

Spatial Interaction Simulation Methods for Ancient Settlement Distributions in Central Italy

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CONTENTS

1. <i>Introduction</i>	8
1.1 General Overview	8
2. <i>Literature Review</i>	11
2.1 History of the Etruscans and Poggio Civitate	11
2.2 Spatial Interaction Theory In Archaeology and Within Etruria	19
2.3 Modern Transportation Geographic Theory	21
2.4 Spatial Interaction Theory and Modeling	22
2.5 Spatial Interaction Modeling in Classical Archaeology	25
3. <i>Problem Statement and Hypothesis</i>	34
4. <i>Methodology</i>	36
4.1 Data	36
4.2 Simulating Networks Using Spatial Interaction Models	43
4.2.1 Preliminary Data Modeling	43
4.2.2 Radiation Model	44
4.2.3 Ariadne Model	44
4.2.4 Agent-based Model	48
4.3 Network Analysis Metrics	50
4.3.1 Node-level Metrics	50
4.3.2 Network-level Metrics	52
5. <i>Results</i>	54
5.1 Radiation Model	54

5.2 Ariadne Model	60
5.3 Agent-based Model	71
6. Discussion	78
6.1 Implications for Poggio Civitate and Etruria	78
6.2 Comparing and Contrasting the Models	79
6.3 Limitations and Future Work	81
7. Conclusion	84
Appendix A.	90

LIST OF FIGURES

2.1	Map of Etruscan territory	12
2.2	View of Poggio Civitate from the immediate periphery	14
2.3	Rendering of Orientalizing era (phase I) monumental architecture . . .	15
2.4	Rendering of Archaic era (phase II) monumental architecture	15
2.5	Rooftop decorations and statues	16
2.6	Results from the XTENT model for Etruria	27
2.7	Results from Rhil and Wilson's maximum entropy gravity model	30
4.1	Study sites within their natural topographic (elevation) environment. .	37
4.2	Direct relationship between energy cost and slope for both walking and running ((Minetti et al., 2002)).	41
4.3	Accumulated least-cost paths between all sites.	42
4.4	Ariadne model runs with initial parameters for average journeys of 60km (A) and 100km (B)	47
4.5	Disconnected network from agent-based framework (60km).	49
5.1	Visualization of a single radiation model run including Murlo.	56
5.2	Visualization of a single radiation model run excluding Murlo.	57
5.3	Total interaction shift by node for radiation model.	59
5.4	Percent total interaction by node for radiation model.	60
5.5	Visualization of a single Ariadne model run including Murlo (60km). .	62
5.6	Visualization of a single Ariadne model run including Murlo (100km) .	63
5.7	Visualization of a single Ariadne model run excluding Murlo (60km). .	64
5.8	Visualization of a single Ariadne model run excluding Murlo (100km) .	65

5.9	Total interaction shift by node for Ariadne (60km).	69
5.10	Percent total interaction shift by node for Ariadne (60km).	70
5.11	Total interaction shift by node for Ariadne (100km).	70
5.12	Percent total interaction shift by node for Ariadne (100km).	71
5.13	Visualization of a single agent-based model run including Murlo.	73
5.14	Visualization of a single agent-based model run excluding Murlo.	74
5.15	Total interaction shift by node for agent-based model.	76
5.16	Percent total interaction shift by node for agent-based model.	77
A.1	Study region slope reclassified according to energy costs.	90
A.2	A-G: PPA results for k equals 1, 2, 3, 4, 5, 7, and 9.	93
A.3	A-G: MDN results for distance thresholds of 25km, 50km, 75km, 85km, 100km, 125km, and 150km.	94
A.4	Parameterization of Ariadne (60km).	95
A.5	Parameterization of Ariadne (100km).	96
A.6	Five sample model runs for the agent model.	98

LIST OF TABLES

4.1	Sites used in the study and their attributes.	38
4.2	Energy cost of walking and running on different slopes ($J \cdot kg^{-1} \cdot m^{-1}$).	40
4.3	Cost classification for each slope range.	41
5.1	Network metrics for radiation model before the destruction of Murlo	57
5.2	Node metrics for radiation model before the destruction of Murlo	58
5.3	Network metrics for radiation model after the destruction of Murlo	58
5.4	Node metrics for radiation model after the destruction of Murlo	59
5.5	Network metrics for Ariadne (60km) model before the destruction of Murlo.	65
5.6	Node metrics for Ariadne (60km) model before the destruction of Murlo.	66
5.7	Network metrics for Ariadne (100km) model before the destruction of Murlo	66
5.8	Node metrics for Ariadne (100km) model before the destruction of Murlo.	67
5.9	Network metrics for Ariadne (60km) model after the destruction of Murlo.	67
5.10	Node metrics for Ariadne (60km) model after the destruction of Murlo.	68
5.11	Network metrics for Ariadne (100km) model after the destruction of Murlo.	68
5.12	Node metrics for Ariadne (100) model after the destruction of Murlo.	69
5.13	Network metrics for agent model before the destruction of Murlo.	74
5.14	Node metrics for Agent model before the destruction of Murlo.	75
5.15	Network metrics for Agent model after the destruction of Murlo.	75
5.16	Node metrics for Agent model after the destruction of Murlo.	76
A.1	Least-cost path distances (km)	91

A.2	As the crow flies distances (km)	92
A.3	Network-level metric results for 25 runs (Ariadne - Before - 60km) . . .	97
A.4	Network-level metric results for 25 runs (Ariadne - Before - 100km) . .	97
A.5	Network-level metric results for 25 runs (Ariadne - After - 60km) . . .	97
A.6	Network-level metric results for 25 runs (Ariadne - After - 100km) . . .	97
A.7	Network-level metric results for 25 runs (Agent Model - Before)	99
A.8	Network-level metric results for 25 runs (Agent Model - After)	99

1. INTRODUCTION

1.1 General Overview

Human Landscapes are created by the necessary struggle of people to meet their social and economic needs. Eckbo states, “Historically, these objectives have run a gamut from utility through increasing convenience, comfort, and luxury to the more conscious and ostentatious display of wealth and power” (1969, p. 8). Thus, as societies have settled and developed urban communities, human culture intensified, which in turn magnified the relationship between the people and the earth. The result is that the landscape is created by human decisions whether it was their intent to do so or not (Eckbo, 1969, 3-8; Anschuetz et al., 2001, 161). These decisions result in connections between people, places, and groups, producing a network of spatial interactions.

Yu-Fi Tuan (1976), writes, “If history is a pillar of the humanities then historical geography ought to be the pillar of humanistic geography” (272). Following this line of thinking, archaeology and humanistic geography can be thought of as overlapping, and thus sharing a common goal of building a history of humans. Tuan also writes, “The vivid depiction of a region is perhaps humanistic geography’s highest achievement” (273). As such, it can be argued that through spatial analysis we will enrich our perception of a region and therefore help answer broader questions about how a place becomes defined through the larger landscape within which it exists (274).

The purpose of this research is to explore the spatial distribution of early Etruscan states within a geographic network structure in order to shed light on how space conditioned their development and then subsequently influenced how these sites interacted

with each other. Specifically, this research will focus on how these spatial effects pertain to the site known as Poggio Civitate (Murlo), which is located approximately 25km southeast of Siena, Italy. By considering the entire region of ancient Etruria, which coincides heavily with the modern Italian province of Tuscany, it will be possible to examine Murlo's individual characteristics as well as its relationship to other settlements within a cohesive Etruscan society. New evidence will be contributed towards existing theories which help to explain the nature of this wealthy settlement which was abruptly destroyed and has henceforth remained uninhabited.

Quantitative modeling will be embraced as the analytical framework within which the proposed spatial analysis will be carried out. Models can help mitigate complexities that arise from large multi-dimensional datasets that quickly become complicated to analyze. They also act as a tool to develop and evaluate hypotheses since the models can be parameterized in such a way to test existing and new theories. Furthermore, by employing a common mathematical language they increase dissemination and communication within and between fields (Wyly, 2009). Quantitative modeling's merits within archaeology are summarized below by (Evans et al., 2012):

“Despite our best attempts at deducing relationships from the artefacts found at them [sites], there is often little direct information about how sites interact. Quantitative modelling provides one response to this challenge. Good quantitative modelling can be insensitive to poor data, make assumptions and biases clear and debatable, and can allow us to provide possible answers to questions that could not be asked any other way. In the best case, such answers can be checked later from the archaeological record.”(1)

Three conceptually unique techniques will be employed in order to simulate relative spatial interactions amongst the sites in the study area: an agent-based model, a radiation analogy model, and a Hamiltonian gravitational model. As a consequence, each model provides varying interpretations of spatial interaction by approaching the problem from 3 different perspectives. A multitude of models offers the ability to

compare and contrast different nuances of a phenomenon using the same spatial inputs. Furthermore, different representations that yield varying yet similar results will provide assurance that we are indeed capturing the intended actions. Subsequent chapters will elaborate on the concepts presented here. Chapter two will begin with a brief history of the Etruscans and how Murlo fits into that narrative. We will then introduce the concept of spatial interaction theory and spatial interaction modeling, followed by a review of spatial interaction studies within the field of archaeology. A final product of Chapter two will be the selection of the three models that will be employed in this research. Next, in Chapter three we will provide an explicit statement of the goals and hypotheses that pertain to this research. Chapter four can be broken into three sections; in the first we will establish the input data that will be used for all three models while in the second we will provide in-depth description of how each model will be used to simulate networks, and, finally, in the third section we will establish the appropriate metrics to analyze the networks. The resulting networks and their properties will be reported in Chapter five. Finally, in the discussions and conclusions (Chapters six and seven) we will provide a holistic summary of the research overall, a comparison of the three models, the implications each has regarding specific research questions, and suggestions for future research.

2. LITERATURE REVIEW

2.1 *History of the Etruscans and Poggio Civitate*

Etruria generally refers to the society that dwelt in ancient Italy from the pre-historic era through to the flourishing of the Roman civilization. Indeed there is much evidence that Etruscan culture was adopted by the Romans and that these two cultures co-existed before the expansion of the Romans and subsequent decline of the Etruscans (Scullard, 1980, 30-32, 56-60). The height of Etruscan culture included complex cities, naval prowess, and intricate craftsmanship. Evidence for occupation within Etruria exists as early as about 4-5 millenniums before the common era (BCE) though it is not until much later that distinct Etruscan culture emerged. Four general time periods can be identified in the assessment of Etruscan historical development: the Late Bronze Age (c. 1300-900 BCE), the Villanovan period (c. 900-750 BCE), the Orientalizing period (c. 750-580 BCE), and the Archaic/Classical period (c. 580-400 BCE). The geographic extent covered by the Etruscans (Figure 2.1) is usually prescribed to Central Italy, though in reality their territory covered a wider region which encompassed modern Lazio, Tuscany, and parts of Umbria, Campania, Emilia and Veneto (Spivy & Stoddart, 1992, 21, 38). Their major cities were generally bound between the Arno river and Tiber river to the North and South and the Tyrrhenian Sea and the Apennine Mountains to the West and East. Within this context the landscape tended to vary so that there were several different environments inhabited by the Etruscans simultaneously. It is hypothesized that the earliest Etruscan populations were egalitarian and fairly spread throughout the landscape with no signs of urban nucleation (Barker & Rasmussem, 1998, 44-46).



Fig. 2.1: Map of Etruscan territory¹.

As early as the 4th millennium B.C.E in Etruria, however, evidence shows that control over the production, distribution and consumption of resources was an important deciding factor in an individual's rank amongst his neighbors. Though there were few social divisions within these early societies, this practice of resource control was the basis for economic, political, and social competition which was the persistent driving force behind the process of their expansion. By the Late Bronze Age (1300-900 BCE) there was already significant intensification which lead to a shift from a landscape of only hamlets and farms to one that included, along with these, proto-urban villages. In this time period there was growth in the population with the appearance of new settlements, mostly on naturally defensible sites, valleys, and by major waterways. Expanded territorial control fueled an increase in larger residences, hierarchical rankings, and economic activity with emphasis on animal secondary products, limited production of metals, and extensions of land use. While this time period still had a healthy population of inhabitants throughout the country, it certainly marks the beginning of the process of nucleation and the formation of chiefdoms (44-59).

Characterized by a dramatic increase in the process of nucleation, the Villanovan period (900-750 BCE), shows signs of further societal development. Settlement numbers shrink considerably though those that prevail increase in population, size, and influence. Production and use of metals, especially iron, became indicators of wealth with much of the metals being obtained from key sources such as the Colline Metallifere, which translates to “Metal-bearing hills”, or from the Tufa Mountains (Spivy & Stoddart, 1992, 75-77). This is also the time period in which the first concrete evidence is recorded for habitation on the archaeological site of Murlo. Located approximately 25km southeast of the Tuscan city of Siena on the eastern edge of the Colline Metallifere, this site shows three distinct phases of occupation on the plateau, Piano del Tesoro, of the commanding hill, Poggio Civitate, which translates to “hill of the civilized” (Figure 2.2). Murlo and Poggio Civitate are used interchangeably to refer to the corresponding

¹ http://en.wikipedia.org/wiki/File:Etruscan_civilization_map.png



Fig. 2.2: View of Poggio Civitate from the immediate periphery².

archaeological site. The earliest phase of occupation, the Iron Age (Coincides with Villanovan phase), is indicated by sparse remnants characteristic of pre-urban villages (Glennie et al., 2013).

The later two phases of occupation differed in that they left behind significant archaeological remains of monumental architecture and are characterized by proto-urban traits such as craft specialization, social stratification, and increased consumption. The earlier of these two phases, starting in the 7th century BCE, consisted of three separate buildings (Figure 2.3) each with a unique purpose: a tripartite building (three rooms) possibly for worship, a residence for an elite population, and a workshop for the manufacturing of bronze, bone, antler, ivory, food products, textiles, and architectural terracottas. A prolific burn layer in the soil stratigraphy along with unfired clay roofing tiles, which contained foot imprints, suggest that the site suffered from a sudden and fatal fire around 650 BCE. The plateau was subsequently scraped level and a new four-winged complex (Figure 2.4), approximately 60m in length each, was constructed (c. 600-580 BCE), which presumably incorporated all of the functions of the previous three buildings. Additional remains suggest the presence of watch towers and defensive walls that extended off of the main building. Unfortunately for the residents of the

² <http://potsplacesstonesbones.blogspot.com/2013/01/bone-dead-babies-and-poggio-civitate.html>



Fig. 2.3: Rendering of Orientalizing era (phase I) monumental architecture³.



Fig. 2.4: Rendering of Archaic era (phase II) monumental architecture⁴.

hilltop complex, it only survived a few decades before it was destroyed and abandoned between 550 and 535 BCE (Nielsen & Tuck, 2001, p. 35-45).

While the exact reason for Poggio Civitate's eradication is unknown, the archaeological remains undeniably indicate that the occupants of the site commanded substantial authority. The monumental architecture had rooftops adorned with captivating decorations (Figure 2.5) which would have been visible from afar and projected a message of social status to those at the site and within its periphery (Tuck, 2006; O'Donoghue, 2013). Additionally, the Archaic phase building featured a series of four recurring plaques displaying the lifestyle of an elite culture (Winter, 2009, 159). Due to a sudden

³ <http://www.archaeological.org/fieldwork/afob/3437>

⁴ <http://www.boscodelaspina.com/the-ancient-village/history-building-hotel-tuscany/>



Fig. 2.5: Rooftop decorations and statues⁵.

destruction of the buildings, many items, normally considered portable, were left behind, including sets of elaborate bucchero cups, imported Greek vessels, large storage vessels, and hundreds of plates. This assemblage, which allows a glimpse into the society that dwelt on this hill, supports the theory that residents partook in banquets and feasts (Barker & Rasmussem, 1998, 162-166). Material evidence signifies that those in control at Poggio Civitate likely dominated control over local natural resources and labor power.

Despite the status of the community at Poggio Civitate, the site was not rebuilt after its destruction in the second half of the Sixth century BCE. In fact it was never reoccupied again and this seems to have been the intended goal of those responsible for the center's obliteration: as the walls were torn down the architectural terracottas were brought crashing to the ground. Some of the debris was then deliberately deposited in depressions throughout the site and covered with stone. The walls, along with soil and terracotta debris, were used to construct a mound, up to four meters high in some areas, along the perimeter of the plateau of Piano del Tesoro (Edlund-Berry, 1994).

⁵ <http://www.italianstay.com/italyinformation/museums/antiquarium.htm>

Additionally, roofing tiles were carried approximately 147.5m away from the Archaic phase building to intentionally seal a well that is speculated to have served a metal smelting industry or perhaps a residual community of Poggio Civitate (Tuck et al., 2010). These actions maintain the theory that the destructors purposefully closed the hilltop site.

The permanent abandonment of the commanding hilltop of Poggio Civitate is surprising since modern civilization has proliferated on the crests of all other local hills. Many of these sites have in turn yielded archaeological remains from multiple eras (Campana, 2001). It can be concluded that much of the landscape has been dotted with communities from ancient times until the present, except for Poggio Civitate. After more than 40 years of excavations it is still unclear what forces caused residents to permanently vacate the hill's premises and why the hill was not resettled.

Everything that is known about Poggio Civitate, lacking formal reference in ancient texts, hails directly from the site's remains and the archaeologists who interpret them. Theories about why the settlement was destroyed or who the residents were must ultimately remain speculative. Modern literature produces a few prevailing, though vague, theories which attempt to answer questions about the origins and destruction of this elite civilization.

Authors Barker and Rasmussen go as far as a general theory on the disappearance of Murlo. They explain that it would have fallen into a category of medium-sized settlements that, due to their inland locations, were out of reach of the political authority of the larger cities. Though they would have initially developed autonomously, eventually these centers were abandoned or destroyed at a time when the major cities were growing in size and power. This is to say, simply, that these smaller centers were the “losers” in the process of urbanization and expansion. The authors distilled their theory out of the fact that Etruscan cities likely controlled extensive land beyond their city limits (Barker & Rasmussem, 1998, p. 100,176). As any municipality grew in

size they would have needed to destroy opposition and maintain a network of governance to ensure hegemony in their territory. Barker and Rasmussen do not develop their speculation any further but from their ideas it is easy to imagine Murlo as a rival settlement where the inhabitants were overthrown by enemies. Setti and Bonamici (1985) posit that the settlement of Chiusi was relatively late in the urbanization process showing its first signs of aristocracy only by the end of the 7th century BCE, and displaying typical behavior of Etruscan cities by the mid-6th century. They list military control of the countryside and abandoning of the small scattered communities as two such indicators of the development process, similar to imagined scenarios based on Barker and Rasmussen's theory. Setti and Bonamici proceed by stating that Murlo, located on the border between Chiusi's and Rusellae's territory, was the first of many (Dolciano Sarteano, Cetona) communities to be abandoned. She pegs the rise of the Chuisian King, Porsenna, and the expansionist policy that he initiated to the approximate date of Poggio Civitate's abandonment in 525 BCE (32-33). Due to Murlo's centrality between the major cities of Volterra, Arezzo, Chiusi, Roselle, and Vetulonia, and the evidence for its ritual status, Edlund-Berry (1994) argued that the site might have operated as a neutral meeting place for a confederation of these cities, under divine protection, until the confederation was abolished when Chiusi changed its political affiliation to the Tarquin dynasty at the end of the sixth century BCE (Barker & Rasmussem, 1998, p. 176-177).

These various theories attempt to answer questions pertaining to Murlo though ultimately they are unable to provide evidence beyond a casual narrative. Generally, they develop their theories by looking to the remains of the site itself or to that of another site to explain the series of events that define Murlo, without considering the space between them. Aspatial, and sometimes site-centric approaches to collecting corroborating evidence or deducing theories, while useful, can be at a serious disadvantage for researching processes that occur at several scales over a large territory. This research is aimed at developing a more rigorous methodology that includes site-centric informa-

tion but also includes a regional setting to test hypotheses pertaining to Murlo. More specifically, spatial interaction models will be deployed to test how Murlo's spatial attributes such as size and location would have defined its role in relation to other sites within the entirety of the Etruscan society. The connectivity networks that result from the models will help to depict the developing Etruscan landscape and subsequently alleviate the mysteries surrounding Poggio Civitate.

2.2 Spatial Interaction Theory In Archaeology and Within Etruria

Interaction within regions seems to enjoy popularity as a theory of drivers of growth within civilizations (Kowalewski, 2008, 226; Binford, 1983, 380). Colin Renfrew (1975) provides one of the most complete theories of interaction, in the form of trade, as a driver for the development of early states. In this archaeological context he identifies examples of territories in which neighbors are modular central places defined by evenly spaced settlements at about a 1500km square area and a mean distance of 40km to neighbors (although this latter measure has been shown to range from 20km to 100km). While Renfrew credits trade as the mechanism behind the spatial interaction, he also discusses how these interactions rely on the interdependence of material and spiritual aspects of human culture and inevitably leads to communication and information flows as well. His argument is that habitual exchange leads to central places, since it requires organization and security and it implies some assumed criteria of value. He is careful to insist, however, that central places do not necessarily require civilization, but that they inevitably result in some form of interaction amongst those within the nucleated settlement (6-7). Ultimately, these central places provide a wealth of benefits in the form of market efficiency, as well as forums for solidarity and conflict resolution. Competing centers result in more specialization that will further demand for the trade of goods between central places, thus promoting greater interaction.

According to Renfrew, trade can be broken down into different categories, including extra-regional trade, internal trade within a settlement's domain and trade between

these domains within a region. It is this last form of trade that Renfrew claims is the least studied despite the idea that its “effect must have been to produce and maintain the uniformity of culture or civilization as a whole” (18). He also states that “Civilization implies the development of a highly structured and differentiated society, with specialist production (craftsmen), a permanent controlling organization disposing of a significant proportion of produce (government), and a developed, explicit set of shared beliefs (cognitive structure), sometimes with large aggregations of population” (35). This suggests that those sites which have remains indicative of increasingly civilized societies would have likely participated in more inter-site trade amongst the larger central places. Similarly, Izzet cites increased encounters with “others” as a driving factor in attitude changes towards ethnic identity. In this process, the differentiation of the self is an effect which takes place only after discovering “others” (2007, 210) . Physical growth and cultural development are therefore inextricably linked and, to a certain degree, controlled through the common process of interacting through space.

It is difficult to differentiate between interaction and the growth of civilization. For example, population increases, which may have resulted from market benefits gained through trade and interaction, would have been likely to cause squabbles over territory. Tension amongst regions would initiate contact as well as competition which results in greater cultural development as well as further interaction (Izzet, 2007, 234). In contrast, the process of state emergence can be envisioned from the standpoint of external trade (Pena, 2011) using the Kipp-Schortmann model. This model holds that when a state society initiates contact with a chiefdom society, the elites of the latter, who will likely be the sole recipients of the initial exchange, will experience an increase in power through the acquisition of new prestige goods. To maintain their authority over access to the new commodities the elites will resort to violating social norms which eventually erodes their legitimacy. From the collapse of their power emerges the new organization of the state. Pena admits that his application of this model within Etruria produces pessimistic conclusions. Interestingly, he doesn’t even consider internal trade as the

mechanism that leads to the formation of states within Etruria. It is easy, however, to envisage this process occurring between social groups with differing ranks within a hierarchical structure without even incorporating external groups. If prestige is gained from trade goods that originate from farther, more prestigious places, then it is evident that distance played an important factor in the development of the involved societies. While it is still difficult to prove that this concept directly lead to more complex civilization, it nicely portrays the importance of spatial context within Etruria, which provides a strong theoretical framework for measuring interactions amongst different groups.

