.00328)
Fitness	0.00465	-0.00402	0.00795	-0.00486
	(0.00598)	(0.00767)	(0.00518)	(0.00796)
Cooperation benefit	0.00198	0.00260	0.00288	0.00317
	(0.0122)	(0.0122)	(0.0122)	(0.0124)
Starvation	0.554**	0.620**	0.518**	0.623**
	(0.254)	(0.255)	(0.257)	(0.257)
Avg. node degree	0.00258	-0.00374***	-0.00300***	-0.00806
	(0.00237)	(0.000909)	(0.000796)	(0.00642)
Giant component (norm)	-0.0509***	-0.0482***	-0.0522***	-0.0481***
	(0.0100)	(0.0102)	(0.00982)	(0.0101)
Network size	-0.000255	0.000731*	-0.000172	0.00101
	(0.000233)	(0.000377)	(0.000231)	(0.000692)
Node deg. (instrum.)	-0.00586**			0.00433
	(0.00276)			(0.00638)
Net size (instrum.)		-0.00116***		-0.00145**
		(0.000391)		(0.000685)
Giant comp. (instrum.)			0.0533*	0.0284
			(0.0293)	(0.0476)
Constant	-0.493*	-0.592**	-0.476*	-0.613**
	(0.258)	(0.261)	(0.263)	(0.268)
DWH test stats	4.6*	8.88***	3.34**	3.14**
	(0.0684)	(0.0031)	(0.0325)	(0.0253)
Observations	415	415	415	415
R-squared	0.371	0.377	0.368	0.377

Robust SEs in parentheses
*** p<.01, ** p<.05, * p<.1

variables, network features, and cooperation. Structural Equation Modeling (SEM) allows for a highly flexible specification of simultaneous equations based upon theoretical insight. Since these equations are estimated simultaneously, SEM is able to mathematically account for the complex web of interrelationships that are at the heart of ecological modeling. As a starting point in specifying each relationship, I regress each major endogenous variable on model exogenous parameters and include each significant result. I then specify bidirectional relationships between each network metric as controls to isolate their unique relationships to the environment. Now I "close the circuit" one-by-one between each exogenous variable and the interconnected core of endogenous variables in a sub-model. Paths determined to be clearly insignificant (p-value > 0.1) are then severed one at a time and the sub-models re-estimated. This technique allows me to incrementally eliminate pathways that do not significantly transmit influence.

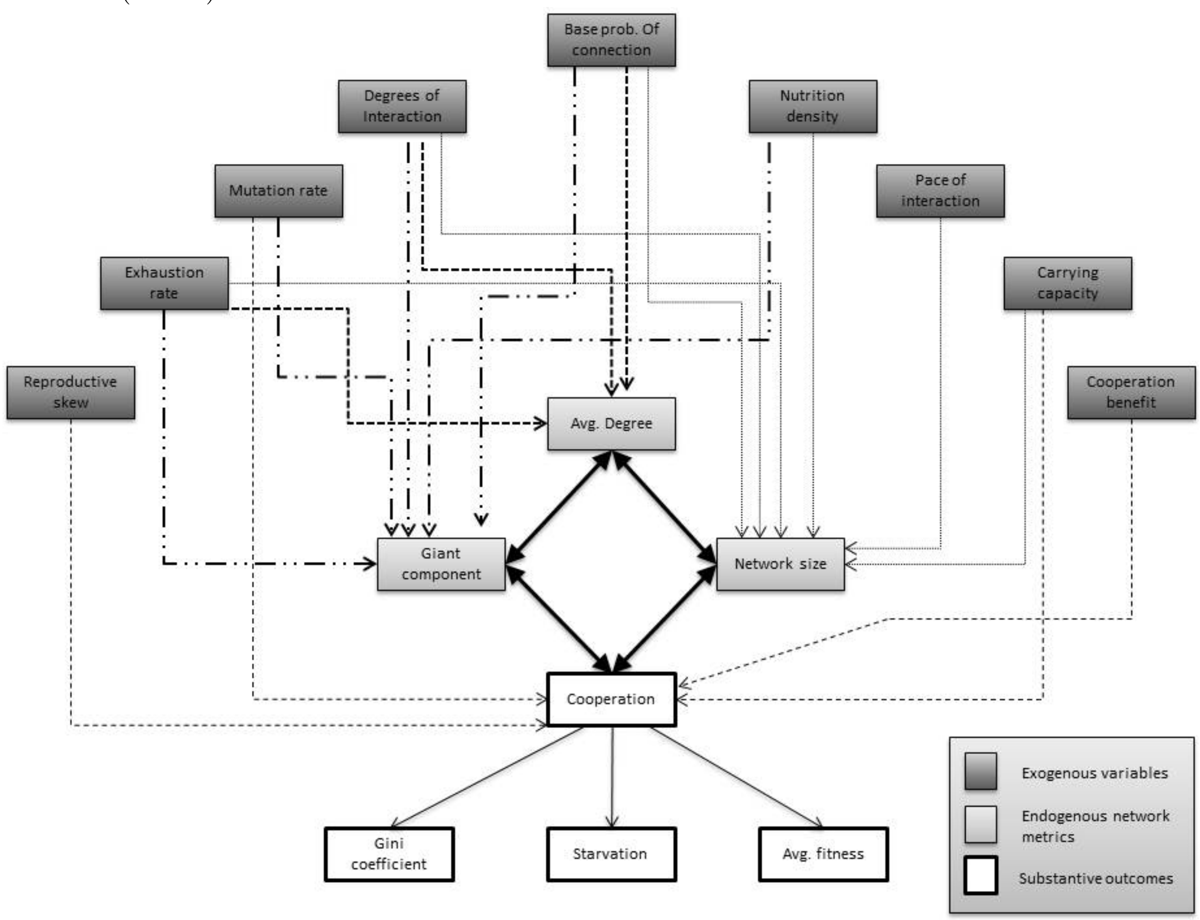
Lastly, I add bivariate regressions of several other substantively interesting model outputs on cooperation, including starvation, average fitness, and inequality (as the Gini coefficient). In each of the bivariate sub-models, the dependent variable is assumed to be a thematic summary of "ecological problems" established entirely from within the ecological and social network models (within the context of this simulation this is true, save for some stochasitc variability). In other words, they constitute the substantively important survival challenges cooperation *may* play a role in resolving.

In total, the SEM consists of a system of 7 simultaneous equations with four endogenous variables as depicted in Figure 1). Tables 7, 8, 9, and 10 present the parameter estimates of the structural model. According to the Rank Test for Identification, the cooperation, average node degree, and giant component equations are *over identified*, while the network size equation is *just identified*.

2.3.2 Cooperation

Cooperation with first degree neighbors is the first key endogenous variable (see Table 7). It represents not only not the closest and most intimate relations, but also serves as a gateway

Figure 1: Structural Equation Model of Network Topology and Cooperation, including exogenous ecological variables (dark grey), network metrics (light grey), and other outcomes of interest (white)



to additional relationships. When applying less traditional research methods, it is encouraging to see the coefficients of a constellation of comparatively well-understood variables in the right direction. According to these data, the direct effect of population size, or *network size*, is negative and significant. Since Olson (1965) the traditional "structure-free" models of collective action have frequently focused on the negative impacts of population size on achieving cooperation in the social dilemma, i.e., the provision of public goods. In some cases structured network models can sometimes produce different effects. For example, Seltzer and Smirnov (2013) find that larger populations can increases the likelihood of cooperative clusters emerging by chance. *Mutation rate* was marginally significant but in the "right" direction. Mutation rate is generally believed to negatively impact cooperation since a random mutation can disrupt cooperative clusters. *Benefit of cooperation* was positive, though also only marginally significant. This suggests that while greater returns to cooperation do make a difference, overtime the magnitude is less important.

Table 7: Results of Structural Equation Model (1/4)

Variable	**Coefficient**	**(Std. Err.)**
Equation 1 : Cooperation (D1) (as propensity)		
Avg. node degree	0.0122**	(0.0032)
Giant component	-0.1083**	(0.0211)
Network size	-0.0008**	(0.0003)
Pace of interaction	-0.0012	(0.0008)
Benefit of cooperation	0.0246	(0.0166)
Reproductive skew	-0.0077†	(0.0042)
Resource volume	0.0001*	(0.0001)
Mutation rate	-2.2379	(1.3860)
Intercept	0.0922**	(0.0251)

More surprisingly, the effect of *average node degree* is highly significant and positive. At first glance this result appears to run counter to expectations. According to Ohtsuki's "simple rule for the evolution of cooperation on graphs", cooperation may evolve if the ratio of cooperation benefits to cost is greater than the number of neighbors k (Ohtsuki et al. 2006), or if $b/c > k$. As average node degree increases we would expect a decrease in cooperation.

Yet average node degree exhibits positive significant direct effects in these data. One key factor potentially explaining the apparent discrepancy is that Ohtsuki's model assumes a homogenous node degree distribution. 'Average node degree' is therefore not equivalent to k. What is likely happening is that cooperation is increasing in average node degree with highly heterogenous degree distributions, as in a scale-free network. Another factor may be that correlation average node degree and clustering is extremely high, such that they are virtually the same variable (r = 0.94). Thus, the benefits to cooperation appear to be increasing in the context of tighter communities which are more robust against defection. If this is the case, it would explain why we observe as an outcome of some structured network models that effect of population size is positive.

As mentioned previously, this has been attributed to increased likelihood of the emergence of cooperative clusters. In these data, however, average node degree may be soaking up these effects since it corresponds far more directly to clustering. Controlling for this, in turn, means that the coefficient on network size is a purer representation of population size effects and should be more in line with what is typically found in the context of structure-free models. Indeed, when average node degree is removed from cooperation equation the coefficient on network size is reduced to virtually nil (*coef.* = 0.0001, *sd* = .0001, p-value = 0.47). There may very well be something else going on, but it is still nonetheless interesting that the omission of average node degree, as a proxy for clustering, should have moved the coefficient in a positive direction.

Another interesting and potentially illuminating finding is that the relative size of the *giant component* is highly significant, negative, and large. The decrease in the mean value of cooperation when the relative size of the giant component goes from its maximum to its maximum accounts for roughly half of the total observed range in cooperation. In other words, cooperation seems to thrive in relatively small, isolated communities. Cooperation also appears to be benefited from lower levels of *reproductive skew*. Meaning, not only does cooperation seem favored in small communities, but such communities appear to be characterized by *less* severe competition for mates.

2.3.3 Structure of Cooperation

These analyses rely on three key social metrics to describe the effects of environment and cooperation on network topology: average node degree (Table 8), the size of the giant component relative to the size of the network (Table 9), and the size of the network itself. All three of these variables appear in each of the relevant simultaneous equations—one on the left-hand side and the other two on the right as controls (Table 10). In terms of average node degree, several interesting patterns emerge. Strikingly, cooperation has a strong and highly significant negative impact on average node degree. This is particularly fascinating because it implies that in terms of broader social outcomes, cooperation inhibits the formation of more strongly connected networks, even though it itself benefits.

How can this be? If high degree networks were advantageous for cooperation, should not cooperators seek to maximize their degrees? One potential explanation could be that cooperation makes connections costly. At low levels of cooperation, the cost of maintaining a connection is virtually nothing. Agents may encounter each other but largely leave each other alone. Nothing is "gambled" on the interaction. They bet nothing, get nothing, and come out of the experience indifferent to the relationship. Consequently, agents are likely to tolerate relationships. Cooperators, on the other hand, need to know that the other individuals they are dealing with will cooperate back, or they may as well be rid of them permanently. At the same time, given that those relationships are cooperative, more of them will be better. Hence, node degree may benefit cooperation while cooperation simultaneously works against average degree.

Another factor is that average node degree appears to heavily mediate the effects of *maximum interaction distance* and *rate of exhaustion* on cooperation. Maximum interaction distance enables agents to interact with agents they are indirectly connected to, which impacts the value of those direct connections that grant such access. Effectively, this means risks of maintaining connections with occasional defectors may be partially mitigated if the

Table 8: Results of Structural Equation Model (2/4)

Variable	**Coefficient**	**(Std. Err.)**
Equation 2 : Avg. node degree		
Cooperation (D1)	-43.1738**	(10.1630)
Giant component	7.9783**	(1.1893)
Network size	0.0514**	(0.0115)
Degrees of interaction	1.3315**	(0.3551)
Base prob. of connection	456.3711**	(172.3552)
Rate of exhaustion	0.5050†	(0.2688)
Intercept	-3.9706**	(0.9222)

Table 9: Results of Structural Equation Model (3/4)

Variable	**Coefficient**	**(Std. Err.)**
Equation 3 : Giant component		
Cooperation (D1)	-5.0278**	(1.1062)
Avg. node degree	-0.0823**	(0.0226)
Network size	-0.0012	(0.0048)
Degrees of interaction	-0.3420**	(0.0366)
Nutrition density	0.4930**	(0.1747)
Base prob. of connection	166.3971**	(27.7861)
Pace of interaction	-0.0353**	(0.0075)
Mutation rate	59.0538**	(13.8057)
Intercept	0.1887†	(0.0999)

Table 10: Results of Structural Equation Model (4/4)

Variable	Coefficient	(Std. Err.)
Equation 4 : Network size		
Cooperation (D1)	-2.3605	(24.3640)
avgdegreeb	0.6554†	(0.3715)
Giant component	19.2052**	(4.2945)
Degrees of interaction	2.9373*	(1.2405)
Nutrition density	20.5579**	(1.8987)
Base prob. of connection	-4587.7813**	(697.2556)
Pace of interaction	1.6352**	(0.1945)
Resource volume	0.0493**	(0.0092)
Rate of exhaustion	-2.1742*	(0.9105)
Intercept	3.8115	(3.1975)
Equation 5 : Starvation		
Cooperation (D1)	-0.0250†	(0.0146)
Intercept	0.9922**	(0.0011)
Equation 6 : Inequality (as Gini)		
Cooperation (D1)	-0.5821	(1.9557)
Intercept	0.4172**	(0.1426)
Equation 7 : Fitness		
Cooperation (D1)	2.5482**	(0.6752)
Intercept	0.5048**	(0.0492)

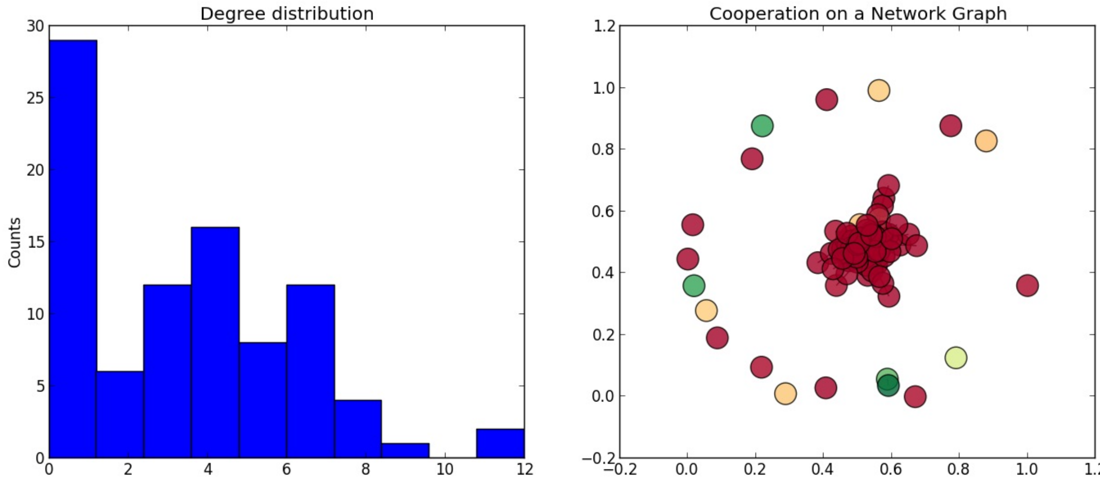
downstream relationships help to compensate for losses. Interestingly, the ability to interact with "friends of friends" has no direct impact on cooperation with first neighbors, but it does lower the cost of having more direct connections. Average node degree also appears to mediate the effect of *rate of exhaustion*. In other words, when agents deprived of resources they need to survive expire faster due to starvation, average node degree significantly increases, which in turn increases cooperation. This suggests that when survival is more precarious, increased connections enable agents to survive more, perhaps by spreading risk of defection over a larger number of partners and also potentially enhancing the effects of cooperative clusters.

Looking at the *giant component* size equation, it appears that networks become significantly more connected in nutrient dense environments. At the same time, they are considerably less cooperative. More puzzling is the very large, negative effect of *degrees of interaction*. One possibility is that extended network interactions simultaneously raise the cost of maintaining poorly performing connections (from a cooperator's perspective), but those which are sustainable provide more stable benefits. In sum, they give agents more reasons to sever bad connections, more reasons to maintain good ones, which are inevitably fewer.

The negative effect of *pace of interaction* is also consistent with this understanding. Pace of interaction allows agents to interact with the same agents many more times—when you interact with someone a dozen times and observe that they cheat you, say, 9 of the 12 times you are much more confident they will cheat you in the future about 75% of the time that if you only interacted with them once. If they happened to cooperate with you in that one instance, your assessment of the situation could be dangerously inaccurate. More interactions means agents will be better be faster to ascertain net beneficial relationships from costly ones, and those which are beneficial will be more stable.

Figures 2 and 3 represent the degree distributions and social network graphs of "typical" runs of the simulation with all parameters at their mean, save maximum and minimum

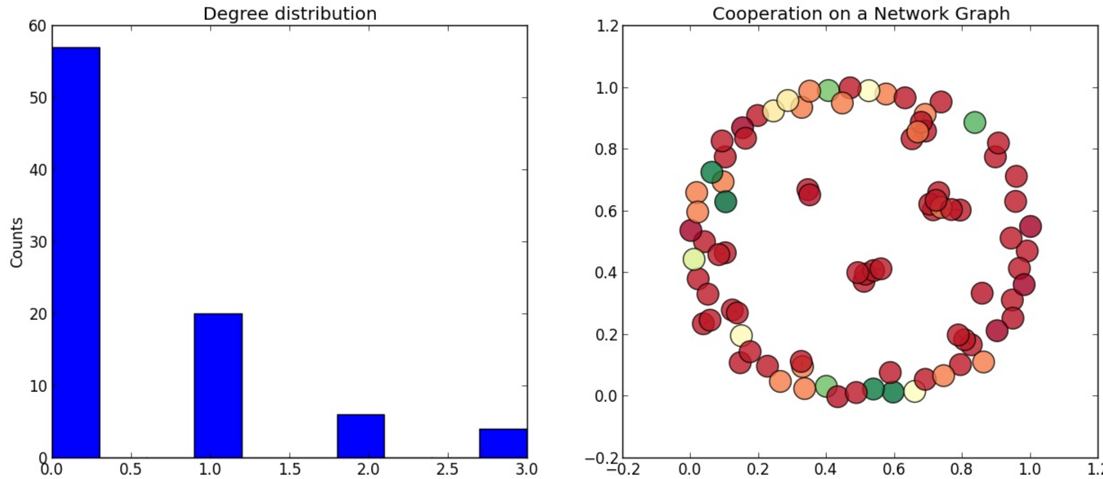
Figure 2: A "typical" run of the simulation with all parameters at their mean with MIN degrees of interaction



values of maximum interaction distance. While the network in Figure 2 appears to be highly connected with a high average node degree, high clustering, etc. Also note that keeping all parameters constant, save for interaction distance, appears to have little or no affect on the proportion of cooperators (cooperators in green, defectors in red). What is troubling, however, is the idea that these relationships may be totally different if cooperation the norm. In these data, cooperation, even when it was stable, did not exceed a propensity of 0.2. If the above reasoning on the determinants of component size are correct, then a prevalence of cooperation over 0.5 might reverse the sizes on those coefficients.

While network size, or population size, exhibits a negative impact on cooperation, cooperation appears to exert no effect on network size. This is contrary to my expectations, since cooperation should in theory allow for a more efficient use of available resources. Rather, population size is most directly impacted by the quantity and quality of resources, even if it results in a less efficient use of them. In particular, higher nutrition densities and resource volume have large direct effects on population size. Population size is also not surprisingly impacted by the rate of exhaustion—when agents are more robust to starvation and expire more slowly, the population increases. In general, variables that result in agents living longer

Figure 3: A "typical" run of the simulation with all parameters at their mean with MAX degrees of interaction



and dying less are associated with higher population.

What is more interesting is that larger networks are possible when agents may interact with other agents at greater social distances. This is apparent in the contrast between Figures 2 and 3. Why this might be could be difficult to tease out without appealing to indirect affects of component size, since the SEM model should assign these effects elsewhere. What is it about interaction distance, in and of itself, that cause population sizes to grow? One possibility is that high interaction distance allows agents to diversify their and leverage risk and opportunities for defection. Agents connected to other agents, and indirectly to yet more agents, may just be more stable. Cheating against neighbors may not kill the neighbor or even cause him to sever the connection, since he may have done well in an interaction with one your neighbors. Similarly, agents will be less reliant on close relationships, which could prevent tragedy in the event of sudden defection. This is consistent with positive, significant result of the pace of interaction, also suggesting that when risk is spread out over multiple interactions with more partners agents can endure longer. The positive coefficient on pace of interaction in conjunction with a negative impact of the base probability of connection further suggests that populations are largest when they grow more slowly and with greater information, or interaction history between agents.

Network metrics and cooperation measures are abstract and do not meaningfully represent something we humans would consider a policy goal, at least in and of themselves. Rather, they are adaptations—or technologies—that enable us to resolve individual survival and social challenges. So what are the net effects of cooperation, taking into account its structures, in real-life terms? Equations 5, 6, and 7 suggest that then net effect of cooperation are a significant reduction in starvation and an improvement in average fitness (Table 10). Somewhat disappointingly, cooperation appears to have no significant impact on inequality, neither exacerbating it nor ameliorating it. In other words, while cooperation does not necessarily imply an increase in overall fairness, it does help us all live better in the face of harsh ecological challenges to survival.

2.4 Discussion

This study presents strong evidence that social network topology should not be considered an exogenous variable in the evolution of cooperation. Rather, these variables are very likely endogenous. A complete picture of their bidirectional effects, as well as spurious correlation that are each independent, direct effects from truly exogenous factors of the environment will require much more research. These data suggest a number of potentially useful starting points.

Broadly speaking, I find that cooperation is favored in the context of small, but more densely networked communities. There were, however, a number of dynamic factors that play into this. In particular, the demand to mitigate the risks of cooperation appear to play a significant role in shaping social structures. The present model is advantageous because it allows agents to structure their social relationships in ways that minimizes their exposure, while maximizing opportunities for reciprocity. Clustering is a primitive and well-studied form of this. Cooperation in smaller networks with fewer, but more trusted connections makes sense since the risk to cooperators increases in proportion to the number of connections they maintain to other agents. In sum, closer relations with fewer individuals appeared to be in most cases preferable to larger numbers of less valuable connections.

Interestingly, as survival becomes more precarious (i.e., agents consume resources faster and are as such at greater risk of starvation), agents were the most willing to expand their number of direct connections even if as it increases their exposure to risk. There are at least a couple reasons why this could be the case: 1) Because their partners are more likely to die, it may pay off to maintain a larger number of relationships, even if they are not quite as cooperative; and 2) A more precarious existence makes defection in the context of a close relationship much more consequential. Agents, therefore, choose to spread risk of defection over a larger number of partners. The ability to interact with socially distant individuals and adopt categorically discriminating behaviors allows seems to mitigate some of the risk associated with additional relationships. Though this ability produced networks that were dramatically more segmented, overall populations were larger and the individuals within each segment were more connected.

Contrary to expectations, the overall volume of resources directly exerts a weak, but *positive* and significant effect on cooperation. However, the size of this effect seems to pale in comparison to the negative indirect effect from the influence of resource abundance on network structure. Resource abundance is broken down into two variables analogous to volume and density. Both resource volume and density massively increase network population as well as the relative size of connected components within it, each bearing a substantively large negative effect on cooperation.

The richest environments tended to produce larger and less cooperative populations. This is not surprising, as the increasing difficulty of collective action with population size is not new. However, traditional approaches have treated population as an exogenous variable and we have neglected to think about it in an ecological, or economic context. In wealthy countries, particularly the United States, the long-standing trend is for people to move to suburbs where they arguably become less cooperative. They occupy single-family homes that are designed to allow them to enter and depart the home with minimal interaction with even their own neighbors. Relevant architectural features include the replacement of front porches with outsized garages with internal access to living spaces. Such suburbs in the United States may feel themselves increasingly disassociated with other *communities*, insofar as such places might be described as "communities", seeing them as increasingly different, parasitic, and outside the legitimate *sphere of redistribution*. This perception of greater social distance, or *othering*, can in turn negatively impact political will for the provision of public goods. The modern suburban home is a model of self-sufficiency–each fitted with own internal durable goods like heavy appliances and machinery, telecommunications systems, and vehicles. Why share when you do not have to? Even individuals within the homes tend to share less, with individual telecommunications systems, computers, vehicles, and televisions. All that pertains commonly to the nuclear family unit is the dinner table, though even this is shared with declining frequency.

One convenient opportunity to study this phenomenon in an ethnographic approach could be the natural dichotomy that exists at public universities in the United States, where the graduate student population is split between comparatively wealthy American nationals and poorer foreign students from South Asia and China. Though family money can often muddy the waters, one major difference in the graduate school experience for these two groups is that the American nationals have the ability to take federal loans to supplement their living stipends that are not available to foreign students. Consequently, American students are able to maintain a lifestyle beyond their means. Based upon my own informal observations as a graduate student at Stony Brook University in Brookhaven, NY, American nationals are far more likely to live alone or with fewer housemates, eat out at restaurants more frequently, own personal vehicles, and describe vehicle ownership as something "essential" to life on Long Island. In contrast, South Asian students are likely to share households, cooperatively cook and share meals, and rely on public transportation or a single vehicle. From a distance, these habits can strike those who abundance for granted as quaint aspects of cultural diversity. However, there are in fact hard economic necessities motivating this behavior.

Scarcity is unavoidable and in their case may only be dealt with through cooperation—and this is a "pay to play" publics goods problem in such a household as in any game theoretic model. Contributions are expected and free-riding is monitored. While communal meals are relatively open to new participants (typically *friends of friends*), there is a subtly communicated but prevailing norm of "bringing something to the table". Newcomers who may be unaware are initially afforded leniency, but a reputation for just "coming for the food" will limit opportunities for longer term relationships within individuals in the household.[14]

Individualism is often believed to be a fundamental characteristic of Western civilization, but this may simply be because the west industrialized first. Now in the late 20th and 21st centuries, Eastern and South Asian societies long described as somehow inherently "collectivist," or "communitarian" in nature are also said to be growing increasingly individualistic. Marxists have long suggested the Western individualism is a capitalist social structural adaptation, establishing a necessary precept to private property and atomizing labor. These analyses do not contradict this, but suggest that individualism may also be in part a reorganization of the structure of cooperation as an economy moves from scarcity to abundance.

In the present model, the concept of 'scarcity' is generally defined but most in consistent the materials individuals need to survive. Scarcities of other sorts exist. In the next chapter, I will present another computational model that retains some aspects of material scarcity, but will also incorporate new features that take into account needs for physical security, which may also be obtained in insufficient or superfluous quantities. In particular, I will consider threats to individual security posed by the collective actions of others.

[14]My observations were informally collected from 2009 to 2013, during which time I had the privilege of calling the inhabitants of such a household close friends, wistfully sharing our lives in good food, good company, and warmish beers from a box on the table.

3 Multilevel Selection Model of Pastoralist Conflict

3.1 Introduction

My dissertation examines the ways in which ecological conditions alter individual incentives to participate in groups. It is, in essence, a contribution to the literature on the evolution of cooperation. This second of three distinct, but related studies employs multi-agent based simulation in order to establish a theoretical basis for linking individual level challenges from the environment to group behavior. The key theoretical insight is that cooperation in groups is a primary adaptation humans evolved in order to overcome environmental challenges, including competition from other groups. In other words, this model suggests that the presence of intergroup competition may shift the evolutionary rewards to individuals with a certain propensity to engage in individually-costly, but group-strengthening behavior.

In the Descent of Man (1871), Charles Darwin famously proclaimed,

> *"A tribe including many members who, from possessing in high degree the spirit of patriotism, fidelity, obedience, courage, and sympathy, were always ready to aid one another, and to sacrifice themselves for the common good, would be victorious over most other tribes, and this would be natural selection."*

This model tests his hypothesis and explores the group processes mediating individuals' interactions with their environment. We do not assume any genetic relatedness between agents. Thus, we may more purely examine individual motives and interests in engaging in altruistic behavior since there is no indirect genetic benefit of helping kin with whom he shares some proportion of genes. If cooperation evolves, it will have done so through multilevel selective mechanisms rather than kin selection. Since Nowak, Tarnita, and Wilson's (2010) publication in Nature suggesting that kin selection was not needed to explain eusociality, biologists of diverse stripes have come out in defense of kin selection (Abbot, Abe, Alcock, Alizon, Alpedrinha, Andersson, Andre, van Baalen, Balloux, Balshine et al. 2011). Fortunately, I am not obligated to take a position on this debate. Kin selection and multilevel selection are not mutually exclusive, and it stands to reason that in some cases multilevel selection may be to explain phenomena kin selection cannot (and vice-versa). A likely such case is large-scale human cooperation. Humans frequently cooperate in large groups including extended-kin as well as non-kin. This is the kind of cooperation we observe in everything from intertribal warfare in eastern Africa to the modern corporation.

The substantive context of the simulation design is abstracted from the arid and semi-arid regions of east Africa, generally encompassing the Great Rift Valley region of northern Kenya in the west and the Mandera triangle on the east, where the borders of Kenya, Ethiopia, and Somalia meet. While constituting relatively small portions of national populations, they occupy large swatches of their countries marginally hospitable territories, including 70% of Kenya (Fratkin 2001). Pastoralists make their living moving herds of animals in search of pasture and water, subsisting on the products of their animals. Though they may occasionally supplement their diets by trading with farmers and fishing, their diets generally consist of milk, meat, and blood tapped from their living animals. Tribesmen of the Boran and Turkana tribes—fairly representative of others in the region—have on average 3.5 to 3.7 tropical livestock units (a TLU equals 1 cow, 0.8 camels, and 11 goats and sheep).

Studying this region offers several advantages. Of the world's total population of pastoralist and agro-pastoralists, Africa is home for roughly one-half, or some 23 million people (Galaty, Johnson et al. 1990). Substantial evidence suggests that degradation of the environment from various sources, including climate change, has already contributed to an increase in violence (Parenti 2011; Hendrix and Salehyan 2012; Suliman 1993; Raleigh and Kniveton 2012; Buhaug and Rød 2006; Kuznar and Sedlmeyer 2005). Over the last three decades, both temperatures and the frequency of droughts have increased, with prolonged drought occurring every 5-6 years (Fratkin 2001). Moreover, the economies of east Africa tend to be heavily agrarian and poorly irrigated. According the United Nations Economic Commission for Africa (2009), only 3.7 percent of agricultural land in sub-Saharan Africa is irrigated. Livestock raiding has existed since at least the 19th century when it was first observed by the British (Fukui and Turton 1979; Parenti 2011). Raiding is done in order to replenish stocks following the dry season when a tribe can lose half of their herds. Young men seeking to marry must sometimes rely on raiding in order to amass a dowry. Though this practice is deeply rooted in the cultures and pasts of these peoples, the combination of a changing climate, land fragmentation, degradation and competing farmers appears to be driving increased frequency and severity of raiding (Parenti 2011; Suliman 1996).

At the same time regional governments lack the capacity or reach to adequately mitigate these challenges, or at least to ensure security in the fall out. To the extent that government policy has reached the arid regions of northern Kenya, northern Uganda, and southern Ethiopia, it has largely done so with the support of western international organizations. Such efforts, however well-intentioned, have in too many cases made an already bad situation worse (Parenti 2011; Fratkin 2001). In 1968, ecologist Garrett Hardin published his seminal piece in *Science* The Tragedy of the Commons, in which he argues that commonly shared resources are inevitably depleted by rational individuals; thus, natural resources should be either regulated or privatized in order to ensure good stewardship. With this in mind, well-intentioned western aid organizations made grim predictions of the sustainability of pastoralist societies and encouraged local governments to implement land use reforms. East African pastoralists found their large, communally shared lands increasingly fragmented by expanding farming operations, private ranches, wheat estates and game parks (Fratkin 2001). One of the advantages of the pastoral economy is that it is viable on marginal land which is too dry for permanent cultivation. The introduction of more intensive agricultural practices has in many cases produced only short-term gains in productivity that are cut short by soil exhaustion (Parenti 2011). According to Swift (1991), land degradation has not been halted and has sometimes increased, livestock productivity has not grown although economic inequality has, and vulnerability to food insecurity and loss of tenure rights has increased. Moreover, since Hardin's seminal paper, anthropologists and others, including Nobel Prize laureate Elinor Ostrom (1990), have documented the rich array of customary institutions regulating resource use in African pastoral societies.

Traditionally, these groups have relied upon kinship ties to cooperatively breed their animals and defend them. The institution of "livestock raiding", in which large groups of pastoralist tribesmen gather in order to conduct raids on other tribes for the purpose of stealing livestock, has existed since at least the 19th century when it was first observed by the British (Fukui and Turton 1979; Parenti 2011). East Africa is highly diverse ethnically, with an ethnic fractionalization Index score of 72 out of 100, making it one of the most highly fractionalized places in the world (Elbadawi and Sambanis 2000). Raiding is done in order to replenish stocks following the dry season when they are likely to lose half of their herds. In general, herders find that the optimal strategy is to maximize the size of their herds, which are typically large and sickly (Fratkin 2001). Maximizing numbers is favored over concentrating resources on fewer animals. Stolen livestock can also make an impressive dowry and be invaluable for a young man seeking marriage. The combination of increasingly frequent and severe drought, land fragmentation, degradation and competing farmers has caused a dramatic uptick in raiding (Parenti 2011; Suliman 1996). Complicating matters further, the legacy of the Cold War has left the region awash in small arms, rendering raids not only more frequent, but substantially more deadly.

3.2 Theory

To recapitulate, global climate change and decreased living space is making violent conflict both a way and a means of life for the tribes of the arid and semi-arid regions of east Africa. The main supposition of my dissertation is that human beings were endowed by evolution with faculties that facilitate collective action in response to environmental challenges. In other words, our ancestors who possessed such faculties to submit a portion of their individual sovereignty to a group processes (implying personally costly behavior), enjoyed greater prospects for reproductive success than those who were not.

The model I propose is designed to explore the process by which this could plausibly have occurred. Specifically, I employ a version of group selection called multilevel selection.

Sidanius and Kurzban (2003) define a "group" as "any set of individuals that have a fitness impact on one another". Importantly, a degree of relatedness is not part of this definition. According to multilevel group selection theory, nature can be said to select for an entire group if, despite some relative fitness inequality between internal phenotypes, members of all phenotypes are on the whole more successful in passing on their genes than individuals belonging to other groups. As the authors explained, this is not "an alternative to the genetic view of ... selection," but rather is "simply another way of keeping track of genes' success by looking at their relative replication rates within and between groups". Modeling how the frequency of these 'genes' changes in response to inputs is the basis of an evolutionary model. Such a model allows us to derive two hypotheses.

Hypothesis 1: Under some environmental circumstances, the evolutionary pay offs individuals enjoy by dint of successful collective action efforts will outweigh the investments they made to ensure their groups' capacity for collective action.

Hypothesis 2: When resources are relatively plentiful, intergroup cooperation will increase and intragroup cooperation will decrease.

