Archaeological Approaches to Population Growth and Social Interaction in Semiarid Environments: Pattern, Process, and Feedbacks

by

Nicolas Edouard Gauthier

A Dissertation Presented in Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy

Approved July 2019 by the
Graduate Supervisory Committee:

C. Michael Barton, Chair
John Anderies
Matthew Peeples

ARIZONA STATE UNIVERSITY

August 2019

ABSTRACT

Population growth, social interaction, and environmental variability are interrelated facets of the same complex system. Tracing the flow of food, water, information, and energy within these social-ecological systems is essential for understanding their long-term behavior. Leveraging an archaeological perspective of how past societies coevolved with their natural environments will be critical to anticipating the impact of impending climate change on farming communities in the developing world. However, there is currently a lack of formal, quantitative theory rooted in first principles of human behavior that can predict the empirical regularities of the archaeological record in semiarid regions. Through a series of models – statistical, computational, and mathematical – and empirical data from two long-term archaeological case studies in the pre-Hispanic American Southwest and Roman North Africa, I explore the feedbacks between population growth and social interaction in water-limited agrarian societies. First, I use a statistical model to analyze a database of 7.5 million artifacts collected from nearly 500 archaeological sites in the Southwest and found that sites located in different climatic zones were more likely to interact with one another than a sites occupying the same zone. Next, I develop a computational model of demography and food production in ancient agrarian societies and, using North Africa as a motivating example, show how the concrete actions and interactions of millions of individual people lead to emergent patterns of population growth and stability. Finally, I build a simple mathematical model of trade and migration among agricultural settlements to determine how the relative costs and benefits of social interaction drive population growth and shape long-term settlement patterns. Together, these studies form the foundation for a unified quantitative approach to regional social-ecological systems. By combining theory and methods from ecology, geography, and climate science, archaeologists can better leverage insights from diverse times and places to fill critical knowledge gaps in the study of food security and sustainability in the drylands of today.

DEDICATION

To my parents, for all those museum trips.

ACKNOWLEDGMENTS

First, I thank the members of my committee for their time, attention, and guidance throughout this process. My chair, Michael Barton has been a peerless mentor and role-model for how to be not only a good scientist but an even better human being. Matt Peeples never hesitated to sit down and help me work through my latest research puzzle, and I am grateful for his generosity in sharing code, data, and insight to help me along the way. Marty Anderies showed me that math is another kind of storytelling, and has forever changed the way I see the world. Thank you all.

I would also like to thank all those groups and individuals who shared the computer code and data that made this research possible. Barbara Mills and the rest of the Southwest Social Networks Project generated the data analyzed in Chapter 2. Their work is a shining example of archaeology at its best. Cedric Puleston kindly provided sample code and advice for the food-limited demography algorithm in Chapter 3. Alexandra Jahn graciously provided the paleoclimate model outputs used in Chapter 3.

And special thanks to everyone who provided guidance, support, and inspiration throughout my graduate career: Ian Allen, Sean Bergin, Tommy Budd, Wendy Cegielski, Rudolf Cesaretti, Adrian Chase, Claudine Gravel-Miguel, April Kamp-Whittaker, Alex Kara, Peter Lawrence, Christina Luke, Kostalena Michelaki-Schwartz, Sarah Oas, Sofía Pacheco-Forés, Jon Paige, Christopher Roosevelt, Christopher Schwartz, Catherine Scott, Irene Smail, Michael Smith, Grant Snitker, Laura Swantek, Charlotte Till, Isaac Ullah, Enrique Vivoni, Joshua Watts, and Amanda Wissler.

This research was supported in part by a Graduate Research Associate Fellowship from Arizona State University, a Graduate Student Fellowship from the National Center for Atmospheric Research's Advanced Study Program, and National Science Foundation grants DEB-1313727 and AGS-1243089.

And finally, Lawrence Fatica listened to every half-baked idea, A/B tested every figure, and took a red pen to every single sentence I wrote. This dissertation simply would not exist without your patience and ingenuity. I owe you so much. And to Wile E Gauthier, who has laid dutifully under my desk each and every day: I'm sorry for stepping on you.

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INTRODUCTION

Humanity is facing existential challenges due to growing populations, finite resources, and a rapidly-changing global climate. The scope of these problems far outstrips the capacity of a single person to understand, let alone address. Globalization and interaction have expanded the reach of human cultures across the world, far beyond a single person's day to day activity. The time scale of change, though accelerating, still falls beyond the lifespan of a single person, constantly shifting our baseline reference point and thwarting our ability to truly see the scope and severity of the changes we face. Naturally, we turn to the sciences for answers.

Unfortunately, when we turn our scientific lens to our role in these challenges, we encounter the same biases and blind spots that drive global change in the first place. We place ourselves at the center of the universe, blind to our fundamental connections to the world around us. The human sciences have yet to face their Copernican revolution. We seek "human universals" in a handful of wealthy, Western college students (Henrich, Heine, and Norenzayan 2010). We seek to study "long term" trends, but our data rarely reach back more than a few decades (Braudel 1970). Even the division of social science disciplines – how we shape and define the knowledge we produce – is a product of the very same historically-contingent and culturally-rooted processes we hope to study in the first place (Wallerstein 2003). What can we hope to achieve?

The archaeological record is a vital source of information about our collective past. It forces us to expend our blinkered focus on the 20th century Western experience to examine the broad scope of human history. Recently, a team of archaeologists defined a set of core outstanding questions in the discipline (Kintigh et al. 2014). Several of these questions directly relate to ongoing problems of global change. *How do humans respond to abrupt environmental change? How does the organization of human communities at varying scales emerge from and constrain the actions of their members? What factors drive or constrain* *population growth in prehistory and history? What are the relationships among environment, population dynamics, settlement structure, and human mobility?* The authors emphasize that the answers to these questions are not to be found with more or better fieldwork alone. Instead, the answers lay in large-scale regional and inter-regional syntheses of existing archaeological data. Indeed, the primary constraints on our understanding has rarely been the amount of data, but rather the lack of theoretical and methodological tools capable of handling the complexity of the data. That is because human societies are prototypical examples of complex adaptive systems, and complex systems like human societies have characteristic properties and behaviors that must be grappled with both conceptually and methodologically.

A complex systems approach can help to unify our theory, methods, and data. Three key concepts underlay this approach:

- **Emergence** – A complex system is a constantly-changing whole that emerges as far more than the sum of its interacting parts. Higher levels of organization emerge from the self-organization of entities at lower levels without top-down control.
- **Scale** – The emergence of higher levels of organization from lower levels results in nested hierarchies. Dynamics can occur both within and across scales, leading to unpredictable behavior.
- **Nonlinearity** – Simple, one-to-one relationships are rare. System behavior is defined by thresholds, feedbacks, and changing returns to scale. These factors cause surprise in such systems, with rapid transitions between large scale system states arising from what on the outside appears to be small events.

These concepts motivate the use of advanced modeling and analysis techniques where personal experience and intuition fail. These techniques include hierarchical nonlinear regression to extract insight from complex, noisy, and nested real-world data, agent-based modeling and simulation to scaffold up in complexity from low-level assumptions, and the mathematical tools from statistical physics that allows us to predict the average behavior of complex systems as the scale of organization increases. These are powerful approaches for the study of complex social systems. But it is less obvious how best to integrate these approaches with the natural world. The social-ecological system concept is a useful tool for formally modeling how humans fit into a broader ecological system.

A social-ecological system is a complex system where both humans and the environment are the core actors. Rather than put the "human" and the "natural" in artificial boxes, this approach highlights the constant actions and interactions between the two. Such a system is bounded by scale on which functional entities interact, not the "humanness" or lack thereof of each entity. The ecological dynamics of coffee cultivation in Mexico and Vietnam, for example, cannot be understood in isolation from one another, as these distant agroecosystems are linked by a single market system (Eakin, Winkels, and Sendzimir 2009).

As a conceptual formalism, social-ecological *networks* build on this approach and encourage us to take explicit account of the flows of conserved quantities such as mass, energy, and information in a real-world social-ecological system, adding much needed concreteness to the study of these complex systems. In a social-ecological network, the nodes represent both social entities (individuals, settlements, polities) and biophysical ones (hillslopes, watersheds, climates) (Janssen et al. 2006; Bodin and Tengo 2012; Gonzales 2012). The edges represent interactions within and between the social and biophysical systems. Indeed, in a generalized mathematical model of a network of "cities" and "resources", latent links between cities by virtue of harvesting the same or connected resources are better predictors of a city's long-term sustainability than were direct inter-city migration links (Qubbaj, Shutters, and Muneepeerakul 2014).

The approach implicit in many conceptual and mathematical models of networks, and social-ecological networks in particular, treats them as static structures on which some dynamic of interest plays out (Wilson 2008). These structures only ever change to the extent that the researcher intervenes by manually adding or removing nodes and edges. This view is common in archaeology (Brughmans 2010) and is understandable given the fragmentary and time-averaged nature of the archaeological record. The alternative advanced here is to treat a network as a dynamical system in which matter, information, and energy flows in constant interaction with its ecological and social environment (Crabtree 2015; Brughmans and Poblome 2016). Focus on the flow networks underlying a social-ecological system reveals structures and dynamics otherwise hidden in each isolated system.

There is a need for quantitative theory on regional-scale social-ecological systems that recognizes these fundamental dynamics beyond a single time or place. Archaeology has been particularly effective at studying local social-ecological systems like the physical landscape around a farming settlement (Barton, Ullah, and Mitasova 2012; Barton et al. 2016). Less common – yet equally important – is the study of *regional* social-ecological systems. Semiarid regions are a prime example. We currently lack a formal, quantitative theory rooted in first principles of human behavior that can predict the empirical regularities of the archaeological record in semiarid regions. What are the general dynamics of population growth and social interaction in water-limited agrarian societies?

1.1 Background to the Case Studies

Here, I use two empirical archaeological case studies from semiarid regions to explore the relationship between the environment, population growth, and social interaction: the late pre-Hispanic American Southwest and the Roman Imperial period in North Africa. Both these regions span areas of about 460,000 square kilometers centered on latitude 35°N, the rough limit of the subtropical ridge that determines the northern extent of the world's hot deserts. Vegetation and crop growth in these arid and semiarid environments is water limited. Winter rainfall is delivered by large-scale precipitation and mesoscale storms brought by westerly winds, and summer precipitation falls from convective storms associated with southerly Monsoonal winds. Rainfall in both seasons varies markedly year-to-year and, because the majority of annual precipitation can fall in only a handful of storms, it is highly unpredictable in space.

Multidecadal drought conditions are also common in these regions. Global atmospheric teleconnections often initiate drought conditions – unusually cool Pacific sea surface temperatures (La Niña phase of the El Niño-Southern Oscillation) in the American Southwest and strong north-south air pressure contrasts over the North Atlantic (positive phase of the North Atlantic Oscillation) in North Africa (Trouet et al. 2009; Ault et al. 2016). Interactions between the land and atmosphere are also strong (Koster et al. 2004), so the length of these dry spells often reflects more localized positive feedbacks between vegetation and soil moisture (Ault et al. 2014). Humans in these regions not only depend on these feedback loops for growing crops, but also play an active role in them through deforestation and irrigation.

Agricultural peoples in these environments have developed similar suites of social and physical infrastructure to grow food and manage environmental risk. Irrigation, in particular via runoff harvesting infrastructure near seasonally flooded streams (*wadis*/*arroyos*), redistributes soil moisture in space and time to create microenvironments for agriculture. But these systems are vulnerable to flooding and would have demanded significant labor investments to monitor and maintain (Shaw 1982; Dominguez and Kolm 2005; Beckers, Berking, and Schütt 2013). Food storage is an effective strategy for preserving bulk grains in dry environments, and storage features are a common archaeological find (Stone 1997; Spielmann et al. 2011). Such strategies would have been effective for managing small-scale variability (year-to-year and field-to-field), but would have been vulnerable to a long-lasting, spatially extensive droughts (Halstead and O'Shea 1989). During such extreme weather events, inhabitants of these regions must mobilize social networks to move food to afflicted settlements or move people away from them.

Rates of site preservation and recovery are exceptionally high in these regions, one of many similarities stemming from their shared climates. Nearly two centuries of survey and excavation have yielded extensive, high quality settlement pattern data in both regions, yet direct, quantitative comparisons of the two remain difficult. In spite of their strikingly similar environmental contexts, the diverging historical trajectories of the American Southwest and North Africa have led to quite different systems of food exchange. The precise nature of these social networks and the means by which this social infrastructure was provisioned varies substantially between the case studies. Consequently, the nature and quality of the empirical records of these systems are inconsistent. For a general understanding of the dynamics of these semiarid agroecosystems, we must use methods and questions tailored to the empirical realities of each case.

1.2 Structure of the Dissertation

In this dissertation, I build models – statistical, computational, and mathematical – of population growth and social interaction in semiarid environments and apply these models to empirical archaeological case studies from Roman North Africa and the pre-Hispanic American Southwest. I approach these case studies using questions and methods tailored to each (Figure 1) to produce a more general quantitative synthesis.

1. Late pre-Hispanic US Southwest: Detailed inventories of material culture at nearly 1,000 archaeological sites provide an unparalleled view of the structure and dynamics of past social networks, and the climate of this period has been intensively studied by paleoclimatologists and climate modelers. Here, I use statistical models to isolate robust social and environmental **patterns** at the macro-scale.
2. Roman Imperial North Africa: Archaeological social network analyses have focused on North Africa as a node in the Roman economy, not as a region in its own right. However, this era is well documented by direct historical sources, making it possible to recreate this system *in silico* using social simulations and climate models. Here, I use computational modeling to isolate key **processes** at the micro-scale of human-environment interactions.
3. Synthesis: Using theory from ecology, geography, and economics and insights from the empirical cases, I develop a mathematical model for understanding the **feedbacks** between social and environmental patterns and processes.

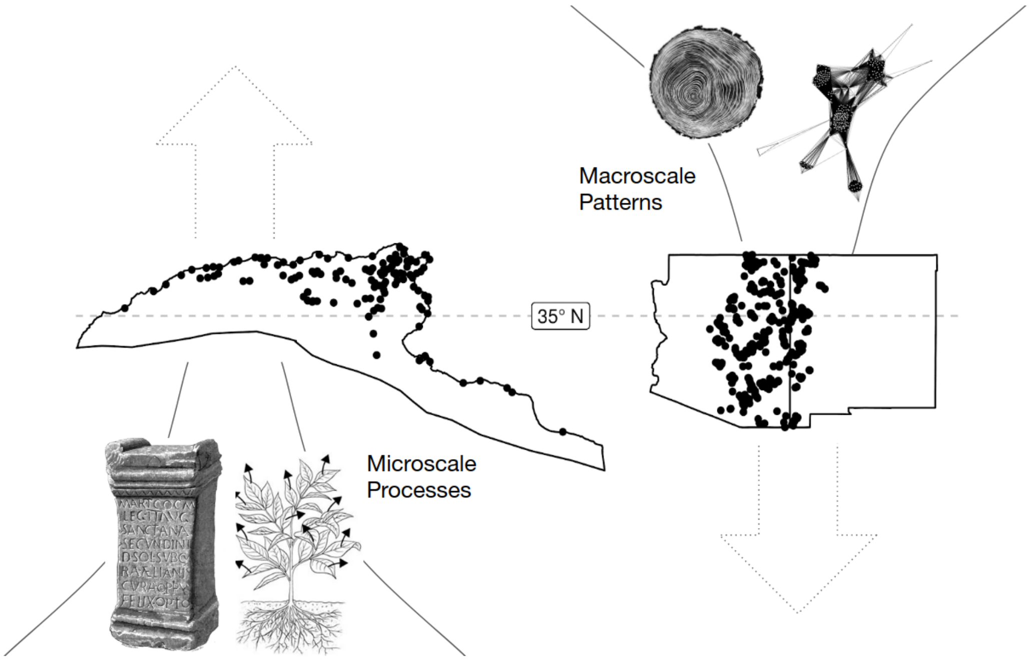

Figure 1. Conceptual outline showing the geographical similarity of the case studies and their distinct methodological approaches. Regional outlines are drawn to scale, and positioned relative to latitude 35°N. Points representing archaeological sites are plotted to show the broad distributions of human occupation. Left: Bottom-up inference from historical records and ecohydrological processes in North Africa. Right: Top-down inference from paleoclimate records and social network data in the American Southwest.

By combining first-principles modeling with extensive empirical data, this research is of a kind sorely needed in the ongoing study of sustainability in social-ecological systems. This interdisciplinary modeling framework and the insights it generates will be of use not only to archaeologists, but also to anthropologists, development economists, and the broader climate-change impact-assessment community by making tractable those problems with hidden, non-trivial human-environmental linkages.

The following three chapters are presented as three stand-alone studies each addressing a topic discussed above:

Chapter 2 In agricultural societies, farmers rely on their social networks to absorb the impacts of droughts and floods by facilitating resource flows to affected settlements and population flows away from them. These benefits depend on how well one's social network connects populations that experience different weather patterns. How do specific, recurring patterns of climate variability influence the structure and dynamics of these networks? Here, I use an empirical archaeological case study from the late pre-Hispanic period in the North American Southwest to examine the relationship between drought variability and human social networks over a 250 year period. I analyze 7.5 million artifacts collected from nearly 500 archaeological sites, and estimate how the flow of social information between sites varied as a function of distance and growing-season hydroclimate variability. Interaction between regions experiencing different oceanic and continental influences was often higher than would be expected by chance and distance alone. However, the intensity of this influence changed over time. This work highlights the importance of distinguishing between different dynamic origins of hydroclimate variability when considering the social impacts of droughts and pluvials in the past and present.

Chapter 3 Feedbacks between population growth, food production, and the environment were central to the growth and decay of ancient agrarian societies. Population growth increases both the number of mouths a society must feed and the number of people working to feed them. The balance between these two forces depends on the population's age structure. Although age structure ultimately reflects individual fertility and mortality, it is households that make decisions about the production and consumption of food, and their decisions depend on interactions with all other households in a settlement. How do these organizational levels interact to influence population growth and regulation? Here, I present a multi-level agent-based model of demography, food production, and social interaction in agricultural societies. I use the model to simulate the interactions of individuals, households, and settlements in a food-limited environment and investigate the resulting patterns of population growth. Using Roman North Africa as a motivating example, I illustrate how abstract properties like "carrying capacity" emerge from the concrete actions and interactions of millions of individual people. Going forward, bottom-up simulations rooted in first principles of human behavior will be crucial for understanding the coevolution of preindustrial societies and their natural environments.

Chapter 4 Archaeological settlement patterns are the physical remains of complex webs of human decision-making and social interaction. Entropy-maximizing spatial interaction models are a means of building parsimonious models that average over much of this small-scale complexity while retaining key large-scale structural features. Dynamic social interaction models extend this approach by allowing archaeologists to explore the coevolution of human settlement systems and networks of social interaction. Yet, such models are often imprecise, relying on generalized notions of settlement "influence" and "attractiveness" rather than concrete material flows of goods and people. Here, I present a disaggregated spatial interaction model that explicitly resolves trade and migration flows and their influence on settlement growth and decline. I explore how the costs and benefits of each type of interaction influence long-term settlement patterns. I find trade flows are the strongest determinant of equilibrium settlement structure, and that migration flows play a more transient role in balancing site hierarchies. This model illustrates how the broad toolkit for spatial interaction modeling developed in geography and economics can aid the precision of quantitative theory building in archaeology and provides a roadmap for connecting mechanistic models to the empirical archaeological record.

