UNDERSTANDING THE GEOGRAPHIC DYNAMICS OF GOAL-DIRECTED SOCIAL BEHAVIORS

by

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DEDICATION

To Colin.

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ABSTRACT

UNDERSTANDING THE GEOGRAPHIC DYNAMICS OF GOAL-DIRECTED SOCIAL BEHAVIORS

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No fundamental empirical research exists to describe the goal-directed behavior of teams in geographic space. This dissertation describes a basic research project that produces new metrics, hypotheses, and distributions of observations about the geographic behaviors of discrete social networks or teams pursuing collective objectives. The motivation is to propose theories that explain and predict how illicit teams – such as groups involved in terrorism, smuggling, and other criminal or politically subversive activities – move and communicate. The research design uses network-based stochastic geosimulation, formal experimental design, and spatiotemporal statistics to perform an experimental analysis of small team behaviors. The project produces theoretical and randomized data about the times, locations, and message traffic of simulated players and teams engaged in 1.11 million repetitions of pursuit-and-evasion, a simple game akin to hide-and-seek. This computer simulation-based project will serve as a basis for future

mixed methods research employing human subjects in laboratory and full-scale instances of the pursuit-and-evasion game. Furthermore, the research approach will support future extensions to understand not only teams, but also multiteam systems. This approach draws from extant research, and applies statistics, methods, and theoretical frameworks from among multiple disciplines including geography, industrial and organizational psychology, network science, operations research, and strategic studies. Development of reliable theories about the geographic patterns of team behaviors will support further basic research as well as applied research in societal instability, criminology, radicalism, social psychology, and simulation of stochastic human geographic processes, ultimately leading to improvements in civil services, social welfare, and public safety.

CHAPTER ONE: INTRODUCTION

Intelligence approaches to the problems of terrorism, insurgency, trafficking, organized crime, and political subversion demand methods to discern and interpret geographic patterns of activity belonging to teams pursuing illicit goals while operating freely among a population. Analysts use terms like "autonomous cells" (Abuza, 2002) and "leaderless resistance" (Kaplan, 1997) to characterize these teams as discrete social networks that are united by common objectives even though they may operate in a decentralized manner and work toward a disparate variety of tasks (Arquilla, Ronfeldt, & Zanini, 1999; Sageman, 2008). Behavioral scientists, especially organizational psychologists, have studied team motivation and performance for many decades and produced sophisticated models of goal-oriented collective action (Salas, Cooke, & Rosen, 2008). Significantly, research focused on the interdependence of teams under conditions of decentralized authority has produced the concept of multiteam systems that may help explain the behaviors of politically subversive groups (Zaccaro, Marks, & DeChurch, 2011). While there is a rich theoretical literature to describe the forms, functions, and functioning of teams, and while there are also numerous examples of theory-driven models of human competition, there is no fundamental empirical research to describe how teams and multiteam systems, especially clandestine teams, actually pursue goals in geographic space.

Two concurrent phenomena have focused researchers' interest upon the dynamic behaviors of social networks in geographic space: the increased capacity of small teams to achieve social and political influence, and improvements in scientific capabilities to measure and model the communications and spatiotemporal movement of these small teams. In the latter half of the twentieth century the phenomena of decolonization, proxy wars, international institutionalism, globalization, and the information revolution have all contributed to a worldwide fragmentation of geopolitical authority. As this dissolution of the centralized international system accelerated after the fall of the Soviet Union, so did the rise of multinational corporatism and radical advances in computing and communications technology. The world today is exceedingly interconnected. Ties of commerce, culture, information, and ideology increasingly and more rapidly transcend physical distance and social boundaries. As a result, societies are far less subject to the control of the state and small social networks are much more capable of achieving social and political influence. This has given rise to many politically subversive groups becoming active worldwide, such as the al-Baghdadi group in Syria and Iraq, Al Qaeda, Hezballah, Hamas, Al Shabaab, and Lashkar-e-Taiba. In several areas around the world, the United States has, as a matter of policy and strategy, become involved in stabilizing societies undermined by the behaviors of illicit teams and multiteam systems.

Setting aside the problems of criminality and political subversion, there are not even any basic geographic models about how legitimate teams pursue commonplace objectives in everyday life, and there are many social phenomena other than security operations that might be better understood via a geographically grounded study of goal-directed team behaviors. All around the world, people move, communicate, and work together with each other while striving to achieve big and small social goals. Commercial relationships are often complicated combinations of competition and cooperation demanding that individuals work simultaneously with and against each other in order to maximize profit. In the cultural domain, mavens, traditionalists, and upstarts interact spatially and conceptually to accumulate influence over social norms and mores. Public safety professionals seek greater awareness not only of rioters, gang members, and organized criminals but also of people displaced or affected by natural and manmade disasters. Public health researchers seek greater knowledge of the epidemiological effects of societal reactions to the outbreak of disease. In short, the increased ability to describe and measure the spatial behaviors of discrete social networks has broad applicability.

There may be observable patterns of team behaviors and their underlying factors. Naïve conjecture would suggest that swarming or scattering, for example, may occur in ways which are both noticeable to casual observers and scientifically measurable. Furthermore, these patterns may occur as a function of objective type, task type, topography, political boundaries, social boundaries, cultural heterogeneities, group cohesion, and/or technologies. However, these behaviors cannot be accurately differentiated and these crude hypotheses cannot be scrutinized or improved upon because geographers have not yet modeled goal-oriented team behaviors. No field-based empirical studies have focused upon the possibility that social groups behave in spatiotemporally coherent ways according to such conjecture. Therein lays the potential to make new discoveries about the geographic dynamics of goal-directed social behaviors.

This dissertation describes a program of basic research that produces new metrics, hypotheses, and distributions of observations about the geographic behaviors of discrete social networks or teams pursuing collective objectives. The ultimate motivation is to propose theories that explain and predict how illicit teams – such as groups involved in terrorism, smuggling, and other criminal or politically subversive activities – move and communicate in geographic space. While it exclusively assesses the behaviors of teams, it is designed to support future extensions that will explore the dynamics of MTSs. Fundamental scientific knowledge about the geographic attributes of team behaviors will support future empirical research aimed at reliably discriminating between malevolent and innocuous social activities. However this research will also lead to generalizable theory usable to understand the behaviors of many different kinds of teams in numerous domains. The research design uses network-based stochastic geosimulation, formal experimental design, and spatiotemporal statistics to perform an experimental analysis of small team behaviors. The project produces theoretical and randomized data about the times, locations, and message traffic of simulated players and teams engaged in 1.11 million repetitions of pursuit-and-evasion, a simple game akin to hide-and-seek. This computer simulation-based project will serve as a basis for future mixed methods research employing human subjects in laboratory and full-scale instances of the pursuit-and-evasion game. The approach draws from extant research, and applies statistics, methods, and theoretical frameworks from among multiple disciplines including geography (e.g. movement analysis, spatial analysis of conflict, dynamic point pattern analysis, geosimulation, location science), industrial and organizational psychology (multiteam systems, teams, motivation, communication, culture), network science (social network analysis, dynamic network theory, reality mining), operations research (network modeling/optimization, stochastic processes), and strategic studies (netwar). This project will support further basic research as well as applied research in human geography, geographic information analysis, societal instability, criminology, radicalism, social psychology, and simulation of stochastic human geographic processes, thereby improving civil services, social welfare, and public safety.

CHAPTER TWO: LITERATURE REVIEW

This project relies upon multiple disciplines including geography, operations research, computer science, network science, sociology, industrial/organizational psychology, international relations, and strategic studies. In particular, it employs theories, methods, tools, and data structures that deliberately integrate geography and geospatial considerations into analyses of social behaviors.

The figure below is a concept map that illustrates the various disciplines and key topics in each discipline that form the basis of the research. The concept map illustrates interrelations among concepts by convergence. Convergence is the property of centrality to the main topic of this research, which is positioned at the center of the concept map. Concepts which are more closely related to the research topic converge towards the center. Those topics which most closely support and connect with the main topic are called proximal topics. Distal topics provide additional support and amplification to proximal topics and/or the main topic. Distal topics may also include concepts that are relevant and interesting to the main topic, but are ultimately discursive. Fundamental topics are those foundational ideas that preceded and underpinned distal and/or proximal topics.

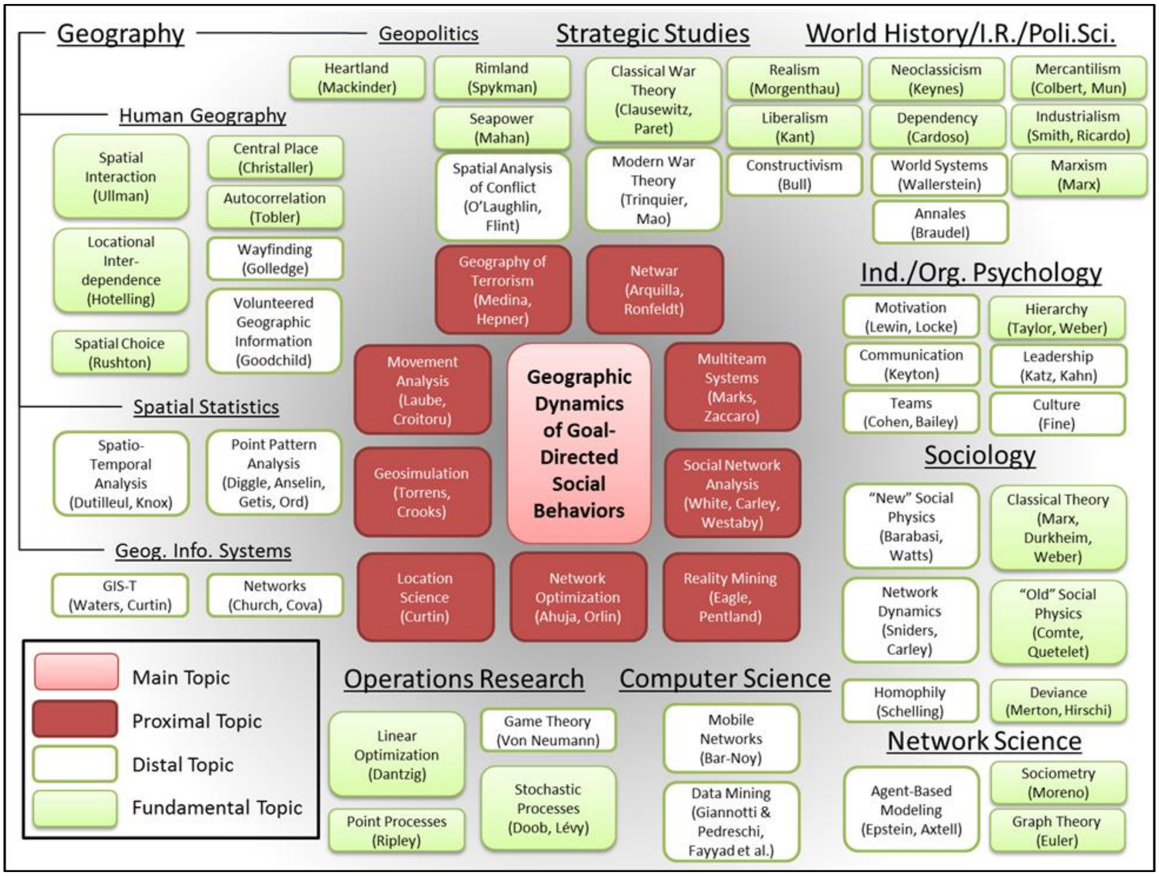

Figure 1: A Concept Map of the Literature Review

This literature review is accompanied by a caveat about vocabulary. The multidisciplinary nature of this literature review introduces troublesome inconsistencies in key terminology. Every academic discipline methodically develops and defends its own lexicon. Since key terms carry critical significance in each discipline, and because terms and topics may be described similarly or differently, the peculiarities of this multidisciplinary vocabulary are very important to understand. The most significant inconsistency is in the description of human groups, which are here described variously as groups, teams, and networks. Whereas "group" can be used as a generic term referring to two or more people who interact with each other, it also may be used in the social psychological sense to refer to a collection of individuals that undergo a process of developing cohesiveness (Tuckman, 1965). "Team" is a term from industrial and organizational psychology that is used in a way similar to the second and more specific usage of "group" to refer to a small collective that comes together to accomplish some discrete purpose. Among industrial and organizational psychologists the distinction between "group" and "team" is a superficial one to be disregarded (Sundstrom, McIntyre, Halfhill, & Richards, 2000). "Network" is a term with various usages in geography, mathematics, biology, physics, environmental science, operations research, sociology, computer science, and communications, among other disciplines (Newman, 2010). Unless otherwise specified, "network" refers herein to generic social constructs defined by sets of individuals and their relationships. Group and team are used interchangeably to refer to a discrete set of individuals and relationships that are distinguished by their collective pursuit of an objective(s).

The Diffusion of Power

At the root of this research's interest in the geographic attributes of team behaviors are two assertions: (1) that the worldwide diffusion of power is growing and (2) that the influence of small social groups upon societies is rising. Now more than ever before in human history, societal values, beliefs, ideas, and events are constructed by everyday interaction among ordinary people as well as people of status. The contemporary societal phenomena of globalization, social networking, information networks, and mobile information technology have permitted independent social groups, most of which are small networks of private individuals, to exert tremendous influence over politics, culture, and economy at local, national, and international scales. In geopolitics, examples of the power of small, independent, and motivated social groups are found in the success of the so-called "color revolutions," the political upheaval of the Arab Spring, the development of international terrorist networks like Al Qaeda, non-state weapons proliferation networks like that of A.Q. Khan, and sub-state insurgent groups like the Taliban (Barker, 2011; Pollack, 2012; Roko, 2012; Wilson, 2010). Quite often political and territorial boundaries have failed to contain these types of groups, and their activities and influence have increasingly transcended international borders (Straus, 2012). Organizing inconspicuously in public or online, discrete social groups communicate, plan, prepare, and ultimately execute important activities that profoundly shape public discourse and government policy (Mascaro & Goggins, 2011; Weimann, 2004, 2006). And many savvy artists, consumers, and businesses have also successfully harnessed the interconnectedness of social groups, although their influence, objectives, and messages may be far less serious than those of terrorist groups (Swamynathan, Wilson, Boe, Almeroth, & Zhao, 2008; Trusov, Bucklin, & Pauwels, 2009). Lately, so-called "flash mobs" have begun exploiting the capacity for rapid social mobilization inherent in mobile communications technology, resulting in both sensationally entertaining (Gore, 2010) and sensationally violent (R. D. White, 2006) public spectacles.

An awareness of the nature of power is available in the major theories of international relations beginning with realism (Gilpin, 1983; Morgenthau, 1967), liberalism (Kant, 1983; Keohane & Nye, 1998), and constructivism (Bull, 2002). Whereas realism and liberalism emphasize the personalities and institutions of the state, constructivism emphasizes societal influences residing within and without the state. Similarly, the evolution of historiographical theory exhibits movement from state-centric explanations (von Ranke, 1976) to styles that focus upon the significance and interrelation of non-state social, cultural, and economic themes (Braudel, 1995a, 1995b) as well as meta-state systems constructed by private businesses, social classes, and identity groups (Wallerstein, 2004). The trajectory of thought among economically minded historians and theorists also begins with concepts of state control in mercantilism (Hinton, 1955; Viner, 1948) and industrialism (Ricardo, 2010; Smith, 2013) but gives way to concepts of the influence of social classes (Marx & Moore, 2011), free markets (Keynes, 2011), and international businesses (Cardoso & Faletto, 1979). There is ample evidence for the phenomena of diffuse power and non-state influence in such theories of world history, politics, and economy.

An examination of the history of geographic ideas about power begins to raise the issue of war and conflict. Mackinder offered a vision of global power that focused upon state control of the "heartland" of the Eurasian land mass (1904). By contrast, Spykman believed that global power derived from containing the "heartland" by occupying the "rimland" (Spykman & Sempa, 2008), and Mahan argued that state control of the seas amounted to control of all continents (Mahan, 1987). Though not a geographer, the Prussian strategist Carl von Clausewitz (1989; Paret, 1993) also offered enduring state-centric explanations of war. While these ideas all stressed notions of state power at a global scale, the events of the post-nuclear era that followed World War II showed the significance of regional and local power as well as the myriad human interactions that can lead to conflict. The experiences of the decolonization era begat theories of insurgency and guerilla warfare (Fall & Minh, 1967; Marighella, 1971; Taber, 2002; Tse-tung, 2013), counterinsurgency (Nagl, 2005; Trinquier, 2006), terrorism (Cruickshank & Ali, 2007), and counterterrorism (Hoffman, 2006; Rubin, Gunaratna, & Jerard, 2011), culminating in the formulation of netwar (Arquilla & Ronfeldt, 2001) that emphasizes the role of networks. While netwar applies to human social networks in physical space, some analysts foresee an era of warfare fought entirely within information networks in virtual space, by both state and non-state actors, with inexpensive computer code as the primary weapon (Farwell & Rohozinski, 2011).

The political geographer Colin Flint offers a vision of conflict shaped by the idea of networks. He has led the development of sophisticated analytical constructs attuned to the complex and numerous social relationships that are associated with places and define conflict (Flint, Diehl, Scheffran, Vasquez, & Chi, 2009; Radil, Flint, & Tita, 2010). Relying upon actor-network theory (Latour, 2005), Flint's conceptualization of conflict examines how individuals and social groups relate themselves to each other, to places, and to ideas about polity, culture, gender, and resources, among others (Flint, 2004; Flint et al., 2009). Although there is value to understanding war as a local state-versus-state phenomena (O'loughlin & Anselin, 1991), Flint's approach goes well beyond the dyadic inter-state relationships and physical boundaries that have traditionally driven concepts of war, exploring conflict within urban networks at the scale of third-order administrative divisions (Lohman & Flint, 2010; Radil et al., 2010). Conflict is also comprehensible as the result of numerous competing political interests simultaneously active at multiple levels of analysis: groups, regions, states and international systems (Raleigh & Dowd, 2013).

An increasingly refined understanding of modern war, combined with the tools and techniques of geographic information science, has led to a revolution in the sophistication and precision of spatial analyses of contemporary conflict. Geography and spatial relations are not an afterthought to the politics and history of violence. Geographers and geographic information scientists offer a distinct and integrative perspective about conflict. First, the vocabulary of conflict introduces spatial nuance into explanations of war. Criminals, insurgents, terrorists, and other subversive actors perpetrate violence from safe havens, with the support of diasporic populations, within territory they aspire to dominate (Richard M Medina & Hepner, 2013). Several analyses locate violent individuals and groups in both material and semiotic spaces (Richard M. Medina & Hepner, 2011). Second, network constructs enable the location of nodes and flows belonging to combatant groups (R. Medina & Hepner, 2009). These network flows may include transfers of instructions, ideas, intelligence, funds, goods, weapons, contraband, recruits, and supporters (Richard M Medina & Hepner, 2013). These locations of nodes and flows within violent groups correspond to patterns of team-based goal-seeking activity as well as behaviors associated with organizing, supporting, preparing, and/or executing violent campaigns. Third, spatial statistical and spatiotemporal event analyses of aggregated violent event data have enabled deeper exploration and understanding of discrete conflict phenomena. Studies of event frequency, intensity/effects, attack type, target type, attacker identity, spatial autocorrelation, temporal autocorrelation, and clustering have proliferated as tools of conflict knowledge and provided a means to empirically investigate asserted hypotheses like conflict migration and contagion (Barker, 2011, 2012; Dowd & Raleigh, 2013; Richard M. Medina, Siebeneck, & Hepner, 2011; O'Loughlin, Witmer, Linke, & Thorwardson, 2010; Siebeneck, Medina, Yamada, & Hepner, 2009). This trend in scholarship recognizes the importance of team- and network-based analyses of trans-border conflict at microscopic (e.g. neighborhood, municipality) and mesoscopic (e.g. county, province) scales.

Locating Social Networks

Human geographers study the human experience in the spaces and places people occupy. The geographic perspective is an integrative one that unites political, economic, cultural, behavioral, social, demographic, and other analyses through the definition of spaces and places (Goodchild & Janelle, 2004). A few fundamental ideas that underpin this scholarly integration of social phenomena include interaction, interdependence, choice, centrality, and autocorrelation. Spatial interaction recognizes that human beings purposefully move objects and themselves to improve their opportunities (Ullman, 1953, 1956). Locational interdependence suggests that the location(s) chosen by an individual is influenced by the locations of others, and vice versa (Graitson, 1982). Spatial choice theory offers ideas about the evaluation of locational alternatives according to individual preferences (which may be economic, physical, political, cultural, or other) and extant constraints (Desbarats, 1983; Rushton, 1969). Central place theory argues that people will gravitate towards those areal centers that serve their various needs, and that these centers exist in interdependent and geometrically explicable hierarchies of human settlement (Christaller, 1966). Autocorrelation in geography refers to the fundamental assumption of dependence among things and people that are near each other (Tobler, 1970).

These principles, among others, help explain the geographic nature of human activity, especially where static settlements offer unambiguous evidence of human decisions about location. In the geographic disciplines they have been particularly useful in explaining patterns of land use and land cover, especially phenomena of urbanization. However these principles also apply in situations and spaces where evidence of human activity is ephemeral. When people interact, communicate, and make decisions that are temporarily observable, geographers must adopt different sorts of tools and approaches to record, analyze, and interpret the patterns that human social groups present.

One example of an unusual approach to the analysis of strategic spatial choice would be to apply the theories of behavioral economists, especially game theory. Two of the fundamental assumptions of economists are that 1) people derive satisfaction from their consumption of a good and 2) people will maximize their consumption of a good according to their preference for it and their means. Geographers who think about space like a commodity have asserted that people will "consume" space by choosing their location according to their preferences and their means (Kaufmann, Bergman, & Joye, 2004; Rushton, 1969). Game theory applies mathematical abstraction to the modeling of cooperative and competitive behaviors (Nash, 1996; Von Neumann, 2007). Game theorists define the choices that confront players, anticipate the interaction that could result from such choices, and enumerate the various quantifiable outcomes associated with each potential interaction. These outcomes, which are also known as pay-offs, are organized into matrices that serve as models of the game. These models assist economists in predicting states of equilibrium that characterize the likely outcomes of the entire interaction. Sometimes, these equilibriums reveal behaviors that can be described heuristically as maximizing the minimum (or maximin) of a variable pay-off (Camerer, 2003). In a situation where an individual wanted to locate themselves as far away from several known points of potential danger, such heuristics might provide an opportunity to anticipate spatial choices at an equilibrium state. Insofar as distance from competitors is a quantifiable result of a choice-based interaction among competing players, it is possible to consider a game theory of spatial choice. The literature that has considered individual spatial preferences has shown that individual spatial choices are characterized by equilibrium, but this literature has thus far not applied a game-theoretic approach (Ahas, Aasa, Silm, & Tiru, 2010; Ahas, Silm, Järv, Saluveer, & Tiru, 2010; Flamm, Jemelin, & Kaufmann, 2008) .

While there are several studies of individual spatial choice, there is little research that applies geographic treatment of social networks. Social networks exist in geographic as well as virtual space (Wellman, 2001). The development of methods by which to geographically understand social phenomena in populated space is a growing area of research interest (Mateos, de Smith, & Singleton, 2011). Social networks are dynamic, in that people who are members of a group vary their location and communications through space, virtual space, and time. Fundamentally, discrete social networks may be decomposed into human members, which can be modeled as network nodes (or vertexes), and their relationships and communications, which can be conceptualized as links (or edges).

Geographers can address the physical and virtual locations of nodes and links by treating node location stochastically and applying spatial statistics. A stochastic process is a system in which the position of a point or set of points varies according to time and some given probability (Doob, 1937). Social network nodes can be modeled in geographic space as points with locations (and other attributes) that comprise a pattern that is presumed to have been stochastically created. Geographically speaking, social networks are therefore best treated as a three-dimensional point pattern, rather than a surface pattern. On the other hand, virtual locations of social groups are probably better modeled as network-based point patterns in conceptual space. Spatial statisticians have developed many techniques for the geographic analysis of point patterns and seen these techniques applied in epidemiology (Gatrell, Bailey, Diggle, & Rowlingson, 1996), plant ecology (Perry, Miller, & Enright, 2006), and criminology (L. Anselin, Cohen, Cook, Gorr, & Tita, 2000), among many other disciplines. A special niche exists among spatial statisticians who focus upon point patterns on networks (Okabe, 2012). Point pattern analyzers use inter-event distance, first moment properties (mean count per unit area) or second moment properties ([co]variance of counts per unit area) to test for departures from complete spatial randomness (Diggle, 2003; B. D. Ripley, 1977), to test for clustering/dispersal (Luc Anselin, 1995; Getis & Ord, 1992), or to compare patterns by descriptive means (Greig-Smith, 1983). Since point patterns are created via spatial point processes, these may also be modeled in order to provide expected values for statistical testing (Baddeley, Gregori, Mahiques, Stoica, & Stoyan, 2005; Getis & Boots, 2008; Illian, Penttinen, & Stoyan, 2008; B. D. Ripley, 1977; Brian D. Ripley, 2005). However useful these techniques are for studying static patterns of stationary points, static instances or “snapshots” of continuously dynamic patterns (Reades, Calabrese, Sevtsuk, & Ratti, 2007), or time-series reconstructions of continuously dynamic patterns (Esker, 2007), there is little utility for analyzing spatiotemporally dynamic patterns in which the locations of point objects (nodes) are continuously variable. This void may be explained, at least until recently, by the scarcity and imprecision of the instrumentation needed to collect data as well as the computational intensity required to perform analysis on such data. Data about the behaviors and activities of individual users and their affiliates is becoming more abundant as a result of greater digitization, miniaturization, availability, and interconnectedness in mobile technology (J. E. Katz & Aakhus, 2002; Rainie & Wellman, 2012). These and other geospatial technologies provide abundant data, and therefore greater opportunity, to study the dynamics of location, movement, and communications within social networks (Gudmundsson, Laube, & Wolle, 2012; Pentland, 2009).