3.3 Methods

The main challenge associated with hypotheses concerning evolutionary processes is that evolution can be virtually impossible to observe in the world. One of the most powerful tools available to us is multi-agent simulation (MAS). Strictly speaking, MAS is an empirical methodology. The reader must, however, acknowledge that the empirical data generated in a simulation are "collected" from a virtual world which operates precisely according to the physics (or rules) we specify. Simulations allow us to view the world that would exist if our models were correct and complete. In other words, they allow us a glimpse at what the world would look like if it worked like we think it does. Simulation can play an important role in the scientific process because it allows us to rigorously examine the implications of our assumptions in ways that, for reasons of inherent complexity and our susceptibility to biased reasoning, would just be too much to expect from a human brain. Quoting Epstein (1999), the canonical agent-based experiment is as follows:

> *"Situate an initial population of autonomous heterogeneous agents in a relevant spatial environment; allow them to interact according to simple local rules and thereby generateor 'grow'the macroscopic regularity from the bottom up."*

Several studies have productively applied agent simulation to the question of pastoralist conflict. Motivated by genocide in Darfur, Kuznar and Sedlmeyer (2005) model how individuals respond to environmental and material challenges, and in turn attempt to describe a process by which collective action (i.e., intergroup violence) can emerge from individual motives. The authors create an intricate model, including detailed and realistically defined geography, agriculture, agent and livestock metabolisms, demography, and a rudimentary trading economy. They find that drought can lead to sustained violent conflict and a breakdown of intertribal relations in terms of mutually beneficial activities, such as trade. Kennedy, Hailegiorgis, Rouleau, Bassett, Coletti, Balan and Gulden (2010) use the MASON agent-based modeling environment to test a conflict model of nomadic herding with data-driven seasonal cycles. They find greater scarcity favors a strategy of domination by a single group. (Hailegiorgis, Kennedy, Balan, Bassett and Gulden 2010) more richly model Mandera triangle region of east Africa, focusing on the tensions that can emerge between groups over utilization of common grazing land. MacOpiyo, Stuth and Wu (2006) develop the Pastoral Livestock Model (PLMMO), which simulates pastoralist foraging and movement patterns across geographic information systems (GIS) based raster landscapes.

It is important to note these are "thick" models, conceived of in a "bottom up" way to mirror reality as closely as possible, given computational constraints and the state of knowledge. In this regard, they are a different animal than the sort of "top down" reductionist models often employed to understand the evolution of cooperation. With a price paid in parsimony, they buy space for the inclusion of expert knowledge provided that it can be expressed quantitatively. This encourages scholars to think through the mechanics of theory that are easily taken for granted. In a circumspect evaluation of these interdisciplinary, computational approaches to modeling complex systems, anthropologists Skoggard and Kennedy (2013) conclude that such models promote a “deeper appreciation of the multi-layered scalar relationships between culture, agency, and the environment.”

3.4 Model

This model is a computational, multi-agent based simulation of the evolution of tribalism, or intra-group cooperation/inter-group conflict. The design is based on two core design principles: 1) multi-level selection, and 2) realistic competition for scarce resources agents need to survive. It is a ‘thick’ model. In this, I mean that it incorporates a more richly textured environment and more cognitively sophisticated agents than conventional models of the evolution of cooperation. This feature carries with it both risks and opportunities: it’s risky in the sense that it creates for a substantially more complex model that is more error prone and more difficult to analyze. The model is highly parameterized and computationally intensive, limiting the potential for Monte Carlo methods of exploring the parameter space.

The advantages of a ‘thick’ model, however, include the opportunity to observe the evolution of cooperation in a more realistic environment with greater external validity at the cost of construct validity. One such feature is a highly tunable ecosystem including seasonality, base averages, and variances, spatial distribution of resources, extreme weather patterns, as well as tunable metabolic and behavioral characteristics of the agents themselves. This allows for more nuanced descriptions of the relationships between agents, the environment, and the moderation effect of cooperation between them. This level of control enabled me to characterize the major features of the arid and semi-arid regions of East Africa, where tribally organized pastoralism has long remained the dominant economic modality.

In sum, this simulation is designed to test the hypothesis that realistic conflict over resources could have played a role in the evolution of tribalism as an organizing principle of human cooperation. Like the previous simulation, the key independent variables describe ecological conditions, allowing for cyclical and non-cyclical fluctuation of relative scarcity and abundance. The key dependent variable is the distribution of cooperative propensities in an evolutionary stable population.

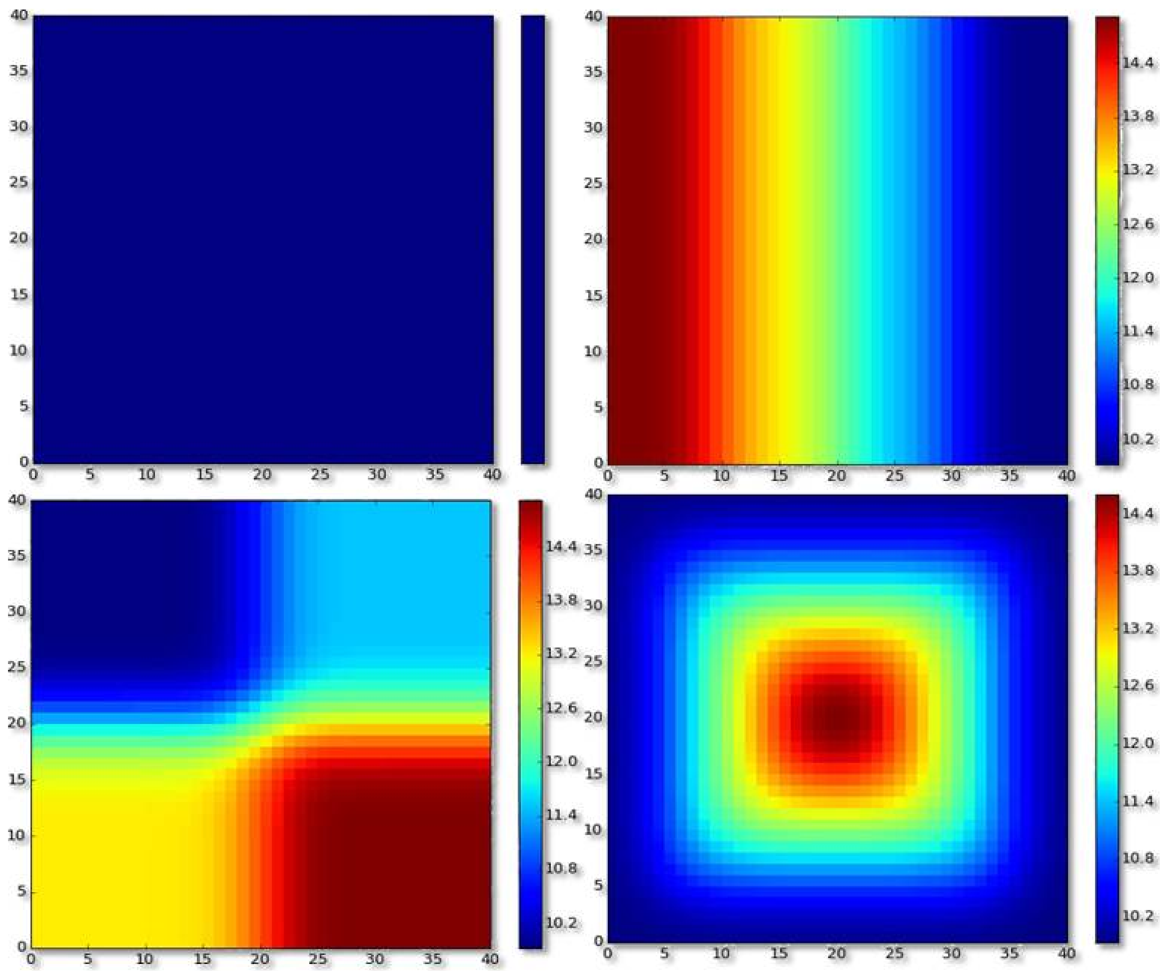
3.4.1 Environment

Space

The simulation takes place on a two-dimensional spatial grid of dimension S x S. Each grid cell has a host of properties including an amount of *grass* and *water*. For the amount of water to be greater than 0, there must be a *well*, which occur randomly at some frequency wf at the onset of the simulation. *Precipitation* causes grass to grow and wells to fill with water. Since both grass and well water are determined by rainfall, it might seem like a good idea to simplify the model and reduce to only a single resource. Research from biology and behavior ecology suggests the way in which resources are distributed over a foraging area (e.g., uniformly or clustered) could potentially impact the dynamics of cooperation (Senft, Coughenour, Bailey, Rittenhouse, Sala and Swift 1987; Waser 1988; Sterck, Watts and van Schaik 1997; Koenig 2002; King, Douglas, Huchard, Isaac and Cowlishaw 2008; Wittig and Boesch 2003). For example, social animals like buffalo and gelada baboons who graze off of uniformly distributed resources of comparatively low-nutritive value may live in very large communities consisting of hundreds of animals. The level of coordination between them, however, is limited. This particular form of cooperation, however, might be less suited in a situation where resources are distributed in clumps, or clusters of comparatively high-nutritive value. Clustered resources may favor a kind of sociality that enables a number of individuals to cooperatively defend or assault a location. This is a model of the evolution of tribalism under pastoralism—an economic modality demanding both widely distributed and clustered resources. A two resource system, therefore, allows modeling of the distribution of resources, without sacrificing the pastoralist character of the model.

Both the maximum amount of grass in a tile as well as rate of growth are determined by the cell's *land quality*. The distribution of land quality is determined at the start of

Figure 4: Spatial distribution of land quality: Uniform (top-left), linearly decreasing gradient (top-right), quadral categories (bottom-left), and radially decreasing (bottom-right)



the simulation according to user selection from four possible conditions. 1) Uniform: The default setting is for all land to be of equal quality; 2) Striped: Land quality is greatest at the left of the grid and decreases in quality gradually in a linear fashion to the right; 3) Radial gradient: Land quality is greatest at the center of the grid and decreases with the radial distance from the center point; 4) Quadral: At is highest in one corner, lowest in one corner, medium-high in one corner, and medium-low in one corner. Quality converges at the center point according to a Gaussian smoothing algorithm. Well depth (well capacity) is affected by land quality, but not rate of fill (see Figure 4).

Precipitation and Climate

The amount of precipitation is determined by a climate model. The basic climate model is determined by a sine wave function establishing four "seasons" defined by the peak (summer), trough (winter), and the inflection points (equinoxes). Seasonality acts as a periodic deviation from a base rate *br* of precipitation. At peak, precipitation is equal to the base rate plus $\frac{br}{ex}$, where ex is a seasonal extremity parameter. When $ex = 2$, peak precipitation is $1.5br$ and $.5br$ at the trough. The actual amount of precipitation will also be affected by exogenously determined "anomalous" weather patterns including extended periods of drought or excess. The frequency, severity, and duration of weather anomalies are parameter controlled.

3.4.2 Agents

Attributes

Agents may be thematically thought of as pastoralist nomads, wandering (prospecting) the grid in search of grass and water to sustain their flocks. Ensuring their flocks are neither too *hungry* nor too *thirsty*, agents maximize their flocks' *health* and in turn the rate at which their flock grows. At any given time a flock's hunger is f is in $[0, 1]$, where a value of 0 indicates that the animal is perfectly starved and a value of 1 indicates it is perfectly satisfied nutritionally. Similarly, thirst w is in $[0, 1]$ where 0 is perfect dehydration. The quantity of food or water an agent's flocks demand is equal to the number of animals in the flock multiplied by f and w, respectively.

Flock hunger: $f \in [0, 1]$

Flock thirst: $w \in [0, 1]$

Flock health: $\frac{Flockhunger + Flockthirst}{2}$

Demanded food: $f * Flocksize$

Demanded water: $w * Flocksize$

For agents, the size of their flock is of critical importance because it affects their likelihood of reproductive success, as well as the size of the "dowry", or the endowment flock with which their offspring begin their own journeys. Importantly, agents are also characterized by a tribal affiliation. While the agents think and act on their own, their actions have an impact on their tribe, the cumulative effects of which can indirectly affect them. This will be explained in greater detail below.

Prospecting

In each time period t, agents survey the environment of the cell they currently occupy as well as the 8 surrounding cells. A multinomial probability distribution is then assigned over the set of tiles based on the expected utilities associated with each. Utilities are in terms of expected health outcomes for an agents' flocks, as determined by each cell's ability to satisfy the nutrition and hydration its animals require. In order to generate the set of expected utilities, the agent imagines itself moving to (or staying in) each of the 9 cells and how any interactions with other agents located there are likely to go. They take into account the tribal affiliation of the occupants, whether interactions are likely to be cooperative or conflictual, and if conflictual how well off they are likely to emerge from the conflict. There are three possible cases:

Agent will occupy cell alone: They will be free to consume whatever resources their flocks demand, and leave what remains (if any).

Agent will occupy cell with fellow tribesmen only: Resources within the cell are initially distributed equally among all fellow tribesmen, with which tribesmen play a standard public goods game. After the game is complete and each agent has received their payoff, they each individually feed their flocks. An agent's strategy in the Public Goods Game (PGG) is an agent-level parameter, cooperation, initially distributed random uniform $[0, 1]$.

Agent will occupy cell with at least one out-tribesmen When agents from multiple tribes are present, the agent imagines two scenarios: A) peaceful coexistence or B) conflict. In the case of peaceful existence, all available resources are distributed equally to all tribesmen from all tribesmen. All agents participate in PGGs with their own tribesmen, but not with members from other tribes. However, if the agent determines that his tribe (or another tribe) is likely to fight for the entire share of the available resources, they will generate an expected payout, which is the product of their possible payoff if their tribe hoarded all of the resources available and the tribe's probability of victory in battle. More on this probability below in the Tribes section.

In so doing, agents generate a vector of expected utilities VU from the 9 cells. However, the actual value of the cell will also be affected by its proximity to water, and agents must take this into account. Accordingly, the agent also generates a corresponding vector of weights VW based on each cell's "water value". The formula for water value is as follows:

$$VW_{cell} = Thirst \sum_{well} \frac{(q_{well}/n_{well})}{d^2_{well}} \tag{5}$$

Where q is quantity of water available, n is number agents present, and d is the distance to the well. It is assumed that the utility of a well decreases with the inverse square of the distance since the water value of a cell should be disproportionately determined by water resources close by. The journey to reach distant wells will require substantial energy, as well as time during which the availability of the resource could change. The agent's thirst value is included because water increases in value with thirst, potentially making distant, but unoccupied, wells more attractive. This formula looks unnecessarily complicated but all it is a weighted average between how much water the agent is likely to receive if it is only split with his tribe versus if it is split with everyone, where the weights are the relative proportions of cohesiveness between the two tribes. The values are also standardized so that weights are in $[0, 1]$.

Figure 5: Percent of an agent's flocks surviving by average of flock health and thirst

The vector defining the multinomial probability distribution over each of the 9 cells is therefore,

$$VN_{cell} = \frac{VU_{cell}VN_{cell}}{\sum VU_{cell}VN_{cell}} \tag{6}$$

A random draw from this distribution determines an agent's location in each subsequent time period.

Metabolism

Every time period, the hunger of an agent's flocks increases by u and their thirst increases by h. The longer they go without food or water, the more likely it will be that they die. The rate of flock exhaustion is calculated according to a survivor function of the form:

$$\%Surviving_{agent'sflock} = 1 + tolerance - e^{-[1.5-(u_i h_i)^3]} \tag{7}$$

Where *tolerance* is a global variable determining how long an agent's flocks may go without food or water before it begins to incur losses. The figure below depicts the functional form with tolerance = .1.

3.4.3 Tribes

Like the real world, agents are independent actors nested inside higher-order units of aggregation. The attributes of tribes are constituted from aggregations of actions their members take. A tribe's attributes, however, may have an indirect impact on what its members are able to do in the future. A key tribal attribute is its *cohesion*. Cohesion is calculated as the average proportion of resources agents contribute in public games with their fellows. The cohesion of an agent's tribe can impact them in several ways.

Fighting

Strong, cohesive tribes have an advantage over other tribes in that where resources might have to be shared globally, they may "fight" for the right to harvest a resource exclusively. This means that the resource shares per agent within the tile will be larger since they are only shared amongst the members of the victories tribes. This may result in weaker, less cohesive tribes actually avoiding coming into contact with cohesive tribes.

When there are members of two or more tribes located on a single cell, they may either "share" the resources or "fight" for them. Sharing resources means that they all just take their share, which they will use as their endowment to play with in a public goods game if any fellow tribesmen are present. This decision to fight or share is made "collectively" by the tribesmen of each tribe. If the "average tribesmen" is better off fighting, then the tribe fights. If one tribe in any dyad of tribes decides to fight, then they will fight. A tribe decides to fight when:

$$EU(fight) > EU(share) \tag{8}$$

such that

$$EU(fight) = Allresourcesgained * Pr(victory) + Noresourcesgained * [1 - Pr(victory)] \quad (9)$$

where $Pr(victory)$ is determined by each sides' relative fighting power pow, or

$$Pr(victory_A) = \frac{pow(Tribe_A)}{pow(Tribe_A) + pow(Tribe_B)} \quad (10)$$

A tribes fighting power pow is determined by

$$pow(TribeA) = (\frac{C_A S_A}{D_{A_{xy}}})^L \quad (11)$$

where

C_A = $TribeA$'s cohesion S_A = $TribeA$'s size $D_{A_{xy}}$ = Average distance of $TribeA$'s members to cell (x, y). L = Lanchester law of combat (linear or square law)

The L parameter, or the Lanchester Law, comes from World War I era military theorist Frederick Lanchester's Law's of Combat. Among these are the *Linear Law* for ancient combat and the *Square Law* of modern combat. For ancient combatin particular phalanx formations of soldiers with spears or swords were pressed into one another and essentially only able to fight one man to a man. Thus, a side's fighting potential may be said to increase linearly with the number of soldiers. However, under so-called "modern" conditions with ranged weapons or in other cases where targeting may be concentrated power is said to increase with the square of the number of units. Dominic Johnson has published articles and a book detailing how human ancestral warfare may be best be characterized according to the square law. In practical usage, it is common for analysts to use an intermediary exponent like 1.5 because it is assumed that combat will be a mixed bag of linear and square elements.

Death in combat

While agents do not directly figure into their cost-benefit calculations in whether or not to go to war, i.e., to fight for a larger portion of a cell's resources, this decision could come back to haunt them—win or lose. An agent's (per time period) probability of meeting a violent death is determined according to the function:

$$Pr(violentdeath_i) = 1 - Y^{b_{i,tribe} v_{i,tribe} c_i} \tag{12}$$

where Y is a global parameter defining a base lethality, or probability of surviving a battle. This base probability is compounded with every battle the agent participates in, however, it is necessary to take into account that not every battle is the same and not every agent fights with the same level of commitment. Accordingly the number of battles an agent participates in b is weighted by his tribe's average probability of victory v and the agent's level of cooperation c. Thus, an agent is more likely to die when is tribe fights with generally poorer odds of victory and if he fights with greater heroism.

Reproduction and cooperative breeding

A basic premise of multi-level selection is that while some inter-group competition exists, mate selection is primarily an intra-group process. In this model agents' likelihood of reproducing is a function of their standing within their own tribe, as determined by the size of their flocks. The probability of reproduction in time t is given by:

$$Pr(Reproduce_i) = MateScore_i * (BirthRate_{base} + CooperativeBreeding_{bonus}) \tag{13}$$

where

$$MateScore_i = \left(\frac{n_{i,tribe} - rank_i}{n_{i,tribe}}\right)^{MateCompetitionSeverity} \tag{14}$$

and

$$CooperativeBreeding_{bonus} = BirthRate_{base} * Cohesion_{i,tribe} * EffectSize_{base} \tag{15}$$

In plain language, within each tribe all tribesmen are arranged in reverse order according to the size of their flocks. This is their raw rank which is normalized by the total number of tribesmen in order to get their percentile rank score. I include one additional parameter, the *mate competition severity factor* (MSF), which allows me to control the "intensity" of mate competition. When MSF is 1, then mate score decreases linearly with rank. At MSF = 2, mating potential decreases exponentially with rank. This value is compounded by the global parameter, natural birth rate. However, cooperative breeding practices may actually enable a tribe to achieve a birth rate greater than the "natural rate". Thus, this rate is increased by the *cooperative breeding bonus*, which is equal to the natural birth rate times the level of a tribe's cohesion, multiplied by an additional global parameter moderating this bonus effect. If the bonus effect is 0, then there is no cooperative breeding bonus. When the bonus effect is 1, the effective birth rate of a perfectly cohesive tribe (cohesion = 1) will be exactly 2 times the natural rate.

The final result is a value bounded $[0, 1]$ unique to every agent, which is treated as a probability of reproduction. All agents in all tribes have a chance to reproduce, but the size of probability is determined only in comparison to fellow tribesmen. The most cooperative tribes get a bonus to birth rate because we assume that cooperative breeding practices enable them to have more babies.

When an agent reproduces, it transfers a number of its flock to the offspring equal to the endowment factor e times flock size. Therefore, the size of the endowment is proportional to the economic success of the parent. This ensures that even though poorer tribes, *ceteris parabis*, are equally likely to produce offspring as wealthier ones, the offspring of wealthier tribes are going to have a better chance at survival since they are able to provide their offspring with larger number of flocks.

3.4.4 Other modeling factors

Migration

In order to account for "gene transfer" between groups, every round agent's probabilistically migrate to another tribe (change tribal affiliation) according to a probability m. This is a global variable, with a default value of 5% chance of migrating within a 20 time step period, or 0.025% per time period.

Mutation

Every round agents will 'mutate' (i.e,. adopt entirely new behavioral strategies) with probability mu.

Tribe splitting and dissolution

If a tribe's membership exceeds $Kmax$, a tribe will fission into two tribes. $\frac{Kmax}{2}$ agents will be selected at random to form a new tribe. If a tribe's membership drops to 0 it is considered dissolved and removed from the simulation.

3.5 Data

In order to examine the implications of this model I will once again begin the analysis with Monte Carlo simulation. This model takes a relatively large number of input parameters, though not all of these are subject to random draws from probability distributions. Table 11 presents the totality of input parameters in their observed distributions across 673 unique runs of the simulation. Note that these data are, indeed, as *observed* in the simulation, as distinct from the probability distributions from which they are drawn. This distinction is important because of all simulations initiated only around 10% of them completed. In all other cases, the population was unable to cope with the environment, as determined by an ecologically unstable or otherwise inhospitable set of parameters, and subsequently perished. These runs of the simulation are eliminated from the dataset, leaving an n of 673 observations over 2000 time periods. Though the number of input parameters is relatively high, the number of output variables are relatively few. These data are summarized in Table 12.

Looking at the summary statistics of model outputs, it is clear that the 673 unique worlds resulted in an incredibly diverse array of outcomes. In some worlds, cooperation was virtually non-existent ($mean = 0.01$), while in others it was highly prevalent ($mean = 0.79$) from a possibility space in $[0, 1]$. Some worlds were diverse, multi-ethnic mosaics of tribal cultures, while others produced ethnically homogenous populations. War was highly frequent in some worlds, while in others it was non-existent. These results in and of themselves are quite fascinating. Ultimately, the goal of this research is to ascertain what are the environmental factors driving *individuals* to engage with their co-ethics in campaigns of violent conflict against other human groups.

Table 11: Complete exogenous parameter descriptive statistics. Not all parameters varied in Monte Carlo simulation. Table depicts only values from simulation runs in which agents survived.

Variable	Mean	Std. Dev.	Min	Max
Initial pop.	100	0	100	100
Migration period	635.25	295.32	2	1502
Migration rate	0.001	0.001	0.0005	0.0025
Mutation rate	0.005	0	0.005	0.005
Initial flock size	7.21	1.34	5	9
Benefit of cooperation	1.51	0.28	1.00	2.00
Initial tribe count	3.10	1.42	1	5
Max members per tribe	105.32	26.59	60	150
Well frequency	0.14	0.04	0.05	0.20
Base resource level	12.34	4.24	5	19
Seasonal extremity	2.45	0.86	1.01	4.00
Acute weather extremity	0.15	0.08	0.00	0.30
Season length	10.00	3.11	5	15
Min. weather duration	2.48	1.10	1	4
Max. weather duration	7.52	1.10	6	9
Min. well depth	31.46	18.11	5	76
Max. well depth	91.98	35.07	30	171
Water accumulation ratio	3.52	0.86	2.01	4.99
Land quality water boost	0.49	0.28	0.00	1.00
Deprivation tolerance	0.02	0.02	-0.06	0.05
Lanchester Law	1.50	0.30	1.00	2.00
War lethality (survivability)	0.89	0.05	0.80	0.97
Food consumption rate	0.23	0.04	0.15	0.30
Water consumption rate	0.07	0.03	0.03	0.15
Calf birth rate	0.17	0.03	0.07	0.20
Mate competition severity	1.51	0.29	1.00	2.00
Birth rate	0.12	0.04	0.05	0.20
Cooperative breeding bonus	1.48	0.29	1.00	2.00
Bride price (dowry)	0.28	0.12	0.10	0.50
Offspring radius	5.98	2.70	2	10
Well distance exponent	1.25	0.14	1.00	1.50
Maximum age	100	0	100	100

Table 12: Descriptive statistics of main outcome variables from Monte Carlo simulation

Variable	Mean	Std. Dev.	Min	Max
Cooperation	0.18	0.13	0.01	0.79
Num. tribes	21.67	11.85	1	72
Avg. tribe size	31.27	10.18	2	65.11
War frequency	93.72	91.61	0	864
Avg. flock size	50.47	31.80	3	233.72

As I argued in the previous chapter, endogeneity between major outcome variables is common in multi-agent based simulation. This is in part because the virtual universes in which they take place are highly simplified worlds where the entirety of the possibility space is defined with relatively few degrees of freedom. With the exception of what we, as modelers, have determined to be the most salient forces and mechanisms at play in the context of the particular phenomenon we are studying, the inestimable complexity of the real universe is largely modeled in the form of random noise.

With so few moving parts, it is therefore common within these virtual universes that just about everything is in some way related to everything else. Maybe this is also in some sense true of the real world, but because these virtual worlds are so much smaller, its a much bigger deal here. This fact, of course, is one of the major motivations for pursuing multi-agent simulation in the first place; they are an open acknowledgment of the many complex interactions that exist within nature and constitute are attempts to account for this complexity. Accordingly, I strongly favor the adoption of statistical methods capable of handling substantively significant endogeneity between major outcome variables.

Table 13: Durbin-Wu-Hausman tests for endogeneity between major outcome variables.

Endogenous variables	Durbin-Wu-Hausman tests (p-values)
Cooperation/War frequency	0.035
War frequency/Average tribe size	0.392
Cooperation/Average tribe size	0.738

For the present study, the three outcomes I am most interested in are the prevalence of cooperation, the frequency of conflict, and the average size of tribes. In order to assess their respective relationships to the environment and to each other I model them together in a three equation system, which I estimate using a *Three-stage Least Squares* (3SLS) estimator. Like a Two-stage Least Square estimator, the 3SLS allows flexible instrumentation to deal with endogeneity, but has the additional advantage of taking into account covariances in the disturbances across all equations in the system. The latter advantage is in my assessment critical in conducting statistical models of simulated worlds. However, for robustness I conduct a battery of Durbin-Wu-Hausman tests for endogeneity between the major outcome variables (see Table 13). These tests strongly suggest the relationships between cooperation and war frequency (p-value = 0.035) contains bidirectional effects. A Sargan test for overidentifying restrictions suggests the instrumentation is valid (p = 0.39, null hypothesis of valid instrumentation holds). Using the traditional 0.05 level of significance, the null hypotheses that the cooperation-tribe size and war frequency-tribe size relationships are exogenous cannot be rejected (p = 0.74 and p = 0.39, respectively).

However, the arbitrary 0.05 cutoff-point is typically employed based on the assumption that the greatest risk to inference is posed by a so-called "Type 1" error, or rejecting a null hypothesis which is objectively *true*. In this case, however, the risk associated with failing to account for endogeneity that does exist (a "Type 2" error) is considerably greater than that of over-specifying a model. This is particularly true since at least one relationship is already confidently determined as endogenous. Furthermore, sufficient restrictions are available to ensure that each equation is over-identified according to the Rank test. If endogeneity exists in the latter two relationships, the 3SLS estimator will yield asymptotically consistent estimates with a tolerable penalty in terms of efficiency. Tables 14, 16, and 17 present the results of the 3SLS estimation.

3.5.1 Three Stage Least Squares Model

Cooperation

Contrary to expectations, the frequency of war did not result in a corresponding increase in cooperation (see Table 14). To recall, it was my contention that individuals nested in groups, which are themselves situated in a condition of mutual threat or hostility, are likely to be more cooperative. We should be interpreting this result, however, because there is a lot of information to unpack. Due to careful model specification, we should keep in mind that the coefficient on war frequency pertains narrowly to the direct effects of war itself—not its fruits. Fighting more, *ceteris parabis*, implies dying more. The most patriotic, altruistically self-sacrificing warriors will in turn die with the greatest frequency. Accordingly, it makes sense that war frequency should negatively impact cooperation, assuming cooperation is a heritable trait. Consistent with this interpretation, the coefficient on war lethality (higher is more survivable) is statistically significant and positive. Previous research by Smirnov, Arrow, Kennett and Orbell (2007) and Bowles (2006) have explored the fitness offsetting effects of reproductive leveling to compensate warriors who risk meeting an untimely end in battle, however this model contains no such provision for assigning individual specific rewards based on demonstrated altruism.

To understand the emergence of cooperation in the context of warring societies, we need to take a more nuanced approach that takes into account not just whether fighting and death occur, but where and for what reasons does such conflict occur, and how does cooperation moderate successful outcomes. Interestingly, conflict does significantly—and dramatically—impact how cooperation is realized. In traditional models of cooperation, the benefits of cooperation are typically modeled as an abstraction of fitness gains owing to, perhaps gains in efficiency in resource usage. At a sufficiently high level of abstraction, this effect includes the totality of possible gains to cooperation from any context. However, in this model we expressly distinguish between gains from resources sharing and gains due to other cooperative behaviors, such as organized violence and cooperative breeding practices. While these data do not suggest a significant link between cooperative breeding and cooperation, I find a substantively large and highly significant link between gains to cooperation from the ability to organize fighting power. This ability, as represented by the Lanchester Law

Table 14: 3SLS estimation results (1/3)

Variable	**Coefficient**	**(Std. Err.)**
Equation 1 : Cooperation		
Average flock size	0.0004*	(0.0002)
Average tribe size	-0.0062**	(0.0008)
Benefit of cooperation	0.0133	(0.0119)
Base precipitation rate	-0.0032*	(0.0013)
Cost of reproduction (dowry)	-0.0897*	(0.0376)
Food consumption rate	0.1861†	(0.0987)
Maximum group size	0.0002	(0.0002)
Lanchester Law exponent	0.0613**	(0.0154)
War survivability rate	0.9025**	(0.0878)
Population size	0.0001**	(0.0000)
Quadral LQ dumm	-0.0325**	(0.0096)
Radial LQ dummy	-0.0100	(0.0091)
Striped LQ dummy	-0.0138	(0.0096)
War frequency	-0.0009**	(0.0002)
Water consumption rate	0.5000*	(0.2278)
Well frequency	-0.5601**	(0.1524)
Well minimum depth	-0.0004	(0.0002)
Intercept	-0.4838**	(0.0848)

exponent, isolates the inherent advantage of concerted action in combat. The advantage conferred upon individuals belonging to cohesive groups was so strong, in fact, that this condition alone appears sufficient to evolve cooperation. This effect even dwarfs that of the direct benefit to cooperation achieved through joint resource utilization, which while positive falls short of statistical significance.

Not surprisingly, the coefficient on average group size is negative. This is consistent with the general rule that collective action becomes increasingly difficult to maintain as group size increases dating back to Olson (1965). Cooperation also becomes less feasible as dowry size increases. At first glance it might seem contrary to the intuition that parents wish to endow their offspring with the greatest opportunity to survive, prosper, and ultimately bear offspring of their own. However, larger dowries will result in more ‘near peers’ within a tribe, potentially increasing incentives for them to risk cheating each other in order to gain superior status and increased relative fitness.

The relationship between cooperation and resources, in terms of both abundance and distribution, was nuanced as expected. As evinced by the negative, significant coefficient on the *base rate* of precipitation, there is a general trend for fewer resources to result in less cooperation. At the same time, the rate at which those resources are consumed tend to increase cooperation. In this model the quantity of resources and the rate at which they are consumed are not equivalent, since the base rate implies a hard upper limit on land carrying capacity, while consumption rate describes a behavior. So while lower carrying capacity tends to inhibit cooperation, independent non-cooperative strategies are still feasible since agents may readily move to surrounding areas where resources remain. Increasing consumption rates, however, make cooperation at a specific time and place much more important in order to ensure that one's flocks survive. Hence, we observe significant and positive coefficients on both water and food consumption rates, as well as average flock size.

Widely dispersed resources, such as *grass* or pasture, seem to promote cooperation when they are abundant and inhibit it when they are in short supply. At first glance, this also appears true of "clumpy" resources like water sources, or *wells*. On average, fewer available resources tended to favor solitary, non-cooperative strategies. Achieving maximal population would entail a more widely distributed population where encounters between agents were less frequent. Consistent with this interpretation, the frequency of wells had on average a negative impact on cooperation. This, I conclude, is because the more frequent occurrence of wells allows for a more widely distributed population able to subsist with relatively less interaction.

But does this pattern always hold? Keep in mind that in this model gains from cooperation may be realized in multiple ways—not just resource sharing. The main supposition of this research is that scarcity in the resources individuals need to survive can inspire agents to cooperate, which under certain external conditions can yield expected (relative) fitness gains. In particular, the ability to cooperate in the form of concerted action creates an opportunity for a group of individuals to expand the amount of resources available to them individually in a zero-sum fashion at the expense of others. This is the central principle of *multi-level selection.* Accordingly, I hypothesize that this ability (modeled as the Lanchester Law), will condition the effect of resource scarcity on cooperation.

To test this hypothesis, I implement an Ordinary Least Squares (OLS) regression of cooperation on a set of variables representing such interactions between resource characteristics and the capacity for concerted action. In total there are for interaction terms, two characterizing the water-based, "clumpy" resource and two characterizing the widely distributed pasture-type resource. The water resource variables include the *well accumulation ratio*, which describes the relative rate at which precipitation accumulates into underground aquifers to be made available for agent usage at wells. Also included are the *water consumption rate* (h) and *well frequency.* The pasture variables are *base rate* of precipitation, which is the largest determining factor of pasture growth, and the *pasture consumption rate*(u). These results are presented in Table 15.

Tellingly, all three interaction terms related to the clustered water resource were significant, while neither of the terms related to the homogenously distributed pasture resources were significant. This strongly affirms previous findings that the spatial distribution of resources plays a key role in the evolution of cooperation. In this case, it appears closely linked to the ability to coordinate self-sacrificing action in violent conflict. These interaction relationships are more easily interpreted visually. Figures 6 through 9 depict them in a series of marginal effects plots. Figure 6 depicts the marginal effects of well frequency on cooperation as Lanchester Law exponent value varies across its from from 1.0 to 2.0. When the Lanchester Law exponent is 1.0, agents are entirely unable to coordinate their attacks. At Lanchester Law equal to 2.0 they are able to coordinate their attacks completely. At the lower end of the Lanchester spectrum, the coefficient on well frequency is negative with the 95% confidence interval well below zero. This implies that when agents are unable to organize their violent potential, increasing the number of wells across the simulation terrain reduces cooperation. This enables individuals to live in greater dispersion, more easily avoiding contact with others from within or without their respective tribes. This fundamentally centripetal social dynamic, however, is reversed at the upper end of the Lanchester spectrum. The ability to engage in concerted, or structured action enables groups to assault and control precious clusters of resources, which can overcome such centripetal forces and shift greater selection pressure to cooperation. Figure 7 depicts the same relationship from a different perspective, focusing on the marginal effects of the Lanchester Law exponent at levels of well frequency. Once established, the increased number of wells seems to merely accelerate this effect by creating more opportunities for organized violence.

Table 15: Results of OLS interaction model of cooperation

Variable	**Coefficient**	**(Std. Err.)**
Well frequency	-1.6926**	(0.4812)
Lanchester Law exponent	0.0845	(0.0910)
Well freq. X Lanchester Law exponent	1.0850**	(0.3014)
Water accumulation rate	0.0343†	(0.0206)
Water accumulation rate X Lanchester Law exponent	-0.0213	(0.0137)
Water consumption rate	1.5816*	(0.6941)
Water consumption rate X Lanchester Law exponent	-0.9779*	(0.4332)
Base precipitation rate	-0.0040	(0.0048)
Base precipitation rate X Lanchester Law exponent	0.0019	(0.0030)
Food consumption rate	0.6375	(0.4001)
Lanchester Law exponent	0.0000	(0.0000)
Base precipitation rate X Lanchester Law exponent	-0.2163	(0.2632)
Average flock size	0.0000	(0.0002)
Average tribe size	-0.0044**	(0.0007)
Benefit of cooperation	0.0168	(0.0160)
Cost of reproduction (dowry)	-0.1474**	(0.0341)
Maximum group size	-0.0003	(0.0002)
War survivability	0.9808**	(0.0801)
Population size	0.0000	(0.0000)
Quadral LQ dummy	-0.0275**	(0.0098)
Radial LQ dummy	-0.0118	(0.0098)
Striped LQ dummy	-0.0130	(0.0110)
War frequency (instrumented)	-0.0004**	(0.0001)
Well minimum depth	-0.0002	(0.0002)
Intercept	-0.6578**	(0.1588)

Now we may state confidently that the clustering of resources tends to produce more cooperation. Given that greater well frequency increases the amount of cooperation, this

Figure 6: When agents are unable to organize their violence, increased water resources reduce cooperation and increase independence. However, when the ability to engage in concerted, or structured action enables groups to assault and control precious clusters of resources. This, in turn, promotes cooperation in the group and enables even lower fitness agents within that group to reproduce faster than those whose access to these resources are blocked.