2.3 Modern Transportation Geographic Theory

Modern geographic theory pertaining to transportation studies is largely in agreement with the theories that have been developed within archaeology and are therefore helpful in providing a supporting theoretical framework for spatial interaction modeling. At the root of transportation theory lies the idea of complementarity which holds that different locations must have varying surpluses and deficits in order for the exchange of goods, ideas or people to occur (Rodrigue et al., 2006). The ensuing interactions are further conditioned by environmental factors such as topography, hydrography, and climate. For example, transportation has historically followed paths along plains, valleys, and mountain passes while avoiding physical impediments. Similarly, available waterways, ports, access to natural resources and severe weather have been major considerations within transportation systems. What each of these factors have in common is that they incur a cost which must be considered against the benefits of carrying out the proposed transportation. Clearly, the spatial structure of the resulting transport network is a product of these environmental factors along with properties at each location which facilitate the creation of supply and demand and therefore affect the associated costs. In archaeology, the decision process of whether or not to interact and subsequently travel from one site to another would have involved the same factors, so

that the derived spatial structure of an interaction network would be subject to the same constraints.

The accessibility, or the measure of a site's ability to reach or be reached by another site, is a product of the established spatial structure. Distance, which is often measured as a cost, has an inverse affect on accessibility, so that more accessible sites tend to be closer together, have less associated costs and are deemed more valuable. Agglomeration and specialization of activities is likely to take place at more valuable locations to reduce transportation costs and therefore further increase the value of a location. A location specializing in a commodity or activity may also drive segregation between itself and other locations as a side effect. In the process of transportation development, two forces are constantly in effect: concentration and dispersion. Coupled with the fact that transportation systems are subjected to the constraints of historical spatial structures it is apparent that these networks are highly dynamic yet they are constantly being conditioned (Rodrigue et al., 2006, 11-28). Typically the networks evolve to increase efficiency, decrease costs, and increase accessibility. Archaeological interaction networks would have been under similar influences making their development equally as dynamic and evolutionary. It is also therefore possible to assume that a proposed interaction network based on physical attributes should approach an approximate maximum efficiency and accessibility. Given the complexities within transportation geography and the overlap in theory with ancient interaction networks it seems appropriate to employ modern analytical methods within archaeological contexts.

2.4 Spatial Interaction Theory and Modeling

Spatial interaction encompasses an array of behaviors, such as communication or movement, which occur over geographic space as a result of a decision process (Fotheringham & O'Kelly, 1989). Its broad definition has allowed it to support a diversity of research within migration, shopping, recreation, commodity and capital flows, communication, transportation networks, and commuting (Haynes & Fotheringham, 1984).

In each application a trade-off is considered between the benefits accrued through interaction versus the costs necessary to traverse space to carry out the interaction. By encoding this spatial interaction into a mathematical model, it is possible to explain an observed phenomena or to use observed data in order to make predictions about the future or alternative scenarios (Fotheringham & O'Kelly, 1989). This is particularly useful in circumstances where the number of locations under consideration or the factors involved in the decision-making process are large. Typically the interaction can be summarized by a matrix in which each row, i , represents a possible origin and each column, j , represents a possible destination. As a result, the interaction between any two locations can be described by flow ij and the total interaction in or out of a site can be found by summing a row or column.

Early spatial interaction models were developed using an analogy to gravitational forces from the field of physics (Roy & Thill, 2004). The Newtonian gravity model is relatively simple:

$$T_{ij} = \frac{k(P_i * P_j)}{D_{ij}} \quad (2.1)$$

where T_{ij} denotes the aggregate flow between origin i and destination j , P_i and P_j represent the size, population, or density of the origin and destination, and D_{ij} is the physical separation between these two locations. It is apparent that given fixed values of P_i and P_j , as D_{ij} is increased, the value for T_{ij} will decrease, therefore accounting for the costs of overcoming further distances. Additional parameters were later added to reflect the relationship of spatial flows and explanatory variables (Fotheringham et al., 2002) which allowed customization of the model for different applications. The gravity model faced criticism for its lack of theoretical foundations despite the fact that it produced reasonably accurate estimates of spatial flows. A more stable theoretical grounding was developed in the 1960's by the work of retail modelers and regional planners (Roy & Thill, 2004). In the 1970's Wilson introduced a new framework for interaction modeling which relied on maximizing the entropy of the flow system. An aggregate

flow between two locations is considered a macro state which can be satisfied by various micro states. The fundamental principle in entropy-maximizing models is that the most likely macro state is one which can be described by the highest number of micro states (Fotheringham et al., 2002). Adding in constraints allows for the derivations of a family of models in which information about origins, destinations, or both can be added to the model before solving for the most likely state (Wilson, 2010). Despite the analytical gains of the maximum entropy models, criticisms arose due to the fact that it was still based on a physical analogy and that many of the applications lacked a behavioral interpretation (O'Kelly, 2004).

Consequently, more contemporary efforts in the development of spatial interaction modeling has been to derive models based on spatial information processing. Fotheringham (1983) developed the competing destinations model to accommodate the fact that during the decision-making process an individual will be faced with a unique spatial distribution of alternative locations for every destination under consideration. The competing destinations model incorporates the fact that individuals do not always consider every other location. The attributes of each alternative can contribute to how and whether or not an individual considers it at all. As a result, it is entirely possible for decisions to be made that do not reflect maximum utility since they may not even evaluate every possible choice. More recently, Simini, et al. (2012) present the radiation model as an entirely new framework which deviates from the gravity law concept (which has been at the core of most previous models). The authors assert that their model overcomes no fewer than six known limitations of some previous gravity law models, most notable of which is that the model is parameter free and therefore requires no previous flow data for calibration. For each possible origin and destination pair, flows are predicted by comparing the benefits of interacting with one proposed destination to the benefits of interacting with each other site within a radius from the origin equal to the distance from the origin to the proposed destination. Formally, these flows are given by the following,

$$T_{ij} = T_i \frac{(M_i * N_j)}{(M_i + S_{ij})(M_i + N_j + S_{ij})} \quad (2.2)$$

where T_{ij} represents the flow prediction, M_i and N_j are density measures (e.g. population or size of a settlement) of the origin and destination respectively, S_{ij} is the total density of all other alternative locations, and T_i is a scaling factor that represents a proportion of the total number of commuters starting at a location which serves to ensure that commuter flows are not larger than the origin population. Thus the model depends not directly on the distance variable but rather the aggregate benefits (e.g. population of a city) available at all other alternative choices between the origin and destination, lending itself to the analogy of radiation and absorption processes.

The radiation model has been shown to perform better than the simple gravity model in a wide range of applications and scenarios (hourly mobility, daily commuting, yearly migrations) (Simini et al., 2012, 4-5, Figure 3). Given the simplicity of the radiation model and its proposed gains in analytical accuracy, it will be chosen as one of the three models proposed for this research. In the context of ancient spatial interaction M_i and N_j will be given by a proxy for population (e.g. urban area) which will provide a relative measure of populations throughout the study region. At present, there is no known research in which this model has been employed in the field of archaeology, which will provide an interesting comparison to past work that is founded upon the gravity law and distance decay.

2.5 Spatial Interaction Modeling in Classical Archaeology

Renfrew and Level's XTENT model (1979) was an attempt to mathematically model the effects of space within an archaeological region using a rigorous theoretical framework. The model, which is based upon Renfrew's previously discussed (Section 2.2) theory of trade and statehood, was designed to divide territory between respective central places and is defined by six axioms (145-146):

1. The human social group is defined by the habitual association of persons with a territory
2. Human organization is segmentary in nature: human spatial organization is therefore cellular and modular.
3. Basic social groups do not exist in isolation, but affiliate together into larger groups, meeting together at periodic intervals.
4. Human society is often hierarchical in nature: Human spatial organization is therefore stratified.
5. The effective polity, the highest order of social unit, may be identified by the scale and distribution of central places.
6. Special interactions between polities undoubtedly take place, creating uniformities in artifact distribution: Such uniformities in themselves do not document societies or people.

Following these lines of thought, we can conclude that a) within social groups, people will periodically interact giving rise to meeting places, b) human societies are often hierarchical, which necessarily implies a spatial patterning, and c) between these social groups or polities there is interaction. They are sure to note that the distribution of artifacts due to these interactions, which would become more uniform with increased exchange, would be less indicative of individual societies. This can be interpreted as warning against the perils of using objects as a proxy for populations and their interactions in certain contexts as opposed to geographic features such as urban extent. The authors admit that their theory gives rise to their own version of Central Place Theory though they maintain that it is different than Christaller's Central Place Theory of economic man (146). Ultimately, his model describes hierarchy through competition rather than evaluating how space mediates interaction within settlement networks. For this reason, the model will not be used in this research, which seeks to directly compare

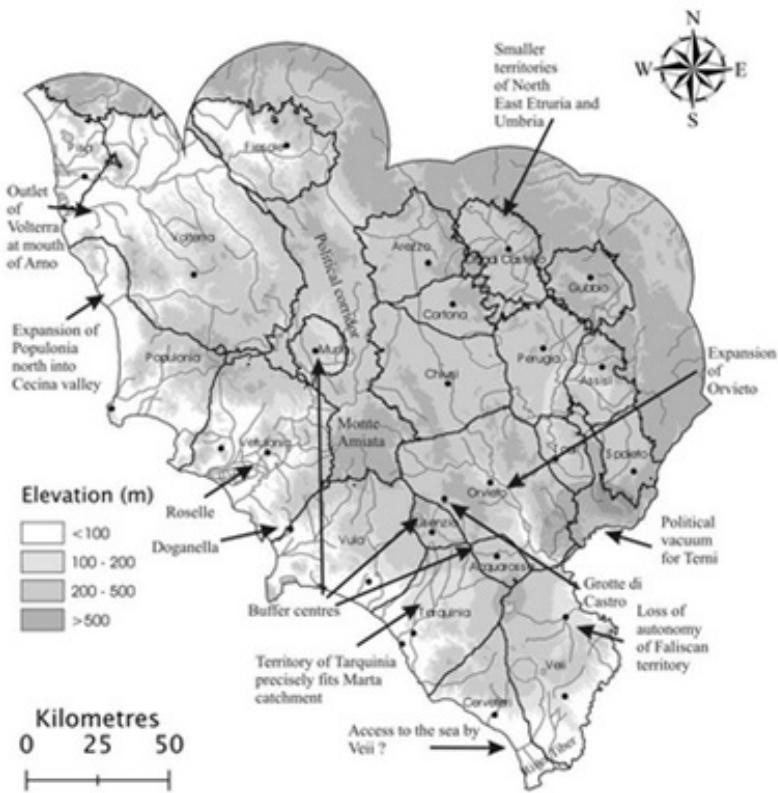


Fig. 2.6: Results from the XTENT model for Etruria (Stoddart & Redhouse, 2011).

relative spatial interaction; however, Stoddard and Redhouse's (2011) extension of the XTENT model to Etruria (Figure 2.6) provides insight into territorial dynamics of the region under inspection. They conclude that Murlo would have initially existed as an autonomous entity outside the reach of larger settlements. Eventual expansion and competition resulted in its absorption, strongly agreeing with the arguments previously explained (Section 2.1). Their interpretations are useful for the comparison of model results presented in later sections of this research.

A simple model which has been employed in archaeology (Broodbank, 2000) for measuring connectivity is proximal point analysis (PPA). In PPA each site is connected to its K nearest neighbors (constant value set by user) so that distance is not considered in the decision making process. In contrast, a maximum distance network (MDN) considers two sites connected if the distance between them is less than model parameter D (constant value set by the user). Both models are inherently prohibitive, MDN's in

that any site beyond the set distance is eliminated from the network and PPA in that a site may only maintain a limited number of links (Evans et al., 2012, 5-10). One defining limitation of PPA approach is that all sites must participate, thus forcing even the farthest sites to connect somewhere despite being potentially isolated. In a sense, both of these models are unrealistic because they only account for a limited set of scenarios. It is possible that sites close in proximity never visited each other due to resource sufficiency or that communities located miles away still benefited from interaction regardless of distance and as a result made long journeys. Additionally, these simple models do not designate flow directions for the links; either two sites are simply connected or they are not, which excludes the option for non-reciprocal relationships. The simplicity of these models makes them easy to apply but leaves many open questions during analysis.

Gravity models were adopted by David Clarke, a prominent spatial theorist within archaeology, who was a proponent of quantitative methods in the late 1960's and 1970's. In Analytical Archaeology he took a systemic and model-driven approach to explain patterns in culture, technology, and the environment (Clarke, 1968) and later in Spatial Archaeology (Clarke, 1977) he tackled issues of scale and space directly along with several additional authors who examined settlement structures, land use patterns and simulated the spread of settlements. This type of work was subjected to the typical critiques of early quantitative methods. It was believed that they over-looked true social theory and that the anthropological neutrality claimed by these methods was actually biased towards the scientists employing them (Hodder, 2003). Despite these critiques, quantitative methods provide a common mathematical language and the ability to test hypotheses, which can be linked to social theory.

Building on previous work with gravity models, Rhil and Wilson (1991) employ maximum entropy principles to simulate settlement patterns in Geometric mainland Greece. They ask the question, "Did location vis-a-vis other settlements have a sig-

nificant effect on their affiliation and union?” (61). They argue that it is sufficient to use “as the crow flies” straight lines despite lacking a true representation of Greece’s rugged terrain because this information would have been incorporated in the dataset through settlements pre-determined locations and density. While they claim this assumption yields effective results it ignores the fact that settlement location selection and travel preferences constitute two different actions. A site may have been initially established for defense or proximity to resources without consideration or even any knowledge of many other site locations. Another important detail in Rhil and Wilson’s model is that all sites start off with the same size and importance due to what they call the “egalitarian hypothesis” and these attributes are then predicted as part of the model. Validation is therefore possible between the model results and the attributes measured from the archaeological record. Two additional parameters, the benefits of concentrated resources and the difficulty of communication, enable the model to be fine tuned. Their work offers an improvement on simple geographic models and elementary gravity models in archaeology by adding constraints and parameters, though it is not without flaws. One limitation is that the model inherently creates networks that are “supply side”. This means that larger cities attract the interactions of the nearest smaller sites, never allowing small sites to connect with each other. In effect, you get a network reminiscent of a star pattern (Figure 2.7) which is helpful for identifying key nodes but still may not represent a realistic network. Their gravity model also lacks the ability to capture the feedback effects of interactions and site size on each other (Knappett et al., 2008, 10).

Ariadne, a model developed by Evans et al., is a type of gravity model that has improved upon the work of Rhil and Wilson. They employ a “Hamiltonian” energy function, H , consisting of four terms, which takes the form,

$$H = -kR - \lambda E + jP + \mu T \quad (2.3)$$

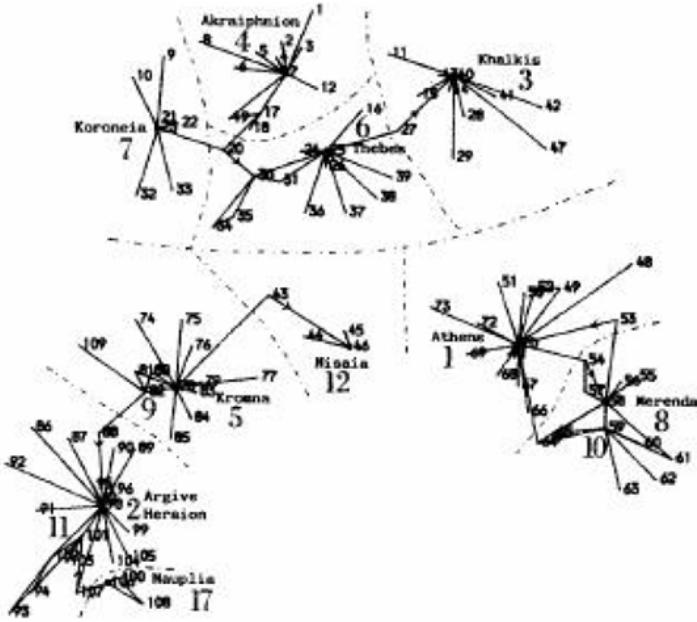


Fig. 2.7: Results from Rhil and Wilson’s maximum entropy gravity model (Rihll & Wilson, 1991).

where R is the benefit of exploiting local resources, E is the benefit of maintaining links, P is the cost of supporting local populations and T is the cost of maintaining links. Each term has a parameter which controls the effect it has within the model. Expanding the terms give H the following form,

$$H = -k \sum_i S_i v_i (1 - v_i) - \lambda \sum_{i,j} V\left(\frac{d_{ij}}{D}\right) \cdot (S_i v_i) \cdot e_{ij} \cdot (S_j e_j) + j \sum_i S_i v_i + \mu \sum_{i,j} S_i v_i e_{ij} \quad (2.4)$$

where S_i is the given size of a site, v_i and e_{ij} are outputs of the model representative of the weight of each settlement and interaction link in the network, and $V\left(\frac{d_{ij}}{D}\right)$ provides a gravity function based on the distance between two nodes (d_{ij}) and an average maximum journey length (D). H provides a tool for balancing the cost and benefits of both “supply” and “demand” between site interactions. Using optimization techniques, a minimum value is obtained for H and the model output values (v_i and e_{ij}) can be read off and visualized as a network (10-24).

The additional output of interaction “strength” (e_{ij}) makes it possible to create a network in which all nodes participate, yet closer sites will have strong links and far-

ther sites will have weaker ones. It is also feasible that some sites may choose not to interact because their costs outweigh the benefits. Unlike Rhil and Wilson, smaller neighbors are free to interact with each other rather than being limited to the hierarchical “star” pattern. Ariadne is also superior because it incorporates “course-graining”, the assumption that the whole is the sum of the parts, meaning that an interaction value associated with a large site can be used to represent the total interaction from many smaller sites proximal to the larger site. In archaeology this is crucial in supporting sometimes incomplete and ambiguous records for local regions and settlement data which varies across different scales. An important feature of the Ariadne model is that it is stochastic rather than deterministic. Each model run yields slightly different results which approach some optimal solution therefore mimicking short-term fluctuations within the system. A comparison of multiple runs allows the isolation of a most likely optimal solution (Evans et al., 2012, 12). Due to Ariadne’s abundance of advantages and ability to produce the most realistic settlement networks, it will be selected as the second model to simulate network interactions in central Italy. Ariadne’s later deployment to investigate the effects of the destruction of a central node in the Greek maritime network as a result of the volcanic eruption of Thera (Knappett et al., 2011) is directly comparable to the study of Poggio Civitate and its abandonment. Analysis in this research will therefore draw heavily from the methodology of Evans, Knappett, and Rivers.

Model three, inspired by the TravellerSim model⁶, introduces an entirely new modeling framework into this research while still building off the work of by Rhil and Wilson. Authors Graham and Steiner (2008) propose a method for observing the emergence of territories from the perspective of the individual. The general motivation for this agent-based approach is that it is not truly possible to know the exact relationship between sub-systems within a larger system. Instead we can assign very simple rules to individuals and then let them interact, thus developing the more complex relationships observed at the macro level. TravellerSim is built upon the same assumptions

put forth by Rhil and Wilson (Rihll & Wilson, 1991, 64, 71), except spatial decisions are now limited to a local vision (approximately 20km from the settlement the agent is currently at). Each round, the agents consider 3 settlements within their vision and then choose to travel to the most “attractive” destination. Attractiveness is calculated using a localized version of Rhil and Wilson’s equation:

$$A = \frac{\text{importance}^\alpha * e^{-\beta D}}{\text{visitors}^\alpha * e^{-\beta D}} \quad (2.5)$$

where the importance is the current importance of a site, α is a parameter to represent the benefits from resources, β is a parameter to represent the cost of communicating over space, and D is the distance from the agent to the settlement whose attractiveness is being calculated. After all agents have moved, settlements then update their importance based on the interaction they received following:

$$\text{NewImportance} = V * \sqrt{\frac{\sum I}{v}} \quad (2.6)$$

where the V is the cumulative total number of visitors who have arrived at a settlement, I is the importance values from each of the settlements an arriving agent had originated from for a given iteration, and v is the number of visitors at each settlement for the current round.

In this manner the authors were able to successfully “grow” fuzzy territories and visualize the spread of influences over the region. Furthermore, by tracking the individual visits of the agents it is possible to produce a weighted directed network similar to the Radiation and Ariadne model. In this respect, TravellerSim is not limited like Rhil and Wilson’s model or the XTENT model despite their shared interest in hierarchy and territory. Overall, the bottom-up approach demonstrated in TravellerSim contributes a solid base on which to develop an interesting alternative to the more top-down concepts employed in the other two models selected for this research and will therefore be

⁶ http://figshare.com/articles/Travellersim_Agent-Based_Model/91976

selected as the third model to study spatial interaction patterns within ancient Etruria.

3. PROBLEM STATEMENT AND HYPOTHESIS

It is apparent from the literature (Section 2.1) that there are two main theories which assume differing relationships over space. Our primary question, therefore, is “was Murlo an autonomous central place or did it feed into a larger hierarchy of settlements?”. We can then propose the following simplified theories from the literature on the nature of Murlo:

1. Murlo was a relatively autonomous settlement which enjoyed independence from the influence and authority of other central places despite its relatively smaller size.
2. Murlo acted as central meeting place for the other Etruscan powers to meet in a neutral setting due to its central location to other settlements.

To test these theories we need to embed Murlo into an interaction network with other contemporary sites. Theory one suggests that Murlo would have engaged in very little interaction given its location and size. More importantly, we must differentiate between incoming and outgoing interaction. For Murlo to remain autonomous we would expect relatively little incoming traffic since it was not subject to the influence of other settlements. Therefore, limited overall interaction will provide evidence for theory one, though some outgoing interactions with minimal incoming interaction would still be considerably strong evidence. Conversely, theory two assumes strong interaction predictions amongst Murlo and its surrounding neighbors, especially in terms of incoming traffic. This is not to say that Murlo’s neighbors would not have also interacted strongly with each other in their regular affairs. Rather, these interactions will be used as the base for a comparison to associations with Murlo.

Another objective of this research is to use a geographical approach to determine how the destruction of Murlo factored into the dynamics of the larger system. Unfortunately, the spatial distribution of settlements does not directly provide information on the demise of Murlo. Instead, we can use the quantitative models to simulate interaction networks with and without Murlo in order to answer the question, “How did the destruction of Murlo effect the strength and distribution of interaction throughout the wider region of Etruria?”. If the network remains relatively unchanged it will count as evidence towards Murlo as an autonomous central place. Likewise, if we record large shifts in the network we can conclude that it is likely that Murlo was playing an important role in the wider region of Etruria and that its destruction may have been related to its favorable location.