Chapter 2

HYDROCLIMATE VARIABILITY INFLUENCED SOCIAL INTERACTION IN THE PREHISTORIC AMERICAN SOUTHWEST

Exchange networks are part of the broad toolkit of social and physical infrastructure humans use to manage environmental risk in social-ecological systems (Anderies 2015). The environment can structure these exchange networks by influencing the costs and benefits of social interaction. Recent theoretical and empirical work highlights how spatial, social, and environmental factors interact with networks of exchange and interaction (Fafchamps and Gubert 2007; Bloch, Genicot, and Ray 2008; Nolin 2010; Verdery et al. 2012; Freeman et al. 2014; Koster and Leckie 2014; Hao et al. 2015; Schnegg 2015). Distance is a key factor in such systems, making it difficult to monitor conditions in potential migration destinations (Anderies and Hegmon 2011) and know the resources and reputation of potential interaction partners (Fafchamps and Gubert 2007), as well as increasing the metabolic costs of transport (Drennan 1984). For agricultural societies in water-limited environments, hydroclimate variability – changes in the balance of precipitation and evapotranspiration – may be another key factor. The benefits of interacting with others in distinct drought regimes can outweigh the costs of traveling longer distances. As a consequence, we might expect a greater "investment of social energy in the maintenance of social ties" between populations experiencing poorly or negatively correlated climate variability (Rautman 1993). Norms and institutions that maintain ties between different climate regimes are likely to evolve (Durante 2009). This process is difficult to measure in the present day due to the mismatch between the generational time scale on which cultural evolution occurs and the limited time horizons available to contemporary social sciences. Instead we can turn to the archaeological record.

Archaeology focuses on the material correlates of human behavior and is unique in addressing how social and physical infrastructure modulate human interactions with the environment over long time spans. Not only do archaeologists catalogue the remains of field systems, road networks, canals, and other components of hard infrastructure directly, but also the ceramics, raw materials, and luxury goods that are the material correlates of past networks of exchange and interaction. A powerful idea in archaeology is that, because of the interaction between societies and their biophysical environments, the spatial and temporal patterns of environmental variability can be used to predict "ideal" cultural responses and compared to archaeological observations (Halstead and O'Shea 1989). Yet in practice it is often difficult to find archaeological data fit for purpose, due to the incomplete nature of the archaeological record and the paucity of detailed paleoclimate data at the scales most relevant to human populations.

The North American Southwest is an exception. The climate of this region has been intensively studied by paleoclimatologists and climate modelers (Cook et al. 1999; Sheppard et al. 2002; McCabe, Palecki, and Betancourt 2004; Herweijer et al. 2007; Cook et al. 2011; Bocinsky and Kohler 2014; Coats et al. 2015; Routson et al. 2016; Ault et al. 2018). Additionally, nearly two centuries of survey and excavation have yielded extensive, high quality settlement pattern data (Hill et al. 2004). Rates of archaeological site preservation and recovery in the Southwest are exceptionally high due to the arid climate and comparatively low density of Euro-American occupation. Hence, detailed inventories of material culture at hundreds of archaeological sites provide an unparalleled view of the structure and dynamics of past social networks. This archaeological record attests to extensive exchange networks of durable goods such as ceramics and obsidian (Malville 2001; Taliaferro, Schriever, and Shackley 2010; Mills, Clark, et al. 2013), and there is evidence for the long-distance transport of limited quantities of maize to the large regional center at Chaco Canyon (Benson, Stein, and Taylor 2009; Benson 2010). The populations of the Southwest also underwent massive social transformation, migration, and population decline in the late 13th century, contemporaneous with one of the worst droughts in the last 1,000 years (Hill et al. 2004). Past work has suggested a relationship between the intensity of social interaction and patterns of drought variability, but has been limited by small sample sizes or sparse climate data (Rautman

1993; Johnson 1990; Cordell et al. 2007). The question is returning to the fore with the advent of high resolution climate observations and reconstructions, facilitating more detailed accounting of the spatial patterns of drought in the North American Southwest (Strawhacker et al. 2017), and more detailed archaeological datasets (Borck et al. 2015). Simulations suggest that the precise nature of environmental variability is critical for exchange dynamics (Freeman et al. 2014). With these advances in our ability to map droughts in space and time comes the need to more precisely define what patterns of climate variability are actually important.

Here, I draw on hydroclimate data from the past and present to isolate specific *modes of variability* – reoccurring climate patterns – in the American Southwest. I then compare

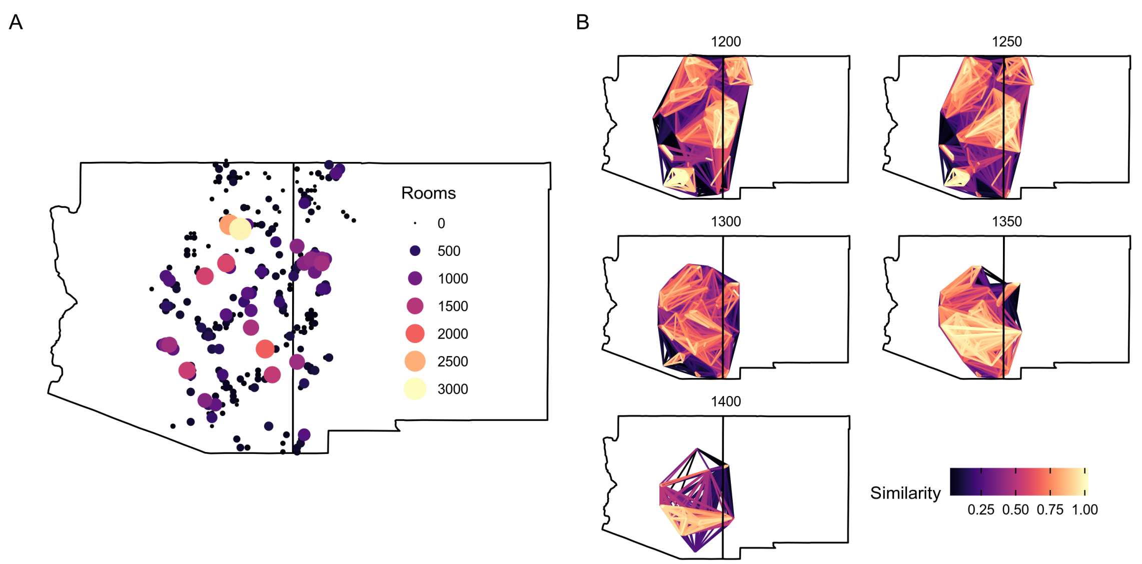

Figure 2. The *Southwest Social Networks* dataset, version 1 (Mills, Clark, et al. 2013). A) Site locations for all time periods in the dataset, aggregated into 10km patches to reduce biases from local settlement aggregation and dispersal. Site sizes are estimated from room counts. B) Social networks reconstructed from ceramic assemblage similarity between each pair of sites. A similarity coefficient of 1 means that the sites share the same decorated ceramic wares in the exact same proportions, and a coefficient of 0 means there is no overlap in the ceramic assemblages. The similarity network can be interpreted as the degree of social interaction and cultural transmission between sites, whether via migration, trade, or copying. Networks are shown over successive 50 year time spans, starting at 1200 CE.

these patterns to prehistoric social networks, inferred from a dataset of 7.5 million ceramic artifacts from nearly 500 archaeological sites (Figure 2), to examine the relationship between hydroclimate variability, distance, and social interaction over a 250 year span.

2.1 Results

2.1.1 Six Drought Patterns Explain 83% of Observed Drought Variability in the American Southwest

Climate can vary for many reasons, so it is important to separate climatic signal from noise. Principal Components Analysis (PCA) of spatiotemporal data is a common tool for extracting modes of variability in the climate sciences (Lorenz 1956; Hannachi, Jolliffe, and Stephenson 2007), but its use for this particular purpose is rare in archaeology (Weiss 1982; Cordell et al. 2007). I used PCA to decompose the gridded observational record of summer moisture availability in the western US, measured at 122 annual time points and 119,882 spatial locations, into orthogonal modes of variability in order to extract the leading patterns that collectively explained the most variability.

The leading 6 PC time series together explain 83% of the variance in the observational record. The principal components (PCs) represent time series that are maximally representative of the entire data set (Figure 3). I rotated the 6 PCs before mapping, in order to capture more physically meaningful patterns and minimize statistical artifacts. PCs beyond the leading 6 were not retained for rotation and mapping, as they represent spatially and temporally incoherent variability and spurious correlations introduced by sampling error in the observational record (see Methods).

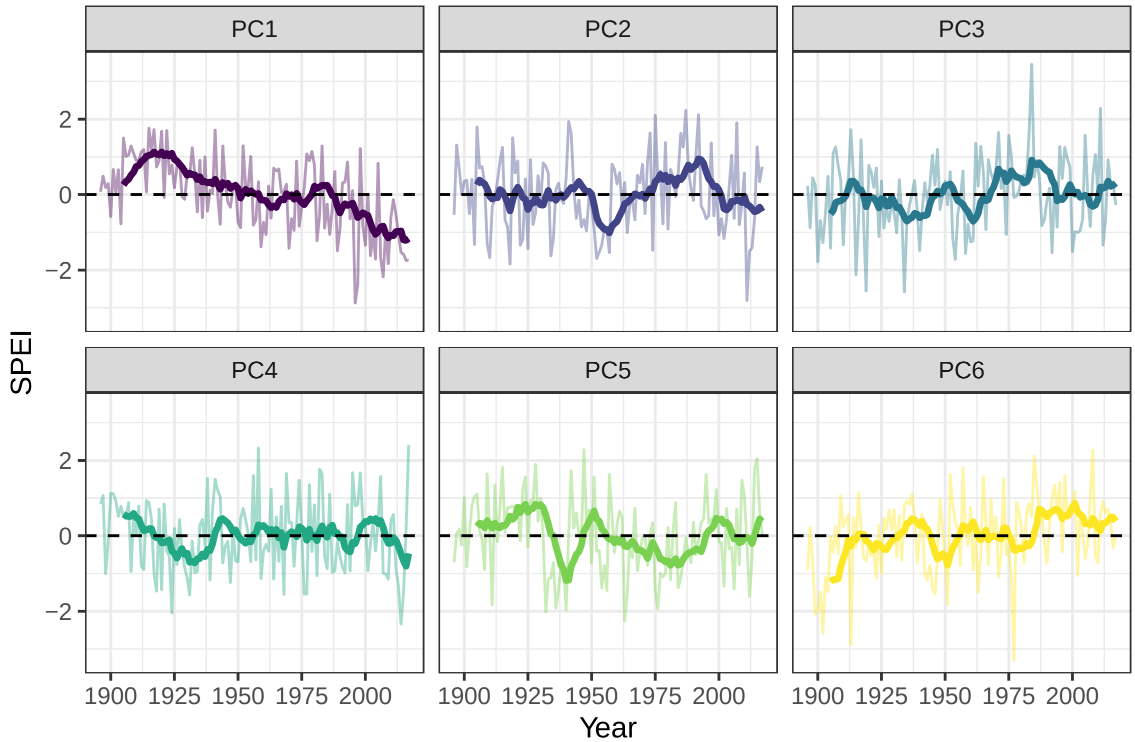

Figure 3. Time series associated with the leading 6 PCs for the observational period, after varimax rotation. The y-axis corresponds to the 12 month Standardized Precipitation-Evapotranspiration Index (SPEI), the normalized deviation from the average climatic water balance for a given month on 12 month time scale. SPEI values can be interpreted as z-scores in a normal distribution (i.e. a value of 1 is one standard deviation wetter than average for that location, -1 is one standard deviation drier). 10 year moving averages superimposed over raw annual values.

2.1.2 Different Drought Patterns Are Associated with Different Zones of Oceanic or Continental Influence

To reveal the latent spatial structures associated with the temporal modes of variability, I mapped the spatial patterns associated with each of the leading 6 PCs (Figure 4). The results are robust, recurring patterns of spatially-coherent variability, and can be interpreted as the degree to which the 122 year record at each grid cell correlates with the associated rotated PC time series. These spatial patterns are known as the (rotated) empirical orthogonal functions (EOFs). The patterns are consistent regardless of the exact SPEI time scale used to calculate them, which supports their robustness. The spatial and temporal patterns associated with the leading 6 PCs allows us to trace the sources of each mode of variability back to the global climate system.

The origins of each drought pattern can be determined by examining the EOF maps, along with the correlations of the PCs to global sea surface temperature and examining extreme dry and wet periods in each observed PC. EOF1 reflects southwesterly flow from the tropical Pacific, bringing moisture across the low desert zones of California and Arizona. The pattern attenuates with elevation and as distance from the ocean increases. PC1 shows a broad drying trend to the present day, possibly related to increased evaporative demand due to recent warming, although the spatial pattern in the associated EOF is not itself anthropogenic. EOF2 similarly represents southeasterly flow from the Gulf of Mexico, centered eastern New Mexico. As with EOF1, the pattern attenuates with increasing elevation and distance from the ocean due to orography and continentality, respectively. It represents cyclonic storms coming from the Gulf of Mexico, in turn influenced by variability in Atlantic sea surface temperatures. PC2 shows a major dry period centered on the Texas/New Mexico drought of 1956. EOF3 represents northerly flow associated with polar continental cold fronts, and its associated PC shows a wet peak in the 1983 Salt Lake City floods. EOF4 represents the influence of westerly flow off the Pacific Ocean and the orographic effect of the Sierra Nevada mountains intercepting this flow, and is associated with events such as the 1924 drought in California. EOF5 is centered over the great plains and attenuates across the Rocky Mountains, and was most strongly expressed during the Dust Bowl of the 1920s. EOF6 is centered on the the Colorado Plateau, likely reflecting hot continental air masses, and is the only pattern not also visible in coarse-resolution reconstructions.

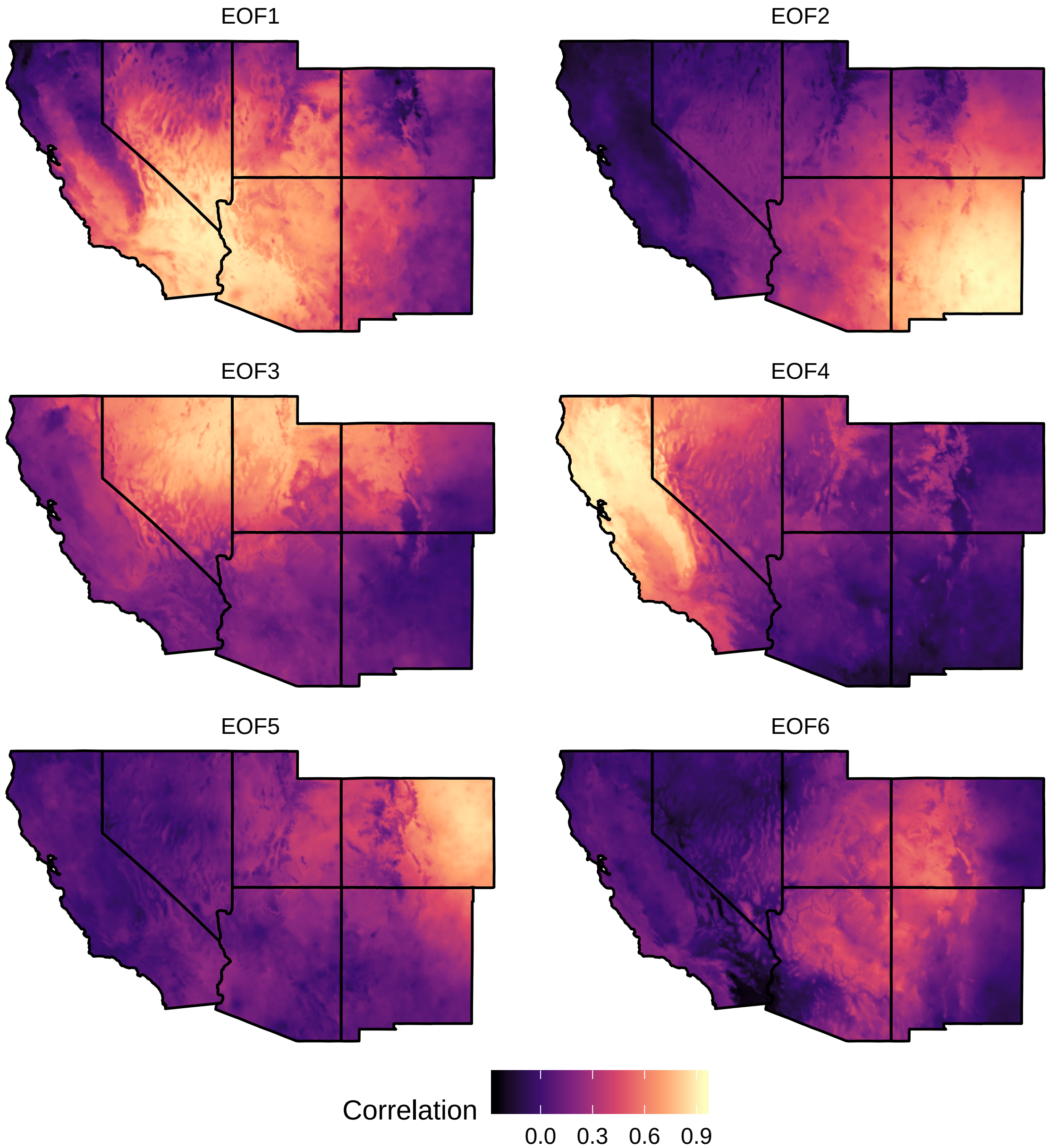

Figure 4. Leading 6 rotated empirical orthogonal functions (EOFs), associated with the respective PC time series in Figure 3. These regions represent different oceanic and atmospheric influences; people living in the same EOF will often experience dry and wet years at the same time as one another.

2.1.3 The Intensity of Social Interaction Decays Nonlinearly with Distance

Distance ultimately constrains social interaction, as the further one travels to interact with a partner the greater will be the cost in time, energy, and other resources. I calculated the cost of moving between each pair of archaeological sites as the shortest amount of time it would take a foot traveler to move between them. I then used a nonlinear regression model to estimate the functional relationship between distance and interaction.

The null model for the statistical network analysis was that distance alone explains the intensity of social interaction, as measured by the similarity in the decorated ceramic assemblages of each pair of sites. This null model was sufficient to explain nearly 35% of the variance in archaeological dataset. The empirical distance deterrence function estimated on all time periods using a penalized regression spline (see methods) predicts a falloff in interaction at distances of more than 100 hours (Figure 5). As expected, the resulting distance-based network predicts many strong interactions at close distances, and the residuals of the model show long distance transitive ties.