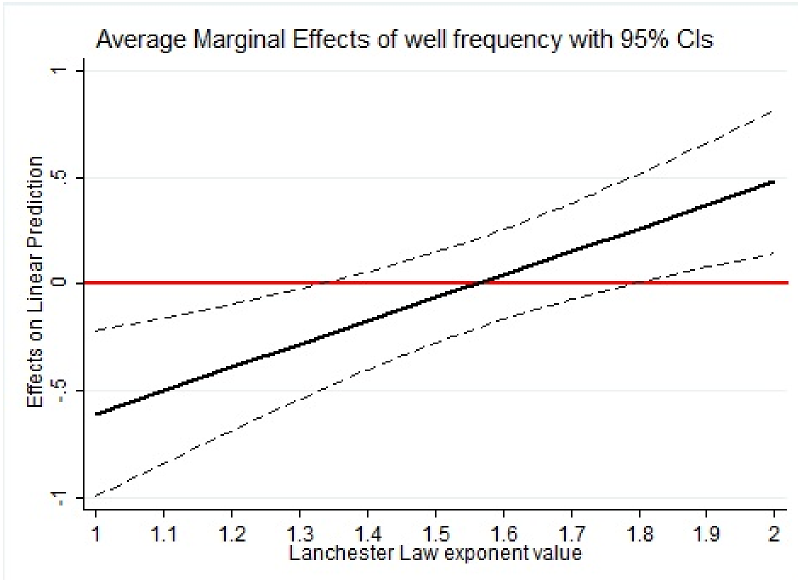
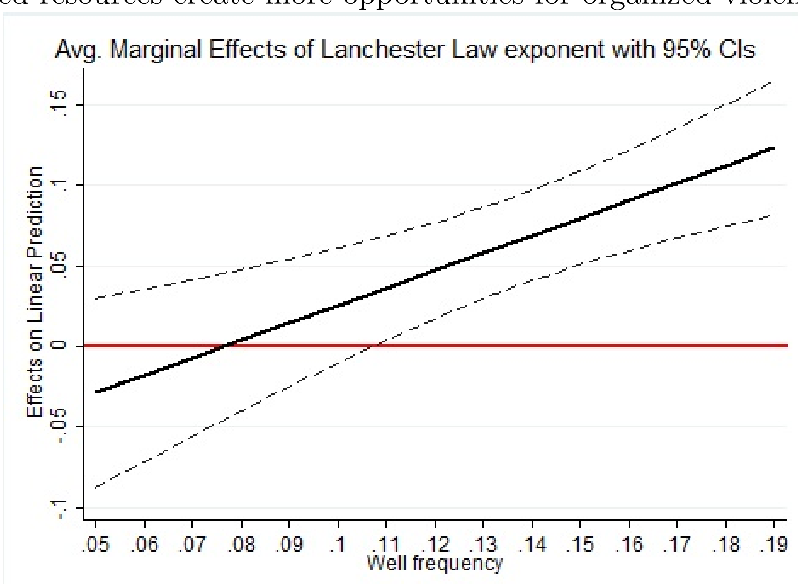


Figure 7: Looking at the same relationship as the previous figure from a different angle. More spot-located resources create more opportunities for organized violence.

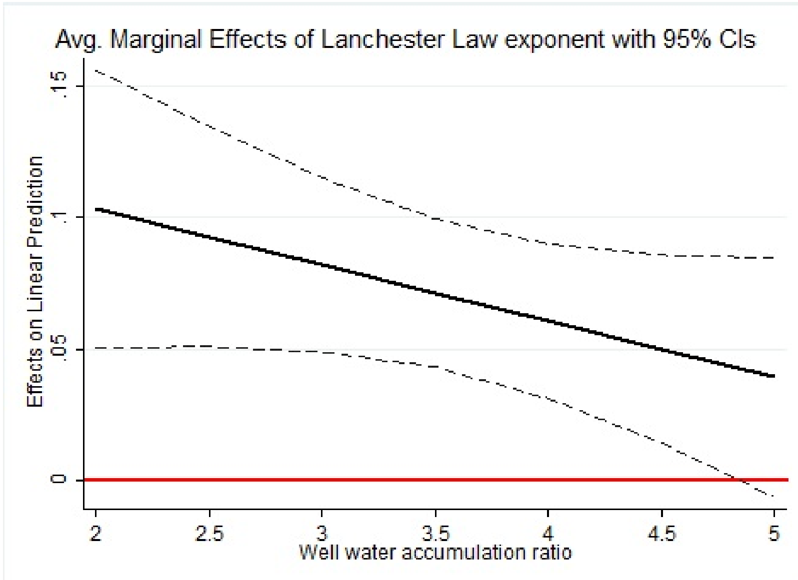


finding appears to affirm the general trend that more resources translate into greater cooperation and fewer resources translate into less. The negative, significant coefficient on the interaction term characterizing the relationship between well water accumulation rate and the Lanchester Law exponent suggests this is not always the case. While well frequency describes the number of such clustered resources over a terrain, the measure contains no information about each well's resource value, or the quantity of resources at that location. Well water accumulation rate does. Figure 8 depicts the marginal effects of the Lanchester Law exponent at levels of accumulation. The Lanchester coefficient is highly significant and positive at the lower band of the accumulation ratio, while steadily decreasing to the point of insignificance at the higher band. In this case, scarcity rather than abundance seems to be driving the evolution of cooperation. Specifically, concerted action appears to be vitally important when wells contain fewer resources. The relative scarcity of water increases their strategic value, rendering total control of a well a crucial strategic goal for agent groups. As more and more water at these sites is available, it appears that groups are more tolerant of each others' presence and the diminished threat of violent conflict between groups is giving individuals less incentive to invest their precious resources in cooperation.

Again, we must be careful to draw unconditional conclusions. The major advantage of a "thick" model is that it allows a richer, more nuanced model of the universe, and so the best conclusions are likely to be more nuanced as well. While the ability to cooperatively take and hold clustered resources is increasingly vital when such resources are scarce, there does appear to be a limit on how much individuals are willing to cooperate if the payoff ultimately is not there. Across most of the water consumption rate spectrum (u), the effect of the Lachester exponent is positive and significant, but the marginal effects are decreasing. At 0.1, the amount of water available, even when shared, may render survival sufficiently precarious that agents will prefer not to gamble their own precious shares on cooperative endeavors, but instead resort to defection against their own tribesmen.

In sum, clustered resources (water wells in this case) seem to cause greater cooperation

Figure 8: Concerted action is particularly important when wells contain fewer resources. This increases the strategic value of wells, rendering total control of them more important for survival. Though the Lanchester coefficient is positive throughout the entire range of the well water accumulation ratio, it is decreasing and non significantly different from zero at the higher end of the well water accumulation.

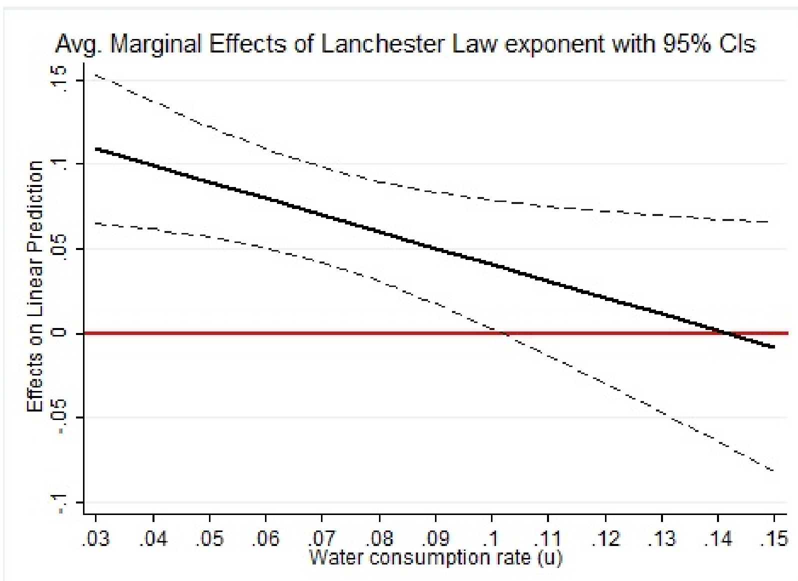


if such cooperation can be organized in such a way to enable groups of individuals to collectively control them. This effect gets stronger as such clusters become more common and increases yet further as the strategic value of each resources is diminished. That being said, individuals' willingness to cooperate with their respective groups in order to secure them is not absolute—if insufficient resources are there for them to ensure that their flocks can survive, even if their group dominates the location, cooperation tends to break down.

War frequency

Turning to the war frequency equation, we see additional evidence of the effects of resource clustering on conflict. The coefficient on well frequency is negative and highly significant, suggesting that when such resources are clustered in fewer locations they are more bitterly fought over. The water consumption rate is also significant and positive, suggesting that warfare is increasing with desperation. Also on the "demand side" of the equation is the *flock birthing rate*. At higher rates of reproduction agents' demand for new resources increases and

Figure 9: While the ability to cooperatively take and hold clustered resources is increasingly vital when such resources are scarce, there does appear to be a limit on how much individuals are willing to cooperate if the payoff ultimately is not there. Across most of the water consumption rate spectrum (u), the effect of the Lachester exponent is positive and significant, but the marginal effects are decreasing. At 0.1, the amount of water available, even when shared, may render survival sufficiently precarious that agents will prefer not to gamble their own precious shares on cooperative endeavors, but instead resort to defection against their own tribesmen.



appears to stir demand for new conquests. These three results are some of clearest evidence so far affirming the hypothesis that agents are motivated to cooperate with their peers in order to secure precious resources from other groups when survival is on the line. This finding, however, comes with the new qualification that the resources be clustered rather than homogenously distributed.

Table 16: 3SLS estimation results (2/3)

Variable	**Coefficient**	**(Std. Err.)**
Equation 2 : War frequency		
Average flock size	0.0100	(0.0888)
Flock reproduction rate	681.5029**	(98.0462)
Cost of reproduction (dowry)	63.1651**	(19.7006)
Cooperation	-51.9388	(39.8730)
Average tribe size	-3.3299*	(1.4481)
Agent birth rate	-503.3715**	(62.7681)
Deprivation tolerance	755.6206**	(116.1634)
Food consumption rate	-388.6403**	(53.8876)
Season length	-0.9659	(0.6099)
Lanchester Law exponent	21.3588**	(7.7782)
Migration rate	8248.7498*	(3491.4119)
Mate competition severity	16.0895*	(6.6704)
Max. Birthing distance	0.9796	(0.7140)
Striped LQ dummy	7.8382	(4.9235)
Population size	0.3958**	(0.0692)
Tribes count	-4.2655*	(1.8490)
Water consumption rate	317.5670**	(98.2175)
Well frequency	-353.4883**	(58.3641)
Water accumulation ratio	-2.5429	(2.2110)
Intercept	16.1032	(47.9630)

These results also suggest a number of other interesting relationships affecting the frequency of conflict. Surprisingly, the food consumption rate is not only *not positive* (as is the clustered, water resource consumption rate), but it is negative and highly significant. One possible explanation is that this is related to the "attrition". Slower food consumption rates imply that individuals and groups will be able to carry out the fight longer over water resources, exhausting local food supplies more slowly. Consistent with this view, higher levels of exhaustion tolerance appeared to allow agents to range farther, deeper into foreign territory and fight longer before they expire.

The effect of the Lanchester Law exponent is positive and highly significant. This is not surprising since it would tend to make warfare a considerably more viable strategy for groups when they find themselves in a situation where they enjoy local numerical superiority. Interestingly, while the Lanchester Law exponent does channel a latent capacity for cooperation into a specific form of collective action, the direct effect of cooperation is negative. The coefficient on cooperation is substantively large with equally large standard errors, such that statistical significance is only marginal. However, assuming the null is rejected one possible explanation is that higher levels of cooperation result in the emergence of local pockets of territory where potential invaders are successfully "deterred" by a cluster of highly cooperative tribesmen. Rather than pursuing the resource they occupy, the would-be invaders may turn elsewhere.

One surprising finding that was contrary to expectations was a negative, significant impact of mate competition severity. In the context of a multi-level selection model, one would expect that within groups defectors are "doing better", enjoying much of the benefits of high levels of aggregate cooperation, or cohesion, such as more land and weaker adversaries. As those defectors are increasingly advantaged in terms of opportunities for reproduction over cooperators within their group, you would expect that cooperation would decrease and the frequency of warfare along with it. These results, however, suggest that warfare decreases with mate competition severity. This would imply mate competition's effect on cooperation is not operative here. Indeed, mate competition severity showed no direct effect on cooperation. Whatever is the nature of the relationship, it must therefore be direct.

In separate analyses, I have tested for interactive effects with the Lanchester Law exponent, migration rate, war survivability, and resource availability and found nothing. One possibility is that greater internal competition simply translates into more intergroup competition. The precise mechanism for this remains unclear to this author, however it would appear that greater external competition influences both cooperators and defectors to be increasingly bellicose, even if cooperators end up paying the lion's share of the costs of battle. What could be the motivation? Aside from increased access to resources, these data suggest a couple other motivations for conflict. The dowry size variable is positive and significant, which could point to one possible explanation. When it costs a larger proportion of one's individual resources to reproduce, warfare is increasingly important. The coefficient on average flock size is not significant, so while warfare may not, on average, lead to greater flock sizes it might enable rapidly growing tribes to replenish their stocks faster by eliminating competition for a time.

Average tribe size

There is not a whole lot surprising in the average tribe size equation. Controlling for overall population size maximum group size, we still find some significant coefficients. Cooperation is negative and significant and war frequency falls just shy of statistical significance at the 0.01 level (2-tailed test). These results affirm the decision to incorporate a model of average tribe size in the system of equations, even if it primarily of interest as an explanatory variable in the other two equations. War survivability is not surprisingly positive since tribes are less likely to incur casualties. One interesting result is that negative and significant coefficient on the Lanchester Law exponent. This is likely because higher values of the Lanchester exponent disproportionately impart strategic advantage on the larger groups. In other words, when the Lanchester expononent is high there there appears to be selection pressures on group size at the group-level of the multi-level selection model.

3.5.2 Assessing the impact of heterogenous land quality

Not yet discussed, the above 3SLS analysis identified significant effects of land quality distribution on the evolution of cooperation. Specifically, the reader should draw their attention to three variables in the cooperation equation labeled *Quadral, Radial, and Striped*. These three dummy variables and the omitted variable *Homogenous* defined static, spatial inequity in terms of the lands overall quality, as described in the modeling section. Notably, all three

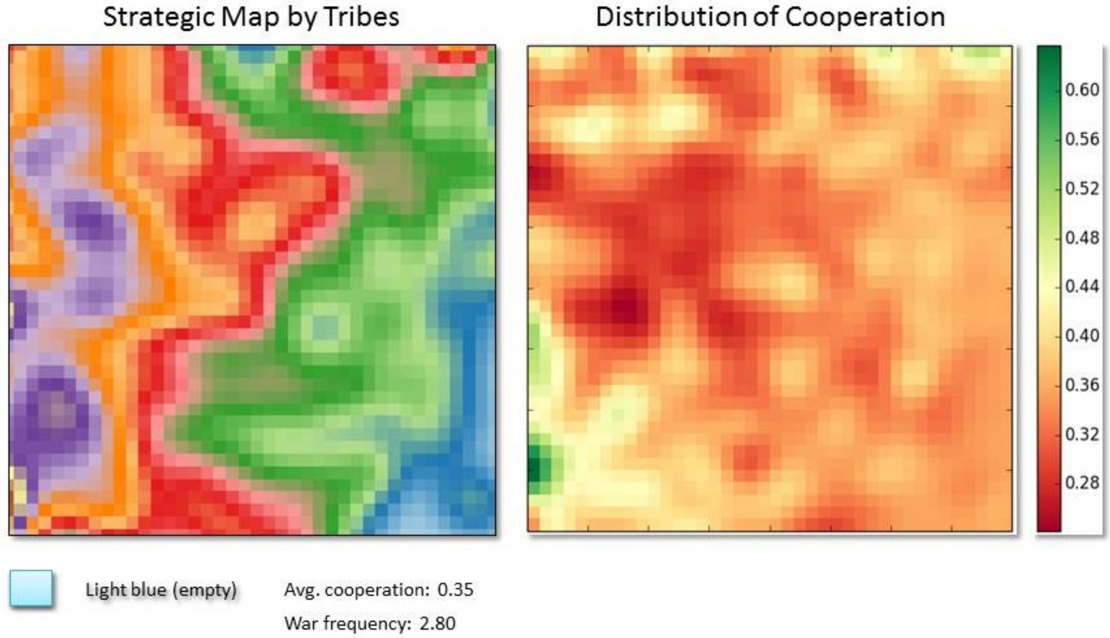
Table 17: 3SLS estimation results (3/3)

Variable	Coefficient	(Std. Err.)
Equation 3 : Average tribe size		
War frequency	-0.0097	(0.0063)
Cooperation	-16.5323*	(6.6320)
Population size	0.0342**	(0.0026)
Maximum group size	0.0666**	(0.0099)
Lanchester Law exponent	-1.5520†	(0.8102)
War survivability rate	25.8055**	(7.4237)
Migration rate	-280.4570	(339.4528)
Cooperative breeding bonus	-0.9636	(0.6067)
Seasonal extremity	0.2699	(0.2049)
Tribes count	-0.8878**	(0.0613)
Max. Birthing distance	-0.0837	(0.0658)
Agent birth rate	8.1209	(5.2668)
Intercept	5.7555	(5.9999)

conditions suggest that, on average, heterogenous land quality results in less cooperation. Though the effects were considerably less pronounced on war frequency, the striped condition does appear to be associated with a net increase in conflict at the 0.1 level of statistical significance. These averaged effects, however, cannot tell us if such heterogeneity resulted also corresponded to heterogeneity in the distribution of cooperation. In other words, while cooperation may decrease overall, it may very well increase on a local basis. This kind of spatial "interaction" cannot be assessed with the Monte Carlo dataset. To do so, it is necessary to assess individual runs of the simulation.

The Figures 10 through 15 are a series of heatmaps which can be used to view spatial variation on the relevant variables intuitively. Each were examples of "typical" runs of the simulation, where all parameters are set to their (observed) means, with the exception of the Lanchester Law exponent and war lethality. The latter two parameters were set at their maximum in order to ensure robust cooperation. Figure 10 (left) represents a "geo-strategic map" of the simulated world with a homogenous distribution of land quality after 2000 time periods. Area is color coded according to a unique identification number corresponding to the dominating the area. Since not every cellular location on the map is occupied it is

Figure 10: Homogenous land quality distribution



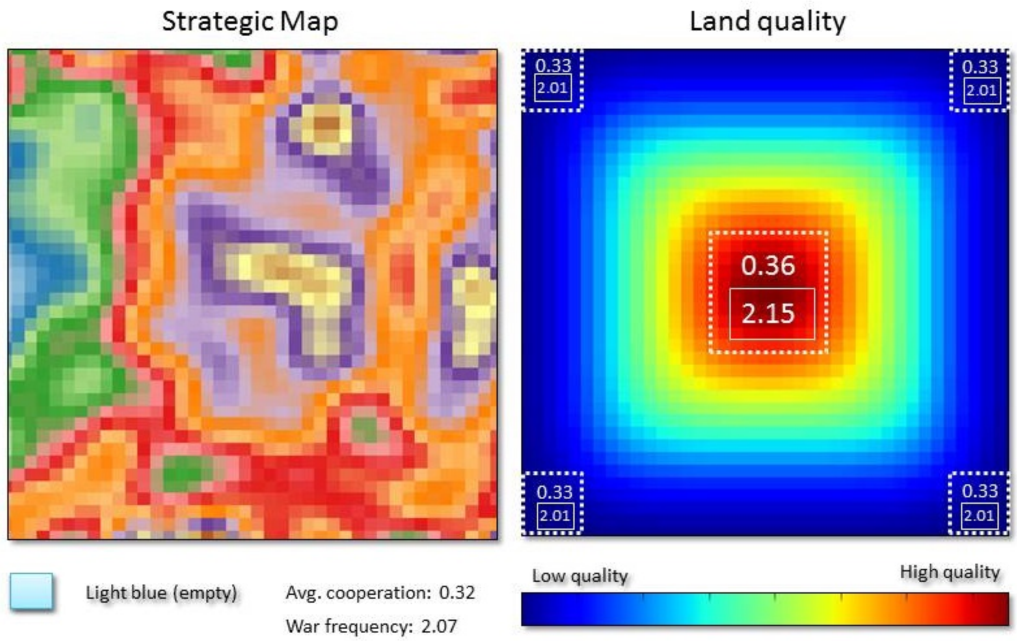
impossible to directly ascertain control of every area. However, in order to get a sense of how far each tribe's dominion extends some interpolation was applied. The lightest blue color indicates that no tribe exerts meaningful influence in that area. Some colors may not actually correspond to a specific tribe, but rather indicate a transitional "border zone" between two or more tribes. Figure 10 (right) is a heatmap distribution of cooperation. Again, since not all cells are occupied some interpolation was necessary. Prior to interpolation empty cells were set at the global mean. While this may result in some inaccuracies, it is still sufficient to get an idea of how cooperation is distributed spatial with respect to land quality. In order to help ensure correct interpretation, the each of the heterogenous land quality configurations are also represented with a basic map of land quality with some smaller sections cut out for statistical summary (see Figure 11, right).

In Figure 10 (left), clear demarcation of rudimentary "borders" between unique tribal entities have emerged. This alone is interesting since the computational model did not expressly provide for the emergence of boundaries, but rather they emerged organically as a result of many agents independent decisions. In the distribution of cooperation (right), we can see the contours along which clusters of relatively high (green) and low (red) cooperating agents correspond to tribal boundaries. This suggests the possibility of group-level variation in terms of cooperation—some tribes are more cooperative than others. Still, the apparent clustering (spatial auto-correlation) of like-types does not appear to follow any particular pattern. Like-types appear next to one another, but there does not appear to be any pattern in where those clusters emerge. Based upon the above regression analysis, our best guess would be that the cooperative clusters are occurring around wells, but the wells themselves are randomly occurring so it would not make this map appear any less random.

Now compare these results to those of the radially distributed land quality simulation in Figure 11. In the strategic map (left) we can see that tribal boundaries are clearly associated with land quality variation. To get an idea of how land quality is conditioning behavior, I isolate a 10 x 10 cell patch at the center of the map (highest land quality) and four 5 x 5 cell patches at the corners (worst land quality) and collect summary statistics. The two numbers in dashed boxes indicate the average level of cooperation (top) and the average number of fights in the 2000th time period standardized by local population count. Though the differences are not massive, it seems clear that the high quality areas are associated with both greater cooperation and more frequent conflict. These differences are visible in the cooperation map (see Figure 12).

One apparent limitation of the radially distributed land quality configuration is that land quality decreases from maximum to minimum in a distance of only half of the map. In comparison, the striped land quality configuration decreases from left to right along the entire length of the map's X-axis (see Figures 13 and 14). This has apparently allowed for more fine grained discrimination of the effects of land quality on cooperation and war frequency, though arguably at the expense of more realistic tribal borders. Here we see much stronger evidence of a positive links between *relative* land quality and both war frequency and cooperation. I emphasize 'relative' land quality because as the above regression analysis demonstrated these links do not appear to exist when land quality is distributed homogenously. In other words, whether we are all on good land or bad does not matter, but if one of us has better land than the other we will fight over it. Further, those who appear to be winning these fights appear to be the best cooperators.

Figure 11: Radial land quality distribution



The case of quadral land quality distribution is arguably the most intriguing. Measured cooperation and war frequency were subject to considerably more variance and it was necessary to repeat the simulation many times in order to reach a stable pattern. The values in each of the four 10 x 10 patches within Figure 15 are averages over 194 simulation runs with identical parameter configuration. For complete summary statistics see Table 18. Box plots of relevant contrasts are presented in Figures 16 through 19. Here an interesting inconsistency turns up depending on how you summarize the data. In the broadest sense we observe the same pattern of increased cooperation and violent conflict in the most sought after territories. In an absolute sense, the bottom portion of the map is higher quality than the top and we observe both more cooperation ($t = 6.24$, p-value < 0.001) and more conflict ($t = 10.91$, p-value < 0.001).

At the same time, the right side of the map is only on average higher quality than the left

Figure 12: Radial land quality distribution

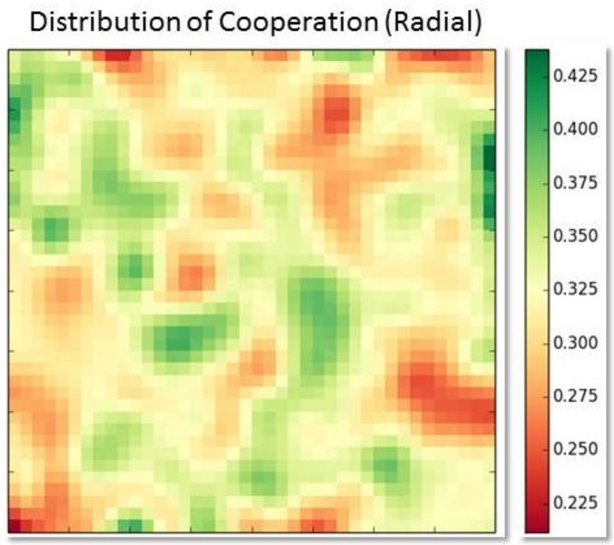


Figure 13: Striped land quality distribution

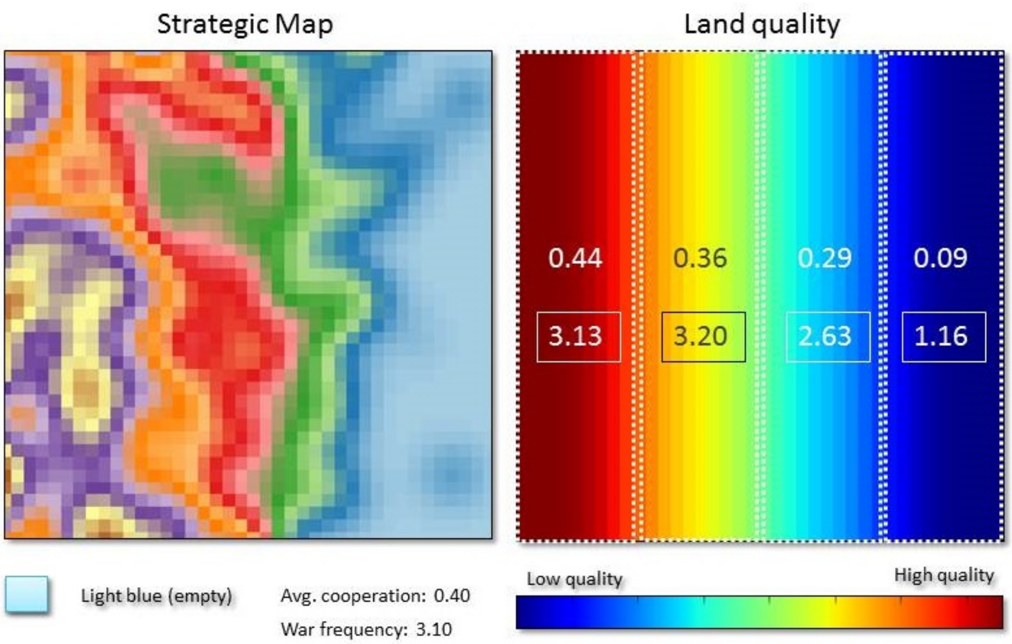


Figure 14: Striped land quality distribution

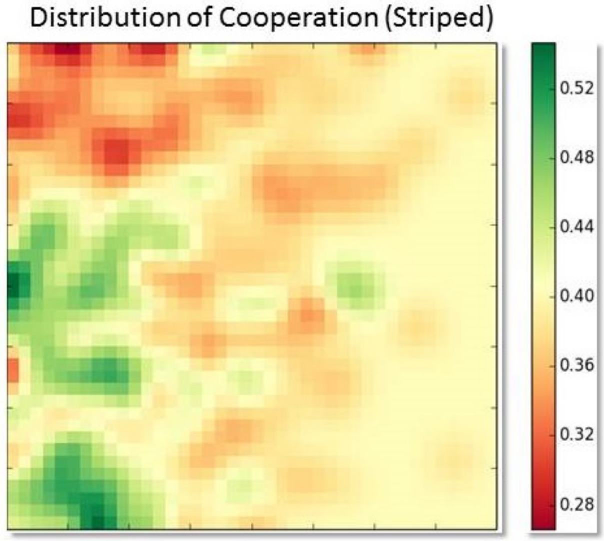


Figure 15: Quadral land quality distribution

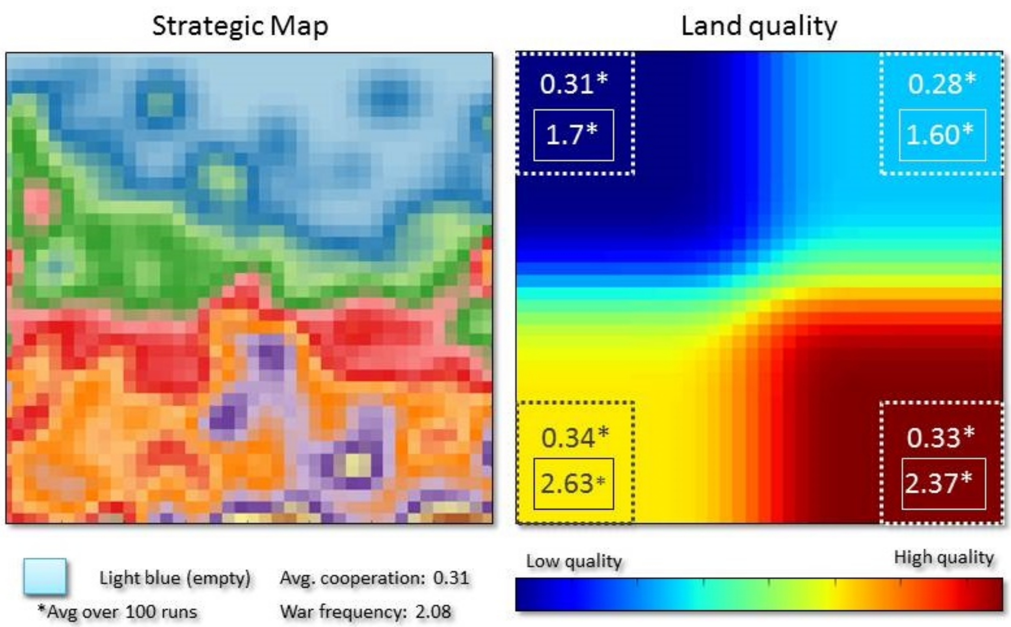


Figure 16: (Strictly) Higher quality land in the bottom hemisphere is associated with greater cooperation. This relationship, however, is not apparent in the (weakly) higher quality land in the right hemisphere.

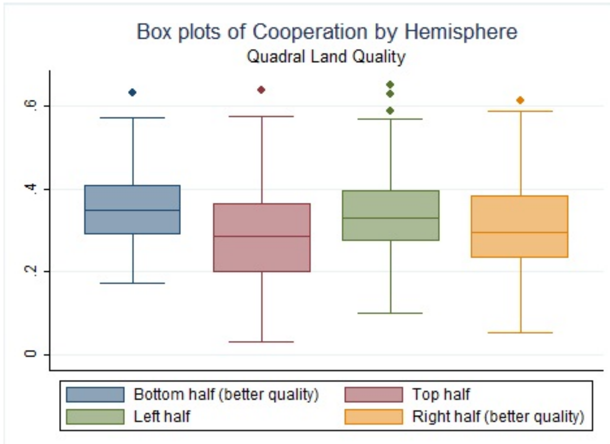


Figure 17: While the link between land quality and cooperation is muddied in the quandral land quality scenario, the link between war frequency and cooperation is sustained across all four hemispheric partitions of the map.

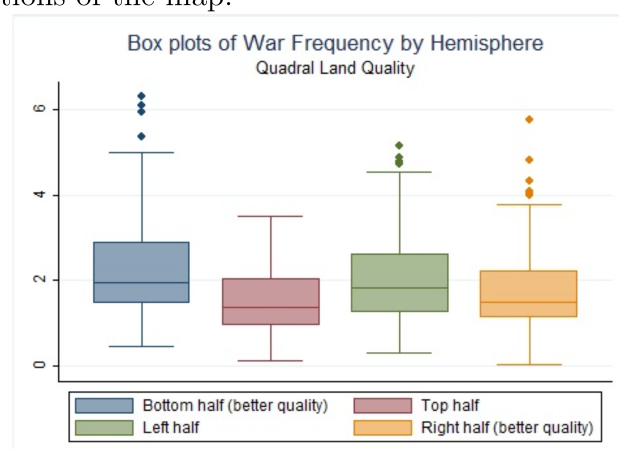


Figure 18: Although the bottom right quadrant contains richer lands, the link between land quality and cooperation is not apparent.

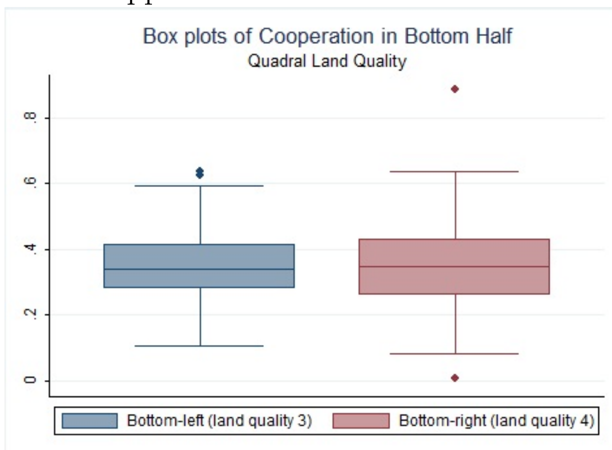


Figure 19: Although the bottom right quadrant contains richer lands, the link between land quality and war frequency is not apparent.

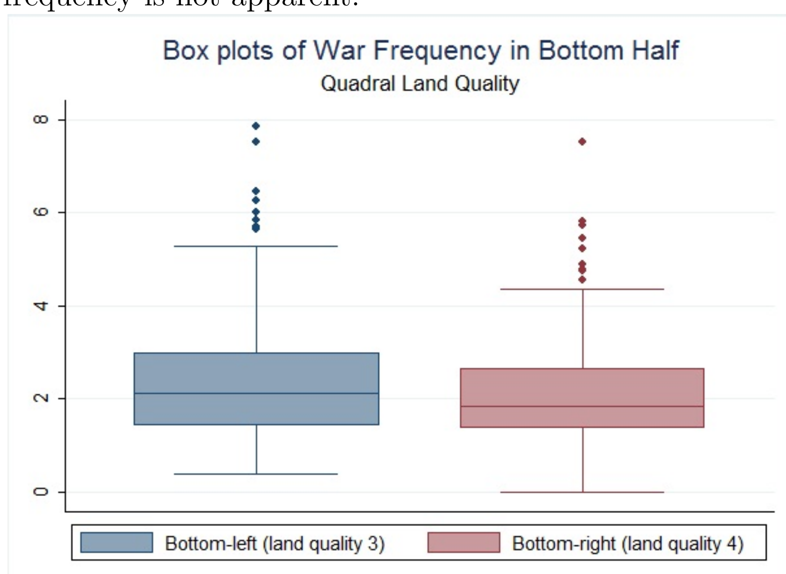


Table 18: Summary statistics of quadral land quality simulations with identical parameter specification

Variable	Obs	Mean	Std. Dev.	Min	Max
Land quality 4 cooperation (best)	194	.3485174	.1220114	.0083368	.8851862
Land quality 3 cooperation	194	.3502337	.0920462	.1078692	.6353916
Land quality 2 cooperation	194	.2693762	.1718228	0	.8130406
Land quality 1 cooperation	194	.3088337	.1530886	0	.9129829
Bottom half cooperation (best)	194	.3493756	.0827713	.172698	.6325235
Top half cooperation	194	.289105	.12125	.0323109	.6383979
Left side cooperation	194	.3295337	.0975421	.0994738	.6502725
Right side cooperation (best)	194	.3089468	.1153891	.0545775	.6135449
Global average cooperation	194	.3192403	.0790974	.1429368	.5123076
Land quality 4 war frequency (best)	194	2.134794	1.194191	0	7.52585
Land quality 3 war frequency	194	2.448339	1.378004	.375	7.859284
Land quality 2 war frequency	194	1.436202	.9544159	0	4.508333
Land quality 1 war frequency	194	1.613632	.9029058	0	4.531548
Bottom half war frequency (best)	194	2.291567	1.113575	.4688198	6.294787
Top half war frequency	194	1.524917	.760679	.1291666	3.492843
Left side war frequency	194	2.030986	.9984808	.3140966	5.155641
Right side war frequency (best)	194	1.785498	.9222744	.0375	5.764369
Global average war frequency	194	1.908242	.8185406	.6970298	4.673974

side and the pattern is reversed; i.e., the lesser quality left has both more cooperation (t = 3.39, p-value < 0.001) and more conflict ($t = 3.39$, p-value < 0.001) than the superior quality right side. How is this possible? If we look only at the best two quadrants of land we see that even though the lesser quality territory (bottom-left) has significantly more conflict ($t = 2.00$, p-value $= 0.024$), there tends to be *less* cooperation. While the differences in cooperation were too small to be statistically significant in a sample of 194, this alone is significant because every other pairwise comparison held up, even with Bonferroni adjustment for multiple hypothesis testing. In sum, the high levels of fighting on the left appear to be are driving higher levels of cooperation. However, the highest levels of cooperation are still occur on the highest quality land, while fighting decreases. One intriguing explanation is that the higher levels of cooperation are affording the most powerful tribes on the best land a rudimentary level of *strategic deterrence*. With more resources, their numbers are larger, which combined with higher levels of cohesion are able to deter enemies from encroaching on their territory.