Movement in Space and Time

Spatial statistics involve methods to collect, organize, and summarize data about events occurring in space with the purpose of drawing conclusions about the nature of those events (Burt, Barber, & Rigby, 2009). Spatiotemporal analysis is an area of spatial statistics that addresses patterns of change along multiple dimensions, relying upon data in well-defined covariance matrices (Eshel, 2011). While the name of this discipline suggests that the dimensions of interest are universally geographic location and chronological time, the techniques of spatiotemporal analysis allow researchers to understand multivariate phenomena in which at least one variable is an ordered coordinate. So "distance" may be understood as conceptual, genetic, or evolutionary proximity, for example, as well as physical or temporal proximity. Although he had important forerunners (Matern, 1986, originally 1960; Whittle, 1951), Knox (1963) introduced the most popular statistic of spatiotemporal interaction. Insofar as the Knox statistic has the problem of population shift bias (Kulldorff & Hjalmars, 1999), there are other notable spatiotemporal statistics including the Mantel test, which is the product-moment coefficient of linear correlation, similar to Pearson's R, but between two matrices of distance. (P. R. L. Dutilleul, 2011; P. Dutilleul, Stockwell, Frigon, & Legendre, 2000; Mantel, 1967). Space Time Scan Statistics - such as the Poisson, Bernouli, and permutation variants – offer capabilities to identify significant event clusters without onerous definition of search radii (Kulldorff, Heffernan, Hartman, Assunção, & Mostashari, 2005). Further, there is specific utility for this project in methods for the statistical evaluation of spatiotemporal clustering on static networks (Eckley & Curtin, 2013). Spatiotemporal heterogeneity may be analyzed in at least eight different modes (P. R. L. Dutilleul, 2011), however there are four such modes that are optimal for studies of social networks and these are first- and second-order properties in space and time of point patterns.

The emerging discipline of movement analysis builds upon basic principles of spatiotemporal analysis and exploits efficient and increasingly available capabilities to track and analyze objects that continuously vary their geographic position (Eagle & Pentland, 2006; Gudmundsson et al., 2012; Laube, 2011). These objects, which are dubbed Moving Point Objects or MPOs, generate individual spatiotemporal trajectories (also called "geospatial lifelines," "geographic lifelines," or "movement traces") that are "series of observations consisting of a triple of id, location and time (P. Fisher, Laube, Kreveld, & Imfeld, 2005; Mark, 1998)." Fundamental movement analysis results in descriptions of speed, acceleration, direction, and path sinuosity of individual trajectories (Laube, Dennis, Forer, & Walker, 2007). Movement analysis has roots in quantitative ecology (Turchin, 1998), however the dynamism present in an urban human population may be orders of magnitude greater than that of wild plant populations, and therefore may demand enhancements for the pace and breadth of activity. Historically, the movement patterns of animal populations have been modeled using Levy Flight and other random walks (Bovet & Benhamou, 1988; Williams, 1992). These models presume that individual movement is demonstrably unpredictable. However, evidence for generalizing such models to human mobility is limited to studies of particle proxies for human movement, notably bank note dispersal (Brockmann, Hufnagel, & Geisel, 2006). Research using mobile phone records rather than proxy particles has shown that individual human mobility patterns are more regular and explicable than previously thought (González, Hidalgo, & Barabási, 2008). Basic research about movement analysis is currently focused on issues of precision, especially scale (Arie Croitoru, Eickhorst, Stefandis, & Agouris, 2006; Hornsby & Egenhofer, 2002; Laube & Purves, 2011), pattern detection in two-dimensions (Graikousis & Photis, 2009; Gudmundsson, van

Kreveld, & Speckmann, 2007; Laube & Purves, 2006), and interpolation of continuous values from discrete observations (Wentz, Campbell, & Houston, 2003). Of particular interest to the proposed project is the computational derivation of emergent group behaviors from analysis of the trajectories of individual actors. Three basic "steering forces" that indicate group behaviors from individual movement include cohesion, separation, and alignment (Reynolds, 1987). Algorithmic approaches relying on nonlinear optimization and swarm intelligence techniques including Particle Swarm Optimization (Kennedy & Eberhart, 1995) offering a promising way to derive these individual steering forces from global observations, and vice versa (A. Croitoru, 2009). Still others investigate collective animal behaviors through the lens of shared cognition, asserting ordered movement and collective memory (Buhl et al., 2006; Couzin, 2009).

Cognitive scientists and geographers with expertise in cognition have discovered processes of spatial knowledge acquisition from their research about human movement (Golledge, 1992, 1993). Unsurprisingly, many of these researchers assert that maps are an appropriate way to understand how the mind builds, stores, and retrieves spatial knowledge. Cognitive maps are the hypothesized neurological construct, resident in the brain's hippocampus, by which spatial relations among environmental features are represented within an environment (Golledge, 2004; O'Keefe & Nadel, 1978). Two processes that are believed to rely on the hippocampus are navigation and wayfinding. Whereas navigation most properly refers to the guiding of ships over bodies of water, wayfinding refers to the way in which people choose paths to an objective location on land, often in networked space (Bovy & Stern, 1990). Wayfinding is a proposed cognitive process by which people “search an environment to a path that can link an origin and a destination (Golledge, 1992).” Wayfinding involves knowledge about places and routes and draws upon cognitive processes to 1) recall place names and locations, 2) link these pieces of information together sequentially, and 3) infer unknown spatial relationships from known characteristics of the environmental configuration (Golledge, 1992; Hirtle & Hudson, 1991). The distinction between navigation and wayfinding is important because navigation implies movement mostly by dead reckoning with instruments, and wayfinding implies the association of landmarks, routes, distances, and angles. Pedestrians negligibly use dead reckoning in everyday life.

At the intersection of point pattern analysis, wayfinding, and movement analysis lays the potential to identify patterns in continuous behaviors of groups of MPOs. Much of the thrust of research here is founded in theoretical simulations (Simini, González, Maritan, & Barabási, 2012) or surrogate realities (Szell, Sinatra, Petri, Thurner, & Latora, 2012), rather than field-based empiricism. One example (Shoshany, Even-Paz, & Bekhor, 2007) used multi-agent simulation and linear programming to study how individuals engaged in flocking, merging, and separation (clustering and de-clustering) through time. However some empirical work has claimed a high degree of predictability in the movement patterns of MPOs (González et al., 2008; Song, Qu, Blumm, & Barabási, 2010 a). Wayfinding may offer supportive theory to such efforts aimed at understanding and interpreting observed movement patterns.

Insofar as groups of human MPOs may also be linked as a social network, a significant scientific advance may lie in a greater understanding of the ways in which the movements of human points (nodes) are influenced by conditions of their links (edges). Geographic network analysis, social network analysis, and theories of information diffusion are all germane to the study of the collective action, in four-dimensions, of groups of individual elements, or what has been termed "dynamic collectives (Galton, 2005)." Here, the identity, affiliation and/or mode of individuals introduces an interesting fifth dimension; the condition of an individual's relationship with the rest of the network (Hornsby & Egenhofer, 2000). Since human beings vary their longitude, latitude, elevation, and relationships to one another over time, it is both reasonable and challenging to pursue social/geographic network dynamics in five dimensions (Radil et al., 2010). Views on affiliation vary, with some researchers emphasizing how relationships endure as a matter of meaningful friendship (Hui, Crowcroft, & Yoneki, 2008), while still others emphasize how relationships in networks are fleeting as a matter of physical or virtual proximity (Eagle & Pentland, 2006). Indeed it may be that the hybrid nature of physical and social space may imbue illicit networks with critical dependencies (Medina & Hepner, 2011a; Medina & Hepner, 2011b) originating in the type and strength of relationships.

Two technological phenomena that enable greater geographic exploration of network dynamics are geosimulation, which is associated with theory-driven approaches, and reality mining, which is more commonly an element of data-driven approaches.

Geosimulation combines the data models of GIS with multiagent simulation to produce spatially explicit agent-based models (Benenson & Torrens, 2004; Crooks, 2010). Geosimulation allows for the evaluation of hypotheses about complex human geographic phenomena via repeated rule-based interaction of large populations of virtual agents in “artificial societies;” this offers an approach that is beneficial for ethical and practical reasons (Epstein & Axtell, 1996; Luke, Cioffi-Revilla, Panait, Sullivan, & Balan, 2005; Tisue & Wilensky, 2004). The efficient integration of entities in geospatial data models and multi-agent simulation models have demanded heuristic computational approaches like spatial indexing that resembles branch-and-cut techniques (Blecic, Cecchini, & Trunfio, 2009). Studies employing applied geosimulation have addressed the topics of land use (Zhao & Murayama, 2007), traffic planning (Torrens, 2004), epidemiology (Bouden, Moulin, & Gosselin, 2008), and civil disturbances (Torrens & McDaniel, 2013) often in urban environments where pervasive social interaction, vertically constructed environments, and propagation along transit networks present important challenges not easily handled on a Euclidean plane. A chronic problem in any application of multi-agent simulation is the quality and diversity of decision rules, which tend to oversimplify cognitive processes, deemphasize collective identities, and presuppose the validity of hypotheses (Castle & Crooks, 2006; O’Sullivan & Haklay, 2000).

Reality mining involves computational analysis of communications, identity, and location data collected from digital emitters and/or sensors such as smart phones (Raento, Oulasvirta, & Eagle, 2009), Bluetooth-enabled devices (Eagle & Pentland, 2006), Wi-Fi devices (Kim & Kotz, 2006), and RFID tags (Roth, Kang, Batty, & Barthélemy, 2011). The predictability of an individual’s location, activity, and proximity to other individuals is the major interest of researchers engaged in reality mining; these scientists grapple with the degree of behavioral entropy (or randomness) extant in an individual's life (Eagle & Pentland, 2006; Phithakkitnukoon, Husna, & Dantu, 2008; Song et al., 2010). An object of the reality mining movement is to develop computational approaches that extract knowledge useful for making sense of complex spatial phenomena from large sets of data collected digital, specifically mobile, electronic devices (Fayyad, Piatetsky-Shapiro, & Smyth, 1996; Giannotti & Pedreschi, 2008).

Reality mining relies heavily upon the emergence of the "sensor web," the system of distributed and networked in situ sensors that now constitute a new kind of earth observation system (Liang, Croitoru, & Tao, 2005). The concepts of Volunteered Geographic Information or VGI are some of the more celebrated explanations of this new sensing paradigm (Goodchild, 2007). Goodchild describes how individual users, enabled by mobile devices with Global Positioning System (GPS) sensors, cameras, and data connections, interact with each other to generate geographic content that is published via the World Wide Web. Lately, VGI has been recast in other terms as Crowdsourced Geospatial Data or CGD (Rice, Paez, Mulhollen, Shore, & Caldwell, 2012) as well as Ambient Geospatial Information or AGI (Stefanidis, Crooks, & Radzikowski, 2013). These concepts carry different notions about the intentions, authority, accuracy, and technologies of the "volunteers." For example, AGI collects information from users who may not have intended to contribute to geographic knowledge and emphasizes social media technology platforms like Twitter (Stefanidis et al., 2013). The popularity and accessibility of social media platforms such as Facebook and Twitter have driven the "GeoSocial" trend in research (A. Croitoru et al., 2012). VGI and CGD, on the other hand, cover information that may have been designed or intended to compete with official sources of geographic knowledge (Rice et al., 2012). Another way to differentiate these approaches is to examine the information that each one emphasizes. Whereas AGI is interested primarily in the content of user contributions, other approaches emphasize metadata such as identity, date, time, and location (P. Fisher et al., 2005; Stefanidis et al., 2013).

Geographic Information Systems that drawn upon VGI, CGD, and AGI make heavy use of GPS technologies. GPS is a nearly ubiquitous location information system that relies upon satellites and is therefore highly effective at locating items outdoors (Hofmann-Wellenhof, Lichtenegger, & Collins, 1993). Since buildings obstruct GPS signals, GPS is less adept at locating items underneath overhead obstructions. Some have resolved this difficulty by combining GPS and cellular phone technologies in what has been termed "Assisted GPS" or aGPS (Djuknic & Richton, 2001). Recent research attention has been devoted to developing indoor location system capabilities (Liu, Darabi, Banerjee, & Liu, 2007). Many of these "indoor positioning systems" or IPSs use ground-based wireless networks, such as 802.11-type WiFi networks, to assess proximity to multiple known access points and triangulate a likely location in a building. Others accomplish the same effect with cellular phone network technologies (A. Bar-Noy & Kessler, 1993; Amotz Bar-Noy, Kessler, & Naghshineh, 1996). IPS technology relies upon accurate "fingerprints" of wireless emissions measured at every discrete location in a building (Haeberlen et al., 2004). Hobbyists, technologists, security professionals, and even criminals have engaged in the practice of "wardriving" or "warwalking" in order to scan locations for wireless emissions associated with nearby access points (Kim, Fielding, & Kotz, 2006). Owing to the high expense associated with mapping and maintaining accurate data about indoor wireless emissions, greater research attention has been paid to technologies that either reduce dependence upon such information or find methods by which to collect this information more easily (Bolliger, 2008; Ledlie et al., 2012; Park et al., 2010). Interestingly, the IPS initiative seeks to inform users about their location using information that users knowingly or unknowingly collected, bringing the ostensible purposes of VGI and CGD to a full circle.

The Science of Societies

Fundamental sociological theory underpins the geosimulation and reality mining approaches that employ knowledge of social structures and influences. Classical sociological theorists explored social constructs and forces such as socioeconomic class and the competition for resources (Marx & Moore, 2011), hierarchy and collective morality (Durkheim, 2006), and individualism and rational authority (M. Weber, 1994). Later, sociologists explored the specific concepts of homophily (McPherson, Smith-Lovin, & Cook, 2001) and deviance, finding deeply individualistic causes in some cases (Hirschi & Gottfredson, 1994; Schelling, 1971), and deeply systemic causes in others (Merton, 1968, 1976). These theories each offer compelling explanations for the behaviors of politically violent groups. More importantly, their ideas introduce a debate among social scientists about the relative importance of social structure and individual agency. Following Durkheim (2006) and Simmel (1964), the structures of group relations primarily shape the nature of the social group. On the other hand, Weber's perspective emphasizes the importance of individual perceptions, rationality, roles, and actions in defining the nature of the group. Sociological analyses of human networks have carried forward this tension between explanations that favor structure and those that favor individual agency, although the tendency has been to favor the structuralist approach (Mizruchi, 1994).

Concerned with knowledge of a "…set of relationships that apply to a set of actors (Prell, 2011)," social network analysis is a body of concepts and methods that is variously described as an interdisciplinary, sub-disciplinary, or altogether independent approach to understanding social phenomena. The origins of structuralist treatment of social networks begin in Europe as early as the thirteenth century (Freeman, 2004) but blossom in the nineteenth century with the rigidly empiricist perspective of sociological research pioneered by Auguste Comte, the French philosopher who fathered positivism (Comte, 1988), and Adolphe Quetelet, Comte's Belgian contemporary who applied statistics in developing what he called "social physics" (Quetelet, 2013). The views of the old "social physicists" developed in earnest in the United Kingdom and the United States in the 1930s (J. Scott, 1988). Jacob Moreno and Helen Jennings produced graphical representations of social groups (called "sociograms") and computed statistical measures of social relationships on their way to developing what they termed "sociometry" (Moreno, 1960; Moreno & Jennings, 1938). In the 1970s, Harvard's Harrison White oversaw a series of revolutionary advances in social network analysis (Boorman & Harrison C. White, 1976; Harrison C. White, Boorman, & Breiger, 1976) that culminated in a theory of social identity that is deferential to the role of relationships and mathematical definitions of their structure (H. C. White, 1992).

Among more recent social network analysts, some have deepened the structuralist techniques of the Harvard revolution by adding new clarifications, measurements, and tests (Snijders, 2003; Wasserman & Faust, 1994; Wellman, 1997) while still others have worked to reinvent the paradigm. Dynamic Network Analysis is a reconceptualization of social network analysis that begins with the premise that actors, their relationships, and social institutions evolve in many ways over time (Carley, 2003). Affiliation, for example, is not a permanent and binary state; affiliation is often partial, conditional, divided, and/or in flux. Representing the choices that independent actors make with respect to their social surroundings is something that researchers have addressed with multi-agent simulations (Louie & Carley, 2004), genetic algorithms (Matthews, Gongora, and Hopgood in Bramer, Petridis, & Hopgood, 2010), and exponential random graph models (Hanneke & Xing, 2007) among other computational tools. Significantly, Tom Snijders has used Markov chain Monte Carlo methods to produce stochastic simulation models of continuous time interactions in social networks (Snijders, 2001) and his work may provide a foundation of theoretical distributions to leverage in developing statistics and analyses of the geographic dynamics of goal-directed social behaviors.

As recently as the 1990s, physicists who specialized in networks began applying their knowledge to social phenomena. With fanfare, new social physicists like Albert-Laszlo Barabasi (Barabasi, 2003) and Duncan Watts (Watts, 2004) argued the structuralist sociological perspective while presenting concepts such as preferential attachment (new network members deliberately seek out other members who are already well-connected (Barabási & Albert, 1999)) and "small-worlds" (networks that are highly clustered with short path lengths (Watts & Strogatz, 1998)). Today, the concepts of so-called "social physics" are highly fashionable, although some scholars contend these analytical paradigms are debatable extensions of basic research in physics and mathematics (J. P. Scott & Carrington, 2011).

Three difficulties with these sociological or social-physical approaches are: placing social networks in geographic space, accounting for human attributes, and generalizing about small social groups. Most practitioners of social network analysis locate nodes in network space, however few attempt to locate nodes geographically (an exception is Radil et al., 2010) owing perhaps to "reductionist traditions in science (Goodchild, Anselin, Appelbaum, & Harthorn, 2000)." This tendency to take geography for granted in pursuit of social scientific elegance is not universally inappropriate. However, remedies must be sought for a theory about the geographic dynamics of goal-directed social behaviors such as that which this review would support. For example, Zipf (1949) explained homophily in expressly spatial terms, finding that distance is a barrier to heterophilous relations. There are numerous studies of communities that find the bonds of networks vary according to distance, although it is as yet unclear the extent to which modern communications technologies are diminishing this distance decay effect (McPherson et al., 2001). While many social network researchers and social physicists emphasize the pursuit of natural laws embedded in the structure of social networks, few emphasize how individual concepts of personality, objective, or agency determine the behavior and influence of a given network. Indeed, even the fundamental factor of gender is often suspended to support structural analyses (Lorrain & White, 1971). And while their analyses of random large-scale networks (such as global internet communities) occur at a level intended to produce generalizable knowledge, it may be useful to reemphasize small-scale or local-level networks that organize to achieve distinct objectives. Study of the latter smaller type of social network might reveal how discrete teams behave, and operate towards their objectives, within larger social contexts (DeShon, Kozlowski, Schmidt, Milner, & Wiechmann, 2004). A fundamental proposition here is that the proposed scale-free properties of large social groups on the internet apply primarily to groups that operate overtly, build predominately shallow interpersonal relationships, and recruit newcomers in public. By contrast, groups that organize privately, forge interpersonal bonds deeply, and recruit prudently are not characterized by the same properties as large scale networks. So the question is how to delineate these smaller social networks and how to begin to understand their nature. Dynamic Network Theory (Westaby, 2011) offers such a starting point because it attributes roles, objectives, and aggregate forces to individuals and groups of people involved in a social endeavor.

Whereas Carley's Dynamic Network Analysis (2003) offers perspectives about the multivariate evolution of the structure of social networks over time, Westaby's Dynamic Network Theory (2011) largely vacates the structuralist view and emphasizes agency, role, and motivation in relation to networks and counter-networks defined in terms of common goals. Carley's paradigm is dynamic primarily because of the notion of multifaceted temporal change, but for Westaby, the word "dynamic" heeds the ways in which countervailing forces of multiple generic types interact and produce net effects upon the accomplishment of goals. Carley acknowledges the many types of nodes and relationships that may reside in a social network, allowing for the different "forces" present in Westaby's models. Insofar as Westaby's "dynamics" surely vary over time, his models may be compatible with Carley's sense of the importance of change, possibly opening the way to an integration of her Analysis with his Theory. This is significant to the proposed research because the dynamism of affiliation and agency present in real-world networks such as teams may reveal important relationships that explain movement and communications patterns.

Network Models and Doctrines

Network modeling is a separate field with a literature grounded in mathematics and operations research, independent of sociology, and largely empathetic to geography. Problems in the area of network modeling that may be relevant to this study are in three broad categories: modeling of objects (individuals, vehicles) physically moving through networked space (e.g. a transportation grid), modeling of flows virtually moving through a social network (e.g. communications), and the development of appropriate network topological models to support each of the foregoing two needs.

Classical problems in modeling network flows originate in the work of Leonhard Euler (1741) and include deriving the shortest path, minimum cost, and maximum flows of entities moving among points on a network, as well as algorithmic treatments thereof (Ahuja, Magnanti, & Orlin, 1993). These approaches use general optimization techniques (Dantzig, Orden, & Wolfe, 1955) and are broadly applicable. For example, information technologists have applied network flow concepts to optimize the distribution of information throughout computer networks (Lucas, 2010) while marketing officers have sought ways to quantify the flows of word-of-mouth product recommendations among networks of potential consumers (Trusov et al., 2009). An entire geographic field known as Geographical Information Systems in Transportation (or GIS-T) has very successfully capitalized upon the incorporation of network models and associated techniques into geographically explicit planning systems (Curtin, 2007; Waters, 1999). Network approaches have addressed optimization topics such as evacuation (Church & Cova, 2000; Cova & Church, 1997), public transit (Biba, Curtin, & Manca, 2010; Bielli, Caramia, & Carotenuto, 2002; Curtin & Biba, 2011), and public safety (Current, Re Velle, & Cohon, 1985; Curtin, Hayslett-McCall, & Qiu, 2010), underpinning an entire geographic field - called location science - concerned with optimal facilities location (Church, 2002; Curtin & Church, 2006, 2007; Hale & Moberg, 2003). Since human beings may desire to locate themselves optimally on an urban network, the field of location science offers an interesting complementary perspective to the behaviorist and cognitive approaches of spatial choice theory.

Where it may be desirable to model the passage of members (nodes) of a social network in and through physically networked space, solutions are well specified. However, a far more useful and yet unresolved application of network analysis principles may be the propagation of communications which themselves substantiate the relationships among members of a social network. Information diffusion through social networks is an important phenomenon to model because it considers not only the structure (edges) of social networks but also the strength and nature of network ties, as well as the communicative behaviors of the members (nodes). Some researchers hypothesize that information diffuses in human networks like infectious outbreaks (Buskens & Yamaguchi, 2002), while others (Iribarren & Moro, 2009) find that network information diffusion follows far more enigmatic processes. It is probable that information diffusion on illicit networks follows some atypical processes because of the value of information secrecy to these networks (Lindelauf, Borm, & Hamers, 2008).

A principal question in the geographic modeling of social networks is to determine what types of data models are appropriate. While social networks may exist on continuous surfaces, we have seen that they behave as groupings of defined nodes that communicate along defined paths. Since social networks are aptly analyzed in geographic space as discrete point patterns rather than continuous surface patterns, it follows that vector data models, rather than raster data models, are suitable. However the challenge of developing vector data models of social networks for geographic applications ultimately lies in graph theoretic topology. Positional information in three dimensions, as well as affiliation and institution variables, must be integrated as attributes of graph theoretic data models in order to support GIS. Graph theory is a foundational element of the emerging science of networks (Steen, 2010).

There are many researchers integrating sociological methods, physics-based models, mathematical theory, systems theory, network models, and/or new computational capabilities to produce new knowledge of our social world (Lazer et al., 2009; Macy & Willer, 2002). Network Science builds upon the advances of graph theory, social network analysis, and systems analysis to study the "…theoretical foundations of network structure/dynamic behavior and the application of networks to many subfields (Lewis, 2009)." The implied objective of many Network Scientists is to predict trends and events that may fundamentally alter society (Vespignani, 2009). While one topic of interest is the resilience of a social network to the removal of highly central nodes, another important subject is the "phase transition," also known as a "tipping point," which is a critical mass event in which large scale systems change from one state (e.g. concern) to another (e.g. revolt) (Barrat, Barthélemy, & Vespignani, 2008). Some researchers have examined how in extreme instances the removal of highly central nodes may give way to "cascading failures" that extensively damage systems of networks and require significant rehabilitation (Grubesic & Murray, 2006). In still other cases, network scientists have been working to develop ways to infer and/or detect links between important nodes (Napoletani & Sauer, 2008). The U.S. government has made several major investments in Network Science in the expectation of discovering and understanding social forces critical to national security and other strategic objectives (Schmorrow et al., 2009).

In fact, over much of the past decade a principal U.S. strategic objective has been to transform its national security capabilities to contend with "shadowy networks" of terrorists, insurgents, covert operatives, and organized criminals (S. Weber, 2004). First articulated in the early 1990s, the concept of netwar focuses upon "…an emerging mode of conflict and crime at societal levels, involving measures short of traditional war, in which the protagonists use network forms of organization and related doctrines, strategies, and technologies… (Arquilla et al., 1999)." A significant feature of netwar is the notion that illicit networks and resistance networks transcend political boundaries with an ease that enables their activities (Routledge, 2000, 2008). Developing strategies to locate illicit networks in geographic as well as social space and to dissociate them from potential sources of power is a central focus of the netwar paradigm. Methods for interrupting flow across networks have appeared in the operations research literature for some time (Hodgson, 1990; Kuby & Lim, 2007), although no application of such flow interdiction or flow covering strategies have yet been made to dynamic social networks. In their work to integrate spatial and social network analyses of conflict, Flint et al (2009) noted the multi-dimensional nature of the challenge: "Actors in a conflict are situated within historical, network, and territorial circumstances that must be analyzed simultaneously." Flint's notion of simultaneity in analyzing the activities of social groups in time and space pervades the project of comprehensively understanding the geographic dynamics of goal-directed social behaviors.

Team Movement and Goal Orientation

The field of industrial and organizational psychology deals with human mentality in the workplace. Areas of interest in this field include organizational structure, motivation, attitudes, leadership, culture, cohesion, communication, stress and strains, interpersonal factors, and the discrete and aggregate effects of these and other determinants upon collective performance (Spector, 2008). The field blossomed in the early 20th century as the industrial revolution came into its fullest maturity. Early influences in this field included Francis Taylor (2011) and Max Weber (Du Gay, 2000; Wagner & Hollenbeck, 2010) who advocated top-down hierarchical management structures as the most efficient means to secure effective performance. The premises of the hierarchical approach include the idea that employees are most highly influenced by rewards and punishments and motivated primarily by the extrinsic benefits of employment (i.e. compensation).