4. METHODOLOGY

4.1 *Data*

For all of the chosen models, the necessary data is a selection of settlements, their geographic coordinates, a measure of each site's population or size, and a measure of distance between all pairs of sites. Considering Renfrew's warning against relying on artifact counts and the unavailability of population estimates, the urban extent of a site's archaeological remains will be used to represent its size. Settlements taken into consideration (Figure 4.1) for this research are those used by Stoddart and Redhouse (2011) to test the Early State Module concept of Colin Renfrew (1975). Under Renfrew's theory, the characteristics of early state societies included autonomous central places, a uniform spacing of about 40km amongst neighbors, approximately 1500 square kilometers of territory per polis, and the region consisted of a cluster of about a dozen sites. Stoddart and Redhouse (2011) provide a list of 25 Etruscan settlements and their corresponding size estimates which co-existed in time period roughly from 900 to 600 BCE. Though their research shows that only a fraction of the sites ultimately meet the ESM standards using the XTENT model, we can nevertheless adopt their study sites for use in our spatial interaction models given that this research has no restriction to solely early states. Their data provides the best available starting point for spatial interaction modeling in this context because they have assembled site size estimates by drawing from various archaeological sources as well as personal experience when no estimation existed (166). Following Stoddart and Redhouse, the sites, as presented in Table 4.1, were all given spatial context via the Latitude and Longitude attributes from the Getty Thesaurus of Geographic Names Online¹ with the exception of Bisen-

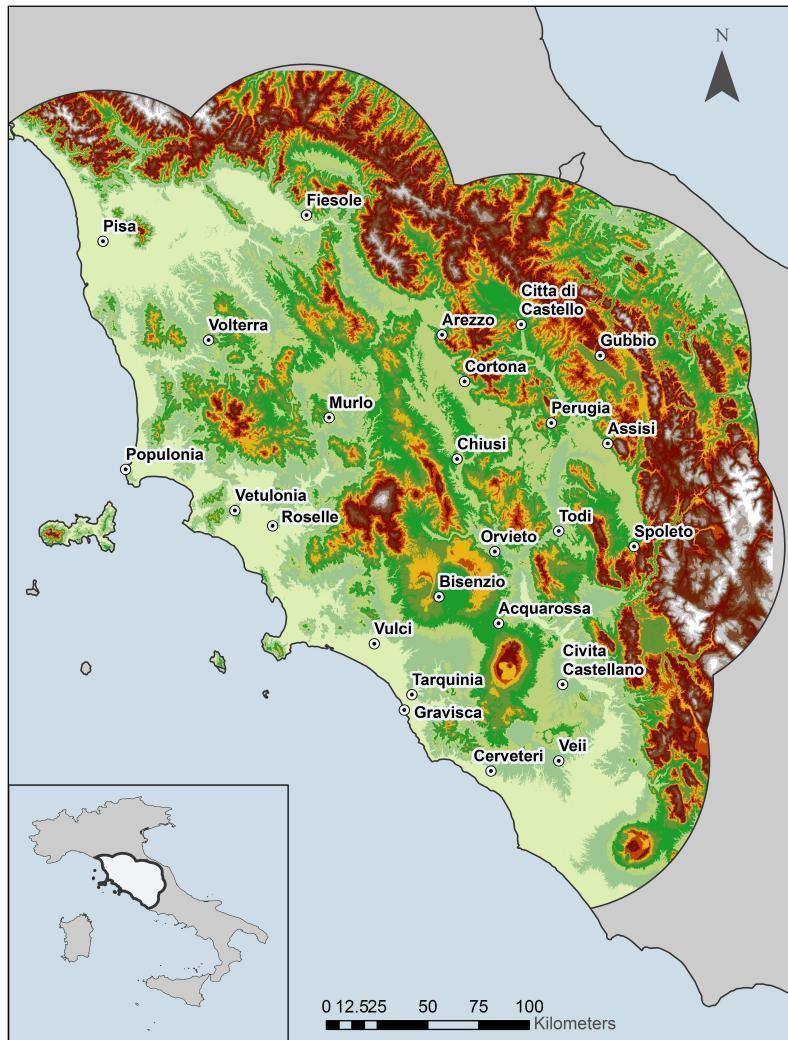


Fig. 4.1: Study sites within their natural topographic (elevation) environment.

szio. Each site's name was queried in the on-line thesaurus, and if an entry existed for the ancient site as opposed to the modern one, then the ancient site was used. If only one entry existed (modern or ancient), then that was utilized. For Bisenzio, which was not listed in the thesaurus, coordinates were estimated visually using its known location via Google Earth. Finally, each settlement's coordinates were transformed using the Web Mercator Auxillary Sphere projection and the WGS1984 datum (EPSG: 3857), in order to perform geo-computation within a GIS.

¹ <http://www.getty.edu/research/tools/vocabularies/tgn/>

Tab. 4.1: Sites used in the study and their attributes.

Name	Number	Size (ha)	GettyLon	GettyLat
Veii	0	185	42.0333	12.4
Cerveteri	1	160	42	12.1
Vetulonia	2	100	42.85	10.9667
Populonia	3	150	42.9833	10.4833
Volterra	4	100	43.4	10.85
Chiusi	5	50	43.0167	11.95
Bisenzio	6	35	42.57	11.87
Acquarossa	7	30	42.4833	12.1333
Perugia	8	32	43.1333	12.3667
Gravasca	9	24	42.2	11.7167
Gubbio	10	20	43.35	12.5833
Assisi	11	20	43.0667	12.6167
Citta di Castello	12	20	43.45	12.2333
Tarquinia	13	150	42.25	11.75
Vulci	14	126	42.4167	11.5833
Roselle	15	40	42.8	11.1333
Murlo	16	10	43.15	11.3833
Pisa	17	20	43.7167	10.3833
Orvieto	18	85	42.7167	12.1167
Arezzo	19	32	43.4167	11.8833
Cortona	20	30	43.2667	11.9833
Civita Castellano	21	26	42.2833	12.4167
Fiesole	22	30	43.8	11.2833
Todi	23	20	42.7833	12.4
Spoletto	24	20	42.7333	12.7333

It is important to note the possible boundary effects that might arise from this data set. While this list includes the significant settlements that existed throughout the time period of interest there would have undeniably been considerable interaction occurring between sites within the study region and those external to it, especially for those settlements close to the study region border. This is a problem that will arise at any scale and for any study region. Regardless, we must limit the boundaries in order to maintain conceptual simplicity as well as managing computing resources.

Many methods are available for obtaining inter-settlement distances. Straight line or “as the crow flies” distance is the simplest measurement to employ since it requires no abstract concept of cost and can be easily computed using Euclidean distance calculations. It is obvious, however, that most network edges cannot be truly represented without incorporating the natural terrain. Bevan (Forthcoming) reviews several alternate methods that have been deployed by archaeologists to integrate the landscape into distance calculations. Arguably an entire study could be completed solely on choosing a proper representation of travel times or costs over space. As a compromise, this research will leverage methods similar to those utilized by Stoddart and Redhouse (165) within the XTENT model whenever possible. This will promote consistency, incorporate the effects of the terrain, and maintain simple and reproducible calculations. Ultimately, though, the method employed here must differ since this research seeks to incorporate the terrain by deriving least accumulated cost paths between sites whereas Stoddart and Redhouse aimed to create cost distance rasters for the entire region.

Distances between sites will be reflective of the least accumulated path given the energy costs ($J \cdot kg^{-1} \cdot m^{-1}$) necessary to traverse natural slopes within the terrain. To carry out this calculation an ASTER² 30m resolution digital elevation model was used to derive the slope of the terrain, which is an improvement in resolution over previous research (Stoddart & Redhouse, 2011). The elevation DEM was clipped (Figure 4.1) to a buffer of two times the average nearest neighbor distance (straight line) of the

Tab. 4.2: Energy cost of walking and running on different slopes ($J \cdot kg^{-1} \cdot m^{-1}$).

Slope	Cost of Walking	Cost of Running
-45	3.46	3.92
-40	3.23	3.49
-35	2.65	2.81
-30	2.18	2.43
-20	1.3	1.73
-10	0.81	1.93
0	1.64	3.4
10	4.68	5.77
20	8.07	8.92
30	11.29	12.52
35	12.72	14.43
40	14.75	16.83
45	17.33	18.93

settlements and to the natural coast line of the Italian peninsula (Stoddart & Redhouse, 2011, 167). A slope raster was then calculated with the clipped DEM as the input. Differing “costs” to travel from one site to another were computed by classifying each slope raster cell by the associated required energy to traverse it as proposed by Stoddard and Redhouse (2011). Data for the average cost of walking and of running for slopes ranging from -45 to +45 degrees (Minetti et al., 2002) is given in Table 4.2.

Since the distances between the sites are long enough to prohibit an average person from running the entire trip, only the values for the cost of walking were considered. It should also be noted that for most slopes the cost of running is not much higher than walking and that both actions follow a similar increasing trend (Figure 4.2). Additionally, the least accumulated cost path calculation does not consider whether the slope is uphill or downhill. Since the direct relationships for the costs of traversing either positive or negative slopes are similar, only the costs associated with positive slopes will be used to re-classify the slope raster due to the more prohibitive costs associated with traveling up hill.

Given the following assumptions, a general cost class was assigned to each slope range (Table 4.3) to produce a cost or friction raster which was used as input to de-

² <http://asterweb.jpl.nasa.gov/>

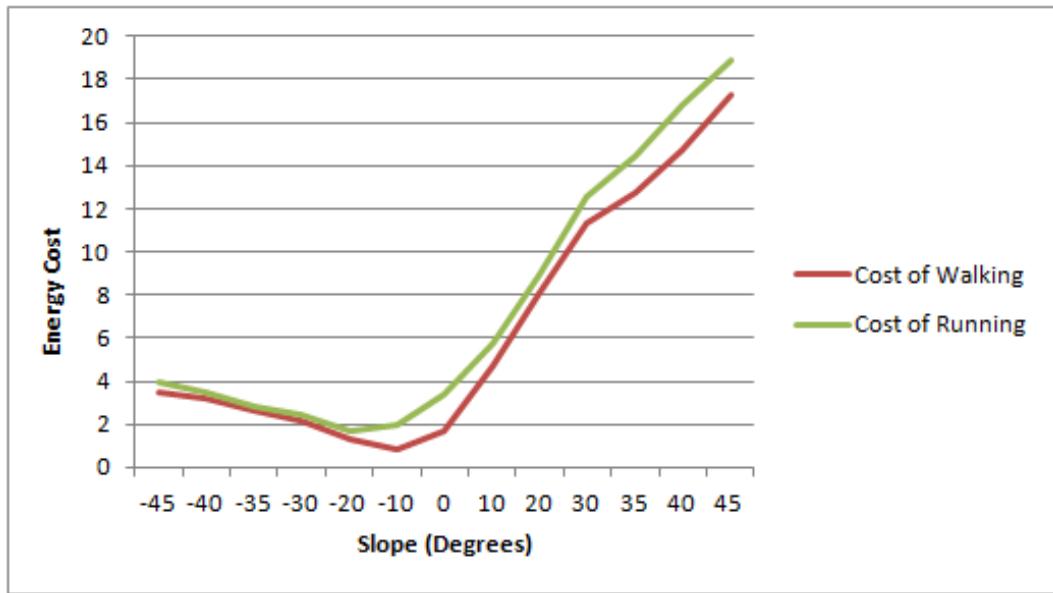


Fig. 4.2: Direct relationship between energy cost and slope for both walking and running ((Minetti et al., 2002)).

Tab. 4.3: Cost classification for each slope range.

Slope Range	Cost Classification
0-10	1
11-20	2
21-35	3
36-45	4
46+	5

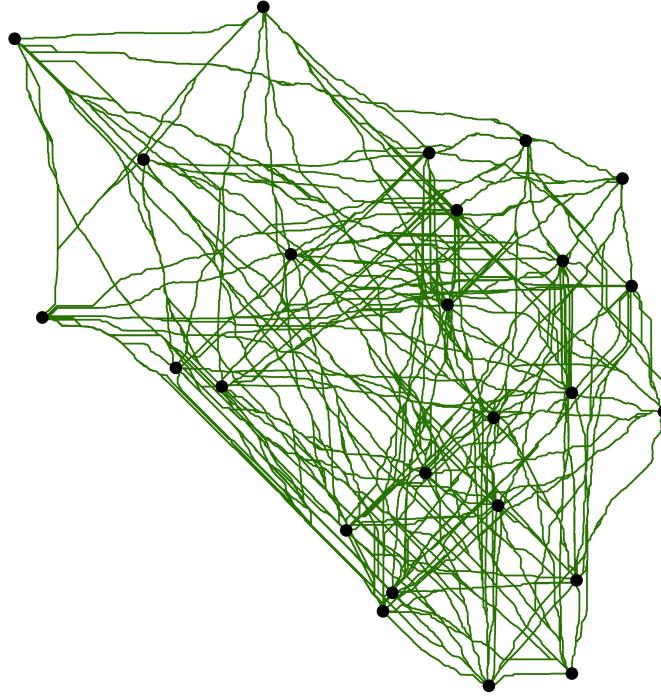


Fig. 4.3: Accumulated least-cost paths between all sites.

rive the least accumulated cost paths in origin-destination matrix format (Etherington, 2011). These calculated values (Appendix Table A.1) are all longer than the straight-line distances (Appendix Table A.2) since they tend to closely gravitate towards areas with lower slopes. They represent the routes (Figure 4.3) which will require the least energy to be exerted without greatly deviating from the shortest possible path. Developing a distance measurement that is representative of a physical transportation network preserves the network's edges length units which enhances the ease with which the model results can be interpreted. Additionally, a non-abstract measure of distance preserves the ability of the data to be verified against both contemporary knowledge and future discoveries of ancient roads within the study region.

4.2 Simulating Networks Using Spatial Interaction Models

4.2.1 Preliminary Data Modeling

Prior to running the selected models, exploratory data analysis was performed using the proximal point analysis and maximum distance network models. While the limitations of these models are apparent (Section 2.5) they can nevertheless enable a basic understanding of which distances or number of nearest neighbors results in different levels of network connectivity. These simple metrics will help calibrate the more complex models chosen for interaction simulations.

Running the proximal point analysis model on the site data using k values of 1, 2, 3, 4, 5, 7, and 9 illustrates how the interaction network becomes more connected as each settlement is forced to connect with an increasing number of nearest neighbors (Appendix Figure A.2). When k equals 1-2 the connectivity network exists only through shorter distance links. Increasing k up to 3-5 enables settlements to make medium distance journeys and to begin making more unrealistic long distance trips. At k values of 7 and 9 it is apparent that the network is too highly connected to accurately resemble any nuance of reality. It is extremely unlikely that some of the smaller sites would have the means to sustain such expensive interactions. Since this model produces reciprocal relationships each value of k is representative of two connections. It is possible to conclude that networks for this study region should have nodes with a minimum average of 6 connections and maximum average of 14 connections.

Similarly, running the maximum-distance network model, using distances of 25km, 50km, 75km, 85km, 100km, 125km, and 150km, generates interaction networks with compounding complexity (Appendix Figure A.3). At distances of 25km and 50km the study region remains extremely disconnected. Increasing the distance threshold to 75km results in a highly connected southern Etruria and a partially fragmented northern Etruria (which is interesting given the general consensus that the south developed

more rapidly). It is not until a threshold of 85km that every site is included within the network though there are still large disparities between the northern and southern regions. Finally, values of over 100km begin to yield overly connected networks which result in the smallest of settlements making great journeys. Overall, it seems that a network in which the distance threshold of about 100km would be the most representative of a highly connected, though still constrained, spatial interaction system.

4.2.2 Radiation Model

To operationalize the radiation model code³ was developed following Simini et al. (2012) with one exception. The term T_i , which is supposed to be a proportion of the total population originating at each site, will instead consider the settlement size estimate at a given location. Alternatively, T_i could be a ratio of the settlement site size to the total of all sizes. Any value which accurately scales calculations by the estimates at the origins is acceptable. Since M_i is also equal to the origin estimate, equation 2.2 from Section 2.3 therefore becomes,

$$T_{ij} = \frac{(M_i^2 * N_j)}{(M_i + S_{ij})(M_i + N_j + S_{ij})} \quad (4.1)$$

The radiation model has no parameters, so there is no further preparations necessary. The code formats the data into an origin-destination matrix and then carries out equation 4.1 for each pair of locations resulting in a matrix of relative spatial interaction between them. Since many flows between sites will have near-zero values the network is filtered by removing all edges with a weight that is less than one percent of the largest edge weight value.

4.2.3 Ariadne Model

Before any interaction data can be harvested from the Ariadne model it must be configured for our study area. We must prescribe a distance which represents the

³ <https://github.com/tayoshan/RadiationModel.git>

average trip length one could complete in a day and therefore in a single journey. Based on conclusions aggregated by Bevan (Forthcoming) the average travel speed over a full day for a pedestrian ranges from 2.5km/h to 5km/h depending on the load they may be carrying. In contrast, horses would have reached speeds of 4km/h - 8km/h when carrying packs and 10km/h - 30km/h when utilized solely for riding. If we take a full day's travel to be about 12 hours, then the maximum distance traveled by a pedestrian in a day is approximately 60km. For travel on horseback (taking the upper limit of the speed of a pack horse) it would be possible to travel about 96km. In reality, a riding horse could reach much higher speeds and therefore cover distances well over 100km. It is apparent that there is a division in the limitations of these two different travel modes and so both will be considered in this model. In each scenario anything longer than these values will incur large costs so that these trips will only be chosen if there are ample benefits to outweigh the costs. An additional distance must be specified in the model which denotes the point at which very close settlements are considered as one entity ("coarse-graining"). A value of 5km is sufficient for this measure, which would combine settlements where pedestrians could interact with travel times around 1-2 hours regardless of mode, though the site distribution for this study is unaffected since all settlements are separated by values larger than this threshold.

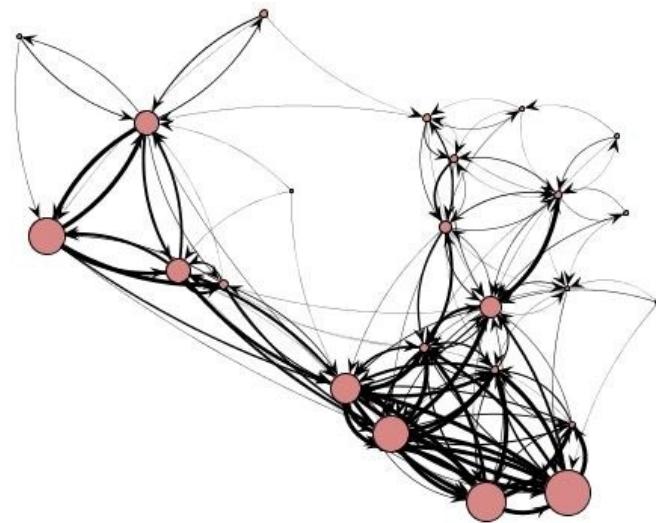
Finally, the model must be parameterized. Ariadne's four parameters k , λ , j , and μ must be adjusted in order to find a network which conforms to a theoretical scenario. Drawing on the experience of previous research (Knappett et al., 2011) we will initiate parameterization using values of $k = 1.0$, $\lambda = 4.0$, $j = -2.0$, and $\mu = 0.1$. For our purpose, we search for a network which allows many nodes to interact, while ensuring the network does not become overly connected. For instance, we should not see small settlements that are sustaining many long distance journeys and no settlements should be sustaining strong long distance links since it would have been prohibitively expensive. In effect, we are seeking a network which represents two different scales (short vs. long) which are differentiated by their strength (strong vs. weak). Parameterization

is a subjective process which requires exploration. While it is arguably unsound to set parameters to satisfy a predefined network structure, we can nevertheless defend our choice by comparing it to other less appealing parameter options given that all other model values are held constant. Sensitivity of parameters was therefore tested by running the model and, in turn, either doubling or halving each initial parameter while holding all others constant (Appendix Figure A.4 and Appendix Figure A.5) and assessing changes to the resulting networks.

By visually examining each network from the parameter tests it is possible to distinguish which values will provide the best representation of interaction, which should resemble a highly connected, yet spatially constrained system defined in Section 4.2.1 (node average of 6-14 connections). For the system assuming 60km average trip lengths, it appears that increasing k , decreasing λ , or decreasing μ will cause the network to become slightly under-connected while decreasing k or increasing λ will result in slightly over-connected networks. Other parameter changes resulted in minimal deviations and overall the system is insensitive. As a result, the initial parameters will be used to produce networks with ideal conditions (Figure 4.4 A) at this scale. It is evident that employing the same initial values for a model accommodating longer trips (Figure 4.4 B) the network will be too dense and permit too many strong long distance relationships. Doubling k or halving λ gives more accurate representations and therefore, by increasing k from 1 to 1.5 and decreasing λ from 4 to 3 it is possible to take a balanced approach to settling on parameters to produce a preferable interaction system.

Due to the stochastic nature of Ariadne it is necessary to take an average of many model runs. This ensures that fluctuations which may occur between different model runs are accounted for within this analysis. All networks produced from this model were filtered to remove near-zero edges using a cutoff value produced by dividing the average edge weight by seven times its standard deviation. This method was chosen, rather than the one employed for the radiation mode, due to the fact that the distribution

(A)

 $j = -2.0, \mu = 0.1, k = 1.0, \lambda = 4.0$

(B)

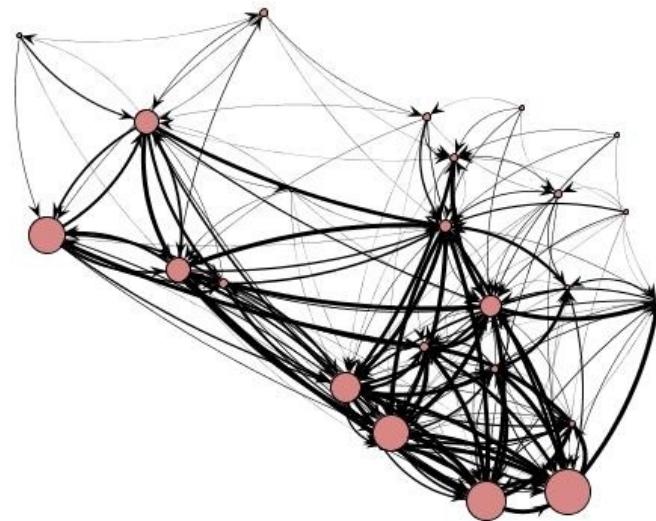
 $j = -2.0, \mu = 0.1, k = 1.0, \lambda = 4.0$

Fig. 4.4: Ariadne model runs with initial parameters for average journeys of 60km (A) and 100km (B)

of network edges for different Ariadne model runs was always similar but that the maximum edge weight value could vary enough so that filtering using a cutoff based upon it would create very different networks.

4.2.4 Agent-based Model

To take an agent-based approach to simulating spatial interaction for this study region, some changes⁴ were imposed upon the TravellerSim model introduced earlier (Section 2.5). First, the local vision was increased from 25km to match the journey limitations proposed for use in the Ariadne model (60km and 100km). This change reflects the additions of horse related transportation and a general increase in spatial awareness that would have been assumed to accompany intensified relationships with the landscape and larger settlements. For this research only the longer distance constraint could be utilized due to the fact that the short distance constraint resulted in an extremely fragmented network (Figure 4.5). Next, the attractiveness of each settlement was calculated each round rather than randomly selecting three from those within a human agent's vision. The original authors (Graham, 2008) explain that this limitation acted primarily as a computation shortcut to prevent lengthy simulation run times and they rationalize this decision by adding that it would have reflected an agent's limited knowledge of their surroundings. It is unknown whether the authors realized that this limitation was the basis for which their model became stochastic (every run yields slightly different results); however, this shortcut was removed due to advances in computing capabilities and the fact that larger, more urbanized sites would have likely had increased knowledge of the region. As a result, the model has become deterministic. To test the stability of the interaction system resulting from this model slight deviations to a site's importance were administered at end of each iteration within the simulation. Each site's importance was increased or decreased with equal probability by a value which was randomly generated according to the Poisson distribution using its current importance as the lambda parameter. Overall, model runs using this alteration (Appendix Figure A.6) manifested remarkably similar structure highlighting the stability

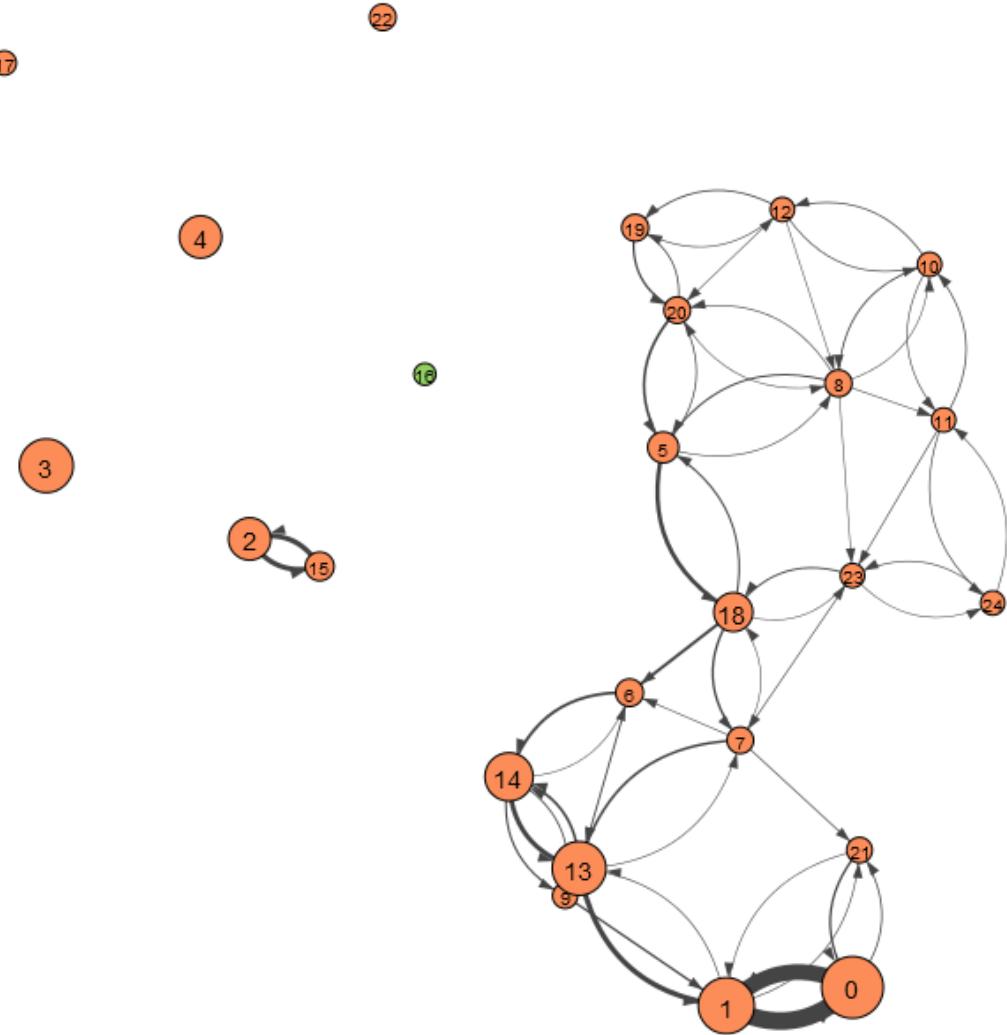


Fig. 4.5: Disconnected network from agent-based framework (60km).

of the modeled process. Another effect of this approach is that the model results will be interpreted statistically, similarly to the Ariadne networks, using the average over many networks.