3.6 Discussion

The computational model presented in this research yielded considerable insight into the emergence of primitive social identities and intergroup conflict. Previous research on cooperation has focused on high-level, game theoretic abstractions. "Thick" models always bear the risks that come with complexity; there is more to go wrong, more to be wrong about, and the challenge of interpreting results can grow to be as inherently artistic as the task of interpreting real-world data. To paraphrase Albert Einstein, scientific models should be "as simple as possible, but not simpler". Even in its relatively simplicity, the present research gives some hint at how immensely complex the evolutionary history of human sociality likely was. Parsimonious models of cooperation accomplished the already monumental achievement of showing us that this trait, arguably the quintessence of human nature *could* have evolved by natural selection. This realization has forever changed our sense of who we are and liberated us from the presumption that something as complex as humanity could have only been the work of a creator. What these models cannot do, however, is tell us *how* it happened. It is unlikely such knowledge will ever truly be secured. However, thick models allow us to gain a deeper understanding by building small universes of our own.

The present research suggests a more nuanced picture of how social dynamics, both cooperative and conflictual, are heavily conditioned by the environment. Somewhat disappointingly, the dynamic components of the climate model underlying this simulation did not appear to influence outcomes of the simulation. Still, much could be gleaned about the roles of relative scarcity, abundance, and resource distributions, from which we may make useful inferences about social responses to ecological change. Scarcity in a broad sense did appear to reduce cooperation, though agents will cooperate more if resources are clustered. Further, scarcity of such resources will actually increase cooperation rather than inhibit it. At some point, however, scarcity may be so severe that cooperation will once again break down. Clustered resources were also significantly associated with conflict. Agents in this simulation were inclined to fight for clustered resources but not those which are homogenously distributed. Interestingly, faster metabolisms were also associated with more cooperation. Larger consumption rates relative to the speed at which resources are replenished probably entail larger ranging areas, increasing the payoff to members whose groups control larger territories.

One of the strongest confirmatory evidences of the hypothesis that intergroup conflict was a driver of the evolution of cooperation is the massive influence of the Lanchester Law exponent. The Lanchester Law is a key variable that directly translates within-group cooperation into a group's effectiveness at advancing their collective interests through warfare. In sum, the better agents are able to coordinate their tactics in battle the greater demand there was for a cooperative 'gene'. This finding is especially interesting from the perspective of human evolution because it also entails a selection pressure on certain cognitive faculties that facilitate more complex coordination. In other words, these data suggest that realistic conflict between groups could have been simultaneously a driver of human intelligence and cooperation, and by extension underly all social complexity.

These three variables—cooperation, coordination, and intergroup conflict—are tied together. Some latent capacity for coordination gives an advantage to those groups who can muster it, while opening up the possibility of organized warfare. Warfare, in turn, drives even further selection on cooperation than can enhance coordination and altruistic sacrifice that may enable a group to gain not only *adaptive advantage* in the evolutionary sense, but *strategic advantage* in the jargon of peace and conflict theory. Dominance ensures primary access to the best resources and at sufficiently high levels of efficiency may facilitate strategic deterrence. The Lanchester Law exponent not only promoted cooperation, but also bellicosity. This ability makes warfare a viable group-based strategy for individuals. This was especially true when resources were clustered.

Good land was also shown to be worth fighting for. This finding was fascinating because the concept of 'good' appears to be strictly relative. If all land is good, we get along. If all land is bad, we get along. If only one of us has good land, we will fight for it.

This observation strongly supports the argument that intragroup cooperation is linked to intergroup competition via a multi-level section mechanism. The group that controls the superior territory will be grow faster, and those groups constituted of members "possessing in high degree the spirit of patriotism, fidelity, obedience, courage, and sympathy... always ready to aid one another, and to sacrifice themselves for the common good" would be able to take it.

4 Climate Change and Social Conflict

4.1 Introduction

In the preceding (two) studies, I used agent simulation to investigate how environment may influence the evolution of social dynamics. A key premise of the second simulation was that once human groups begin to emerge, the presence of "outgroups" becomes an aspect of the environment. These models establish the micro-foundations of what could be the basis of an individual-level theory of intergroup conflict. Such a theory would hold that insofar as individual's are reliant upon collective action for access to resources, competition for the same resources from other groups will motivate individuals to further increase their investment in social living. It follows then that changes in the characteristics of resources such as energy density and dispersion should impact should impact this decision. In more traditional sociological terms, I theorize that changes in the distribution of resources will affect the salience of social identities around which collective action (for the attainment of those resources) is organized. This theory leads to the prediction that as resources fluctuate, conflict is likely to occur along ethnic lines, especially in parts of the world where ethnic ties are the dominant community organizing principle.

In this chapter, I test this hypothesis the Gridded Environmental Conflict in Africa Dataset (GECAD), a new dataset for the investigation of potential impact of climate change on political instability and conflict. Climate scientists warn that as the planet warms, extreme weather is likely to increase, including longer and deeper droughts and stronger storms (IPCC, 2014). According to the US National Intelligence Council Global Trends 2030, this is likely to result in degraded agricultural productivity, tightened global food supply and ultimately undermining food security, especially in already impoverished regions. While leading national and international institutions have expressed concern over a possible nexus between climate change and political instability[15], scholarship has struggled to demonstrate

[15] Also see the US Department of Defense Quadrennial Defense Reviews 2010 and 2014, EU Council (2008), and the National Intelligence Council (2012).

such a connection empirically. While it appears we are moving towards a consensus that the relationship exists, relatively little is understood about the mechanisms through which climate is causing conflict. One reason for this is that this is a exceptionally difficult question that strains existing datasets and statistical tools to their limits (and arguably beyond). In addition to testing a novel explanation for the moderating role of ethnic identity in material conflict, this study using GECAD may also contribute to the ongoing debate whether—and importantly how—, climate change has implications for peace and conflict.

4.2 Background

Despite some holdouts of anthropogenic climate change denialism, there exists a near-universal consensus within scientific circles that the Earth is undergoing warming effects inexplicable by naturally occurring, cyclical climatic processes (IPCC 2007; U.S. Climate Change Science Program 2008). Specifically, greenhouse gas emissions associated with human activity are enhancing the atmosphere's greenhouse effect, causing the planet to retain more of the sun's energy in the form of heat. Consequently, scientists do not expect a regression to the mean of past global temperatures. In the Spring of 2014, a draft report of the Intergovernmental Panel on Climate Change expressed deep concern that rising temperatures pose substantial challenges for human and geopolitical security this century (IPCC, 2014). Thus far, impacts on the more temperate zones of the northern hemisphere have been sufficiently minimal that those properly motivated may ignore them or write them off to normal, cyclical climate patterns. At the same time, scientists show that the impacts of global warming have been more pronounced in the warmer, sub-tropical and equatorial regions—regions which also have a tendency to be the most dependent on agriculture and possess the least governmental capacity to ameliorate the worst impacts disturbances (IPCC 2007). Therefore, if security implications of climate change exist it seems likely that such effects would be observed first in the third world.

The hypothesized relationship between resource scarcity and conflict has a long, well-credentialed intellectual history. In the *Leviathan*, Thomas Hobbes reasoned that the searing "pain of privation" was an inevitable fact in a world where appetites always exceeded supply. Humans desperate to assuage the pain are driven to all manner of gruesome atrocity, rendering society impossible. Such a life was so "nasty, brutish, and short", that tyranny became an attractive alternative if it meant some semblance of security. In 1798, the English cleric Thomas Robert Malthus published *An Essay on the Principle of Population*. In what would later be called the Malthusian Principle, he observed that while population tends to grow geometrically, the means of subsistence grows arithmetically. Since population cannot exceed the means of subsistence, population is necessarily repressed "by misery and vice." By implication, the Malthusian Principle predicts that when resources are plenty, population will grow until scarcity, brutality in tow, re-emerge. According to the same reasoning, conflict would accompany a sudden drop in the availability of resources.

More recently, concern over the relationship between resource scarcity and violent conflict was renewed with Gardin Hardin's seminal paper The Tragedy of the Commons (1968), and the emergence of neo-Malthusianism. Since the 1970s, it has since grown to become a vigorously debated topic in the field of security literature. More recently, fears the world will struggle to adapt to anthropogenic climate change have focused speculation on future global security challenges. Yet despite prolonged interest, the academic jury remains unsettled whether there is a connection.

Concern for the rising security implications of climate change have not remained confined to academia. For the first time, the US Department of Defense in its 2010 Quadrennial Defense Review declared that climate change could have significant geopolitical impacts around the world, contributing to poverty, environmental degradation, and the further weakening of fragile environments (Department of Defense 2010). This concern was again emphasized in the just released 2014 review. The US Navy linked CNA Corporation commisioned a panel of generals and admirals to assess security implications of climate change. They concluded that climate change will act as a *threat multiplier*, exacerbating existing conflicts over water and material security, destabilizing already fragile regimes and leading to large-scale human migrations (CNA Corporation 2006). The European Commission reached similar conclusions (EC 2008) and a 2008 report by the US National Intelligence Council warned that perceptions of a rapidly changing environment could dispose nations to take unilateral actions in order to secure resources, territory, and their interests (NIC 2008). Such resources may include fresh water resources, arable land, or newly opened regions of the Arctic Circle.

Within political science, the debate has generally run along two concerns. First, it is argued that increasing temperatures and changing patterns of precipitation could upset agriculture (Homer-Dixon and Blitt 1998; Purvis and Busby 2004). Empirical evidence to support these fears is mixed. For example, Hendrix and Glaser (2007) find that conflict is more likely in climates already ill-suited for agriculture. Just such a location is the African Sahel. Using a fascinating combination of climate data and court cases from the Mopti region of Mali, Benjaminsen, Alinon, Buhaug and Buseth (2012) find no connection. Meier, Bond and Bond (2007) find no relationship between precipitation and conflict among the pastoralist peoples of the Horn of Africa, but also find a positive effect of increased vegetation. This discrepancy could be a result of problematic data and is in any case difficult to interpret. It does, however, implicate a relationship between the productivity of the environment and conflict.

Hendrix and Salehyan (2012) looked at rainfall deviations over 20 years in Africa and find that extreme weather years, in either direction, are strongly associated with violent conflict. This implies that the connection between climate change and conflict not necessarily a response to drought, but to the economic disruption which can follow any kind of extreme weather. Koubi, Bernauer, Kalbhenn and Spilker (2012) are unable to discern a climate connection, but do find that poorer countries are more likely to turn violent in response to economic shocks. Raleigh and Kniveton (2012) offer a compelling insight into why we are likely to observe these kinds of conflicting results. They point to the problem of data over-aggregation (which I discuss in greater detail below). Quite reasonably, they argue that the large units of analysis the more state-driven political dynamics of large—scale conflicts drown out the more nuanced causes of small-small scale conflict, where social linkages with the physical environment are far more immediate and direct.

The second major concern is that shifting agricultural patterns and rising sea levels could create hundreds of millions of environmental refugees. Some two-thirds of the population lives within 100 km of a coastline. Lower-lying regions are vulnerable to seasonal, event related flooding and even total submersion. One particularly troubling hotspot is the low-lying, riverine country of Bangladesh. The highly fertile alluvial soil has historically supported a disproportionately large population; today, Bangladesh is the most densely populated country in the world. More intense seasonal monsoons and even modest sea level increases could cause its hundreds of rivers to burst their banks, pushing tens of millions of people off their lands. Environmentally induced migration can then, in turn, increase competition for resources at destinations. In the case of Bangladesh, the most likely destination would be the already impoverished east of India. Because we have yet to definitively witness many such climate change-induced migrations, these claims are difficult to assess empirically. It is hardly contested that migration is a major source of conflict. From Exodus to the "Zoot Suit Riots" of 20th century United States, migration and conflict have gone hand-in-hand. The resultant conflict following large-scale migrations of the last century on the sub-continent are well studied (see Rajan 2011 for comprehensive examination). These ethno-religious fires still burn, particularly in the northeastern Indian states of Gujarat. In a bold attempt to catch a glimpse of the future impacts of climate change, Reuveny (2007) finds that the migration-induced conflict is most likely to occur in developing countries who lack the capacity to absorb the new population, giving some credence to the view.

Outside of political science, a steadily growing body of research is discovering how climate change has contributed to social, political, and military instability in the past (Hodell, Curtis and Brenner 1995; Zhang and Brecke 2007). These studies generally present a Malthus-inspired argument that temperature variation causes instability in land-carrying capacity (as measured by agricultural production). Decreases in agricultural output compounded by growing populations, in turn, can make warfare an adaptive ecological choice. There is a long, empirical record of climate-induced instability with consequences for civilization. Using high-resolution, reconstructed paleo-climate data, Polyak and Asmerom (2001) and others have identified correlations between prehistoric cultural collapses and agricultural failure (Weiss and Bradley 2001). Zhang and Brecke used a set of global climate proxies and showed that the war has historically correlated with cyclical climate change since 1400 C.E. Some more recent studies have focused more directly on the link between global temperature and agricultural yields in key regions of concern, such as Africa Lobell and Burke (2010); Dell, Jones and Olken (2008). Following the argument to its logical conclusion, Hendrix and Salehyan (2011) and Burke et al. Burke, Miguel, Satyanath, Dykema and Lobell (2009) look beyond intermediary outcomes and examine directly the relationship between climate change and increasingly socio-political unrest in a modern context. They predict that anthropogenic climate change is likely to result in a dramatic increase in violent conflict and political instability over the course of this century.

Despite such deep intellectual roots and the attention of the world's most powerful political and security institutions, the reality of what lies beneath them has remained a vexing question. Optimists are no doubt encouraged by a general trend away from conflict globally, despite steady warming. Conflict in Africa reached its pinnacle in the early 1990s in the wake of the so-called "Third Wave" of democratization and disruption associated with the Washington Consensus reforms (Human Security Report 2012; Buhaug 2010; Theisen et al 2011). The reasoning seems sound, so perhaps the problem lies in the data? Measurement challenges have long plagued the empirical conflict literature. An analyst must inevitably make decisions over what, precisely, constitutes a conflict. There is no naturally correct answer; it is an informed judgment based largely on what the analyst is interested in. For example, Buhaug's 2010 study focuses on the frequency of new onsets of national-scale conflicts—in particular civil wars in African states. As pointed out my Raleigh and Kniveton (2012) , however, conflicts of that magnitude tend to be complex and are not readily attributable to acute causes. Rather, these authors hypothesize that if a nexus between climate change and conflict exists, it is more likely to be discovered at the level of localities, where the relationship between communities and their environment is most “intimate and direct”. Within a dataset aggregated at the level of nation-state, this category of localized conflict is likely to fall below to threshold of detection.

There is a growing chorus of voices from both academia and journalistic circles that this precisely what is happening. One such case involves changing patterns in the customary practice of cattle raiding among the pastoralist tribes of the African horn. This practice has deep cultural roots in the region and has been observed at least since the 19th century when anthropologists began to take an interest in such behaviors (Gray et al, 2003). Local cultures have historically viewed participation in cattle raids as a rite of passage for young men entering adulthood. It provides an opportunity for them to distinguish themselves as being courageous, bring honor to their clans and families, and to secure a dowry allowing them to marry (Richardson, 2011). While violence has always been an integral feature of this practice, first hand reports claim that these low-scale conflicts are intensifying and becoming increasingly deadly (Parenti 2011; Leff 2009; IRIN, 2009). These authors point to several interacting factors, including ill-suited land-use policies rapidly exhausting soils, which is further exacerbated by unprecedented drought. The result is extensive desertification and the diminution of the vast territories that make a pastoralist economic modality viable in this arid region. Herders have become reliant on raiding to replenish dwindling flocks and secure bride prices and are ranging beyond their traditional lands, placing them at odds with sedentary agriculturalists. When two distinct sub-national groups come into conflict the risk of escalation to wider scale instability increases. For example, the ongoing civil war in Sudan (and South Sudan post-2011) pitting its predominantly Arab north against its sub-saharan Black south is believed to have roots in drought-induced land disputes between semi-nomadic herders and sedentary agriculturalists (**?**Bechtold 2009).

The concern that climate change may lead to increased conflict does not exist in a vacuum. By this I mean that we have observed a variety of situations where environmental degradation has beget political instability and sometimes violence. The recent film Captain Phillips, which depicted the pirate hijacking of a commercial shipping vessel off the coast of Somalia, offered some insight into the desperate economic conditions that drive this behavior. In particular, international fishing fleets have depleted Somali fisheries leaving its own fishermen in a state of desperation (Daxecker and Prins, 2013; Sone, 2010). Two other examples from the African continent include the oil-dilapidated south of Nigeria, where the dense mangrove forests have long provided a living to the inhabitants there. Oil industrial pollution has dramatically affected the viability of communities and led to the formation of localist insurgent groups, such as the Movement for the Emancipation of the Niger Delta, or MEND (Ibeanu 2000; Onduku 2001; Opukri and Ibaba 2008). As well, booming demand for rare-earth metals and minerals has precipitated so-called "land grabs" by large international firms. These land grabs are large-scale acquisitions of metal and mineral rich land and account for more than 2/3rds of foreign direct investment in Africa (Chatham House). Such acquisitions frequently involve the uprooting of entire communities and firms have a mixed record of following through on promises to offer compensation (Peters and Kambewa 2007; Peters 2013). The result are large numbers of environmental refugees who often end up migrating to already congested cities with few prospects for employment and stressing delicate infrastructure.

These concerns have motivated a growing number of more nuanced datasets and specialized methods within the empirical conflict literature. Raleigh and Kniveton (2012) attempt to circumvent the problem of overaggregation by focusing on small-scale conflict within a more confined area in East Africa. Rather than expanding the scope of the study over time, the authors observe this one area over time. Their evidence suggests that not only do conflicting forcefully compete for dwindling resources, but an abundance of resources may spur violent opportunism. Hendrix and Salehyan (2011; 2012) affirm this result. Too much rain can be as detrimental as drought. Employing two distinct research designs, the authors find violent conflict in sub-Saharan Africa is associated with especially wet years as well as dry years. Flooding can be highly destructive to infrastructure, transportation, goods and service flows and crops. Floods can contaminate existing water supplies with deadly and debilitating waterborne diseases. On the whole, almost all countries in the region lack the basic economic and political capacities to effectively develop and manage their fluctuating water resources. Hendrix and Salehyan further speculate combatants may be more likely to make trouble if dense foliage is available to provide cover, or if mudslides wipe out infrastructure preventing the government from responding to outbreaks of violence in remote areas.

Most recently, Hsiang, Burke and Miguel (2013) published an impressively scoped meta-analysis of 60 individual studies on environmental change and human aggression in the journal Science. The breadth of the study ranged from the rise and fall of civilizations to interpersonal interactions, such as the likelihood of a Major League Baseball pitcher throwing at a batter. According to their findings, temperature was significantly associated with violence at any level of analysis, from interpersonal to intersocietal. It is worthwhile to point out that these authors are econometricians, not conflict scholars. While their findings are difficult to challenge on empirical grounds, conflict scholars such as John Busby and Idean Salehyan have critiqued the study as overbroad, sacrificing too much detail to get a handle on potential causal mechanism. As Salehyan pointed out, "It's hard to see how the same causal mechanism that would lead to wild pitches would be linked to war and state collapse" (Morello 2013).

In this Spring of 2014 the IPCC released the AR5 Working Group II report, which for the first time includes a chapter on human security. The authors of the report were careful to emphasize they could state the existence of a relationship between climate change and conflict only with medium confidence (IPCC 2014). Now does not mean we should ignore the remarkable headway into what is truly a challenging empirical question. One obstacle to progress is the problem of aggregation. It seems no matter how we slice the data, we leave ourselves vulnerable to the ecological fallacy. When data is overaggregated, as what I argue is the case when data is aggregated at the level of nation-state, we run the risk of assuming what is true of the whole is also true of the part. Small-scale environmental conflict we function differently than large-scale ones—and as Raleigh and Kniveton emphasize, there is good reason to suppose they do. On the other hand, by focusing on a single locality we are obliged to make the unreasonable assumption that conflict here is unrelated to events occurring elsewhere. For example, if we are supposing that food shortages lead to instability, it is reasonable that a food shortage may be a consequence of events occurring in other parts of the same country or even the world.

4.3 The GECAD

Studying the relationship between climate change and violent conflict empirically, particularly in sub-Saharan Africa, is a challenging endeavor. Data is plagued with issues of measurement, definition, zero-inflation, small samples, and unreliable data reporting mechanisms. Major data sources for studying war currently available to political scientists, such as the Correlates of War (CoW), Penn World Tables and the World Banks African Development Indicators, store data points at the state-level of analysis. Information at this level may be suitable for economically and politically advanced states, but this may not hold for developing states which frequently lack adequate capacities for regular, objective data collection and management.

The assumption of reliable data collection in undeveloped countries seems highly suspect. As one illustrative example, former Sudan (now Sudan and South Sudan) occupied a territory roughly a third the size of the contiguous United States, with a national budget a third the size of that of the state of New Jersey. How are we to assume that a regime based in Khartoum which only meaningfully exerted power beyond its hinterlands is able to collect reliable data from the Darfur? Measurement error is not the only threat to inference in state-level data; we are also susceptible to ecological fallacy. Continuing with the preceding example, it is unclear what the sovereign dominion of Khartoum means in practical terms in Darfur, or what the dominion of Kinshasa, Congo (a country with a GDP of roughly 15.3

Figure 20: Minimally distorted, relative size of the contiguous United States, Ethiopia, and the DR Congo

billion USD in 2010) means nearly 1000 miles distant from the capital at its border with Uganda (US State Department of African Affairs).

If the national government does not meaningfully exert any governing influence in a region, then nationally aggregated statistics seem inappropriate for explaining events there. As Buhaug and Lujala (2005) point out, this problem plagues scholars of ethnic and civil conflict. Many of the most commonly proposed variables explaining civil war, such as political, economic, cultural, and demographic attributes are measured at the state level. Yet these aggregated measures may, in fact, provide little information about the facts in specific regions. In explaining ethnic and civil conflict, the information we lose at such locations beneath the country level is likely to be important, leaving our conclusions subject to the ecological fallacy.

Data disaggregation using geographic information systems (GIS) has emerged as a powerful alternative approach to studying civil war. The first study to my knowledge was conducted by Buhaug and Rød (2006), wherein they arbitrarily broke apart Africa into 100km by 100km cells. Using georeferenced conflict data, they overlaid the map with polygon-shapes demarcating regions of peace and conflict. They added additional layers of shapes representing spatial distributions of key variables, such as population density, distance from the capital, roughness of terrain, and the presence of gemstone or mineral rich fields, and found that conflict-ridden areas covaried with them.

In regard to methodology they write,

> *"Our central contention is that whenever we investigate theories of civil war that have an element of geography, we should seriously consider abandoning the habitual country level of analysis in favor of a disggregated approach. Otherwise, we are likely to fall prey to the ecological fallacy by explaining local phenomena from aggregated data".*

Yet despite strong methodological justification for data disaggregation, a Google Scholar search produces only a single study in which the approach to study the relationship between climate change and conflict. Raleigh and Urdal's (2007) monumental study examines the effects of land degradation and water scarcity, which are presumed to be the result of climate change. Contrary to expectations, they find these variables had no direct effect on violent conflict, but established a firmer basis for explanations based upon political and economic causes.

While an undoubtedly innovative study, the research design had several limitations that could have resulted in underestimation of the effects of environmental variables. First, while the data structure successfully captured geographic variance across the several included environmental variables, it is not strictly speaking the geographic variance of these parameters we are most interested in. Local economies have ways of adapting to whatever the local ecology supports. For example, pastoralism is an economic system evolved to thrive on already marginal environments. Rather, what we are most interested in is variance in the environment over time (not space). It is the nature of climate change to upset economic systems adapted over time to prior conditions. Political instability is most likely to occur following a disruption of this delicate balance between human society and nature. The Raleigh and

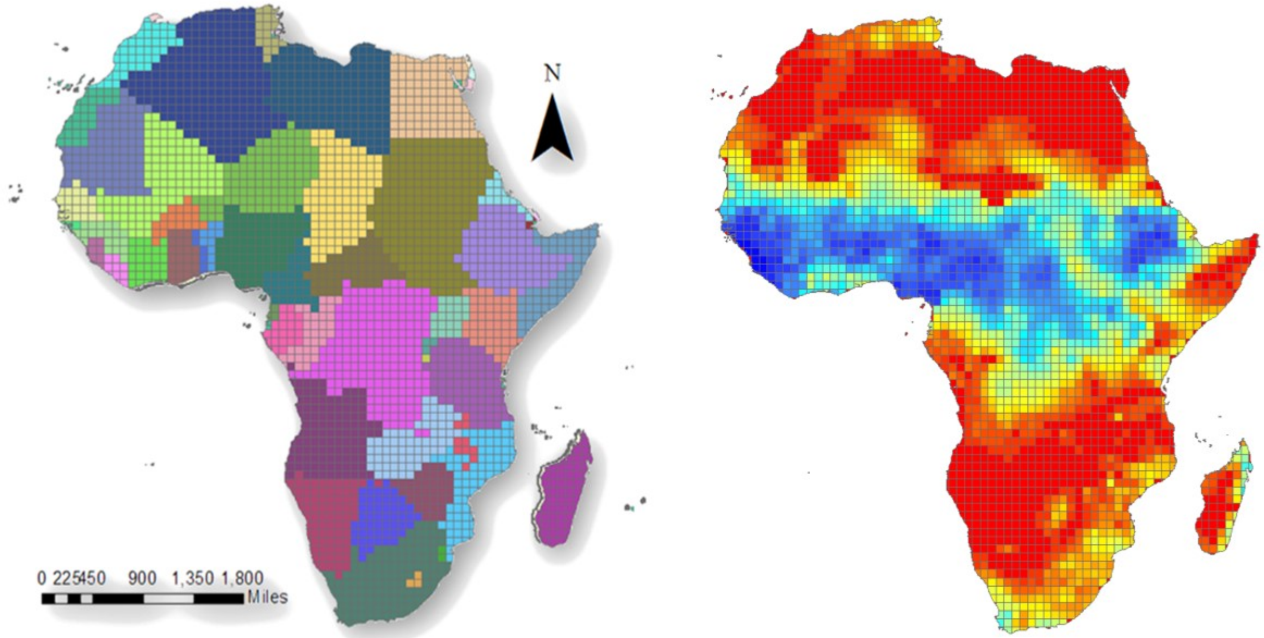
Urdal data, however, is not optimized to capture these [delta] changes.

Building off of these pioneering efforts, I have constructed the Gridded Environmental Conflict in Africa Dataset (GECAD). The principle goal of GECAD is to create an event dataset allowing researchers to test hypotheses concerning environmental drivers of conflict and instability in a way that is robust to many of the above challenges to inference. To achieve this, GECAD expands on the gridding technique pioneered by Buhaug and Rød and Raleigh and Urdal. The process begins by overlaying a 1 decimal degree by 1 decimal degree grid, or "fishnet" in GIS jargon over the continent of Africa. These cells are serve as an arbitrary unit of aggregation, allowing for summary of virtually any dataset with a geographical reference. While technically arbitrary, it should be noted that I adopt this valley in keeping with Buhaug and Rød (2006). Further, like states these units are persistent in time. This allows for observations to be collected repeatedly and summarized over any arbitrary unit of time, as in a longitudinal panel. In building GECAD I sought to use the highest quality, validated climate data publically available. Within the earth and atmospheric sciences, much of this data is kept at monthly intervals, which the GECAD inherits. Therefore, the units of analysis in GECAD is a 1 degree X 1 degree cell-month. In total, there are 2853 cells, or panels, observed over a duration of 216 months. This amounts to 624,672 unique observations. Figure 21 depicts the resultant map of Africa colored according to nation state (left) and precipitation (right).

4.3.1 Dependent Variables

GECAD's gridded structure creates a flexible platform for combining diverse datasets in virtually any format, so long as some special reference exists that can locate the data on a map. The principle dependent variables are taken from several popular event datasets. These include the Uppsala Conflict Data Program's Georeferenced Event Dataset and the Global Database of Language and Tone (GDELT). While not used in the present study, GECAD also includes events from the Strauss Centers Social Conflict in Africa Database

Figure 21: GECAD cells by nation state (left) and by precipitation (right)



(SCAD), and the Armed Conflict Location and Event Data Project (ACLED).

Global Database of Language and Tone (GDELT)

GDELT is a machine-coded dataset maintained by the tireless Kalev Leetaru of Georgetown University, which in its entirety, consists of upwards of a quarter billion events. These data are generated using the Textual Analysis by Augmented Replacement Instructions (TABARI) system, an automated system for encoding large amounts of text (Schrodt 2009). One complicating factor associated with the use of GDELT is that the number of reports per year has increased at an exponential rate since the early 1990s. This is a global phenomenon linked to the proliferation of digital communications. GECAD includes a subset of GDELT limited to events taking place within the African continent, where both the actor and target of an action are actors native to Africa. In 1989 (the first year in GECAD), GDELT contains just over 200,000 unique events meeting these criteria. The most common approach to handling the exponential increase in reports is to simply normalize counts of events meeting particular selection criteria by the total number of records within a given (e.g., by year). In

Figure 22: GDELT events by location

building GECAD, however, I hesitate to make the assumption that the relative proportions of events of any particular category is solely affected by the total number of events. Alternatively, GECAD takes a random sample of 200,000 records from all years. This approach maintains relative proportions of event categories and has the added advantage of greatly reducing the volume of data which must be stored and processed. Figure 22 depicts the spatial coordinate plot of the GDELT events included in GECAD. In GECAD, these data are represented as counts on a per cell basis.

UCDP Georeferenced Event Dataset

This new dataset has several distinct advantages over datasets previously available. First, conflicts are located with the highest level of precision to date. A violent event is represented spatially as a X-Y coordinate (point feature) and may be represented on a digital map. Secondly, previous datasets have generally only included cases of violent conflict which met comparatively narrow criteria (e.g., at least one of the belligerents was a state or at there were at least 1000 battle deaths). The new DPCR data contains information inter-state conflicts, conflicts in which one party was a state, and conflicts in which no party was a state. Further, it includes events with as few as a single casualty. Events are not only georeferenced, but time-referenced in two attributes: a start-date and an end-date, from 1989-2010. This allows the modeler flexibly to determine whether to focus on new conflict onsets, probabilities of continuation, or to assume no distinction between the two. In GECAD, these data are represented as counts on a per cell basis.

Temperature and Precipitation

Temperature and precipitation are the principle independent variables representing the effects of climate change. I will employ the **?** Gridded Precipitation and Temperature data. The curators took combined data from the Global Historical Climatology Network and Global Surface Summary of Day, and interpolate down to a resolution of 30 arc-seconds by 30 arc-seconds, making these data the most precise available. In addition to temperature, Hendrix and Salehyan (2011) offer three justifications for taking into account the direct effects of rainfall. First, rainfall is a reliable measure of rural income and food security. This is particularly true for sub-Saharan Africa given the poor condition of irrigation systems throughout Africa and reliance upon rainfall for agriculture and consumption. Secondly, unlike other environmental variables such as soil erosion and water quality, rainfall is not directly affected by human behavior. Thus, the validity of causal arguments about climate change and conflict are enhanced. Lastly, while climate projections are inherently error prone, rainfall is one aspect in which they are generally the most accurate. This will not affect the quality of estimates, but still nonetheless increase their usefulness as estimators of future conflict in applied settings. In keeping with the findings of Hendrix and Saleyhan and Raleigh and Kniveton, I construct this variable so as to capture temperature and precipitation extremity, which is an absolute deviation from what is "normal" for a given location. Per Hendrix and Salehyan (2010), I take the absolute value of the monthly deviation from the mean (for that cell, or panel), divided by the standard deviation of the panel:

$$X_i', t = abs[\frac{X_{i,t} - \bar{X_{i,m}}}{sd(X_{i,m})}] \tag{16}$$

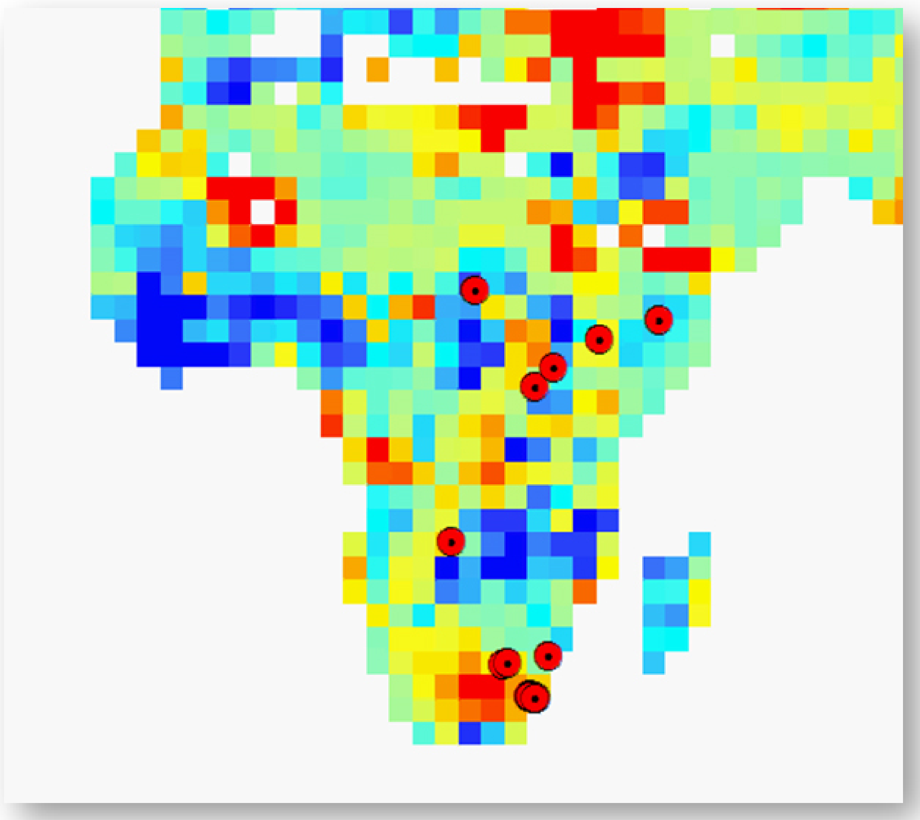
Palmer Drought Severity Index

The PDSI is a combined measurement of climatic dryness taking into account both precipitation and temperature. I apply the Dai, Trenberth and Qian (2004, updated for 2010) Global Dataset of Palmer Drought Severity Index for 1870-2010. These are annual data. The PDSI is calculated based on a supply-and-demand model of moisture in soil, taking into account not only how much precipitation has occurred, but how much is lost due to evapotransporation, averages, need, and other factors. Figure 23 depicts one month violent conflict interval over a one time period on Dai's PDSI. Red areas indicate areas under unusually dry conditions.