2.1.4 Hydroclimate Variability Explains a Moderate but Clear Proportion of the Intensity of Social Interaction

A model predicting information flow using distance and climatic dissimilarity, measured as the absolute difference between the EOF loadings of a pair of sites, explains approximately 41% of the variance in the ceramic similarity data. The increase over the distance-only null model is moderate but statistically significant, and the EOF model is superior in all measures of parsimony and goodness-of-fit. This difference changes over time, and refitting each model on data from each time step individually reveals that the improvement in the explanatory power of the EOF model over the distance-only null is most pronounced at and after 1300 CE (Figure 6). The improvement in explanatory power over the null model is quite small

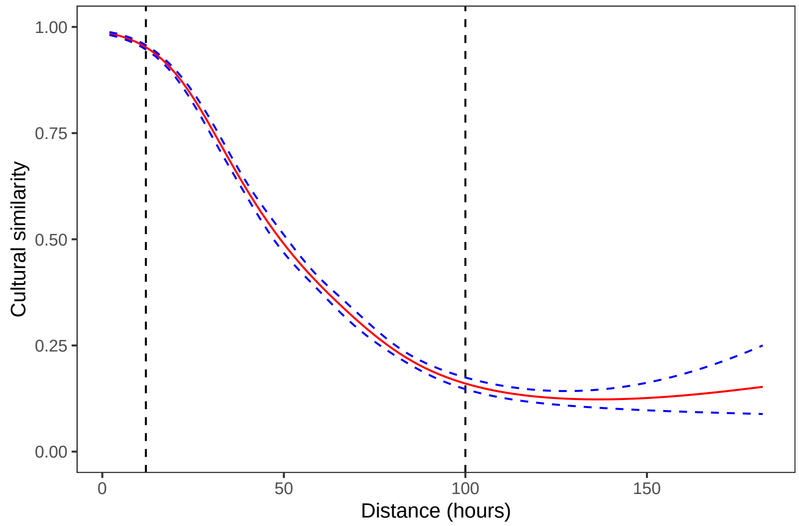

Figure 5. Empirical distance deterrence function estimated with a generalized additive model, describing how the intensity of social interaction, defined as the information flow between two settlements and measured by the similarity in their decorated ceramic assemblages, decreases as a function of distance. Blue dashed lines indicate the 95% confidence interval for the smooth function. Black dashed lines indicate key thresholds in the function at 10 and 100 hours.

in the 1200 and 1250 CE time steps. This pattern suggests that ties shaped in part by the EOF patterns are more common during and after the period of regional relocation around 1300 CE.

The smooth functions estimated in the EOF model are all close to piecewise linear on the scale of the linear predictor, but the intensity of these functional relationships varies smoothly over time and across EOFs (Figure 7). Increasing distance along a particular EOF sometimes increases the intensity of social interaction, as was expected ahead of time, but some EOFs (3, 6) appear to slightly reduce social interaction at larger differences. The smoothness penalty also selects some EOFs out of the model entirely by estimating functions close to a horizontal line, and almost all the functions are flat when the climate differences are less than 0.2. Surprisingly, the fluctuations in the effect size of a particular EOF have no clear association with the sign of the associated PC amplitude time series reconstructed for each period, suggesting that additional dynamic processes are in effect on time scales

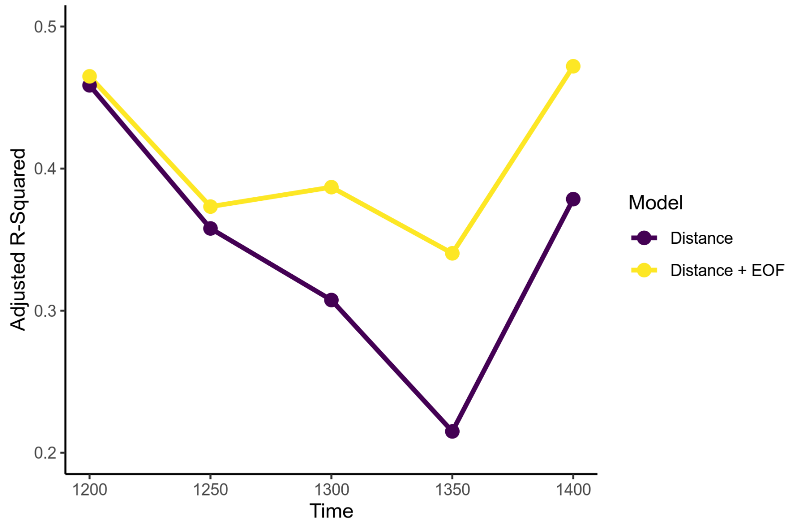

Figure 6. Change in adjusted R-squared over time, for the distance-only and EOF and distance models fit to each time period separately.

longer than a single generation, such as cultural memory or institutional growth and decay. These processes may explain why different sets of EOF patterns appear to influence social interaction before and after the interregional migration period ca. 1300 CE.

2.2 Discussion and Conclusions

The six spatial patterns of hydroclimate variability isolated here are consistent with the general mechanistic understanding of hydroclimate variability in the American Southwest. These patterns represent different zones of moisture transport, reflecting the influence of topography and marine or continental moisture sources (Liu, Bowen, and Welker 2010; Hu, Feng, and Oglesby 2011). These spatial and temporal drought patterns, and their hypothesized forcings from the global climate system, are largely consistent with those from other studies using varied observational data and time windows (Comrie and Glenn 1999; Cook et al. 1999; McCabe and Dettinger 1999; McCabe, Palecki, and Betancourt 2004; Ryu et al. 2010; Seager and Hoerling 2014; Herrmann et al. 2016). These same patterns from the

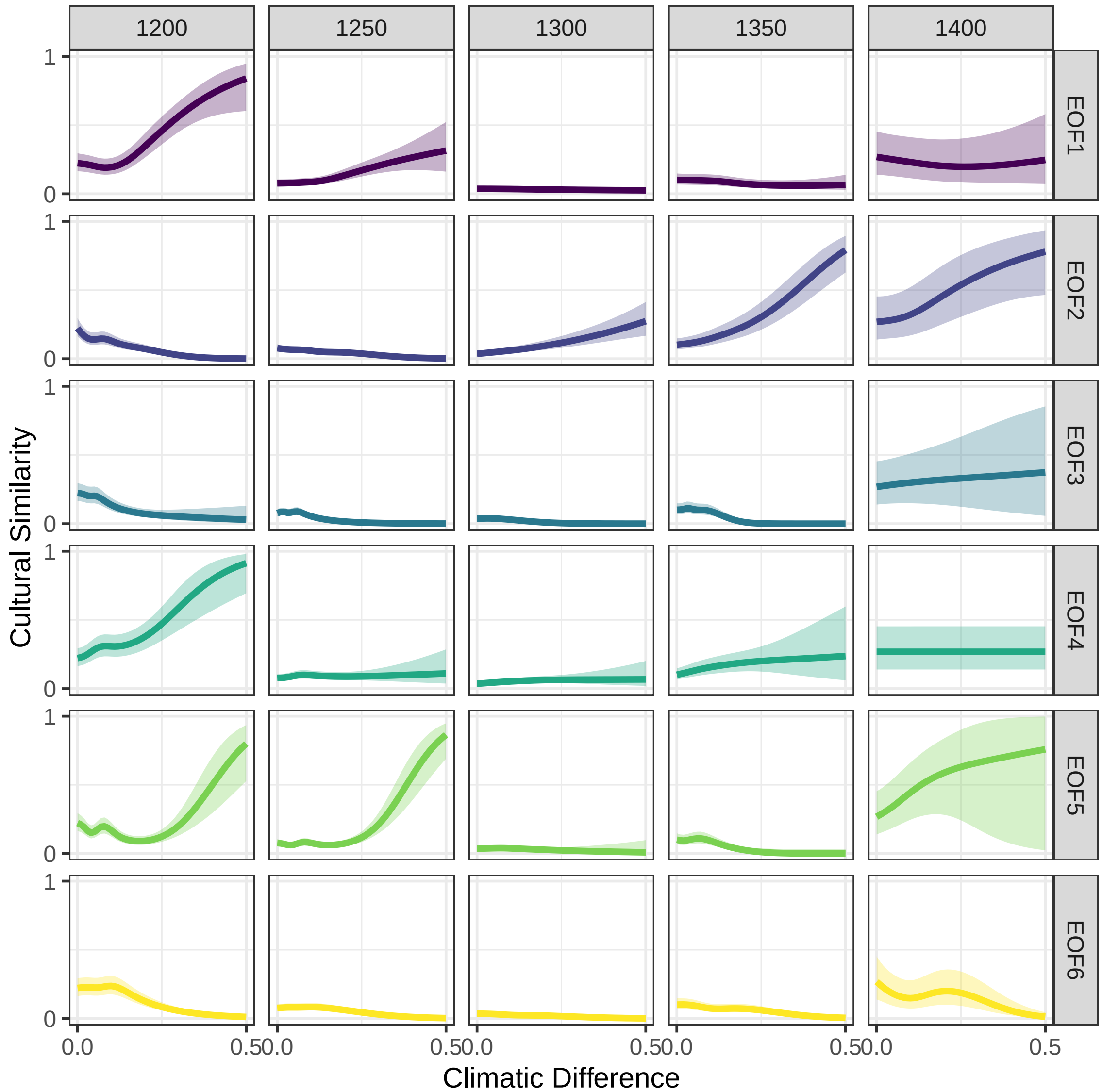

Figure 7. Estimated smooth functions describing how the intensity of social interaction increases or decreases with increasing distance along each of six spatial drought patterns from Figure 4, compared over five time steps. As above, information flow is inferred from the similarity of the decorated ceramic assemblages at each pair of sites. Climatic distance is defined as the absolute difference between the EOF loadings of each pair of sites. Shaded regions correspond to the 95% confidence intervals for the smooth functions. Unlike in Figure 6, these functions are estimated from the model fit on all time periods simultaneously.

observational period also appear in drought reconstructions spanning the past millennium, emphasizing the fact that these are robust, time invariant spatial modes.

Objective measures of hydroclimate variability, rather than point-to-point sample correlations, allow us to isolate the most important drivers of that variability. Droughts and pluvials associated with tropical Pacific and Atlantic influences seem to have been most important for structuring social interaction, with ties connecting these regions greater than expected by chance and distance alone. Tropical Pacific sea surface temperatures are known to be the primary driver of variability in Southwest, with additional influences from moisture sources in the North Pacific and Atlantic (McCabe, Palecki, and Betancourt 2004). A disruption in these patterns is thought to be one reason why droughts in this period led to such social transformation, as the networks of social infrastructure that had developed over previous centuries were unable to adapt fast enough to unusual conditions (Cordell et al. 2007).

Populations in the late pre-Hispanic Southwest were clearly out of equilibrium (Hill et al. 2004). Exchange networks take time to develop and effort to maintain. Social dynamics such as free-riding can lead to the breakdown in this critical social infrastructure when it is most needed (Kohler and West 1996). Yet the change of the functional forms for the EOF patterns over time still points to dynamics occurring longer than our 50 year time scales. Future studies should leverage these findings to construct dynamic simulation models. It will be important to model the evolution of social flows and physical paths separately (Bevan and Wilson 2013) in order to capture this time lag effect. A simulation approach would be better able to capture the influence year-to-year variability, as well as the time averaging and bias introduced by the use of archaeological similarity data to represent dynamic social processes (Crema, Kerig, and Shennan 2014; Crema, Kandler, and Shennan 2016).

In spite of the robustness of these spatial patterns, there remains considerable diversity in the functional responses of human social networks to these drought patterns. Differences in drought regime are just as likely to inhibit social interaction as they are to enhance it. One possible explanation is that large-scale climate regimes also influence the formation of ethnolinguistic groups. Kinship, or perceived kinship (ethnicity) are important for structuring social exchanges (Nolin 2010). Small-scale, quotidian interactions may have tracked shared ethnolinguistic affiliation, while interregional exchange may have occurred higher up a sociopolitical hierarchy. The flows of goods and information often proceeded hierarchically, a dynamic poorly-captured in simple spatial interaction models (Crumley 1979). Perhaps then the strongest flows were between sociopolitical elites at terminal sites.

The residuals from the fitted network models retain unexplained structure. These broadly correspond to large cultural clusters, a common feature in social networks that is not accounted for by either distance or drought variability. On a microscale, the residuals display a pattern of high transitivity and triad closure, which is to say there are a great many more closed triangle structures than would be expected by chance. Although this feature is common in human social networks, it is also to be expected from the semi-metric nature of the data, as full transitivity is to be expected in a metric subject to the triangle equality. Statistical methods specifically designed for such structures may be preferable in future work (Stillman et al. 2017). In addition, the archaeological data are not spatially extensive enough to sample the full range of hydroclimate variability. Given the relative spatial scales of our environmental and cultural data, there is a risk that many different correlated climate patterns will be indistinguishable at the scale of the cultural data. Correlation between competing hypotheses as a source of error in model selection using information criteria (Shirk, Landguth, and Cushman 2018). In spite of these shortcomings, these results highlight two more novel points: the importance of objective, physically-meaningful measures of drought spatial variability and that social interaction dynamics are out of equilibrium with the biophysical environment.

These results refine our understanding of the geography of human adaptation to climate and climate change. Prehistoric exchange infrastructure evolved in part in response to robust, time-invariant spatial climate structure. The EOF patterns acted as the selective environment in which norms and institutions regulating social interaction emerge. Social responses adapted to a particular mode of variability can be fragile to changes in that variability (Janssen, Anderies, and Ostrom 2007). These findings emphasize the importance of institutional evolution in increasing the robustness of human populations to environmental variability. Much of the world's food is still grown on small farms, and these farmers rely on complex networks of formal and informal arrangements in much the same way as their forbears have for 1,000s of years. Tracing the flows of information and energy within these complex social-ecological systems is essential for understanding their long-term behavior, and leveraging our archaeological understanding of why societies succeed or fail will be critical to anticipating the impact of impending climate changes on farming communities in the developing world.

2.3 Data and Methods

2.3.1 Hydroclimate Variability

I analyzed a 122-year gridded record of the Standardized Precipitation-Evapotranspiration Index (SPEI) calculated from interpolated weather-station data over the states of Arizona, New Mexico, Colorado, Utah, and California (Daly, Taylor, and Gibson 1997). SPEI is the normalized deviation from the average climatic water balance for a given month on varying time scales (Vicente-Serrano et al. 2010). I focused on the 12-month SPEI calculated in the August of each year, a measure which integrates the water balance over the year leading up each summer growing season. I calculated the space-time covariance matrix from the stack of 122 gridded SPEI maps, and estimated the the empirical orthogonal functions (EOFs) of the data via a singular value decomposition of the covariance matrix [1], multiplying each grid cell by the cosine of latitude to account for areal distortion. Then, I selected the leading eigenvalues for rotation using both a scree test and North's rule of thumb, which is a method to detect degenerate EOF patterns caused by temporal autocorrelation in the observed data (North, Bell, and Cahalan 1982). I rotated the leading eigenvalues using a varimax

[1] This step is equivalent to working on the correlation matrix, as SPEI is already standardized to unit variance at each location.

rotation in order to relax the spatial orthogonality constraints of the PCA analysis to reveal coherent, physically meaningful patterns (Richman 1986). The resulting eigenvectors were then multiplied by the square root of the corresponding eigenvalues to yield correlation coefficients, and were mapped in space. I refer to these resulting spatial patterns as EOFs, and their associated time series as PCs (principal components). The PC amplitude time series were then compared to the observational record, and the signs of the eigenvalues and vectors were reversed to match the historical record (so that a positive time series value corresponded to a positive SPEI and *vice versa*). To determine whether these patterns were robust over time, the observed EOFs were compared to the EOFs of a SPEI reconstruction over the past millennium (Steiger et al. 2018).

2.3.2 Archaeological Interaction Networks

The Southwest Social Networks (SWSN) database is a compendium of material-culture data from nearly 1,000 well-dated archaeological sites west of the Continental Divide in Arizona and New Mexico (Mills, Roberts Jr, et al. 2013; Mills, Clark, et al. 2013; Peeples and Haas 2013; Borck et al. 2015; Hill et al. 2015; Mills et al. 2015). The SWSN project recorded nearly 4.7 million ceramic artifacts and nearly 5,000 obsidian artifacts (Mills et al. 2015). Version 1.0 of the SWSN database provides quantitative estimates of the topology of the region-wide social network during five 50 year time steps spanning the period 1200-1450 CE (Mills, Clark, et al. 2013). Raw site-level ceramic counts were allocated to each time step according to an apportioning procedure that combined the occupation span of each site and the production span of each ware type with a parametric assumption of the wares' changing popularity through time (Mills, Clark, et al. 2013; Peeples and Haas 2013).

I aggregated the point-based SWSN data into 10km grid cells[2] so that the network

[2] The choice of 10km grid cells reflects a day's round-trip travel, bounding the area for farming and raw material collection around a site, so the procedure effectively smooths over the approximate area of each site's resource catchment (Varien 1999; Hill et al. 2015)

estimates were less sensitive to local settlement dispersal or aggregation as reflected in the assemblages at individual sites (Paliou and Bevan 2016). Then I calculated the modified Jensen-Shannon divergence between the empirical frequency distributions of 15 decorated ceramic wares at each of the grid cells as

$$D_{ij} = H\left(0.5P_i + 0.5P_j\right) - 0.5H(P_i) - 0.5H(P_j), \tag{2.1}$$

where D_{ij} is the divergence between the empirical frequency distributions of ceramic wares at sites i and j, P_i is a vector of the proportions of ceramic ware type k in the assemblage at site i, and $H(P) = -\sum_k p_k \ln_2 p_k$ is the Shannon entropy of P measured in bits. This equation measures the similarity of two sites by the distributions of the ceramic types shared by both sites and the types exclusive to each (Masucci et al. 2011). Analogous to the use of divergence measures in population genetics, divergence here is a (inverse) proxy for information flow. The resulting network structure is similar to that resulting from other similarity measures such as the Brainerd-Robinson index (Mills, Clark, et al. 2013) save for different behavior in the tails of the distribution, but the Jensen-Shannon index provides a more natural interpretation as a measure of information flow. By focusing on a general measure of information flow, aggregate patterns of social interaction can be inferred regardless of precise mechanisms of that interaction (e.g. trade, migration, shared history or raw materials). The index can thus be loosely interpreted as a probability of interaction between two sites, with identical patterns of ceramic discard at two sites indicating a higher probability of interaction than between sites that share no ware types in common.

2.3.3 Least-Cost Networks

I calculated the least-cost network between all sites in the SWSN network. The topography of the study area was represented using 90m SRTM DEM, resampled to 250m to reduce computation time and smooth fine-scale topographic noise. A cost matrix was calculated containing, for each DEM cell, the amount of time in seconds it would take a foot traveler to move to each of the 16 neighboring cells. Time costs were calculated using a version of Tobler's hiking function, which estimates walking speed from terrain slope. The function was modified to make it isotropic (i.e. averaging the uphill and downhill walking speeds) and adding an extra penalty to very steep slopes consistent with human cognitive biases (Pingel 2010). This cost matrix (time) was then inverted to represent conductance (speed), facilitating a sparse matrix representation and estimation of least cost paths using efficient graph theoretic algorithms (Etten 2014). The resulting transition matrix was used to calculate all pairwise isotropic least cost paths between the centroids of each pair of 10km grid cells containing archaeological materials.

2.3.4 Spatial Interaction Models

Spatial interaction models are used across the social and natural sciences (Wilson 1971a; Fotheringham and O'Kelly 1989; Sen and Smith 1995; Bavaud 2008; Murphy et al. 2010; Head and Mayer 2015). In a regression context, a spatial interaction model estimates the pairwise flow – resources, migrants, information – among entities as a multiplicative function of predictors influencing the production and attraction of flows as well as measures of their mutual separation or other generalized costs of moving. Archaeologists have used *statistical* spatial interaction models sparingly (Tobler and Wineburg 1971; Hodder 1974; Johnson 1990) because of the rarity of archaeological data on social interaction strength, although the method is common in simulation studies where data quality is less of a restriction (Bevan and Wilson 2013; Evans, Rivers, and Knappett 2011; Davies et al. 2014; Paliou and Bevan 2016). The conceptual justification for the use of spatial interaction models on archaeological networks is similar to that used in molecular ecology (Murphy et al. 2010), with information flows among a spatially-structured metapopulation measured by the divergence of those populations (Mesoudi 2018). Data of this type have three features that make traditional statistical spatial interaction modeling difficult. These are: 1) the data are bounded between 0 and 1, 2) the measures are pairwise symmetric 3) we have no exact functional expectations for the specific terms in the spatial interaction model because empirical work on this scale and type is rare. To address these issues, I used a generalized additive model (Wood 2006), a semiparametric extension to generalized linear models useful for more complex spatial interaction models (Lebacher, Thurner, and Kauermann 2018).