A more sensitive and humanistic approach argues that people are also influenced by the likability and expertise of their leaders and gain intrinsic satisfaction from their work (D. Katz & Kahn, 1978). Others understood that human beings behave in ways that are shaped by their independent goals, intentions, and plans (Ryan, 1970). Ryan and others found that motivation is a factor independent of organization. Motivation is the individual process of resolving preferences for different intentions; motivation ultimately leads to the establishment and pursuit of goals (Lewin, 1951). The setting of goals can affect performance by directing, increasing, and sustaining effort, and can lead to unanticipated discoveries and the development of skills (Locke & Latham, 2002; O Leary-Kelly, Martocchio, & Frink, 1994). While individuals are guided by their own motives and goals, they communicate in groups as they develop their awareness of potential intentions. Group communication is another factor influencing goal-setting. Members of a group may influence one another interdependently, by verbal and non-verbal messaging, and with emphasis on objective or subjective observations (Keyton & Beck, 2008). The process of communication leads to a rationalization of problems, goals, and actions that become manifest in that group's behavior (Keyton & Beck, 2008). The shared awareness that results from this communication has been referred to as "team cognition" (Beck & Keyton, 2012).Groups also maintain an awareness of shared norms, values, and attitudes that partly form the group's culture. Every human group exists within a society that possesses a culture with its own forms; these forms necessarily and inconspicuously shape how that group behaves (Benedict, 1959; Geertz, 1973). Idioculture refers to the unique system of knowledge, beliefs, behaviors, and customs that are shared by members of a discrete group and provide the basis for sustained interaction among the members of that group (Fine, 1979). Industrial and organizational psychologists who have recognized the forces of leadership, motivation, communication, and culture have advanced beyond hierarchy to team-based organizations (Cohen & Bailey, 1997; Hackman, 1987; Stewart, Manz, & Sims, 1999).

Teams are social constructs of at least more than one individual who work together to accomplish some common goal(s) (Sundstrom et al., 2000). Teams may be formal or informal in origin and may be confined within organizational boundaries or reach across organizational divisions (Espinosa, Cummings, Wilson, & Pearce, 2003; Sundstrom et al., 2000). In-team influence may be founded in notions of rank, friendship, norms, or other social factors (Rank & Tuschke, 2010; Salk & Brannen, 2000). Some researchers have applied categories to teams such as management, service, production, and advisory (Cohen & Bailey, 1997; Sundstrom et al., 2000). Others have extended the concept of teams to include virtual teams who collaborate via information technology and distributed teams who collaborate remotely (Hertel, Konradt, & Orlikowski, 2004). Task interdependence, communications, conflict, roles, and leadership are persistent themes in the team research literature (Bell & Kozlowski, 2002; Curseu, Schalk, & Wessel, 2008;

S. G. Fisher, Hunter, & Macrosson, 1998; Hinds & Bailey, 2000, 2003; Rico & Cohen, 2005; Senior, 1997; Yoo & Alavi, 2004; Zaccaro, Rittman, & Marks, 2001).

Insofar as some team members will integrate the observations and perceptions of their team members into their own cognitive maps and shared mental models, individual cognition becomes team or social cognition (Beck & Keyton, 2012; Borgatti & Foster, 2003; Mathieu, Heffner, Goodwin, Salas, & Cannon-Bowers, 2000). Given this literature, it is anticipated that movement –based progress towards team objectives will improve commensurately with team facilities to exploit their collective awareness and memory of each other's locations, perceptions, and communications, as well as their understanding of team performance and interaction (Mathieu et al., 2000; Yoo & Kanawattanachai, 2001). Baseline individual capacities for social cognition about geographic goal-directed processes are as yet unknown.

However, prior research about team processes in general has revealed a fundamental distinction between transition phases, in which teams observe, orient, set goals, and plan, and phases of action phases, in which teams execute, pursue goals, and coordinate work (Marks, Mathieu, & Zaccaro, 2001). Goal-oriented team processes involve repetitive cycles of transition and action phases known as "performance episodes" or simply "episodes." Episodes are "…distinguishable periods of time over which performance accrues and is reviewed (Mathieu & Button, 1992)." Two challenges set out by this literature are therefore (1) defining what geographic and communications behaviors conform to transition or action phases and (2) using these patterns and phases to "distinguish" performance episodes and cycles. It is possible that a combination of spatial statistics, social statistics, and isolated steering forces will reveal such behaviors, phases, and episodes. However, no prior research exists to describe and categorize such behaviors.

Team movement patterns necessarily involve individuals moving coherently, but it is unclear the extent to which team wayfinding is a socially constructed behavior or merely composited from sets of individual behaviors. Wayfinding is a goal-directed cognitive process (Golledge, 1999; Montello, 2005). While the wayfinding literature addresses the cognitive aspects relating to the motivated movements of individuals, there is no research that explores team wayfinding in general or task-oriented team wayfinding specifically. Rarely do authors in the behavioral sciences mention spatial or geographic aspects of teams except to discuss static geographical dispersal in the context of virtual or distributed teams. While some effort has been devoted to spatial analysis of team behaviors in sports, none has been dedicated to dynamic geographic attributes of team behaviors in non-athletic pursuits (Bartlett, Button, Robins, Dutt-Mazumder, & Kennedy, 2012; Coutts & Duffield, 2010; Sukthankar & Sycara, 2006a, 2006b). It is possible that concepts of goal-oriented team wayfinding would combine ideas about spatial cognition (identification and association of routes and landmarks) with ideas about social cognition (cognitive maps, shared mental models) and other team-focused concepts (roles, leadership, communications, interdependence, etc.).

Multiteam Systems (MTSs) are networks of teams that interdependently achieve their own team-level tasks while striving to accomplish some overarching system-level goal(s) (Mathieu, Marks, & Zaccaro, 2002). Insofar as MTSs may be understood as teams of teams, MTSs exhibit some similarities with teams in the significance of communications, culture, and leadership. MTSs organize individuals, according to roles and tasks, into teams that work interdependently (Zaccaro, DeChurch, & Marks, 2012). MTSs demand leadership that can iteratively make sense of complex requirements, establish objectives, and coordinate the achievement of these requirements (DeChurch & Marks, 2006). Culturally, MTSs rely upon normative processes and shared meaning rooted in systems of values rather than rules or constraints (Zaccaro & DeChurch, 2012). MTS leaders set these cultural conditions that enable the fulfillment of these requirements by intergroup problem solving. More importantly, MTSs also organize teams according to their tasks and enable team interdependence so that cross-boundary work-sharing occurs where needed to efficiently achieve system-level goals (Davidson & Hollenbeck, 2012). Thus, inter-organizational collaborative effort is the cornerstone of the MTS idea. MTS communication, in turn, enables collaboration by creating a sense of shared meaning that illuminates task requirements and priorities (Keyton, Ford, & Smith, 2012). While there is some mention of geographic processes in the MTS literature, such mention is limited to discussion of the effect of geographic distribution upon the functioning of MTSs. No scholarly examination has assessed the geographic attributes of the behaviors of MTS members in the way proposed by this research project.

The development of MTS concepts conforms to the assertions, offered above, of growing decentralization of power and increased influence of teams. MTSs are particularly attuned to descriptions of illicit social movements that perpetrate political violence. In an infamous 1,600-page treatise, the influential Al Qaeda strategist known as

Abu Musab al-Suri exhorted his followers to perpetrate a global resistance in which small autonomous groups organized to achieve locally-determined goals in support of Al Qaeda's larger objective of restoring the Islamic caliphate (Cruickshank & Ali, 2007). Other observers have recognized that terror groups exhibit a hybrid structure in which a supreme leadership facilitates interdependence among a distributed network of semi-autonomous teams, also called cells (Richard M Medina & Hepner, 2013). The MTS construct aptly describes resilient, adaptive, and non-hierarchical systems of terror cells observed by terrorism experts (Hoffman, 2002; Sageman, 2008).

Naïve Hypotheses

This literature provokes several naïve hypotheses which are listed below. These are conjecture and merely a starting point from which this and future projects build towards theoretical concepts about the geographic dynamics of goal-directed social behaviors.

1. Human groups have a geographic presence that is temporally dynamic.
2. The geographic presence of human groups is describable with network concepts and comprised of: point locations of members (network nodes); communications and relationships among members (network links); facts of identity, affiliation, or disaffiliation (boolean variable); and patterns of movement (spatio-temporal network topology). The topological structure used to understand this presence is therefore a combination of interrelated networks that exist in physical, virtual, and hybrid space.

3. The communications and geographic presence of discrete human groups exhibits heterogeneity. Potential factors of this heterogeneity are: cultural influences, idioculture, social objectives, strength of links or communications, network structure, physical or social barriers, individual roles, leadership, internal conflict, factors of social cognition, and technology.
4. Individual group members make decisions about their locations and move in pursuit of goals according to their perceptions of geographic optima. These perceptions derive from the spatial knowledge, spatial preferences, and the spatial behaviors of those individual team members as well as the spatial knowledge, spatial preferences, and the spatial behaviors they observe in their teammates, adversaries, and others. Since spatial knowledge and individual knowledge about teammates, adversaries, and others is imperfect, individual perceptions of geographic optima are flawed.
5. Patterns of group movement and communication are characterized by transition phases and action phases. These phases are recognizable in behavioral changes that are distinguishable from random behaviors and therefore recognizable via statistical inference.
6. Exploring the geographic dynamics of goal-directed social behaviors offers the potential to understand and predict social behaviors as a

function of the factors of heterogeneity, enhancing knowledge of forces influential in the polity, economy, and culture of contemporary societies.

7. Empirical observation of the dynamics of human social networks is sensitive to parameters including scale of analysis, sampling rate, timestamp rate, and sensor type, among others.

The literature reveals that no scientific effort to understand the geographic dynamics of goal-oriented team behaviors has yet been undertaken, and any such effort must draw from among many scientific disciplines. Furthermore, this review supports the observation that such research is now much more possible as a result of numerous scientific, technological, and social advances. While game theory has been successfully exported to numerous academic disciplines, it has not yet integrated notions of distance and spatial preference into game theoretic models and geography has yet to bring such knowledge of strategic cooperation and competition into the geographic domain. Much attention in industrial and organizational psychology has been paid to the effects of geographic dispersion upon work performance in teams; however there is no other deeply substantive treatment of location integrated within the theories and models of this discipline. Reality mining is leading to discoveries about how individuals reason spatially, but it has not yet yielded reliable research about group behaviors. Despite the significant influence of the concept of netwar, there is a negligible amount of research that has considered some of its propositions under empirical conditions with the help of human subjects. Geosimulation has offered theory-driven evidence about the root causes of spatially manifest social phenomena; however these ideas could benefit from empirical examination of the sort that can only be obtained by full-scale experimentation with human subjects. While important human geographic theory has derived from behavioral approaches, these theories are rarely developed with information gleaned by geographic optimization, and this combination could enable greater awareness of the geographic decisions of individuals, teams, and larger social systems. Accounting for the geographic ways in which individuals act upon messages they receive from their friends and acquaintances, in the context of their goals and their technologies, will illuminate social processes of political mobilization and subversion. Alternatively, this research could provide insight about social behaviors to improve public services and the offerings of commercial ventures.

CHAPTER THREE: METHODS

General

The purposes of this research are to produce new metrics, hypotheses, and distributions of observations about the geographic dynamics of goal-directed social behaviors. The research design uses network-based stochastic geosimulation, formal experimental design, and spatiotemporal statistics to perform an experimental analysis of small team behaviors. A series of computer simulation experiments uses a simple game to isolate and distill one type of goal-directed team behavior that is associated with illicit group activities: hiding when being actively sought. This game, called here "pursuit-and-evasion," is similar to the schoolyard game of hide-and-seek. Pursuit-and-evasion is offered as an abstraction of military and law enforcement activities oriented against clandestine cells engaged in terrorism, insurgency, or political subversion. In each experiment exercise there are two teams, a pursuing team and an evading team, that seek to achieve goals that depend upon the location of the opposing team. The pursuing team's goal is to identify and locate each member of the evading team. Conversely, the evading team's goal is to avoid being identified and located by the pursuing team. The game ends when either the pursuers achieve their goal or a predetermined period of time concludes and at least one of the evaders have successfully avoided detection and location. In the interest of simplicity, this game assumes that all players are pedestrian in their mobility.

Study Area

The area of this study is within a 670-acre contiguous university campus, the George Mason University (GMU) Main Campus in Fairfax, Virginia. The study area was virtually represented as a set of terrain models within the computer simulation model. The campus is a combination of residential, academic, and administrative buildings set amid a network of pedestrian walkways in a Mid-Atlantic woodland environment. Although there are two arterial roadways adjacent to the campus (Virginia State Routes 123 and 620), there is a limited road network within the university's property. This road network includes Patriot Circle, which circumnavigates the periphery of the central campus and links large parking facilities. Virginia State Route 123 bisects the campus, separating the athletics facilities in the West Campus from the remaining area of the campus. Bicycle transportation is prohibited in many areas. Pedestrian travel is the most common method of movement on the GMU campus. See Figure 2.

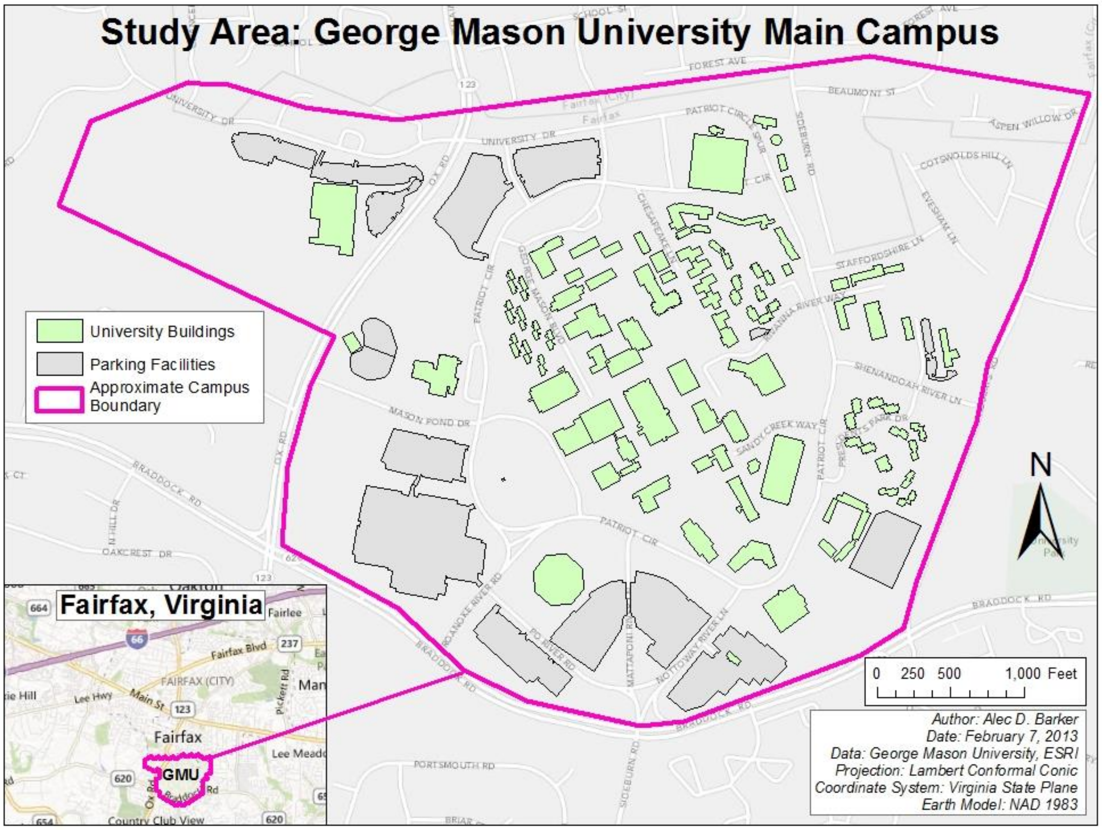

Figure 2: A Map of the George Mason University Campus in Fairfax, Virginia

This map uses Virginia State Plane coordinate system that is commonly used by governmental activities in Virginia, Fairfax County, and the City of Fairfax. Lambert Conformal Conic is the projection associated with Virginia’s State Plan coordinate system which uses the North American Datum of 1983 as the Earth Model. This Lambert Conformal Conic projection uses standard parallels set at 38.033 and 39.200. By law, the Virginia State Plane uses the foot as a standard unit of distance. Although the Lambert Conformal Conic is best at preserving the shape of geographic features, this projection minimizes distortion of distance and direction when standard parallels are customized to the geographic region and the scale is sufficiently large that localities such as towns fully contain the map's extent. This map's scale is approximately 1:9,000.

Experimental Design

This project employs the methods of experimental design, also known as the statistical design of experiments (or DoE). Experimental design is an approach to planning, executing, and analyzing experiments in order to understand multivariate causation while achieving efficiency and internal validity. Experimental design is a proven set of quantitative methods that enables scientific investigators to explore data and make discoveries that become hypotheses. One feature of the DoE approach is efficiency because the approach allows investigators to obtain reliable estimates of input-output effects at a fraction of the computational and time expense that would be required for a full and complete analysis of those effects. Another feature is the ability to identify not only the effects of an input variable on an output variable but also the interaction effects of input variable upon each other and output variables. It is therefore well-suited to the objectives of this research. DoE methods as applied to simulation modeling are extensively described in (Box, 2005; Croarkin & Tobias, 2013; Law & Kelton, 2000). This section presents a summary of these authors' descriptions of DoE as they pertain to the methods employed in this research project.

A primary objective of the DoE approach is to produce a process model that closely approximates the interaction of several controlled input variables, called "factors," and one or more output or "response" variables. A process model that fits the data well can serve to explain the nature of a set of multivariate interactions as well as predict potential outcomes of future multivariate interactions. Models are most commonly linear or quadratic in form. Linear models include terms for the main effects of each factor as well as the possible effects of the interaction of multiple (usually two) factors. Quadratic models add squared terms to allow for curvature.

The DoE approach begins by defining factors (k) and response variables (R). This involves judging what independent and dependent variables are operative within the system of interest. When there are few factors (i.e. $k = 2$, $k = 3$, or $k = 4$), simulation resources are inexpensive, and time is plentiful, it may be easy to test every possible combination of factors with the simulation model. This situation in which an investigator tests every possible combination of factors is called a full factorial design.

Although factors may exist as continuous variables along a significant range, it is not necessary or efficient to test at every possible value of a factor. To estimate the effects of factor changes, it is only necessary to test at two value levels for each factor: a high level and a low level. Running a set of simulations at every combination of both factor levels (2^k) gives a design that comprehensively describes the solution space (known as a hypercube) in which all response values must be contained.

The technique of 2^k full factorial experimentation yields understanding about not only the main effects of each factor upon the response, but also about the multi-factor and non-linear effects of every factor upon the response. Since multiple factors may work together to exert different effects upon the response than each would independently, it is advantageous to understand the effects of factor combinations.

Full factorial 2^k designs may be impractical when $k \geq 5$, simulation resources are costly, and/or time is scarce. In these situations, investigators may test some fraction of those factor combinations to gain an estimate of the probable results of the full factorial design. These types of designs, called fractional factorial designs, are constructed by taking a subset (2^{k-p}) of the full factorial set of factor-and-level combinations (2^k). The experimenter runs simulations for the factor combinations contained only in the subset; therefore only $1/2^p$ of 2^k possible combinations are run.

Since a fractional factorial design samples a subset of points that define the full parameter space, it only partially captures the interactions among factors and responses. The terms "aliasing" and "confounding" refer to the state in which some relationships cannot be meaningfully differentiated from others using a fractional factorial design. Although the aliasing problem cannot be entirely avoided without employing a full factorial design, the problem can be mitigated if the experimenter understands the probability that, for example, a multi-factor interaction is more influential than single-factor main interaction with which it is aliased. Part of the design process is determining, in a deliberate way, how to manage aliasing between and among factors, as well as the risk that a particular response may be improperly associated with a factor or combination of factors.

Experimental designs are expressed in a design matrix. Design matrices describe the factor level combinations to be tested in an experiment, as well as the order in which they should be tested. Each test run is described in a row containing the combination of factor levels. Factor levels may be described generically (i.e. + or -) or with specific values (e.g. 1 or 100). Proper ordering of the test runs is important to control for the possible effects of pseudo-random number generation. Design matrices present runs in both standard order (the generic order in which the design was created) and actual order (the random rearrangement of the standard order).

The closer a design is to a full factorial design, the more desirable are the alias patterns that result from the design. The term "resolution" is used to describe the qualities of an experimental design that produce more useful outputs. Resolutions are designated with Roman numerals and range from I (one) to VI (six), with resolutions I and II being generally not useful and resolution VI being considered inefficient. Generally, resolution III designs are used to cost effectively "screen" out unimportant relationships and factors. Higher resolution designs (IV and V) afford aliasing patterns that allow one to assert importance to certain factors and relationships. The explanatory power of resolution IV and V designs can be increased with the addition of center points, or test runs with factor combinations set at the geometric center of the hypercube.

Response Surface Methods refer to a family of techniques used in the second-order (i.e. non-linear or non-planar) analysis of the information that results from formally designed experiments. Response surface models are second-order polynomial models used to approximate curvature in functions describing non-linear or non-planar phenomena.

Response Variables

This research project employed six response variables by which to measure the outcomes of each simulation experiment:

1. The success rate of the pursuing team: The rate at which the pursuers find and engage (or "tag") every member of the evading team before the expiration of a user-defined game duration. The difference of 1 and the success of pursuers is the success of evaders.
2. The success rate of the evading team: The rate at which the evaders avoid being found and engaged such that at least one evader remains active at the expiration of a user-defined game duration. The difference of 1 and the success of evaders is the success of pursuers.
3. The mean time-to-win of pursuers, when game duration is unconstrained: The mean length of time in which the pursuing team finds and engages every member of the evading team. This value is unconstrained by the user-defined game duration. Effectively, this variable is partly the answer to the question, "How long could it possibly take the pursuers to win the game?"
4. The standard deviation of the time-to-win of pursuers, when game duration is unconstrained: The standard deviation of the length of time in which the pursuing team finds and engages every member of the evading team. This value is unconstrained by the user-defined game duration. Effectively, this variable is partly the answer to the question, "How long could it possibly take the pursuers to win the game?"
5. The players' preference for locations adjacent to a boundary (termed here "boundariness"): The ratio of the amount of time in which a player

occupies a location on the outer boundary of the study area to the total duration of that player's involvement in a game.

Spatiotemporal Analysis

The space-time permutation scan statistic, a method originally developed to provide early warning of disease outbreaks, makes "…minimal assumptions about the time, geographical location, or size of the outbreak, and it adjusts for natural purely spatial and purely temporal variation," (Kulldorff et al., 2005). Unlike many other spatiotemporal tests, Kulldorff et al's permutation scan does not require the user to define time or space windows because the statistic evaluates many thousands or millions of potential space-time windows in search of "unusual" quantities of observations. Another feature of the space-time permutation scan statistic is that it does not require information about the underlying geographic or temporal distribution of the population at risk. The statistic operates solely on case data, which it uses to produce both observed and expected values for every space-time window that gets "scanned."

One disadvantage of the space-time permutation scan statistic is computational intensity. This is partly because the statistic applies intensive Monte Carlo hypothesis testing. One way to reduce the runtime necessary to apply the space-time permutation scan statistic to many simulated runs is to aggregate the times of cases at user-defined intervals.

In this project, application of the space-time permutation scan statistic to every model run without time aggregation would have been prohibitively expensive in terms of computer resources. Each application elapsed over approximately twenty minutes in preparatory testing. If every application required twenty minutes, analysis of every simulation run in this project would have required approximately 35 years of continuous processor time.

In this project, this statistic's computational burden was mitigated in two ways. First, case times were aggregated at fifteen-minute intervals. Second, the project randomly sampled thirty runs from among 190,000 generated in one of the seven experiments. Thirty observations provide mere indications of the characteristics of the entire population; however, far greater resources and time than are available to this project are needed to comprehensively apply the space-time permutation scan statistic to every run of the computer simulation model.

CHAPTER FOUR: DATA

Terrain Model

This project required the generation of a two network-based terrain models used in the computer simulation experiments: a "concealment-variegated" terrain model and a "concealment-isotropic" alternative. These terrain models represented the study area described in the methods section above. In particular these terrain models expressed the attributes of concealment and pedestrian accessibility that prevailed across the George Mason University Fairfax campus.

Both terrain models were geometrically tessellated networks of nodes, hexagonal cells, and arcs. Two variables to consider in developing a regular geometric tessellation are the shape and size of each cell. Regular geometry shows that a continuous arrangement of hexagonal cells in which the cell centroids follow a triangular pattern ensures maximal dispersion and total areal coverage. Prior research about distances of interpersonal visual recognition suggest that facial features are recognizable at a maximum distance of about 150 feet (Loftus & Harley, 2005). Given this previous research, it is reasonable to assert that non-facial characteristics contributing to suspicion or recognition of another's identity, such as body morphology, hairstyle, complexion, and clothing, may be seen at some marginal distance thereafter, perhaps as far away as 300 feet. Mean pedestrian speed among people in the greater Richmond, VA – Washington, DC area aged 14-64 years has been measured at about 4.7 meters, or 15.4 feet, per second

(Knoblauch, Pietrucha, & Nitzburg, 1996). In a minute, the average adult VA-DC pedestrian could traverse as many as 925 feet. However, the pedestrians in this prior research were motivated by vehicular traffic to cross a street, and this pace is probably neither reliable without such motivation nor sustainable over longer distances and durations.

In accordance with this preceding research, an appropriate hexagonal cell could use a 200-foot apothem and 230-foot radius. 200-230 feet is a reasonable and conservative distance at which to scan a 360-degree zone, suspect a person's identity, and move near to them within one minute, assuming that the targeted person is located near the edge of an adjacent hexagon and potentially ambulant at a similar pace. See Figure 3 for a hexagonal lattice of the study area set at a 200-foot apothem and 230-foot radius.