Normalized Difference Vegetation Index

The NDVI is a graphical *raster* dataset generated through remote sensing, in this case a space platform, describing the spatial distribution of live green vegetation. This is advantageous because it does not rely upon human measurements. The intuition is that live, green plants absorb solar radiation in certain wavelengths useful satisfying their energy requirements via photosynthesis, but must reflect other wavelengths (especially the near infra-red)

Figure 23: One month snapshot of Palmer Drought Index color coded heatmap. Red circles indicate ongoing conflict.



in order to prevent overheating. Thus, green plants appear dark in certain wavelengths and bright in others. By comparing the relative brightnesses in these wavelengths, it is possible to generate an accurate estimate of the overall vibrancy of plant life in a given location. The figure below depicts a NDVI raster dataset overlaid with violent conflict in November of 1990. More dense vegetation is darker. I use NDVI datasets from the Global Inventory Modeling and Mapping Studies program (GIMMS), which is derived by Tucker, Pinzon, Brown and Molly (2004, updated for 2006) from imagery obtained from the Advanced Very High Resolution Radiometer (AVHRR) onboard US National Oceanic and Atmospheric Administration (NOAA) satellites (see Figure 24). I use these data as measure of agriculture production, which while may only be considered an approximation, circumvents the need to rely on self-reports from unreliable local government agencies. Like temperature and precipitation, with this value I am also interested in monthly deviations from what is normal for that space. However, here I am interested in the effects as precipitation and plant density move from minimum to maximum. Accordingly, I do not take the absolute value.

$$X_i', t = \frac{X_{i,t} - \bar{X_{i,m}}}{sd(X_{i,m})} \tag{17}$$

Population Density

I apply the Socioeconomic Data and Application Center's (SEDAC) Gridded Population of the World, version 3 (GPWv3) collection of raster datasets. These raster datasets render global population at a scale and extent useful for the demonstration of spatial relationships between human populations and other geo-referenced data features. The grid resolution is 2.5 arc-minutes by 2.5 arc-minutes, or roughly 5km at the equator. Population estimates are available for 1990, 1995, 2000, and 2005. In the time series, I use the temporally most proximate reference. See Figure 25.

Ethnographic composition/ Ethnic Fractionalization Index

Figure 24: Normalized Difference Vegetative Index is a remotely sensed measure of the intensity of plant life. Yellow circles are ongoing conflicts. These satellite images are recorded at intervals of 15 days.

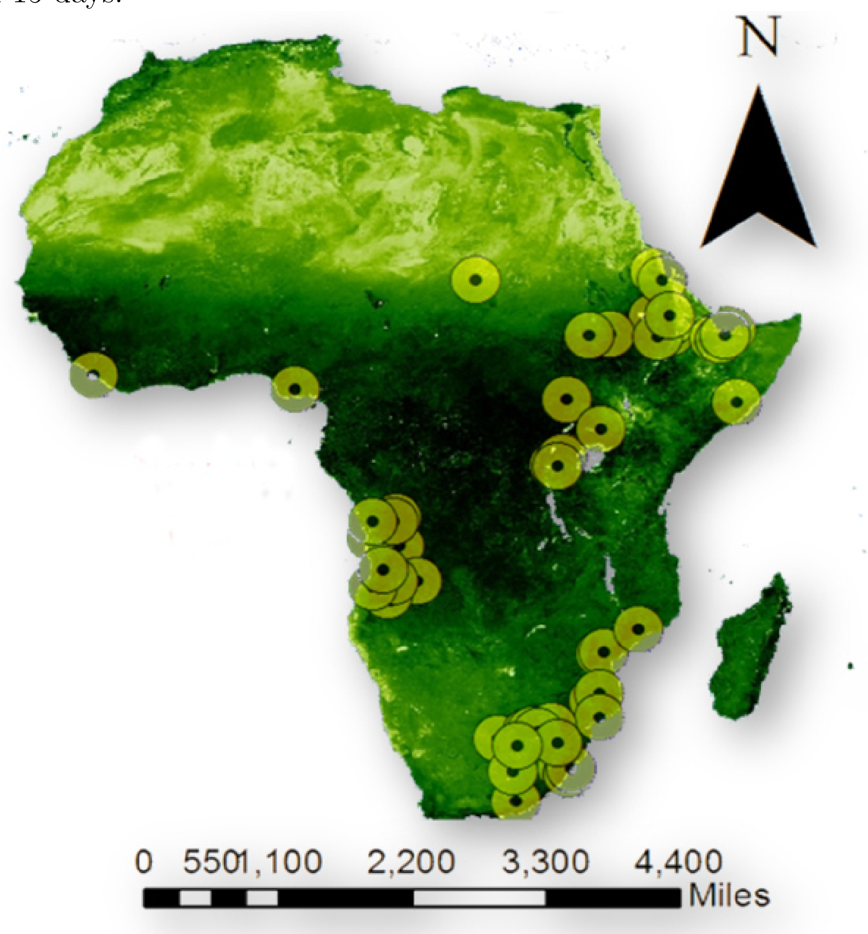


Figure 25: SEDAC's population density raster dataset uses satellite and other data to create precise measures of population distribution without the need for state-collected statistics. Each "pixel" is a unique, continuous value representing the population within a 2.5 arc-minute square unit.

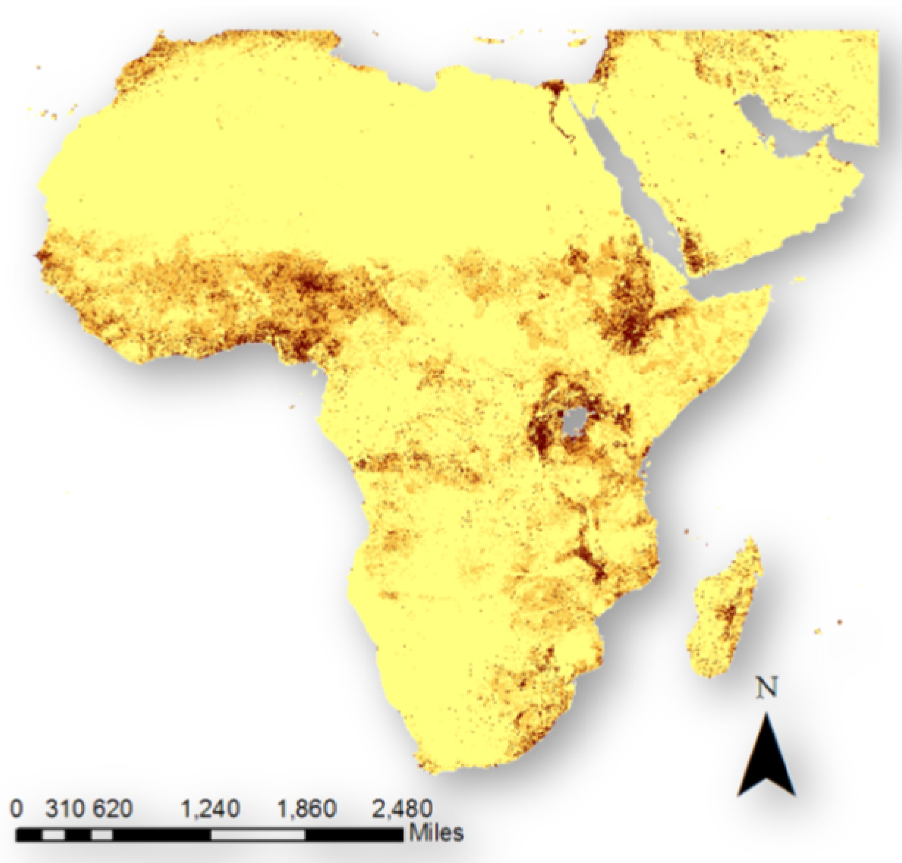
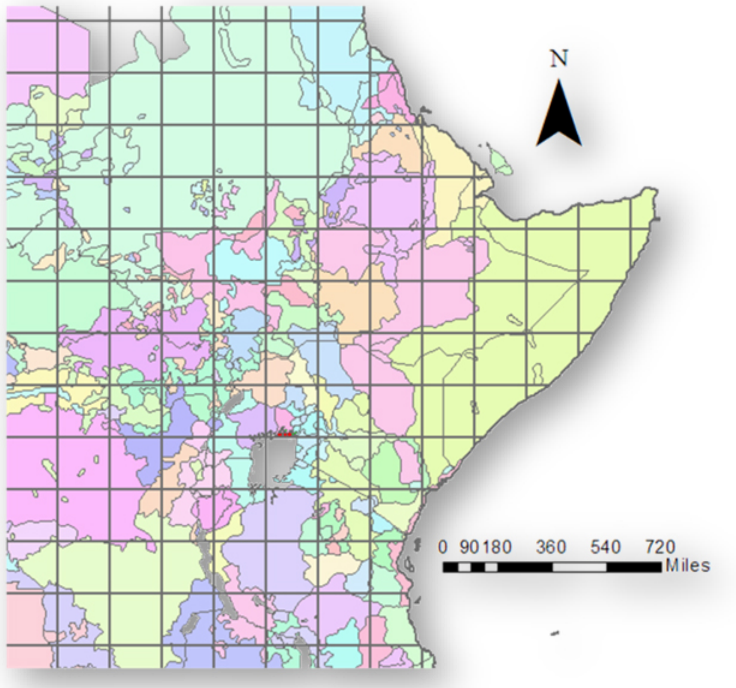


Figure 26: Using the Weidmann et al Georeferencing of Ethnic Groups (GREG) dataset, investigators may calculate a more accurate, locally driven ethnic fractionalization index.



In order to model the effects of ethnographic composition, I begin with the Weidmann, Rø d and Cederman (2010) Georeferencing of Ethnic Groups (GREG) dataset. Scholars of African civil war, the creators sought to build a data set specifically addressing the problem of over-aggregation of empirical data, typically to the state-level. In order to open the "black box of the state", the creators generated a polygon dataset representing the spatial distributions of ethno-linguistic groups. The number of polygons intersecting offers a practical measure of the number of different ethnic groups interacting in the specified area. See Figure 26.

Mineral Resources

Following Collier and Hoeffler (2001, 2004), which linked resources to conflict, I incorporate a variable taking into account the presence, proximity, and estimated value of mineral and fossil resources. The Mineral Resources Data System (MRDS) is a collection of point-referenced reports describing metallic and nonmetallic mineral resources, including gemstones, throughout the world. These data are captured in GECAD as resource densities; i.e., the number of known resources within a given cell.

Cities/Urban Centers

GIS allows me to generate a new variable defined as the distance (in kilometers) between the centroid of a tile and the capital of the state in which the majority of the tile falls within. Similar variables are easily generated describing the distance to other major urban centers.

Other Geo-referenced Data

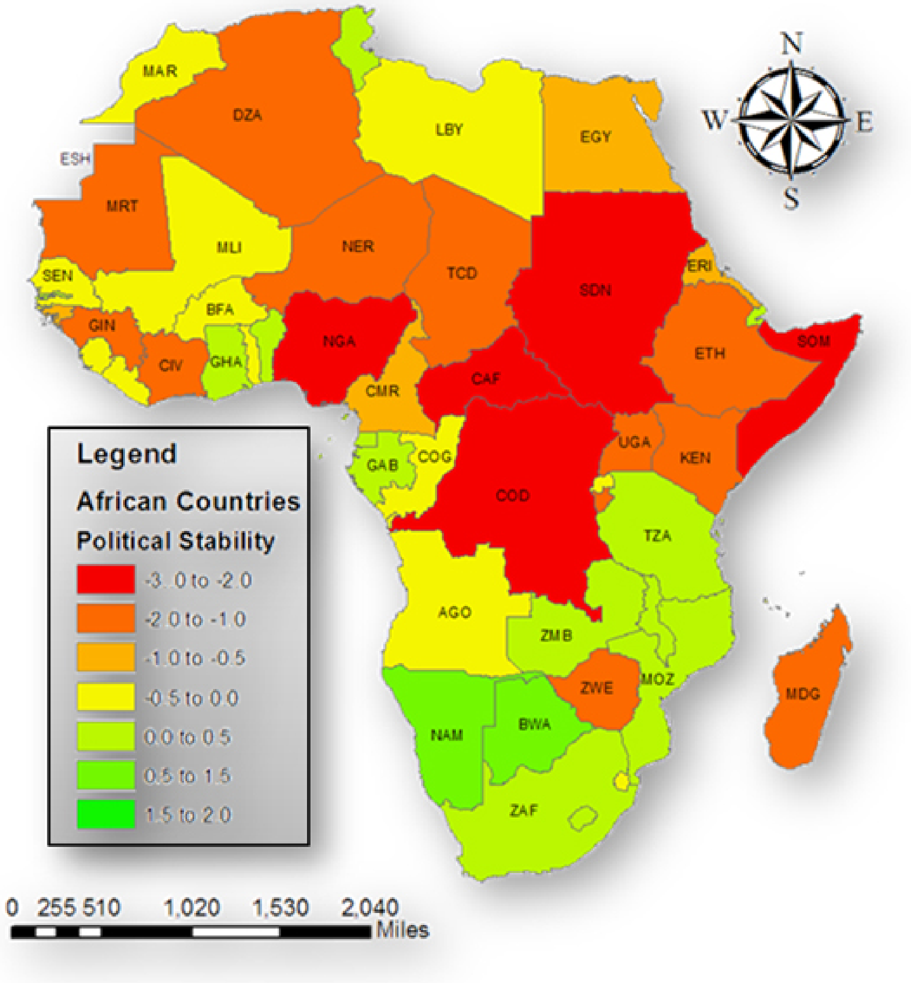
In total there are more than 150 variables included in GECAD. A complete codebook is currently in the works. A notable subset of them include the following:

- Soil degradation from the Global Assessment of Human Induced Soil Degradation (GLASOD) Digital Database.
- Soil suitability for agriculture from Ramankutty, Foley, and McSweeney (2002).
- Terrain gradation from ESRI Corporation.

State-level variable desegregations *Disaggregated State-level Variables.* The above data sources are not based on national boundaries. One useful tool in GIS is the ability to take data from the state-level and disaggregate it to smaller units of analysis. In order to incorporate some of the more traditional variables from civil war research, I draw data from the World Bank's African Development Indicators (Mundial 2012). Using country reference codes, I can associate these national level data to nation-state polygons, and in turn, disaggregate into tiles. Selected independent variables include:

- Proportion of GDP from export of commodities
- GDP/capita (excluding product associated with the export of commodities)
- Political stability index

Figure 27: World Bank ADI data may be imported into a GIS database. Country color is coded by political stability. Once imported, the fishnetted 2.5 x 2.5 degree units may inherit political stability or other state-level variables from the states they fall within.



- Gini index
- Combined polity index
- Regulatory quality

Figure 27 depicts the political stability as reported in the ADI for 2010 in the form of a graduated color map.

4.4 Using GECAD

In this section I use to GECAD to test the hypothesis that climate change is causing conflict, and as well to elucidate potential mechanisms, or influence pathways. One such potential pathway concerns the role of ethnic fractionalization. Scholars have long suspected a moderating role, however the empirical literature is mixed. Fearon and Laitin (2003) find that it makes no difference at all, whereas Collier and Hoeffler (2000; 2001) find just the opposite. Blimes (2006) argues that ethnic fractionalization is a significant cause of war, and the reason why previous studies had been mixed is because they were inappropriately looking for direct effects. Using a heteroskedastic probit model, they contend that in countries with low levels of ethnic fractionalization, variables with known direct effects on civil war will have greater error variance than countries with higher levels. In other words, the effect of variables such as GDP per capita, prior war, and political instability are significantly more pronounced in ethnically heterogeneous countries. A previously supported explanation Homer-Dixon (1999) is that fractionalization establishes an abundance of convenient lines of division along which a society may organize itself during desperate times.

4.4.1 Hypotheses

There is good reason to suspect ethnic identity could play a moderating role between acute resource instability and conflict. Over the last half century a perspective of human nature that emphasizes innate sociality has been gradually gaining steam. Drawing from fields as diverse as evolutionary theory, anthropology, psychology, political, and now increasingly computer science, this perspective holds that human sociality is a core adaptation with which individuals of our species respond to adaptive challenges. In other words, whereas another species might rely upon its powerful jaws, lightning speed, or biological camouflage, we humans meet our environments with cooperation.

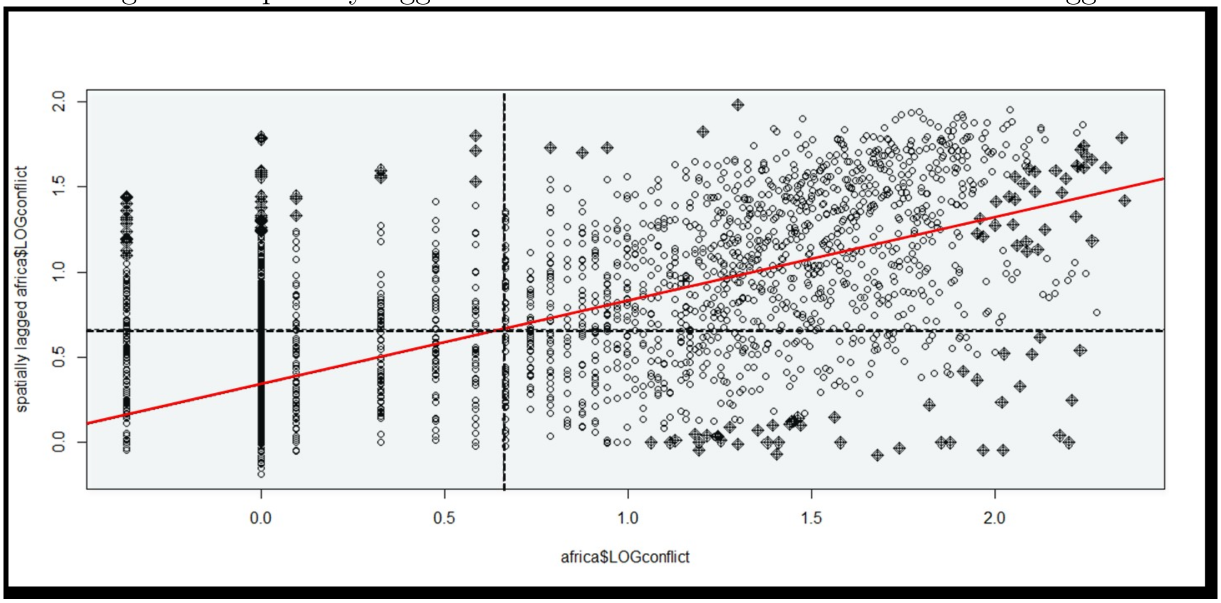
A full review of this literature is forthcoming as part of my dissertation. However, I will at least note several relevant, recent studies offering empirical support for the theory.

Gibson (2008) conducted an admirably large survey in South Africa, asking respondents to react to an experimental vignette in which a black squatter is evicted from land on which she is squatting. He finds that black South Africans who identify strongly with their ethnic group are far less likely to believe that justice has been adequately performed. Typically, procedural justice (which is manipulated in the study) increases the perceived fairness of the eviction but this is less true for the majority of black South Africans who identify with either their racial or ethnic group (e.g., Zulu, Xhosa) as opposed to the nation as a whole. The clear implication of these findings is that principles of justice are applied more broadly by those who identify with the nation. Without a sense of national identity, black South Africans question the fairness of government actions. Riek, Mania, Gaertner, McDonald and Lamoreaux (2010) find that making salient a shared identity as an American can reduce perceived partisan threat among both Democrats and Republicans. Eifert, Miguel and Posner (2010) find that exposure to political competition significantly impacts whether individuals identify themselves ethnic terms. The finding is of particular importance to the present research because it demonstrates that ones understanding of ethnicity is not constant. Rather, the salience of any particular identity is situationally determined.

In sum, I theorize that when faced with acute economic hardship in the aftermath of severe climatic anomaly, individuals look toward coordinate with their ethnic kin in order to secure larger shares of dwindling resources through collective action. This establishes an influence pathway from severe weather to ethnic identity to intergroup conflict. Accordingly, I derive the following hypotheses to be tested with GECAD.

Hypothesis 1: Severe weather, in either direction, will be associated with increased conflict.
Hypothesis 2: Ethnic fractionalization will moderate this effect.

Figure 28: Spatially lagged values of conflict as a function of conflict logged



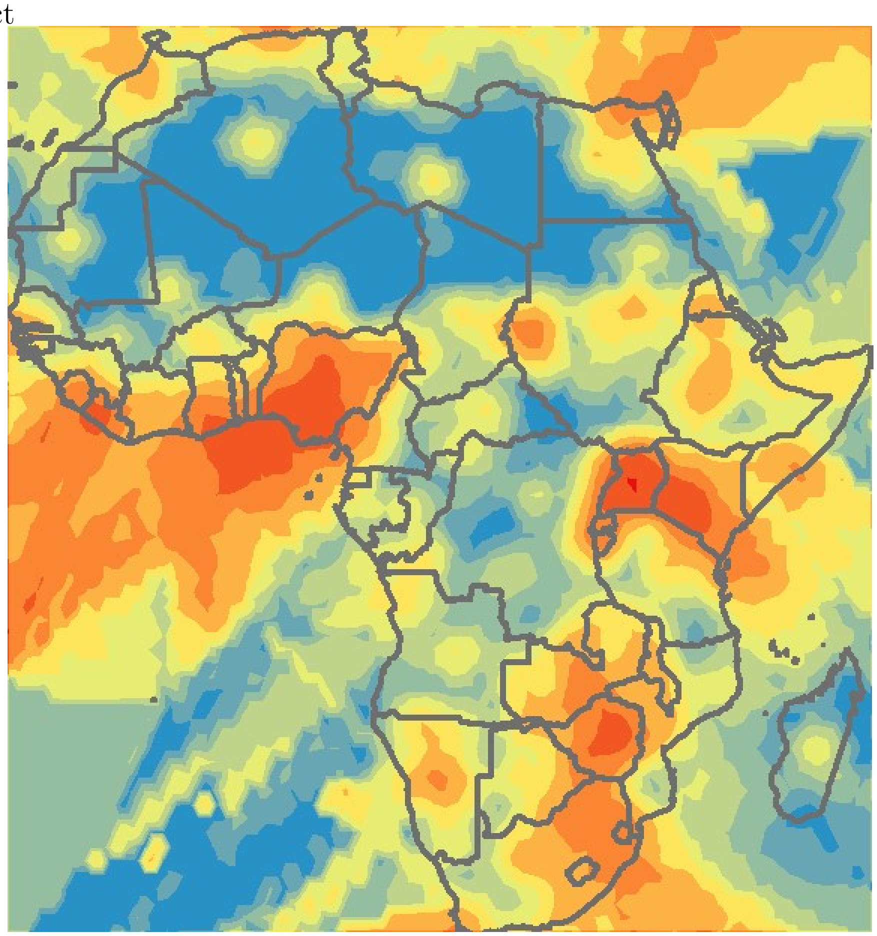
4.4.2 Model

The gridding technique allows transformation of spatially referenced data (maps) to a more traditional data matrix suitable for the standard suite of statistical tools political scientists and econometricians are accustomed to. One must keep in mind, however, that since cases are (cells) drawn from a map at a particular time and place the observations are not independent, since cells will be related to nearby cells spatially and temporally. This violates the G-M assumption of a spherical error distribution. As well, observations are nested within clusters of observations, such as nations or climate classification (desert, forest, arid plains, etc). Accordingly, our choice of models and specification must take these factors into account.

Spatial Autocorrelation

In order to diagnose spatial autocorrelation I conduct a Moran test using the count of conflict events in the GDELT dataset in a cell-month. Moran's I is calculated at 50.78 ($p < 0.0001$). We reject the null hypothesis that there is no spatial autocorrelation. Figure 28 plots spatially lagged variable (conflict) against the log. A positive linear pattern is clear, implying that in line with intuition conflict is likely to spill over to surrounding areas.

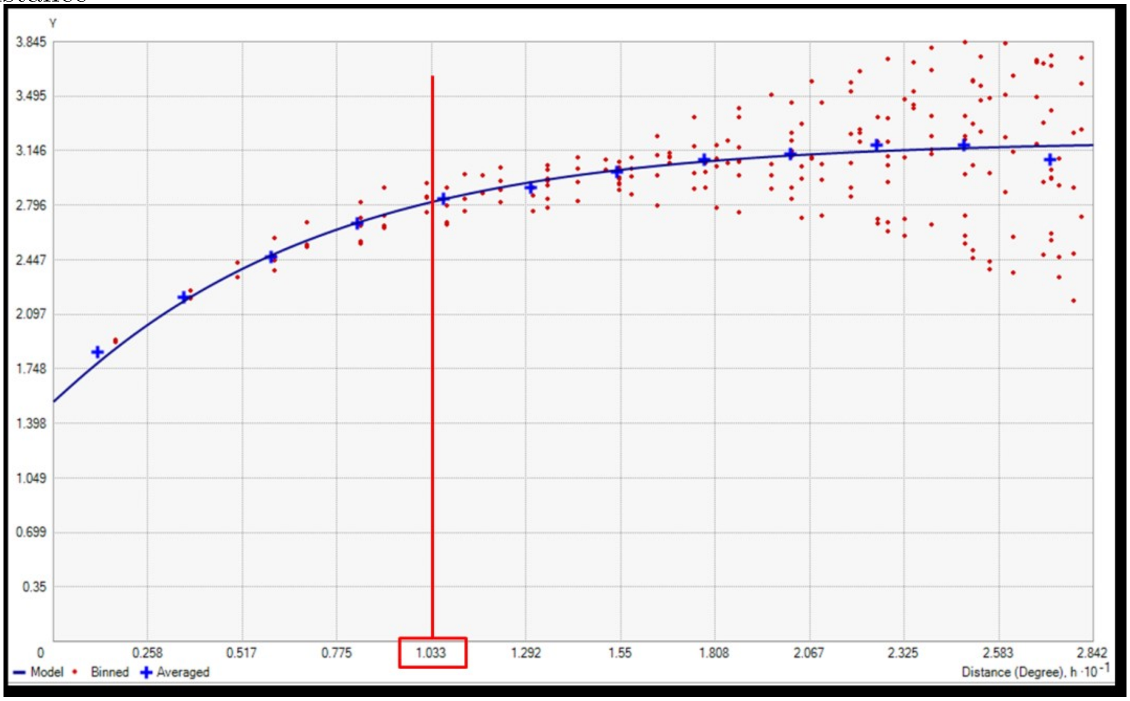
Figure 29: Kriging is a method of geostatistical interpolation. Redder colors indicate higher rate of conflict



Still, to properly account for the autocorrelation in a statistical model we need to measure the magnitude of the effects in more useful units. I employ a three step process to accomplish this. First, I apply a method of geostatistical interpolation called kriging. Figure 29 depicts the distribution of conflict over the Africa. Conflict appears visibly "clumpy", but what is more important are the gradients as we move from high conflict zones to low.

Kriging allows us to calculate a useful curve called a semi-variogram (Figure 30). A semi-variogram is essentially a plot of the covariance (semi-variance) between all points in a field at some distance h. When a slope exists, it may be stated that the covariance between any two points is a function of the distance between them. The approximate area along the curve where the slope begins to approach zero, therefore, indicates that beyond this area the relationship is no longer a function of distance. In the figure below the red line over the value

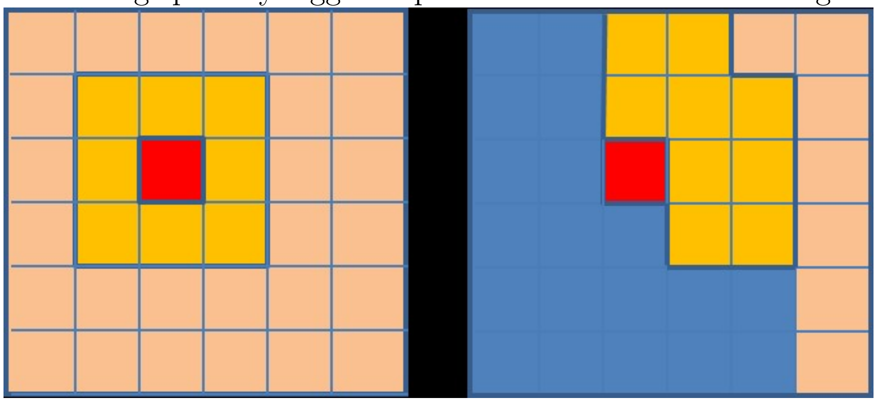
Figure 30: Calculated semivariogram: Flattening indicates semivariance no longer a function of distance



of 1 on the X-axis encounters the curve as it is nearly flat. Keep in mind that the cellular nature of the data demands that spatial lag only be measured with integer-level precision. According to this result, generating a spatially lag of the dependent variable (conflict) based upon surrounding cells at one unit of distance (or 1 degree) should suffice. Two units of distance would offer little additional power, but be far more computationally intensive to calculate.

For added robustness, I create two spatially lagged variables based, respectively, on the mean and maximum values of the eight nearest cells (see Figure 31). Note that cells along the coast will include tiles at greater than 1 unit, since they are not surrounded on all sides. This method of generating spatial lags on a gridded dataset is consistent with Tollefsen et al 2012. Using several cross-validation techniques, they determined that this method was able to produce low mean-square error estimates in the face of spatial autocorrelation.

Figure 31: Calculating spatially lagged dependent variables based on eight nearest cells



Temporal autocorrelation

Diagnosing temporal autocorrelation is more conventional. Several unit-root tests for panel data exist. I employ the Levin-Lin-Chu and the Im-Pearson-Shin tests (Levin, Lin and James Chu 2002; Im, Pesaran and Shin 2003). These two make a useful pairing because the formulation of the test hypotheses are contrary. In both case we reject the null ($P-values < 0.0001$), which allows us to conclude neither all of the panels are stationary, nor are all of the panels unit-roots. These data, therefore, are likely to be fractionally integrated. At the time of this writing, no established estimator exists for fitting models with fractionally integrated panel data. Lebo and Weber will propose an ARFIMA-MLM model in a forthcoming issue of the American Journal of Political Science. However, for the present iteration I will rely upon temporal lags of the independent variable to pick up dependencies on past histories. Lagged independent variables are also useful because I do not necessarily suspect that conflict arises from contemporaneous fluctuations in weather. Rather, the effects are likely to be disjointed in time since it may take a while for, say, foodstocks to deplete or for foliage to densify. In consideration of all of the above challenges, I estimate a pooled time-series mixed-effects regression model. Mixed-effects regression is commonly used with panel data where unobserved heterogeneity is likely. As well, I may allow for national and climate categorical fixed effects.

4.5 Results

In testing this model, I am primarily interested in the effects of extreme weather or climate change patterns in Africa on conflict in Africa. Therefore, it is necessary to include some kind of control for global trends. To do this, I include the Food and Agriculture Organization Global Food Price Index. This would, for example, allow me to account for the effects of a below average wheat yield in Russia. The table below depicts the results of the mixed-effects regression.

One useful feature of GDELT is that it classifies every event according to the Conflict and Mediation Event Observations (CAMEO) coding scheme. This allows all events to be further summarized in a nominal-level variable as either material cooperation, verbal cooperation, verbal conflict, or material conflict (in GDELT this is the quadclass variable). The three sets of columns report the results of the regression with three constructions of the dependent variable (conflict), using verbal and material conflict individually and combined. These variables are each broad aggregations of conflict events ranging from leaders' issuance of fiery statements regarding the opposition to mass violence. Therefore, these variables are best understood as measures of generalized instability. The narrower verbal and material conflict variables are still high-level aggregations. For example, material conflict may include anything from a riot to genocide. Both verbal and material conflict are still generalizations of instability. The key distinction lies in the notion that in the case of material conflict the implication that, at least in some degree, life and limb are on the line. It may therefore capture reactions to circumstances which are a scale upward in terms of severity and desperation. In three constructions of the DV, we observe global trends in food prices to yield a significant, positive affect on generalized social conflict and instability in Africa. A contemporaneous effect exists in all three cases. Interestingly, I find a significant effect of global food prices in the preceding month. This suggests some pace of escalation, or tension

Table 19: Results of Mixed-effects Regression Model

	Log(Combined)		**Log(Mat. conf)**		**Log(Verb. Conf.)**	
Variable	Coef.	Std. err.	Coef	Std. Err.	Coef.	Std. err
Temporal lag	37.42***	0.1	33.48***	0.129	35.252***	0.128
Avg. 8 nearest						
Contemporaneous	6.64***	0.09	26.106***	0.366	21.604***	0.354
Lag 1	0.12***	0.09	2.688***	0.368	4.531***	0.356
Max. 8 nearest						
Contemporaneous	-0.69***	0.01	-4.68***	0.163	-3.85***	0.156
Lag 1	0.12***	0.01	-0.47***	0.163	-0.73***	0.156
FAO Index						
Contemporaneous	-0.08***	0.02	-0.04***	0.017	-0.083***	0.015
Lag 1	0.01	0.02	0.009	0.017	0.031**	0.015
Temp. extremity						
Contemporaneous	0.14*	0.08	0.113*	0.068	0.142**	0.061
Lag 1	-0.02	0.08	-0.03	0.068	0.008	0.062
Lag 2	0.14	0.08*	0.067	0.068	0.101*	0.061
Precip. extremityˆ						
Contemporaneous	-0.11*	0.07	0.095*	0.057	-0.089*	0.051
Lag 1	-0.01	0.07	0.031	0.057	-0.039	0.051
Lag 2	0.14**	0.07	0.083	0.057	0.091*	0.051
Ethnic fract.ˆ	0.94***	0.27	0.651	0.215	0.783	0.229
Temp X EF.	0.13***	0.04	0.053*	0.034	0.112***	0.031
Precip X EF.	0.02	0.03	0.013	0.029	0.070*	0.039
NDVI						
Contemporaneous	0.02*	0.05	0.013	0.042	0.092***	0.038
Lag 1	0.17***	0.02	0.073*	0.044	0.103***	0.039
Lag 2	0.09*	0.05	0.056	0.042	0.003	0.038
PDSI	0.04*	0.02	0.02	0.018	-0.008	0.017
Cluster res.	1.54***	0.5	1.21***	0.375	0.562	0.398

All coefficients and std. errs multiplied by a factor of 100
ˆCond. coeffs for contemporaneous Precip x EF not shown.

building, as food prices increase. In other words, populations raise their voices before their fists.

Now turning attention to the climate variables, we see mixed evidence of direct effects of temperature and precipitation on conflict. Extreme precipitation (in either direction) two months prior yields crosses the threshold of significance at the 0.05 level. Note: Since the interaction term between precipitation and ethnic fractionalization was not significant, I only report the coefficient of precipitation at its mean, rather than zero. This lagged effect is consistent with hypothesized mechanisms of climate-related conflict based on abundance or scarcity (as crops/foliage takes time to grow if nourished). In the case of the deluge hypotheses (flooding, infrastructure destruction, etc), we would expect to see the preeminence of contemporaneous effects. The positive, highly significant effects of vegetative density (NDVI) further reinforces the abundance argument. As you recall, the precipitation measure is a measure of extreme deviation from normal levels, whereas NDVI only captures vegetative density. This should not be interpreted as implying that scarcity does not cause conflict (in fact, the weakly significant coefficient on the Palmer Drought Severity Index suggests that scarcity does). However, the effects of NDVI offer clear evidence that abundance can as well. Specifically, this finding is consistent with proposed mechanisms suggesting that greater abundance increases the value of spoils (i.e, makes land or cattle more worth taking). It is also consistent with suggestions that denser foliage offers potential rebels greater opportunities for cover and is conducive to guerrilla-style warfare.

Since precipitation has the more obvious effect on the landscape and crops, it is not surprisingly the relationship between temperature and conflict appears to be more nuanced than that of precipitation. I hypothesized that ethnic fractionalization will moderate the effect of climate change, or at least extreme weather. I tested both temperature and precipitation for such interactive effects. Interestingly, these data suggest such an interaction exists for temperature but not precipitation. The moderating effect is also quite large. Figure 32 depicts the marginal effects of temperature extremity as a linear function of ethnic fractionalization. When ethnic fractionalization is 1 (i.e., only a single ethno-linguistic group occupies the area), the effect of temperature extremity is not significantly different from zero. However, as the number of groups collocated within a cell increases so does the effect of temperature extremity. With two groups the effect is marginally significant and highly significant at three groups. Why would this be? One perhaps less than satisfying explanation is that human societies are simply that sensitive to changes in the environments they are adapted to. Extreme temperature may not have a direct or obvious link to the things societies engage in conflict to secure, but it may result in some kind of psychological stress. Extreme temperature may fuel a vague sense that somehow things are not as they should be. Change from habituated contexts is a known psychological stressor, as it makes the future less certain. Moreover, they might be right. While extreme temperature itself is not likely to cause the kind of acute resource shortages that might be attributed to extreme precipitation, these two variables are likely to be correlated. In GECAD the correlation coefficient between temperature and precipitation, by cell and normalized, is - 0.12 *(p-value ¡ 0.001)*. This may not sound like a lot, but predicting precipitation is a complex mess and it would be quite surprising if temperature alone accounted for the lions share of its variance. In short, extreme temperature may make people less comfortable, and at the social level this can manifest as greater tension between social cleavages.