Parameterization of the agent model includes choosing the logistical variables of how many human agents should start at each settlement agent and how many iterations the model should be run for, as well as model variables such as the difficulty of communication and benefits derived from resources. Testing the simulations with varying numbers of agents or iterations holding other parameters constant demonstrated that the model was insensitive to these logistical inputs. Five agents and 10 iterations were chosen to

⁴ <https://github.com/tayoshan/AgentModel.git>

ensure enough complexity in the model without utilizing unnecessary computing time. The model variables were tested in a similar manner; values for the range .01 to 5 were tested for each parameter holding the other one constant. Again, the system structure proved extremely resilient to these deviations so values of 1 were employed for both variables. Networks produced from the agent-based model do not result in near-zero values for edge weights and therefore do not need to be filtered.

4.3 Network Analysis Metrics

4.3.1 Node-level Metrics

Questions pertaining to the context of individual sites can only be achieved using metrics which consider the properties for each node within a network. Equally vital is the ability to validate the accuracy of each network by comparing the properties developed at each settlement to observed data and the overall usefulness it contributes to archaeological studies. Further, changes within these attributes will provide the interpretations that will ultimately help answer specific questions regarding Poggio Civitate's purpose in the region and the effects of its destruction. This section will establish and review which node-level metrics were employed for site-specific analysis.

Interaction Strength

Interaction is an output of each of the models which does not require any additional computing. Visualization these interactions it is possible to quickly note where interactions are predicted to have occurred in higher volume. It is also possible to take the sum of either all incoming or outgoing interactions for each node. This translates roughly into how much trade, information, or people may have been transferred to this site in comparison to all other sites within the region.

Degree Centrality

The degree is the number of edges connected to a node. Since this research looks at directed networks we must differentiate between the number of edges arriving at a node and the number of edges originating at a node or, more simply, the “in degree” and “out degree”. A settlement is considered more important if it has a higher degree and therefore has many other settlements connecting to it (Rodrigue et al., 2006).

PageRank

Originally developed by Google as a mechanism to ranks web sites, the PageRank algorithm is useful in many networks for ranking nodes based on the structure of incoming links (Page et al., 1999; Langville & Meyer, 2005). It was first suggested for use within archaeological networks by Evans, Knappett, and Rivers (2008) who adopted it due to its ability to account for weighted links and nodes which were characteristic of their simulated interaction networks. Specifically, they were able to find settlements or nodes which “punched above their weight”, meaning they had high PageRank values given their node size, likely acting as a gateway community between clusters (8-11). This measure will be particularly useful for measuring the importance of smaller sites such as Murlo which have been theorized to have great importance.

HITS (Authorities and Hubs)

The hyperlink-induced topic search (HITS) algorithm (Kleinberg, 1999; Page et al., 1999) is similar to PageRank in that it uses links to find nodes of importance, but it computes a value for both incoming links (“authorities”) and outgoing links (“hubs”). This metric will provide validation against the PageRank values and will be helpful in distinguishing between “supply-side” and “demand-side” relationships of nodes.

4.3.2 Network-level Metrics

A core component of this study is to evaluate an entire network, which is representative of a region, in order to compare results from differing models and parameters. Newman (2003) suggests that there are features of networks which arise frequently and are therefore helpful for analysis, such as the small-world effect, transitivity/clustering, degree distributions, network resiliency, mixing patterns, and community structure. Methods for measuring each of these properties which are pertinent to this study will be reviewed, which are typically employed for analysis within transportation studies (Rodrigue et al., 2006). Indices compare one attribute against another to express more complex relationships within a network's structure. The network level metrics and indices reviewed in this section will facilitate comparison between generated interaction networks.

Average Node Degree

Average node degree is similar to the degree measure described previously, except that it does not distinguish between incoming and outgoing relationships. It is, in effect, an average for all degree values calculated for individual nodes. Higher degrees are associated with more connected networks.

Assortativity Coefficient (Degree and Size)

Assortativity measures the similarity of connections in the graph with respect to a given attribute. In this case, the relationship between connectivity and total interaction flowing through a node is being calculated. A higher coefficient means there is a stronger relationship between these two variables within the network (Newman, 2003).

Diameter

The diameter is a measure of the shortest path (number of links traversed) between the most distant nodes in a network. It is a helpful measure because more connected

networks will tend to have smaller diameters and it can be useful to measure how the diameter changes as the network is altered in order to get an idea of changing connectivity.

Transitivity/Average Clustering

A clustering coefficient, which measures transitivity, is most easily described in terms of social networks, in which it is the mean probability that a friend of a friend is also your friend. In network terminology, this relationship is referred to as a triangle and the coefficient measures the ratio of all triangles present in a network compared to the total possible triangles (Newman, 2003). Similarly, to get a network-level measure of transitivity it is possible to calculate the mean cluster coefficient from individual nodes. The coefficient will provide insight into the clustered nature of the generated networks.

Beta Index

The beta index measures network connectivity through the ratio of the number of links to the number of nodes. Simpler networks with less than one cycle (a closed path where no node appears twice and the first and last node are the same) are not very connected, and have a beta index of one, while those which are well connected and have more than one cycle have a beta index greater than one. Holding the number of nodes constant, the higher the number of links, the more paths possible, which corresponds to a higher beta index.

Gamma Index

The Gamma index compares the number of links with the maximum number of possible links. The values range from 0 to 1 with higher values representing more connected networks. The Gamma index is especially useful for measuring changes in networks over time. It is unique because it provides a measure of connectivity independent of nodes.

5. RESULTS

In all of the models, network visualizations offer the first clues into system structures and how Murlo (node 16) factors into the region. Next, network-based and individual node metrics will be provided for each model for a system including Murlo and then again after removing this node from the study region to mimic its destruction. Graph visualizations will also be presented to illustrate the changes in interaction between the two scenarios within each framework. Interaction deviations will be reported as percent increase/decrease from total interaction (incoming and outgoing) at each node for all settlements within the study region. Values of 999 within the following tables represents instances where a metric calculation is not available for a node.

5.1 *Radiation Model*

Network results of the radiation model indicate that Murlo was not a highly connected node and, therefore, that its spatial orientation would not have granted it superior network advantages. Rather, this model indicates that Murlo would have actually been quite isolated, generally lacking the ability to achieve outward interaction. Even the sole incoming interaction to Murlo (Table 5.2) is evidence against its role as a central node within the network since it is the weakest interaction within the entire system. A low PageRank value confirms that it was not, in fact, punching above its weight and did not have a large importance in the overall network connectivity.

A Medium transitivity value (Table 5.1) suggests that there is some mild neighborhood associations within the network but that it is not the defining factor. Frequent weak long-distance interactions in the visualization (Figure 5.1) confirm that small

communities do not prevail as the core structure. Interestingly, upon the removal of Murlo, there is slight increase in the overall connectivity of the network. It is expected that beta index (Table 5.3) will increase with the removal of any nodes (links/nodes), especially minimally connected ones, but values for the transitivity and gamma index also support this slight trend. The gamma index is especially indicative here since it is independent of the number of nodes. Globally, the structure seems not to be influenced (Figure 5.2 and Table 5.4) and is corroborated by the fact that the network diameter remains unchanged. The new system state supports approximately five percent increases in interaction for nodes 4 and 5 while node 22 approaches a 20 percent gain in interaction (Figures 5.3 and 5.4) (corresponding node name's located in Figure 4.1).

Visualizations

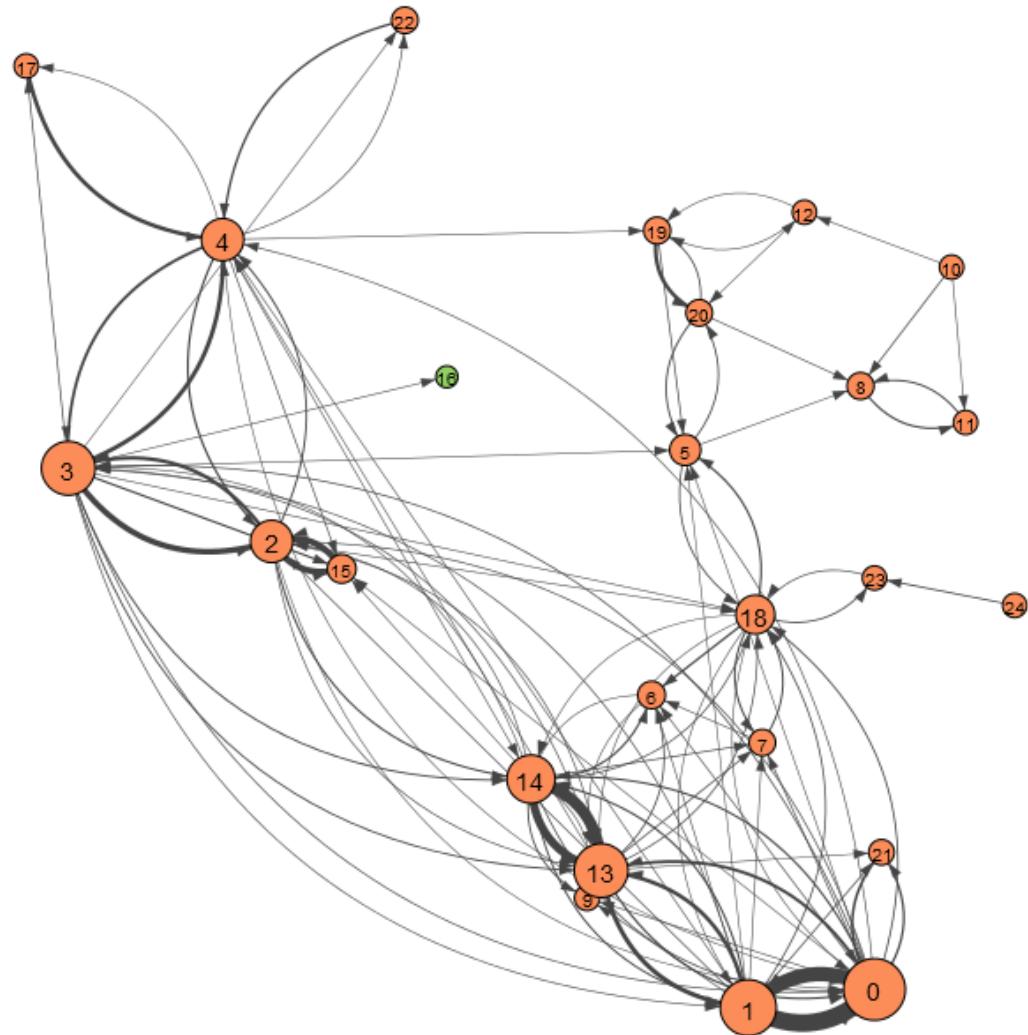


Fig. 5.1: Visualization of a single radiation model run including Murlo.

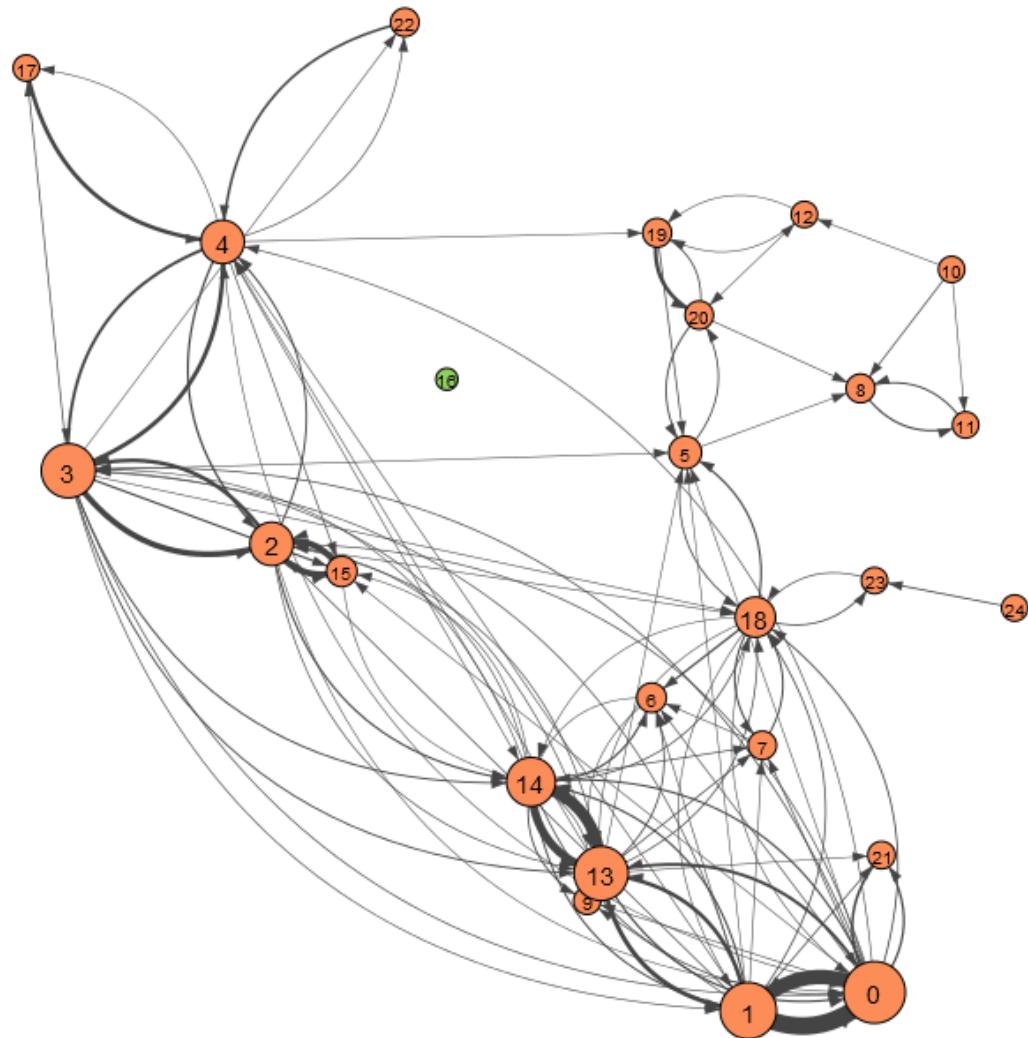


Fig. 5.2: Visualization of a single radiation model run excluding Murlo.

Metrics

Tab. 5.1: Network metrics for radiation model before the destruction of Murlo

Metric	Assortativity	Diameter	Average Degree	Transitivity	Beta	Gamma
Radiation Model (Before)	-0.06080357	5	8.72	0.44292804	4.36	0.1744

Tab. 5.2: Node metrics for radiation model before the destruction of Murlo

Node	Interaction In	Interaction Out	Degree In	Degree Out	PageRank	Hubs	Authorities
0	108.75090365	111.16414012	8	13	0.06751344	0.14177813	0.40598155
1	96.07389215	122.16387527	5	12	0.06478559	0.44423172	0.13413920
2	67.87638768	56.74109960	7	7	0.06741936	0.02266724	0.02894542
3	33.31327788	68.03210348	6	12	0.03977904	0.03765628	0.02027152
4	49.93975449	25.07446728	7	8	0.03640718	0.01098481	0.01785142
5	15.57227832	7.52633653	6	3	0.03935866	0.00092203	0.00707285
6	19.07883554	2.10864198	6	2	0.03306262	0.00306255	0.01858651
7	13.05993630	6.04581589	5	2	0.02289676	0.00165243	0.01460570
8	9.06115422	5.47008547	4	1	0.09012996	0.00000000	0.00001391
9	27.85788453	22.08000000	4	2	0.02778622	0.03360924	0.04525178
10	0.00000000	4.73429952	0	3	0.00623404	0.00000042	0.00000000
11	6.67781494	4.44444444	2	1	0.08419627	0.00000072	0.00000001
12	2.59301085	1.79757322	2	2	0.00909824	0.00000210	0.00000296
13	94.33529348	113.27241140	8	11	0.10268830	0.14690874	0.13064157
14	78.80731418	62.97010450	9	10	0.07948022	0.08401978	0.11709181
15	38.35885414	28.57142857	5	1	0.04194336	0.00969919	0.01136807
16	1.30662021	0.00000000	1	0	0.00688343	0.00000000	0.00050247
17	3.35917313	16.66666667	2	1	0.00866548	0.00348936	0.00101027
18	23.34730839	24.57352717	9	8	0.06042608	0.01249645	0.02455853
19	5.22510994	19.24215940	3	3	0.02471582	0.00020864	0.00013203
20	19.71195355	8.70209059	3	3	0.04181020	0.00035005	0.00006471
21	9.95700623	9.26644932	3	1	0.01146410	0.04412081	0.02097623
22	2.45524664	7.26744186	2	1	0.00862441	0.00152152	0.00051184
23	6.61742424	2.08793908	2	1	0.01839718	0.00060137	0.00041967
24	0.00000000	3.33333333	0	1	0.00623404	0.00001641	0.00000000

Tab. 5.3: Network metrics for radiation model after the destruction of Murlo

Metric	Assortativity	Diameter	Average Degree	Transitivity	Beta	Gamma
Radiation Model (After)	-0.06149662	5	8.8	0.46039604	4.58333333	0.19097222

Tab. 5.4: Node metrics for radiation model after the destruction of Murlo

Node	Interaction In	Interaction Out	Degree In	Degree Out	PageRank	Hubs	Authorities
0	108.87945837	111.28995232	8	13	0.06801471	0.14163172	0.40324103
1	96.24280876	122.25482314	5	12	0.06532898	0.44076822	0.13419461
2	68.33916527	58.24965169	7	7	0.06611103	0.02357307	0.02983908
3	35.08523104	67.13766184	6	11	0.04047912	0.03834858	0.02094712
4	51.88176247	26.33777091	7	8	0.03687712	0.01148110	0.01822987
5	16.86599343	7.52633653	7	3	0.04070164	0.00092053	0.00847579
6	19.07883554	2.10864198	6	2	0.03333116	0.00305249	0.01855696
7	13.05993630	6.04581589	5	2	0.02306993	0.00164857	0.01457395
8	9.06115422	5.47008547	4	1	0.09093085	0.00000000	0.00001483
9	27.85788453	22.08000000	4	2	0.02786109	0.03345954	0.04514594
10	0.00000000	4.73429952	0	3	0.00625000	0.00000046	0.00000000
11	6.67781494	4.44444444	2	1	0.08489646	0.00000077	0.00000001
12	2.59301085	1.79757322	2	2	0.00909570	0.00000236	0.00000405
13	94.47431256	114.20909230	8	12	0.10355927	0.14659166	0.13024651
14	80.00784943	63.28116180	10	10	0.08076402	0.08412710	0.11706552
15	38.48556453	29.43232320	5	2	0.04082815	0.01116279	0.01174679
16	0.00000000	0.00000000	999	999	999	999	999
17	3.51731602	16.66666667	2	1	0.00878597	0.00355765	0.00108121
18	23.44998253	24.63662226	9	8	0.06125753	0.01268673	0.02454451
19	5.26560692	19.60770605	3	3	0.02481946	0.00028580	0.00014456
20	19.71195355	8.70209059	3	3	0.04209021	0.00041828	0.00007691
21	9.95700623	9.26644932	3	1	0.01151002	0.04375314	0.02090135
22	2.55094330	8.96057348	2	1	0.00868424	0.00191272	0.00054308
23	6.61742424	2.08793908	2	1	0.01850335	0.00060007	0.00042632
24	0.00000000	3.33333333	0	1	0.00625000	0.00001664	0.00000000

Interaction Shifts

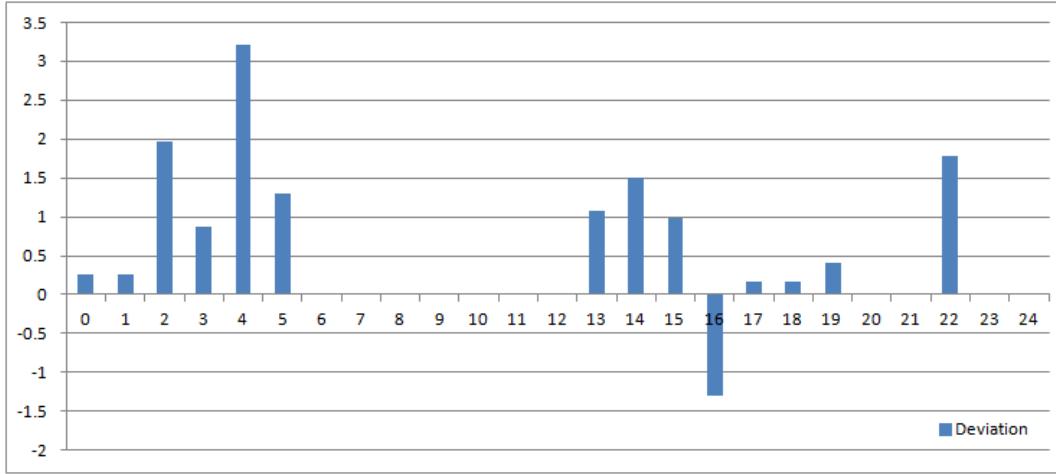


Fig. 5.3: Total interaction shift by node for radiation model.

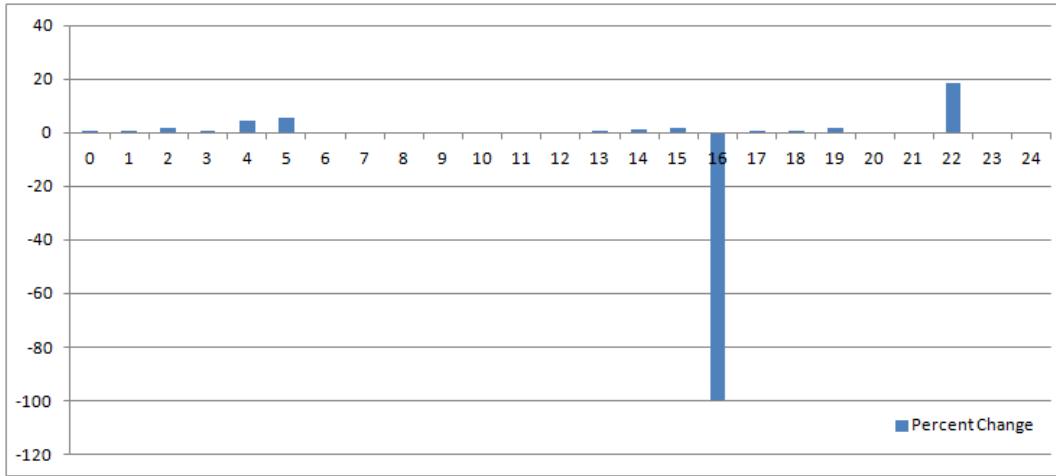


Fig. 5.4: Percent total interaction by node for radiation model.