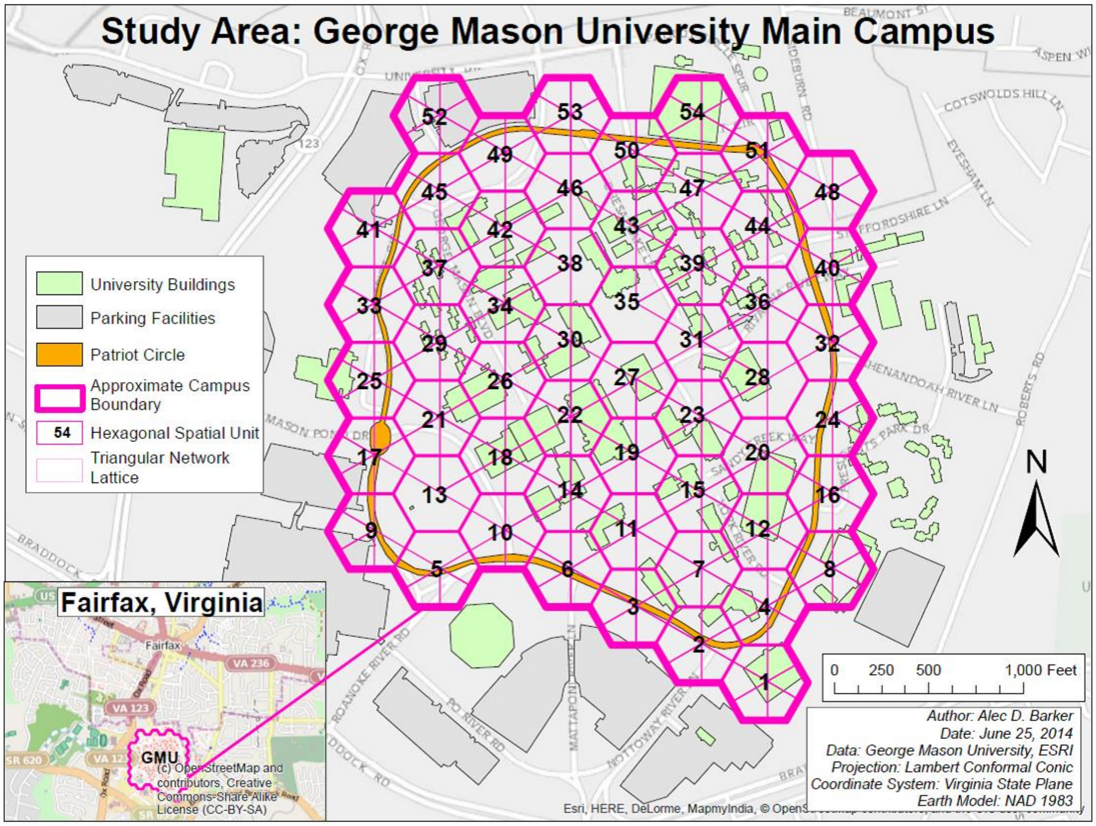

Figure 3: A Hexagonally tessellated lattice of the study area

Both terrain models contained 256 arcs among 54 nodes/cells. Arcs were not modeled where there was no pedestrian access between adjacent cells. For example, Mason Pond is a large water feature that comprises most of Cell 13. Since it was not possible to walk from that cell to two of six adjacent cells, there are no arcs in the terrain model among those cells.

In the concealment-variegated terrain model, each node/cell was assigned a concealment value representing the percentage of the cell circumference through which people and objects in adjacent cells could be clearly seen. The development of cell concealment values required an extensive concealment survey that was conducted on foot in June 2014. Every cell was surveyed for concealment properties attributable to vegetation, buildings, or terrain-based inter-visibility. Concealment was also adjusted to account for boundary properties. The proportion of a cell circumference that faced areas outside of the study area (i.e. "boundary-based" concealment) was added to the proportions that were assessed as concealed by any other cause.

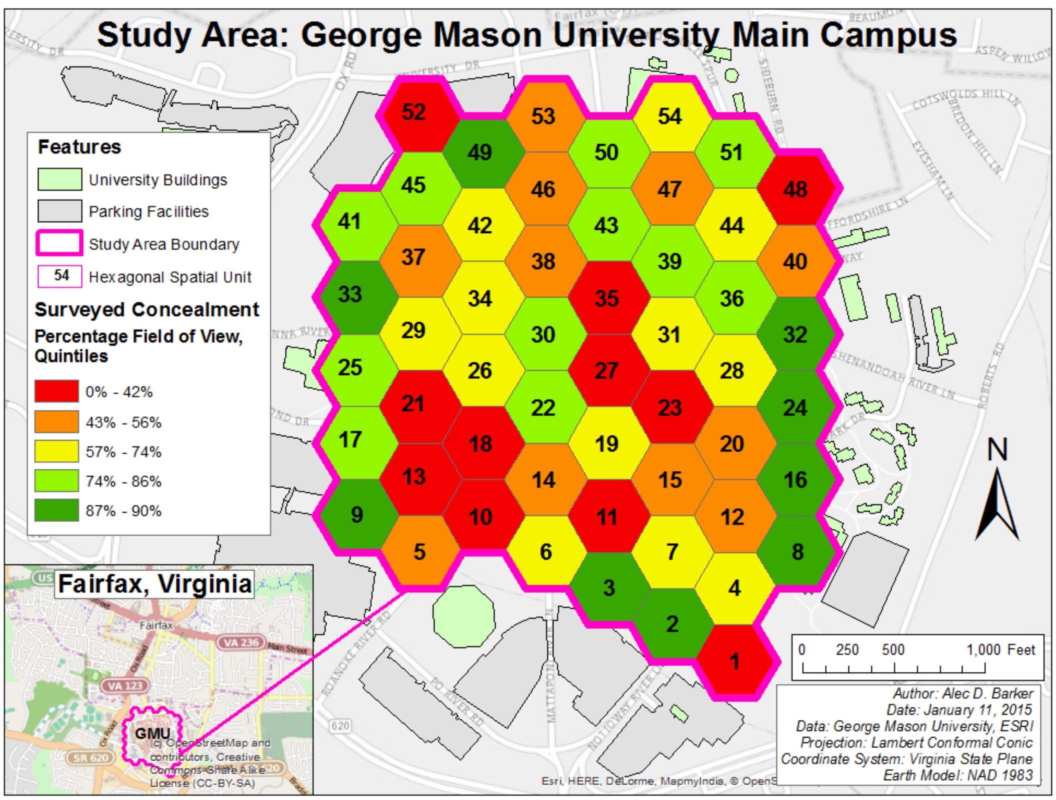

Figure 4: Concealment values for the concealment-variegated terrain model

The concealment-isotropic terrain model artificially applies uniform concealment values across the study area, effectively removing vegetation, buildings, terrain-based inter-visibility, or boundary-based concealment as variables in the computer simulation experiments. In the concealment-isotropic terrain model every node/cell was assigned a concealment value of 50%.

Computer Simulation Model

This research project developed a family of computer simulation models to produce data to help understand how groups move and communicate in pursuit of collective goals. The models are examples of geosimulation insofar as they are both agent-based and spatially explicit. They are turn-based insofar as all active agents apply rule sets to make "choices" at fixed time increments.

The premises of the models are that individuals make choices rationally according to their natural tendencies, their group's objective, and their relative preferences for any of the location and communication options available to them.

Natural tendencies are represented by user-defined parameters for the movement preferences, communication preferences, and memory capacities of each individual. Movement preference is the endogenous probability that an individual player would desire to relocate if no actionable information is available. Communication preference is the endogenous probability that a player will notify teammates of his/her own observations. Communications preferences also include a set of parameters that govern how and to whom individuals transmit messages. Memory capacity is the period of time over which a player retains and uses information, whether by choice or by nature.

The models initialize player locations randomly or according to user definitions. The user also defines the potential duration of the game by entering a maximum value for the number of turns in each instance of the game. Each turn follows a five-step cycle of events in which players 1) observe who else is at their immediate location, 2) attempt to tag or avoid being tagged by opponents, 3) scan adjacent areas for opponents, 4) generate messages to teammates, and 5) decide if and where to move next. Tagging, movement, and communications transactions do not occur until every player has processed its intentions so that events occur simultaneously and no individual enjoys the advantages of being the first to act. Each instance of the game concludes when either of two conditions is met: every evader is tagged (and the pursuers win) or the maximum turn limit is reached (and the evaders win).

Observation and tag events are governed by Monte Carlo methods. When pursuers and evaders attempt to observe opponents, the observation is determined by comparison of a random draw and the concealment value available at the opponent's location. When pursuers attempt to tag evaders, the tag is determined by comparison of a random draw and a constant probability of 0.5. In this way pursuers and evaders have equal chances of tagging or avoiding being tagged by an opponent with whom they are co-located. When a pursuer successfully tags an evader, the evader ceases activity and the pursuer cannot move or tag another player until the subsequent turn.

Communication events are also governed by Monte Carlo methods. When a tag has not occurred, evaders and pursuers who have made observations of opponents will communicate with their teammates according to a comparison of a random draw and the individual's communication preference value. The messages communicate when and where an opponent was sighted. Recipients store this information for use in determining movements.

Evaders and pursuers implement distinct movement decision processes when they possess or do not possess actionable information. Table 1 summarizes these distinct processes.

Table 1: A Summary of Movement Decision Processes in the Computer Simulation Models

	Does Not Have Actionable Information	***Has Actionable Information***
Evader	CONCEALMENT MAXIMIZATION Maximizes concealment available at any of the seven nodes in the immediate area	RISK MINIMIZATION Minimizes risk by evaluating cumulative concealment, pursuer proximities, and information quality at each of the seven nodes in the immediate area
Pursuer	RANDOM SEARCH Applies random draws to movement preferences to determine if and where to move	COST MINIMIZATION Minimizes cost by evaluating cumulative distance required to move to a node where an evader(s) was observed and information quality

At each turn, each individual evaluates choices by comparing movement and communication parameters against separate Monte Carlo draws. If the Monte Carlo draw exceeds either parameter, then the individual chooses to move or communicate, respectively. Separately, evaders and pursuers execute procedures to determine where to move or what, to whom, and how to communicate. The following ten paragraphs describe those procedures.

Evaders possessing no actionable information move to maximize the concealment afforded by the options available in their immediate area: the cell they currently occupy and the six cells immediately adjacent to them. Although it is possible that human evaders would make uninformed movement decisions based on a rationale different from that of concealment maximization, this project plans to identify, evaluate, and – if warranted – justify such possibilities and rationales through future experimentation with human subjects. In the Phase 2 computer simulation experiments described below, the probability that evaders will disregard concealment and move spuriously according to endogenous movement preferences is held constant at zero.

Evaders possessing actionable information prepare to move by evaluating the risk that they will be detected by a pursuer at each location in their immediate area. The evader scores that risk and chooses to move to the cell that minimizes the score. The risk score is computed by summing the natural probability of detection at cell x (symbolized P_{dx}, given by the difference of 1 and the concealment value) with the known or suspected proximities of pursuers to that cell. Pursuer proximities are derived from what the evader has observed in his/her own surroundings and from the reports of the evader's teammates. Where the total number of pursuer observations is symbolized n, distance(s) along the shortest path between the evader's current location and pursuer locations are symbolized $d_1, d_2, d_3 ... d_n$.

Evader proximities are weighted by the passage of time: older observations of pursuers exert less influence over the evaders' evaluations of movement options. Observations that are older than the evader's memory capacity are forgotten. Where the evader's memory parameter is symbolized m and the current turn is symbolized t, the memory function purges information received prior to t-m. Where the total number of pursuer observations is symbolized n, the time that has elapsed since each report of observation is symbolized $e_1, e_2, e_3 ... e_n$.

The risk score at each of the evader's potential movement options (symbolized R_x) is therefore:

$$R_x = P_{dx} + ((1/ d_1)+(1/ e_1)) + ((1/ d_2)+(1/ e_2)) + ((1/ d_3)+(1/ e_3)) ... + ((1/ d_n)+(1/ e_n))$$

Equation 1: Evader Movement Risk Score

Pursuers possessing no actionable information move according to a sequence of two random draws. The first draw applies the pursuer's movement preference to determine if the pursuer will move. The second draw, which occurs only if the pursuer will move, randomly selects one cell from among the seven options available in the pursuer's immediate area. Although it is possible that human pursuers would make uninformed movement decisions using a rationale different from a random walk, this project plans to identify, evaluate, and – if warranted – justify such possibilities and rationales through future experimentation with human subjects.

Pursuers possessing actionable information prepare to move by evaluating the distance costs that will be incurred by traveling along the shortest path to each location where an evader has been observed by the pursuer or a pursuer's teammate. The pursuer evaluates that distance cost and chooses to move to the cell that minimizes the cost. When distance costs are equal for multiple movement options, the pursuer chooses the option with highest natural probability of detection. Where the total number of evader observations is symbolized n, distance(s) along the shortest path between the pursuer's current location and evader locations are symbolized $d_1, d_2, d_3 ... d_n$.

Distance costs are weighted by the passage of time: older observations of evaders exert less influence over the pursuers' evaluations of movement options. Observations that are older than the pursuer's memory capacity are forgotten. Where the pursuer's memory parameter is symbolized m and the current turn is symbolized t, the memory function purges information received prior to t-m. Where the total number of evader observations is symbolized n, the time that has elapsed since each report of observation is symbolized $e_1, e_2, e_3 ... e_n$.

The cost value at each of the pursuer's potential movement options (symbolized C_x) is therefore:

$$C_x = d_1 + e_1 \, , d_2 + e_2 \, , d_3 + e_3 \ldots d_n + e_n$$

Equation 2: Pursuer Movement Cost Value

Evaders and pursuers who have made observations in a given turn will determine how to communicate with teammates according to two user-defined parameters. The first parameter governs how many teammates an individual will contact. This value may be preset or configured as a random draw. The second parameter governs which teammates an individual will contact. An individual may select recipient teammates by random draw, proximity to the observation, or proximity to the individual sending the message.

The simulation models were written in Microsoft Visual Basic for Applications and Microsoft Excel. The computer simulation experiments were run on an array of twelve CPUs installed with Intel Core i3-3217U 1.8 GHz microprocessors and 4 GB of RAM. Each simulation batch consisted of ten thousand repetitions and required about eight hours of runtime, meaning that an experimental design of twelve or fewer batches could be completed in about eight hours and an experimental design of thirteen to twenty-four batches could be completed in about sixteen hours.

Simulation Output

The computer simulation models produced five comma separated value (.csv) tables for analysis in R and SaTScan as well as keyhole markup language (.kml) files for visualization in Google Earth. The five data tables recorded game outcomes, player movements, player communications, detection and engagement events, and cell occupancies. Table 2 describes the fields contained in each data table.

Table 2: Data Fields in the Data Tables Produced by the Computer Simulation Models

Data Table	Data Fields
Game Outcomes	game serial number, game end time, number of evaders, number of evaders engaged
Player Movements	game serial number, turn, player, start cell, end cell, start latitude, start longitude, end latitude, end longitude
Player Communications	game serial number, turn, sender, message type, receiver, message cell, sender cell, receiver cell, message latitude, message longitude, sender latitude, sender longitude, receiver latitude, receiver longitude
Detections and Engagements	game serial number, turn, observer, target, result, observer cell, target cell, observer latitude, observer longitude, target latitude, target longitude
Cell Occupancies	game serial number, cell, number of occupants, turn, team

Phase 1

Phase 1 was an exploratory effort that used a "beta" version of the computer simulation model. It was comprised of three experiments and ran from May to September of 2014. In all, 460,000 simulation runs were produced during Phase 1.

Experiment One

The first simulation experiment comprised a 2^{6-3} fractional factorial (Resolution III) design. The purpose of Experiment One was to isolate variables and variable combinations deserving further investigation. The response variables for this experiment were the success of pursuers and the success of evaders.

This experimental design, illustrated in Table 3, involved eight batch runs of 10,000 repetitions each for a total of 80,000 repetitions. Every repetition was constrained to a maximum of 180 minutes. The input variables were the pursuers' probability of movement (P_Pmove), pursuers' probability of communication (P_Pcomm), pursuers' memory (P_Mem), evaders' probability of movement (E_Pmove), evaders' probability of communication (E_Pcomm), and evaders' memory (E_Mem). Values for P_Pmove, P_Pcomm, E_Pmove, and E_Pcomm varied between 0.10 (low level) and 0.90 (high level) while values for P_mem and E_mem varied between 1 minute (low level) and 180 minutes (high level). Experiment One used a generic terrain model that evenly applied dispersed concealment values of 0.25, 0.5, or 0.75 to each third of the cells in the network.

Table 3: Experiment One Design

Run Number		Pursuer Variables			Evader Variables		
Actual Order	Standard Order	Movement	Communications	Memory	Movement	Communications	Memory
		P_Pmove	P_Pcomm	P_mem	E_Pmove	E_Pcomm	E_mem
1	8	10	10	1	10	10	1
2	6	90	10	180	10	10	180
3	1	90	90	180	10	90	1
4	4	90	10	1	90	90	180
5	3	10	10	180	90	90	1
6	7	90	90	1	90	10	1
7	2	10	90	180	90	10	180
8	5	10	90	1	10	90	180

Experiment One was conducted on 3-6 June 2014 and produced 3.97 GB of data. The response data is summarized in Table 4.

Table 4: Experiment One Response Data

Run Number		Response Variables	
Actual Order	Standard Order	Success Rate	
		Evader	Pursuer
1	8	4629	5371
2	6	1515	8485
3	1	783	9217
4	4	1876	8124
5	3	6552	3448
6	7	783	9217
7	2	7676	2324
8	5	8508	1492

Experiment Two

The second simulation experiment comprised a 2^{6-2} fractional factorial (Resolution IV) design with three center points. The purpose of Experiment Two was to deepen and confirm the findings of Experiment One. The input variables remained the same in this experiment as they were in the first experiment. While the response variables of evader and pursuer success remained, Experiment Two added the response variables of game duration (mean and standard deviation), as well as boundariness for both evaders and pursuers.

This experimental design, illustrated in Table 5, involved nineteen batch runs of 10,000 repetitions each, for a total of 190,000 repetitions. The maximum run time for each repetition was unconstrained; each repetition ended whenever every evader was caught. The levels/values used for the six input variables remained the same as they were in Experiment One. Centerpoint values used 0.50 for P_Pmove, P_Pcomm, E_Pmove, and E_Pcomm and 90.5 for P_mem and E_mem. Experiment Two used the concealment-variegated terrain model.

Table 5: Experiment Two Design

Run Number		Pursuer Variables			Evader Variables		
Actual Order	Standard Order	Movement P_Pmove	Communications P_Pcomm	Memory P_mem	Movement E_Pmove	Communications E_Pcomm	Memory E_mem
1	0	50	50	90.5	50	50	90.5
2	12	90	90	1	10	10	180
3	16	90	90	180	90	90	180
4	13	10	10	180	90	90	180
5	7	10	90	180	10	10	180
6	11	10	90	1	90	90	1
7	15	10	90	180	10	10	1
8	1	10	10	1	10	10	1
9	9	10	10	1	10	10	180
10	0	50	50	90.5	50	50	90.5
11	5	10	10	180	90	90	1
12	14	90	10	180	10	10	1
13	6	90	10	180	10	10	180
14	2	90	10	1	90	90	180
15	8	90	90	180	90	90	1
16	10	90	10	1	90	90	1
17	4	90	90	1	10	10	1
18	3	10	90	1	90	90	180
19	0	50	50	90.5	50	50	90.5

Experiment Two was conducted on 25-30 June 2014 and produced 6.81 GB of data. The response data is summarized in Table 6.

Table 6: Experiment Two Response Data

Run Number		Response Variables					
Actual Order	Standard Order	Success Rate		Pursuer Time-to-Win		Boundariness	
		Evader	Pursuer	Mean	Std. Dev.	Evader	Pursuer
1	0	2313	7687	135.75	82.65	0.747625	0.473693
2	12	2462	7538	116.88	74.05	0.731902	0.473082
3	16	1726	8274	108.02	67.89	0.740573	0.510539
4	13	7894	2106	409.61	304.05	0.749876	0.424862
5	7	8470	1530	424.39	296.62	0.693366	0.44947
6	11	8605	1395	448.67	291.6	0.68063	0.393282
7	15	7669	2331	377.2	269.38	0.502997	0.400789
8	1	6486	3514	317.38	267.52	0.426233	0.3575
9	9	7668	2332	349.34	282.51	0.636885	0.390206
10	0	2313	7687	137.07	82.73	0.747625	0.473693
11	5	7321	2679	379.94	297.09	0.640571	0.402561
12	14	3833	6167	180.23	179.95	0.444116	0.39109
13	6	3313	6687	133.3	92.18	0.736214	0.462884
14	2	3743	6257	140.9	106.8	0.743341	0.44366
15	8	2314	7686	107.48	64.99	0.669375	0.427942
16	10	4040	5960	179.69	123.81	0.618321	0.403805
17	4	1964	8036	136.22	126.48	0.479059	0.380971
18	3	8788	1212	481.75	312.04	0.764216	0.429962
19	0	2357	7643	137.49	85.66	0.74868	0.475293

Experiment Three

The third simulation experiment also comprised a 2^{6-2} fractional factorial (Resolution IV) design with three center points. Experiment Three was similar to Experiment Two with one critical difference: this experiment used the concealment-isotropic terrain model rather than the concealment-variegated terrain model. The input, response variables, variable values, and design remained the same in this experiment as they were in the second experiment. The purpose of Experiment Three was to provide a basis against which to compare the results of other experiments in order to understand the effects of concealment upon team behaviors and game outcomes.

Experiment Three was conducted on 29 July – 5 August 2014 and produced 8.07 GB of data. The response data is summarized in Table 7.

Table 7: Experiment Three Response Data

Run Number		Response Variables					
Actual Order	Standard Order	Success Rate		Pursuer Time-to-Win		Boundariness	
		Evader	Pursuer	Mean	Std. Dev.	Evader	Pursuer
1	0	1493	8507	113.93	70.99	0.747625	0.473693
2	12	248	9752	82.14	40.41	0.731902	0.473082
3	16	150	9850	74.01	36.85	0.740573	0.510539
4	13	7676	2324	422.92	321.36	0.749876	0.424862
5	7	7614	2386	434.43	338.14	0.693366	0.44947
6	11	8672	1328	480.42	308.28	0.68063	0.393282
7	15	6763	3237	346.18	277.89	0.502997	0.400789
8	1	5233	4767	263.28	244.71	0.426233	0.3575
9	9	6610	3390	335.12	278.76	0.636885	0.390206
10	0	1493	8507	113.93	70.99	0.747625	0.473693
11	5	7538	2462	397.86	299.27	0.640571	0.402561
12	14	238	9762	76.43	41.81	0.444116	0.39109
13	6	438	9562	85.58	48.17	0.736214	0.462884
14	2	460	9540	83.88	49.57	0.743341	0.44366
15	8	654	9346	100.41	47.65	0.669375	0.427942
16	10	418	9582	87.41	45.60	0.618321	0.403805
17	4	322	9678	84.52	43.55	0.479059	0.380971
18	3	8425	1575	477.81	331.00	0.764216	0.429962
19	0	1389	8611	112.71	70.15	0.74868	0.475293

Phase 2

Phase 2 commenced after the computer simulation model completed “beta” testing and a thorough code review that resulted in several improvements. It was comprised of another three experiments similar in design to those of Phase 1. Phase 2 ran from September to November 2014. In all, 650,000 simulation runs were produced during Phase 2.

Experiment Four

The fourth simulation experiment comprised a 2^{5-2} fractional factorial (Resolution III) design. The purpose of Experiment Four was to isolate variables and variable combinations deserving further investigation. The response variables for this experiment were the success of evaders, the success of pursuers, the mean and standard deviation of the distribution of pursuer time-to-win, and the mean "boundariness" values for both pursuers and evaders.

This experimental design, illustrated in Table 8, involved eight batch runs of 10,000 repetitions each for a total of 80,000 repetitions. Every repetition of the simulation was unconstrained by time; however the output was analyzed according to a three-hour (180-minute) game duration for the purpose of evaluating pursuer and evader success rates. The input variables were P_Pmove, P_Pcomm, P_Mem, E_Pcomm, and E_Mem. Values for P_Pmove, P_Pcomm, and E_Pcomm varied between 0.10 (low level) and 0.90 (high level) while values for P_mem and E_mem varied between 1 minute (low level) and 180 minutes (high level). Experiment Four used the concealment-variegated terrain model.

Table 8: Experiment Four Design

Run Number		Pursuer Variables			Evader Variables	
Actual Order	Standard Order	Movement	Communications	Memory	Communications	Memory
		P_Pmove	P_Pcomm	P_mem	E_Ecomm	E_mem
1	7	90	90	1	90	1
2	6	90	10	180	10	1
3	5	10	90	1	10	180
4	1	90	90	180	10	180
5	8	10	10	1	10	1
6	4	90	10	1	90	180
7	2	10	90	180	90	1
8	3	10	10	180	90	180

Experiment Four was conducted on 31 October – 3 November 2014 and produced 89.1 GB of data. The response data is summarized in Table 9.

Table 9: Experiment Four Response Data

Run Number		Response Variables					
Actual Order	Standard Order	Success Rate		Pursuer Time-to-Win		Boundariness	
		Evader	Pursuer	Mean	Std. Dev.	Evader	Pursuer
1	7	7268	2732	315.13	198.07	0.524338	0.383842
2	6	8440	1560	418.68	272.21	0.534331	0.392048
3	5	8939	1061	523.31	340.06	0.384273	0.384141
4	1	4560	5440	188.88	95.25	0.451990	0.413580
5	8	8114	1886	471.11	358.96	0.362833	0.384717
6	4	8446	1554	511.36	380.14	0.395647	0.384356
7	2	8981	1019	530.18	337.09	0.410428	0.425522
8	3	8388	1612	494.26	352.09	0.363661	0.401757

Experiment Five

The fifth simulation experiment comprised a 2^{5-1} fractional factorial (Resolution V) design with three center points. The purpose of Experiment Five was to deepen and confirm the findings of Experiments One, Two, Three, and Four. The response variables for this experiment were the success of evaders, the success of pursuers, the mean and standard deviation of the distribution of pursuer time-to-win, and the mean "boundariness" values for both pursuers and evaders.

This experimental design, presented in Table 10, involved nineteen batch runs of 10,000 repetitions each, for a total of 190,000 repetitions. The maximum run time for each repetition was unconstrained; each repetition ended whenever every evader was caught. Pursuer and evader success was measured at a threshold of 180 minutes. The levels/values used for the five input variables remained the same as they were in Experiment Four. Centerpoint values used 0.50 for P_Pmove, P_Pcomm, and E_Pcomm and 90.5 for P_mem and E_mem. Experiment Five used the concealment-variegated terrain model.