Specifically, I fit models of the form

$$logit\,(D_{ijt}) = f(dist_{ij}) + f_t(EOF_{ij}) + \tau_{it} + \tau_{jt} + \epsilon_{ijt}, \tag{2.2}$$

where the logit function maps the data from $[0, 1]$ to $[-\infty, +\infty]$, t is the time step, $f()$ is an arbitrary function estimated during model fitting using penalized cubic regression splines, τ_i and τ_j are time-varying random effects for the nodes incident on each edge, and ϵ is Gaussian error. This model assumes only that information flows are at equilibrium with settlement population, not that the populations themselves are at equilibrium (Wilson 2008). The τ terms account for the non-independence of edges that share a node, and were estimated using a maximum likelihood population effects correlation structure appropriate for pairwise data (Clarke, Rothery, and Raybould 2002). I compared the AIC, BIC, and R^2 of models fit using maximum likelihood with and without the EOF terms, and refit the best performing model using restricted maximum likelihood (Clarke, Rothery, and Raybould 2002; Shirk, Landguth, and Cushman 2018).

Chapter 3

MULTILEVEL SIMULATION OF DEMOGRAPHY AND FOOD PRODUCTION IN ANCIENT AGRARIAN SOCIETIES: A CASE STUDY FROM ROMAN NORTH AFRICA

The combined forces of population growth and food production transformed global and regional environments throughout the Holocene (Kaplan, Krumhardt, and Zimmermann 2009; Hunt and Rabett 2014; Klein Goldewijk et al. 2017; Wright 2017; Roberts et al. 2019). Expanding populations made significant downstream impact on natural biogeophysical and biogeochemical cycles through deforestation, irrigation, and agropastoral land use (Kaplan et al. 2010; Fuller et al. 2011; He et al. 2014; Koch et al. 2019). Likewise, climate variability has influenced the growth and decline of human societies, (Benson et al. 2007; Kaniewski et al. 2013; Bevan et al. 2017; Nooren et al. 2018), although this relationship is neither simple nor constant in space and time (Danti 2010; Dunning et al. 2013; Shennan et al. 2013; Lawrence et al. 2016). Understanding the nature of two-way feedbacks between climate and society requires first closing the loop between demography, food production, and climate (Dean 1996; Butzer 2012; Bevan et al. 2017).

The feedback between a population's food supply and its health and well-being is the essential mechanism of population regulation in humans (Lee 1987; Wood 1998). Populations will grow until they reach a stable state where births equal deaths and growth stops: the *demographic saturation point* (Wood 1998). Long-run changes in population will arise only from changes in this point (Boserup 1965; Wood 1998). Famines, epidemics, and other catastrophic mortality events that do not change this point soon experience renewed growth due to reduced population pressure (Watkins and Menken 1985). Related to, but distinct from, the demographic saturation point is the idea of environmental "carrying capacity" or the maximum population supportable by food production in the local environment (Dewar 1984). The key variables determining environmental carrying capacity for preindustrial societies are, predictably, arable land area and potential agricultural productivity (Fanta et al. 2018a). However, "carrying capacity" varies not only across environments but also among different cultures and time periods (Currie et al. 2015). Farmers can invest their time in building terraces or building irrigation infrastructure, constructing local agricultural niches and consequently raising the local carrying capacity (Lansing and Fox 2011; Bevan et al. 2013; Kaptijn 2015; Wilkinson, Rayne, and Jotheri 2015). The result is a two-way feedback; population size depends on carrying capacity and carrying capacity depends on population size. How do these factors interact?

We can close this feedback loop by defining the demographic saturation point as a function of the productive capacity of the entire society, integrating social, ecological, and technological factors (Wood 1998). A population's age structure is particularly important here not only because it constrains its food needs and sensitivity to food shortfalls, but also the proportion of the population capable of producing food in the first place. By explicitly modeling the interaction between population age structure, productive capacity, and vital rates, we can predict the nature and timing of population growth and regulation (Lee and Tuljapurkar 2008; Puleston and Tuljapurkar 2008; Puleston, Tuljapurkar, and Winterhalder 2014). One factor such models tend to leave out, however, is the nested organization of human groups.

Like many complex systems, real-world human populations are organized in nested hierarchies (Simon 1962). People act and interact within groups of varying sizes: as individuals, households, settlements, and societies. It is important to recognize this organization for understanding the population dynamics of heterogeneous human populations (Read and Leblanc 2003). While fertility and mortality occur on the individual level, decisions about food production, storage, and consumption often occur at the household level, and spatial organization of production is often determined at the settlement level. This modular organization can have major consequences for the underlying population dynamics (Chayanov 1986; Wood 1998). How might we incorporate this organizational complexity into models of food-limited demography?

To address this gap, I propose a hierarchical simulation framework (Figure 8) for modeling food-limited predindustrial populations. I use a multilevel agent-based model to capture the hierarchical organization of agricultural societies, resolving dynamics on the individual, household, and settlement scales as well as interactions across scales. The complexity of such models arises from the interaction of simple agents with heterogeneous information, objectives, and resources. One difficulty with agent-based modeling is that simulating the perceptions and decision-making of millions of interacting agents can quickly become computationally intractable. However, a multilevel simulation model selectively varies the level of abstraction to capture complex, cross-scale feedbacks in a population of millions of agents with limited computational overhead. The model presented here focuses on the emergent patterns of population growth and regulation arising from individual fertility and mortality, household decision making, and interactions among households and settlements. By foregrounding the role of human decision-making in food production and population growth, the model is able to bridge the gap between environmental and demographic change.

The Roman Imperial period in North Africa is a motivating case study. North Africa is a region of close land-atmosphere coupling, and experienced massive Roman-era population growth and land-use and land-cover change driven by multiple endogenous and exogenous environmental and social factors. Although the present model of demography and food production is intended to be broadly applicable, it is nevertheless useful to analyze its behavior in light of a specific social, ecological, and technological context because quantities like carrying capacity or demographic saturation point are so locally contingent. Bottom-up simulation of these factors can shed light on key mechanisms and interactions otherwise obscured in top-down reconstructions of past population and land use.

3.0.1 Case Study: Roman North Africa

Two millennia ago, the province of Africa Proconsularis in North Africa – roughly modern day Tunisia, Algeria, and Libya – was a breadbasket of the Roman Empire (Kehoe 1988;

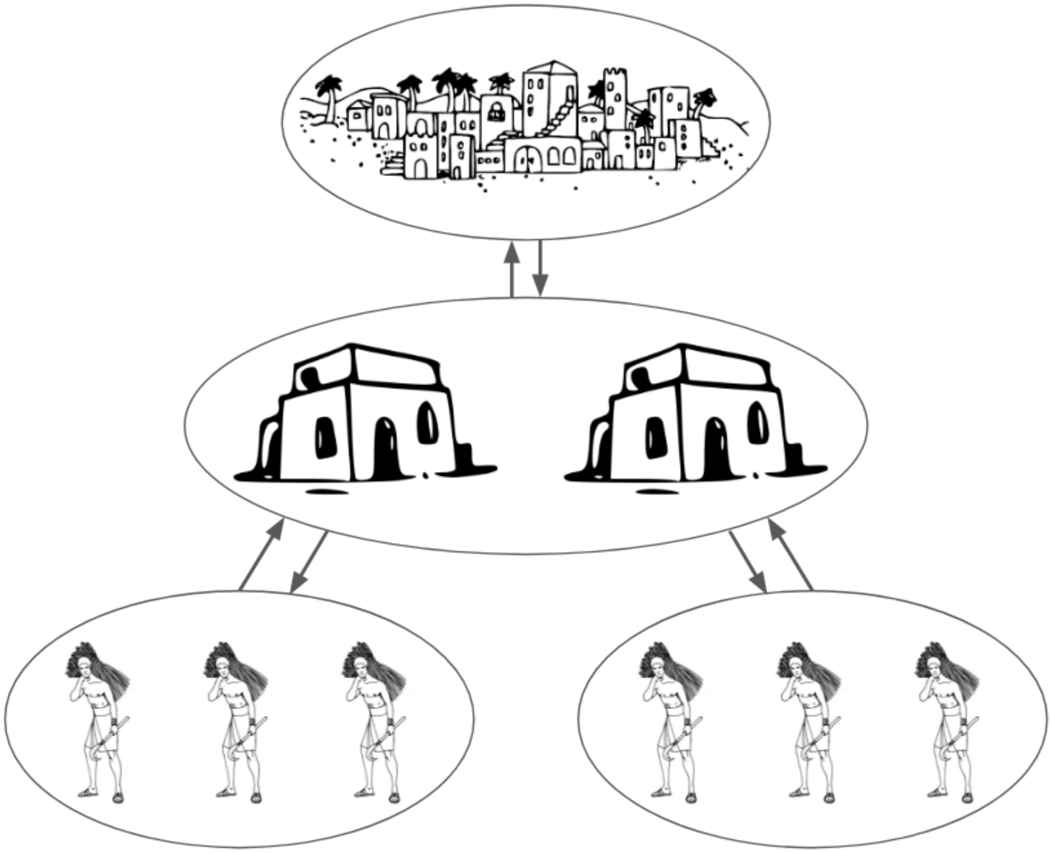

Figure 8. Hierarchy of agent decision making. Individuals are grouped into households, which are in turn grouped into settlements. Demography occurs at the individual level, but is influenced by the household, land use occurs at the household level, and land use and social interaction occurs at the settlement level.

Garnsey 1989). Today, cereal agriculture is limited to a narrow coastal strip at the northern edge of this semiarid region (Latiri et al. 2010). The causes and consequences of this apparent shift in productivity have long been debated (Murphey 1951). Climate change seems to have played a key role, with a millennial-scale drying trend since the mid-Holocene punctuated by century-scale fluctuations driven by oceanic variability in the North Atlantic (Dermody et al. 2012). Proxies for geomorphic change during the period suggest a primary role for climate, although second-order human impacts were also apparent (Faust et al. 2004).

An alternative perspective holds that social and technological change lead to North Africa's past agricultural productivity. The Roman state and society as a whole exerted strong social and legal pressure to bring uncultivated fields under the plow and invest in agricultural infrastructure (Kehoe 1988; Stone 1997; Stone 1998; Hilali 2013). Local niche construction via irrigation and runoff harvesting was particularly common, combining indigenous landscape management practices with the Empire's experience in hydraulic engineering projects (Shaw 1982; Mattingly and Hitchner 1995; Beckers, Berking, and Schütt 2013).

Implicit in this discussion is the assumption that climate change and socio-technical innovation are mutually exclusive. Yet, natural climatic drying was supplemented by extensive anthropogenic deforestation for food and fuel production (Hughes 2011). Paleoclimate simulations have suggested that Roman-era transformation of the land surface may have itself contributed climatic drying (Reale and Dirmeyer 2000; Reale and Shukla 2000; Gates and Ließ 2001). So was North Africa's agricultural productivity under Roman rule the result of a briefly favorable regional climate, human management of the local environment, or feedbacks between the two?

The global land-use and population hindcasts often used by the paleoclimate modeling community are ill-suited for answering such a question (Kaplan et al. 2010; Klein Goldewijk et al. 2017). This top-down approach to estimating land use at equilibrium with population density is understandable given the tradeoffs that exist in generating global syntheses, but leave much to be desired in cases such as Roman North Africa where the direction of influence is less clear. Reliance on external, fixed population hindcasts precludes estimates of the two-way feedbacks between population growth and food production.

3.1 The Model

Agent-based models are a flexible simulation tool, allowing researchers to start with the first principles of human behavior and scaffold up to a more flexible treatment of diverse cultures and time periods. The core principles of this particular model are:

1. Human population growth is food limited (Lee 1987; Wood 1998).
2. Households are the principal unit of food production and consumption (Chayanov 1986; Sherbinin et al. 2008).
3. Humans are boundedly-rational decision makers that attempt to make "good-enough" choices given finite information and resources (Simon 1990).

For the North Africa case I added two additional assumptions: wheat grown under a biennial fallowing regime is the primary food resource, and households are able to improve their fields with infrastructure for harvesting surface runoff to increase local water availability to crops.

The purpose of this model is to capture the essential feedbacks between the food production, population growth and regulation, and the local environment in preindustrial agricultural populations. It simulates three agent types operating in a nested hierarchy: individuals, households, and settlements. Individual agents reproduce and die according to the amount of food in the household. Household agents allocate their land and labor to produce food, seeking to grow enough food to satisfy its occupant's needs while storing the surplus. Settlement agents mediate the competition for land among their constituent households, and exchange flows of food and people with neighboring settlements. I analyze the model both in the abstract, focusing on processes of population growth and regulation, and parameterized to represent the Roman Imperial period in North Africa, focusing on stable patterns of population density and agricultural productivity.

The model is implemented in R, primarily using packages in the `tidyverse` paradigm. The `tidyverse` uses flat, potentially nested data tables as the basic computational unit and emphasizes code that is concise, expressive, and modular. Specifically, the model uses the nesting and iteration functions in the `tidyr`, `dplyr`, and `purrr` packages to allow for interactions across scales and seamless parallel processing. The model code itself is available as an open source R package, and is available for download, reuse, and modification at https://github.com/nick-gauthier/Silvanus. R's strengths as a functional programming language contrast with the object-oriented languages commonly used for agent-based modeling.

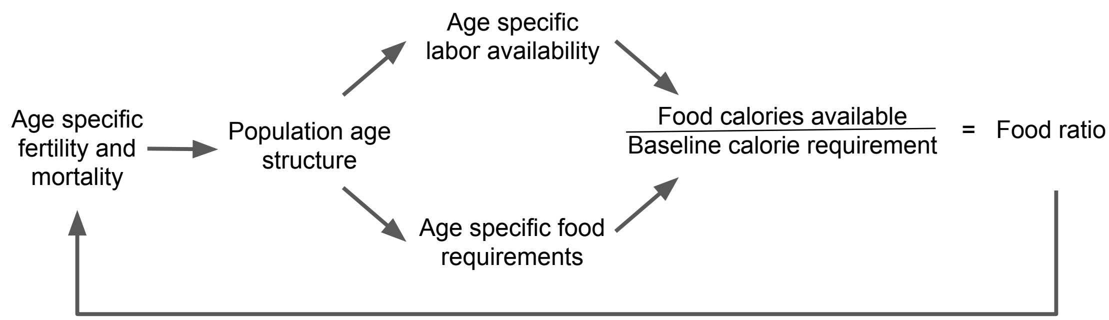

Figure 9. Food-limited demography, adapted from Puleston, Tuljapurkar, and Winterhalder (2014). The food ratio reflects the balance of food calories available to the calories required to support the population. The food ratio feeds back to influence these variables by altering the size and age structure of the population.

The functional programming paradigm shifts the focus away from the agents themselves and towards what the agents *do* in the modeled world using well-documented and tested functions.

3.1.1 Food-limited Demography

Population dynamics in the model are food limited, whereby fertility and mortality rates reflect the ratio of a population's food supply to the its caloric needs (Puleston, Tuljapurkar, and Winterhalder 2014). This *food ratio* acts as a negative feedback on population size (Figure 9). Population growth increases both the the number of mouths to feed and the number of people working to feed them. Which of these these two numbers grows faster depends on the size and age structure of the population. The food ratio falls below 1.0 when caloric demand outstrips supply, which reduces age-specific fertility and increases age-specific mortality until the population stops growing entirely. The exact mechanisms of this sensitivity (e.g. stress, starvation, fertility control, infanticide) are less important to the dynamics than their net effect on age structure (Puleston, Tuljapurkar, and Winterhalder 2014).

Much theoretical modeling of food-limited demography has relied on the population projection matrices used in ecology to model age-structure in populations (Lee and Tuljapurkar 2008; Puleston and Tuljapurkar 2008; Puleston, Tuljapurkar, and Winterhalder 2014). These allow for precise, analytical exploration of these models to determine features such as equilibrium age structure and demographic saturation point. Yet in order to achieve such analytical clarity the models assume continuous, well mixed populations that collectively produce and share food equal to their abilities and needs. These approaches have done much for establishing theoretical baselines for key variables and processes. But they lack the ability to incorporate complex social structure.

Here I use a discrete-time, individual-based implementation of food-limited demography. Each individual in the simulation has an age and is associated with a household. The probability of an individual giving birth or dying is a function of their age and the food available to all individuals in a household. Age-specific fertility and mortality tables and elasticities are derived from empirical syntheses (Lee and Tuljapurkar 2008). Baseline age-specific fertility and mortality data are derived from Coale-Demeny model "West" life tables (Coale, Demeny, and Vaughan 1983). All individuals in a household share food equally, and decisions concerning food production and consumption are made instead on the household level.

3.1.2 Household Decision-making

The births and deaths of individual agents determine the labor availability and food requirements of their associated household. The household agent then decides what it must do to achieve those requirements. The agents represent smallholder agricultural households, producing all of their food calories from a mix of rainfed and irrigated wheat (or any staple crop). These households are boundedly rational, using local information and simple heuristics to allocate their limited land, labor, and capital.

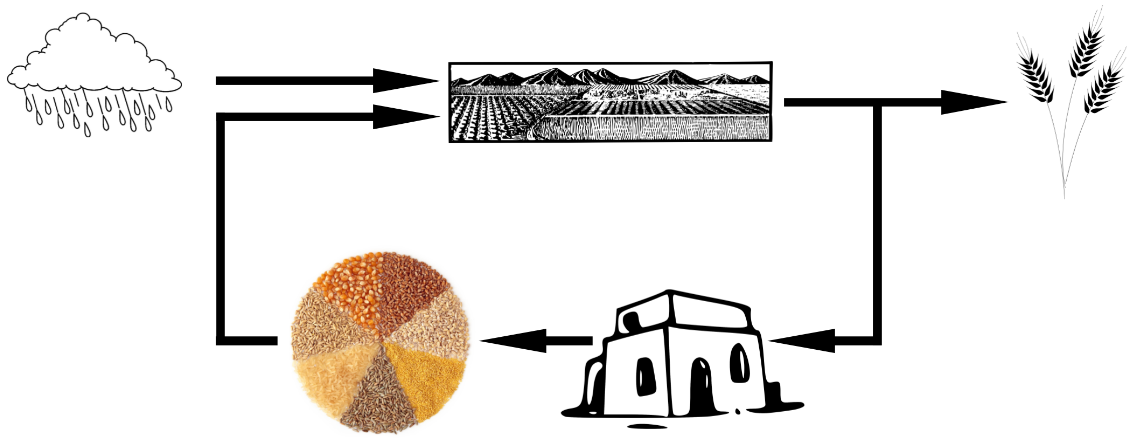

Figure 10. Conceptual diagram of household-level food production. Precipitation is the primary driver of food production, via the land surface. Households monitor crop yields and make allocate their land, labor, and capital accordingly. These decisions feed back to influence the productivity of the land surface.

First, a household allocates its labor between different activities. Here, its options are to spend time farming or maintaining irrigation infrastructure. Given knowledge of the irrigation system and simple heuristics for relative returns to labor farming and maintaining infrastructure, the households solve a constrained optimization problem to determine of the proportion of available time they should devote to each activity so as to maximize their expected utility (Figure 11) (Yu et al. 2015). The amount of time spent farming constrains the amount of land a household can cultivate (White 1965). The amount of time spent maintaining infrastructure determines the efficiency of irrigation, and thus the proportion of available runoff a household can direct to its fields. The performance of irrigation infrastructure is a piecewise linear function of labor inputs (Yu et al. 2015). Here, the model is parameterized to make infrastructure scalable, that is the agents can spend more or less time maintaining infrastructure and still be assured of at least some water.