5.2 Ariadne Model

In each scenario, the network-level metrics converged to steady values within 25 averaged model runs (Appendix Tables A.3, A.4, A.5, A.6). At the lower distance threshold the Ariadne model indicates that on average, Murlo would have sustained 2-3 outgoing interactions and 0-1 incoming interactions (Table 5.6) though they would have been among some of the weakest links within the network. Increasing the distance threshold does not have an impact on Murlo's connectivity (Table 5.8) despite the overall increase in connectivity suggested by a decreasing diameter value (Table 5.5 and 5.7). Both model variations produce PageRank and HITS values (Tables 5.6 and 5.8) that are extremely small and therefore confirm Murlos's relative lack of importance within the system.

High transitivity values suggest strong neighborhood effects within all of the Ariadne model results. It is easy to visually extract communities in the lower distance threshold results (Figure 5.5 and 5.7) though the longer distance threshold results (Figures 5.6 and 5.8) present an interesting deviation for settlements in the northeast. The increased travel distance capabilities seem to have decreased the frequency with which these sites interact with themselves. Instead of forming their own community, they tend to

explicitly interact with larger more distant nodes. It is difficult to quantify changes within the Ariadne networks after the destruction of Murlo. For both variations of the model the metrics present mixed evidence (Tables 5.9, 5.11, 5.10, and 5.12) for whether or not the system becomes more connected. Additionally, none of the resulting values represent large deviations, so the variations within the measurements are likely due to the stochastic nature of the model. Ultimately, the removal of Poggio Civitate does not cause significant shifts within the network. There is a split in the number of nodes which gain interaction and those which lose interaction for the 60km threshold (Figures 5.9 and 5.10). Nodes 3, 5, 9, 20 , and 22 show the largest increases, with node 5 (Chiusi) having the highest, at about 21 percent. In contrast, nodes 6, 14, 15, 23, and 24 decrease the most significantly with maximum loses of 20 percent by node 15. The 100km threshold (Figures 5.11 and 5.12) is dominated by decreasing interaction shifts. Seventeen nodes proved to have decreased interaction, with 7 of the nodes (0, 1, 9, 11, 13, and 19) having loses between 20-30 percent. Nodes 4, 8, and 22 show substantial gains of 10-20 percent.

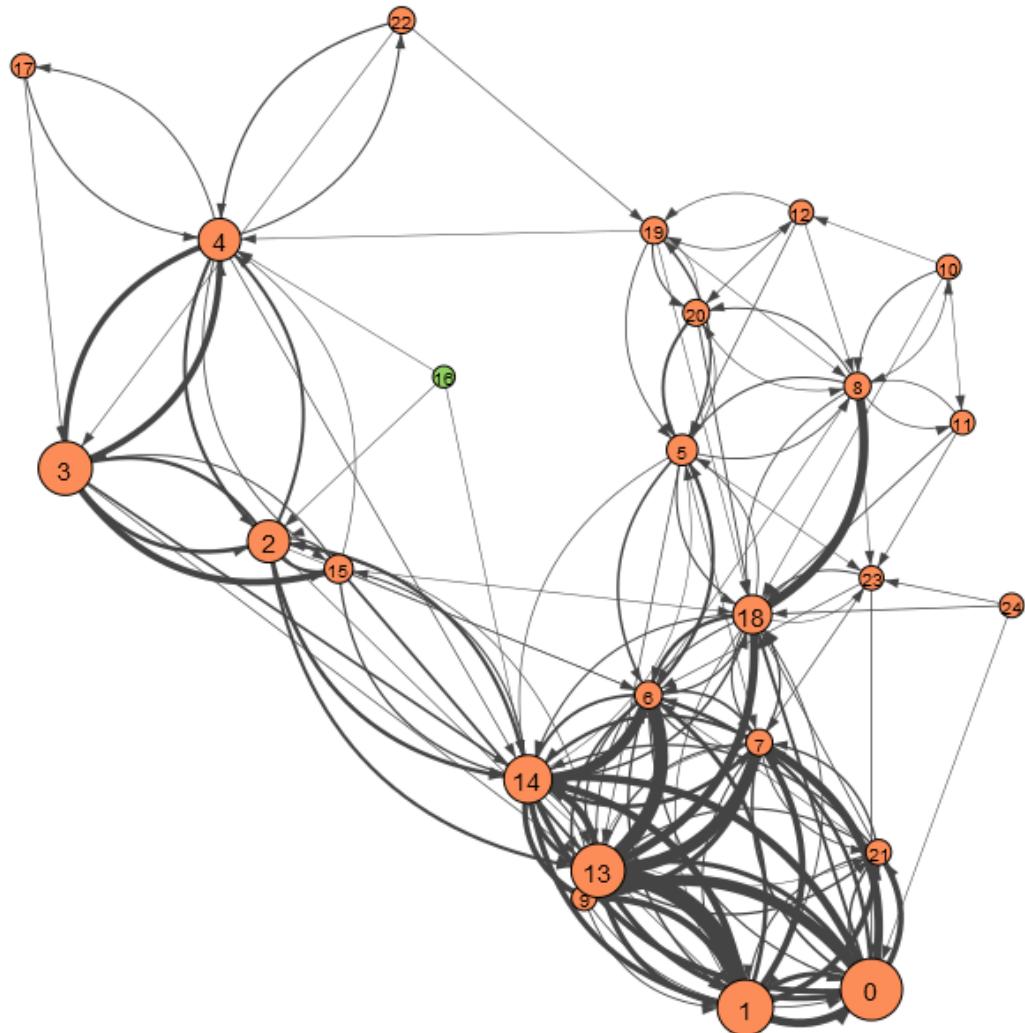
Visualizations

Fig. 5.5: Visualization of a single Ariadne model run including Murlo (60km).

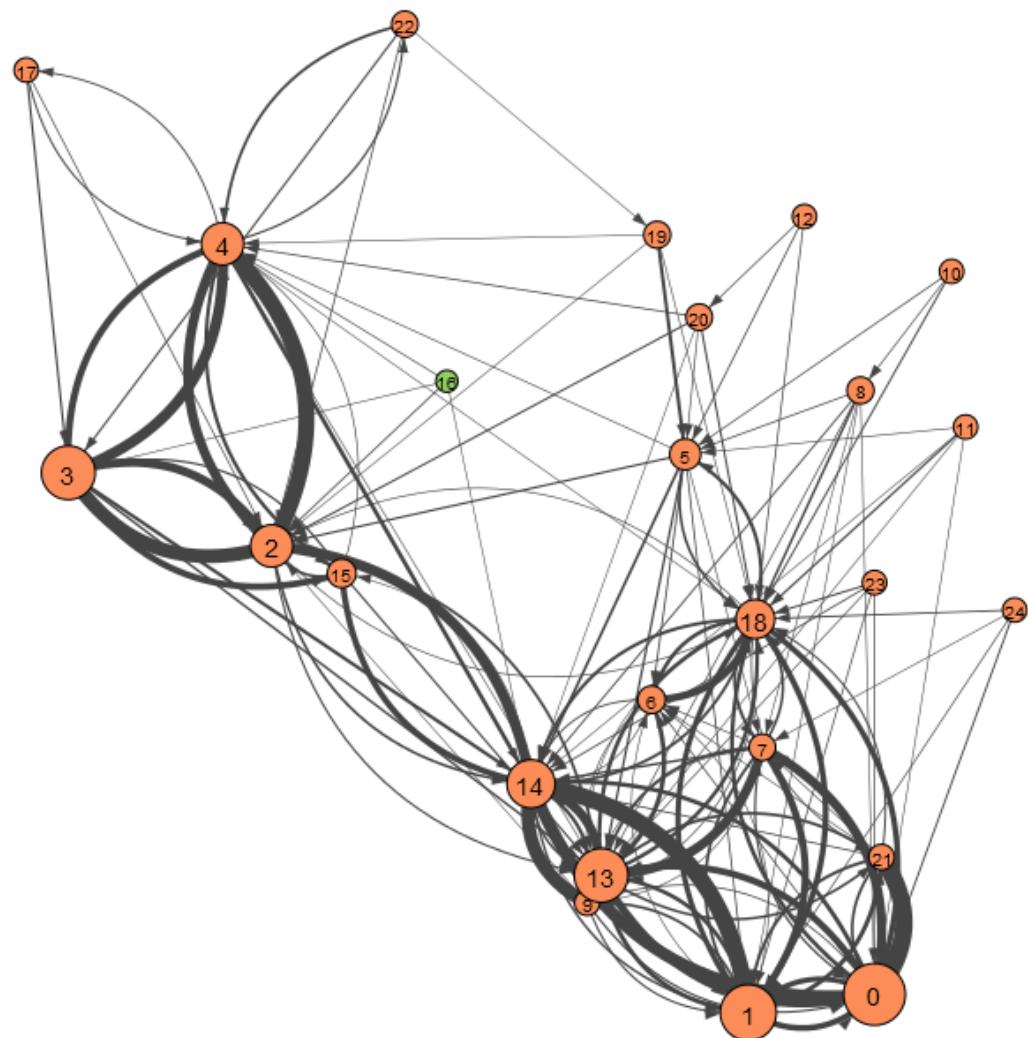


Fig. 5.6: Visualization of a single Ariadne model run including Murlo (100km).

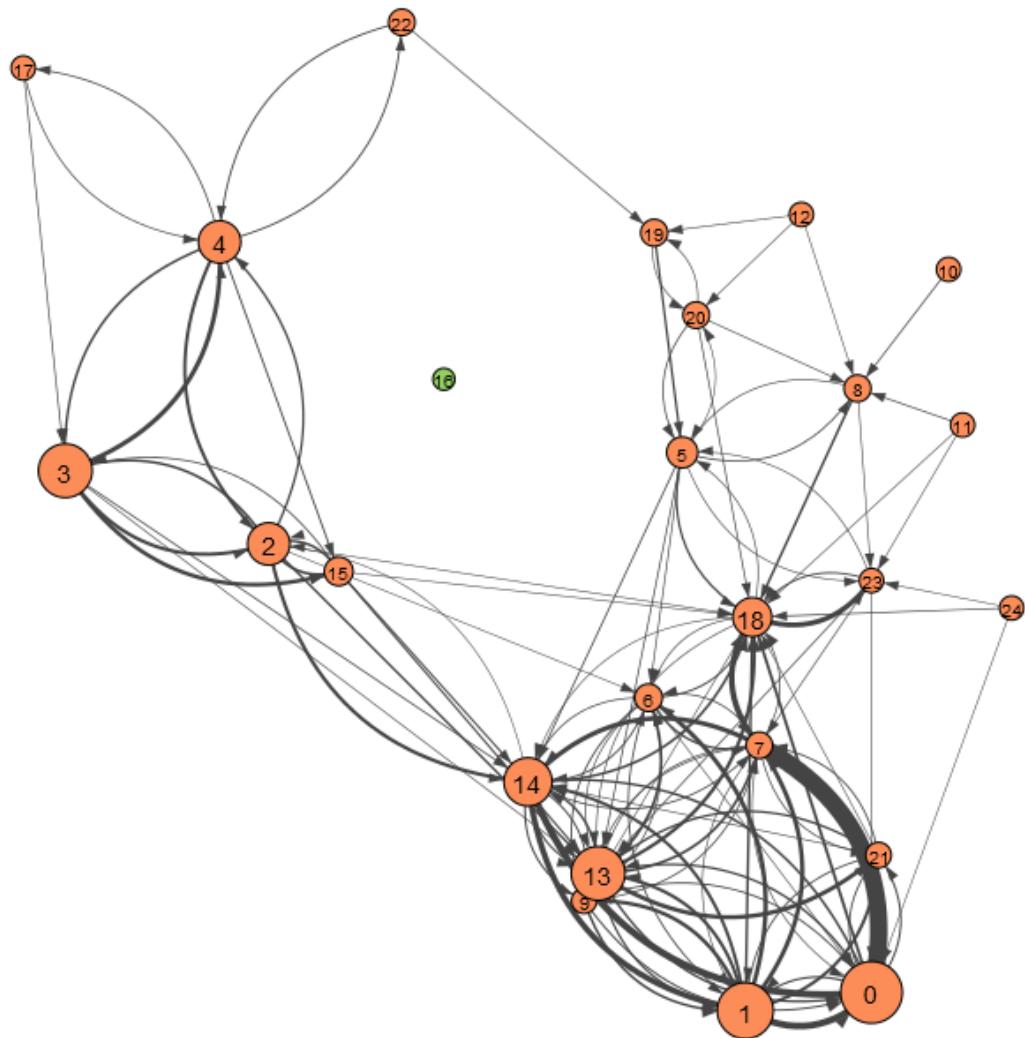


Fig. 5.7: Visualization of a single Ariadne model run excluding Murlo (60km).

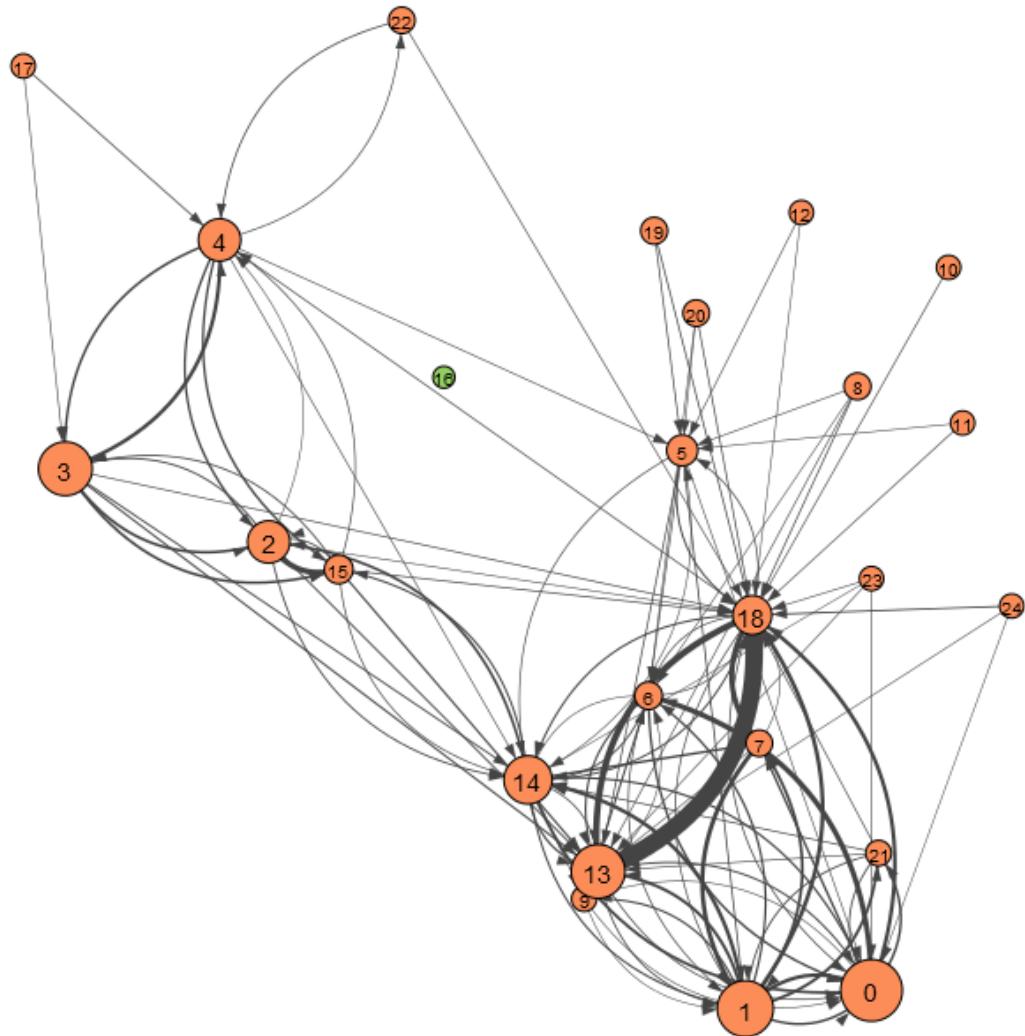


Fig. 5.8: Visualization of a single Ariadne model run excluding Murlo (100km).

Metrics

Tab. 5.5: Network metrics for Ariadne (60km) model before the destruction of Murlo.

Metric	Assortativity	Diameter	Average Degree	Transitivity	Beta	Gamma
Ariadne (Before: 60km)	-0.05119454	4.1600	11.6288	0.70893446	5.8144	0.232576

Tab. 5.6: Node metrics for Ariadne (60km) model before the destruction of Murlo.

Node	Interaction In	Interaction Out	Degree In	Degree Out	PageRank	Hubs	Authorities
0	5.15605044	10.37701864	9.0000	7.9600	0.06366162	0.20301292	0.08377937
1	4.78002280	10.50274632	8.6800	8.0400	0.06119557	0.17104314	0.08207493
2	4.37817908	4.00114796	6.8800	7.0400	0.05291583	0.03862894	0.03790744
3	2.33393132	4.43702164	4.7200	5.3600	0.03687551	0.02893478	0.00651458
4	2.45377924	2.54004316	5.2000	6.2400	0.03412294	0.00863165	0.00737997
5	1.40997460	1.56258092	7.0800	6.8800	0.04080041	0.01457215	0.00298033
6	5.68686764	2.35101684	10.3600	7.2000	0.06827045	0.02891943	0.08440798
7	5.83026388	2.09756240	9.6000	7.2000	0.06808746	0.02972334	0.08683485
8	0.89294904	0.82821912	5.8800	5.2400	0.02871467	0.00346677	0.00064527
9	4.70216060	2.03496144	5.8000	6.5600	0.04789472	0.02954883	0.10339356
10	0.04208724	0.32914720	0.6800	4.0000	0.00705151	0.00033416	0.00000596
11	0.16607516	0.38591676	1.7600	3.6800	0.01023432	0.00225924	0.00003969
12	0.20469996	0.37850296	2.5200	4.0000	0.01064349	0.00004972	0.00002770
13	7.94302340	10.75129336	13.2000	8.9200	0.09234654	0.19751654	0.13496315
14	7.99095508	7.94175732	12.9200	9.2400	0.09671460	0.14070298	0.13147314
15	3.65079068	1.81954172	5.0000	6.1600	0.04215937	0.01908715	0.03044919
16	0.02997972	0.16392172	0.4800	2.4000	0.00637868	0.00080004	0.00013414
17	0.20060956	0.38098608	1.0000	2.5200	0.00830969	0.00058663	0.00023103
18	6.67819704	3.98009484	15.8800	8.2800	0.09394147	0.04162679	0.10691481
19	0.44540620	0.68159284	3.3200	4.6000	0.01687598	0.00126330	0.00019425
20	0.89644132	0.79641936	4.8000	4.8000	0.02820003	0.00252656	0.00084704
21	4.74922272	1.84394700	5.6000	6.3600	0.04352903	0.02428703	0.09637430
22	0.18489916	0.50844160	1.0000	3.4400	0.00801272	0.00059727	0.00016563
23	0.86265308	0.63189508	3.8400	5.2000	0.02632835	0.00780512	0.00223517
24	0.01772372	0.36116640	0.1600	4.0400	0.00673504	0.00407552	0.00002649

Tab. 5.7: Network metrics for Ariadne (100km) model before the destruction of Murlo

Metric	Assortativity	Diameter	Average Degree	Transitivity	Beta	Gamma
Ariadne (Before: 100km)	-0.05581519	3.12	11.6576	0.69901818	5.8288	0.233152

Tab. 5.8: Node metrics for Ariadne (100km) model before the destruction of Murlo.

Node	Interaction In	Interaction Out	Degree In	Degree Out	PageRank	Hubs	Authorities
0	4.89983452	8.32066644	12.0000	8.2000	0.08609509	0.19495887	0.10330187
1	5.65126364	8.52547084	12.3200	8.2000	0.08667110	0.20906030	0.09710958
2	3.62511764	3.19648376	10.2400	8.0000	0.05521474	0.03331761	0.07971386
3	1.93787876	3.88205340	5.7200	6.6400	0.03461827	0.06809476	0.00905391
4	2.01789728	2.54596744	6.0400	7.4800	0.03514888	0.01994091	0.01186065
5	1.89805124	1.26250424	9.5200	6.5200	0.04565378	0.01767523	0.02984303
6	3.00178612	1.37872700	7.9600	6.1600	0.05573647	0.01598653	0.04757637
7	3.31958660	1.40210708	7.4400	6.7200	0.05190872	0.02035527	0.06626117
8	0.23871468	0.57470524	2.0000	4.6800	0.01353769	0.00719601	0.00115689
9	3.67211716	1.25457724	5.0800	5.8000	0.05740215	0.02130661	0.13629920
10	0.00000000	0.23889756	0.0000	3.4800	0.00600000	0.00253050	0.00000000
11	0.01417564	0.30614564	0.1200	3.8400	0.00651435	0.00446946	0.00000928
12	0.00624680	0.24945936	0.0400	3.4800	0.00611249	0.00229586	0.00000497
13	7.01137616	7.85547568	16.2800	9.7200	0.10442409	0.15895122	0.13394608
14	5.87803916	5.48273092	16.4400	8.7200	0.09823489	0.11429405	0.08765036
15	2.10607784	1.24976596	4.3600	5.9200	0.03282420	0.01499822	0.02142376
16	0.02693540	0.13393868	0.2400	2.2400	0.00651135	0.00186924	0.00038813
17	0.21029052	0.36706780	0.9600	3.0000	0.00855607	0.00137643	0.00096169
18	5.20334476	3.14990504	18.7200	8.6400	0.09951101	0.04250434	0.08257974
19	0.32510116	0.49862944	1.4000	5.1200	0.01390796	0.00508193	0.00077852
20	0.24431164	0.50793272	1.7200	4.2000	0.01420025	0.00675260	0.00065684
21	2.68562484	1.27637096	4.5200	6.0800	0.03734474	0.01960192	0.08137327
22	0.27613360	0.51696952	1.2400	3.9600	0.00994763	0.00260495	0.00115287
23	0.55702292	0.48574020	0.8800	4.8800	0.02056382	0.00794017	0.00575367
24	0.25766600	0.40230192	0.4800	4.0400	0.01336026	0.00683703	0.00114427

Tab. 5.9: Network metrics for Ariadne (60km) model after the destruction of Murlo.

Metric	Assortativity	Diameter	Average Degree	Transitivity	Beta	Gamma
Ariadne (After: 60km)	-0.05325428	4.24	11.3152	0.72501267	5.89333333	0.24555556

Tab. 5.10: Node metrics for Ariadne (60km) model after the destruction of Murlo.