Table 10: Experiment Five Design

Run Number		Pursuer Variables			Evader Variables	
Actual Order	Standard Order	Movement	Communications	Memory	Communications	Memory
		P_Pmove	P_Pcomm	P_mem	E_Ecomm	E_mem
1	0	50	50	90.5	50	90.5
2	7	10	90	180	10	180
3	10	90	10	1	90	180
4	1	10	10	1	10	180
5	9	10	10	1	90	1
6	6	90	10	180	10	180
7	4	90	90	1	10	180
8	13	10	10	180	90	180
9	8	90	90	180	10	1
10	0	50	50	90.5	50	90.5
11	11	10	90	1	90	180
12	14	90	10	180	90	1
13	15	10	90	180	90	1
14	12	90	90	1	90	1
15	16	90	90	180	90	180
16	3	10	90	1	10	1
17	5	10	10	180	10	1
18	2	90	10	1	10	1
19	0	50	50	90.5	50	90.5

Experiment Five was conducted on 3-6 November 2014 and produced 194 GB of data. The response data is summarized in Table 11.

Table 11: Experiment Five Response Data

Run Number		Response Variables					
Actual Order	Standard Order	Success Rate		Pursuer Time-to-Win		Boundariness	
		Evader	Pursuer	Mean	Std. Dev.	Evader	Pursuer
1	0	5812	4188	230.02	131.94	0.4276659	0.4107197
2	7	8871	1129	504.04	328.25	0.3791843	0.4232464
3	10	7980	2020	360.38	220.15	0.4319030	0.3850005
4	1	8308	1692	489.05	362.23	0.3798896	0.3857387
5	9	8444	1556	515.35	385.28	0.4092193	0.3853954
6	6	7770	2230	330.65	196.58	0.4828914	0.3918563
7	4	6209	3791	245.51	139.19	0.4676431	0.3849776
8	13	8388	1612	494.26	352.09	0.3636613	0.4017569
9	8	6279	3721	253.61	151.36	0.5102036	0.4126537
10	0	5812	4188	230.02	131.94	0.4276659	0.4107197
11	11	8837	1163	509.35	340.34	0.3674745	0.3847943
12	14	8521	1479	429.39	281.39	0.5435609	0.3917369
13	15	8966	1034	530.18	337.09	0.4104277	0.4255224
14	12	7268	2732	315.13	198.07	0.5243384	0.3838418
15	16	4144	5856	181.87	96.00	0.3826467	0.4100588
16	3	9132	868	550.23	349.18	0.4057831	0.3881745
17	5	8669	1331	548.65	400.62	0.3975343	0.4059593
18	2	8742	1258	460.91	300.79	0.5452036	0.3867329
19	0	5812	4188	230.02	131.94	0.4276659	0.4107197

Experiment Six

Like Experiment Five, the sixth simulation experiment also comprised a 2^{5-1} fractional factorial (Resolution V) design with three center points. Experiment Six was similar to Experiment Five with one critical difference: this experiment used the concealment-isotropic terrain model rather than the concealment-variegated terrain model. The purpose of Experiment Six was to provide a basis against which to compare the results of other experiments in order to understand the effects of concealment upon team behaviors and game outcomes.

This experimental design, presented in Table 12, involved nineteen batch runs of 10,000 repetitions each, for a total of 190,000 repetitions. The maximum run time for each repetition was unconstrained; each repetition ended whenever every evader was caught. Pursuer and evader success was measured at a threshold of 180 minutes. The levels/values used for the five input variables remained the same as they were in Experiment Five. Centerpoint values used 0.50 for P_Pmove, P_Pcomm, and E_Pcomm and 90.5 for P_mem and E_mem. Table 12 provides the design of Experiment Six.

Table 12: Experiment Six Design

Run Number		Pursuer Variables			Evader Variables	
Actual Order	Standard Order	Movement	Communications	Memory	Communications	Memory
		P_Pmove	P_Pcomm	P_mem	E_Ecomm	E_mem
1	0	50	50	90.5	50	90.5
2	7	10	90	180	10	180
3	6	90	10	180	10	180
4	11	10	90	1	90	180
5	10	90	10	1	90	180
6	4	90	90	1	10	180
7	5	10	10	180	10	1
8	16	90	90	180	90	180
9	8	90	90	180	10	1
10	0	50	50	90.5	50	90.5
11	3	10	90	1	10	1
12	1	10	10	1	10	180
13	13	10	10	180	90	180
14	2	90	10	1	10	1
15	15	10	90	180	90	1
16	12	90	90	1	90	1
17	14	90	10	180	90	1
18	9	10	10	1	90	1
19	0	50	50	90.5	50	90.5

Experiment Six was conducted on 5-7 November 2014 and produced 134 GB of data. The response data is summarized in Table 13.

Table 13: Experiment Six Response Data

Run Number		Response Variables					
Actual Order	Standard Order	Success Rate		Pursuer Time-to-Win		Boundariness	
		Evader	Pursuer	Mean	Std. Dev.	Evader	Pursuer
1	0	2305	7695	134.69	78.17	0.5579077	0.4365456
2	7	8649	1351	571.26	399.85	0.5238876	0.4406719
3	6	492	9508	89.14	47.54	0.5093680	0.4290204
4	11	8895	1105	560.06	365.43	0.5836499	0.4030292
5	10	293	9707	77.59	44.09	0.5542713	0.4163354
6	4	379	9621	88.82	43.90	0.5166048	0.4234999
7	5	8360	1640	472.53	324.25	0.4710663	0.4056108
8	16	275	9725	85.58	40.88	0.5778764	0.4556257
9	8	715	9285	102.07	50.13	0.5073927	0.4385668
10	0	2305	7695	134.69	78.17	0.5579077	0.4365456
11	3	8971	1029	530.14	338.90	0.4925432	0.4032518
12	1	7869	2131	444.50	336.18	0.4937044	0.3794809
13	13	8275	1725	492.19	355.81	0.5743407	0.4104402
14	2	624	9376	91.55	51.19	0.4962815	0.4062297
15	15	8957	1043	577.34	363.59	0.5911065	0.4438814
16	12	688	9312	99.79	49.67	0.5858506	0.4132829
17	14	794	9206	99.69	54.28	0.5753192	0.4239743
18	9	8209	1791	464.91	327.81	0.5755076	0.3819812
19	0	2305	7695	134.69	78.17	0.5579077	0.4365456

Experiment Seven

Experiment Seven was designed to produce a baseline distribution of random team movements for comparative analysis of boundariness. Therefore, Experiment Seven required no special design. This experiment applied a random walk algorithm to each individual in a five-person team and used no other variables. Experiment Seven involved nineteen batch runs of 10,000 repetitions each, for a total of 190,000 repetitions. The maximum run time for each repetition was constrained to 180 minutes. Experiment Seven was conducted on 19 September - 21 November 2014 and produced 4.2 GB of data. The response data is summarized in Table 14.

Table 14: Experiment Seven Response Data

Run	Boundariness
1	0.3617195
2	0.3616914
3	0.3615570
4	0.3621451
5	0.3613460
6	0.3615560
7	0.3616221
8	0.3617681
9	0.3621159
10	0.3613275
11	0.3622756
12	0.3628125
13	0.3615151
14	0.3611688
15	0.3615015
16	0.3617325
17	0.3632115
18	0.3616566
19	0.3608473

CHAPTER FIVE: RESULTS

Correlates of Team Success

Experiments One, Two, Four, and Five suggested that the outcomes of a game of pursuit and evasion correlated most strongly with the basic probability that a pursuer would decide to move if the pursuer did not possess actionable information (P_Pmove). Experiments Two and Five also suggested that the outcomes of a game of pursuit and evasion are also correlated with the interaction of the basic probabilities that a pursuer would decide to move and communicate (P_Pmove:P_Pcomm).

A half-normal probability plot is a graphical tool that relies on least squares estimation to develop ordered estimates of the absolute effects of input factors upon response variables (Croarkin & Tobias, 2013). Half-normal plots are useful to determine which factors are statistically unimportant (i.e. having near-zero effects upon responses) and important (i.e. having effects that are removed from zero beyond a certain threshold). In Experiment One, P_Pmove was the sole input factor revealed to have statistically important effects upon success of both teams at the threshold of $\alpha = 0.05$. Figure 5 and Figure 6 are half-normal plots illustrating the absolute effects of P_Pmove on Evaders' Success (evade_succ) and Pursuer Success (pursu_succ), respectively. Unsurprisingly, the absolute effects on both response variables appear to be identical to each other. Each response is merely the difference between 1 and the other response.

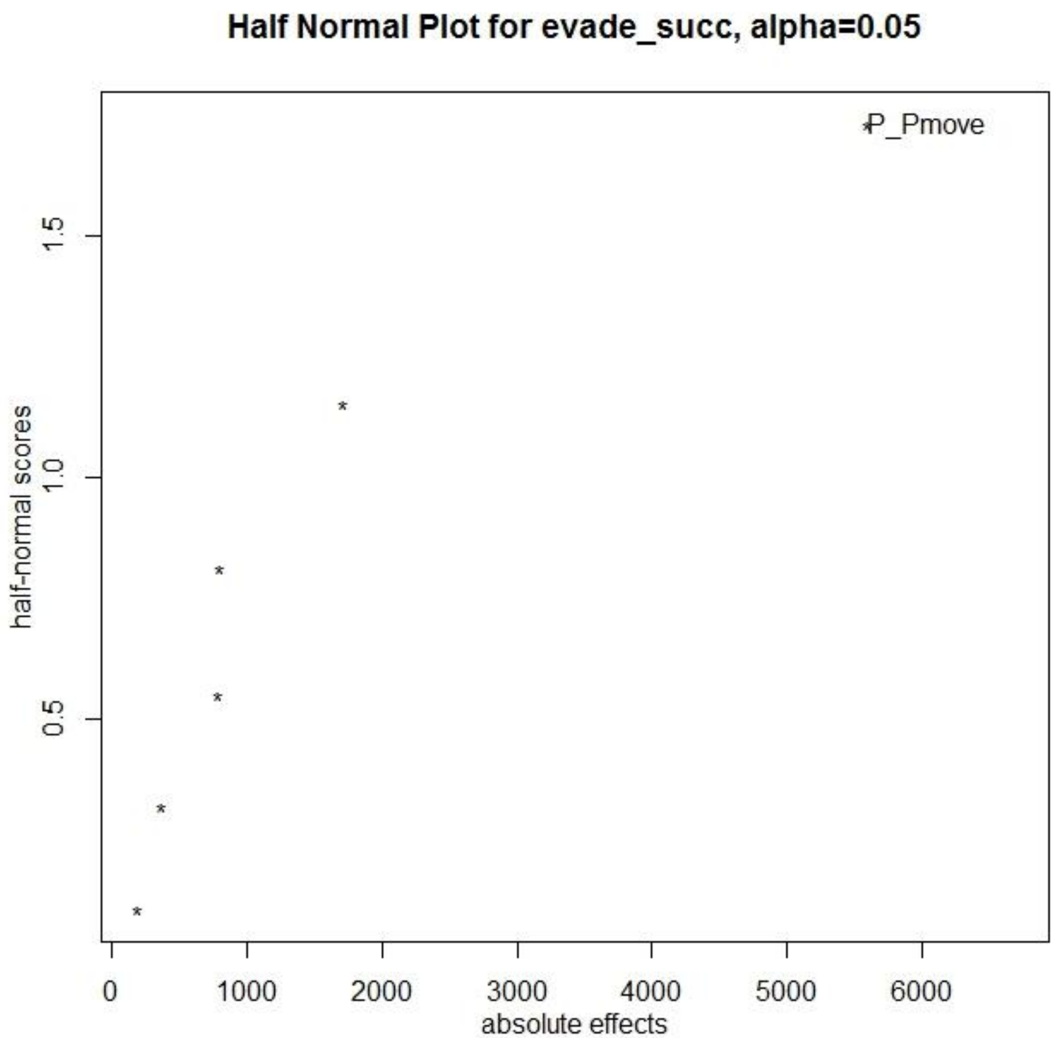

Figure 5: Half Normal Plot for Evader Success, Experiment One, α= 0.05

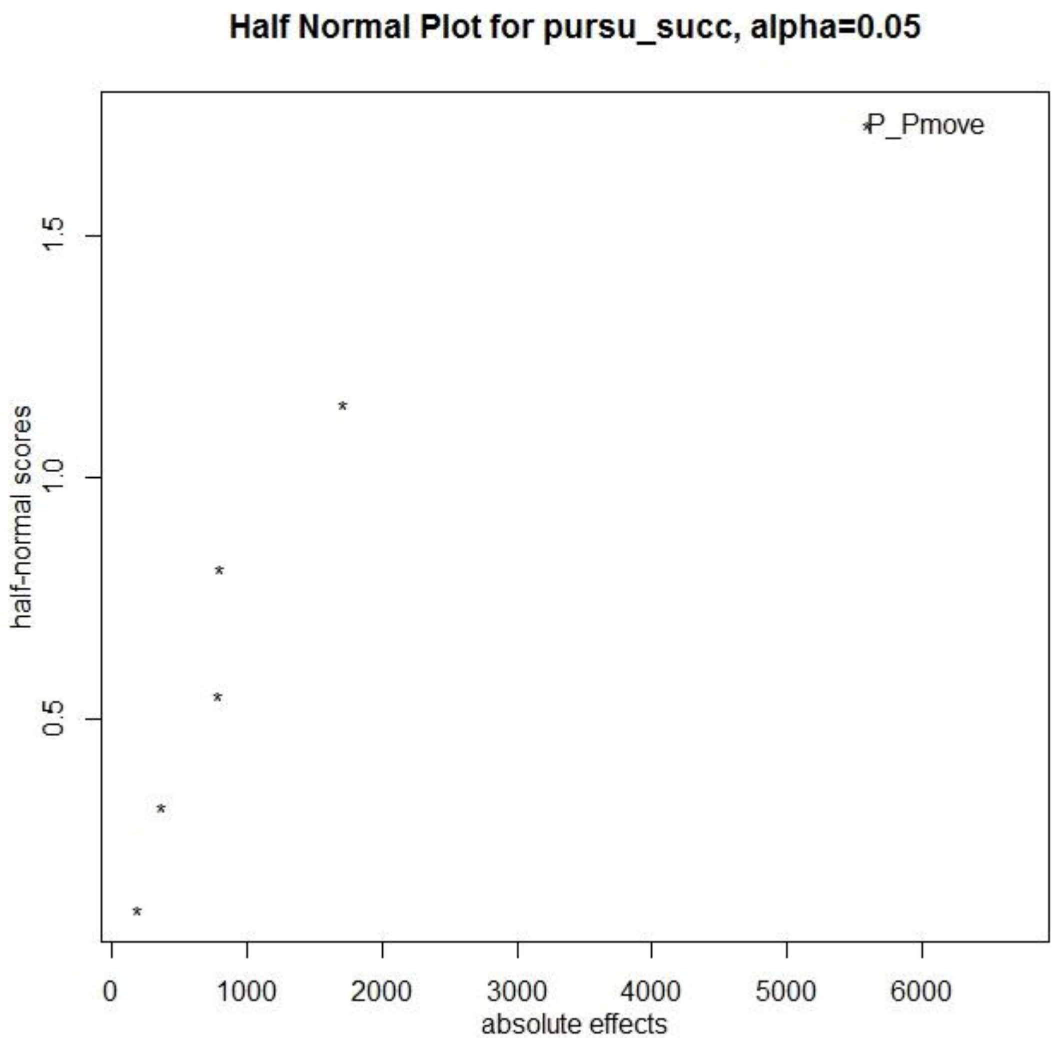

Figure 6: Half Normal Plot for Pursuer Success, Experiment One, α= 0.05

An attempt to fit a linear model to the evade_succ results of Experiment One yielded imperfect results. While the model achieved a good fit measured by an adjusted R-squared value of 0.9305, it failed an F-test that produced an F-statistic of 16.61 on 6 and 1 degrees of freedom and a p-value of 0.1856. These results suggested some non-linearity in relationships among the dominant input factors and the response variables of team success.

Experiment Two corroborated the results that suggested the dominant correlation of P_Pmove and the team success response variables. However the increased resolution afforded by Experiment Two also revealed the statistical significance of a two-factor interaction involving P_Pmove and the basic probability that a pursuer would choose to communicate with teammates, P_Pcomm. Figure 7 is a half normal plot that illustrates the significance of the main effect of P_Pmove on team success as well as the two-factor interaction of P_Pmove:P_Pcomm on team success at the threshold α=0.05.

An attempt to fit a linear model to the evade_succ results of Experiment Two yielded poor results. This provided further evidence of non-linearity in the relationships among the dominant input factors and the response variables of team success.

An attempt to fit a response surface model to the evade_succ results of Experiment Two yielded very strong results. The model achieved excellent fit measured by an adjusted R-squared value of 0.9959, and an F-statistic of 316.9 on 14 and 4 degrees of freedom with a corresponding p-value of 2.263e-05. These results strengthened earlier indications of non-linearity in relationships among the dominant input factors and the response variables of team success. This response surface model revealed the strengths of the main effect of P_Pmove, the two-factor interaction of P_Pmove:P_Pcomm, as well as the pure quadratic effect of P_Pmove (i.e. P_Pmove:P_Pmove) on team success, as defined by p-values smaller than 1e-04 and (absolute value) coefficients of 2469.12, 664.12, and 3065.83 respectively. Figure 8 and Figure 9 illustrate the bivariate function of pursuer propensities to move and communicate upon the success of evaders. Figure 10 and Figure 11 illustrate the bivariate function of pursuer propensities to move and communicate upon the success of pursuers. The pure quadratic effect of P_Pmove is clearly visible along the x1 axis of all four plots.

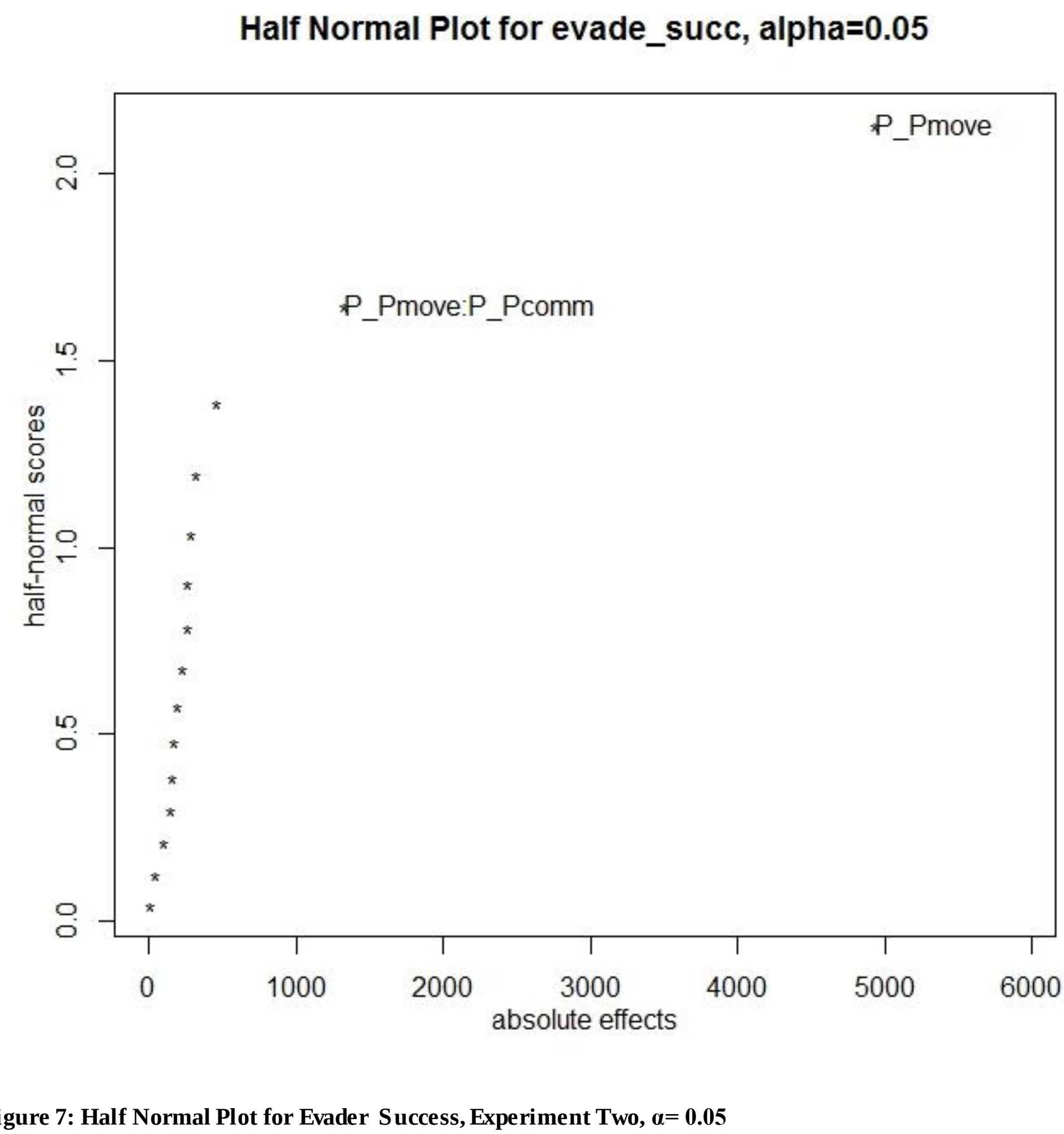

Figure 7: Half Normal Plot for Evader Success, Experiment Two, α= 0.05

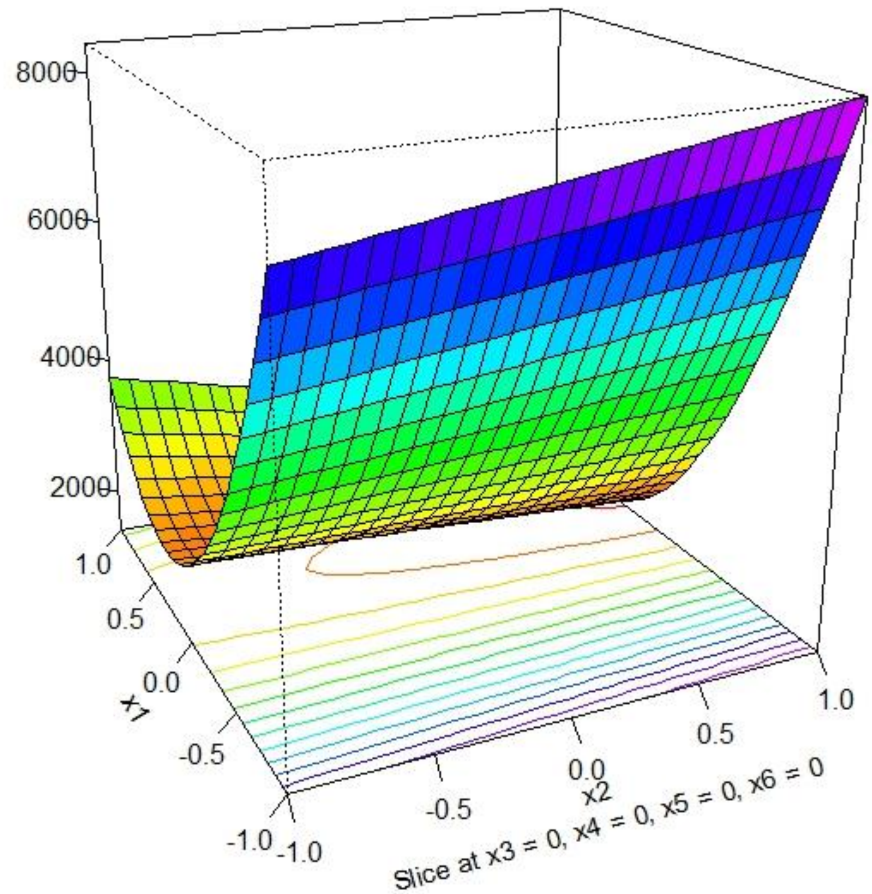

Figure 8: Response Surface Plot (3D) for Evader Success, Experiment Two, x1=P_Pmove, x2=P_Pcomm

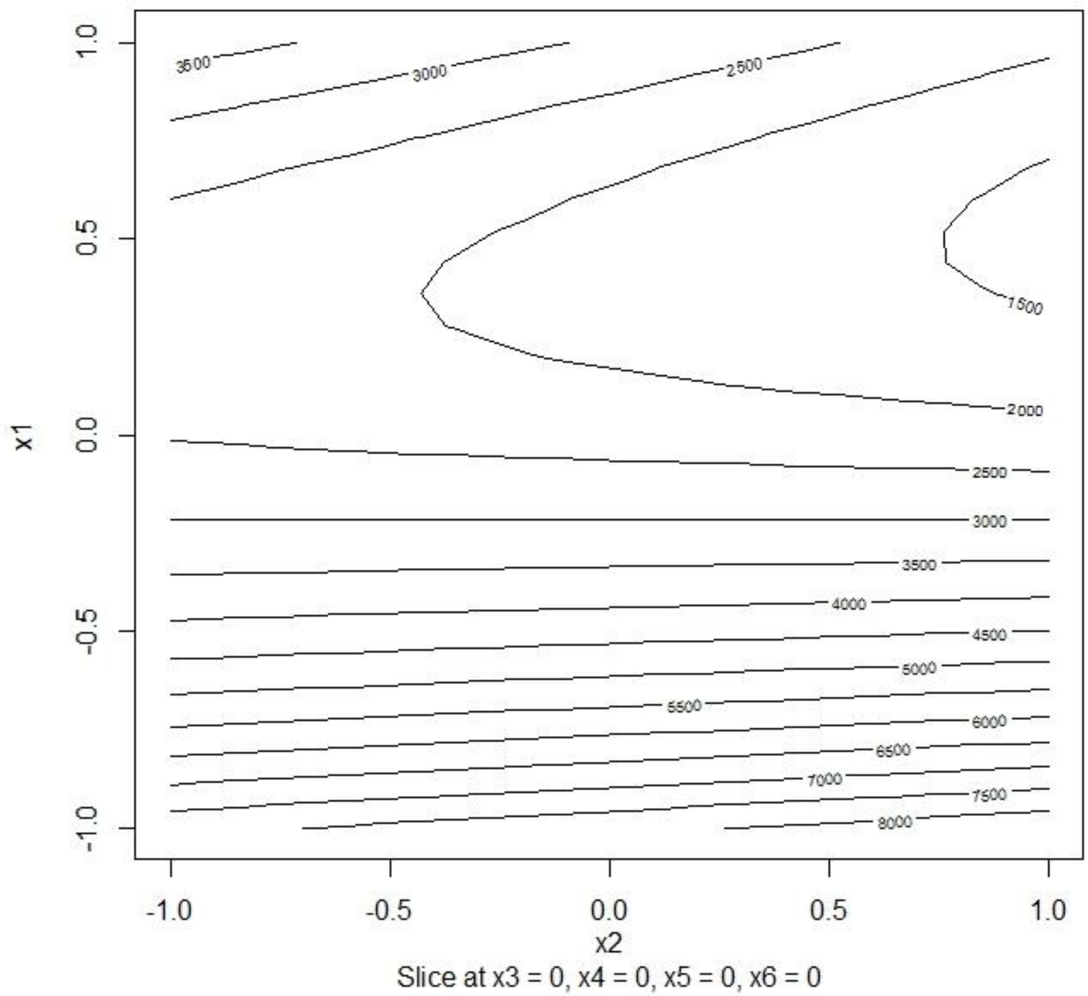

Figure 9: Response Surface Plot (2D) for Evader Success, Experiment Two, x1=P_Pmove, x2=P_Pcomm