Though not a part of the climate model, these data offer other potentially useful insights into the environmental causes of conflict. In particular, soil suitability for agriculture is negatively associated with conflict. Further, the mixed-effects regression technique allows us to conclude that this is unlikely to be an artifact the relatively large portion of the dataset falling into the sparsely populated Sahara desert. Importantly, these data suggest that this relationship is exacerbated by soil degradation. The effect of soil degradation is negative and highly significant, suggesting that conflict tends to move away from areas that are no longer producing as efficiently as in the past. Rather, conflict appears to be moving toward more productive areas. This is consistent with witness reports that soil degradation is forcing

Figure 32: The effect of temperature with no ethnic fractionalization is not significantly different from zero. However, the relationship is significant as fractionalization increases

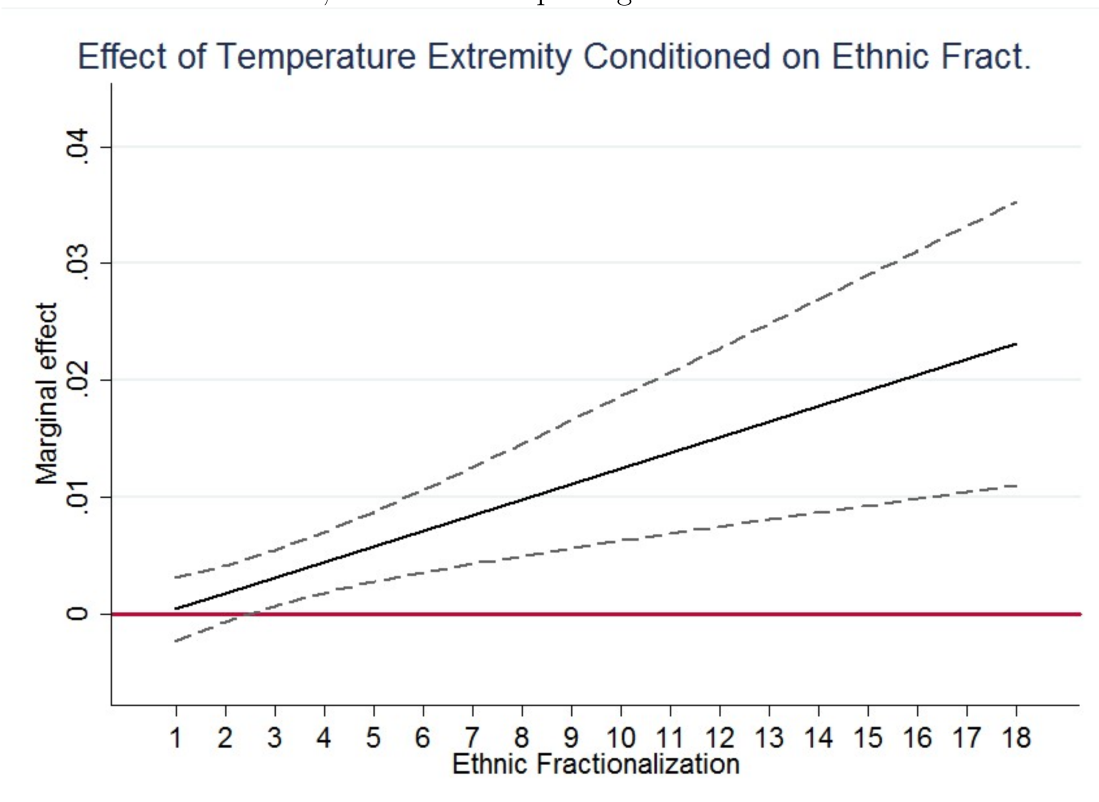
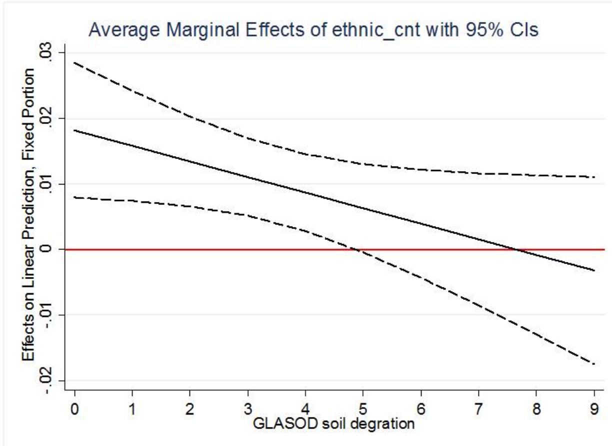
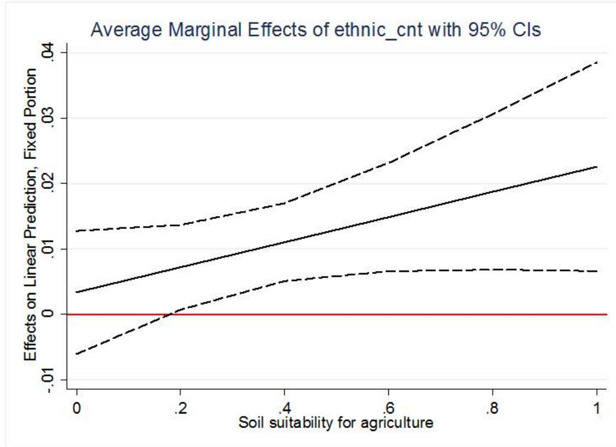


Figure 33: The effect of ethnic fractionalization is not significantly different from zero when soils are heavily degraded.



more groups into contact with one another, as in the case of Sudan. Soil degradation, of course, may be due to a variety of causes unrelated to climate change. Notably, evolving land use policies (often at the behest of international bodies) is known to be associated with degradation. Some such mechanisms include intensive monocropping (Parenti, 2011) and mining operations (Peters, 2014). Particularly in the transitional zones of the Sahel (striding the boundary of the Sahara and the heavily forested central African regions) ethnic lines are frequently coextensive with economic modalities. Accordingly, I suspected such conflict would inevitably run along ethnic lines and thought to test for the same hypothesized interactive effects of ethnic fractionalization with soil degradation and soil suitability (see Figures 33 and 34). I find both interaction terms significant with a common story to tell: ethnic fractionalization is most associated with conflict when such land based resources are plentiful. In other words, groups conflict with each other over good land, rather than bad land. Unfortunately, since these variables are not dynamically captured over time, I am unable to determine the effect of /emphdwindling land quality. These findings also suggest conflict over the best land could be a result of environmental refugees moving into areas historicaldwindlly occupied by other groups. Again, dynamic measures would offer a more definitive answer.

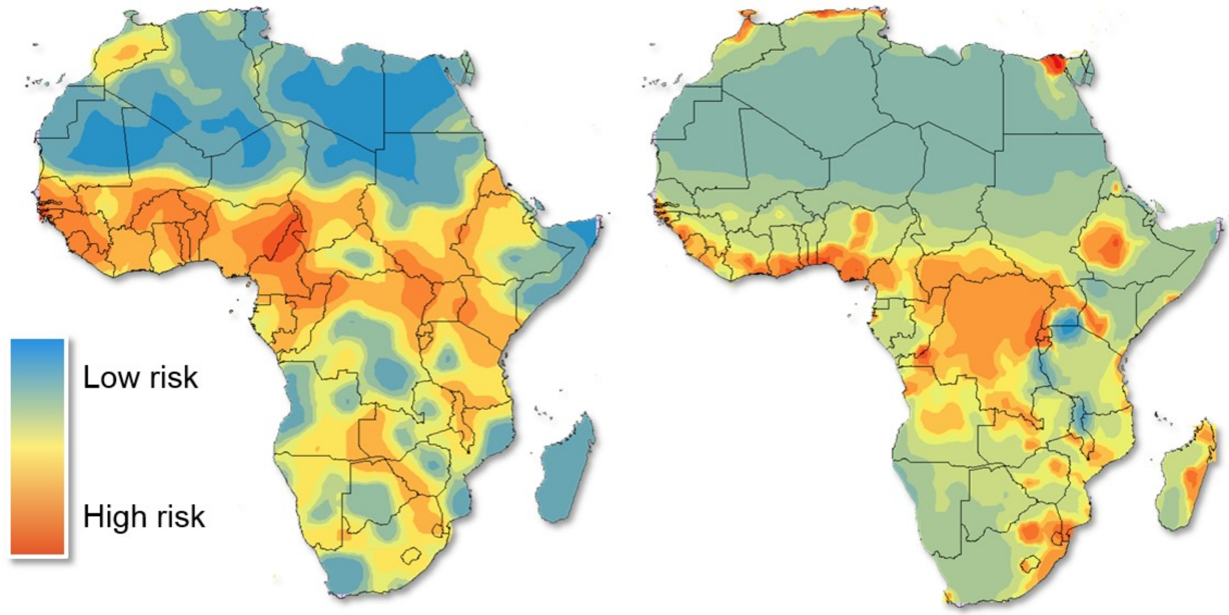
Figure 34: The effect of ethnic fractionalization is highest in locations that are best suited for agriculture



Of more peripheral importance to the present research, these data affirm much of previous research on the correlates of conflict, including a number of the geographic factors argued by Buhaug and Rod. The relative density of controllable resources appears to cause conflict. That these resources are fixed, bounded areas means they can be controlled by force. The digital elevation model (DEM) is highly significant and positive. DEM, as a measure of how mountainous a location is, reinforces arguments about the role of geography and insurgency.

Using GIS software, I incorporated the above parameter estimates into a geo-statistical model of climate conflict vulnerability (see Figure 35). The first image (left) presents predicted risk areas strictly as a function of the climate model, accounting for the interactive effects of ethnic fractionalization. Areas within the transitional zones of the Sahel appear to be particularly at risk. This stands out in sharp contrast to the predictions of the fully specified model (right), which leans more toward the historically more unstable sub-Saharan, central regions. This contrast suggests that, overall, extreme weather potentially as a result of climate change does not appear to be the principle driving force of conflict in Africa broadly. However, such effects are most strongly pronounced in the transitional areas where climate change is likely to have the greatest impact on local economic modalities; i.e., where the need to transition from one economic modality to another is more acute.

Figure 35: Predicted risk of conflict and instability: Climate-only model (left) and fully-specified model (right)



4.6 Discussion

GECAD is a new dataset for the study of social responses to climate change and the role of the environment in conflict more broadly. In this initial study, I used GECAD to assess competing findings that extreme weather, potentially as a result of climate change, is causing instability in Africa. I affirm findings that extreme precipitation—in either direction—is associated with conflict. Moreover, these data suggest the mechanism lies in precipitations determining role of scarcity and abundance of resources and vegetation, rather than explanations based on infrastructural damage. In hindsight, GECAD in its current form lacks key variables that would elucidate such a mechanism (the latter), and therefore I cannot conclude that infrastructural damage does not cause conflict. Temperature is a significant driver of conflict, but this effect is substantially moderated by ethnic fractionalization. The mechanism here is unclear and more research is needed. However, this finding does demonstrate the fundamental premise that ethnic identities are flexibly salient in response to environmental variables. What is puzzling is that this moderating effect did not exist for precipitation. In other words, while extreme precipitation does appear to be linked with conflict, the lines between the actors do not appear to be drawn along ethnic cleavages. Alternatively, it may be the case that to the extent extreme precipitation may threaten populations, the anxiety it generates is directed at governments rather than other sub-national groups. This is speculation, of course, however it is consistent with previous (and replicated) findings that denser foliage is can be more conducive to types of conflict commonly directed at governments, such as guerrilla warfare. In GECAD's current revision it cannot adequately test this hypothesis. However, a long-awaited update to the GDELT is planned for this summer which, once incorporated into GECAD should yield this capability.

Though not strictly climate change related, these data provide strong evidence of the role of environment in conflict. Replicating Hendrix and Glaser (2007), I find a clear signal in these data suggesting soil degradation is leading to conflict and instability. Further, the moderating relationship of ethnic identity which I have put forth appears to in part explain the dynamics of the conflict. There are numerous causes of soil and environmental degradation in Africa, climate change included. Unfortunately, the current revision of GECAD lacks a dynamic measure of soil degradation or adequate controls to demonstrate this as a possible causal pathway.

Some qualifications that come with the above findings include an inherent problem of trying to explain relatively fast-moving dependent variables (conflict) with relatively slow moving independent variables (climate change). This is perhaps why so much of the current literature (including this paper) is focused on anomalous weather, which is of course more mercurial. Also, while we struggle to tease out a causal relationship between climate change and conflict, it is important to note that we have yet to see the kind of rapid, dramatic change that could occur this century. Up until now, climate change has paced sufficiently slowly that many people continue to doubt its existence. Should we eventually cross so-called "tipping points", as scientists fear, we could see a pace and scale of change that are really quite a different beast.

5 Conclusion

This dissertation examined ways in which ecological conditions alter individual incentives to participate in groups; i.e., to rely upon collective action such as cooperation and intergroup conflict in order to resolve individual adaptive challenges. It describes a mechanism connecting ecological challenges individuals face to emergence and subsequent behavior of groups as unitary actors. In the simplest conception, as circumstances compel individuals to pursue more group-centric strategies, groups may negotiate higher levels of commitment in terms of submission of individual decision sovereignty to social processes. The result is that groups become more like decision-making units of analysis as their constituents deindividuate. Thus, the individual-group dichotomy is called into question. Rather, these two states exist at opposite ends of a spectrum: Groups are "unitary" to the extent they are cohesive, and they are cohesive to the extent that we submit to their rules and maintain our commitments. The incentives individuals face in this negotiation are circumstantial, determined in a dynamic ecological marketplace where neither the supply nor demand for cooperation are constant.

5.1 Findings

The three studies presented in this dissertation explored this question from distinct perspectives. In Chapter 2, a coevolutionary model of network topology and cooperation demonstrated that these two concepts are bound together, shaped in conversation with each other in response to continually changing environmental circumstances. Every social network is a unique, socially-generated solution to a complex ecological problem space, dynamically reached as a result of many thousands of interactions between selfish actors each looking out for their own interests. Generally speaking, the management of the risk of defection for cooperators appeared to be a fundamental design principle of social network architecture. The model determined that cooperation is favored in the context of small, but more densely networked communities. Agents maintained relationships that minimizes their exposure to defection, while maximizing opportunities for reciprocity. Primitive clustering emerged out of tendencies for agents to maintain connections with a smaller, but more carefully chosen number of individuals.

As survival becomes more precarious, however, agents were the most willing to expand the number of their connections even if as it increases their exposure to risk. There are at least a couple reasons why this could be the case: 1) Because their partners are more likely to die, it may pay off to maintain a larger number of relationships, even if they are not quite as cooperative; and 2) A more precarious existence makes defection in the context of a close relationship much more consequential. Agents, therefore, choose to spread risk of defection over a larger number of partners. The ability to interact with socially distant individuals and adopt categorically discriminating behaviors also seems to mitigate some of the risk associated with additional relationships. Though this ability produced networks that were dramatically more segmented, overall populations were larger and the individuals within each segment were more connected. Indeed, the richest environments tended to produce larger and less cooperative populations.

In chapter 3 we gained insight into the emergence of primitive social identities and their curious entanglement with intergroup conflict. This study offered preliminary, but robust evidence that the presence of internally cooperating groups *does not* imply cooperation between groups. On the contrary, the present of this new, more potent form of competition for limited resources appeared to compel others to invest in groups of their own. But this was not always the case. In fact, it appeared to significantly depend on how the resources individuals needed to survive and prosper were distributed spatially. Individuals were likely to fight over resources that were clustered together rather than widely distributed. Further, social conflict emerged when land quality was unequal. In sum, these two results emphasize the finding that when the successful progress of violent conflict can afford a group premium access to the highest quality resources at the exclusion of others, its members are more willing to submit their autonomy to the group in order to enhance its combat potential. Moreover, when individuals' environments were dominated by the pervasive presence of violent conflict, *how* they cooperated mattered as much as *if* they cooperated. The Lanchester Law is a key variable that directly translates within-group cooperation into a group's effectiveness at advancing their collective interests through warfare. The better agents are able to coordinate their tactics in battle the greater demand there was for a cooperative 'gene'.

The studies presented in Chapters 2 and 3 sought to establish a theoretical basis for understanding groups, qua unitary actors, as emergent phenomena arising from the many countless decisions of individuals interacting with each other and with their environment. If true, this would lead us to hypothesize that a significant role of group identity as a moderator of realistic conflict. Chapter 4 introduced a massive new dataset to test this hypothesis at an aggregate level using event data from Africa and climate data from the years 1989 to 2006. These data affirm temperature extremity to be a significant driver of conflict. However, this effect appeared to be substantially moderated by ethnic fractionalization in line with predictions. While the mechanism at work could not be ascertained, this finding does demonstrate the fundamental premise that ethnic identities are flexibly salient in response to environmental variables. These data affirm previous findings that extreme precipitation—in either direction—is associated with conflict, as well as significant effects on violent conflict for a wide variety of environmental variables. In particular, soil degradation appears to be an indirect cause of conflict as it creates environmental refugees, forced off their land to complicate the economic livelihoods of groups living elsewhere. Additionally, these data offer corroborating support for the conclusion conflict is most strongly associated with clustered resources.

5.2 Implications for political understanding

Thinking of cooperation as a kind of currency individuals may judiciously invest in social living establishes a theoretical link between the emergence of groups and adaptive problems they assist individuals in responding to. Both the supply of cooperation and the demand for the adaptive benefits it yields determine price. These variables are in constant approach to an ever-shifting equilibrium, dynamically responding to the evolving realities of a complex ecological marketplace. Accordingly, the prevalence of cooperation is not constant; it ebbs and flows like a tide in response to forces we are now only beginning to identify, much less understand.

In the summer of 2014, the number of human beings on planet Earth is roughly 7.2 billion in 193 countries[16], themselves comprised of between 5 and 6 thousand distinct ethnic groups (Doyle 1998; The Joshua Project 2014).[17] Wealth and the means of production are distributed highly unequally.[18] In the past, such inequities may have mattered less, but early 21st century society is global. With only very few (and still dwindling) exceptions, no populations exist in blissful ignorance of the immense disparities that exist. As the global warming and resultant climate disruption advance, these inequities are likely to be exacerbated in the decades ahead (IPCC 2014). Added to this, of course, are non-climate related resource depletion and degradation.

Therefore, I do not believe it would be controversial to assert that some of the most pressing challenges we—as a global society—face today are linked to the environment. Equipped with a solid understanding of the connections between individuals, groups, the environment, and conflict, political science and ultimately policymakers will be on far better footing to meet them effectively.

Climate change and conflict

As demonstrated in Chapter 4, a potentially critical application of such a theory is to better understand and predict social responses to climate disruption, extreme weather disasters, and other forms of rapid ecological change. This would enable smarter and faster policy responses on the part of governments, intergovernmental organisations (IGOs) non-governmental actors

[16] United Nations recognition

[17] Estimates vary depending on opinions over who constitutes a unique ethnic group. Estimates in the range of 5 to 6 thousand count all ethnic groups once, regardless of how many countries they appear in. If each ethnic group is counted once for every country it appears The Joshua Project estimates the total to be around 16,000.

[18] The Economist estimated the global Gini coefficient as 0.65 in 2008 (Economist 2012).

(NGOs) in order to mitigate the threat to political instability and violent conflict. Using GECAD, the present research identified such regions in Africa where destabilizing effects are already being realized. In addition to more targeted delivery of mitigation efforts, such knowledge may point the way to better management of environmental refugees and economic and land-use reforms that may assuage conflict risk.

Moreover, it should not be too much to hope that accurate predictive models of ecological conflict should serve to reinforce the consequences of inaction in the minds of leaders. Climate change is a fact and it is happening presently. Its ultimate severity, however, is undecided. The choices we make in the near-term about how our economies continue to rely on fossil fuel energy sources and other carbon-emitting practices will determine the extent of the threat we face. With a clearer picture of what is at at stake, this line of research could stimulate policy action that could prevent the worst case scenarios.

Deconstructing conflict

One of the greatest challenges in conflict resolution is how to get past the often overwhelming power of sectarian differences that emerge in the narrative perspectives of the causes of the conflict. During the dismantling of South African apartheid, progressive leaders including Archbishop Desmond Tutu established the Truth and Reconciliation Commission (TRC) in order to arrive at a universally agreed upon historical narrative. Counter-intuitively, the purpose of such commissions is not necessarily to find the truth, but to find some narrative that all interested parties can agree to and thus serve as a basis for moving forward with the peace process. One of the major conclusions of this research is that social identities are dynamically responsive to material conflict. Cultural histories, like symbols, can act as centripetal forces rendering communities more cohesive, reinforce solidarity, and better equipped to carry out collective action. The substance of such histories need not reflect underlying material conflict, but may persist as unifying elements. Thus, they may in some cases actually distract from the *true* causes of the conflict and hinder resolution. Understanding the ways underlying material realities can either increase or decrease demand for collective action can potentially point to methods for deescalating conflicts through targeted development or public works projects that relieve such demand.

Foreign aid and relief

The multiple findings in this dissertation linking conflict to clustering of resources has direct implications for the foreign aid and relief community. Clustered resources creates ecological incentives for groups to monopolize resources through collective action. Particularly in regions where security and governance are weak, this could lead to warlordism and other forms of sectarian strife as groups battle for control of the distribution sites.

As well, these findings suggest the foreign aid community should exercise extreme care when providing aid directly to governments lacking a robust democratic tradition or where government is historically dominated by a single ethnic group. This kind of direct aid establishes capture of the government as an immensely valuable prize, and would encourage widespread activation of ethnic identities to fuel a protracted conflict.

Interest group politics

From a standpoint of interest group politics, it might help to illuminate how individual firms cooperate in the form of industrial lobbies for a clustered, finite resources in the form of legislative influence, trying to steer public policy in a direction favorable to that industry at the expense of other industries. Alternatively, we might illuminate the circumstances in which firms choose to engage in their own lobbying efforts to promote policies that benefit them individually against not only other industries, but also their peer competitors.

6 Appendix

6.1 Computer codes

6.1.1 Co-evolution of Cooperation and Social Networks

This model was programmed in Python 2.7 and executed on a cluster of four computers including an 8-core AMD FX-8150 CPU, two dual Intel Core i5-4320m CPUs, and a dual core Intel T2200 CPU. Code begins on next page.

```
import random as rd
import networkx as nx
import matplotlib.pyplot as plt
import numpy as np
import time
from random import choice
import uuid
import math
import pylab

''' Also consider adding the additional constraint that strategyD1 = strategyD2
   = strategyD3 '''
#-----------------------------------------
# Declare Parameters
#-----------------------------------------
# Type
SingleShot = False
max_res_model = True
maxD = 3
MC = 10
maxN = 40
maxR = 60
T = 2000

# Monte Carlo variables

# Single shot parameters
if SingleShot == True:
   MC = 1      # Single shot
   N = 40     # Initial network size
   P = .0025    # Base probability of forming connection
   R = 5       # Number of games/rounds per time period
   SF = 10      # Starting fitness, fixed SF=0
   Res = SF*maxR # Total resources in the world
   Mcost = 2    # Metabolic cost of survival
   D = 3       # Maximum number of degrees between i and j may interact
   C = 1       # Cost of cooperation
   B = 1.3 * C  # Benefit of cooperation
   mut = 0.005  # Mutatation rate, random uniform 0 - 0.005
   SR = 1.5    # Starvatation rate exponent.
   rskew = 1.5    # Reproductive skew. High values incease adv. to hi fit agents.
```

```
Num_parameters = 12
Num_outputs = 31
#-------------------------------------------
# Create custom functions
#-------------------------------------------
def strategy_profile():
    return np.random.uniform(0, 1, D + 1)

def create_edges(W, agents, P):
    for i in agents:
        for j in agents:
            if i != j:
                barabasi = j.popul
                denominator = float(max(len(W.edges()),1))
                pr_connection = P  + (barabasi * i.pref_bias * P)
                if rd.uniform(0,1) < pr_connection:
                    W.add_edge(i, j)

def get_detailed_map(agent, D):
    ''' Generate a list of lists, like a list of bins.
        go through ext_network and sort each j into bin according to distance
        return list of lists '''

    neighborhood = [[] for deg in range(D)]
    ext_network = nx.single_source_shortest_path(W,agent,cutoff = D)
    for d in range(D +1):
        for e in ext_network:
            if len(ext_network[e]) == d + 2:
                neighborhood[d].append(e)
    return neighborhood

def giant_comp(W):
    comps = nx.connected_components(W)
    list_comps = [len(i) for i in comps]
    largest = max(list_comps)
    return largest

def gini(agents):
    fitnesses = []

    for agent in agents:
        fitnesses.append(agent.fitness)
```

```
    n = len(fitnesses)
    fitnesses.sort()  # increasing order
    G = sum( xi * (n-i) for i, xi in enumerate(fitnesses))
    G = 2.0*G/(n*sum(fitnesses))
    return 1 + (1./n) - G

def plot_all(W, agents, T, data, D):
    duration = T
    outfile = "singleshot.png"
    outfile2 = "hist_graph.png"
    x = range(duration)
    fig = pylab.figure(figsize = (18, 6))
    ax = fig.add_subplot(231)
    ax.grid(True)
    ax.set_title("Number of Agents Living (Network Size)")
    ax.set_ylabel("Total Surviving")
    ax2 = fig.add_subplot(232)
    ax2.grid(True)
    ax2.set_title("Bias to connect with popular agents")
    ax2.set_ylabel("Level of Bias")
    ax3 = fig.add_subplot(233)
    ax3.grid(True)
    ax3.set_title("Average Strategy Profiles by Type")
    ax3.set_ylabel("Propensity to Cooperate")
    ax4 = fig.add_subplot(234)
    ax4.grid(True)
    ax4.set_title("Average Node Degreee")
    ax4.set_ylabel("Degree")
    ax5 = fig.add_subplot(235)
    ax5.grid(True)
    ax5.set_title("Fitness Inequality")
    ax5.set_ylabel("GINI Coefficient")
    ax6 = fig.add_subplot(236)
    ax6.grid(True)
    ax6.set_title("Average Clustering")
    ax6.set_ylabel("Clustering Coefficient")
    population = []
    pref_bias = []
    degree_avg = []
    gini = []
    clustering = []
    for time in x:
```

```
    population.append(data.Sdata[time][24])
    pref_bias.append(data.Sdata[time][15])
    degree_avg.append(data.Sdata[time][18])
    gini.append(data.Sdata[time][23])
    clustering.append(data.Sdata[time][19])

ax.plot(x, population)

z = [[data.Sdata[time][12 + d] for time in x] for d in range(D)]

ax2.plot(x, degree_avg)

line1c,  = ax3.plot(x,  z[0])
try:
    line2c,  = ax3.plot(x,  z[1])
except:
    pass
try:
    line3c,  = ax3.plot(x,  z[2])
except:
    pass
ax4.plot(x, pref_bias)
ax5.plot(x, gini)
ax6.plot(x, clustering)
fig.savefig(outfile)

fig2 = pylab.figure(figsize = (15, 6))
ax2_1 = fig2.add_subplot(121)
ax2_2 = fig2.add_subplot(122)
ax2_1.set_title("Degree distribution")
ax2_1.set_ylabel("Counts")
ax2_2.set_title("Network by Degree Centrality")
hist_vector = []
centrality_vector = []
degree_dict = W.degree()
for agent in W.nodes() :
    hist_vector.append(degree_dict[agent])
    centrality_vector.append(agent.strategy[0])
cvect = np.asarray(centrality_vector)
ax2_1.hist(hist_vector)
nx.draw_networkx(W, with_labels = False, node_color = cvect, ax = ax2_2)
fig2.savefig(outfile2)
```

```
    return pylab.show()

#------------------------------------------
# Create classes
#------------------------------------------
# Agent class

class Agent:
    counter = 0

    def __init__(self, SF):
        self.uid = Agent.counter
        self.strategy = strategy_profile()
        self.pref_bias = rd.uniform(0,1)
        self.fitness = SF
        self.degree = 0
        self.ledger = {}
        self.age = 0
        self.rcounter = 0
        self.popul = 0
        self.starving = 1
        self.neighbors = None
        self.neighborhood = None
        self.ev_centrality = None
        self.deg_centrality = None
        self.bet_centrality = None
        self.close_centrality = None
        Agent.counter += 1

# Data class

class Data:
    def __init__(self, Num_parameters, Num_outputs, MC, N, T):
        self.Sdata = np.zeros((T, Num_parameters + Num_outputs))
        self.MCdata = np.zeros((MC, Num_parameters + Num_outputs))

#------------------------------------------
# Build data frames
#------------------------------------------

data = Data(Num_parameters, Num_outputs, MC, maxN, T)
```

```
#------------------------------------------
# Start MC loop
#------------------------------------------

mcloop_start = time.time()
for mc in range(MC):
   if SingleShot == False:
      # Parameters
      N = np.random.randint(25, maxN)      # Initial network size
      P = rd.uniform(0.001, 0.004)         # Base probability of forming connection
      R = np.random.randint(1, 10)         # Number of games/rounds per time period
      SF = np.random.randint(2, 5)         # Starting fitness
      Res = SF*maxR                        # Total resources in the world
      Mcost = rd.uniform(1.5, SF)          # Metabolic cost of survival
      D = np.random.randint(0, 3)          # Max degrees for interaction
      C = rd.uniform(1, SF+1)              # Cost of cooperation
      B = (1 + rd.uniform(.1, .5)) * C     # Benefit of cooperation
      mut = rd.uniform(0, 0.005)           # Mutatation rate, random uniform 0 - 0.005
      SR = rd.uniform(1, 2.5)              # Starvatation rate exponent.
      rskew = rd.uniform(1, 2.5)           # Reproductive skew. High values incease adv
   #------------------------------------------
   # Game matrices and data arrays
   #------------------------------------------

   gm = np.zeros((2,2))
   gm[0,0] = B-C
   gm[0,1] = -C
   gm[1,0] = B
   gm[1,1] = 0

   #------------------------------------------
   # Generate initial network and conditions (Genesis)
   #------------------------------------------
   W = nx.Graph()
   for i in range(N):
      W.add_node(Agent(SF))

   #------------------------------------------
   # Start main simulation loop
   #------------------------------------------
   simloop_start = time.time()
```

```
data.Sdata = np.zeros((T, Num_parameters + Num_outputs))
for t in range(T):
  t_time = time.time()

  # Update network (create edges) and reset values
  old_edges = len(W.edges())
  broken_edges = 0
  create_edges(W, W.nodes(), P)
  new_edges = len(W.edges()) - old_edges
  degrees = W.degree()
  if max_res_model == True:
    if len(W.nodes()) > maxR:
      for agent in W.nodes():
        agent.fitness = Res / len(W.nodes())
        agent.degree = degrees[agent]
        agent.rcounter = 0

    else:
      for agent in W.nodes():
        agent.fitness = SF
        agent.degree = degrees[agent]
        agent.rcounter = 0

  else:
    for agent in W.nodes():
      agent.fitness = SF
      agent.degree = degrees[agent]
      agent.rcounter = 0

  # Do trades (currently they may sometimes interaction more than once/per
  trades_time_start = time.time()

  for agent in W.nodes():
    if agent.degree > 0:
      agent.neighborhood = get_detailed_map(agent, D + 1)
      agent.neighbors = agent.neighborhood[0]
      agent.ledger = {}  # Keeps current account of profit by connec
      for neighbor in agent.neighbors:
        agent.ledger[neighbor] = 0

  agent_queue = rd.sample(list(W.nodes()), len(W.nodes()))
```

```
for agent in agent_queue:
    if agent.degree > 0:
        if agent.rcounter < R:
            interactions_needed = R - agent.rcounter
            available_peeps = get_detailed_map(agent, D + 1)
            for d in range(D + 1):
                for neighbor in available_peeps[d]:
                    if neighbor.rcounter < R:
                        pass
                    else:
                        available_peeps[d].remove(neighbor)

            num_partners = 0
            partners = []
            while num_partners < interactions_needed:
                bins = []
                for d in range(D + 1):
                    bins.append(available_peeps[d])
                    bin_choices = []
                    for dist in range(len(bins)):
                        if len(bins[dist]) > 0:
                            bin_choices.append(dist)

                if len(bin_choices) > 0:
                    bin_choice = choice(bin_choices)
                    chosen = choice(available_peeps[bin_choice])
                    chosen.rcounter += 1
                    partners.append(chosen)
                    num_partners += 1
                    if chosen.rcounter >= R:
                        available_peeps[bin_choice].remove(chosen)
                else:
                    num_partners = interactions_needed

            if len(partners) == 0:
                pass
            else:
                for partner in partners:
                    agent.rcounter += 1
                    j = partner
                    path = nx.shortest_path(W, agent, j)
                    path_j = nx.shortest_path(W, j, agent)
```

```
                neighbor_type = len(path) - 2 # indexing/remove agnt
                i_strat = np.random.binomial(1,
                    agent.strategy[neighbor_type], 1)[0]
                j_strat = np.random.binomial(1,
                    j.strategy[neighbor_type],1)[0]
                agent.fitness += gm[i_strat, j_strat]/float(R)
                j.fitness += gm[j_strat, i_strat]/float(R)
                connecting_agent = path[1]
                connecting_agent_j = path_j[1]
                agent.ledger[connecting_agent] += gm[i_strat,
                    j_strat]/float(R)
                j.ledger[connecting_agent_j] += gm[j_strat,
                    i_strat]/float(R)

        # Sever losing connections
        if len(agent.ledger) > 0:
            for connecting_agent in agent.ledger:
                if agent.ledger[connecting_agent] < 0:
                    try:
                        W.remove_edge(agent, connecting_agent)
                        broken_edges += 1
                    except:
                        W.add_edge(agent, connecting_agent)
                        W.remove_edge(agent, connecting_agent)

    # Grim Reaper cometh, taketh the dead away

    bodycount = 0
    for agent in W.nodes():
        agent.fitness -= Mcost
        if agent.fitness < 0:
            agent.starving += 1
            if rd.uniform(0, 1) > 1/math.pow(agent.starving, SR):
                W.remove_node(agent)
                bodycount +=1
        else:
            agent.starving = 1


    trades_time_end = time.time()
    #print "Total trades time: " + str(trades_time_end - trades_time_start)
##      print "Dead agents: " + str(bodycount)
```

```
##       print "New edges: " + str(new_edges)
##       print "Broken edges: " + str(broken_edges)
##       print "Num nodes: " + str(len(W.nodes()))
##       print "Time period: ", t
##       print "Simulation run: ", mc

        # Replication (births)/ aging / mutation / reset SF / Centrality
        total_fitness_to_power = sum(math.pow(max(agent.fitness,0),
                            rskew) for agent in W.nodes())
        if total_fitness_to_power == 0: total_fitness_to_power = 1

        nursury = 0
        for agent in W.nodes():
            agent.age += 1
            if rd.uniform(0, 1) < math.pow(max(agent.fitness,0),
                            rskew)/total_fitness_to_power:
                baby_agent = Agent(SF)
                baby_agent.strategy = agent.strategy
                baby_agent.pref_bias = agent.pref_bias
                W.add_node(baby_agent)
                nursury += 1

            if rd.uniform(0,1) < mut:
                agent.strategy = strategy_profile()
                agent.pref_bias = rd.uniform(0, 1)

        #print "Baby agents: " + str(nursury)
        #-------------------------------------------
        # Value totals
        #-------------------------------------------
        N_at_t = float(len(W.nodes()) + 1)
        total_fitness = sum(agent.fitness for agent in W.nodes())
        total_pref_bias = sum(agent.pref_bias for agent in W.nodes())
        total_age = sum(agent.age for agent in W.nodes())
        total_starving = sum(agent.starving for agent in W.nodes())
        total_coop_degs1 = sum(agent.strategy[0] for agent in W.nodes())
        total_coop_degs2 = 0
        total_coop_degs3 = 0
        if D > 0:
            total_coop_degs2 = sum(agent.strategy[1] for agent in W.nodes())
        if D > 1:
            total_coop_degs3 = sum(agent.strategy[2] for agent in W.nodes())
```

```
degree_dict = W.degree()

for agent in W.nodes():
    agent.degree = degree_dict[agent]
    agent.popul = agent.degree/float(len(W.nodes()))

degree_total = sum(agent.degree for agent in W.nodes())

#-------------------------------------------
# Record Single-run data
#-------------------------------------------
data.Sdata[t, 0] = N
data.Sdata[t, 1] = P
data.Sdata[t, 2] = R
data.Sdata[t, 3] = SF
data.Sdata[t, 4] = Res
data.Sdata[t, 5] = Mcost
data.Sdata[t, 6] = D
data.Sdata[t, 7] = C
data.Sdata[t, 8] = B
data.Sdata[t, 9] = mut
data.Sdata[t, 10] = SR
data.Sdata[t, 11] = rskew
data.Sdata[t, 12] = 1 - (total_coop_degs1/N_at_t)  # Avg. Cooperation d1
data.Sdata[t, 13] = 1 - (total_coop_degs2/N_at_t)  # Avg. Cooperation d2
data.Sdata[t, 14] = 1 - (total_coop_degs3/N_at_t)  # Avg. Cooperation d3
data.Sdata[t, 15] = total_fitness/N_at_t          # Avg. fitness
data.Sdata[t, 16] = total_pref_bias/N_at_t        # Avg. pref bias
data.Sdata[t, 17] = total_age/N_at_t              # Avg. age
data.Sdata[t, 18] = total_starving/N_at_t         # Avg. starvation
data.Sdata[t, 19] = degree_total/N_at_t           # Avg. degree
if len(W.nodes()) > 0:
    data.Sdata[t, 20] = nx.average_clustering(W)      # Avg. Clustering
    data.Sdata[t, 21] = nx.transitivity(W)            # Avg. Transitivity
    data.Sdata[t, 22] = nx.is_connected(W)            # Graph is connected?
    data.Sdata[t, 23] = nx.number_connected_components(W) # Num of conn. com
    data.Sdata[t, 24] = gini(W.nodes())               # Gini-coefficient
    data.Sdata[t, 25] = len(W.nodes()) + 1            # Population size
    data.Sdata[t, 27] = giant_comp(W)
else:
    data.Sdata[t, 20] = 6666      # Avg. Clustering
```

```
        data.Sdata[t, 21] = 6666          # Avg. Transitivity
        data.Sdata[t, 22] = 6666          # Graph is connected?
        data.Sdata[t, 23] = 6666 # Num of conn. com
        data.Sdata[t, 24] = 6666                # Gini-coefficient
        data.Sdata[t, 25] = 0            # Population size
    data.Sdata[t, 26] = 6666



    # Generating eigenvalues and centrality measures only after last t period
    # Have to do a try/except because nx.eigenvector_centrality doesn't always
    # converge.


    #--------------------------------------------
    # Single-shot Analysis
    #--------------------------------------------

    try:
        eigen_centrality = nx.eigenvector_centrality(W)
    except Exception:
        eigen_centrality = {}
        for agent in W.nodes():
            eigen_centrality[agent] = 9999

    betweenness_centrality = nx.betweenness_centrality(W)
    degree_centrality = nx.degree_centrality(W)
    closeness_centrality = nx.closeness_centrality(W)
    for agent in W.nodes():
        agent.ev_centrality = eigen_centrality[agent]
        agent.deg_centrality = degree_centrality[agent]
        agent.bet_centrality = betweenness_centrality[agent]
        agent.close_centrality = closeness_centrality[agent]

    t_time_end = time.time()
    #print "Time period duration: ", t_time_end - t_time
#------------------------------------------
# End main simulation loop
#------------------------------------------
simloop_end = time.time()
print "Single-shot runtime", simloop_end - simloop_start
print "Simulation run: ", mc
```

```
if SingleShot == True:
    plot_all(W, W.nodes(), T, data, D)


#-------------------------------------------
# End Monte Carlo loop; save MC data
#-------------------------------------------
data.MCdata[mc, 0] = N
data.MCdata[mc, 1] = P
data.MCdata[mc, 2] = R
data.MCdata[mc, 3] = SF
data.MCdata[mc, 4] = Res
data.MCdata[mc, 5] = Mcost
data.MCdata[mc, 6] = D
data.MCdata[mc, 7] = C
data.MCdata[mc, 8] = B
data.MCdata[mc, 9] = mut
data.MCdata[mc, 10] = SR
data.MCdata[mc, 11] = rskew
data.MCdata[mc, 12] = data.Sdata[T-1, 12]  # Avg. Cooperation d1
data.MCdata[mc, 13] = data.Sdata[T-1, 13] # Avg. Cooperation d2
data.MCdata[mc, 14] = data.Sdata[T-1, 14]  # Avg. Cooperation d3
data.MCdata[mc, 15] = data.Sdata[T-1, 15]  # Avg. fitness
data.MCdata[mc, 16] = data.Sdata[T-1, 16]  # Avg. pref bias
data.MCdata[mc, 17] = data.Sdata[T-1, 17]  # Avg. age
data.MCdata[mc, 18] = data.Sdata[T-1, 18]  # Avg. starvation
data.MCdata[mc, 19] = data.Sdata[T-1, 19]  # Avg. Degree
data.MCdata[mc, 20] = data.Sdata[T-1, 20]  # Avg. Clustering
data.MCdata[mc, 21] = data.Sdata[T-1, 21]  # Avg. Transitivity
data.MCdata[mc, 22] = data.Sdata[T-1, 22]  # Graph is connected?
data.MCdata[mc, 23] = data.Sdata[T-1, 23]  # Num of conn. com
data.MCdata[mc, 24] = data.Sdata[T-1, 24]  # Gini-coefficient
data.MCdata[mc, 25] = data.Sdata[T-1, 25]  # Population size
data.MCdata[mc, 26] = simloop_end - simloop_start
data.MCdata[mc, 27] = data.Sdata[T-1, 27]
# averager over last 200 time periods
if T > 1000:
    data.MCdata[mc, 28] = sum(data.Sdata[T-201:T-1, 12])/200.0  # Avg. Cooperation d1
    data.MCdata[mc, 29] = sum(data.Sdata[T-201:T-1, 13])/200.0 # Avg. Cooperation d2
    data.MCdata[mc, 30] = sum(data.Sdata[T-201:T-1, 14])/200.0  # Avg. Cooperation d3
    data.MCdata[mc, 31] = sum(data.Sdata[T-201:T-1, 15])/200.0  # Avg. fitness
    data.MCdata[mc, 32] = sum(data.Sdata[T-201:T-1, 16])/200.0  # Avg. pref bias
```

```
    data.MCdata[mc, 33] = sum(data.Sdata[T-201:T-1, 17])/200.0  # Avg. age
    data.MCdata[mc, 34] = sum(data.Sdata[T-201:T-1, 18])/200.0  # Avg. starvation
    data.MCdata[mc, 35] = sum(data.Sdata[T-201:T-1, 19])/200.0  # Avg. Degree
    data.MCdata[mc, 36] = sum(data.Sdata[T-201:T-1, 20])/200.0  # Avg. Clustering
    data.MCdata[mc, 37] = sum(data.Sdata[T-201:T-1, 21])/200.0  # Avg. Transitivity
    data.MCdata[mc, 38] = sum(data.Sdata[T-201:T-1, 22])/200.0  # Graph is connected?
    data.MCdata[mc, 39] = sum(data.Sdata[T-201:T-1, 23])/200.0  # Num of conn. com
    data.MCdata[mc, 40] = sum(data.Sdata[T-201:T-1, 24])/200.0  # Gini-coefficient
    data.MCdata[mc, 41] = sum(data.Sdata[T-201:T-1, 25])/200.0  # Population size
    data.MCdata[mc, 42] = sum(data.Sdata[T-201:T-1, 27])/200.0

#-------------------------------------------
# Close datafile and analysis
#-------------------------------------------
np.savetxt("MCdata_endogenous_network.csv", data.MCdata,
        delimiter =',', fmt = '%1.7f')



#------------------------------------------
# End all simulations; close up shop!
#------------------------------------------
mcloop_end = time.time()
print "Monte Carlo runtime", mcloop_end - mcloop_start

done = 1;
```