Node	Interaction In	Interaction Out	Degree In	Degree Out	PageRank	Hubs	Authorities
0	5.16036156	10.47627292	8.8000	8.1200	0.06567145	0.19987111	0.08149631
1	5.23551720	11.09284644	9.0000	8.0000	0.06563621	0.22235560	0.08286413
2	4.09353752	4.00969188	6.1200	6.4400	0.04967571	0.02580089	0.03167777
3	2.89074720	4.70419836	4.5200	5.4400	0.04058895	0.02506704	0.00572947
4	2.78197232	2.62088708	4.4000	5.7600	0.03650362	0.00796128	0.00729260
5	1.96130524	1.66822824	7.3200	6.8000	0.05233911	0.01776381	0.00499504
6	4.68613712	2.23687204	10.2400	8.0400	0.05813292	0.03338689	0.07890425
7	5.93678260	2.06810156	9.4800	7.4800	0.06582744	0.02921817	0.11104847
8	0.89386664	0.81513760	5.7600	5.1600	0.03269063	0.00363226	0.00088401
9	5.63912128	2.09009756	6.2400	7.2400	0.05185054	0.03139406	0.13298361
10	0.05323988	0.31759552	0.7600	3.6000	0.00783581	0.00029367	0.00001598
11	0.17444720	0.36762904	1.6400	3.5200	0.01275970	0.00213306	0.00005358
12	0.21906448	0.37656312	2.2800	3.7200	0.01182928	0.00014320	0.00003602
13	7.58302480	10.38153036	12.6800	9.4000	0.08908923	0.17368731	0.14408559
14	7.05862416	7.22942652	12.8000	8.9600	0.08587737	0.12400177	0.10205289
15	2.77190060	1.63238884	4.1600	5.7200	0.03197597	0.01657326	0.01461682
16	0.00000000	0.00000000	999.0000	999.0000	999	999	999
17	0.18248772	0.37659180	1.0000	2.3600	0.00857153	0.00049695	0.00019297
18	6.36680940	3.74639724	15.4400	7.9200	0.09275439	0.04109655	0.09139855
19	0.46389328	0.69044140	3.4000	4.2800	0.01935123	0.00093279	0.00021101
20	1.02280624	0.83296720	4.7200	4.4800	0.03604473	0.00268190	0.00103421
21	4.97287868	1.90607880	6.3600	7.0800	0.04788491	0.02784183	0.10603521
22	0.25915400	0.51584076	1.0000	3.3600	0.00957424	0.00069252	0.00028271
23	0.71327764	0.63059148	3.2400	4.9600	0.02103774	0.00866464	0.00204226
24	0.01100452	0.34558552	0.0800	3.6000	0.00649732	0.00430945	0.00006656

Tab. 5.11: Network metrics for Ariadne (100km) model after the destruction of Murlo.

Metric	Assortativity	Diameter	Average Degree	Transitivity	Beta	Gamma
Ariadne (After: 100km)	-0.05695306	3.08	10.9184	0.67954338	5.68666667	0.23694444

Tab. 5.12: Node metrics for Ariadne (100) model after the destruction of Murlo.

Node	Interaction In	Interaction Out	Degree In	Degree Out	PageRank	Hubs	Authorities
0	3.06643424	6.07401580	10.2400	8.0400	0.07545583	0.12093972	0.05003812
1	3.83291536	6.11571240	10.8000	8.5600	0.07693095	0.17498175	0.09110773
2	3.67581112	3.18717124	9.8000	7.6000	0.06189563	0.05298723	0.09799815
3	2.00754312	3.94399972	5.4800	6.5200	0.04231811	0.10390300	0.02089409
4	2.32559364	2.70775716	6.0400	7.2400	0.04216085	0.03195118	0.04732999
5	1.80055964	1.22150472	9.0000	5.8000	0.04532250	0.02270255	0.02714574
6	3.01853756	1.26870548	7.9200	6.2400	0.05922607	0.02041338	0.06835380
7	2.98474928	1.24622852	7.0400	6.3200	0.05939650	0.02258723	0.06634617
8	0.37216576	0.54676900	2.6800	4.5600	0.01924075	0.00807622	0.00184202
9	2.27813524	0.97101088	4.3200	5.4400	0.04395270	0.01802054	0.06755565
10	0.00000000	0.21901440	0.0000	2.8800	0.00625000	0.00204394	0.00000000
11	0.00285328	0.24479564	0.0400	2.8400	0.00631119	0.00316273	0.00000068
12	0.00000000	0.24383828	0.0000	3.2000	0.00625000	0.00229727	0.00000000
13	4.62837940	5.87608252	14.8000	8.8000	0.09805619	0.19027115	0.08701165
14	4.98773616	4.62298124	14.9200	9.4400	0.09624714	0.10113253	0.11419163
15	2.25499136	1.21904160	4.5200	5.6400	0.03922334	0.02023867	0.06115087
16	0.00000000	0.00000000	999	999	999	999	999
17	0.18038704	0.37240288	1.0800	2.9200	0.00893836	0.00326753	0.00173073
18	4.43973696	2.94574080	17.9200	7.9200	0.09698155	0.04840445	0.07125558
19	0.20792500	0.46888040	1.7200	4.6000	0.01190047	0.00565915	0.00059329
20	0.08612292	0.47842216	1.3200	4.3600	0.00873340	0.00914215	0.00010721
21	2.84477672	1.11921204	4.8000	5.8000	0.05199142	0.02056158	0.11730373
22	0.41162352	0.51311336	1.2000	3.8000	0.01329582	0.00474654	0.00261211
23	0.54839324	0.39617168	0.6800	4.4800	0.02041257	0.00736051	0.00359720
24	0.37564960	0.32844824	0.1600	3.4800	0.00950866	0.00514898	0.00183386

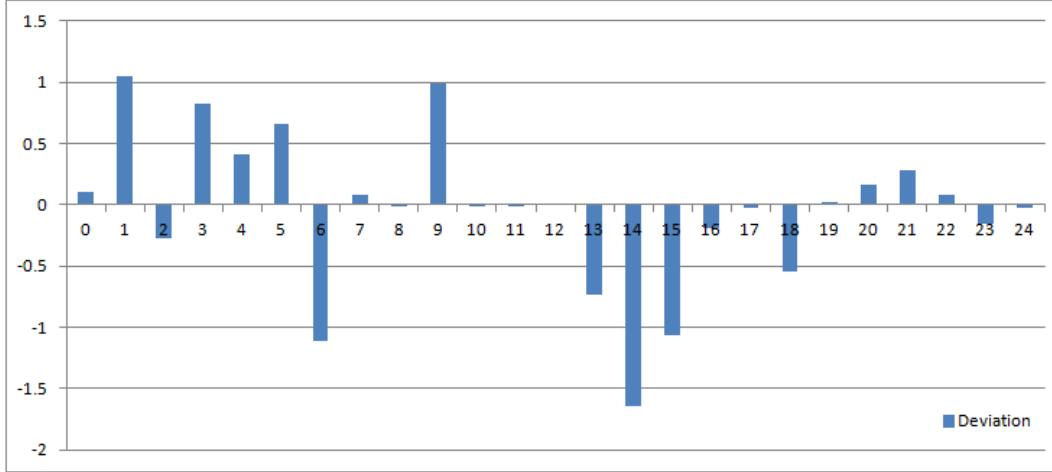
Interaction Shifts

Fig. 5.9: Total interaction shift by node for Ariadne (60km).

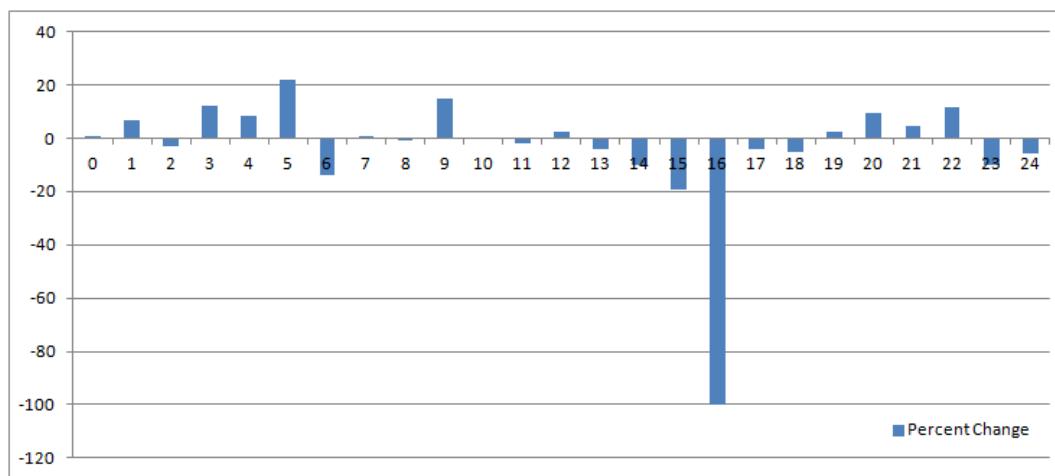


Fig. 5.10: Percent total interaction shift by node for Ariadne (60km).

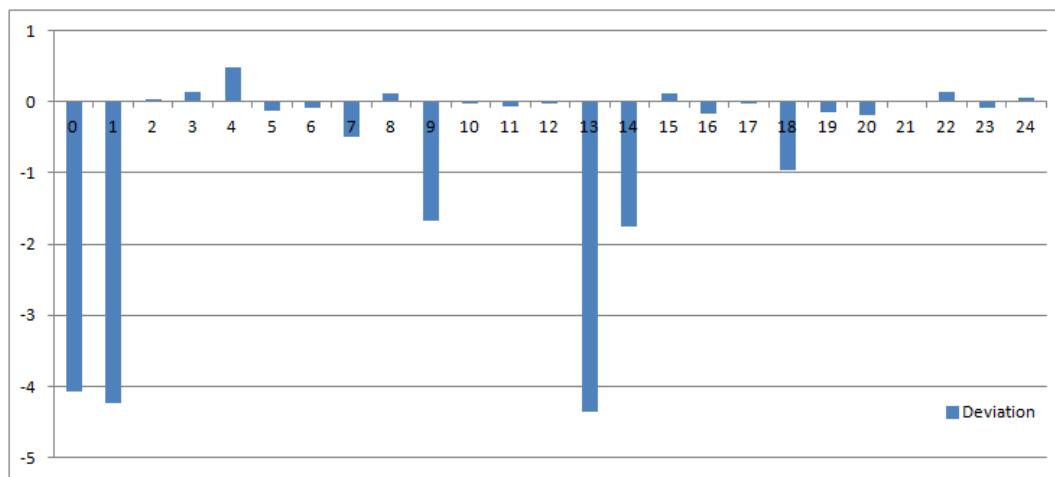


Fig. 5.11: Total interaction shift by node for Ariadne (100km).

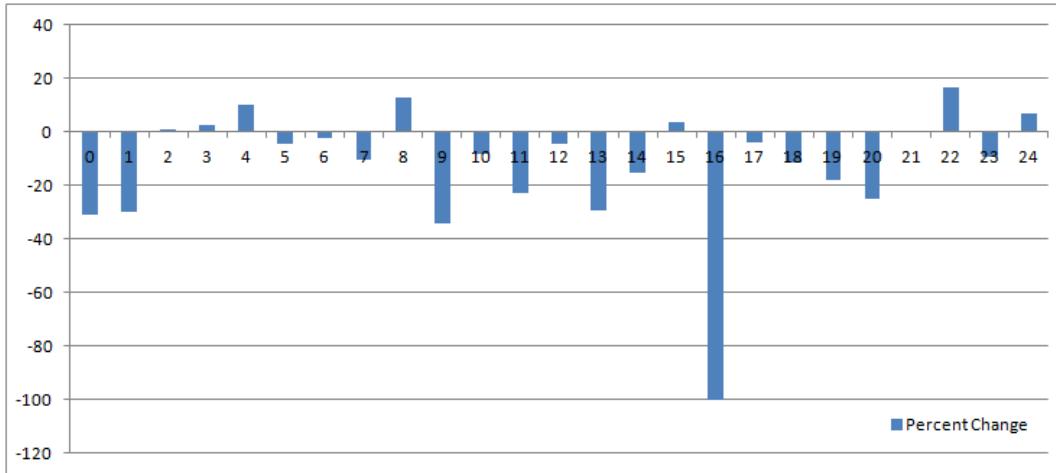


Fig. 5.12: Percent total interaction shift by node for Ariadne (100km).

5.3 Agent-based Model

The agent-based model network-level metric results converged to steady values within 25 models runs (Appendix Tables A.7 and A.8). While Murlo does not appear to be highly connected, it does seem to be central to the northern settlements (Figure 5.13). On average the model results suggest that Murlo would have maintained 2-3 incoming edges and about 3 outgoing edges (Table 5.14). Though the agent-based model has produced the most promising evidence for Murlo as a central node, the interaction quantity maintained over its edges would still have been among the weakest within the system. Even if Murlo did sustain connections with as many as six other settlements, it was likely not fostering strong affiliations. PageRank and HITS values are very small and therefore do not indicate that Murlo was serving an important central function.

Visually, the networks from this model seem to result in communities with higher connectivities (Figures 5.13 and 5.14). Transitivity values (5.13) show that there is some association between neighbors. Overall, these networks are less connected than previous models, which is supported by a smaller average degree (Table 5.13). The removal of Murlo (Table 5.16 does not seem to suggest any strong fluctuations within the system. Minor decreases in the average degree and beta index Tables 5.13 and

5.15 suggest slightly less connectivity while small increases in the gamma index suggest higher connectivity. All of these variations are small and do not provide strong evidence towards any real transformations of the network. Similar to the Ariadne results, the mixed observations are likely due to noise generated from the stochastic nature of the model. Individual nodes are split between interaction gains and loses and most variations occur at less than 10 percent deviations). Nodes 18, 19, and 20 show moderate increases around 15-20 percent while node 24 shows intense gains of about 50 percent. Likewise, 7 and 11 have the highest loses which approach 20 percent (Figure 5.15 and 5.16).

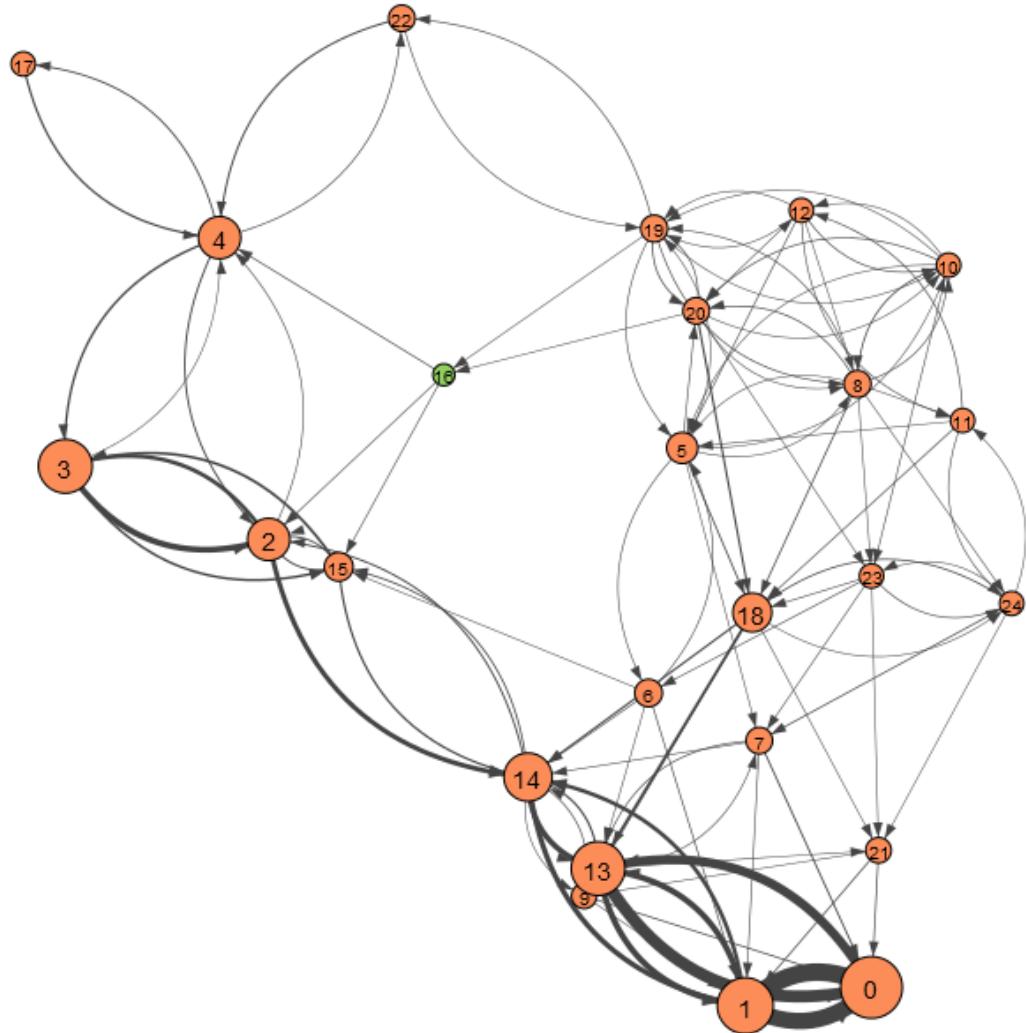
Visualizations

Fig. 5.13: Visualization of a single agent-based model run including Murlo.

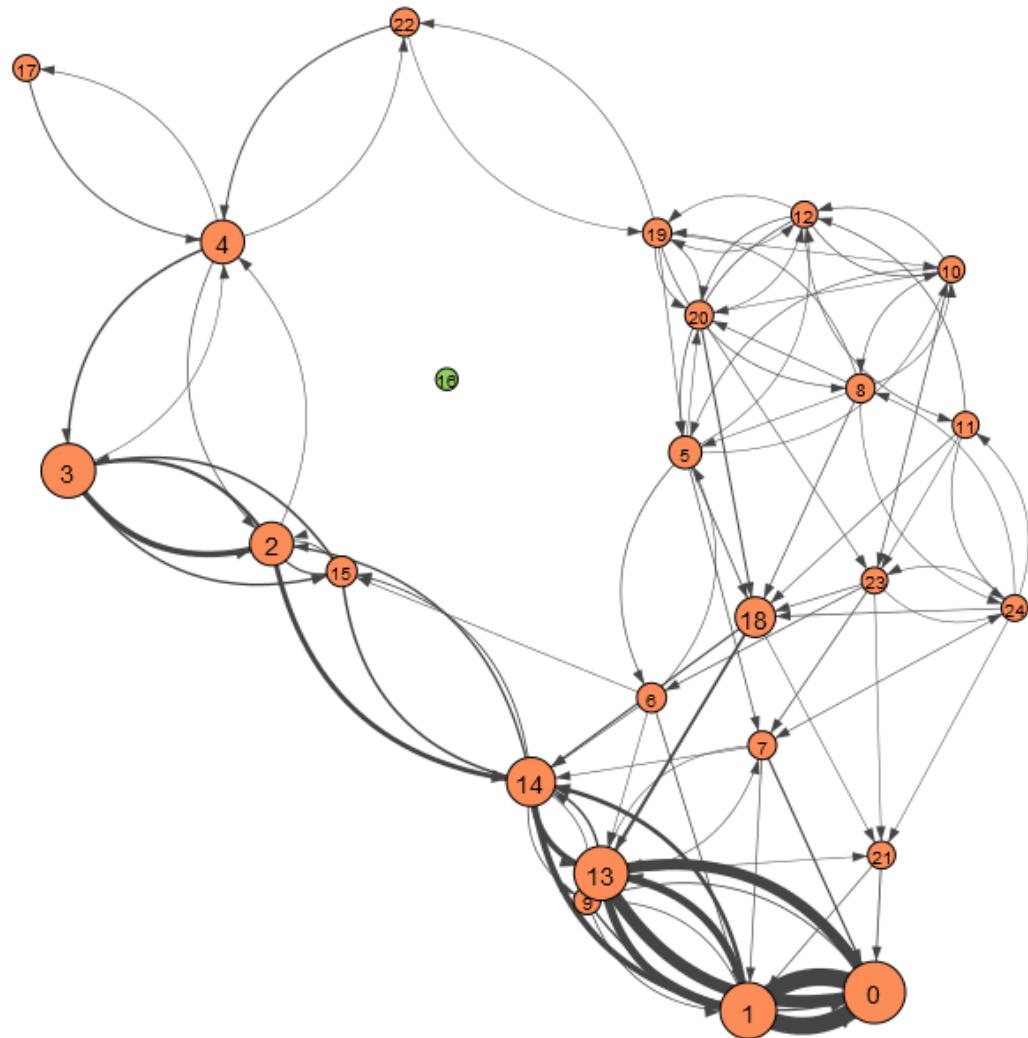


Fig. 5.14: Visualization of a single agent-based model run excluding Murlo.

Metrics

Tab. 5.13: Network metrics for agent model before the destruction of Murlo.

Metric	Assortativity	Diameter	Average Degree	Transitivity	Beta	Gamma
Agent Model (Before)	-0.03900133	5.0	8.3136	0.43295384	4.1568	0.166272

Tab. 5.14: Node metrics for Agent model before the destruction of Murlo.

Node	Interaction In	Interaction Out	Degree In	Degree Out	PageRank	Hubs	Authorities
0	268.8800	235.3600	5.0000	3.5200	0.20116159	0.27213437	0.35633480
1	252.7200	222.3600	7.0000	4.2800	0.18596166	0.28471034	0.29682130
2	84.6000	87.0000	5.0000	4.2400	0.05479031	0.00688518	0.00568801
3	73.8400	77.1200	3.0000	3.0000	0.04913631	0.00196484	0.00214724
4	26.9200	31.9200	5.0000	4.1600	0.02688070	0.00030261	0.00009308
5	12.9600	17.9600	5.8000	5.7200	0.01715167	0.00009261	0.00012245
6	10.3200	15.3200	2.4400	5.1600	0.01464954	0.01140266	0.00029078
7	9.1200	13.8800	4.0400	4.2000	0.01425532	0.01648979	0.00502421
8	7.5600	12.5200	3.4000	5.4800	0.01281434	0.00000104	0.00000039
9	24.2400	26.8000	5.6000	4.0400	0.02329927	0.03309842	0.02744999
10	5.5200	10.5200	3.0800	4.7600	0.01080427	0.00000177	0.00000036
11	5.7600	10.7200	3.2000	4.4000	0.01145565	0.00000112	0.00000585
12	6.0400	10.8800	3.1600	4.0000	0.01133522	0.00000173	0.00000011
13	223.5600	194.9200	7.6000	6.0000	0.16549250	0.25261614	0.26289842
14	85.5600	86.4800	8.0000	5.4000	0.06104593	0.08582814	0.03723831
15	32.0400	36.2800	4.5200	3.2000	0.02433631	0.00220370	0.00178417
16	3.6800	8.6800	2.5200	3.1600	0.00896006	0.00011064	0.00001616
17	5.7600	10.7600	1.0000	1.0000	0.01010698	0.00000425	0.00000882
18	20.9600	25.9600	5.8000	4.8000	0.02543693	0.01577961	0.00001974
19	7.8800	12.8000	3.5200	5.6800	0.01263052	0.00000167	0.00000015
20	7.2000	12.1600	3.8000	4.8000	0.01221435	0.00000113	0.00001020
21	7.1600	11.9200	4.1200	2.8000	0.01275270	0.01624084	0.00398420
22	7.9200	12.8800	2.0000	2.0000	0.01208800	0.00000397	0.00000625
23	4.9600	9.9600	3.1200	5.1200	0.01091704	0.00007750	0.00001999
24	4.8400	4.8400	2.2000	3.0000	0.01032283	0.00004596	0.00003502

Tab. 5.15: Network metrics for Agent model after the destruction of Murlo.

Metric	Assortativity	Diameter	Average Degree	Transitivity	Beta	Gamma
Agent Model (After)	-0.02370421	5.0	7.9744	0.44168669	4.15333333	0.17305556

Tab. 5.16: Node metrics for Agent model after the destruction of Murlo.