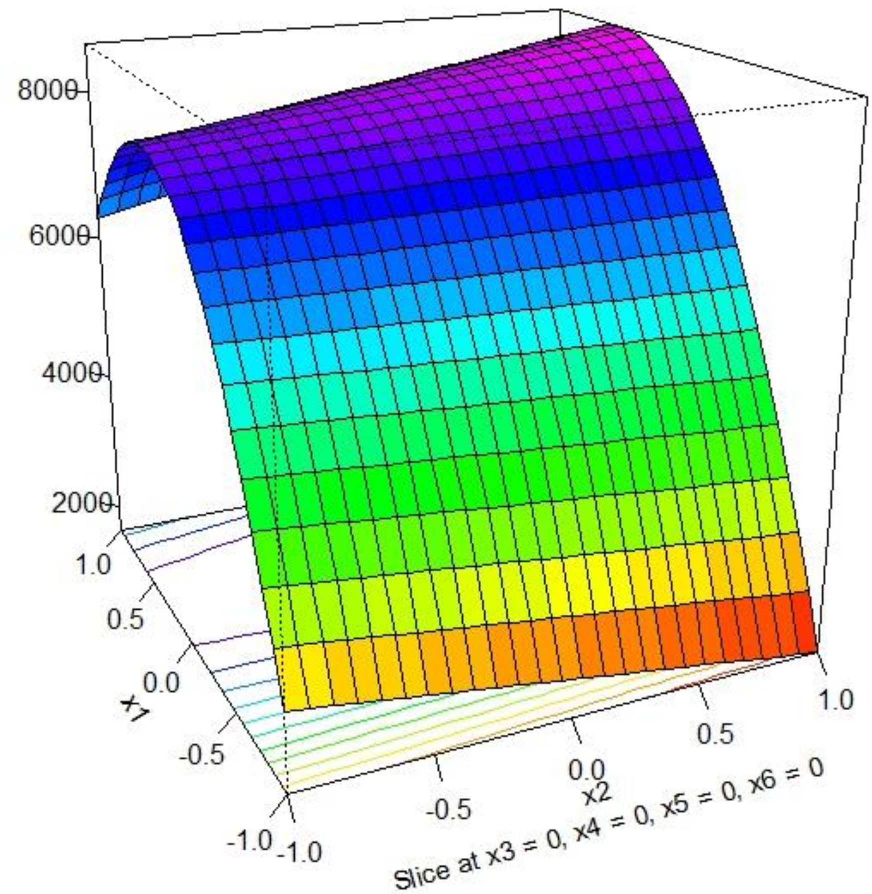

Figure 10: Response Surface Plot (3D) for Pursuer Success, Experiment Two, x1=P_Pmove, x2=P_Pcomm

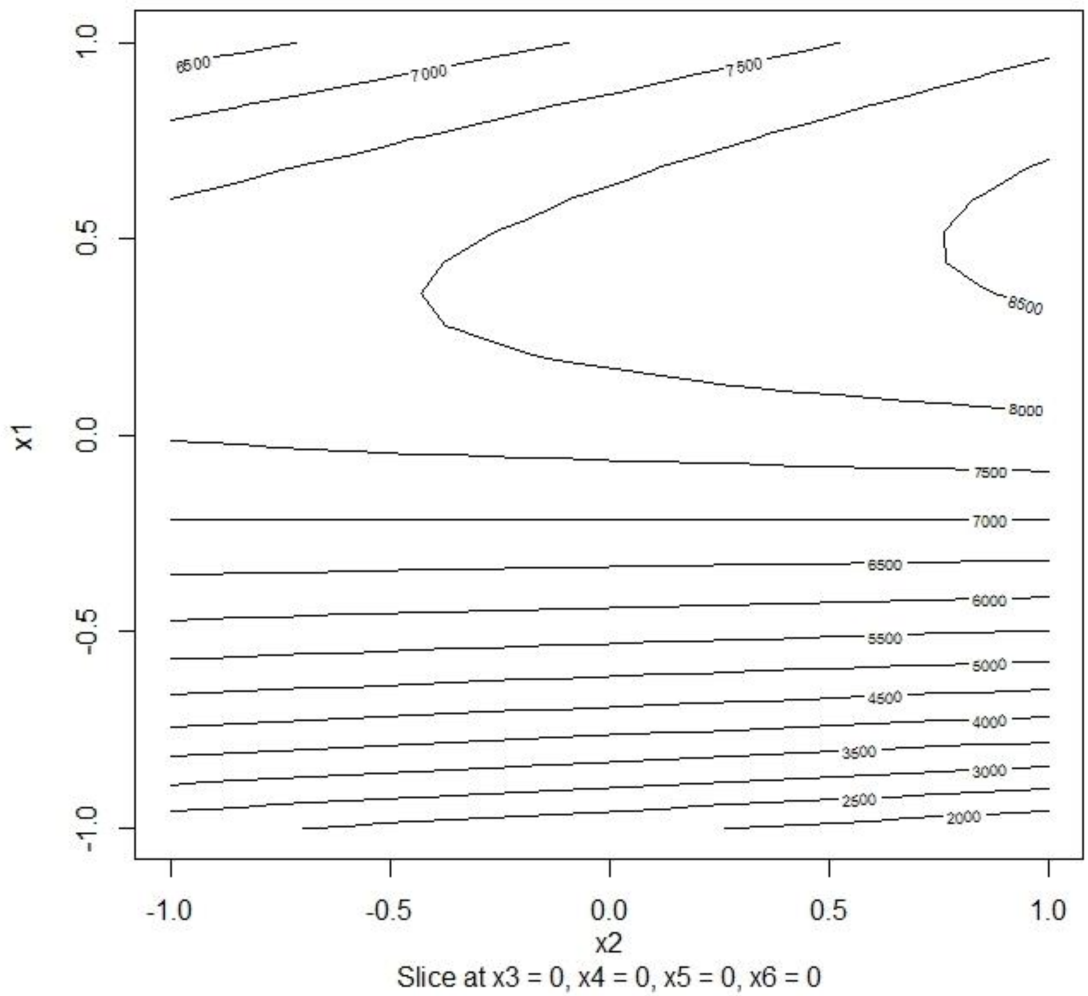

Figure 11: Response Surface Plot (2D) for Pursuer Success, Experiment Two, x1=P_Pmove, x2=P_Pcomm

Experiment Four did not produce statistically significant results about the team success response variables, and attempts to fit linear models to the team success results of Experiment Four produced poor results. However, Experiment Four continued to demonstrate the relative strength of P_Pmove, albeit at a level below the $\alpha = 0.05$ threshhold. Figure 12 depicts the main effects of the Experiment Four input factors upon evader success. Pursuer propensity to move is most strongly correlated with changes in team success in the results of Experiment Four.

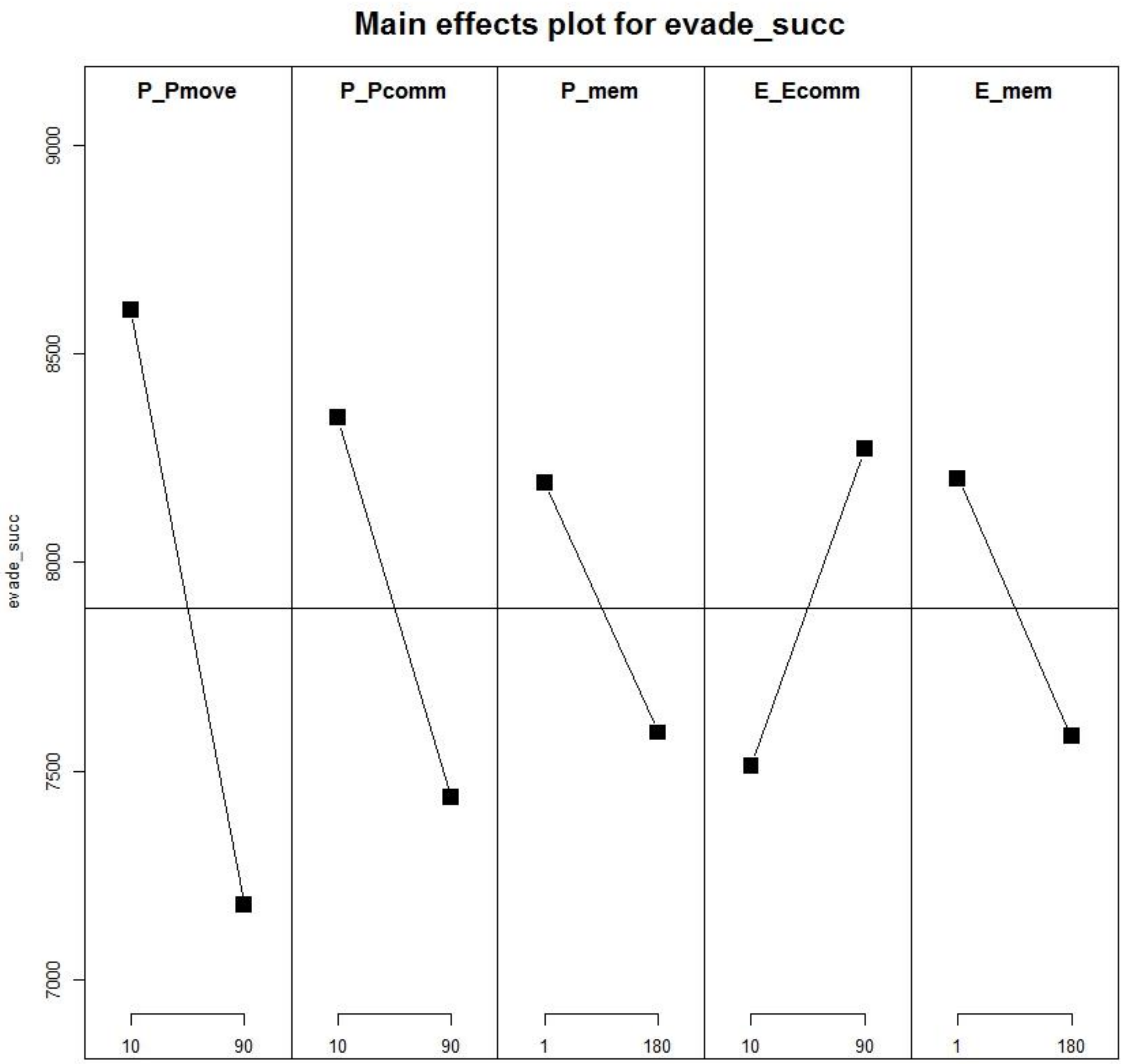

Figure 12: Main Effects Plot for Evader Success, Experiment Four

Experiment Five corroborated the results that suggested the dominance of correlations of both P_Pmove and P_Pmove:P_Pcomm and the team success response variables. Figure 13 is a half normal plot that illustrates the significance of the main effect of P_Pmove on evader success, as well as the two-factor interaction of P_Pmove:P_Pcomm on evader success, at the threshold $\alpha=0.05$.

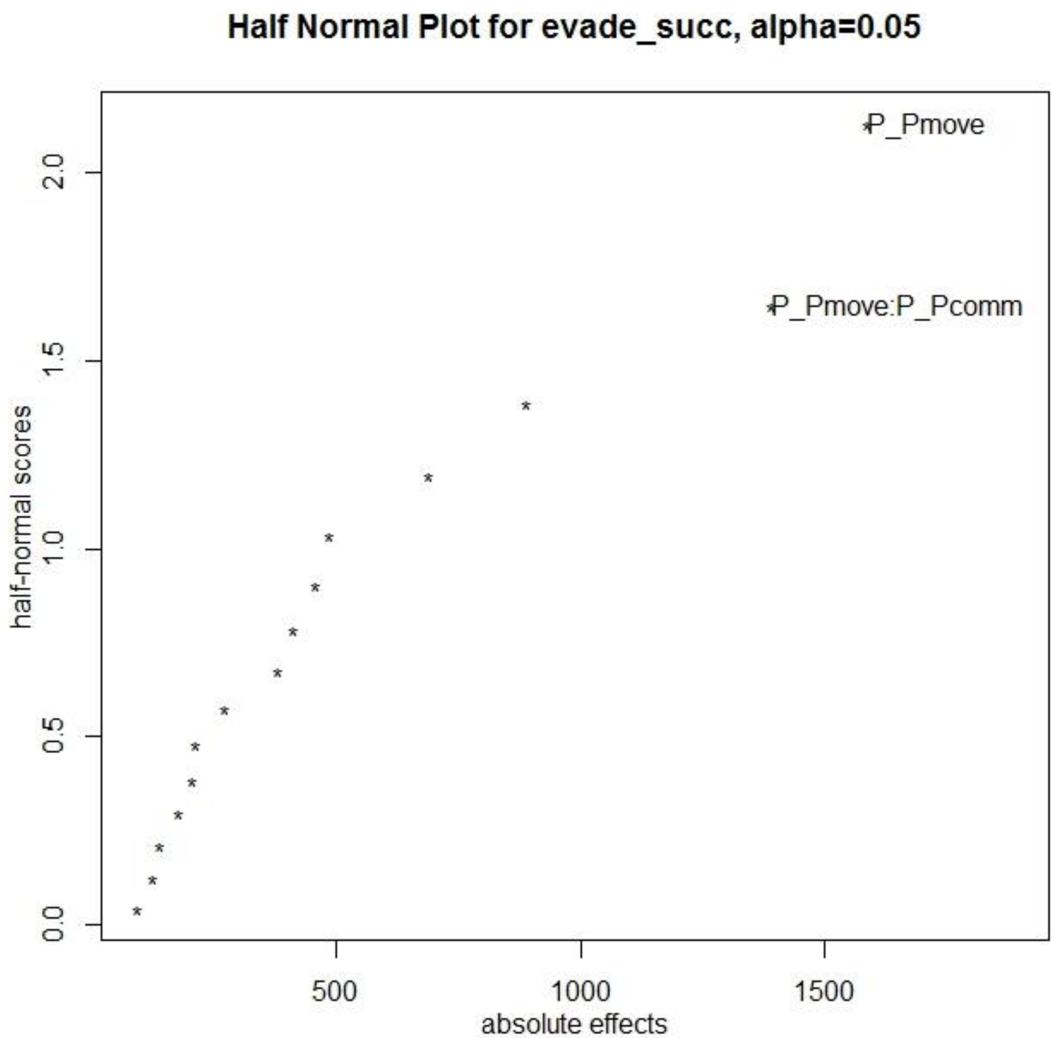

Figure 13: Half Normal Plot for Evader Success, Experiment Five, α= 0.05

An attempt to fit a linear model to the evade_succ results of Experiment Five yielded poor results. This provided further evidence of non-linearity in the relationships among the dominant input factors and the response variables of team success.

An attempt to fit a response surface model to the evade_succ results of Experiment Five yielded very strong results. The model achieved very good fit measured by an adjusted R-squared value of 0.9511, and an F-statistic of 32.84 on 11 and 7 degrees of freedom with a corresponding p-value of 5.867e-05. These results strengthened earlier indications of non-linearity in relationships among the dominant input factors and the response variables of team success. This response surface model revealed the strengths of the main effect of P_Pmove, the main effect of P_Pcomm, the two-factor interaction of P_Pmove:P_Pcomm, as well as the pure quadratic effect of P_Pmove on team success, as defined by p-values smaller than 1e-04 and (absolute value) coefficients of 793.88, 444.75, 694.38, and 2096.00, respectively. Figure 14 and Figure 15 illustrate the bivariate function of pursuer propensities to move and communicate upon the success of evaders. Figure 16 and Figure 17 illustrate the bivariate function of pursuer propensities to move and communicate upon the success of pursuers. The pure quadratic effect of P_Pmove is clearly visible along the x1 axis of all four plots.

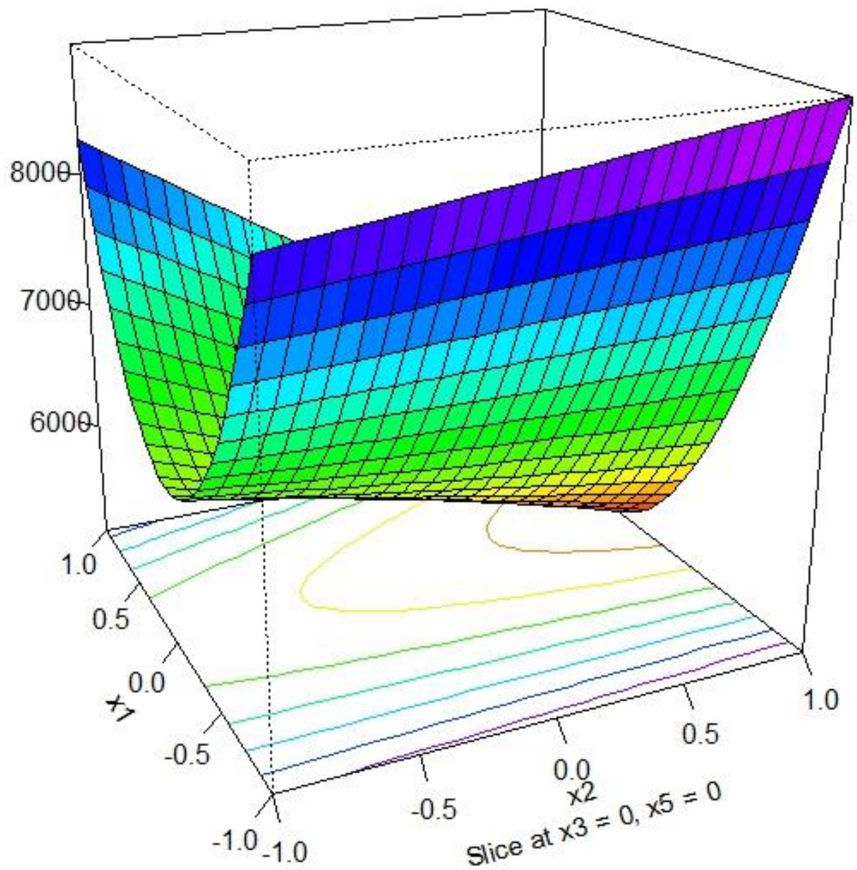

Figure 14: Response Surface Plot (3D) for Evader Success, Experiment Five, x1=P_Pmove, x2=P_Pcomm

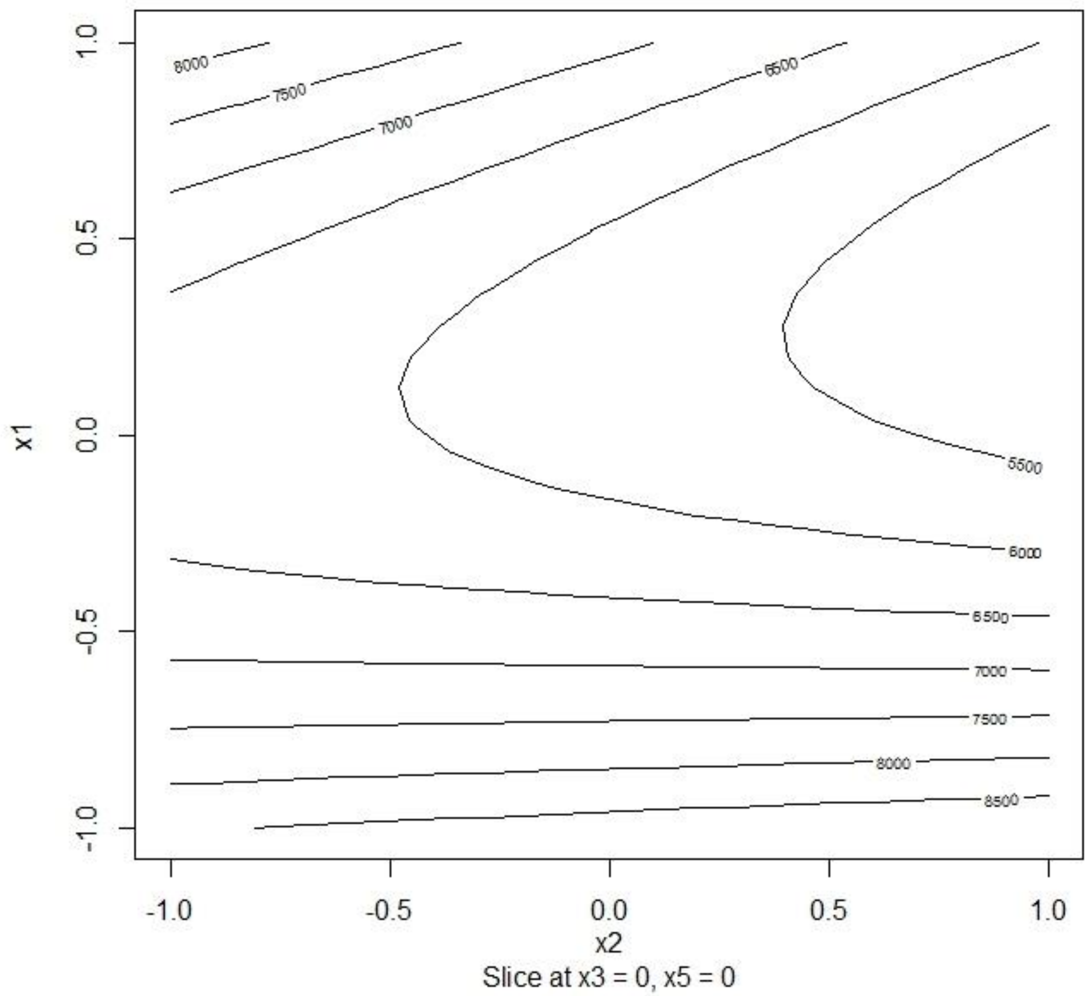

Figure 15: Response Surface Plot (2D) for Evader Success, Experiment Five, x1=P_Pmove, x2=P_Pcomm

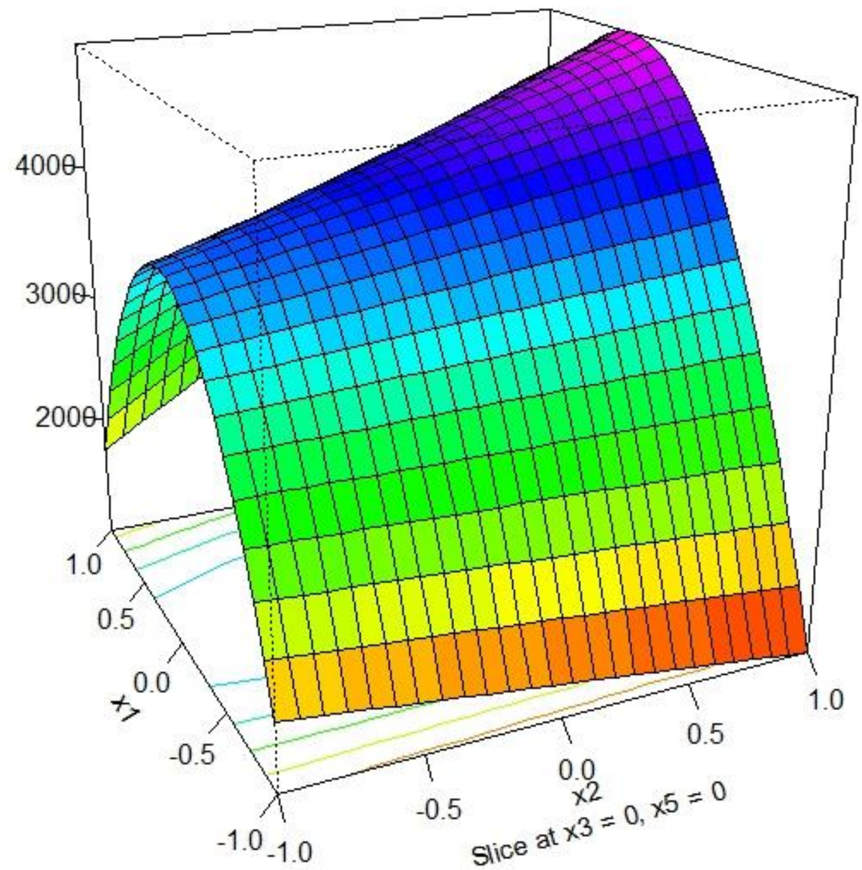

Figure 16: Response Surface Plot (3D) for Pursuer Success, Experiment Five, x1=P_Pmove, x2=P_Pcomm

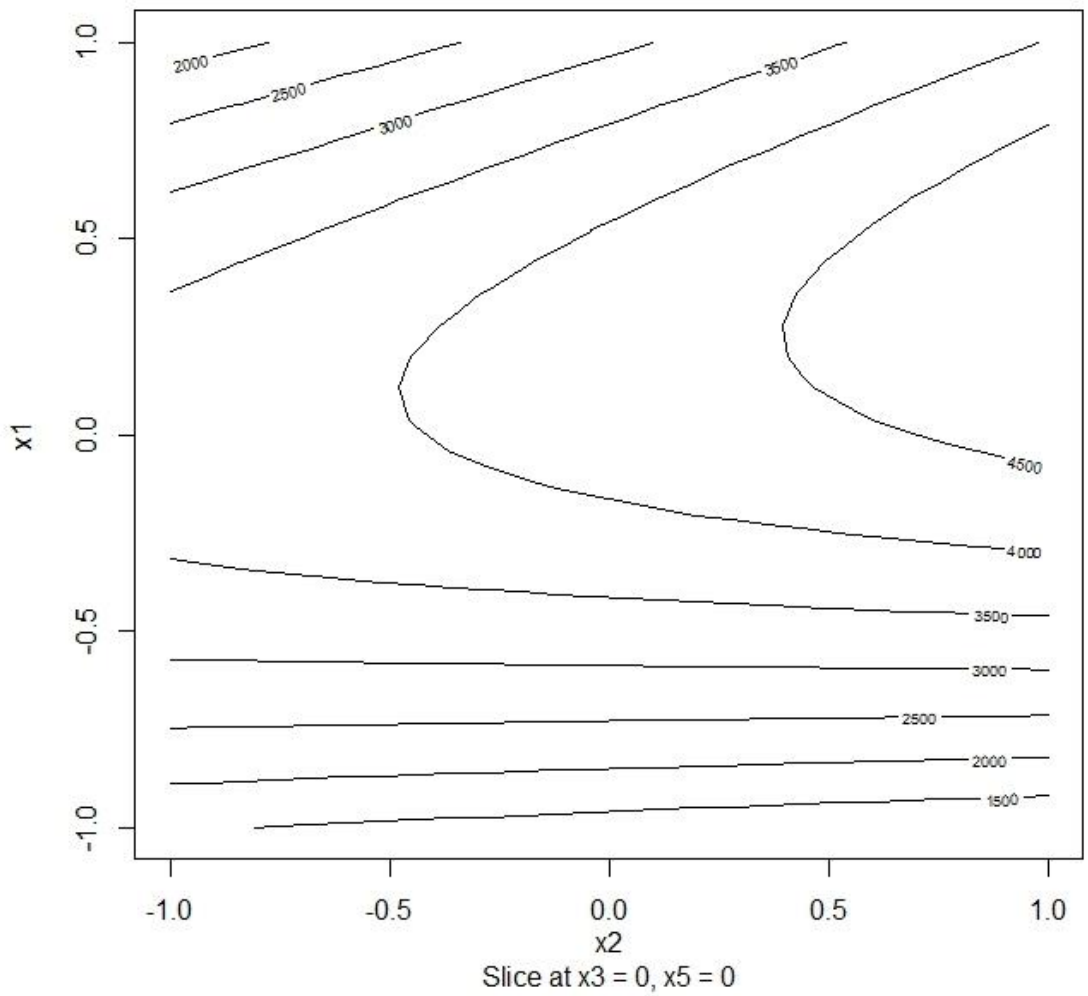

Figure 17: Response Surface Plot (2D) for Pursuer Success, Experiment Five, x1=P_Pmove, x2=P_Pcomm

Spatiotemporal Clustering Behaviors

Evidence of spatiotemporal clustering in team movement behaviors is observable in thirty game repetitions randomly sampled from Experiment Five. Table 15 presents the results of an application of the Space Time Scan Statistic to the movements of both the pursuing and evading teams in the sample set.