Next, a household determines how much land it needs to feed its inhabitants based on the productivity of the land (Barton, Ullah, and Mitasova 2012). Baseline agricultural productivity is a function of water available to crops, which reflects both annual precipitation

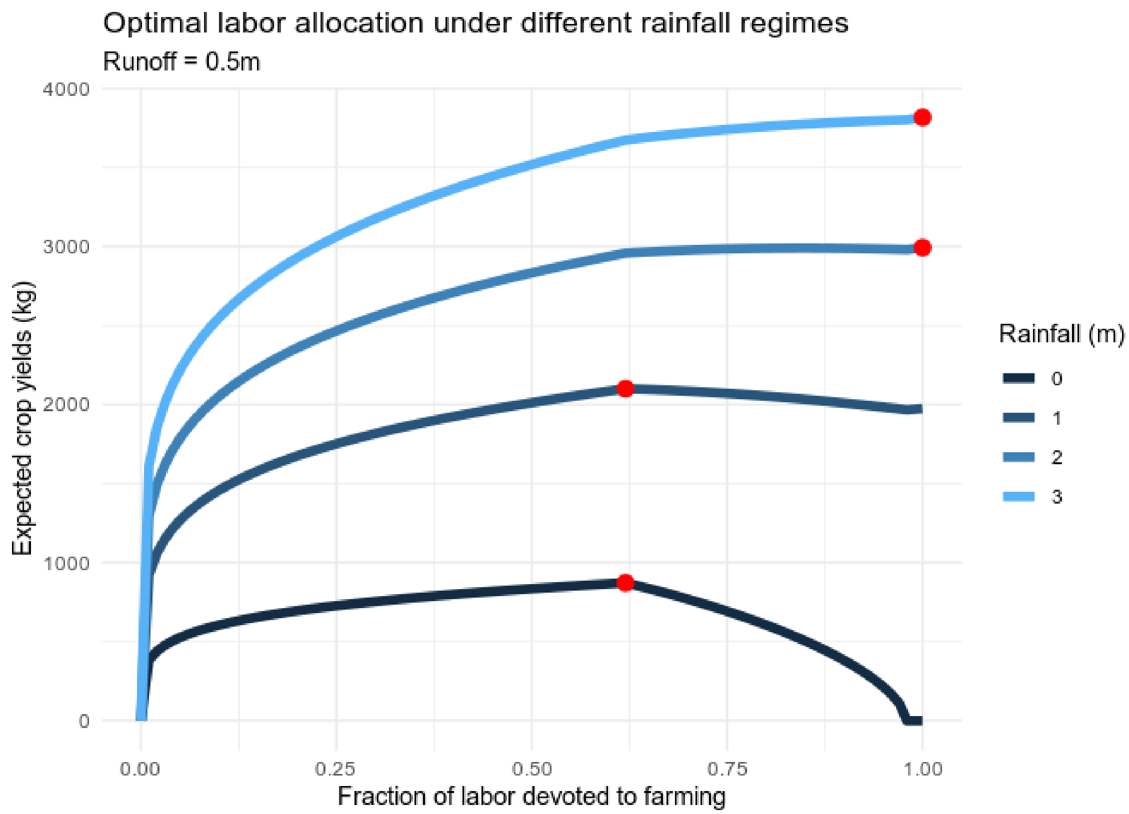

Figure 11. Household decision making as a constrained allocation problem. Households maximize their expected yields while minimizing their total labor by allocating labor to farming or irrigation. The optimal labor allocation depends on the infrastructure and the environment. Here, as an example, the amount of runoff is (unrealistically) fixed to 0.5m per year and annual rainfall is allowed to vary. The fraction of labor devoted to farming versus infrastructure maintenance that maximizes the expected crop yields is highlighted in red.

accumulation and runoff (identical for all households in a settlement) and irrigation inputs (based on household-level infrastructure maintenance). Given this expected yield value, the household calculates the area of land required to meet its needs under a biennial fallowing regime. If this land requirement is below the household's current land holdings, then it reduces its land holdings. If more land is needed, the household will attempt to acquire it up to the limit of the total cultivable area of a settlement. If there is not enough cultivable area to satisfy the requests of all households in that settlement, then the remaining land is divided evenly.

A household then produces food on its land and consumes it. The total harvest is calculated based on the land area and crop yields and halved to account for biennial fallow. A proportion of the harvested biomass is removed to sow fields in the next year, and for taxation if necessary. Food in excess of a household's need is added to its storage, but will spoil in two years (Winterhalder, Puleston, and Ross 2015). The household calculates its food ratio based on its stored supply as well as what remains of the current year's harvest. This new food ratio is then used to adjust the birth and death rates of the individuals living in that household according to the age-specific vital-rate elasticities discussed above.

Finally, households that have grown too large may fission. The number of laborers in a household reflects the age structure of the individuals within it. For each household with more than five laborers, there is a small probability that each laborer may leave the household and start a new, single-person household. If there is enough land to support all the original occupants, then each departing individual takes an amount of land proportional to its needs from the household total. If arable land is restricted, the new household starts with no land holdings. The nature and extent of available land is determined at the settlement level.

3.1.3 Land Use and Settlement Patterns

A group of household agents combine to form a settlement agent. At the settlement scale, the model divides the landscape into a regular hexagonal lattice. Each settlement is associated with a hexagonal tile that represents the physical settlement and its associated hinterland. The locations of settlements do not change over time, only the distribution of population within settlements. A settlement is defined as the aggregate of all households in a hexagonal grid cell, and the model makes no distinction between dispersed or aggregated physical settlements within a cell. By default each hexagonal tile has a radius 5km approximating the agricultural catchment within a walking distance of 1-2 hours. The model acts as a cellular automaton, with the state of each hexagon evolving over time as a function of its current state and its neighboring cells.

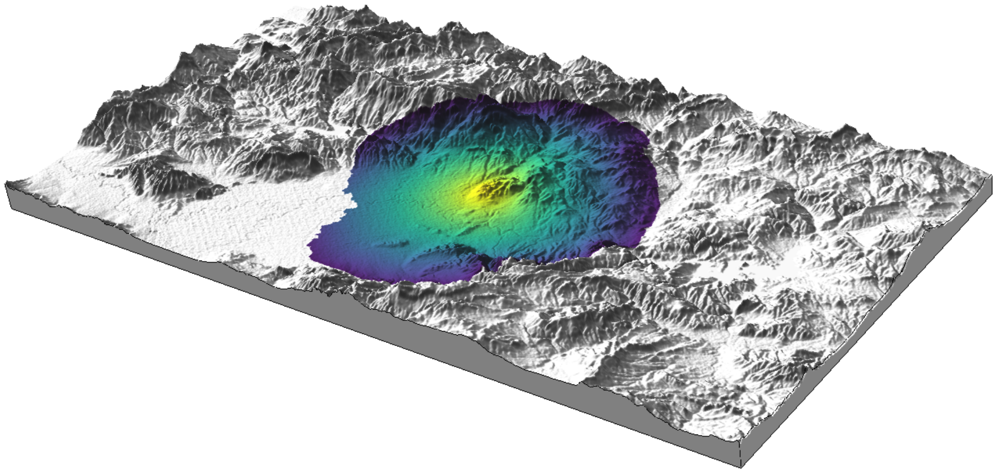

Figure 12. Example of a settlement agent and its hexagonal hinterland. Fine-resolution geographic data shown here, such as distance from the settlement (color) and slope (shading), is aggregated to the tile level. Subgrid scale heterogeneity in land use and land cover types are modeled using subgrid scale "tiles", calculated as proportions of the total grid cell area.

Although the hexagonal tiling is rather coarse resolution, the model incorporates high-resolution geographic information (Figure 12). The model simulates the environment within each hexagonal grid cell using a subgrid scale tiling approach similar to that used in land surface and Earth system models (Avissar and Pielke 2002). Different land use and land cover types are conceptualized as a mosaic of "tiles" taking up a proportion of the total grid cell area, allowing for precise areal scaling of the processes associated with each. The land-use tiles include rainfed agricultural land, irrigated agricultural land, urban area, and grazing land. All except the latter type are restricted to land with less than 5° slope. Wilderness land cover tiles vary by vegetation type, including barren, grass, shrub, and woodland zones.

3.2 Results

3.2.1 Agricultural Populations Grow Fast When Food Is Abundant, but Quickly Reach Their Limits

The intrinsic growth rate of a population is the potential growth rate in the absence of any form of population regulation. These growth rates are characteristic of colonists or frontier populations expanding onto a pristine landscape with abundant food. Such growth is rarely maintained for long in the real-world before population regulation brings fertility and mortality closer into alignment. Nevertheless, a population's intrinsic growth rate sets its baseline tempo of change, and constrains the speed at which a population can adjust to changes in its demographic saturation point and its resilience in face of catastrophic mortality. In the model, the intrinsic growth rate is an emergent property of the underlying individual and household dynamics, and must be estimated numerically.

I estimated the model's intrinsic growth rate by repeatedly simulating 600 years of growth among a starting population of 15 25-year-olds. The food ratio was fixed at one, so growth was unrestrained by food availability. After allowing a 300-year burn-in period to account for initial random fluctuations in the population, I estimated the growth rate as the slope of a log-normal generalized linear mixed model, with a random intercept for each replication. The average intrinsic growth rate was 1.35%, with a range of 1.1 - 1.6%.

With an intrinsic growth rate this high, food-limited populations will quickly reach their demographic saturation points. To assess the population trajectory as it approaches equilibrium, I repeated the above experiments while allowing the food ratio to vary based on food production and consumption (Figure 13). Initially, the simulated populations grow close to their intrinsic growth rate as as in the food-unlimited case. At this speed, it takes only 200-300 years for an initial population of 30 reach its carrying capacity. High growth is sustained until quite late, with growth slowing only decades before growth ceases. This dynamic contrasts with the slow decline of simple logistic growth, which takes twice as long to reach carrying capacity.

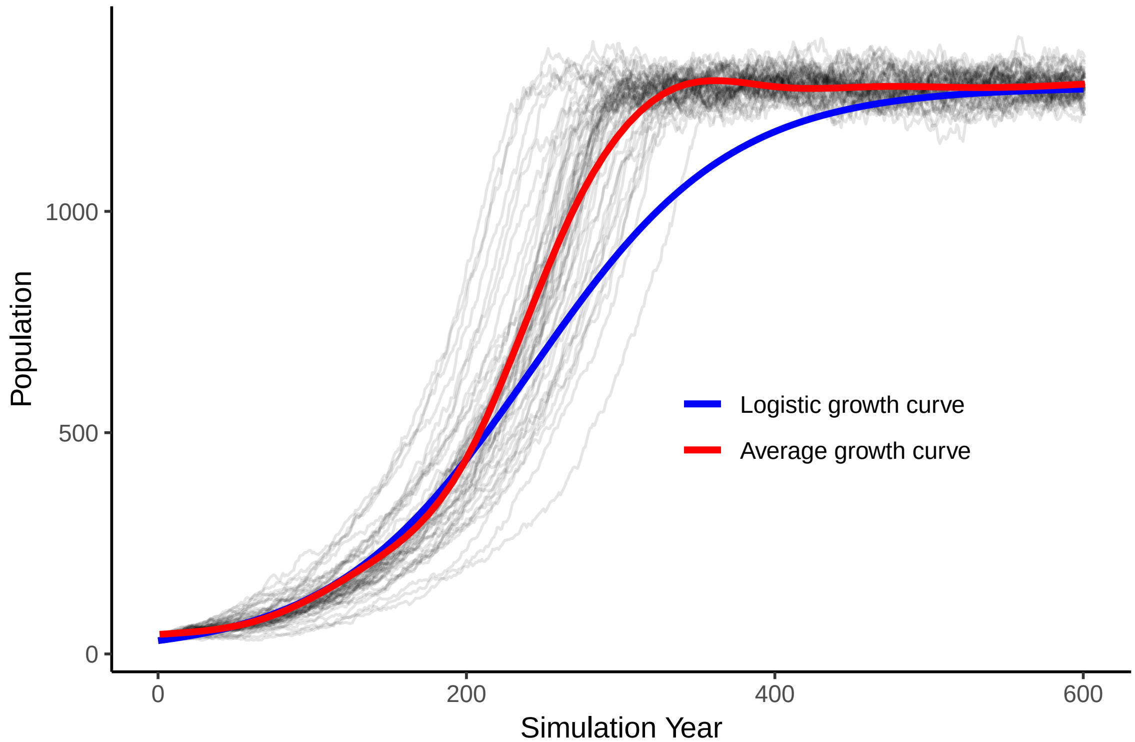

Figure 13. Population growth curves from 50 simulations under food-limited demography. Raw simulation outputs are in black, with an average curve computed using a scatterplot smoother in red. Compared to a growth curve based on logistic growth (blue), population growth continues unchecked up to a few generations before carrying capacity is reached, after which the population rapidly stabilizes. All simulations began with a population of 30 25-year-olds living in a pristine agricultural landscape 10 km^2 in area receiving 700mm of rainfall annually.

The model has inherent demographic stochasticity, which influences the dynamics. When the population is small, it is very sensitive to random fluctuations. A single laborer's death could have a disproportionate impact on the food ratio of the entire household depending on the number of dependents. As is the nature of exponential growth in the population's early phases, small initial variations can propagate forward in time indefinitely. Similarly, an initially fortuitous set of births and deaths can give a household initial advantages that become locked in via food storage and competition for land, leading to marked inequality among households as time progresses. Even when population reaches equilibrium it varies within 2-7% of the demographic saturation point. This demographic stochasticity helps to illustrate the range and role of natural, internal variability in real-world populations.

3.2.2 Age Structure Oscillates as It Approaches Equilibrium

A critical factor in a population's growth and regulation is its age structure, which can be summarized by the *dependency ratio* – the ratio of number of non-producing consumers, such as children and the elderly, to the population directly involved in food production. A population's dependency ratio is a feature of its age structure, determined by the differential fertility and mortality of individuals in different age classes. How does a population's age structure emerge from the interactions of individual demography and household level food production?

From an initial population of 25 year-olds the dependency ratio grows quickly as the founder population ages out of the labor force. The dependency ratio oscillates around its equilibrium value for several centuries, finally stabilizing at 75 in about 400 years (Figure 14). When food limitation is introduced, the equilibrium dependency ratio drops to 65 at the demographic saturation point, because the decreased food ratio increases infant mortality faster than it does for the rest of the population.

The population's fluctuating age structure as it approaches equilibrium has consequences for its response to catastrophic mortality events that selectively target individuals of certain ages. Past baby booms or busts can introduce demographic inertia, adding "memory" to the system so that external and internal disruptions propagate through several generations. This demographic inertia can also cause the population to temporarily overshoot its demographic saturation point, as it may take more than one generation before reduction in food resources is fully felt by the entire population.

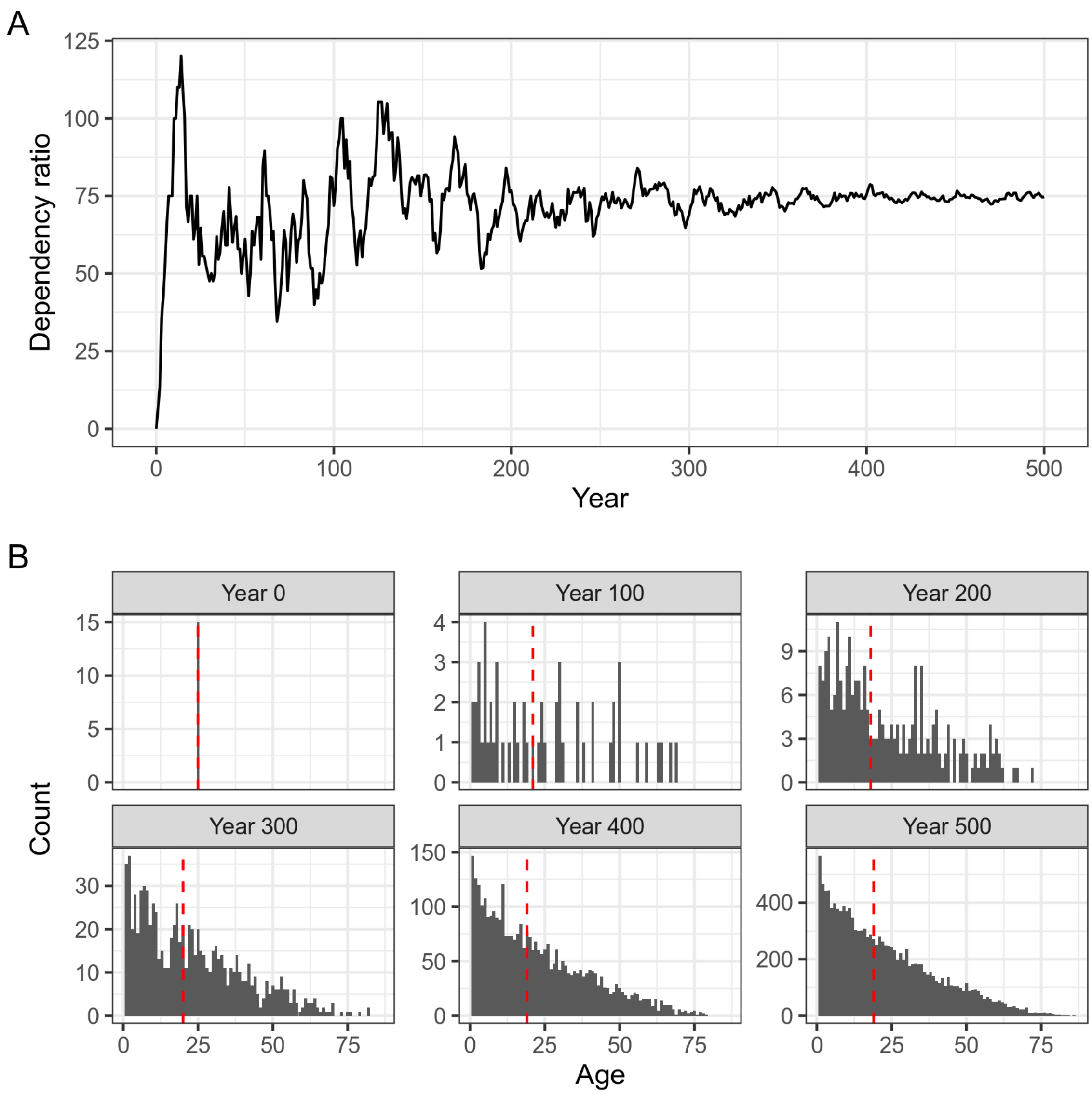

Figure 14. A. The ratio of food consumers to food produces over time in the absence of food limitation. From a starting population of 15 individuals aged 25 years, the population undergoes damped oscillations as it repeatedly overshoots then undershoots its equilibrium age structure of 75, finally stabilizing in 300-400 years. B. The evolution of the age structure in A to a young and fast-growing equilibrium. Median age denoted in red.

3.2.3 Increased Rainfall Was Key to Increased Agricultural Production in Roman North Africa

Having explored the transient dynamics of preindustrial population growth and age structure in an abstract setting, I applied the model to a concrete case study. Was the potential agricultural productivity in Roman North Africa higher than it is today and was climate change or technological intensification the more important factor? To answer this question I ran a set of simulation experiments over a spatial domain from 5°N to 11.5°N and 34°E to 37.5°E, covering portions of modern-day Algeria and Tunisia.

Each simulation was initialized by seeding all hexagonal cells in the spatial domain with 10 identical households, each containing three 25-year old individuals. From these initial conditions the model was run for 600 years, allowing the population in each grid cell to reach its stable demographic saturation point. Where water availability or cultivatable land area were not enough to sustain food production, the populations were allowed to die out without any recolonization from neighboring cells. Four scenarios were compared, with annual precipitation set to present day averages and simulated averages at 200 CE, and with and without the possibility for localized runoff-harvesting. Estimates of annual precipitation from the century bracketing 200 CE are extracted from a previously-run paleoclimate simulation of the last 2,000 years (Jahn 2018, unpublished data). This experimental design allowed for the assessment of the degree to which climatic factors or infrastructure contributed to the possible greater agrarian population suggested for the Roman period.