Node	Interaction In	Interaction Out	Degree In	Degree Out	PageRank	Hubs	Authorities
0	276.0400	242.0000	5.0000	2.9200	0.20667059	0.27516427	0.35770363
1	254.9600	223.4800	7.0000	3.8400	0.18786417	0.28145215	0.29851473
2	73.8800	77.5600	4.0000	4.0000	0.04860014	0.00605907	0.00559860
3	64.0800	68.3600	3.0000	3.0000	0.04413701	0.00148406	0.00142513
4	27.6400	32.4800	4.0000	4.0000	0.02751972	0.00025992	0.00009594
5	12.8800	17.8800	6.0400	5.3200	0.01752550	0.00003045	0.00013090
6	11.6800	16.6800	2.2000	5.2000	0.01611379	0.01251641	0.00054420
7	7.1600	12.1600	3.6400	4.1200	0.01230714	0.01444776	0.00272638
8	8.4800	13.3600	4.0400	5.0000	0.01372132	0.00000107	0.00000038
9	26.7600	28.7600	5.0800	4.0800	0.02518492	0.03464417	0.02987861
10	6.2800	11.2400	3.4000	4.8400	0.01175978	0.00000163	0.00000024
11	4.2400	9.2400	2.6400	4.4400	0.01008040	0.00000061	0.00000030
12	5.8000	10.7600	3.0000	4.5200	0.01139420	0.00000154	0.00000015
13	230.8400	200.4000	7.6400	5.8800	0.17007393	0.25537514	0.26237901
14	86.3200	88.5600	8.0000	5.0000	0.06153044	0.08244504	0.03534963
15	29.1600	33.7200	3.8400	3.0400	0.02266485	0.00209317	0.00221989
16	0.0000	0.0000	999	999	999	999	999
17	6.0800	11.0800	1.0000	1.0000	0.01065550	0.00000445	0.00000777
18	24.3200	29.3200	6.0000	4.5200	0.02741361	0.01860784	0.00000198
19	9.6400	14.4800	4.1600	4.7200	0.01456341	0.00000150	0.00000011
20	9.3200	14.3200	4.8400	4.6000	0.01433156	0.00000092	0.00001689
21	6.5600	11.3600	4.2000	2.8800	0.01171616	0.01529332	0.00336850
22	8.1600	13.0800	2.0000	1.8000	0.01293553	0.00000434	0.00000313
23	4.8400	9.8400	2.7200	5.5600	0.01060208	0.00006222	0.00000047
24	4.8800	9.8800	2.2400	5.4000	0.01063426	0.00004895	0.00003342

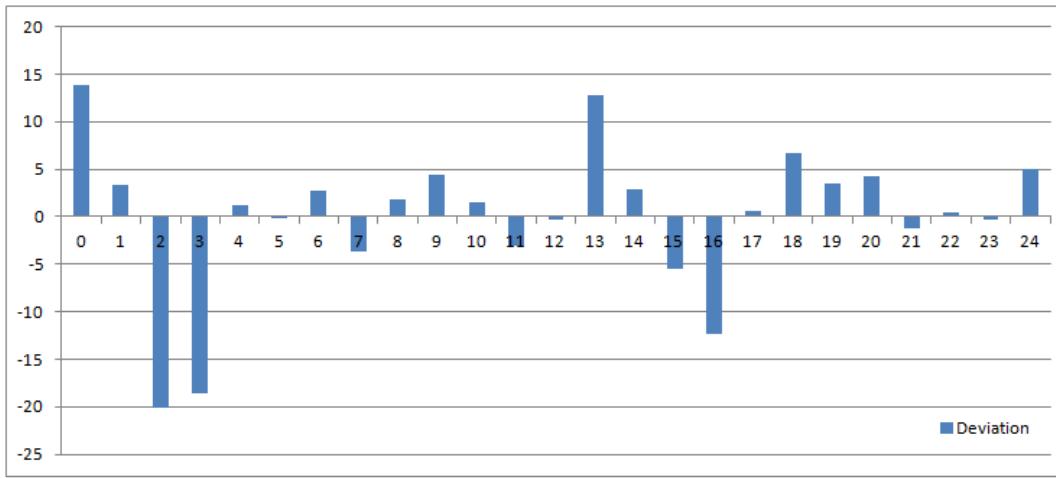
Interaction Shifts

Fig. 5.15: Total interaction shift by node for agent-based model.

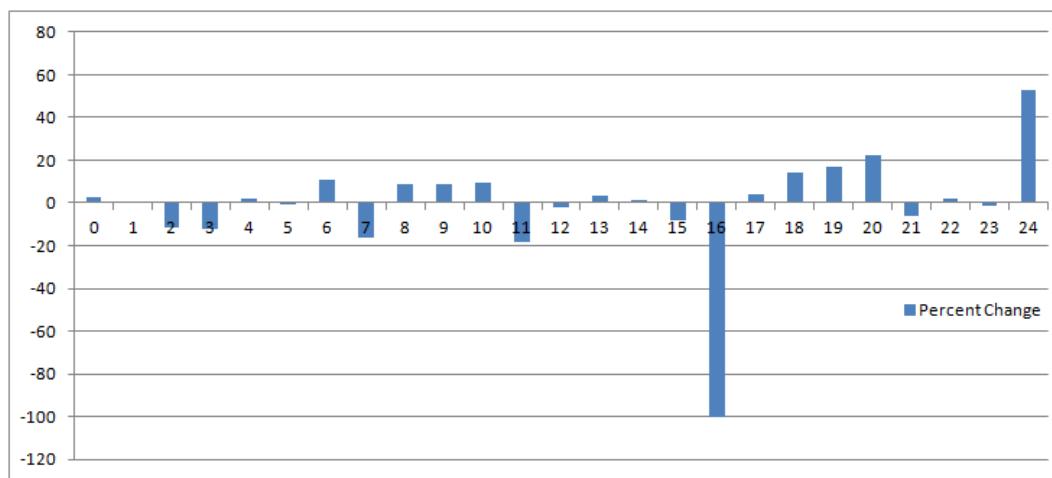


Fig. 5.16: Percent total interaction shift by node for agent-based model.

6. DISCUSSION

6.1 Implications for Poggio Civitate and Etruria

None of the models in this research indicate that Poggio Civitate was home to a highly connected central settlement within a larger network. Only within the context of the agent-based model did this geographically central settlement command mild network centrality, and even then it was not enough to drastically alter the network once the site was destroyed. It is therefore important to differentiate between these two concepts. Given Murlo’s size and the collective distances required to travel to other settlements, it is highly unlikely that it leveraged any natural geographic advantages. Individual node metrics such as PageRank and HITS did not show any signs that Murlo was punching above its weight (maintained high levels of interaction despite its relatively smaller size). Instead, it seems probable that the elite society which dwelt upon the hilltop site enjoyed relative autonomy, which is in agreement with conclusions drawn in previous research (Stoddart & Redhouse, 2011). Upon the removal of Murlo, there were no

Within all models, the connections Murlo held with other settlements were always amongst the weakest interaction levels throughout the system and would be representative of loose affiliations. Those in control could have exploited these limited relationships in order to grow their authority and power. It is also clear that the distances prescribed within the models to differentiate between transportation by walking or horseback produced different results. The agent-based model suggests that those limited to walking would have been at a severe disadvantage for participating in the wider network, especially in the north. Similarly, the Ariadne networks with higher distance

thresholds (100km) resulted in higher connectivity. If access to horses can be seen as a luxury, only for those with elite status, then it is also possible to differentiate between varying interaction networks within a society depending on social hierarchy. Moreover, the Ariadne (100km) results suggest that networks governed less by spatial restrictions may have been less resilient, and that removing nodes could have a larger impact on overall interaction sustainability. Arguably, the total decrease in interaction could call for a complete system shift, which would require model parameter alterations thereby producing a much less connected network, similar to the research concerning Thera in the Greek Mediterranean during the Bronze Age (Knappett et al., 2011).

It is intriguing that in two different scenarios (radiation and Ariadne (60km) models) node number 5 (Chiusi) gained significant interaction increases. This provides initial agreement with existing theories towards a motive for the destruction of Murlo. To further test the theory that Chiusi eliminated the society at Poggio Civitate in order to better situate itself in the regional network it will be necessary to continue testing the stochastic models and collect further results. Current interaction shift results, which are averaged, proved difficult to compare across the models. By running the stochastic models many more times it would be possible to derive a probability that can be assigned to the likelihood of a particular observation. It would be interesting to use this additional output to examine whether or not patterns emerge inferring relationships between Murlo's demise and shifts in any other settlement.

6.2 Comparing and Contrasting the Models

Each model used in this research returned spatial interaction networks which were similar in their general structure. This advocates that there was certainly a spatial component to each model that was successfully being captured. Nevertheless, the different analytical frameworks produced unique results each with their own characteristics.

The radiation model's relative simplicity, especially that it does not require any parameters, makes it ideal for preliminary model runs. Avoiding the subjective process of parameterization maintains a high level of objectivity within the model results, which is important for research concerned with dynamic inputs for differing scenarios, however; without parameters the model lacks the ability to reach the same analytical complexity of either the agent-based or Ariadne models. It cannot test different distance thresholds nor can it be adjusted for experimentation. As a result, when it is not possible to validate model results against observed data, this model should be employed alongside another model to provide further evidence that it captures a similar process and is appropriate for analysis. In contrast, it would be very useful to apply this model to compare different study regions since it would not be necessary to worry about uncertainty introduced during parameterization.

Within the context of this research, the radiation model produced networks with interactions that were more homogeneous when compared to the other two models. It also appears that there may be too many weak long distance interactions, suggesting that the filter applied to the interaction system may need to be more finely tuned. Compared to the radiation mode, the Ariadne and agent models both displayed networks with more diverse and varying interaction strengths. The Ariadne model resulted in the most heterogeneous interaction networks (strong/short-distance vs. weak/long-distance) supporting the claim that this model has the ability to efficiently portray interaction occurring differently over varying scales. This complexity helps to paint more vivid interaction landscapes, though these benefits come with increased uncertainty. Due to the model's relatively sensitive parameters and it's subjective parameterization process, it is the most susceptible to a researcher's bias compared to the other models. This model is, therefore, best employed when there is sufficient proof to support the selected phenomenon being modeled.

The agent-based model, while also susceptible to researcher's bias, is not as vulnerable since it's parameters proved to be resilient. Changing any of the model's variables resulted in networks which manifested similar structure. Instead, this model's main weakness is that it is the least grounded within spatial interaction theory. It is more difficult to derive specific theories pertaining to individuals than it is for a society as a whole. In effect, the equations used lack the rigorous derivation of other spatial interaction methods. This model, therefore, is best applied in conjunction with other models as it was within this research.

-Assortativity

6.3 Limitations and Future Work

In the agent model, distance is treated as a barrier which, at a certain distance, no agent can traverse. This binary characteristic is problematic since humans have always been known to travel extreme distances in extenuating circumstances or when the rewards were great enough. One solution to this problem would be to give the agents the ability to traverse longer distances to arrive at a settlement if the potential settlement has extra perks such as unusually high connectivity, which could be leveraged by the agent in the following round of simulation. This model could also be more closely customized to the study region by scaling the starting population at each site by the site's size rather than using a uniform number of agents. Further, the model could be made more complex by altering Equation 2.6 so that it considers only the number of visitors a settlement received in the current iteration rather than the cumulative number of visitors arriving there throughout the entire simulation. This adjustment would prevent positive feedback loops from forming between agents and key settlements as quickly, which might provide more interesting results.

The results of this research are largely dependent upon the filtering techniques applied to each model to remove ineffective interaction links. Two different methods were employed due to the fact that the magnitude and distribution of the interaction values

differed in each model. By transforming or scaling the interaction values it may be possible to define one filtering approach for all of the models, which would allow for more effective comparisons amongst them.

Any research that is model-driven is only as good as the data that it utilizes as input. For this research, the quality of the estimates of the site's sizes are paramount to the final results. It is obvious that within the field of archaeology these values are approximations which are debatable and susceptible to change over time as new information is gathered. If a research question pertains to a single settlement, it would be interesting to test how sensitive the entire system is to the specific site's size estimate. By holding all other variables constant and varying a single site's size it is possible to test which sites may cause the most volatility within the network. It would then be possible to identify key sites whose size estimates should be reconsidered. This could offer a new technique for selecting where to further excavate or conduct archaeological survey.

Spatial interaction methods are also strongly conditioned by the selected input distances between places of interest. This research considered distance by recording the length of the path between two places which required the least energy costs to traverse the natural terrain. In light of new evidence from this work, which suggests contrasting interaction networks for different transportation modes, it would be more appropriate to define energy costs in terms of each specific transportation mode. For example, the energy cost constraints for humans and horses to traverse the same terrain is likely to be quite different and may produce completely unique paths between two places. Alternatively, distance could be interpreted as the time cost associated with each journey. Obviously, a horse has the ability to travel more quickly than humans and so it would be expected that the travel time distance would be shorter for horses than for humans over the same physical distances. Indeed, the distance values can also be increased in accuracy by more closely modeling the physical environment. By employ-

ing higher resolution elevation data, more accurate slopes could be calculated, which would result in better cost estimates. Additionally, data representing waterways should be incorporated, which could bestow advantages upon settlements with rivers nearby and disadvantages to those that must consider sailing across lakes. Lastly, it would be interesting to place restrictions into the landscape to represent known socio-political barriers in order to include them in the spatial interaction decision process.

7. CONCLUSION

Networks provide the ability to take static components and weave them together to more closely look at how a system that was truly dynamic in nature would have evolved. By employing three conceptually unique quantitative models, this research has produced relative spatial interaction networks which embody the regional relationships amongst settlements within ancient Etruria. Applying the same spatial inputs, each of the models produced results which were similar in their overall structure such that the networks consistently produced visible communities of more intense interaction with weaker interaction binding them all together. Additionally, all of the models produced networks in which interaction occurred more frequently amongst the southern settlements than the northern ones. Observing these characteristics across multiple models provides proof that we are indeed capturing the spatial phenomenon that we set out to.

By embedding Murlo within the larger region of central Italy it was possible to consider its individual characteristics against all of the other settlements within a spatial context. Model results consistently support the hypothesis that Murlo was generally an autonomous settlement, mostly exempt from the influences of larger and more powerful sites. It is important to note that the models do not suggest that Murlo was completely void of any relationships with its neighbors. Instead, the limited interactions which were observed can be interpreted as rare opportunities to acquire important information or goods for the inhabitants at Murlo. If authoritative figures at Murlo were able to dominate the relationships with the wider region, it likely provided increased power and wealth over those who were excluded. Furthermore, the produced

networks from this research advocate that different modes of transportation would have facilitated varying interactions across the landscape. Those without access to horses would have been severely restricted in their ability to interact within Etruria while those with horses would have enjoyed increased mobility, which provided higher connectivity in the overall network.

Diverging landscapes, due to transportation disparities, could have played a role in the ultimate fate of Etruscan society. This research suggests that when interactions are permitted to occur over longer distances that local ties are diluted, reducing the overall connectivity of the network. Settlements may have become more vulnerable to ensuing advances from enemies such as Rome as they increasingly structured their relationships towards greater socio-economic advantages offered from long-distance trade, thereby sacrificing the resilience of local communities. In this manner, the future landscape would have been strongly influenced by the current spatial dynamics within the region.

Each of the three models in this research displayed different advantages that could be leveraged in order to test more specific hypotheses within future research. Specifically, the radiation model's simplicity is helpful when comparing results across regions while the Ariadne and agent-based models are necessary to test varying distance thresholds theorized to affect the spatial decision making process. This study has provided a wealth of spatial interaction network simulation methods that can serve as a starting point for further inquiries. They can be improved upon within the context of other study regions as well as within the contexts of Etruria in order to shed more light on the enigmatic site of Murlo.

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Appendix A

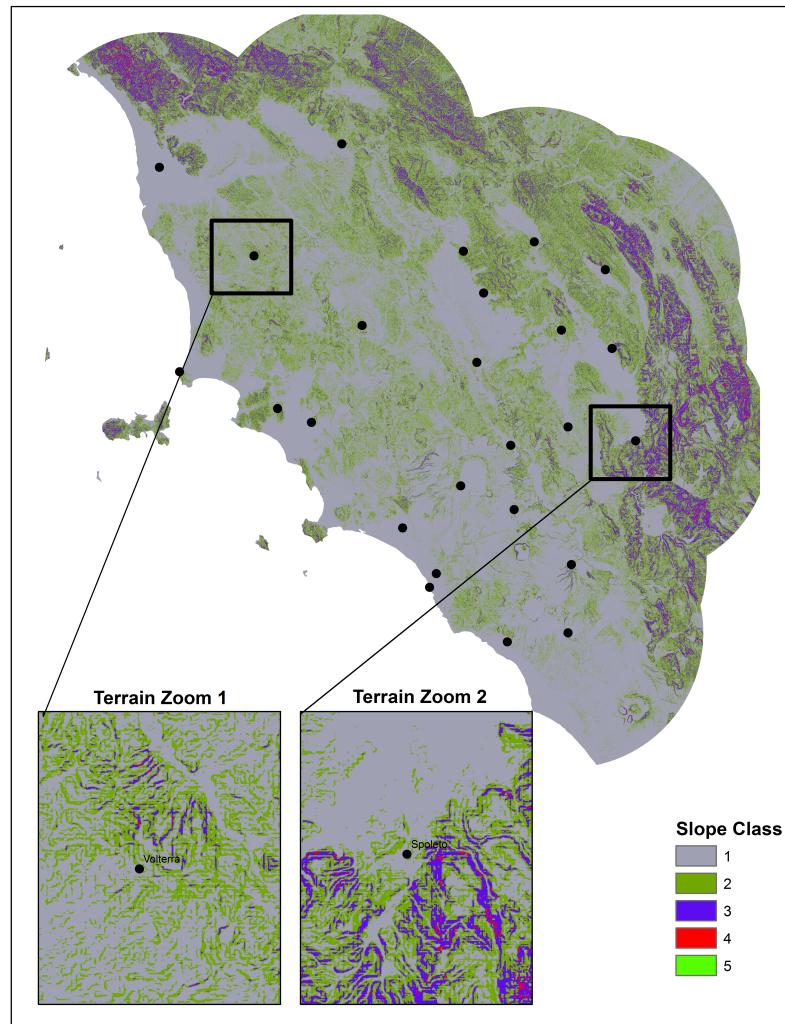


Fig. A.1: Study region slope reclassified according to energy costs.

Tab. A.1: Least-cost path distances (km)

-	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	
0	0	36	211	274	282	170	105	80	172	87	211	167	227	86	115	190	217	354	116	234	207	39	321	119	123	
1	36	0	185	244	272	162	97	75	185	55	228	185	232	57	89	168	207	343	112	227	199	57	313	133	142	
2	211	185	0	63	91	120	119	153	175	134	213	198	181	128	97	22	68	161	137	139	140	197	161	168	210	
3	274	244	63	0	83	168	181	216	191	259	245	227	189	161	84	112	122	199	199	184	186	260	165	228	271	
4	282	272	91	83	0	147	179	209	186	223	205	218	165	217	185	106	75	74	186	120	135	254	83	212	253	
5	170	162	120	168	147	0	72	90	54	135	94	77	81	126	108	105	72	220	53	65	40	133	152	66	106	
6	105	97	119	181	179	72	0	35	109	63	153	117	152	54	42	97	112	252	37	134	112	79	216	73	108	
7	80	75	153	216	209	90	35	0	110	64	153	112	158	57	65	132	137	282	38	154	127	45	241	59	85	
8	172	185	175	221	186	54	109	110	0	172	44	33	55	163	147	159	113	258	75	81	52	132	169	55	78	
9	87	55	134	191	223	135	63	64	172	0	215	175	215	9	39	118	160	293	97	193	174	83	266	122	149	
10	211	228	213	259	205	94	153	153	44	215	0	47	46	206	190	198	148	271	119	86	74	171	177	96	103	
11	167	185	198	245	218	77	117	112	33	175	47	0	77	167	158	182	143	290	81	109	84	129	200	54	56	
12	227	232	181	227	165	81	152	158	55	215	46	77	0	206	189	167	116	225	121	45	45	187	131	110	132	
13	86	57	128	189	217	126	54	57	163	9	206	167	206	0	33	112	154	287	88	185	165	77	260	113	142	
14	115	89	97	161	185	108	42	65	147	39	190	158	189	33	0	79	121	255	78	167	148	101	227	115	150	
15	190	168	22	84	106	105	97	132	159	118	198	182	167	112	79	0	65	176	117	131	125	176	163	149	190	
16	217	207	68	112	75	72	112	137	113	160	148	143	116	154	121	65	0	148	111	73	74	181	107	137	178	
17	354	343	161	122	74	220	252	282	258	293	271	290	225	287	255	176	148	0	258	188	207	326	106	285	325	
18	116	112	137	139	186	53	37	38	75	97	119	81	121	88	78	117	111	238	0	118	90	80	205	37	75	
19	234	227	139	184	120	65	134	154	81	193	86	109	45	185	167	131	73	188	118	0	28	198	94	121	150	
20	207	199	140	186	135	40	112	127	52	174	74	84	45	165	148	125	74	207	90	28	0	170	116	93	122	
21	39	57	197	260	133	79	45	132	83	171	129	187	77	101	176	181	326	80	198	170	0	285	79	85		
22	321	313	161	165	83	152	216	241	169	266	177	200	131	260	227	163	107	106	205	94	116	285	0	209	238	
23	119	133	168	228	212	66	73	59	55	122	96	54	110	113	115	149	137	285	37	121	93	79	209	0	41	
24	123	142	210	271	253	106	108	85	78	149	103	56	132	142	150	190	178	325	75	150	122	85	238	41	0	

Tab. A.2: As the crow flies distances (km)

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	
-	0	0	34	202	257	270	100	74	166	80	200	158	216	79	108	182	203	340	108	217	192	38	296	113	112	
0	0	0	180	233	254	154	90	73	174	52	211	171	220	54	85	162	191	323	108	216	192	55	288	123	131	
1	34	0	174	0	58	85	112	109	141	162	129	195	187	168	126	95	20	65	148	130	134	130	183	150	160	197
2	202	180	0	58	85	112	109	141	162	129	195	187	168	126	95	20	65	148	130	134	130	183	150	160	197	
3	257	233	58	0	76	163	167	199	211	181	240	238	207	179	150	78	103	113	186	169	172	240	154	216	253	
4	270	254	85	76	0	136	170	200	174	206	193	203	154	201	170	97	71	71	175	115	128	243	78	196	233	
5	157	154	112	163	136	0	68	83	50	126	87	75	73	118	100	97	66	205	49	62	38	123	141	61	97	
6	100	90	109	167	170	68	0	32	102	58	143	112	140	50	39	89	103	241	35	129	107	75	199	67	99	
7	74	73	141	199	200	83	32	0	102	63	141	104	147	55	62	121	131	271	35	145	120	44	222	54	77	
8	166	174	162	211	174	50	102	0	102	41	30	51	150	139	146	110	238	69	69	47	129	158	53	73		
9	80	52	129	181	206	126	58	63	159	0	199	165	198	8	36	111	149	274	90	186	164	79	248	116	139	
10	200	211	195	240	193	87	143	141	41	199	0	43	42	191	180	182	137	251	110	79	68	163	160	89	95	
11	158	171	187	238	203	75	112	104	30	165	43	0	72	72	157	151	170	138	268	77	98	77	121	186	49	52
12	216	220	168	207	154	73	140	147	51	198	42	72	0	190	173	158	105	210	210	113	39	40	178	119	103	123
13	79	54	126	179	201	118	50	55	150	8	191	157	190	0	31	108	142	270	81	178	156	74	242	108	132	
14	108	85	95	150	170	100	39	62	139	36	180	151	173	31	0	77	113	239	75	156	137	95	214	106	137	
15	182	162	20	78	97	97	89	121	146	111	182	170	158	108	77	0	60	163	110	126	118	163	154	141	178	
16	203	191	65	103	71	66	103	131	110	149	137	138	105	142	113	60	0	141	105	69	69	175	100	126	163	
17	340	323	148	113	71	205	241	271	238	274	251	268	210	270	239	163	141	0	246	173	191	314	101	266	302	
18	108	108	130	186	175	49	35	35	69	90	110	77	113	81	75	110	105	246	0	110	85	73	190	33	69	
19	217	216	134	169	115	62	129	145	69	186	79	98	39	178	156	126	69	173	110	0	26	182	89	112	141	
20	192	192	130	172	128	38	107	120	47	164	68	77	40	156	137	118	69	191	85	26	0	157	113	87	116	
21	38	55	183	240	123	75	44	129	79	163	121	178	74	95	163	175	314	73	182	157	0	263	76	77	77	
22	296	288	150	154	78	141	199	222	158	248	160	186	119	242	214	154	100	190	89	113	263	0	199	229	229	
23	113	123	160	216	196	61	67	54	53	116	89	49	103	108	106	141	126	266	33	112	87	76	199	0	38	
24	112	131	197	253	233	97	99	77	73	139	95	52	123	132	137	178	163	302	69	141	116	77	229	38	0	