Table 15: Space-Time Clusters Observed in 30 Randomly Sampled Observations of Experiment Five.

Data Source			Pursuer		Evader	
Sample	Run	Game	Number of clusters	Maximum p-value	Number of clusters	Maximum p-value
1	13	9958	5	1E-17	1	1E-17
2	11	7182	4	1E-17	3	1E-17
3	5	9791	5	1E-17	3	1E-17
4	16	5404	5	4.7E-15	1	1E-17
5	10	6087	5	1E-17	5	1E-17
6	5	8185	3	1E-17	2	0.041
7	11	2367	4	1E-17	2	1E-17
8	4	4704	6	1.2E-15	3	0.0000013
9	3	4072	2	0.0000086	1	0.00074
10	16	1120	5	1E-17	3	1.7E-14
11	13	2999	3	1E-17	4	0.017
12	13	186	4	1E-17	2	1E-17
13	3	7178	5	0.028	3	0.0012
14	7	2915	4	3.2E-12	4	2.2E-16
15	9	3143	3	1E-17	3	0.017
16	9	5945	5	0.038	1	0.0033
17	9	2947	2	1E-17	2	1E-17
18	10	1364	5	0.000017	1	1E-17
19	4	6071	6	1E-17	1	1E-17
20	8	107	4	1E-17	4	0.033
21	17	4286	10	0.0083	4	0.00088
22	15	5314	3	0.0000011	2	0.0059
23	11	5716	7	1E-17	1	1E-17
24	8	9228	5	0.00031	1	0.0012
25	3	5874	4	0.00013	2	7.4E-11
26	17	8051	4	1E-17	3	1E-17
27	5	7666	5	1E-17	1	3.3E-16
28	4	227	12	0.0000023	3	1.4E-13
29	14	2015	4	0.018	4	0.0013
30	16	9306	5	1E-17	2	2.7E-10
		Mean	4.8	Mean	2.4	
		St. Dev.	2.007	St. Dev.	1.172	

Spatiotemporal clustering behaviors were observed in every game repetition in the sample set. P-values for this analysis were very low; the majority of p-values were smaller than 1E-10 and the maximum was 0.028.

Spatiotemporal clustering behaviors were more strongly represented in the movements of the pursuing team; there were twice as many clusters observed in pursuit behaviors than there were in evasion behaviors, on average. This is not surprising because the goal of team pursuit requires that individuals converge upon discrete objectives when those objectives are known and individuals can share information with each other. It is less clear if or when evaders need to locate themselves together; however the analysis of this sample suggests that evaders regularly engage in spatiotemporal clustering behaviors. Figure 18 illustrates the presence of clustering behaviors in evading team movements in the 30-repetition sample set.

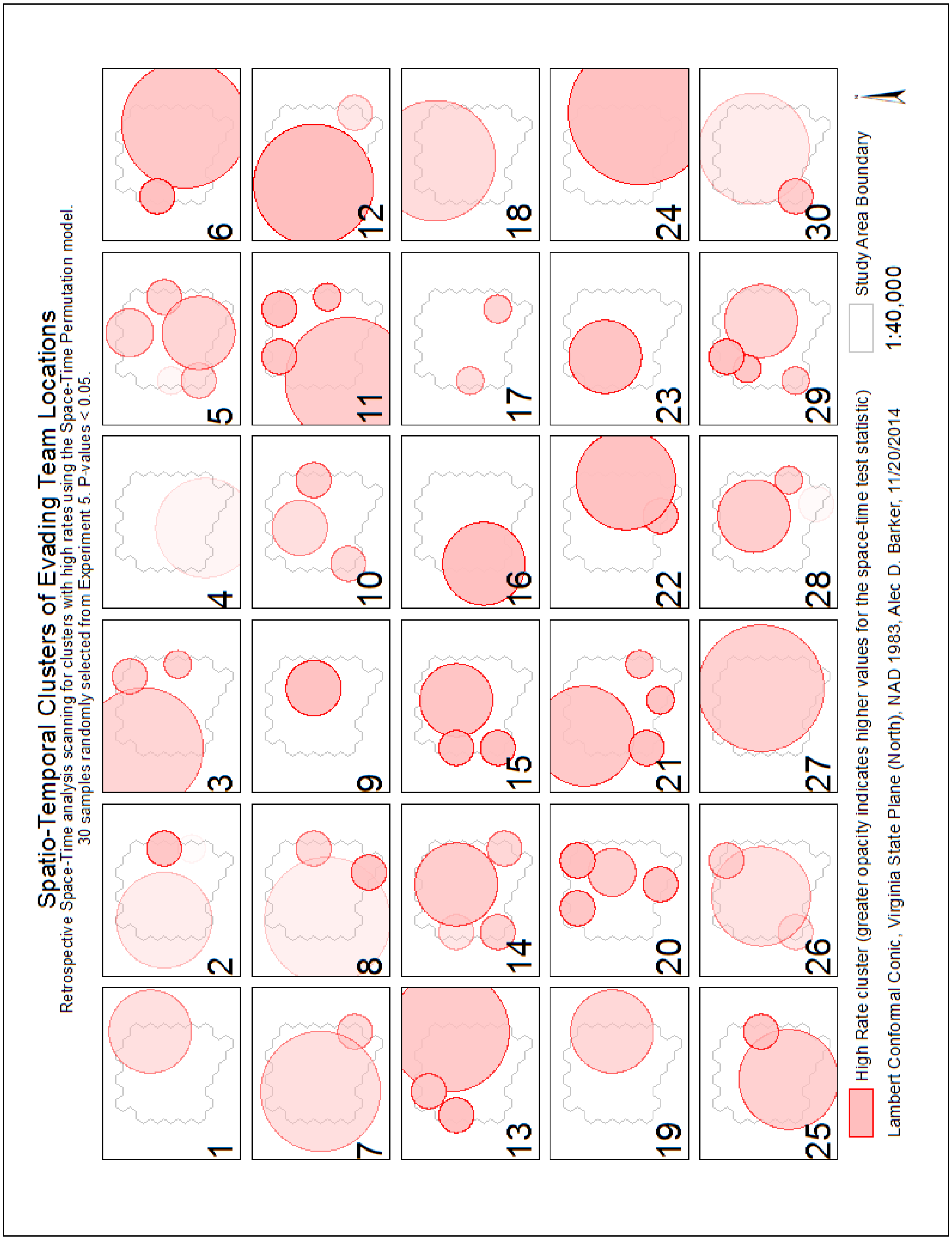

Figure 10. A Visualization of Space-Time Clusters Observed in 30 Randomly Sampled Observations of Evading Team Locations in Experiment Five.

Boundary-Seeking Behaviors

This set of experiments reveals very strong evidence for the primacy of boundaries and borders in the location decisions of teams engaged in pursuit and evasion. Comparison of the "boundariness" values generated for each team in Experiments Two, Three, Five, and Six with boundariness values generated in Experiment Seven support the idea that evading teams seek locations on areal boundaries, whether or not concealment is available in interior areas. Consequentially, pursuing teams also occupy boundary locations more frequently than in random walk models. Experiment Seven demonstrated that the boundariness of randomly moving, five-player teams in this study area may be understood as a constant value of 0.3617668. Although intuition might have suggested that the boundariness constant for randomly moving teams would approximate the percentage of locations adjacent to boundaries, the constant derived via simulation is notably less than the percentage of locations along the boundary in the terrain models (26/54 or 0.481481).

These findings are shown in an analysis of boundariness values using the t-Test for paired samples of means. Under the null hypothesis that a team's preference for boundary locations is not differentiable from random and the alternate hypothesis that a team's preference for boundary locations is differentiable from random, we apply a two-tailed test. Under the null hypothesis that a team's preference for boundary locations is not differentiable from random and a second alternate hypothesis that a team's preference for boundary locations both is differentiable from and higher than random, we apply a one-tailed test. In every experiment analyzed, the two-sample means test for both teams shows statistically significant evidence to reject the null hypothesis. P-values were no larger than 3.43 e-05 for any test performed in this analysis. Table 16 contains the team boundariness values for each experiment analyzed as well as test statistics and p-values.

Table 16: Analysis of Boundary-Seeking Behaviors (α=0.05, 18 DF)

	Experiment 2		Experiment 3		Experiment 5		Experiment 6		Experiment 7
Run	Evader	Pursuer	Evader	Pursuer	Evader	Pursuer	Evader	Pursuer	Random
1	0.745243	0.437785	0.747625	0.473693	0.427666	0.41072	0.557908	0.436546	0.3617195
2	0.716672	0.435616	0.731902	0.473082	0.379184	0.423246	0.523888	0.440672	0.3616914
3	0.718161	0.467971	0.740573	0.510539	0.431903	0.385001	0.509368	0.42902	0.3615570
4	0.757495	0.40434	0.749876	0.424862	0.37989	0.385739	0.58365	0.403029	0.3621451
5	0.706365	0.410647	0.693366	0.44947	0.409219	0.385395	0.554271	0.416335	0.3613460
6	0.714624	0.362571	0.68063	0.393282	0.482891	0.391856	0.516605	0.4235	0.3615560
7	0.619595	0.372221	0.502997	0.400789	0.467643	0.384978	0.471066	0.405611	0.3616221
8	0.601929	0.361069	0.426233	0.3575	0.363661	0.401757	0.577876	0.455626	0.3617681
9	0.682364	0.372156	0.636885	0.390206	0.510204	0.412654	0.507393	0.438567	0.3621159
10	0.742302	0.436982	0.747625	0.473693	0.427666	0.41072	0.557908	0.436546	0.3613275
11	0.698811	0.388055	0.640571	0.402561	0.367475	0.384794	0.492543	0.403252	0.3622756
12	0.658497	0.424791	0.444116	0.39109	0.543561	0.391737	0.493704	0.379481	0.3628125
13	0.723792	0.438443	0.736214	0.462884	0.410428	0.425522	0.574341	0.41044	0.3615151
14	0.728494	0.419683	0.743341	0.44366	0.524338	0.383842	0.496282	0.40623	0.3611688
15	0.716022	0.469493	0.669375	0.427942	0.382647	0.410059	0.591107	0.443881	0.3615015
16	0.731489	0.419389	0.618321	0.403805	0.405783	0.388175	0.585851	0.413283	0.3617325
17	0.636518	0.384479	0.479059	0.380971	0.397534	0.405959	0.575319	0.423974	0.3632115
18	0.771624	0.393543	0.764216	0.429962	0.545204	0.386733	0.575508	0.381981	0.3616566
19	0.746039	0.437359	0.74868	0.475293	0.427666	0.41072	0.557908	0.436546	0.3608473
Mean	0.706107	0.412452	0.657979	0.429752	0.43603	0.398927	0.542237	0.420238	0.3617668
Std.Dev.	0.046738	0.033199	0.112895	0.04102	0.05619	0.013462	0.036524	0.019677	0.0005264
t Stat	31.93491	6.616392	11.40215	7.168108	5.464802	11.3746	20.41046	12.18945	
P(T<=t) one-tail	1.33E-17	1.64E-06	5.72E-10	5.64E-07	1.72E-05	5.94E-10	3.39E-14	1.96E-10	
t Critical one-tail	1.734064	1.734064	1.734064	1.734064	1.734064	1.734064	1.734064	1.734064	
P(T<=t) two-tail	2.65E-17	3.27E-06	1.14E-09	1.13E-06	3.43E-05	1.19E-09	6.78E-14	3.92E-10	
t Critical two-tail	2.100922	2.100922	2.100922	2.100922	2.100922	2.100922	2.100922	2.100922	

The evidence suggesting high boundary-seeking activity prompted the question, “Does boundariness correlate with team success?” An analysis of Experiment 5 suggests that there is little evidence to support a correlation of boundariness and success. The correlation coefficient of the evading team’s boundariness and success rate was both negligible and negative at $r = -0.07$. The correlation coefficient of the pursuing team's boundariness and success rate was weakly positive at $r = 0.27$.

CHAPTER SIX: CONCLUSIONS

The geographic dynamics of goal-directed team behaviors are a fertile research area with numerous potential vectors of analysis. This research project has produced several datasets, demonstrated a methodological approach, and constructed some tools useful for continuing research of this kind. It has built baseline distributions and developed hypotheses about the geographic dynamics of goal-directed social behaviors. This project began with three fundamental lines of inquiry in order to produce a starting point or cornerstone for the creation of a much larger analytical framework that will be useful for understanding how groups of people move and communicate in pursuit of their collective goals. This project provides evidence for several conclusions and hypotheses resulting from those three lines of inquiry: factors of team success, clustering behaviors, and boundary-seeking behaviors.

In the computer simulation model, pursuers' movement preferences are the primary positive correlate of evading team failure and pursuing team success. The effect of pursuers' movement is non-linear, suggesting that pursuers who increase their endogenous propensity to move will only increase their chances of team success and goal accomplishment to an optimum, after which they will experience diminishing returns. The interactive effect of pursuer movement and pursuer communications is another, generally positive correlate of evading team failure and pursuing team success. This interaction also exerts a non-linear influence upon team success.

If the computer simulation model faithfully represents real-world dynamics, then pursuing teams could optimize movements and communications to maximize pursuer success rate. This optimum is defined by a response surface model and a corresponding "sweet spot" in which just enough movement and communication produces the pursuing teams' best results. While optimization of pursuing team movements could by itself lead to improvements in pursuing team outcomes on the order of 75% (from a basic success rate of ~20% to a basic success rate of ~35%), optimization of movements *and* communications could enlarge the "sweet spot" sufficiently to achieve improvements on the order of 200% (from a basic success rate of ~15% to a basic success rate of ~45%).

Preliminary analysis of the computer simulation data indicates that both evading and pursuing teams exhibit movement behaviors characterized by spatiotemporal clustering. This finding must yet be confirmed through sustained analysis requiring high computational intensity. However, the constant observation of spatiotemporal clusters in a random sample (n=30) of simulation runs confidently suggests the prevalence of such behaviors in the entire population of simulation runs. If these findings are confirmed and if the computer simulation model faithfully represents real-world dynamics, then both pursuing and evading teams could develop and exploit indications of spatiotemporal clusters to benefit their teams. Pursuers and evaders could use this information to both reduce risk in their own movement behaviors and develop anticipatory strategies to capitalize on the clustering behaviors of opponents.

In the computer simulation model, evading team players locate themselves at peripheral locations at a rate that is both differentiable from and consistently greater than teams moving randomly. This suggests a strong tendency to occupy locations along boundaries, even when concealment is available at interior locations. Since evaders tend to choose locations along boundaries, pursuers who follow evaders also tend to occupy boundary locations. If the computer simulation model faithfully represents real-world dynamics, then these results suggest that pursuing teams could improve their basic rate of success by establishing and reinforcing boundaries and emphasizing boundary search strategies.

CHAPTER SEVEN: FUTURE RESEARCH

Validation by Empirical Investigation

While knowledge can be derived via exclusive application of the methods of computer simulation, knowledge is best developed through iteration of inductive inquiry (such as modeling) and deductive inquiry (like observation of natural phenomena). Cyclic induction and deduction produces feedback that can be applied to refine the set of beliefs about the true state of nature. Collectively these beliefs are known as the conceptual model. Accordingly, it is inadvisable to rely solely on computer simulation results as the basis for theoretical knowledge about human behaviors, and it is much more desirable to repeatedly compare computer simulations with real-world phenomena. Such comparison will spur improvements to the conceptual model and thereby improve the validity of the ideas incorporated in the simulation model.

In the study of human phenomena, especially social phenomena, it is often impossible, inadvisable, or unethical to consider conducting controlled experiments in the real world with human subjects. This is the case when the experiments would necessarily expose the subjects to harm or the potential of harm, or when the resources, organization, and/or logistics needed to conduct the experiment would be prohibitive. In these cases, scientists have relied on a combination of computer simulation, casual observation, and natural experiments to suggest approaches to theory.

In the case of this research, there are no such barriers preventing the study of goal-oriented team behaviors like pursuit and evasion with human subjects under controlled circumstances in the real world. Simulating these behaviors in the real world is as easy, safe, and inexpensive as playing a controlled version of the schoolyard game hide-and-seek. Participant risk is mitigated via standard human subjects protections such as informed consent and anonymity. The problem of precisely measuring the complete set of movement and communication decisions undertaken by human participants in these simulations can be overcome at the affordable expense of relatively simple software and common smartphone technology.

In the future, extensions to this research project will engage in two types of controlled experiments by which to perform deduction through the observation of human subjects: table-top exercises and full-scale exercises. Generally, the table-top and full-scale exercises will, at very low cost and risk, explore the real goal-seeking behaviors of human teams engaged in pursuit and evasion. These experiments will employ mixed methods, meaning that they will collect and analyze data quantitatively (via statistical, spatial statistical and spatio-temporal statistical analysis of movement and communications information) as well as qualitatively (via surveys and structured elicitation). The feedback gained in these experiments will serve to validate, refine, and improve the conceptual model of team pursuit and evasion that underpins the computer simulation model so that both models more faithfully represent real social phenomena. The researchers and software developers will perform periodic code reviews to ensure regular verification of the programming and implementation that instantiate the conceptual model in the computer simulation model software.

Table-Top Exercises

The table-top exercises will employ a map-and-turn-based game instantiated in Visual Basic .NET on a network of up to thirteen personal computers. The game interface, illustrated in Figure 19, will present a map of the study area, a simple smartphone, and a few buttons. On each turn, player/participants will decide where to locate themselves and how to move to those locations by drawing paths along the map. Player/participants will also decide how and what to communicate with their teammates using the smartphone. After all player/participants submit their turns, observers/controllers will automatically adjudicate the results of the turn, and process feedback for the player/participants. The feedback will inform the player/participants how far they moved toward their desired location, what messages they received from their teammates, what they observed, and if they engaged (or were engaged by) another player. This automated and networked system will produce and store output tables that detail movements, communications, and interactions among players in this virtualized environment. The table-top exercises will also employ a pre-exercise demographic survey and a post-exercise structured interview to collect qualitative information from the player/participants about themselves as well as their decisions and actions during each exercise.

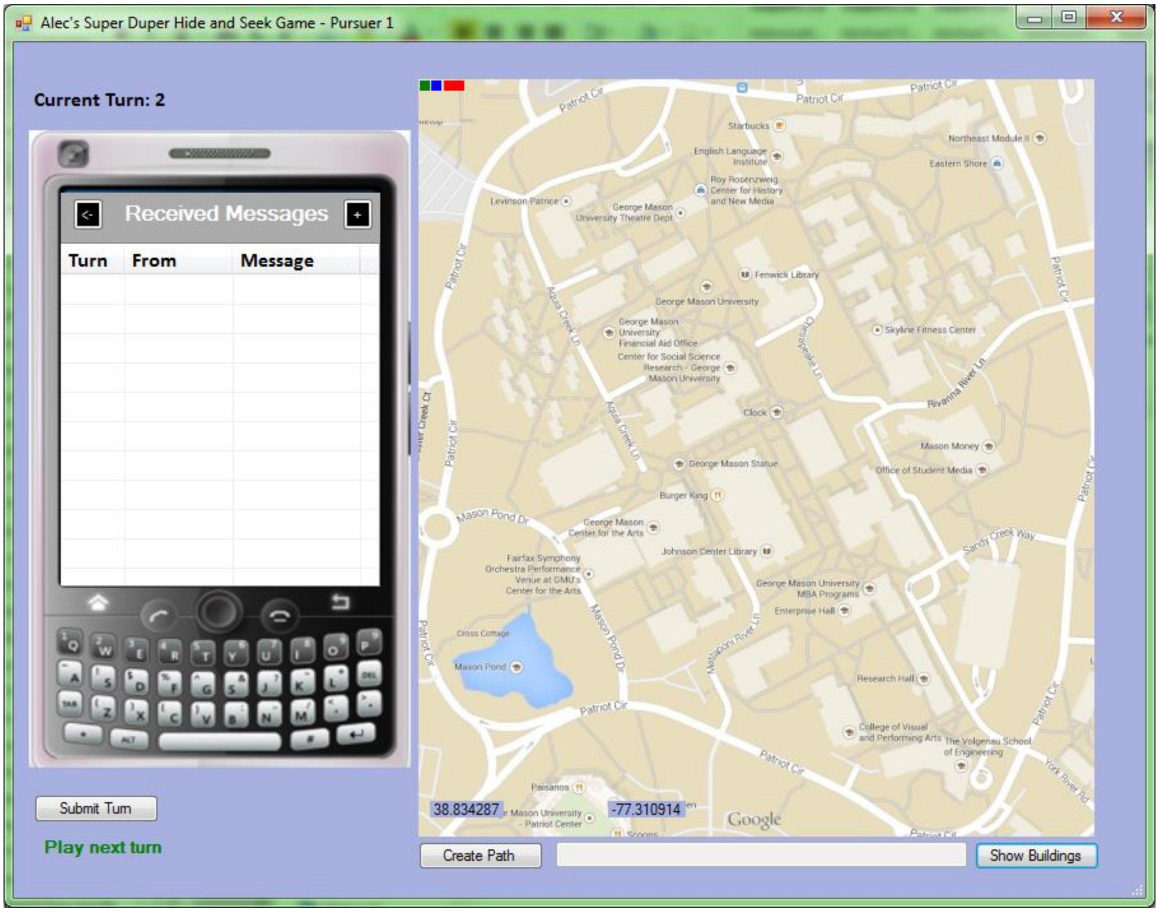

Figure 19: The User Interface of the Table-Top Pursuit and Evasion Game

The computers will be configured in a laboratory setting where player/participants (the human subjects) will sit in individual carrels. Observers/controllers will run the exercise from an adjudication interface on a display located in a separate area of the laboratory. Player/participants will not be able to see the adjudicator interface. Observers/controllers will be able to supervise the player/participants as they complete exercise tasks. Figure 20 illustrates the proposed layout of the table-top laboratory.