6.1.2 Multilevel Selection Model of Pastoralist Conflict

This model was programmed in Python 2.7 and executed on a cluster of four computers including an 8-core AMD FX-8150 CPU, two dual Intel Core i5-4320m CPUs, and a dual core Intel T2200 CPU. Code begins on next page.

```
import random as rd
import matplotlib.pyplot as plt
import numpy as np
import time
import math
import uuid
from scipy import ndimage as nd
import sys
#plt.ion()
np.set_printoptions(threshold = 10000)
#------------------------------------------
# Declare Parameters
#------------------------------------------
# Type
SingleShot = False
show = False    # Change this year to turn the viewer on and off
printStuff = False
timeLimit1 = 10
timeLimit2 = 15
timeLimit3 = 20
timeLimit4 = 25
timeLimit5 = 30
tcut1 = 0.05
tcut2 = 0.05
tcut3 = 0.05
tcut4 = 0.1
tcut5 = 0.1

# Static parameters
MC = 250
N = 100
T = 2000
S = 30
mp = 20      # Migration period
mu = 0.005   # Mutation rate
wfill = 0.5  # Well initial fill level
gfill = 0.5  # Grass initial fill level
cap = 2      # Land carrying capacity (max res. is multiple of growth at t)
max_age = 5*mp              # Max age

if SingleShot == True:
   LQ_selector = 0 # 0-mono, 1-radial, 2-quads, 3-stripes
```

```
MC = 1      # Single shot
T = 50    # Number of periods
N = 100     # Initial population size
S = 40      # World size (SxS)
mp = 20     # Migration period
m = 0.05/float(mp) # Migration rate
mu = 0.005   # Mutation rate
f = 10      # Initial flock size
b = 1.0     # Benefit of cooperation (contribution multiplier)
Kt = 2      # Initial tribe count
kmax = 70   # Maximum number of members per tribe
wf = .05    # Well frequency
wfill = 0.5  # Well initial fill level
gfill = 0.5  # Grass initial fill level
ba = 2      # Base grass per tile.
ex = 2.0    # Seasonal extremity (Higher is LOWER extremity), float
A = ba/float(ex)    # Seasonal extremity (Higher is LOWER extremity)
V = .01     # Drought/Rain extremity, range [0,.5]
k = 5       # Season length parameter
L4 = .5 * ba # High-quality land bonus
L3 = .33 *ba # Good-quality land bonus
L2 = .16 *ba # Low-quality land bonus
L1 = 0 * ba  # inferior-quality land bonus
wd = 5      # Persistant weather pattern duration
cap = 2     # Land carrying capacity (max res. is multiple of growth at t)
wdmin = 3    # Minimum weather duration in time periods
wdmax = 5    # Maximum weather duration in time periods
wmin = 4 * ba   # Minimum well depth
wmax = 5 * ba  # Maximum well depth
wg_ratio = 3    # Ratio of water accummulation to grass growth at given precip
lq_boost = .1   # How much land quality affects well depth, [0, 1]
dtoler = .1     # Deprivation tolerance. [-.2, .5] roughly. lower die faster.
lan_law = 1.5     # Lanchester's Laws of Combat: Linear (1) or Square (2)
lethal = .9     # Base probability of surviving a battle
fc_rate = .3    # Food consumper rate. (hunger increase per turn)
wc_rate = .1    # Water consumption rate. (water consumption per turn)
calf_rate = .1  # Reproduction probability of animals (per flock, per period)
mate_comp = 2   # Mating competition factor. 1-linear, >1 - increasing rate
birth_rate = .1 # Reproduction probability of tribesmen per time period.
cbb = 1        # Cooperative breeding bonus factor
bprice = .25    # "Bride price," percent of flocks given to offspring.
of_rad = 3      # radius offspring birth around parenting agent.
```

```
    well_dist_exp = 1.5 # Well distance value atrophy exponent
    max_age = 5*mp  # Maximum age

Num_parameters = 46
Num_outputs = 5
report_depth = 7
''' Depth:
    0 - grasslands
    1 - wells
    2 - well depth
    3 - dominion
    4 - conflict
    5 - cooperation
    6 - populated (numerical category, by tribe)
    '''
precip_depth = 8
''' Precip_depth:
    0 - Growth in cell at t
    1 - Land quality
    2 - PDSI
    3 - Well depth
    4 - Well level
    5 - Well present (0,1)
    6 - Grass level
    7 - Max grass level (grass depth)
    '''
#-------------------------------------------
# Create custom functions
#-------------------------------------------

def smooth_grid(landgrid):
    new_grid = nd.gaussian_filter(landgrid, 3, mode='nearest')
    return new_grid

def pr_victory(x, y, a_tribe, b_tribe, lanchester_law):
    # Get average euclidean distances of members for each tribe
    a_coordinates = []
    a_total_distance = 0
    b_coordinates = []
    b_total_distance = 0
    a_size = float(len(a_tribe.members))
    b_size = float(len(b_tribe.members))
```

```
    for a in a_tribe.members:
        a_coordinates.append(a.location)

    for coord_pair in a_coordinates:
        x2, y2 = coord_pair
        a_total_distance += math.sqrt((x - x2)**2 + (y - y2)**2)

    a_avg_dist = (a_total_distance / a_size) + 1

    for b in b_tribe.members:
        b_coordinates.append(b.location)

    for coord_pair in b_coordinates:
        x2, y2 = coord_pair
        b_total_distance += math.sqrt((x - x2)**2 + (y - y2)**2)

    b_avg_dist = (b_total_distance / b_size) + 1

    a_strength = (a_tribe.cohesion*a_size/float(a_avg_dist))**lanchester_law
    b_strength = (b_tribe.cohesion*b_size/float(b_avg_dist))**lanchester_law

    pr_vic_a = a_strength / float(a_strength + b_strength)

    return pr_vic_a

def PGG_tribes_list(fight_pairs, tribes_list):
    fight_tribes = []
    for pair in fight_pairs:
        trA, trB = list(pair)
        fight_tribes.append(trA)
        fight_tribes.append(trB)

    fight_tribes = set(fight_tribes)
    PGG_tribes = list(set(tribes_list) - fight_tribes)
    return PGG_tribes

#------------------------------------------
# Create classes
#------------------------------------------

# Agent class
```

```
class Agent:
    counter = 0
    def __init__(self, x_coord, y_coord, tribe, flocks, coop_in, coop_out):
        self.uid = Agent.counter
        self.location = (x_coord, y_coord)
        self.old_loc = (x_coord, y_coord)
        self.next_loc = None
        self.tribe = tribe
        self.cooperation_in = coop_in
        self.cooperation_out = coop_out
        self.risk_aversion = rd.uniform(0, 1)
        self.flocks = flocks
        self.thirst = 0.0
        self.hunger = 0.0
        self.appetite = 0.0 * flocks
        self.thirstiness = 0.0 * flocks
        self.current_water = None
        self.current_food = None
        self.rank = None
        self.age = 0
        self.mate_score = None
        Agent.counter += 1

    def _del__(self):
        return

    def get_expectation(self, x, y, b, world, precipgrid, lan_law):
        agent = self
        available_food = precipgrid[x, y, 6]
        available_water = precipgrid[x, y, 4]
        ''' Agent's hunger is how hungry his animals are. Appetite is how
            much the agent wants to consume, given the number of animals.'''
        appetite = agent.hunger * agent.flocks
        thirstiness = agent.thirst * agent.flocks
        agents = []
        if len(world[x][y]) > 0:
            agents.extend(world[x][y])
            if agent.location == (x, y):
                agents.remove(agent)
            if len(agents) == 1:
                j = agents[0]
                H2Oshare = available_water/2.0
```

```
foodshare = available_food/2.0
if agent.tribe == j.tribe: # check if they're the same tribe
  # Play PGG only
  '''Use J's cooperation_in instead of average cooperation_in
    (cohesion) because agents are of the same tribe and
    can be assumed to recognize each other.'''
  sm_pot = b * foodshare * (j.cooperation_in + \
    agent.cooperation_in)
  sm_kettle = b * H2Oshare * (j.cooperation_in + \
    agent.cooperation_in)

  agent_food = foodshare * (1 - agent.cooperation_in)
  agent_water = H2Oshare * (1 - agent.cooperation_in)

  agent_food += (sm_pot/2.0)
  agent_water += (sm_kettle/2.0)

  if agent_food > appetite:
    hunger = 0.0
  else:
    appetite -= agent_food
    hunger = appetite / float(agent.flocks)
  ''' Same with water/third '''
  if available_water > thirstiness:
    thirst = 0.0
  else:
    thirstiness -= agent_water
    thirst = thirstiness / float(agent.flocks)

  happiness = 1 - ((hunger + thirst)/2.0)

else:
  # Play FPGG and PGG. Compare outcomes.
  # Play PGG only
  '''Use out-tribe average cooperation_out instead of j's
    cooperation_out because agent's will only know what
    tribe to expect at a new location, not the individual,
    who they will not know or recognize individually.'''
  # solo_happiness
  if available_food > appetite:
    hunger = 0.0
  else:
```

```
            appetite -= precipgrid[x][y][6]
            hunger = appetite / float(agent.flocks)
        ''' Same with water/third '''
        if available_water > thirstiness:
            thirst = 0.0
        else:
            thirstiness -= precipgrid[x][y][4]
            thirst = thirstiness / float(agent.flocks)

        solo_happiness = 1 - ((hunger + thirst)/2.0)

        # FPGG happiness
        agent_water = H2Oshare
        agent_food = foodshare
        if agent_food > appetite:
            hunger = 0.0
        else:
            appetite -= agent_food
            hunger = appetite / float(agent.flocks)
        ''' Same with water/third '''
        if agent_water > thirstiness:
            thirst = 0.0
        else:
            thirstiness -= agent_water
            thirst = thirstiness / float(agent.flocks)

        split_happiness  = 1 - ((hunger + thirst)/2.0)
        # Determine probabilty of victory in battle
        pr_vic_a = pr_victory(x, y, agent.tribe, j.tribe, lan_law)

        loss_happiness = 1 - ((agent.hunger + agent.thirst)/2.0)
        FPGG_happiness = (pr_vic_a * solo_happiness) + \
                              (1-pr_vic_a)*(loss_happiness)

        happiness = max(split_happiness, FPGG_happiness)

# Greater than 2 agents
else:
    # Determine how many tribes
    num_agents = len(agents) + 1
    tribes_list = []
    for ag in agents:
```

```
    tribes_list.append(ag.tribe)
tribes_list.append(agent.tribe)
'''Converting to set and back removes duplicates'''
tribes_list_set = list(set(tribes_list))
tribe_count = len(tribes_list_set)

if tribe_count == 1: # If all same tribe
    H2Oshare = available_water/float(num_agents)
    foodshare = available_food/float(num_agents)
    collective_plate = 0
    collective_kettle = 0
    for ag in agents:
        collective_plate += b * ag.cooperation_in * foodshare
        collective_kettle += b * ag.cooperation_in * H2Oshare

    agent_food = foodshare * (1- agent.cooperation_in)
    agent_water = H2Oshare * (1- agent.cooperation_in)

    agent_food += (collective_plate / float(num_agents))
    agent_water += (collective_kettle / float(num_agents))

    if agent_food > appetite:
        hunger = 0.0
    else:
        appetite -= agent_food
        hunger = appetite / float(agent.flocks)
    ''' Same with water/third '''
    if available_water > thirstiness:
        thirst = 0.0
    else:
        thirstiness -= agent_water
        thirst = thirstiness / float(agent.flocks)

    happiness = 1-((hunger + thirst)/2.0)

else: # If two tribes or more
    # Get how many agents in each out-tribe
    agents_i = []
    agents_i.extend(agents)
    agents_i.append(agent)
    tribes_census = {}
    tribes_strategy_book = {}
```

```
tribes_list_no_agent = []
tribes_list_no_agent.extend(tribes_list_set)
tribes_list_no_agent.remove(agent.tribe)

for tribe in tribes_list_no_agent:
    tribes_census[tribe] = 0
    for ag in agents_i:
        if ag.tribe == tribe:
            tribes_census[tribe] += 1
            tribes_strategy_book[tribe] = 0

# First get in-tribe PGG payoffs and adj. resource shrs.
ingroup = list(set(agent.tribe.members) & set(agents_i))
ingroup_size = len(ingroup)
# Resource sharing with competition eliminated
ag_food = available_food / float(ingroup_size)
ag_water = available_water / float(ingroup_size)

ingroup_foodplate_nc = b*sum(ag_food*
        tribesman.cooperation_in for tribesman in ingroup)
ingroup_waterkettle_nc = b*sum(ag_water*
        tribesman.cooperation_in for tribesman in ingroup)

agent_foodshare_nc = ag_food * (1 - agent.cooperation_in)
agent_H2Oshare_nc = ag_water * (1 - agent.cooperation_in)

agent_foodshare_nc += (ingroup_foodplate_nc/float(
            ingroup_size))
agent_H2Oshare_nc += (ingroup_waterkettle_nc/float(
            ingroup_size))

if agent_foodshare_nc > appetite:
    hunger = 0.0
else:
    appetite -= agent_foodshare_nc
    hunger = appetite / float(agent.flocks)
''' Same with water/third '''
if agent_H2Oshare_nc > thirstiness:
    thirst = 0.0
else:
    thirstiness -= agent_H2Oshare_nc
    thirst = thirstiness / float(agent.flocks)
```

```
happiness_nc = 1 - ((hunger + thirst)/2.0)

# Determine which other tribes agent's tribe will fight
for tribe_out in tribes_list_no_agent:
    '''Iterate thru each out-tribe to figure out calculate
       outcome with each other tribe individually'''
    outgroup = list(set(tribe_out.members) & set(agents_i))
    all_agents = list(set(ingroup) | set(outgroup))
    outgroup_size = len(outgroup)
    net_num_agents = ingroup_size + outgroup_size
    # Ingroup PGG based on proportion of resources.
    # In-group/out-group PGG:
    ag_food_comp = available_food/float(net_num_agents)
    ag_water_comp = available_water/float(net_num_agents)

    ingroup_contr_f = b * ag_food_comp * sum(
        tribesman.cooperation_in for tribesman in ingroup)

    ingroup_contr_w = b *ag_water_comp * sum(
        tribesman.cooperation_in for tribesman in ingroup)

    total_pot_f = ingroup_contr_f
    total_pot_w = ingroup_contr_w

    agent_share_f = ag_food_comp * (1-agent.cooperation_in)
    agent_share_w = ag_water_comp * (1-agent.cooperation_in)
    agent_share_f += (total_pot_f /float(ingroup_size))
    agent_share_w += (total_pot_w /float(ingroup_size))

    if agent_share_f > appetite:
        hunger = 0.0
    else:
        appetite -= agent_share_f
        hunger = appetite / float(agent.flocks)
    ''' Same with water/third '''
    if agent_share_w > thirstiness:
        thirst = 0.0
    else:
        thirstiness -= agent_share_w
        thirst = thirstiness / float(agent.flocks)
```

```
    peace_happiness = 1 - ((hunger + thirst)/2.0)

    # Generate Pr_vict and weight expected outcomes
    pr_vic_a = pr_victory(x, y, agent.tribe, tribe_out,
      lan_law)

    win_happiness = happiness_nc
    loss_happiness = 1 - ((agent.hunger + agent.thirst)/2.0)

    fight_happiness = (pr_vic_a * win_happiness)+ \
      (1-pr_vic_a)*(loss_happiness)

    if fight_happiness > peace_happiness:
      tribes_strategy_book[tribe_out] = 1 # will fight

  # calculate total expected payoffs given strategy book
  for tribe_out in tribes_strategy_book:
    # Find out how many:
    # 1. Fellows
    # 2. Outgroup cooperators.
    # 3. Outgroup fighters.
    coop_tribes = []
    fight_tribes = []
    num_fellows = ingroup_size
    num_out_coops = 0
    num_out_fight = 0

    if tribes_strategy_book[tribe_out] == 1:
      ''' distribute resources based on unilateral expectat-
      ations of battle outcomes.'''
      fight_tribes.append(tribe_out)
      num_out_fight += len(list(set(tribe_out.members) &
        set(agents_i)))
    else:
      coop_tribes.append(tribe_out)
      num_out_coops += len(list(set(tribe_out.members) &
        set(agents_i)))

    # Get compounded PR_victory (surviving against all Ts)
    pr_vic_comp = []
    for enemy in fight_tribes:
      pr_vic_comp.append(pr_victory(x, y, agent.tribe,
```

```
        enemy, lan_law))

if len(pr_vic_comp) == 0:
    win_all_prob = 1
else:
    win_all_prob = reduce(lambda x, y: x*y, pr_vic_comp)

# Distribute resources accordingly
num_coops_ttl = num_fellows + num_out_coops
f_per_coop = available_food / float(num_coops_ttl)
w_per_coop = available_water / float(num_coops_ttl)

# Get in-group contributions
in_contribs_f = b * f_per_coop*sum(
    tribesman.cooperation_in for tribesman in ingroup)

in_contribs_w = b * w_per_coop*sum(
    tribesman.cooperation_in for tribesman in ingroup)

# Calculate payoff
ttl_pot_f = in_contribs_f
ttl_pot_w = in_contribs_w

ag_food = f_per_coop * (1 - agent.cooperation_in)
ag_water = w_per_coop * (1 - agent.cooperation_in)

ag_food += (ttl_pot_f/float(num_fellows))
ag_water += (ttl_pot_w/float(num_fellows))

if ag_food > appetite:
    hunger = 0.0
else:
    appetite -= ag_food
    hunger = appetite / float(agent.flocks)
''' Same with water/third '''
if ag_water > thirstiness:
    thirst = 0.0
else:
    thirstiness -= ag_water
    thirst = thirstiness / float(agent.flocks)

pos_happiness = 1 - ((hunger + thirst)/2.0)
```

```
            los_happiness = 1 - ((agent.hunger + agent.thirst)/2.0)

            happiness = win_all_prob * pos_happiness + \
                (1 - win_all_prob) * los_happiness

    else:  #Agent will occupy the cell alone
        if available_food > appetite:
            hunger = 0.0
        else:
            appetite -= precipgrid[x][y][6]
            hunger = appetite / float(agent.flocks)
        ''' Same with water/third '''
        if available_water > thirstiness:
            thirst = 0.0
        else:
            thirstiness -= precipgrid[x][y][4]
            thirst = thirstiness / float(agent.flocks)

        happiness = 1 - ((hunger + thirst)/2.0)

    return happiness

def well_weight(self, x, y, wells, world, precipgrid):
    weights = []
    th = self.thirst
    for x_well,y_well in wells:
        agents = world[x][y]
        c = precipgrid[x_well][y_well][4]
        d = wells[(x_well,y_well)] + 1 # add 1 so d can't equal 0.
        value = (c/float((len(agents) + 1)))/float(d**well_dist_exp)
        weights.append(value)

    weight = th * sum(weights)

    return weight

def wander(self, x_coord, y_coord, b, world, precipgrid, wells, lan_law):
    ''' Look at the 9 possible moves (including move 0). Find the move that
        maximizes the utility function.

        |m1|m2|m3|
        ----------
```

```
    |m4|m0|m5|
    ----------
    |m6|m7|m8|


    Outcomes * weights

    # Don't forget to tally victories_this_period, make list of pr_victs
      for later incorporation into battle death likelihoods. Could
      possibly do this without an additional parameter.

'''
## Generate well weights
## Possible moves:'
possible_moves = {}
possible_moves[(x_coord, y_coord)] = 0      # m0
possible_moves[(x_coord-1, y_coord-1)] = 0  # m1
possible_moves[(x_coord-1, y_coord)] = 0    # m2
possible_moves[(x_coord-1, y_coord+1)] = 0  # m3
possible_moves[(x_coord, y_coord-1)] = 0    # m4
possible_moves[(x_coord, y_coord+1)] = 0    # m5
possible_moves[(x_coord+1, y_coord-1)] = 0  # m6
possible_moves[(x_coord+1, y_coord)] = 0    # m7
possible_moves[(x_coord+1, y_coord+1)] = 0  # m8

# Generated expected utilities of each possible move and well weights
for move in possible_moves:
    x,y = move
    if x == S: x = S-1 # edge detection
    if x == -1: x = 0
    if y == S: y = S-1
    if y == -1: y = 0
    exp_value = agent.get_expectation(x, y, b, world, precipgrid,lan_law)
    weight = agent.well_weight(x, y, wells, world, precipgrid)
    possible_moves[(x,y)] = exp_value * weight

# Here I need to take the dictionary of moves with weighted values and
# assign a probability distribution over each one. Then draw one at
# random.
moves = possible_moves
min_val_key = min(moves, key = moves.get)
min_val = moves[min_val_key]
```

```
        for move in moves:
            if moves[move] != 0.0:
                moves[move] += abs(min_val)

        total_payoffs = sum(moves.itervalues())

        for move in moves:
            moves[move] = (moves[move]/float(total_payoffs))

        pairs = moves.items()
        probabilities = np.random.multinomial(1, zip(*pairs)[1])

        result = zip(probabilities, zip(*pairs)[0])
        for res in result:
            if res[0] == 1:
                next_loc = res[1]

        return next_loc

# Tribe class
class Tribe:
    counter = 0

    def __init__(self, N, kt, starting):
        if starting == 1:
            KT = N/kt
        if starting == 0:
            KT = N
        self.uid = Tribe.counter
        self.members = []
        self.cohesion = None
        self.cooperation_out = None
        self.risk_aversion = None
        self.current_food = 0
        self.current_water = 0
        self.war_count = 0
        self.war_food = 0
        self.war_water = 0
        self.pr_vic_record = []
        self.avg_pr_vic = None
        self.population_old = 1
        self.population_new = 1
```

```
        self.growth_rate = 0
        Tribe.counter += 1

    def _del__(self):
        return


# Climate
class Climate:
    def __init__(self, S, precip_depth):
        shape = (S, S, precip_depth)
        self.precipgrid = np.zeros(S * S * precip_depth).reshape(*shape)

    def climate_vector(self, A, k, T):
        x = np.arange(1,T,.1)
        A = 1
        k = 5

        y=[]
        for period in x:
            y.append(A*math.sin(k*period))

        return y

    def pdsi(self, ba, V):
        drought = np.random.randint(0,3)
        if drought == 0:
            pdsi = -1
        if drought == 1:
            pdsi = 0
        if drought == 2:
            pdsi = 1

        pdsi = pdsi * ba * V
        pdsi_matrix = np.tile(pdsi, (S, S))
        return pdsi_matrix

    def distribute_wells(self):
        shape = (S, S, 3)
        well_matrix = np.zeros(S * S * 3).reshape(*shape)
        for x in xrange(S):
            for y in xrange(S):
```

```
            if rd.uniform(0, 1) < wf:
                well_matrix[x, y, 0] = np.random.randint(wmin, wmax)
                well_matrix[x, y, 1] = well_matrix[x, y, 0] * wfill
                well_matrix[x, y, 2] = 1
    return well_matrix

def land_quality_mono(self):
    landgrid = np.ones(shape = (S, S))
    return landgrid

def land_quality_stripes(self):
    S = len(self.precipgrid)
    strip_size = S / 4
    landgrid = np.zeros((S, S))
    landgrid[:, 0:strip_size]= L4
    landgrid[:, strip_size:2*strip_size] = L3
    landgrid[:, 2*strip_size:3*strip_size] = L2
    landgrid[:, 3*strip_size:] = L1
    return landgrid

def land_quality_radial(self):
    S = len(self.precipgrid)
    step = S / 8
    origin = (S / 2)
    landgrid = np.zeros((S, S))
    landgrid[origin-4*step:origin+4*step, origin-4*step:origin+4*step] = L1
    landgrid[origin-3*step:origin+3*step, origin-3*step:origin+3*step] = L2
    landgrid[origin-2*step:origin+2*step, origin-2*step:origin+2*step] = L3
    landgrid[origin-step:origin+step, origin-step:origin+step] = L4
    return landgrid

def land_quality_quads(self):
    S = len(self.precipgrid)
    origin = (S / 2)
    landgrid = np.zeros((S, S))
    landgrid[0:origin, 0:origin] = L3    # Upper-left
    landgrid[0:origin, origin:S] = L4    # Upper-right
    landgrid[origin:S, 0:origin] = L1    # Bottom-left
    landgrid[origin:S, origin:S] = L2    # Bottom-right
    return landgrid

def calculate_climate_t(self, t, climate_vector, precipgrid):
```

```
        pg = climate.precipgrid
        climate_t = np.zeros((S, S))
        climate_t = ba + climate_vector[t] + pg[:,:,1] + (V*pg[:,:,2])
        return climate_t


# World
class World:
    def __init__(self, size, report_depth, climate):
        self.grid = [[[] for s in range(S)] for s in range(S)]
        self.well_distance_grid = [[[] for s in range(S)] for s in range(S)]
        shape = (S, S, report_depth)
        self.status_grid = np.zeros(S * S * report_depth).reshape(*shape)

    def __getitem__(self):
        pass

    def well_distances(self, x_coord, y_coord, well_locations):
        well_dictionary = {}
        for well in well_locations:
            well_x = well[0]
            well_y = well[1]
            distance = math.sqrt((x_coord - well_x)**2 + (y_coord - well_y)**2)
            well_dictionary[well] = distance
        return well_dictionary

# Data
class Data:
    def __init__(self, Num_parameters, Num_outputs, MC, T):
        self.Sdata = np.zeros((T, Num_parameters + Num_outputs))
        self.MCdata = np.zeros((MC, Num_parameters + Num_outputs))

#-------------------------------------------
# Build data frames
#-------------------------------------------

data = Data(Num_parameters, Num_outputs, MC, T)



#-------------------------------------------
# Start MC loop
#-------------------------------------------
```

```
mcloop_start = time.time()
for mc in range(MC):
   all_dead = False
   if SingleShot == False:
      LQ_selector = np.random.randint(0, 5)
      m = rd.uniform(0.01/float(mp), 0.05/float(mp)) # Migration rate
      f = np.random.randint(5, 10)     # Initial flock size
      b = rd.uniform(1, 2)           # Benefit of cooperation (contribution multiplier)
      Kt = np.random.randint(1, 6)     # Initial tribe count
      kmax = np.random.randint(60, 151)# Maximum number of members per tribe
      wf = rd.uniform(.05, .2)        # Well frequency
      ba = np.random.randint(5, 20)    # Base grass per tile.
      L4 = .5 * ba # High-quality land bonus
      L3 = .33 *ba # Good-quality land bonus
      L2 = .16 *ba # Low-quality land bonus
      L1 = 0 * ba  # inferior-quality land bonus
      ex = rd.uniform(1, 4)           # Seasonal extremity (Higher is LOWER extremity), float
      A = ba/float(ex)                 # Seasonal extremity (Higher is LOWER extremity)
      V = rd.uniform(0, .3)           # Drought/Rain extremity, range [0,.5]
      k = np.random.randint(5, 16)     # Season length parameter
      wd = np.random.randint(3, 16)    # Persistant weather pattern duration
      wd_range = np.random.randint(1, 5)
      wdmin = 5 - wd_range         # Minimum weather duration in time periods
      wdmax = 5 + wd_range         # Maximum weather duration in time periods
      w_range = np.random.randint(1, 5)
      wmin = (5 - w_range) * ba       # Minimum well depth
      wmax = (5 + w_range) * ba       # Maximum well depth
      wg_ratio = rd.uniform(2, 5)      # Ratio of water accummulation to grass growth at given precip
      lq_boost = rd.uniform(0, 1)      # How much land quality affects well depth, [0, 1]
      dtoler = rd.uniform(-.2, .05)     # Deprivation tolerance. [-.2, .5] roughly. lower die faster.
      lan_law = rd.uniform(1, 2)       # Lanchester's Laws of Combat: Linear (1) or Square (2)
      lethal = rd.uniform(.8, .97)       # Base probability of surviving a battle
      fc_rate = rd.uniform(.15, .3)    # Food consumper rate. (hunger increase per turn)
      wc_rate = rd.uniform(.03, .15)   # Water consumption rate. (water consumption per turn)
      calf_rate = rd.uniform(.05, .2)  # Reproduction probability of animals (per flock, per period)
      mate_comp = rd.uniform(1, 2)   # Mating competition factor. 1-linear, >1 - increasing rate
      birth_rate = rd.uniform(.05, .2) # Reproduction probability of tribesmen per time period.
      cbb = rd.uniform(1, 2.0)        # Cooperative breeding bonus factor
      bprice = rd.uniform(.1, .5)    # "Bride price," percent of flocks given to offspring.
      of_rad = np.random.randint(2, 11) # radius offspring birth around parenting agent.
      well_dist_exp = rd.uniform(1, 1.5) # Well distance value atrophy exponentif SingleShot == False:
```

```
data.MCdata[mc, 0] = MC
data.MCdata[mc, 1] = T
data.MCdata[mc, 2] = N
data.MCdata[mc, 3] = S
data.MCdata[mc, 4] = mp
data.MCdata[mc, 5] = m
data.MCdata[mc, 6] = mu
data.MCdata[mc, 7] = f
data.MCdata[mc, 8] = b
data.MCdata[mc, 9] = Kt
data.MCdata[mc, 10] = kmax
data.MCdata[mc, 11] = wf
data.MCdata[mc, 12] = wfill
data.MCdata[mc, 13] = gfill
data.MCdata[mc, 14] = ba
data.MCdata[mc, 15] = ex
data.MCdata[mc, 16] = A
data.MCdata[mc, 17] = V
data.MCdata[mc, 18] = k
data.MCdata[mc, 19] = L4
data.MCdata[mc, 20] = L3
data.MCdata[mc, 21] = L2
data.MCdata[mc, 22] = L1
data.MCdata[mc, 23] = wd
data.MCdata[mc, 24] = cap
data.MCdata[mc, 25] = wdmin
data.MCdata[mc, 26] = wdmax
data.MCdata[mc, 27] = wmin
data.MCdata[mc, 28] = wmax
data.MCdata[mc, 29] = wg_ratio
data.MCdata[mc, 30] = lq_boost
data.MCdata[mc, 31] = dtoler
data.MCdata[mc, 32] = lan_law
data.MCdata[mc, 33] = lethal
data.MCdata[mc, 34] = fc_rate
data.MCdata[mc, 35] = wc_rate
data.MCdata[mc, 36] = calf_rate
data.MCdata[mc, 37] = mate_comp
data.MCdata[mc, 38] = birth_rate
data.MCdata[mc, 39] = cbb
data.MCdata[mc, 40] = bprice
```

```
    data.MCdata[mc, 41] = of_rad
    data.MCdata[mc, 42] = LQ_selector
    data.MCdata[mc, 43] = well_dist_exp
    data.MCdata[mc, 44] = max_age

#-------------------------------------------
# Generate world and populate (Genesis)
#-------------------------------------------
climate = Climate(S, precip_depth)
climate_vector = climate.climate_vector(A, k, T)
climate.precipgrid[:,:,3:6] = climate.distribute_wells()

if LQ_selector == 0:
    climate.precipgrid[:,:, 1] = smooth_grid(climate.land_quality_mono())
if LQ_selector == 1:
    climate.precipgrid[:,:, 1] = smooth_grid(climate.land_quality_radial())
if LQ_selector == 2:
    climate.precipgrid[:,:, 1] = smooth_grid(climate.land_quality_quads())
if LQ_selector == 3:
    climate.precipgrid[:,:, 1] = smooth_grid(climate.land_quality_stripes())

climate.precipgrid[:,:, 3] += climate.precipgrid[:,:, 3] *lq_boost * \
    climate.precipgrid[:,:, 1]
''' Set initial grass levels '''
climate.precipgrid[:,:, 6] = ba * cap * gfill

wells_locations = []
for x in xrange(S):
    for y in xrange(S):
        ''' Record well locations '''
        if climate.precipgrid[x, y, 5] > 0:
            wells_locations.append((x, y))

world = World(S, report_depth, climate)
for x in xrange(S):
    for y in xrange(S):
        # For each cell, dict of wells (keys), with distances (values)
        world.well_distance_grid[x][y].append(world.well_distances(
                x, y, wells_locations))

tribes = [Tribe(N, Kt, starting = 1) for tr in xrange(Kt)]
for tribe in tribes:
```

```
    tribesmen = []
    for individual in xrange(N/Kt):
        x_coord = np.random.randint(0,S)
        y_coord = np.random.randint(0,S)
        c_in = rd.uniform(0, 1)
        c_out = rd.uniform(0, 1)
        tribesmen.append(Agent(x_coord, y_coord, tribe, f, c_in, c_out))
    tribe.members.extend(tribesmen)
    tribe_size = len(tribe.members)
    tribe.cohesion = sum(tribesman.cooperation_in for tribesman
                    in tribe.members)/float(tribe_size)
    tribe.cooperation_out = sum(tribesman.cooperation_out for tribesman
                    in tribe.members)/float(tribe_size)
    tribe.risk_aversion = sum(tribesman.risk_aversion for tribesman
                    in tribe.members)/float(tribe_size)

    for individual in tribe.members:
        world.grid[individual.location[0]][individual.location[1]].append(
                                            individual)
    tribe.population_old = len(tribe.members)
    tribe.population_new = len(tribe.members)
    tribe.growth_rate = 0

big_board = np.zeros((S, S))
#-------------------------------------------
# Start main simulation loop
#-------------------------------------------
data.Sdata = np.zeros((T, Num_parameters + Num_outputs))