Mapping the resulting equilibrium population levels from these experiments reveals North Africa's estimated agricultural carrying capacity (Figure 15). These values represent the potential *rural* population directly involved in food production, independent of external economic influences from urban centers or the broader Roman world. Although many factors determine the precise equilibrium point, the key variables that influence *environmental* carrying capacity are precipitation and the area of cultivable land. The carrying capacity varies linearly with cultivable area and nonlinearly with water availability.

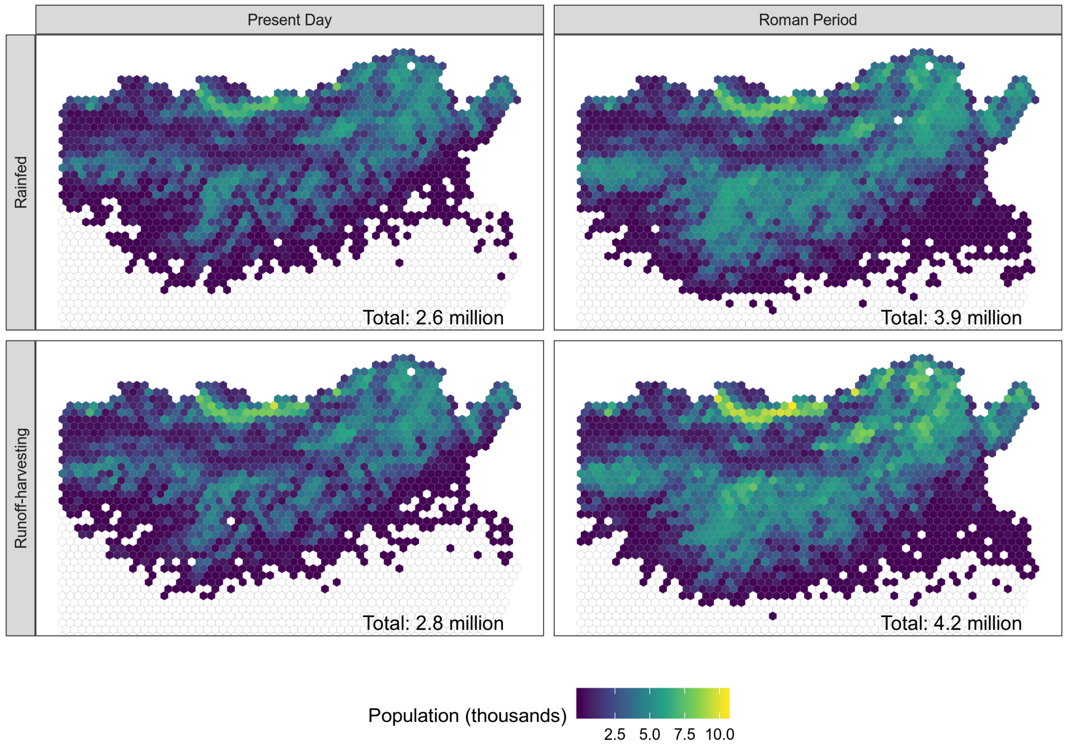

Figure 15. Simulated rural population equilibria in Roman North Africa, assuming no influences from urban centers or the greater Roman world. Four experimental scenarios are presented: with average annual rainfall at 200 CE and present-day levels, and with and without local runoff-harvesting.

The wetter conditions ca 200 CE were able to support about 50% more rural population as could present-day conditions. Broadly, this increase in population was achieved by a southern movement of the habitable zone into the Atlas mountains and pre-desert steppe, rather than by intensification in existing zones. By contrast, local niche construction via runoff harvesting has a more modest impact on population, generally increasing population density in already inhabited regions rather than shifting the habitable zone. This result contrasts with previous suggestions that hydraulic infrastructure, not climate, played a critical role in maintaining high rural populations during the Roman period. In general, runoff harvesting is constrained by the available moisture supply. While the practice has marginal utility in regions already experiencing some rainfall it is less able to expand settlement in regions with extremely dry conditions.

3.2.4 Regions of High Simulated Rural Population Correspond to Regions of Dense Roman-period Settlement

Comparing these population estimates to the composite settlement pattern data (Bagnall 2018) from the Roman and pre-Roman periods (using 30 BCE as a cutoff) allows for an assessment of the model's ability to generate the broad spatial patterns of Roman population distribution and to test whether the simulated dynamics are consistent with the empirical record (Figure 16). Overall, the simulated population density corresponds well to the location of known Roman settlements.

Simulated populations were highest in the coastal zones in the northern and eastern portion of the study region, reaching from 8,000 to 10,000 people per 5km grid cell ($65km^2$, or roughly 150 people per km^2). This area includes the hinterlands of major cities like Carthage and Hippo Reggius, as well as known agricultural regions like the Bagradas River valley. Populations of 2,000 to 8,000 people were sustainable further inland along a broad band trending from the northeast to the south central portion of the study area, corresponding to higher-elevation zones in the Atlas mountains such as the Belezma Plain. The difference between the pre-Roman and Roman settlement patterns is striking, and clearly reflects expansion south consistent with the southerly extension of rainfall during the Roman period. In particular, a major difference of Roman and pre-Roman settlement is found in the Belezma plains in central zone of the study region, precisely where the model predicts an expansion of potential agricultural carrying capacity due to increased rainfall.

There are notable exceptions to the correspondence between simulated population and archaeological settlement patterns, however, particularly in pre-Sahara region in the south of the domain and the semi-arid step zone in the southeast. Indeed, the model generally *under-estimates* this southern expansion of settlement during the Roman period. Archaeological sites in these areas generally correspond to local springs, oases, or regions with intermittent streamflow – potential sources of irrigation water not represented in the model. Settlements in the semiarid southeast of the study domain may also have relied on olive cultivation to

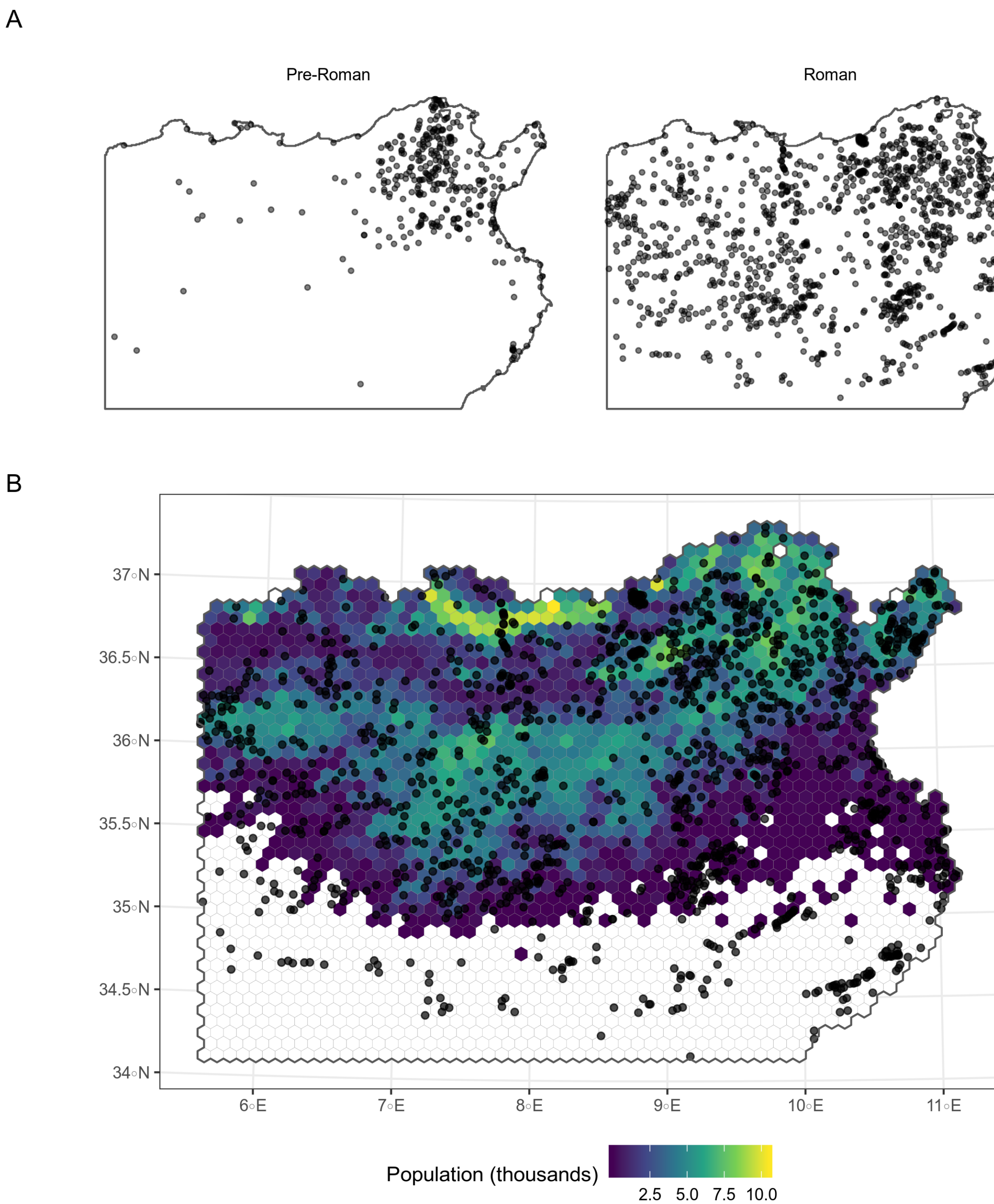

Figure 16. A) Settlement patterns in North Africa, before and after 30 BCE (Bagnall 2018). Initial settlements clustered in the north east of modern-day Tunisia near the city of Carthage, and expanded inland to the semi-arid steppe and pre-desert zone during the Roman period. B) Roman-period settlement patterns overlain on simulated rural populations supported by runoff harvesting and rainfall at 200 CE. Regions of high productivity generally correspond to denser settlement, including in well-documented breadbasket regions, and settlements beyond the productive land are associated with more specialized irrigation systems or olive cultivation.

provide extra food calories and economic benefits, also not included in the present version of the model. Also of note is paucity of archaeological sites in the northern coastal strip where the model predicts the highest carrying capacity. This region receives a large amount of rainfall to this day and remains well-vegetated, so perhaps archaeological sites are hidden under vegetation or modern development.

3.3 Discussion

Overall, these results suggest the first principles underlying the model are able to generate realistic emergent patterns. Intrinsic growth rates match those attested during short-run periods of high population growth in the archaeological record (Cowgill 1975). Populations grow quickly to their demographic saturation point, and the mechanisms of food-limitation curtail growth in a few short generations before demographic saturation occurs (Puleston, Tuljapurkar, and Winterhalder 2014). External shocks to fertility or mortality are quickly absorbed by renewed population growth, as long as the demographic saturation point remains fixed (Watkins and Menken 1985). Instabilities in the age structure can lead to oscillations as the population returns to equilibrium. The exact location of this point is determined by land availability and agricultural productivity (Fanta et al. 2018b), which in turn are influenced by the social and technological factors internal to the population (Wood 1998).

In the case of Roman North Africa, the model echoes findings from independent geomorphic proxy records that climate change played a primary role in the North African environment history, and that anthropogenic factors were important but secondary (Faust et al. 2004). Increased rainfall at ca 200CE explains much of the increased sustainable rural population in North Africa, save for in the driest pre-desert zones where unmodeled irrigation or agropastoral practices appear to have been more important. Major breadbasket regions attested in the historical and archaeological records, such as the Bagradas River valley and the Belezma plains (Kehoe 1988; Mattingly and Hitchner 1995), correspond to areas of high estimated agricultural carrying capacity in the simulation. Areas in the simulation where there are sharp boundaries between more and less productive land generally correspond to breaks or clusters in archaeological settlement pattern data (Bagnall 2018).

As is generally the case when modeling complex systems, a collection of simple, interacting modules is preferable to having a overly-detailed model of a single process that fails to capture the relevant interactions. I have thus prioritized breadth over depth in this model by relying on existing algorithms and conceptual implementations where available – no matter how simple – in order to ensure the main processes are represented. In this study, I have presented a modeling framework that acts as a first step towards a more precise representation of population dynamics in the past. The model can now act as a baseline for successive iterations, allowing us to focus our attention on the specific submodules, state variables, and parameters that are most crucial for the operation of the system as a whole. Future work will focus on currently unexplored factors that will increase or decrease population growth rates, as well as unexpected external shocks.

This model currently resolves only rural agricultural settlement. Additional work will also focus on elaborating the land use portion of the model, including adding functionality for multiple crop types (e.g. barley, pulses, olives, and grapes) (Dermody et al. 2014), as well as the rearing of sheep and goat in more extensive pastoral production systems (Ullah 2011; Barton, Ullah, and Mitasova 2012). Although food resources are removed from each household to represent taxation and other food redistribution mechanisms, at present this food leaves the system entirely. Future elaborations of this model will redirect these resources to feed distinct elite and urban populations who are not primary food producers. The sublinear or superlinear scaling of population density to food supply can also be explored (Qubbaj, Shutters, and Muneepeerakul 2014). Elite agent food requirements will scale superlinearly with population, reflecting more extravagant lifestyles, but a proportion of the food resources will also be reinvested into social and physical infrastructure that can temporarily increase the rural carrying capacity. Having two such populations will allow for the exploration of structural-demographic cycles arising from mismatched growth rates and bidirectional feedbacks between these two populations (Turchin 2003). The non elite urban population will exhibit sublinear scaling of food requirement with population, reflecting efficiencies in urban living (Hanson, Ortman, and Lobo 2017). This approach will also allow for a fuller exploration of inter-urban trade and migration in the Roman world using existing transport models (Scheidel, Meeks, and Weiland 2012).

The goal of this study was not to recreate Roman North Africa in detail. Rather, it was to present the conceptual and methodological framework for generating land use and demographic estimates for premodern agrarian societies with populations of millions of agents using multilevel social simulation. Roman North Africa provides a concrete illustration of the possibilities of this approach. The multilevel simulation approach presented here will also be generalized to other agricultural societies in space and time. The model was designed to be as general as possible, with all details relating to the Roman case study executed via parameterizations stored in static configuration files. New configuration files can be developed to represent other societies, clearing a path to broader cross-cultural comparisons.

Chapter 4

TRADE, MIGRATION, AND THE DYNAMICS OF SPATIAL INTERACTION

Regional archaeological settlement patterns arise from the interactions of many individual agents, each making decisions with imperfect and incomplete information about the perceived costs and benefits of social interaction. Yet in spite of the intricate complexity visible at the scale of individuals, empirical regularities begin to emerge at increasingly larger scales. So-called “entropy-maximizing” spatial interaction models capitalize on this change-of-scale property. Entropy maximization is a means of estimating the large-scale properties of a system by making the fewest possible assumptions about micro-scale dynamics (Pressé et al. 2013; Thurner, Corominas-Murtra, and Hanel 2017). Here entropy is a measure of uncertainty at the micro-scale, and maximizing it reveals the most probable macro-scale configuration. An entropy-maximizing spatial interaction model estimates the macro-scale *flows* of a constrained quantity such as goods and people between discrete spatial zones as a function of their distance and measures of their mutual “attractiveness” (Wilson 1971b). They model social interaction by systematizing the basic costs and benefits used in decision-making and scaling them up while ensuring that simple self-consistency constraints (such as total inflows equals total outflows) are met.

Archaeologists in particular have embraced this modeling paradigm, as its focus on the relationship between micro-scale behaviors and macro-scale structures mirrors the struggle to infer past human behaviors from the large-scale settlement patterns visible on the landscape. Archaeologists have successfully used these models to determine the sensitivity of estimated settlement structures to uncertainty in the archaeological record (Bevan and Wilson 2013; Paliou and Bevan 2016), model the evolution of site hierarchies in the absence of top-down centralizing forces (Altaweel 2015), assess the role of historical contingency in the development of major settlement centers (Evans and Rivers 2017), and to determine important factors contributing to the rise of known urban centers in different locations and time periods (Davies et al. 2014; Altaweel, Palmisano, and Hritz 2015; Palmisano and Altaweel 2015; Filet 2017).

In isolation, an entropy-maximizing interaction model is essentially a statistical tool, estimating the most likely configuration of flows between settlements given the relevant constraints. *Dynamic* spatial interaction models, on the other hand, combine these flow estimates with one or more mechanistic models to describe how these flows wax and wane over time (Harris and Wilson 1978). In such cases, the spatial interaction model captures the "fast" dynamics – the balance of flows between locations as a function of their relative size or importance – and the mechanistic model captures the "slow" dynamics governing how the locations grow or decline because of their access to those flows. As implemented in archaeology, the slow dynamics are typically a simple equilibrium-seeking behavior in which settlements evolve only to balance inflows and outflows. As a result, many archaeological applications of these models use them as heuristic tools for finding equilibrium settlement distributions rather than as true dynamical models that explicitly resolve the time evolution of settlement systems (Bevan and Wilson 2013).

Powerful alternatives to the equilibrium-seeking slow dynamic in archaeological spatial interaction models are Lotka-Volterra consumer resource equations. Lotka-Volterra equations are used in ecology to model energy flows in a food web. More generally, these models can represent energy flows in any social-ecological system, such as an agricultural settlement consuming resources from its hinterland (Anderies and Hegmon 2011; Qubbaj, Shutters, and Muneepeerakul 2014). Spatial interaction models are particularly useful for incorporating spatial richness into Lotka-Volterra models, which would otherwise resolve space only implicitly (Wilson 2006). Models that use entropy maximization to estimate the "fast" flow dynamics and consumer-resource equations to represent the "slow" settlement dynamics are known as Boltzmann-Lotka-Volterra models (Wilson 2008). These systems of equations are able to capture the dynamic feedbacks between settlements and the networks connecting them.

In order to keep them flexible, archaeological spatial interaction models are also typically abstract and highly aggregated. The flows are assumed to be some aggregate of trade and migration reflecting the “influence” of each site on another, and the settlement state variable that evolves in time is some generalized notion of “attractiveness”. While these generalizations are useful for empirical work, they elide much of the processual granularity that makes these models such a useful tool for quantitative theory building. Metabolic costs, such as the energy expended producing and transporting food over space where transportation infrastructure is sparse, provide constraints on energy flows in exchange systems (Drennan 1984; Verhagen, Nuninger, and Groenhuijzen 2019). In any particular case, the balance between these costs and the metabolic benefits of social interaction influences whether resources are moved in bulk to populations in a settlement or whether those populations move themselves to the available resources. In order to determine how the balance of these flows influence long run settlement patterns, it is thus necessary to replace the generalized notion of flows of “influence” with more direct estimates of trade and migration flows and a more concrete mechanistic model for how these flows influence settlement dynamics.

Here, I present a dynamic spatial interaction model that explicitly tracks the flows of trade and migration within a settlement system. I use a variant of the Lotka-Volterra equations known as a “competition for resources” model, in which a population of urban settlements competes for access to food from multiple agricultural resource patches. The populations of these settlements grow and decline according to the flow of resources into the settlements and the flow of migrants between them. Using a disaggregated, two-part spatial interaction model, I model the flows of food to people (“trade”) and the flows of people to food (“migration”) separately and explore how varying the relative costs of each type of movement influences the resulting population distribution at equilibrium. I show that the constraints on moving food to people are the primary determinants of long-run settlement patterns, influencing the extractive reach of settlements and their ultimate population carrying capacity. Migration costs play a secondary role, serving to enhance or diminish existing settlement hierarchies depending on the specific objectives of the migrants. These findings contribute to the ongoing development of quantitative theory of spatial interaction in premodern societies, but also provide important caveats for interpreting statistical analyses of archaeological networks.