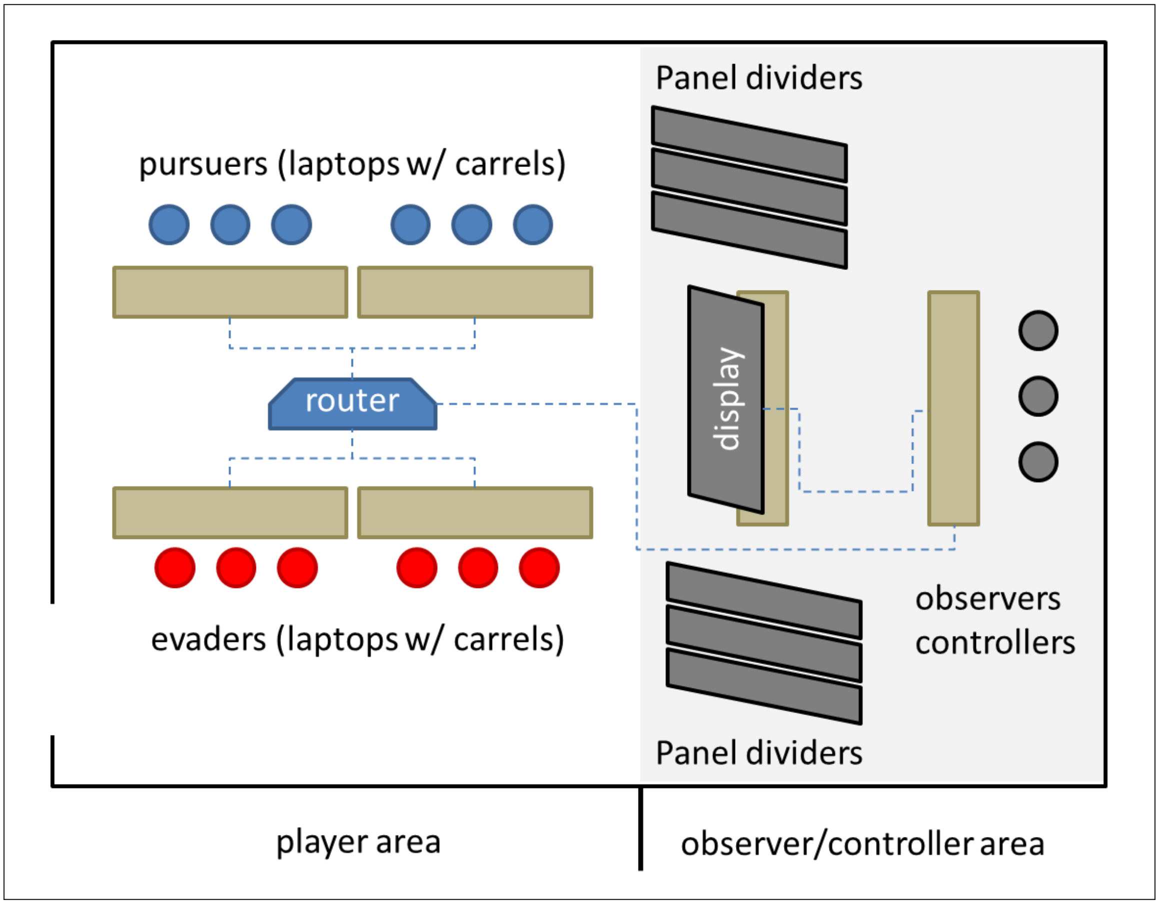

Figure 20: A Diagram of the Proposed Configuration of the Table-Top Experiment Laboratory

The carrels (and the exercise observers/controllers who supervise them) will prevent player/participants from seeing or communicating with each other via any means other than the computer game. Figure 21 depicts four player/participant carrels in the laboratory.

Figure 21: Computers and Player/participant Carrels in the Table-Top Laboratory

The global representation of player interaction in a table-top exercise will be collected automatically by the adjudication application and will be visualized using a GIS-based terrain model. For example, a three-dimensional relief model in Google Earth, when overlaid with the study area and animation of player movements, can serve well to track the locations and progress of players in each exercise. Figure 22 illustrates this concept using blue (pursuer) and red (evader) player symbols. This approach also permits visualization of player locations and sightlines using realistic building models as depicted in Figure 23.

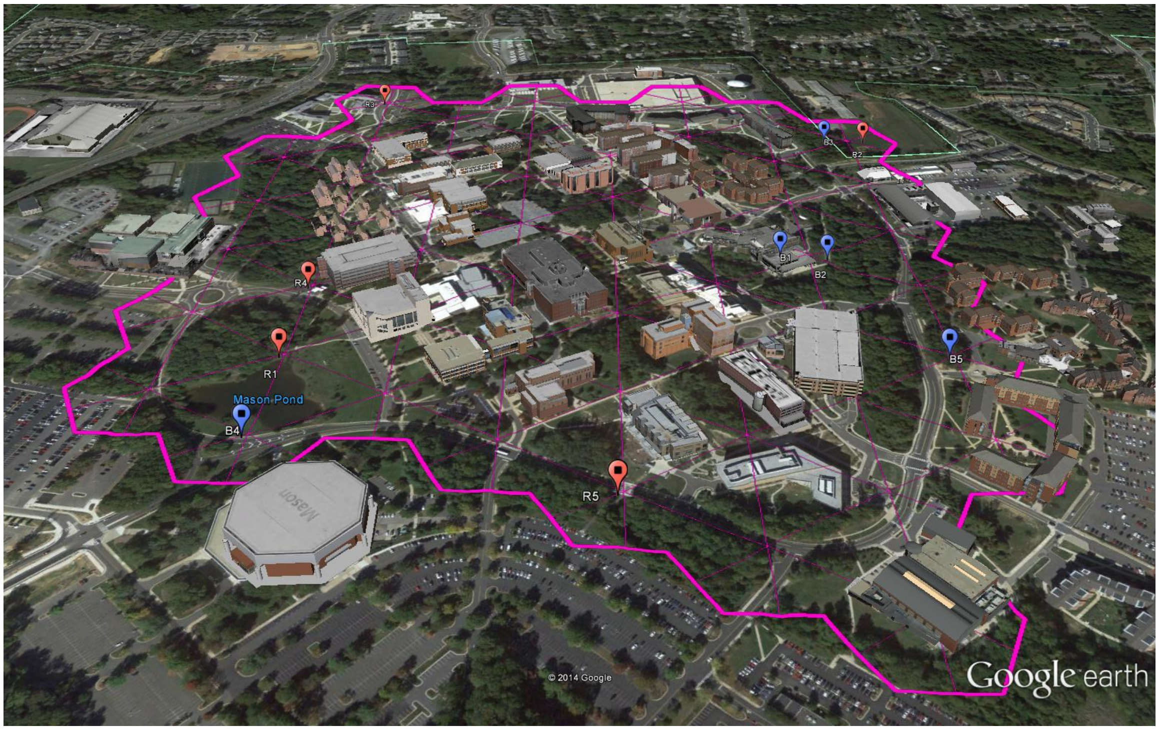

Figure 22: Three-Dimensional Visualization of a Table-Top Exercise (Study Area Highlighted in Pink)

Figure 23: Three-Dimensional Visualization of a Table-Top Exercise (Buildings and Sightlines Example)

Full-Scale Exercises

During the full-scale exercises, player/participants will interact with each other in the actual study area, the Fairfax campus of George Mason University. Data will be automatically collected by customized smartphones (and associated applications and information networks) given to each participant. The smartphones will collect and assemble player communications and movement information into tabular form and relay this information securely to the researcher. Figure 24 is an illustration of the envisioned data collection architecture, herein described as a “Smartphone-based Reality Mining Architecture.”

Smartphone-based Reality Mining for Geographic Dynamics of Goal-Directed Social Behaviors

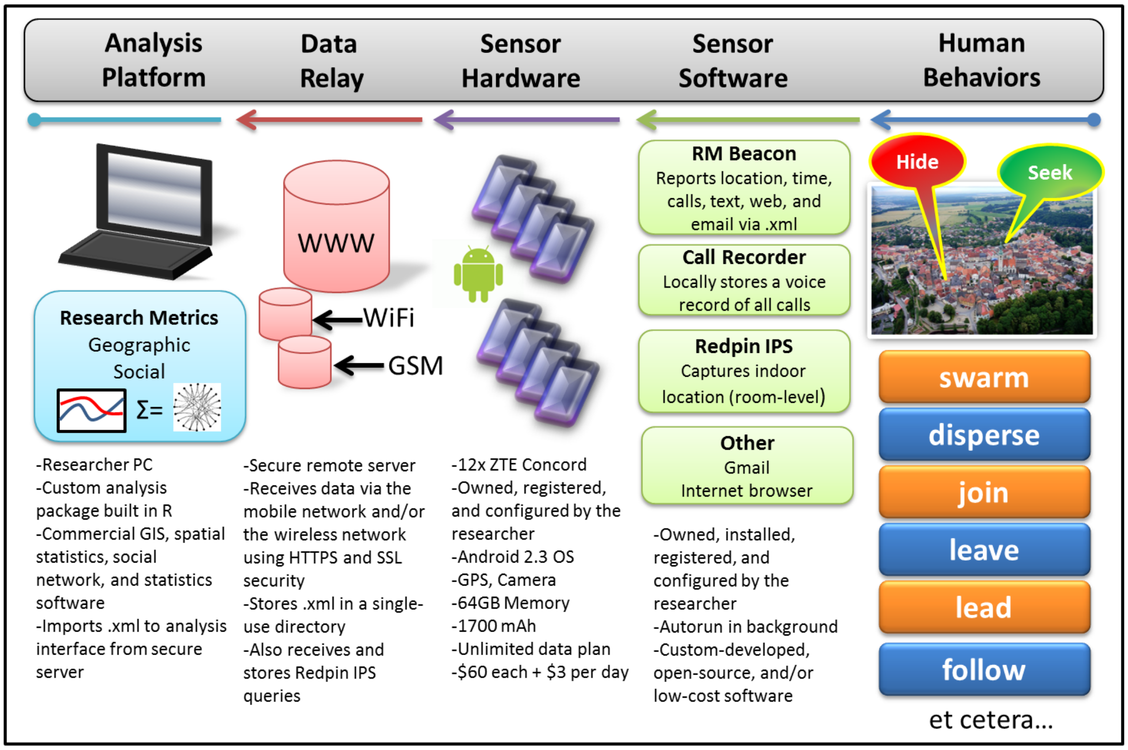

Figure 24: A Smartphone-Based Reality Mining Architecture

This instrumentation system will rely on an analysis platform (the researcher's computer system), data relay (a secure web-based server and an information network), sensor hardware (client device smartphones), and sensor software (client smartphone applications). The system will use a set of applications developed in the R programming language to perform inferential, spatial, spatio-temporal, and social network analysis.

The server will be a remotely operated, physically secured, and internet-based computer system that communicates using Secure Sockets Layer (SSL) protocol with client cellphones on the mobile phone network as well as the wireless network. The server will receive and store output files in a specific directory to be accessed only by the researcher. It will also function as an indoor positioning system (IPS) server, receiving, storing, and fulfilling IPS queries.

The primary information network is the mobile communications network associated with the contracted mobile service provider. It is anticipated that this network will use the Global System for Mobile Communications (GSM) digital cellular network protocol. No limitations on data volume are anticipated. The precise configuration of this system is subject to the availability of resources by which to procure network services. The alternate information network is the wireless data network (the WiFi network) installed and maintained in the study area by the University.

The targeted sensor platform is a smartphone similar to ZTE Concord, equipped with an 823 MHz Broadcom BCM21553 processor, Android v2.3, 512 MB of RAM, 512 MB of integral storage, 2 GB of micro SD memory card storage (expanded to 32 GB), 802.11 b/g/n WiFi, a GPS receiver, and mobile network frequencies including GSM 850/900/1800/1900 MHz and HSPA/UMTS 850/1900 MHz/AWS. Figure 25 depicts the ZTE Concord. This smartphone provides appropriate functionality, ample processing and storage capacity, and configuration flexibility at a reasonable expense. Furthermore, participants are likely to be familiar with low-cost Android smartphones and will therefore require little familiarization and training.

Figure 25: The Full-Scale Exercise Sensor Platform: The ZTE Concord Android Smartphone

This desired client software is a mobile device application written in the Java programming language and developed for the Android operating system. The application will be named RM Beacon and will be activated and deactivated using a password-protected user interface. RM Beacon will run in the operating system's "background" and passively collect the communications (metadata and non-voice content) and location information (geographic coordinates) attributable to the mobile device (See Table 17 for a description of the communications information to be collected). RM Beacon will assemble and convert this data into a table via a specific .xml file format. RM Beacon will transmit this .xml data securely using SSL to the remote server. RM Beacon will automatically transmit collected information at user-defined time intervals as well as on ad hoc designated events.

Table 17: Message Types and Data Fields to be Collected by RM Beacon

Message type	Data fields
SMS	date, time, location, sender ID, recipient ID, message content
MMS	date, time, location, sender ID, recipient ID(s), message content, multimedia
email (Gmail)	date, time, location, sender address, recipient address(es), message content, attachment metadata
web browsing	date, time, location, URL, download metadata
phone/voice	date, time, location, caller ID (phone number), called ID(s) (phone numbers)

Since IPSs are imperfect technologies that remain under development, the instrumentation system used for full-scale exercises will not integrate indoor localization into the client software. Instead, each client device will run the Redpin IPS separately from the RM Beacon (Bolliger, 2008). Positional reporting via Redpin will be collected at the server and stored separately from the .xml files transmitted via RM Beacon.

Similarly, each smartphone will be separately installed with a phone call recording application (Call Recorder) to capture and store voice calls on local drives. These voice recordings will not be transmitted and will instead be removed from the devices at the conclusion of each exercise.

Each smartphone will also be installed with a customized Gmail client and an internet browser. Each Gmail client will be configured to operate exclusively with a user account that is established and controlled by the researcher for the exclusive purpose of enabling email communication during the exercises.

The Smartphone-based Reality Mining Architecture will enable exploration of real team behaviors, rather than those that were hypothesized and programmed in the computer simulation model. Real team behaviors will likely exhibit unanticipated patterns, spurring subsequent investigation into the characteristics and root causes of those patterns.

Investigating Phase Transitions in Team, Multiteam, and Social Behaviors

An exciting future branch of this research is the development of quantifiable indications of phase transitions in social behaviors, relying on geographic information science, behavioral science, the application of non-linear optimization, and analysis of Reynolds' individual-level steering forces of cohesion, separation, and alignment (Reynolds, 1987, 1999). The analysis of individual-level steering forces following Croitoru (2009) may provide a quantified means to isolate individual and team movement behaviors. A first goal would be to separate coherent (i.e. nonrandom) team behaviors from incoherent (i.e. indistinguishable from random) behaviors within large datasets of social activity. A second goal would be to characterize and classify coherent behaviors according to the strength and type of movements observed. A third goal would be to isolate transitions between distinct behaviors in order to understand phase transitions in team activity.

Separation is the force that prevents crowding; it is the measurement of the distance maintained by an individual from others nearby. Cohesion is the force that brings groups closer together; it is the measurement of the vector that brings an individual to the mean center of the locations of others nearby. Alignment is the force that causes an individual to move in the same direction and speed as the group; it is the difference between the individual's current velocity and the average velocity of others nearby. The sum total of the displacement effects achieved by separation, cohesion, and alignment is called "steering activity." See Figure 26.

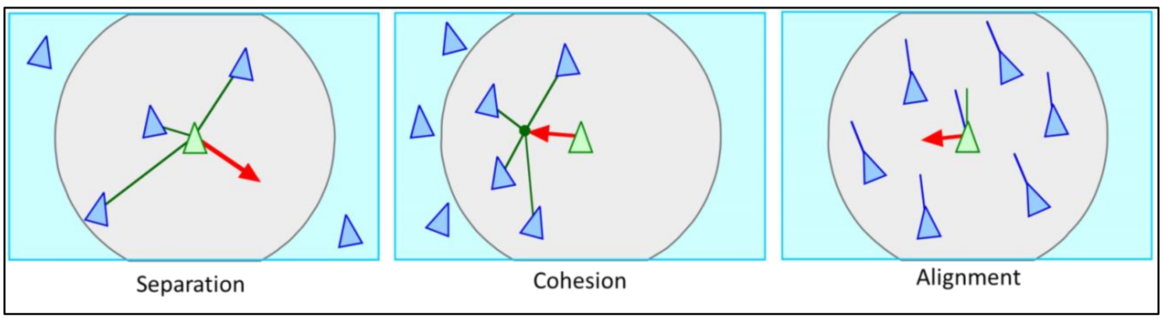

Figure 26: Individual-Level Steering Forces as given by Reynolds (1999)

Morphological enumeration of the potential combinations of active steering forces offers a method by which to define every potential team movement behavior. Table 18 lists every possible combination of individual-level steering forces, where "+" indicates significant observations of a steering force and "0" indicates observations that are indistinguishable from random. Each combination can be described with a name, an intensity of the steering activity associated with that behavior, and a phase (transition or action) associated with the performance episode.

Table 18: Hypothesized Team Behaviors and their Characteristics

Behavior	Separation	Alignment	Cohesion	Steering Activity	Team Performance Phase
Immobile Disoriented	0	0	0	Low	Transition
Immobile Cooriented	0	+	0	Low	Transition
Converge	0	0	+	Moderate	Action
Disperse	+	0	0	Moderate	Action
Swarm	0	+	+	High	Action
Fan	+	+	0	High	Action
Mobile Disoriented	+	0	+	High	Action
Mobile Cooriented	+	+	+	High	Action

Changes from one team movement behavior to another could indicate the start or end of a performance episode as well as the beginning of an action phase. These could also lead to identification of coordinating behaviors or changes in tasks or task assignments. Hypothetically, there is a finite set of changes in team movement behavior dyads. This set is enumerated in Table 19. The predecessor behavior appears in the first column while the successor behavior is in the second column. There is a descriptive name for each change in team movement behaviors in the third column. The fourth column identifies changes between team activity phases: transition to action (T->A), action to transition (A->T), or no change (None).

Table 19: Hypothesized Changes in Team Behaviors

Behavior 1	Behavior 2	Behavioral Change	Phase Change
Immobile Disoriented	Immobile Cooriented	Facing	None
Immobile Disoriented	Converge	Scanning Smaller	T->A
Immobile Disoriented	Disperse	Scanning Bigger	T->A
Immobile Disoriented	Swarm	Opportunistic Swarm	T->A
Immobile Disoriented	Fan	Opportunistic Fan	T->A
Immobile Disoriented	Mobile Disoriented	Scanning Start	T->A
Immobile Disoriented	Mobile Cooriented	Facing Start	T->A
Immobile Cooriented	Immobile Disoriented	Scanning	None
Immobile Cooriented	Converge	Facing Smaller	T->A
Immobile Cooriented	Disperse	Facing Bigger	T->A
Immobile Cooriented	Swarm	Directed Swarm	T->A
Immobile Cooriented	Fan	Directed Fan	T->A
Immobile Cooriented	Mobile Disoriented	Scanning Start	T->A
Immobile Cooriented	Mobile Cooriented	Facing Start	T->A
Converge	Immobile Cooriented	Facing Halt	A->T
Converge	Immobile Disoriented	Scanning Halt	A->T
Converge	Disperse	Reversal In-to-Out	None
Converge	Swarm	Deliberate Swarm	None
Converge	Fan	Reversal Burst Out	None
Converge	Mobile Disoriented	Gather to Hover	None
Converge	Mobile Cooriented	Gather to March	None
Disperse	Immobile Cooriented	Facing Halt	A->T
Disperse	Immobile Disoriented	Scanning Halt	A->T
Disperse	Converge	Reversal Out-to-In	None
Disperse	Swarm	Reversal Burst In	None
Disperse	Fan	Deliberate Fan	None
Disperse	Mobile Disoriented	Release to Hover	None
Disperse	Mobile Cooriented	Release to March	None
Swarm	Immobile Cooriented	Facing Halt	A->T
Swarm	Immobile Disoriented	Scanning Halt	A->T
Swarm	Converge	Dissipated Swarm	None
Swarm	Disperse	Dispersed Swarm	None
Swarm	Fan	Reversed Swarm	None
Swarm	Mobile Disoriented	Swarm to Hover	None
Swarm	Mobile Cooriented	Swarm to March	None
Fan	Immobile Cooriented	Facing Halt	A->T
Fan	Immobile Disoriented	Scanning Halt	A->T
Fan	Converge	Converged Fan	None
Fan	Disperse	Dissipated Fan	None
Fan	Swarm	Reversed Fan	None
Fan	Mobile Disoriented	Fan to Hover	None
Fan	Mobile Cooriented	Fan to March	None
Mobile Disoriented	Immobile Cooriented	Facing Halt	A->T
Mobile Disoriented	Immobile Disoriented	Scanning Halt	A->T
Mobile Disoriented	Converge	Hovering Smaller	None
Mobile Disoriented	Disperse	Hovering Bigger	None
Mobile Disoriented	Swarm	Hover to Swarm	None
Mobile Disoriented	Fan	Hover to Fan	None
Mobile Disoriented	Mobile Cooriented	Hover to March	None
Mobile Cooriented	Immobile Cooriented	Facing Halt	A->T
Mobile Cooriented	Immobile Disoriented	Scanning Halt	A->T
Mobile Cooriented	Converge	Marching Smaller	None
Mobile Cooriented	Disperse	Marching Bigger	None
Mobile Cooriented	Swarm	March to Swarm	None
Mobile Cooriented	Fan	March to Fan	None
Mobile Cooriented	Mobile Disoriented	March to Hover	None

Future experimentation could extend this research from studies of team dynamics and processes to studies of MTS dynamics and processes. Such an extension would require modifying the experiment's design in order to isolate characteristics of MTSs. A modified design would involve multiple pursuit teams and evasion teams organized into competing MTSs. Each MTS would operate across multiple zones of team-level responsibility that represent and bound distinct team-level goals. Opposing MTSs would operate in areas that were incongruently overlapped with each other to allow teams to interact across internal zone boundaries.

Each team would be comprised of individual players with different roles and goals. An MTS extension of the Pursuit and Evasion game could employ three types of players for each team: "Kings," "Rabbits," and "Scouts." The goal of the King Evader would be to not be caught. If the Pursuers caught the King Evader before time runs out, the Evaders would lose and the game would ends. The goal of Rabbit Evaders would be to protect the King Evader by trying to divert Pursuers. The goal of Scout Evaders would be to protect the King Evader by observing and communicating what the Pursuers are doing. Conversely, the King Pursuer's goal would be to catch the King Evader by coordinating and the actions of all pursuing teams. The goal of Rabbit Pursuers would be to intercept Evaders, especially the King. The goal of Scout Pursuers would be to capture the King Evader by observing and communicating what the Evaders are doing. Communication among players would be restricted to superior-subordinate, in-team, and in-role dyads. Kings on both teams would make decisions about where to locate themselves (which could be anywhere in any zone) and what the subordinate teams do.

However these directions to subordinate teams would be limited to breaking ties, directing some movements, and adjusting decision rules.

Figure 27 illustrates how the study area, team zones, and players could be arranged at the start of an instance of MTS Pursuit-and-Evasion.

The image part with relationship ID rId16 was not found in the file.

Figure 27: An Illustration of the P&E Game Design when Extended from Team to Multiteam System Format

Applied Research and Technology Development

A program of basic research in geographic dynamics of goal-directed social behaviors may lead to promising applications in any interest area where it would be useful to understand how teams and systems of teams move and communicate as they pursue goals in geographic space. Some examples of potential applied research topics and questions include:

- Targeting and Decision Support in Irregular Warfare – What patterns of movement and communication may permit identification of hidden discrete teams operating within large populations? How can understanding the geographic dynamics of goal-directed social behaviors assist in differentiating illicit social networks operating clandestinely to achieve politically subversive goals?
- Migration, Trade, and Trans-border Communication – What factors influence how teams move, communicate, and make decisions in different socio-economic and political contexts? How do these factors change with differences in culture, security conditions, or communications technologies?
- Cohesion and Culture – How do teams and systems of teams behave in ways that improve cohesion, relational bonds, and goal accomplishment? How do changes in organizational culture correlate with changes in the operational activities of front line teams? When and how do outwardly observable behaviors indicate serious dissension within teams?
- Transportation and Urban Planning – How can geographic measures of coherent social behaviors assist in efficient allocation of transportation and public safety services during periods of extraordinary transportation demand? How do urban design attributes shape the movement and communication behaviors – as well as the resulting resource demands – of social groups? What group movement behaviors may be anticipated in the design of evacuation systems and networks?

- Disaster Response and Recovery – How do survivors move and communicate as teams in the aftermath of natural and manmade disasters? What team behaviors correlate with successful disaster response and recovery operations like urban search and rescue? How do teams of long-term relief workers learn about their environment, wayfind, and communicate with each other?
- Criminology and Law Enforcement – What variables may indicate the time, location, and severity of mob behaviors such as rioting, looting, vandalism, and other unlawful "flash mobs?" What variables or measures suggest when and where these behaviors are likely to metastasize, relocate, or subside?
- Art, Taste, and Influence Networks – How do discrete influence networks propagate memes in geographic space? What concepts are transferrable to understanding influence networks in virtual space? What indicators suggest how, when, and where economic, cultural, and political "tipping points" occur?
- Economics and Society – How do teams associate, move, and communicate to maximize revenue in industries characterized by mobility and cooperative competition (street vendors, fisheries, taxicabs, etc.)? What behavioral geographic measures reliably distinguish among competition, collusion, cartelism, and monopoly?

Once corroborated by further field research and experimentation, development of theory and method about the geographic dynamics of goal-directed social behaviors may also invoke tool development in the areas of network-based simulation modeling, graph theoretic multi-agent simulation, and geosimulation. This research will one day lead to the development of tools such as geospatial intelligence analytics and decision support systems applicable to security, military, and intelligence as well as commercial, cultural, and recreational purposes. While this research project suggests many potential outgrowths in applied research and technological development, the strongest research potential exists in sustaining a program of fundamental science that leads toward theory.

Sustained Basic Research

The geographic dynamics of goal-directed team behaviors are so fundamental to human experience that there is great potential to expand this research effort in many different directions. For example, a multi-year basic research agenda could explore the variables of demographics, culture, terrain, goal type, leadership, affiliation, cohesion, and diurnal rhythm. Such research could involve repeating the series of computer-simulated, table-top, and full-scale experiments described heretofore in various locations, such as urban, suburban, or rural settings in domestic and foreign environments. It could involve recruiting experiment participants from a demographically varied subject pool, thereby assessing the influence of age, place of origin, or terrain familiarity. The project could examine the impact of exogenous social activities (such as meal time, work/class, prayer time, or rush hour) by varying the time of day at which full-scale exercises occur. Leadership, cohesion, and affiliation could be investigated via controlled interventions in team organization. The influence of goal types may be examined through simulation and experimentation involving different combinations of competitive behaviors like smuggling-and-interdiction or security-and-infiltration. The effort could be informed by more economic research regarding the game theory of locational choice, or more qualitative inquiry into the psychological aspects of team spatial cognition.

While this research project focused on team behaviors, it is intended to use team-based hypotheses, methods, and tools to explore the geographic dynamics of multiteam systems pursuing organizational objectives. If it is true that the phenomena that originally inspired this project – illicit and subversive activities like terrorism – are better understood as the products of multiple interdependent teams rather than discrete teams, then future basic research must apply the multiteam system framework. Such research would involve increased sophistication of the experimental design, especially the addition of multiple interdependent hierarchies of actors, teams, tasks, and goals.

Insofar as multiteam systems are purposive social networks, research approaches that examine the social structures of multiteam systems engaged in goal-oriented activities will likely yield useful insight. In particular, role, relationship intensity, and variability of affiliation provide interesting vectors of inquiry, as will investigation of the spatial, temporal, and spatiotemporal dynamics of social structures in both geographic and virtual space.

Continued basic research will develop and assess hypotheses, building towards a geographic theory of social behaviors. While the experimental phases of this project does not directly address the naïve hypotheses offered in the literature review, this research does demonstrate parts of an analytical framework which could be used to make theoretical advances in the area of human collective behaviors.

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