simloop_start = time.time()
wd_counter = wd = 4        # This value doesn't matter.
for t in range(T):
    tloop_start = time.time()
    all_agents = []
    for tribe in tribes:
        all_agents.extend(tribe.members)
        tribe.war_count = 0
        tribe.current_food = 0
        tribe.current_water = 0
        tribe.pr_vic_record = []

    # Eat food and drink water
    for agent in all_agents:
```

```
    agent.hunger += fc_rate
    agent.thirst += wc_rate

#------------------------------------------
# Run precipitation and ecological models
#------------------------------------------
if wd_counter == wd:
    climate.precipgrid[:,:,2] = climate.pdsi(ba, V)
    wd = rd.uniform(wdmin, wdmax)
    wd_counter = 0

''' Make it rain! '''
climate.precipgrid[:, :, 0] = climate.calculate_climate_t(t,
                climate_vector, climate.precipgrid)

'''Watch the grass grow'''
climate.precipgrid[:, :, 6] += climate.calculate_climate_t(t,
                climate_vector, climate.precipgrid)
climate.precipgrid[:, :, 7] = climate.precipgrid[:, :, 0] * cap

'''Fill the wells'''
climate.precipgrid[:, :, 4] = climate.precipgrid[:,:,5] * (
                climate.precipgrid[:,:,4] +
                climate.precipgrid[:,:,0] * wg_ratio)

''' Make sure more grass and water doesn't go beyond capacities '''
for x in xrange(S):
    for y in xrange(S):
        if climate.precipgrid[x, y, 4] > climate.precipgrid[x,y,3]:
            climate.precipgrid[x, y, 4] = climate.precipgrid[x,y,3]

        if climate.precipgrid[x, y, 6] > climate.precipgrid[x, y, 7]:
            climate.precipgrid[x, y, 6] = climate.precipgrid[x, y, 7]

        big_board[x, y] = len(world.grid[x][y])

#------------------------------------------
# Agents wander, looking for food and water
#------------------------------------------

##------------------
# Move determination
```

```
##------------------
for x in xrange(S):
   for y in xrange(S):
      agents = []
      if len(world.grid[x][y]) > 0:
         agents.extend(world.grid[x][y])
         wells = world.well_distance_grid[x][y][0]
         for agent in agents:
            agent.next_loc = agent.wander(x, y, b, world.grid,
               climate.precipgrid, wells, lan_law)

# Go to new locations
# 1. get list of all agents.
travel_queue = []
for tribe in tribes:
   for tribesman in tribe.members:
      travel_queue.append(tribesman)

# 2. Go
for agent in travel_queue:
   x,y = agent.old_loc
   x2,y2 = agent.next_loc
   agent.old_loc = (x2, y2)
   agent.location = (x2, y2)
   world.grid[x][y].remove(agent)
   world.grid[x2][y2].append(agent)

#-----------------------------------------
# Resolve encounters
#-----------------------------------------
for x in xrange(S):
   for y in xrange(S):
      agents = []
      if len(world.grid[x][y]) > 0:
         agents.extend(world.grid[x][y])
         available_food = climate.precipgrid[x][y][6]
         available_water = climate.precipgrid[x][y][4]
         #--------------------------------------------
         # If only one agent is present at location x,y
         #--------------------------------------------
         ''' Determine if more than one agent is present. If only
            one, just take the resources. No bonuses, no
```

```
    penalties.'''
if len(agents) == 1:
    ''' Agent's hunger is how hungry his animals are.
        Appetite is how much the agent wants to consume,
        given the number of animals.'''
    appetite = agents[0].hunger * agents[0].flocks
    thirstiness = agents[0].thirst * agents[0].flocks

    if available_food > appetite:
        agents[0].hunger = 0.0
        climate.precipgrid[x][y][6] -= appetite
    else:
        appetite -= climate.precipgrid[x][y][6]
        agents[0].hunger= appetite / float(agents[0].flocks)
        climate.precipgrid[x][y][6] = 0.0
    ''' Same with water/third '''
    if available_water > thirstiness:
        agents[0].thirst = 0.0
        climate.precipgrid[x][y][4] -= thirstiness
    else:
        thirstiness -= climate.precipgrid[x][y][4]
        agents[0].thirst=thirstiness/float(agents[0].flocks)
        climate.precipgrid[x][y][4] = 0.0

    agents[0].happiness = 1 - ((agents[0].hunger + agents[0].thirst)/2.0)

#-------------------------------------------------
# If two or more agents are present at location x,y
#-------------------------------------------------
if len(agents) > 1:
    tribes_list = []
    tribes_census = {}
    all_strategies = {}
    for ag in agents:
        tribes_list.append(ag.tribe)
    '''Converting to set and back removes duplicates'''
    tribes_list_set = list(set(tribes_list))
    tribe_count = len(tribes_list_set)
    #--------------------------
    # If only one tribe present
    #--------------------------
    if len(tribes_list_set)==1:
```

```
portion_food = available_food/float(len(agents))
portion_water = available_water/float(len(agents))

intribe_contr_f = sum(agent.cooperation_in for agent
   in agents) * b * portion_food
intribe_contr_w = sum(agent.cooperation_in for agent
   in agents) * b * portion_water

ag_food = intribe_contr_f / len(agents)
ag_water = intribe_contr_w / len(agents)

leftover_f = 0
leftover_w = 0

for agent in agents:
   fd = portion_food * (1 - agent.cooperation_in)
   wt = portion_water * (1 - agent.cooperation_in)
   fd += ag_food
   wt += ag_water

   leftover_f_i = 0
   leftover_w_i = 0

   appetite = agent.hunger * agent.flocks
   thirstiness = agent.thirst * agent.flocks

   if fd > appetite:
      agent.hunger = 0.0
      leftover_f_i += fd - appetite
   else:
      appetite -= fd
      agent.hunger= appetite / float(
         agent.flocks)
      leftover_f_i = 0

   ''' Same with water/third '''
   if wt > thirstiness:
      agent.thirst = 0.0
      leftover_w_i += wt - thirstiness
   else:
      thirstiness -= wt
      agent.thirst=thirstiness/float(agent.flocks)
```

```
        leftover_w_i = 0

    leftover_f += leftover_f_i
    leftover_w += leftover_w_i

    agent.happiness = 1-((agent.hunger+agent.thirst)/2.0)

# Eat and drink the leftovers:
needy_agents = []
food_left = leftover_f
water_left = leftover_w

if leftover_f > 0:
    hungry_tribesmen = []
    for agent in agents:
        if agent.hunger > 0:
            hungry_tribesmen.append(agent)
            needy_agents.append(agent)

    if len(hungry_tribesmen) > 0:
        hungry = 1
        extra_helping = leftover_f / float(len(
            hungry_tribesmen))

        for hungry_guy in hungry_tribesmen:
            appetite = hungry_guy.hunger * \
                hungry_guy.flocks

            if extra_helping > appetite:
                hungry_guy.hunger = 0.0
                food_left  -= appetite

            else:
                appetite -= extra_helping
                hungry_guy.hunger= appetite / float(
                    hungry_guy.flocks)
                food_left -= extra_helping

if leftover_w > 0:
    thirsty_tribesmen = []
    for agent in agents:
        if agent.thirst > 0:
```

```
            thirsty_tribesmen.append(agent)
            needy_agents.append(agent)

        if len(thirsty_tribesmen) > 0:
            extra_cup = leftover_w / float(len(
                thirsty_tribesmen))

            for thirsty_guy in thirsty_tribesmen:
                thirstiness = thirsty_guy.thirst * \
                    thirsty_guy.flocks
                if extra_cup > thirstiness:
                    thirsty_guy.thirst = 0.0
                    water_left -= thirstiness

                else:
                    thirstiness -= extra_cup
                    thirsty_guy.thirst= thirstiness / \
                        float(thirsty_guy.flocks)
                    water_left -= extra_cup


    if len(needy_agents) > 0:
        for needy_guy in needy_agents:
            needy_guy.happiness = 1 -((needy_guy.hunger + needy_guy.thirst)/2.0)

    # Update precipgrid with remaining resources.
    climate.precipgrid[x][y][6] = food_left / b
    climate.precipgrid[x][y][4] = water_left / b

#------------------------------------
# If two or greater tribes are present
#------------------------------------
else:
    for tribe in tribes_list_set:
        other_tribes = []
        other_tribes.extend(tribes_list_set)
        other_tribes.remove(tribe)
        tribes_census[tribe] = 0
        all_strategies[tribe] = {}
        for ag in agents:
            if ag.tribe == tribe:
                tribes_census[tribe] += 1
```

```
# for tribe in other_tribes, decide if PGG or Fight
for other in other_tribes:
  ingroup = list(set(tribe.members) &
    set(agents))
  outgroup =list(set(other.members) &
    set(agents))
  in_size = len(ingroup)
  out_size = len(outgroup)
  ttl_size = in_size + out_size
  in_prop = in_size / float(ttl_size)
  out_prop = 1 - in_prop
  foodshare = available_food / float(ttl_size)
  watershare = available_water / float(
    ttl_size)
  tfood = foodshare * in_size
  twater = watershare * in_size

  # In group PGG
  in_contrib = sum(member.cooperation_in for \
    member in ingroup)

  avg_contrib = in_contrib / float(in_size)

  commonfood = b * avg_contrib * tfood

  commonwater = b * avg_contrib * twater

  PGG_food = commonfood / float(in_size)
  PGG_water = commonwater / float(in_size)

  in_payoff_f = PGG_food * (1 - avg_contrib)
  in_payoff_w = PGG_water * (1 - avg_contrib)

  in_payoff_f += PGG_food
  in_payoff_w += PGG_water

  avg_appetite = sum(member.appetite for \
    member in ingroup) / float(in_size)

  avg_thirstiness = sum(member.thirstiness for
    member in ingroup) / float(in_size)
```

```
avg_hunger = sum(member.hunger for member \
   in ingroup) / float(in_size)

avg_thirst = sum(member.thirst for member \
   in ingroup) / float(in_size)

loss_hunger = avg_hunger
loss_thirst = avg_thirst

avg_flocks = sum(member.flocks for member \
   in ingroup) / float(in_size)

if in_payoff_f > avg_appetite:
   avg_hunger = 0.0
else:
   avg_appetite -= in_payoff_f
   avg_hunger = avg_appetite / \
      float(avg_flocks)

''' Same with water/third '''
if in_payoff_w > avg_thirstiness:
   avg_thirst = 0.0
else:
   avg_thirstiness -= in_payoff_w
   avg_thirst = avg_thirstiness / float(
      avg_flocks)

p_happiness = 1 - ((avg_hunger + avg_thirst)/2.0)

# Fight PGG (in group only)
foodfight = available_food / float(in_size)
waterfight = available_water /float(in_size)

in_contrib = sum(member.cooperation_in \
   for member in ingroup)

avg_contrib = in_contrib / float(in_size)

commonfood = b*available_food* avg_contrib

commonwater = b*available_water* avg_contrib
```

```
FPGG_food = commonfood / float(in_size)
FPGG_water = commonwater / float(in_size)

avg_appetite = sum(member.appetite for \
   member in ingroup) / float(in_size)

avg_thirstiness = sum(member.thirstiness for
   member in ingroup) / float(in_size)

avg_hunger = sum(member.hunger for member \
   in ingroup) / float(in_size)

avg_thirst = sum(member.thirst for member \
   in ingroup) / float(in_size)

in_payoff_f = FPGG_food * (1 - avg_contrib)
in_payoff_w = FPGG_water * (1 - avg_contrib)
in_payoff_f += FPGG_food
in_payoff_w += FPGG_water

if in_payoff_f > avg_appetite:
   avg_hunger = 0.0
else:
   avg_appetite -= in_payoff_f
   avg_hunger= avg_appetite / float(
      avg_flocks)

''' Same with water/third '''
if in_payoff_w > avg_thirstiness:
   avg_thirst = 0.0
else:
   avg_thirstiness -= in_payoff_w
   avg_thirst = avg_thirstiness / float(
      avg_flocks)


win_happiness = 1 - ((avg_hunger + avg_thirst)/2.0)

loss_happiness = 1 - ((loss_hunger + loss_thirst)/2.0)

# Determine probabilty of victory in battle
```

```
        pr_vic = pr_victory(x, y, tribe, other,
          lan_law)

        f_happiness = (pr_vic * win_happiness) +\
                  ((1-pr_vic)*loss_happiness)

        if f_happiness > p_happiness:
          all_strategies[tribe][other] = 1
        else:
          all_strategies[tribe][other] = 0

    # determine final payoffs to each group
    # See who is fighting whether they like it or not.
    fight_pairs = set()
    for tribe in tribes_list_set:
      for other in all_strategies[tribe]:
        if all_strategies[tribe][other] == 1:
          fight_pairs.add(frozenset((tribe,
            other)))

    # Determine which tribes don't fight at all.
    PGG_tribes = PGG_tribes_list(fight_pairs,
            tribes_list)

    # Distribute Resources to tribes.
    portion_food = available_food/float(len(agents))
    portion_water = available_water/float(len(agents))
    for tribe in tribes_list_set:
      tribe.current_food = portion_food * \
        tribes_census[tribe]
      tribe.current_water = portion_water * \
        tribes_census[tribe]

    for pair in fight_pairs:
      tribeA, tribeB = list(pair)
      tribeA.war_count += 1
      tribeB.war_count += 1
      pr_vic = pr_victory(x, y,tribeA,tribeB, lan_law)
      tribeA.pr_vic_record.append(pr_vic)
      tribeB.pr_vic_record.append(1 - pr_vic)

      if rd.uniform(0, 1) < pr_vic:
```

```
        tribeA.current_food += tribeB.current_food
        tribeA.current_water += tribeB.current_water
        tribeB.current_food = 0
        tribeB.current_water = 0
        PGG_tribes.append(tribeA)
    else:
        tribeB.current_food += tribeA.current_food
        tribeB.current_water += tribeA.current_water
        tribeA.current_food = 0
        tribeA.current_water = 0
        PGG_tribes.append(tribeB)

# Remove possible duplicates, finallize PGG teams
PGG_tribes = list(set(PGG_tribes))

# Play final PGG
# find out how many teams
if len(PGG_tribes) == 1: # play ingroup PGG
    ingroup=list(set(PGG_tribes[0].members) & set(
        agents))
    ig_size = len(ingroup)
    food = available_food / float(ig_size)
    water = available_water / float(ig_size)

    sharefood = b*food*sum(member.cooperation_in for
        member in ingroup)
    sharewater = b*water*sum(member.cooperation_in \
        for member in ingroup)

    ag_food = sharefood / float(ig_size)
    ag_water = sharewater / float(ig_size)

    leftover_f = 0
    leftover_w = 0

    for agent in ingroup:
        fd = ag_food * (1 - agent.cooperation_in)
        wt = ag_water * (1 - agent.cooperation_in)
        fd += ag_food
        wt += ag_water

        leftover_f_i = 0
```

```
    leftover_w_i = 0

    appetite = agent.hunger * agent.flocks
    thirstiness = agent.thirst * agent.flocks

    if fd > appetite:
        agent.hunger = 0.0
        leftover_f_i += fd - appetite
    else:
        appetite -= fd
        agent.hunger = appetite / float(
            agent.flocks)

    ''' Same with water/third '''
    if wt > thirstiness:
        agent.thirst = 0.0
        leftover_w_i += wt - thirstiness
    else:
        thirstiness -= wt
        agent.thirst = thirstiness/float(
            agent.flocks)

    leftover_f += leftover_f_i
    leftover_w += leftover_w_i

    agent.happiness = 1 - ((agent.hunger + agent.thirst)/2.0)

# Eat and drink the leftovers:
needy_agents = []
food_left = leftover_f
water_left = leftover_w

if leftover_f > 0:
    hungry_tribesmen = []
    for agent in agents:
        if agent.hunger > 0:
            hungry_tribesmen.append(agent)
            needy_agents.append(agent)

    if len(hungry_tribesmen) > 0:
        hungry = 1
        extra_helping = leftover_f / float(len(
```

```
            hungry_tribesmen))

        for hungry_guy in hungry_tribesmen:
            appetite = hungry_guy.hunger * \
                hungry_guy.flocks

            if extra_helping > appetite:
                hungry_guy.hunger = 0.0
                food_left  -= appetite

            else:
                appetite -= extra_helping
                hungry_guy.hunger= appetite / \
                    float(hungry_guy.flocks)
                food_left -= extra_helping

if leftover_w > 0:
    thirsty_tribesmen = []
    for agent in agents:
        if agent.thirst > 0:
            thirsty_tribesmen.append(agent)
            needy_agents.append(agent)

    if len(thirsty_tribesmen) > 0:
        extra_cup = leftover_w / float(len(
            thirsty_tribesmen))

        for thirsty_guy in thirsty_tribesmen:
            thirstiness = thirsty_guy.thirst * \
                thirsty_guy.flocks
            if extra_cup > thirstiness:
                thirsty_guy.thirst = 0.0
                water_left -= thirstiness

            else:
                thirstiness -= extra_cup
                thirsty_guy.thirst= thirstiness/ float(thirsty_guy.flocks)
                water_left -= extra_cup

if len(needy_agents) > 0:
    for needy_guy in needy_agents:
        needy_guy.happiness = 1 - ((needy_guy.hunger + needy_guy.thirst)/2.0)
```

```
        # Update precipgrid with remaining resources.
        climate.precipgrid[x][y][6] = food_left / float(b)
        climate.precipgrid[x][y][4] = water_left / float(b)


    if len(PGG_tribes) > 1: # play multigroup PGG
        ttl_players = sum(tribes_census[tribe] for \
            tribe in PGG_tribes)
        remain_food = 0
        remain_water = 0

        for tribe in PGG_tribes:
            ingroup = list(set(tribe.members) & set(
                agents))
            ig_size = tribes_census[tribe]
            avail_food = tribe.current_food
            avail_water = tribe.current_water
            agt_food = avail_food / float(ig_size)
            agt_water = avail_water / float(ig_size)

            tr_food = b * sum(member.cooperation_in * \
                agt_food for member in tribe.members)
            tr_water = b * sum(member.cooperation_in * \
                agt_water for member in tribe.members)

            unit_f = tr_food / float(ig_size)
            unit_w = tr_water / float(ig_size)

            leftover_f = 0
            leftover_w = 0

            for agent in ingroup:
                fd = agt_food * (1 - agent.cooperation_in)
                wt = agt_water * (1 - agent.cooperation_in)
                fd += unit_f
                wt += unit_w

                appetite = agent.hunger * agent.flocks
                thirstiness = agent.thirst * agent.flocks

                if fd > appetite:
```

```
        agent.hunger = 0.0
        leftover_f += fd - appetite
    else:
        appetite -= fd
        agent.hunger= appetite / float(
            agent.flocks)

    ''' Same with water/third '''
    if wt > thirstiness:
        agent.thirst = 0.0
        leftover_w += wt - thirstiness
    else:
        thirstiness -= wt
        agent.thirst=thirstiness / float(agent.flocks)

    agent.happiness = 1 - ((agent.hunger + agent.thirst)/2.0)

# Eat and drink the leftovers:
food_left = leftover_f
water_left = leftover_w
needy_agents = []
if leftover_f > 0:
    hungry_tribesmen = []
    for agent in ingroup:
        if agent.hunger > 0:
            hungry_tribesmen.append(agent)
            needy_agents.append(agent)

    if len(hungry_tribesmen) > 0:
        hungry = 1
        extra_helping = leftover_f / float(len(
            hungry_tribesmen))

        for hungry_guy in hungry_tribesmen:
            appetite = hungry_guy.hunger * \
                hungry_guy.flocks

            if extra_helping > appetite:
                hungry_guy.hunger = 0.0
                food_left  -= appetite

            else:
```

```
                    appetite -= extra_helping
                    hungry_guy.hunger= appetite \
                        / float(hungry_guy.flocks)
                    food_left -= extra_helping

        if leftover_w > 0:
            thirsty_tribesmen = []
            for agent in ingroup:
                if agent.thirst > 0:
                    thirsty_tribesmen.append(agent)
                    needy_agents.append(agent)

            if len(thirsty_tribesmen) > 0:
                extra_cup = leftover_w / float(len(
                    thirsty_tribesmen))

                for thirsty_guy in thirsty_tribesmen:
                    thirstiness = thirsty_guy.thirst * \
                        thirsty_guy.flocks
                    if extra_cup > thirstiness:
                        thirsty_guy.thirst = 0.0
                        water_left -= thirstiness

                    else:
                        thirstiness -= extra_cup
                        thirsty_guy.thirst= thirstiness\
                            / float(thirsty_guy.flocks)
                        water_left -= extra_cup

        if len(needy_agents) > 0:
            for needy_guy in needy_agents:
                needy_guy.happiness = 1 - ((needy_guy.hunger + needy_guy.thirst)/2.0)

        # Update precipgrid with remaining resources.
        remain_food += food_left  / float(b)
        remain_water += water_left  / float(b)

    climate.precipgrid[x][y][6] = remain_food
    climate.precipgrid[x][y][4] = remain_water

for tribe in tribes:
    if tribe.war_count == 0:
```

```
        tribe.avg_pr_vic = 1
    else:
        tribe.avg_pr_vic=sum(tribe.pr_vic_record)/float(tribe.war_count)
#--------------------------------------------
# Calculate flock changes and resets
#--------------------------------------------
for agent in all_agents:
    agent.current_food = 0
    agent.current_water = 0
    agent.appetite = agent.hunger * agent.flocks
    if agent.thirst > 1: agent.thirst = 1.0
    agent.thirstiness = agent.thirst * agent.flocks
    health = (agent.hunger + agent.thirst) / 2.0
    survival_rate = (1 + dtoler)-(math.exp(-(math.pow(1.5-health, 3))))
    agent.flocks = int(agent.flocks * survival_rate)
    if agent.flocks > 0:
        agent.flocks += np.random.binomial(agent.flocks, calf_rate)

    #--------------------------------------------
    # Death, aging, migration, and mutation
    #--------------------------------------------
    death = 0
    if agent.flocks <= 0:
        death = 1

    if agent.age > max_age:
        death = 1

    battles = agent.tribe.war_count
    prv = 1 - agent.tribe.avg_pr_vic
    pr_violent_death = 1 - (lethal**(battles*prv*agent.cooperation_in))

    if rd.uniform(0, 1) < pr_violent_death:
        death = 1

    if death == 1:
        agent.tribe.members.remove(agent)
        x, y = agent.location
        world.grid[x][y].remove(agent)
        all_agents.remove(agent)

    else:
```

```
        agent.age += 1
        # Migration
        if len(tribes) > 1:
            if rd.uniform(0, 1) < m:
                tribes_out = []
                tribes_out.extend(tribes)
                tribes_out.remove(agent.tribe)
                new_tribe = rd.choice(tribes_out)
                agent.tribe.members.remove(agent)
                agent.tribe = new_tribe
                agent.tribe.members.append(agent)

        # Mutation
        if rd.uniform(0, 1) < mu:
            agent.cooperation_in = rd.uniform(0, 1)


#------------------------------------------
# Reproduction
#------------------------------------------
for tribe in tribes:
    if len(tribe.members) == 0:
        tribes.remove(tribe)

    cb = birth_rate * cbb * tribe.cohesion #Cooperative breeding bonus
    # sort tribes.members on flock size, calculate mate_score
    tribe.members.sort(key=lambda x: x.flocks)
    ranker = 1
    top_dog = len(tribe.members)
    agent_nursury = []
    for member in tribe.members:
        member.rank = ranker
        ranker += 1
        member.mate_score = (member.rank / float(top_dog))**mate_comp

        # baby appears in random location near parent
        if member.flocks > 5:
            if rd.uniform(0, 1) < (birth_rate + cb) * member.mate_score:
                c_in = member.cooperation_in
                c_out = member.cooperation_out
                dowry = int(member.flocks * bprice) - 1
                member.flocks -= dowry
```

```
            tri = member.tribe
            x,y = member.location
##          x2 = np.random.randint(0, S)
##          y2 = np.random.randint(0, S)

            x2 = x + np.random.randint(-of_rad, of_rad)
            y2 = y + np.random.randint(-of_rad, of_rad)
            if x2 < 0: x2 = 0
            if x2 > S-1: x2 = S-1
            if y2 < 0: y2 = 0
            if y2 > S-1: y2 = S-1

            agent_nursury.append(Agent(x2,y2,tri, dowry,c_in,c_out))

    for baby in agent_nursury:
        if baby.flocks <= 3: baby.flocks = 4
        x, y = baby.location
        baby.new_loc = (x, y)
        baby.old_loc = (x, y)
        baby.tribe.members.append(baby)
        world.grid[x][y].append(baby)

    tribe.population_old = tribe.population_new
    tribe.population_new = len(tribe.members)
    tribe.growth_rate = (tribe.population_new - tribe.population_old)/ \
        float(tribe.population_old)


#-----------------------------------------
# Tribe splitting and dissolution
#-----------------------------------------
if len(all_agents) > 0:
    for tribe in tribes:
        if len(tribe.members) <= 0:
            tribes.remove(tribe)

    nu_tribes = []
    for tribe in tribes:
        if len(tribe.members) > kmax:
            splitnum = len(tribe.members) / 2
            splitters = rd.sample(tribe.members, splitnum)
            nu_tribe = Tribe(N, Kt, starting = 0)
```

```
            print "Tribe split"
            nu_tribes.append(nu_tribe)
            for splitter in splitters:
                tribe.members.remove(splitter)
                nu_tribe.members.append(splitter)
                splitter.tribe = nu_tribe

    if len(nu_tribes) > 0:
        tribes.extend(nu_tribes)



    for tribe in tribes:
        tribe_size = len(tribe.members)
        tribe.cohesion = sum(tribesman.cooperation_in for tribesman
                        in tribe.members)/float(tribe_size)
        tribe.cooperation_out = sum(tribesman.cooperation_out for tribesman
                        in tribe.members)/float(tribe_size)
        tribe.risk_aversion = sum(tribesman.risk_aversion for tribesman
                        in tribe.members)/float(tribe_size)
else:
    all_dead = True

if all_dead == True:
    break

teloop_end = time.time()
if teloop_end - tloop_start > timeLimit1:
    unlucky = rd.sample(all_agents, int(round(tcut1*len(all_agents))))
    for badluck_brian in unlucky:
        badluck_brian.tribe.members.remove(badluck_brian)
        x, y = badluck_brian.location
        world.grid[x][y].remove(badluck_brian)
        all_agents.remove(badluck_brian)

if teloop_end - tloop_start > timeLimit2:
    unlucky = rd.sample(all_agents, int(round(tcut2*len(all_agents))))
    for badluck_brian in unlucky:
        badluck_brian.tribe.members.remove(badluck_brian)
        x, y = badluck_brian.location
        world.grid[x][y].remove(badluck_brian)
        all_agents.remove(badluck_brian)
```

```
if teloop_end - tloop_start > timeLimit3:
    unlucky = rd.sample(all_agents, int(round(tcut3*len(all_agents))))
    for badluck_brian in unlucky:
        badluck_brian.tribe.members.remove(badluck_brian)
        x, y = badluck_brian.location
        world.grid[x][y].remove(badluck_brian)
        all_agents.remove(badluck_brian)

if teloop_end - tloop_start > timeLimit4:
    unlucky = rd.sample(all_agents, int(round(tcut4*len(all_agents))))
    for badluck_brian in unlucky:
        badluck_brian.tribe.members.remove(badluck_brian)
        x, y = badluck_brian.location
        world.grid[x][y].remove(badluck_brian)
        all_agents.remove(badluck_brian)

if teloop_end - tloop_start > timeLimit5:
    unlucky = rd.sample(all_agents, int(round(tcut5*len(all_agents))))
    for badluck_brian in unlucky:
        badluck_brian.tribe.members.remove(badluck_brian)
        x, y = badluck_brian.location
        world.grid[x][y].remove(badluck_brian)
        all_agents.remove(badluck_brian)

avg_cooperation = sum(agt.cooperation_in for agt in all_agents)/float(len(all_agents))
avg_flock = sum(agt.flocks for agt in all_agents)/float(len(all_agents))
war_freq = sum(trb.war_count for trb in tribes)

#-----------------------------------------
# End main simulation loop; record data
#-----------------------------------------
tloop_end = time.time()
print "Single time period runtime", tloop_end - tloop_start
print "Time period", t
print "Simulation run", mc
print "Total agents = ", len(all_agents)

if printStuff == True:
    counttribe = 0
    for tribe in tribes:
        counttribe += 1
        print "--------------------------------"
```

```
        print "-----Tribe ", counttribe, "-----"
        print "--------------------------------"
        print "Cohesion = ", tribe.cohesion
        print "Population = ", len(tribe.members)
        print "Growth Rate = ", tribe.growth_rate

if show == True:
    heatmap = plt.pcolor(big_board, cmap = plt.cm.Blues)
    plt.draw()

data.Sdata[t, 0] = MC
data.Sdata[t, 1] = T
data.Sdata[t, 2] = N
data.Sdata[t, 3] = S
data.Sdata[t, 4] = mp
data.Sdata[t, 5] = m
data.Sdata[t, 6] = mu
data.Sdata[t, 7] = f
data.Sdata[t, 8] = b
data.Sdata[t, 9] = Kt
data.Sdata[t, 10] = kmax
data.Sdata[t, 11] = wf
data.Sdata[t, 12] = wfill
data.Sdata[t, 13] = gfill
data.Sdata[t, 14] = ba
data.Sdata[t, 15] = ex
data.Sdata[t, 16] = A
data.Sdata[t, 17] = V
data.Sdata[t, 18] = k
data.Sdata[t, 19] = L4
data.Sdata[t, 20] = L3
data.Sdata[t, 21] = L2
data.Sdata[t, 22] = L1
data.Sdata[t, 23] = wd
data.Sdata[t, 24] = cap
data.Sdata[t, 25] = wdmin
data.Sdata[t, 26] = wdmax
data.Sdata[t, 27] = wmin
data.Sdata[t, 28] = wmax
data.Sdata[t, 29] = wg_ratio
data.Sdata[t, 30] = lq_boost
data.Sdata[t, 31] = dtoler
```

```
        data.Sdata[t, 32] = lan_law
        data.Sdata[t, 33] = lethal
        data.Sdata[t, 34] = fc_rate
        data.Sdata[t, 35] = wc_rate
        data.Sdata[t, 36] = calf_rate
        data.Sdata[t, 37] = mate_comp
        data.Sdata[t, 38] = birth_rate
        data.Sdata[t, 39] = cbb
        data.Sdata[t, 40] = bprice
        data.Sdata[t, 41] = of_rad
        data.Sdata[t, 42] = 9999
        data.Sdata[t, 43] = well_dist_exp
        data.Sdata[t, 44] = LQ_selector
        data.Sdata[t, 45] = max_age
        data.Sdata[t, 46] = len(all_agents)
        data.Sdata[t, 47] = avg_cooperation
        data.Sdata[t, 48] = len(tribes)
        data.Sdata[t, 49] = war_freq
        data.Sdata[t, 50] = avg_flock

    simloop_end = time.time()
    print "Single-shot simulation runtime", simloop_end - simloop_start

#-------------------------------------------
# End Monte Carlo loop; save MC data
#-------------------------------------------
    data.MCdata[mc, 45] = simloop_end - simloop_start
    data.MCdata[mc, 46] = len(all_agents)
    data.MCdata[mc, 47] = avg_cooperation
    data.MCdata[mc, 48] = len(tribes)
    data.MCdata[mc, 49] = war_freq
    data.MCdata[mc, 50] = avg_flock
#-------------------------------------------
# Close datafile and analysis
#-------------------------------------------
np.savetxt("MCdata_africa_sim.csv", data.MCdata, delimiter =',', fmt = '%1.7f')

#------------------------------------------
# End all simulations; close up shop!
#------------------------------------------
mcloop_end = time.time()
print "Monte Carlo runtime", mcloop_end - mcloop_start
```

```
#plt.plot(range(T),data.Sdata[:,47])
#plt.show()
done = 1;
```

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