4.1 Methods

4.1.1 Population Growth and Decay: The "Slow" Dynamics

I explore a simple model of agricultural settlements in a patchy environment. The basic unit is a settlement, representing any urban or semi-urban population in an agrarian society that consumes food from resource patches to support a population of non-farmers. The dynamics of food production are left external to the model, and it is assumed that a fixed volume of food resources are produced each year. The core dynamic of the urban population is represented as

$$\dot{N} = rN, \tag{4.1}$$

where $\dot{N}$ is the time rate of change of population N and r is the realized growth rate. The realized growth rate depends on the amount of resources consumed by N as

$$r = \begin{cases} \epsilon\left(X - N\right) & \text{if } \epsilon\left(X - N\right) < r_{max} \\ r_{max} & \text{otherwise,} \end{cases} \tag{4.2}$$

where X is the amount of available resources, ϵ is a parameter that controls the rate at which the resource surplus increases or decreases the population, and r_{max} is the maximum growth rate. This equation states that the population grows or shrinks in proportion to its consumption of resources, but it cannot grow faster than a biological maximum rate. For simplicity, assume that X is scaled to units of N so that one unit of resource is sufficient to maintain one unit of population. The resulting process is a hybrid of exponential and logistic growth, with the population growing quickly when consumption is far above population

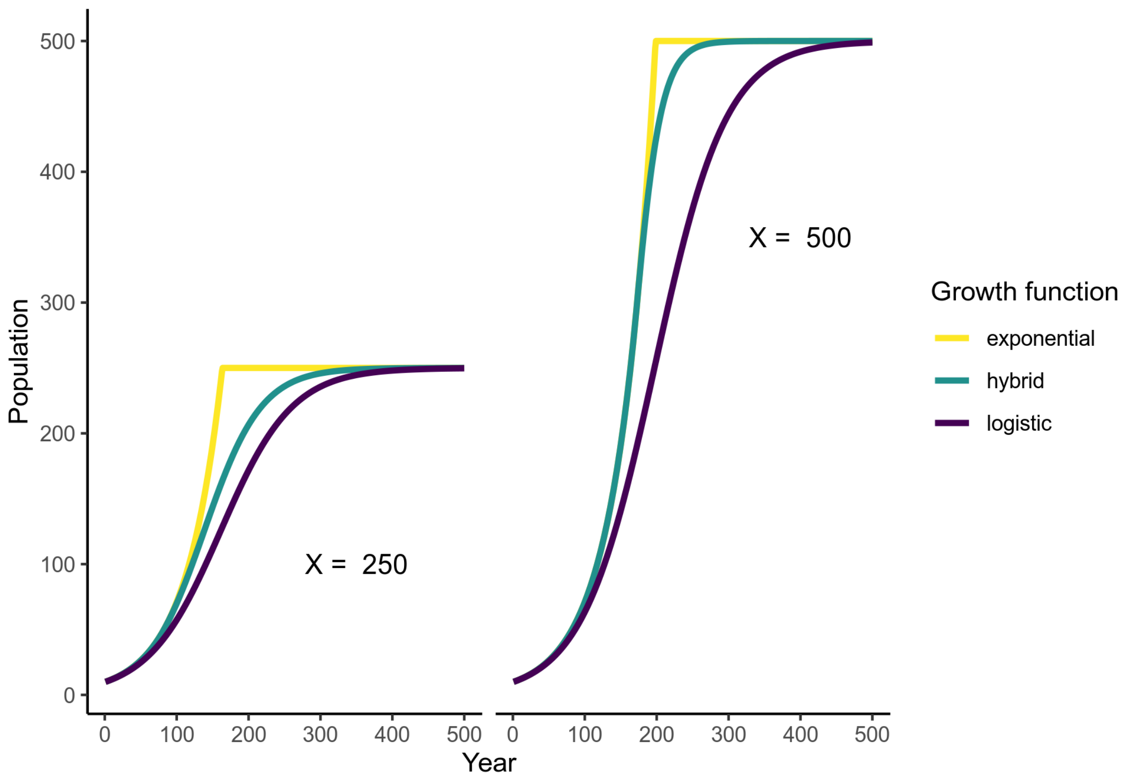

Figure 17. Simulations from the growth model, compared to exponential and logistic growth for two levels of resource surplus X over the same time span. X acts as a carrying capacity. When X is low, the potential for growth is low and the population approaches carrying capacity gradually similar to logistic growth. When X is far above N the population exponentially, with growth rates only declining shortly before carrying capacity is reached.

and more gradually when consumption is close to the current needs of the population (i.e. "carrying capacity") (Figure 17).

Rather than a single settlement-resource system, the model represents a network of hundreds of interacting settlements and resource patches (Figure 18). The landscape is discretized into hexagonal resource patches with radius 5km, over which settlements are uniformly distributed. Settlements compete with one another for the fixed resources produced in each patch each time step, a dynamic analogous to the "competition for resources" models common in ecology. Not only do settlements interact indirectly with one another by harvesting the same patch, but they interact directly by exchanging population through migration. Each

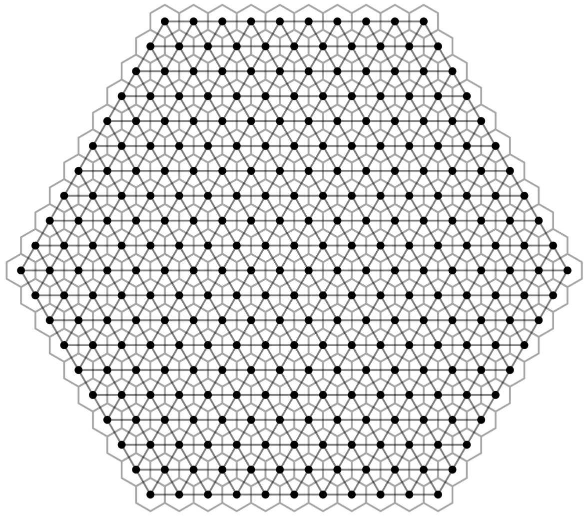

Figure 18. Spatial domain for the simulation experiments. The resource patches are 300 evenly-sized hexagons with radius 5km arranged in a continuous tiling with a total size of approximately 19,500 km2. Settlements are arranged in a triangular lattice located at the centroids of each hexagonal patch, and are connected by a system of physical paths joining each settlement to its six nearest neighbors.

model year, a fixed proportion of a settlement's population leaves each city. These migrants select their destination based on the size and distance of potential migration destinations (including their origin location) and the relative *per capita* resource extraction rate of each settlement.

The simple mathematical model presented above can thus be extended into a social-ecological network of multiple interconnected consumer-resource systems. First, disaggregate X and N into X_i and N_j, representing the resources at location i and the population at location j. Then, introduce two flow matrices $\mathbf{T}$ and $\mathbf{M}$ that represent trade and migration flows, respectively, such that the volume of resources produced in patch X_i that are consumed by the population in settlement N_j is T_{ij}, and the number of migrants moving from settlement N_i to N_j is M_{ij}. For simplicity, the harvest of resources from patches is referred to as "trade", although it generally reflects any movement of food from one location to a population center in another, including non-market forms of exchange such as sharing, exchange, or tribute.

Assuming a *per capita* out migration rate of of ν, the expanded version of Eq. 4.1 and 4.2 is thus:

$$\dot{N}_j = rN_j - \nu N_j + \sum_i M_{ij}, \tag{4.3}$$

$$r = \begin{cases} \epsilon\left(\sum_i T_{ij} - N_j\right) & \text{if } \epsilon\left(\sum_i T_{ij} - N_j\right) < r_{max} \\ r_{max} & \text{otherwise.} \end{cases} \tag{4.4}$$

Together, these equations state that the population of each settlement grows according to the total inflow of resources from every patch and the total inflow of migrants from every settlement. Because all settlements compete for resources from every patch and compete with each other for migrants, the growth of one settlements depends in part on that of all other settlements. Next, I show how the resource and migrant flows represented in $\mathbf{T}$ and $\mathbf{M}$ themselves emerge from these population dynamics.

4.1.2 Trade, Migration, and Spatial Interaction: The "Fast" Dynamics

The model tracks two kinds of spatial flows using separate spatial interaction models: movement of resources from patches into settlements and movement of people between settlements. Both cases use similar "production-constrained" spatial interaction models. The general approach, first used in archaeology by Rihll and Wilson (1991), takes a fixed volume of flow "produced" at each location and allocates it among all potential destinations in proportion to the relative costs and benefits of interacting with each. Benefits are assessed as a power function of one or more settlement-level variables (such as size) that attract flows, and costs are assessed as a negative exponential function of distance (Figure 19). Two parameters, α and β, control the strength of these influences. When $\alpha > 1$ the benefits of interaction exhibit increasing returns to scale. β is in units of distance, and can be interpreted as the distance at which the strength of interaction decays to about two-thirds of its original value.

The spatial interaction model for trade is a simple "gravity" model, in which settlement population N is the only variable determining a settlement's attractiveness. Thus the flow of resources from patch i to settlement j, is

$$T_{ij} = X_i \frac{N_j^{\alpha_1} \exp\left(-c_{ij}/\beta_1\right)}{\sum_k N_k^{\alpha_1} \exp\left(-c_{ik}/\beta_1\right)}, \tag{4.5}$$

where X_i is the amount of resources produced in the patch – the "production" term that is "constrained" in the model – and c_{ij} is the cost of moving from i to j (distance in kilometers). The terms in the fraction simply assess the relative costs and benefits, with the numerator representing the utility of moving food to settlement i and the denominator the sum of the utilities for all potential destination locations, together ensuring that the total outflows equal the total resources in X_i. Because of this balancing factor, all trade flows among settlements can be computed simultaneously and there is no need to evaluate the flows to each settlement sequentially. A settlement has no special access to its local resource patch, save only for its proximity relative to other settlements ($c_{ij} = 0$ if $i = j$).

The migration flows depend in part on the trade flows, and are modeled in a similar fashion. The number of migrants moving from settlement i to j is

$$M_{ij} = \nu N_i \frac{N_j^{\alpha_1} W_j^{\alpha_2} \exp\left(-c_{ij}/\beta_2\right)}{\sum_k N_k^{\alpha_1} W_k^{\alpha_2} \exp\left(-c_{ik}/\beta_2\right)}, \tag{4.6}$$

where νN_i is the number of migrants originating in i and $W_j = \sum_i T_{ij}/N_j$ is the *per capita* welfare of j, defined as the ratio of trade inflows to population. As with trade, all migrant flows occur simultaneously in a time step due to the production constraint term, and after all trade flows are computed. Unlike in the trade equation above, the attractiveness of a given settlement as a migration target depends on both its population size and its welfare. Migrants will thus seek out destinations with lots of well-fed people, and the relative values of α_1 and α_2 determine the relative importance of each factor.

In summary, the flow of resources from each resource patch to each settlement is determined by Equation 4.5, which depends on the underlying distribution of resources and

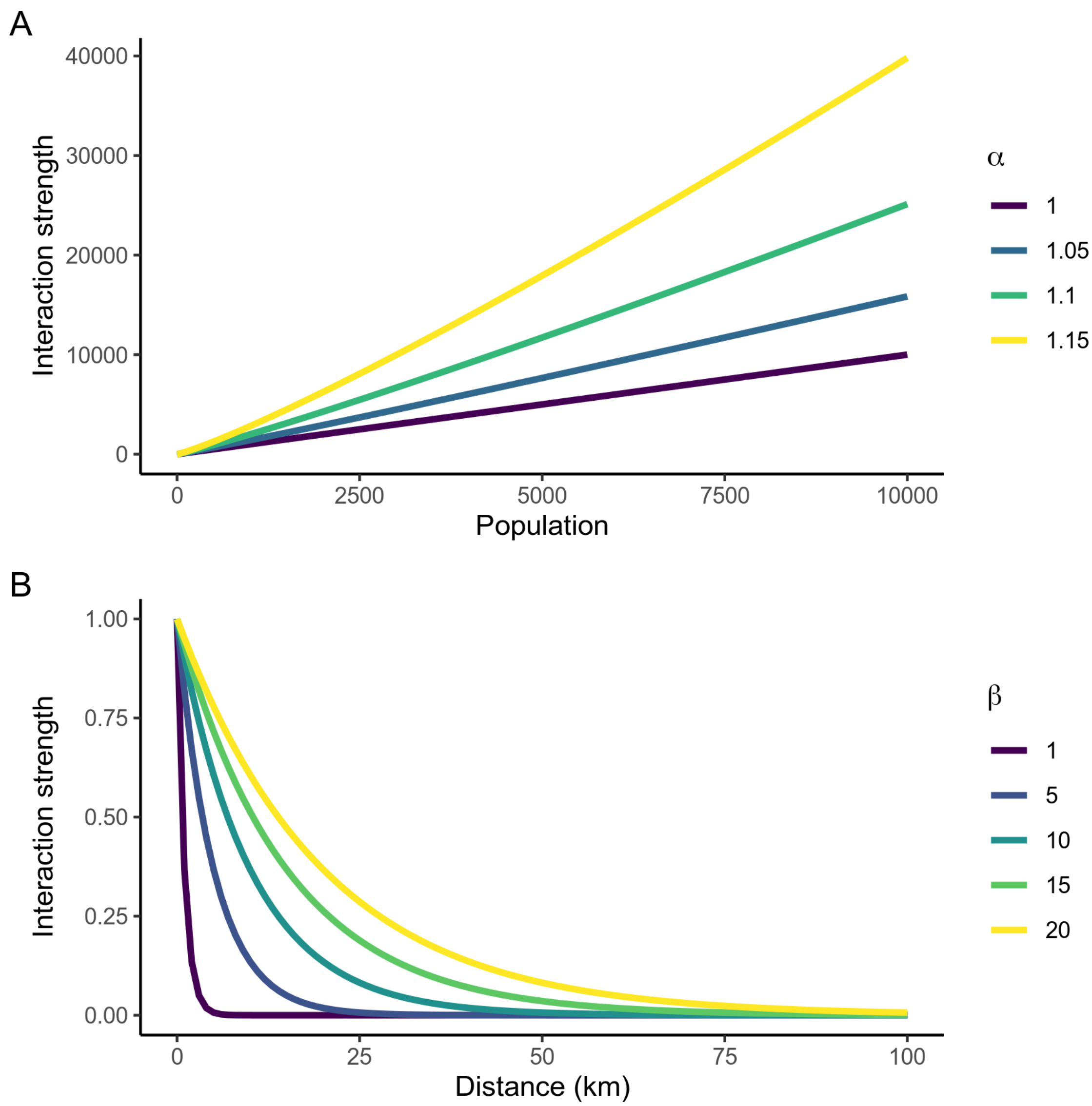

Figure 19. Functional forms for the spatial interaction models. A) Settlement-level variables influence the attractiveness of each settlement via a power function, with the parameter α governing the importance of that variable. B) The costs of moving over space take the form of a negative exponential function, with the parameter β determining the steepness of the falloff of interaction with distance (higher values of β allow interaction to occur at farther distances).

settlement populations. Then, the flow of migrants between settlements is determined by Equation 4.6, based on the settlement populations and the flow of resources. Finally, the populations of the settlements grow both by consuming trade resources and by accepting new migrants according to Equation 4.3, and this new population distribution will feed back to influence future trade and migrant flows. The entire system is a complicated web of nonlinear interaction, as the growth and decline of settlements can potentially depend on all other settlements. The complexity of this system increases geometrically as the number of settlements increases, precluding exact analytic solutions. We must instead leverage numerical simulations to capture these complex interactions computationally.

4.2 Analysis

The disaggregated spatial interaction model was run from uniform initial conditions, with $X = 200$ and $N = 25$, for a period of 2000 years or until the system reached an equilibrium. This analysis focuses on the behavior of system under different combinations of the parameters that control the costs and benefits of interaction $\alpha_1, \alpha_2, \beta_1, \beta_2$. The parameter α_1 determines how the population size of a settlement influences its attractiveness as a target for trade and migration, and α_2 determines how this attractiveness depends on *per capita* welfare. β_1 and β_2 both correspond to units of distance (here kilometers) and determine the impact of distance on the intensity of flows, with the former representing the ease of moving resources to population centers and the latter the ease of moving people among population centers. Settlement patterns under different parameterizations were assessed via graphical comparison and statistical analysis of aggregate quantities including the total population, count of settlements, and an index of population dispersion and concentration. The following analysis focuses on the area of the parameter space where $\alpha_{1,2} \geq 1$ and $\beta_1 \leq \beta_2$, reflecting assumptions that there are positive returns to scale in attractiveness and that moving people over the landscape is easier than moving bulk food supplies.

Table 1. Parameters, their default values, and ranges explored.

Parameter	Value	Interpretation
ϵ	0.0001	Consumption adjustment rate
r_{max}	0.02	Maximum growth rate
ν	0.05	Migration rate
α_1	[1.0, 1.05, 1.1, 1.15]	Returns to population size
α_2	[0, 1.0, 1.05, 1.1, 1.15]	Returns to *per capita* welfare
β_1	[5, 10, 15, 20]	Ease of moving food to people
β_2	[5, 10, 15, 20]	Ease of moving people to food

4.2.1 The Movement of Food to People Defines Settlement Territory Size, Migration Costs Mediate the Distribution of Population

How does the cost of moving food and people over distances, as encoded in the β parameters, influence settlement patterns at equilibrium? The β parameters are the primary way space is introduced into the model. By design, the costs of moving food and other resources from resource patches to settlements will be different from the costs of moving people between settlements. The balance of these cost factors can introduce complexity into the spatial patterns that result from these interactions.

For cases where migration is based only on population size, not welfare ($\alpha_1 = 1.15, \alpha_2 = 0$), increasing β_1 to allow food to be moved longer distances to reach settlements decreases the number of inhabited settlements and increases their size at equilibrium (Figure 20a). As the number of settlements at equilibrium decreases, these major settlements also move closer to the center of the domain, corresponding to the locations with the maximum access to resources given the travel costs. This competition for resource access can be visualized by connecting each resource patch to the settlement to which the majority of its resources travel (Figure 20b).

If the costs of moving resources to settlements, as encoded in β_1, strongly determine the size and spacing of major settlements, what role to the migration costs embedded in β_2 play?