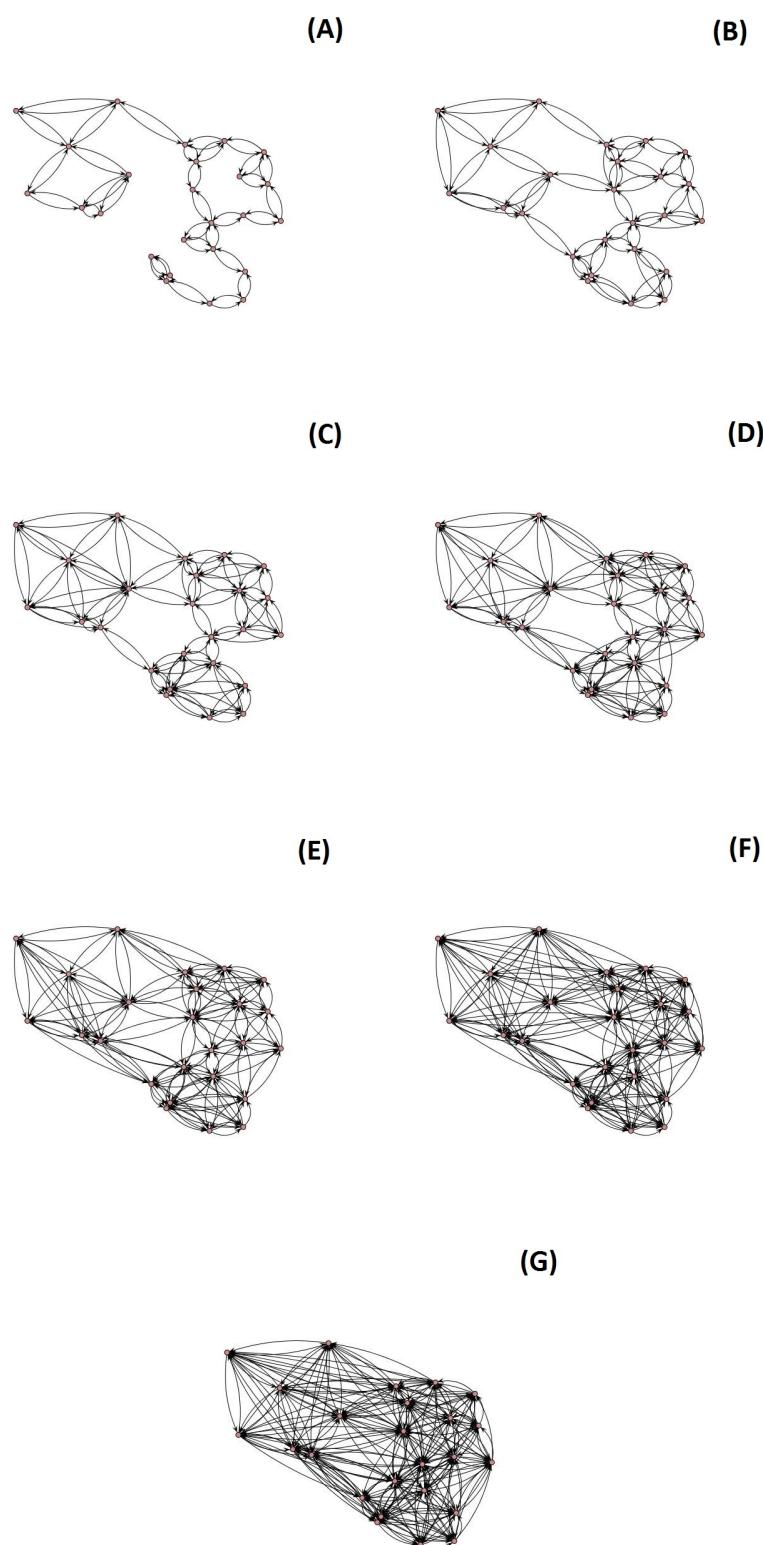


Fig. A.2: A-G: PPA results for k equals 1, 2, 3, 4, 5, 7, and 9.

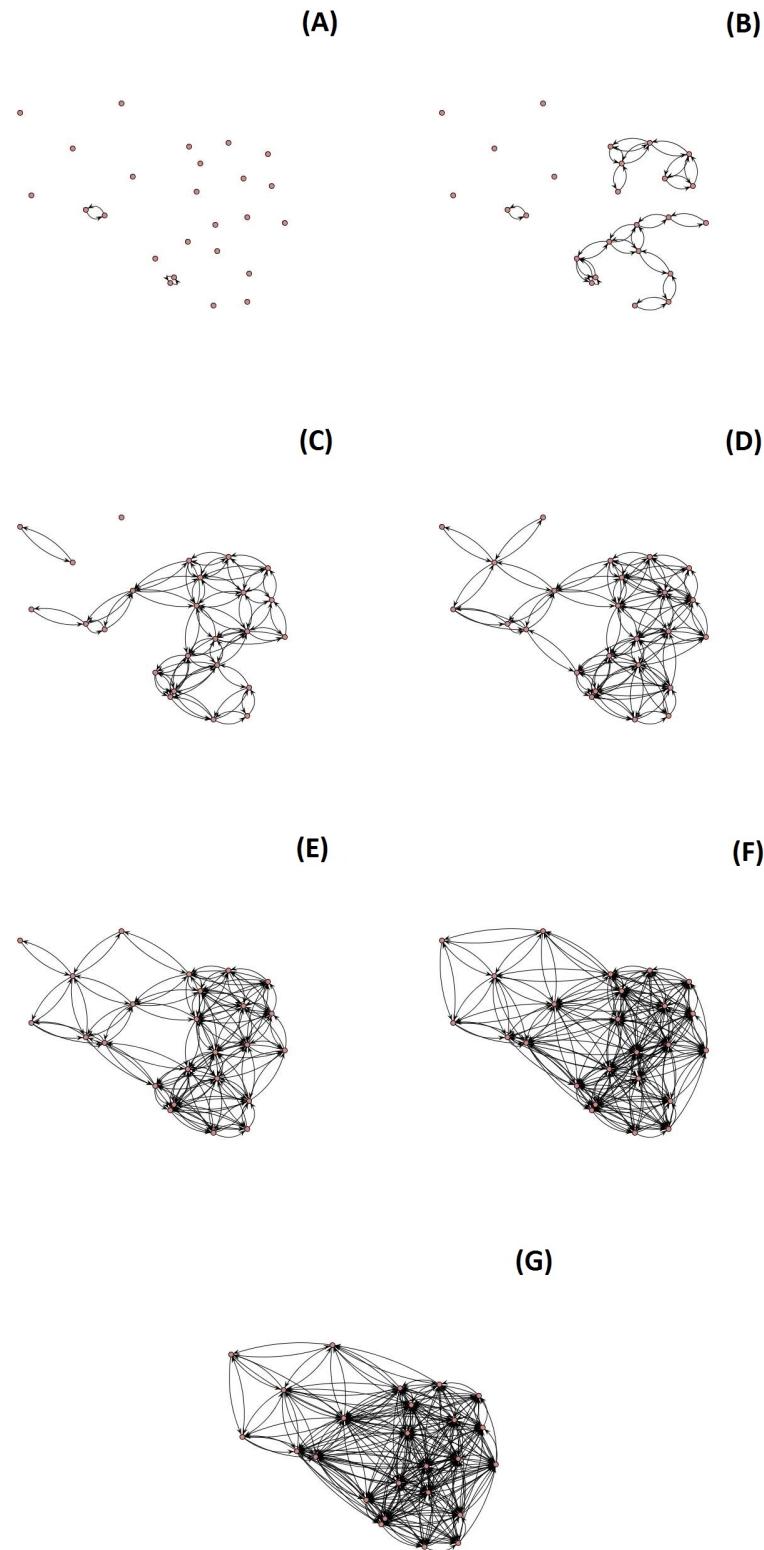


Fig. A.3: A-G: MDN results for distance thresholds of 25km, 50km, 75km, 85km, 100km, 125km, and 150km.

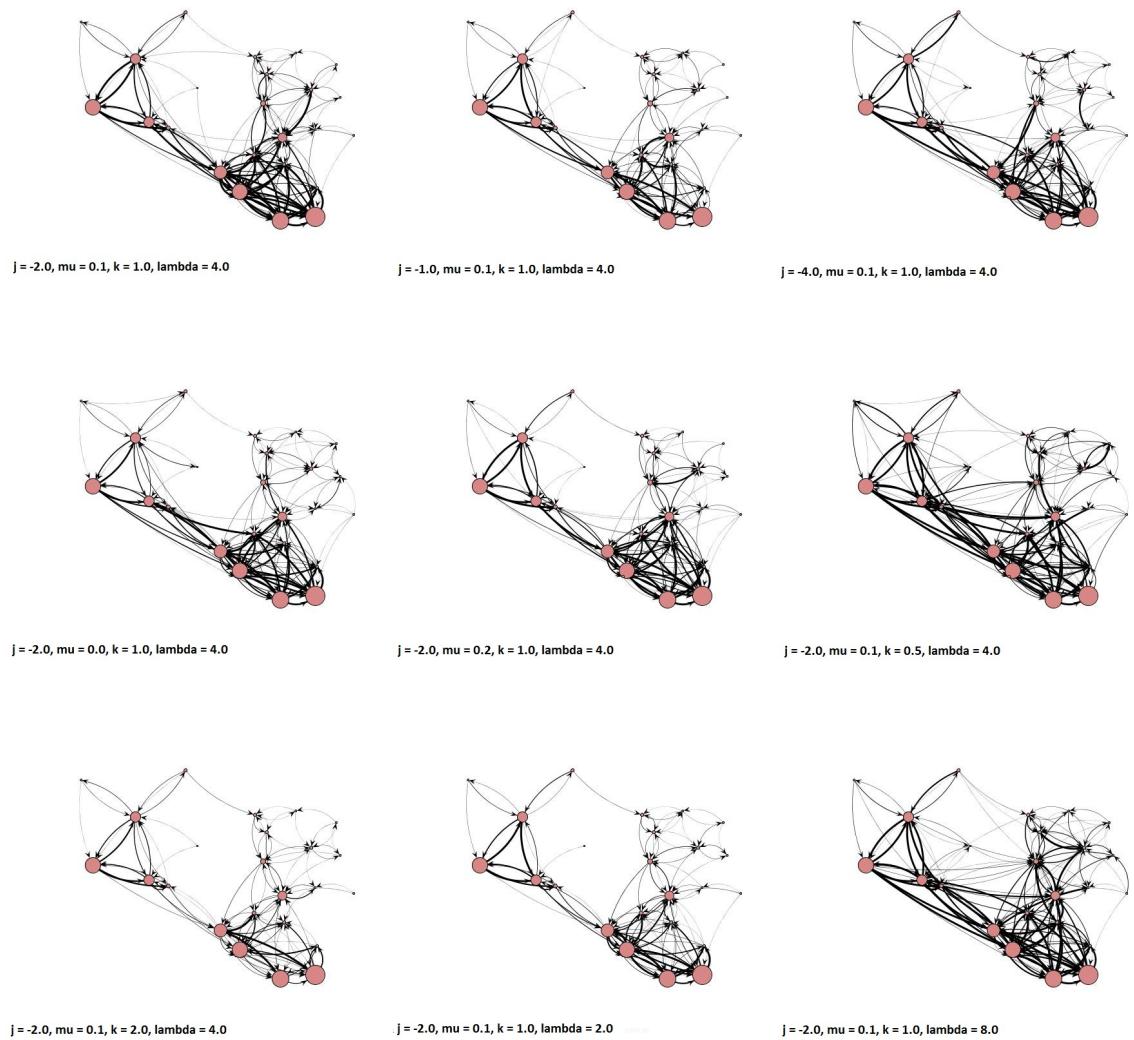


Fig. A.4: Parameterization of Ariadne (60km).

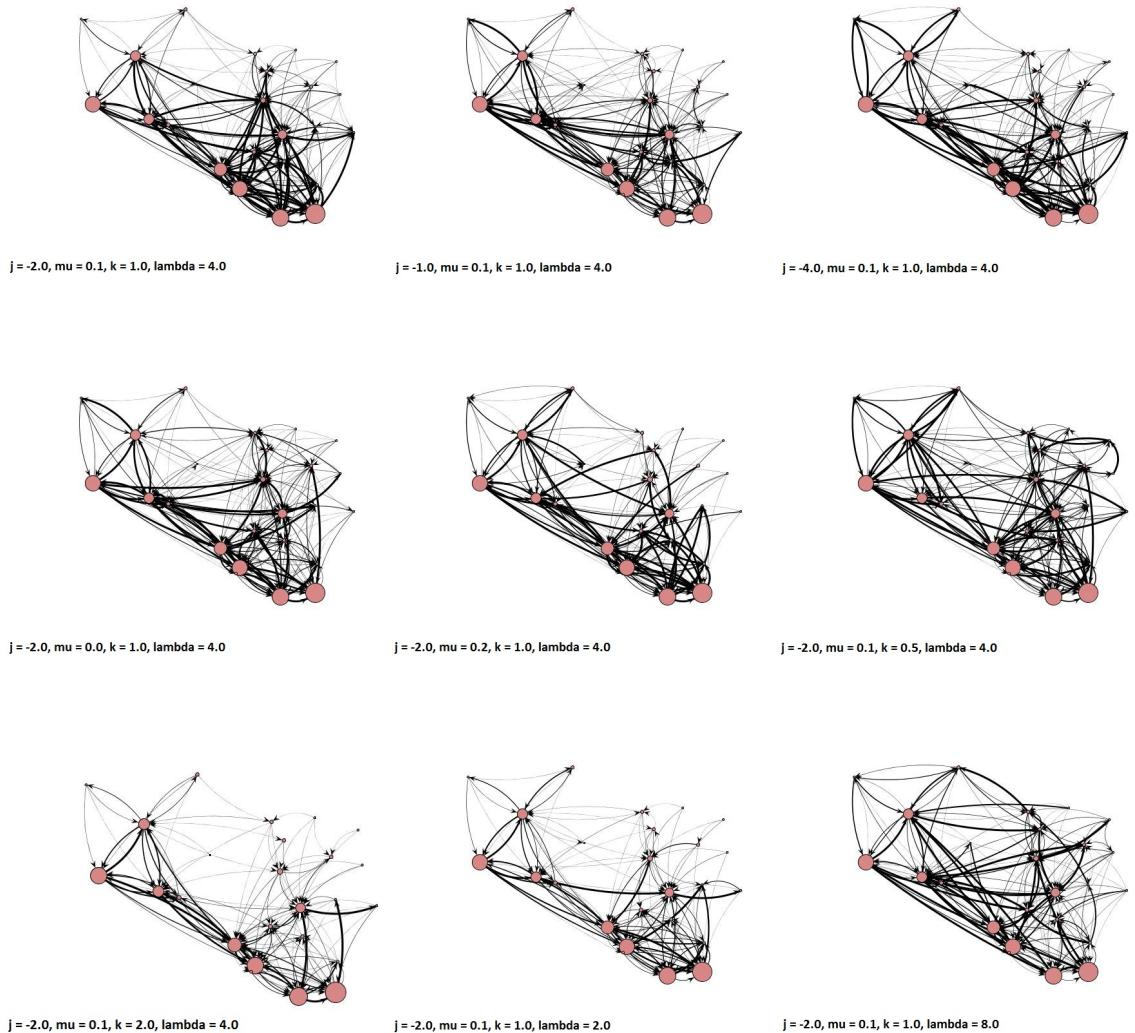


Fig. A.5: Parameterization of Ariadne (100km).

Tab. A.3: Network-level metric results for 25 runs (Ariadne - Before - 60km)

Run Number	Assortativity	Diameter	Average Degree	Transitivity	Beta	Gamma
5	-0.05140299	4.40000000	11.68000000	0.70671354	5.84000000	0.23360000
10	-0.05091950	4.20000000	11.71200000	0.71293931	5.85600000	0.23424000
15	-0.05081230	4.20000000	11.64266667	0.70496897	5.82133333	0.23285333
20	-0.05107444	4.20000000	11.63600000	0.70794023	5.81800000	0.23272000
25	-0.05119454	4.16000000	11.62880000	0.70893446	5.81440000	0.23257600

Tab. A.4: Network-level metric results for 25 runs (Ariadne - Before - 100km)

Run Number	Assortativity	Diameter	Average Degree	Transitivity	Beta	Gamma
5	-0.05526671	3.00000000	12.14400000	0.73106504	6.07200000	0.24288000
10	-0.05538473	3.00000000	11.84800000	0.69957622	5.92400000	0.23696000
15	-0.05541665	3.13333333	11.96800000	0.70008067	5.98400000	0.23936000
20	-0.05569742	3.10000000	11.63600000	0.69305360	5.81800000	0.23272000
25	-0.05581519	3.12000000	11.65760000	0.69901818	5.82880000	0.23315200

Tab. A.5: Network-level metric results for 25 runs (Ariadne - After - 60km)

Run Number	Assortativity	Diameter	Average Degree	Transitivity	Beta	Gamma
5	-0.05294613	4.60000000	11.42400000	0.71058266	5.95000000	0.24791667
10	-0.05346564	4.50000000	11.18400000	0.71911467	5.82500000	0.24270833
15	-0.05322030	4.33333333	11.24266667	0.72488791	5.85555556	0.24398148
20	-0.05322119	4.25000000	11.37600000	0.72831435	5.92500000	0.24687500
25	-0.05325428	4.24000000	11.31520000	0.72501267	5.89333333	0.24555556

Tab. A.6: Network-level metric results for 25 runs (Ariadne - After - 100km)

Run Number	Assortativity	Diameter	Average Degree	Transitivity	Beta	Gamma
5	-0.05840201	3.20000000	10.46400000	0.66037357	5.45000000	0.22708333
10	-0.05642575	3.10000000	10.87200000	0.67265716	5.66250000	0.23593750
15	-0.05726372	3.06666667	11.03466667	0.69067383	5.74722222	0.23946759
20	-0.05687748	3.10000000	11.01200000	0.68319655	5.73541667	0.23897569
25	-0.05695306	3.08000000	10.91840000	0.67954338	5.68666667	0.23694444

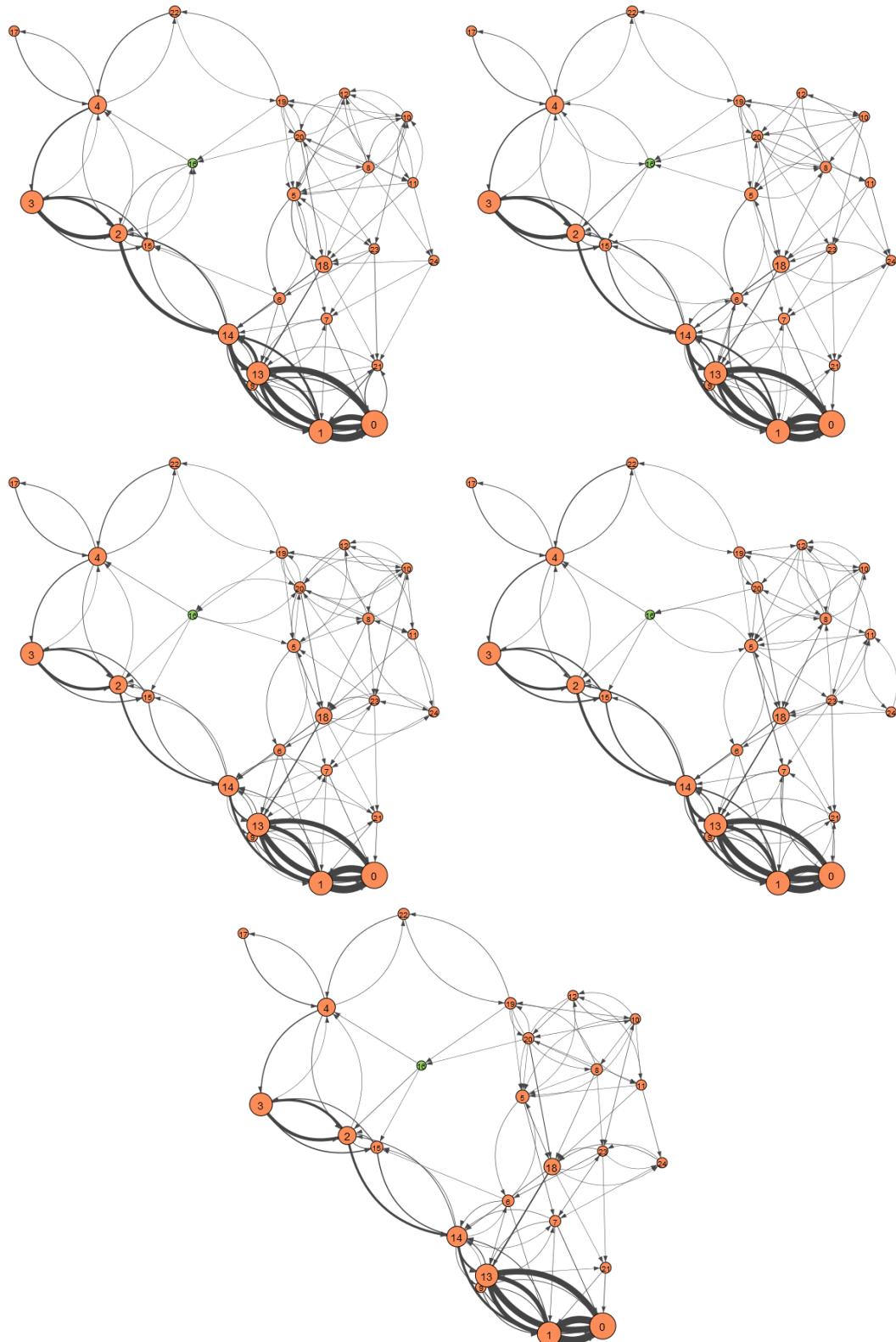


Fig. A.6: Five sample model runs for the agent model.

Tab. A.7: Network-level metric results for 25 runs (Agent Model - Before)

Run Number	Assortativity	Diameter	Average Degree	Transitivity	Beta	Gamma
5	-0.04980000	5.00000000	8.37000000	0.43800000	4.18000000	0.16700000
10	-0.04030000	5.00000000	8.36000000	0.44100000	4.18000000	0.16700000
15	-0.03890000	5.00000000	8.42000000	0.43600000	4.21000000	0.16800000
20	-0.04120000	5.00000000	8.39000000	0.43500000	4.20000000	0.16800000
25	-0.03900133	5.00000000	8.31360000	0.43295384	4.15680000	0.16627200

Tab. A.8: Network-level metric results for 25 runs (Agent Model - After)

Run Number	Assortativity	Diameter	Average Degree	Transitivity	Beta	Gamma
5	-0.02416639	5.00000000	7.93600000	0.43904952	4.13333333	0.17222222
10	-0.02245842	5.00000000	7.92000000	0.43448981	4.12500000	0.17187500
15	-0.02198818	5.00000000	7.94666667	0.43704930	4.13888889	0.17245370
20	-0.02568726	5.00000000	7.96000000	0.44110698	4.14583333	0.17274306
25	-0.02370421	5.00000000	7.97440000	0.44168669	4.15333333	0.17305556