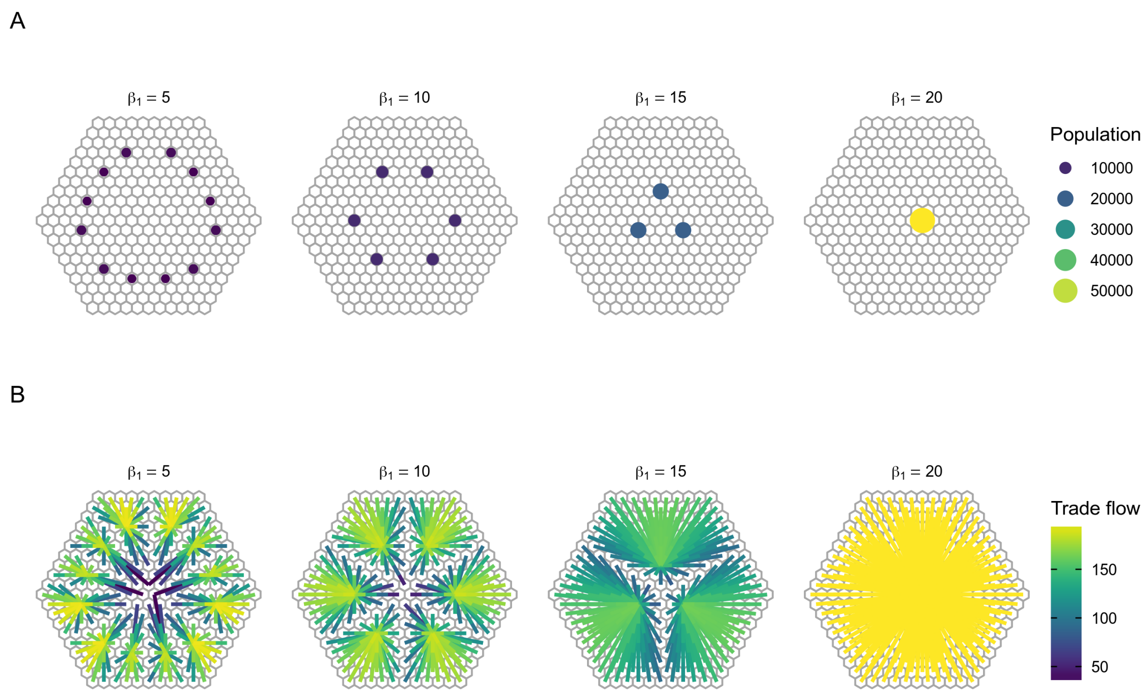

Figure 20. The role of the ease of movement for trade in settlement size and spacing. A) Equilibrium settlement patterns and populations for different levels of β_1, with $\beta_2 = 20, \alpha_1 = 1.15, \alpha_2 = 0$. The β parameters are scaled to distance units (here kilometers). B) Same as A, but for each patch an edge is drawn connecting it to the settlement to which the majority of its resources flow. Trade flow is measured in units of food to support 1 person per year.

Holding β_1 constant at a low value (5km) and varying β_2 allows migrants to move further across the landscape than food resources. The result is a pattern of concentric rings at low values of β_2 (Figure 21a). When it is difficult to move food over space, migration acts in lieu of food transport by increasing the size of the terminal centers (allowing population to move to populated zones), but this effect and the resulting size of the population is not nearly as strong as that induced by varying β_1.

A settlement's ability to gain an initial surplus because of its position is key to its long-term survival. The absolute productivity of the land is less important than access to resources systems without significant competition from other settlements. Changing β_1 to

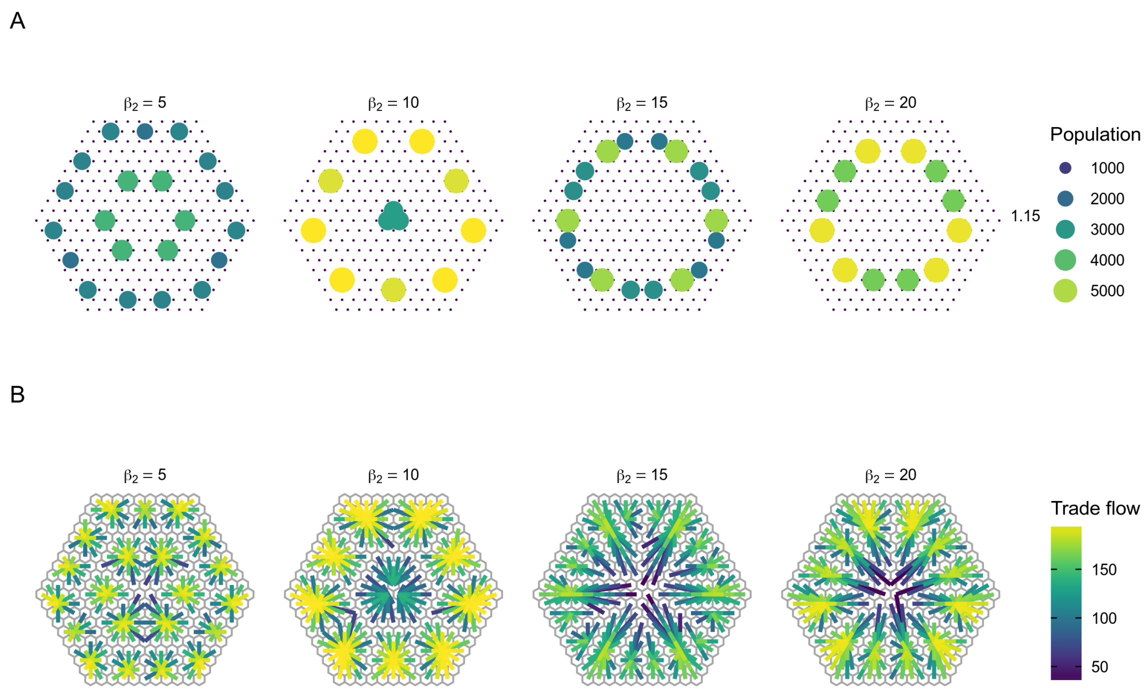

Figure 21. Settlement population (A) and trade flows (B) at equilibrium for different levels of β_2, the ease of movement for migration, with $\beta_1 = 5, \alpha_1 = 1.15, \alpha_2 = 0$.

facilitate easier resource transport acts to increase the competition between settlements for productive land, making it easier for larger, more distant settlements to out-compete smaller nearby settlements for access to a given resource system. Although the model does not explicitly account for edge effects at the boundary of the spatial domain, in practice the distance scale of spatial interaction encoded in the β parameters is much less than the scale of the spatial domain as a whole. That said, the *shape* of the spatial domain does influence the dynamics, as it should in the real world. The initial benefits to a site because of its position in the spatial domain related to other patches leads to increased population growth, which feeds back to allow the settlement to compete for resources and population from sources further afield.

4.2.2 Population-based Migration Increases Settlement Hierarchy; Welfare-based Migration Reduces It

The parameters α_1 and α_2 control the relevance of site population and *per capita* welfare in attracting flows of food and migrants. Introducing superlinear scaling parameters to the population size and welfare by increasing α_1 and α_2 doesn't change the basic interaction between the β parameters, but does impact the size hierarchy. Alternately setting $\alpha_2 = 0$ or $\alpha_2 \geq 1$ allows the model to represent scenarios in which only population size determines the attractiveness of a settlement to migrants, or situations in which the balance of population and *per capita* welfare influence migrant decision-making.

In the first scenario with only population-based migration, there are nonlinear interactions between the migrant attractiveness and ease of movement parameters (Figure 22). Generally, increasing α_1 increases the concentration of populations in fewer centers. As before, the settlements near the edge grow fastest because there is less competition for access to resources. There is a break in this pattern at $\beta_2 \geq 15$ and $\alpha_1 = 1$, where the center becomes filled with multiple settlements of similar size in a hexagon pattern. The number of settlements in this central zone increases with increasing migration. These settlements only extract food from their local resource patch. This core settlement zone is a result of the size and shape of the spatial domain, as at long distance interaction the size and shape of the domain more strongly constrains the possible configurations. These inner zones are only present when β_1 is low or when $\alpha_1 = 1$, as this zone represents situations where no settlement can get an initial advantage from its location or increasing returns to scale and growth ceases. Settlements at the edge get initial advantages because they have fewer nearby cities competing with them for resources. At low β_2, this dynamic matters little, but at high β_2 it sets off a feedback loop as population migrates to the sites with initial advantages. This central zone disappears if $\beta 1$ or α_1 is increased, allowing for some sites to gain initial advantages that feed forward in time. In these cases, β_2 no longer changes the broad settlement pattern but rather serves to concentrate more people in fewer, closer core settlements.

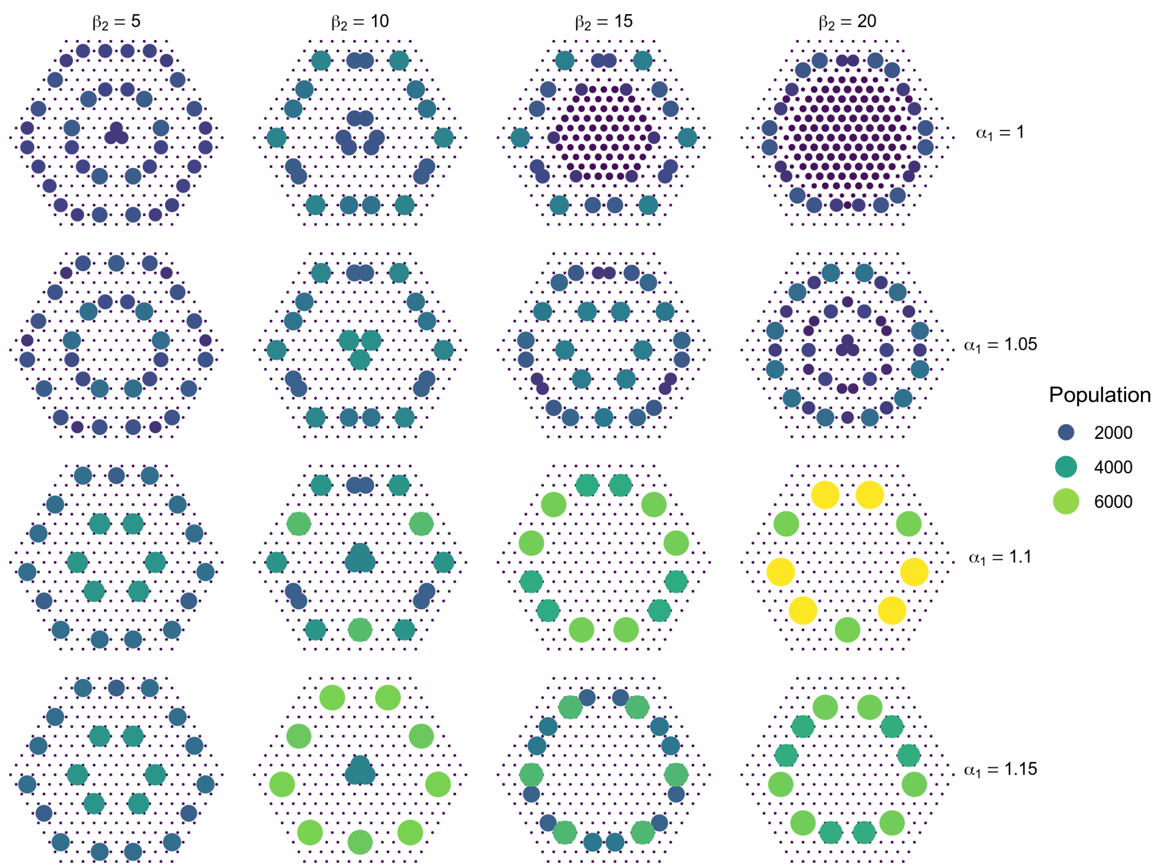

Figure 22. Interaction between the ease of movement for migrants (β_2, columns) and the returns to attractiveness for population size (α_1, rows), when the moving food to settlements is difficult and migrants make decisions based only on settlement population size ($\beta_1 = 5$ and $\alpha_2 = 0$). The β parameters are scaled to distance units for interpretability, and the α parameters are dimensionless.

Allowing $\alpha_2 \geq 1$, so that people avoid settlements with low welfare, considerably increases the complexity of the system when trade costs are high (Figure 23). If migrants are attracted to zones with high *per capita* welfare, migration acts to smooth over variations in settlement size due to differential access to resources. The uniform central zone of low population

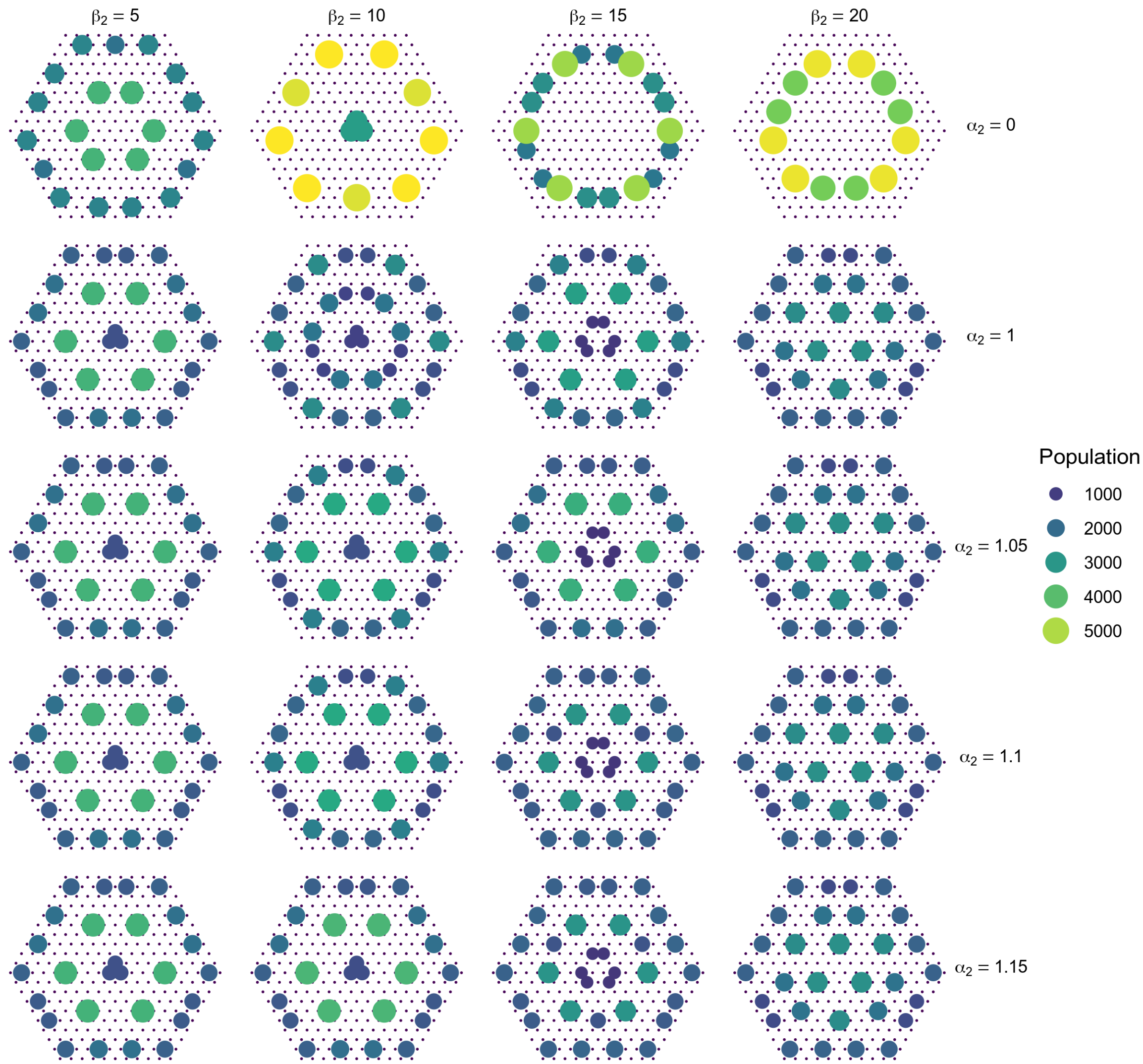

Figure 23. Interaction between the ease of movement for migrants (β_2, columns) and the returns to attractiveness for *per capita* welfare (α_2, rows), when the moving food to settlements is difficult and migrants make decisions based on both settlement population size and *per capita* welfare ($\beta_1 = 5$ and $\alpha_1 = 1.15$).

centers discussed earlier arises at even shorter distance migration. This reflects situations where movement is generally easy, but there are few advantages to living in more populated sites so migration acts as a counterbalance to the competition for resources.

4.3 Discussion

This study sought to explore the relative influence of the costs of transporting food into settlements and the those for moving migrants between them. Analysis of a disaggregated spatial interaction model revealed that trade costs were ultimately more important than migration costs for shaping overall settlement patterns. These results highlight that the precise nature of spatial interaction in a settlement system has important consequences for understanding the development and maintenance of stable settlement patterns in the archaeological record.

The costs of moving resources from resource patches to settlements determine the territorial reach of resource extraction, which is the primary determinant of equilibrium site size and spatial configuration. Even small initial differences in the number of people the local resource patches can support can increase consumption enough to set off a positive feedback between settlement population and resource extraction. The importance of trade flows here is consistent with related modeling efforts that highlight the role of trade networks in extending local carrying capacity in simple consumer resource networks (Qubbaj, Shutters, and Muneepeerakul 2014; Dolfing, Leuven, and Dermody 2019).

This dynamic has empirical support. The pattern of 5km settlement-patch modules self-organizing into nucleated settlements harvesting from larger 15-20km "compound catchments" with larger settlements thus spaced 30-40km on the landscape has been documented in Bronze Age northern Mesopotamia and Hungary (Wilkinson 1994; Duffy 2011). These "compound catchments" need not themselves be hexagonal. When migration costs are low relative to resource transport, the model predicts fan-shaped compound catchments arising not from centralization around the target settlement but competition with other neighboring settlements, a situation visible in the settlement patterns of central Mexico (Hirth 1978). In general, it appears that the configuration of resource flows into settlements directly influences the emergent spatial and social structure (Crabtree et al. 2017).

The spatial scale of settlement structure in these examples implies the flow of overland food transport attenuates at around 20km, reflecting a value of β_1 value of 4-5km. This value is supported by analysis of settlement structures across a broad swath of northern Mesopotamia (Menze and Ur 2012). Of course this value will vary for different modes of travel, but it provides an appropriate baseline for exploring settlement patterns in other small-scale societies lacking specialized transport technology. An increase in inter-site spacing or the growth of sites in once marginal zones suggests innovations in moving food resources over space, such as the shift from "hubs" and "endogenous upstarts" to "exogenous upstarts" in the settlement history of Mesopotamia with the advent of extensive sheep and goat pastoralism and long-distance trade (Lawrence and Wilkinson 2015; Lawrence et al. 2016).

Migration has a more subtle influence than trade in the model, acting to redistribute population among settlements with less impact on aggregate settlement structure. Migration is most important when food transport costs are particularly high and the territorial reach of small settlements is low. When migrants choose where to travel based on population size alone, the resulting dynamic is one of nucleation and stratification. This phenomenon is ubiquitous in the archaeological record, from the coalescence of Hohokam communities in the US Southwest (Hill et al. 2004), to Jomon-era Japan (Crema 2013), and the synoikism of classical Greek *poleis* (Mackil 2004). Several factors can lead to apparent aggregation and the formation of settlement hierarchy in the archaeological record (Duffy 2011), but many are special cases of this population-based dynamic. External threats of warfare or benefits from socio-economic activity may all encourage people to live together, for example, but from an individual's perspective the choice of destination is still made based on population size.

The ubiquity of nucleation in the archaeological record suggests that the second determinant of migration in the model, *per capita* food supply, is less relevant to migrant decision-making than absolute population. Aggregation in the southern US Southwest is associated with net population decline, for example, as migrants from the north stressed local productive capacity and reduced local welfare (Hill et al. 2004). Perhaps long-term cycles of dispersion and aggregation, as evidenced in the US Southwest and Jomon-era Japan (Crema

2013), reflects shifts in the relative importance of absolute population and food supply to population flows.

An important point that emerges from the archaeological record is the importance of external environmental factors. Settlement aggregation in both the US Southwest and Mesopotamia often occurred in areas with high irrigation potential, or with easy topographic access to other settlements (Hill et al. 2004; Lawrence et al. 2016). Although the model is capable of capturing these influences, this study simulated a regular lattice of settlements overlaying a uniform environment in order to isolate the effects of the spatial interaction on the system's behavior. But the resulting dynamics are nonlinear, which means that the initial and boundary conditions of the settlement system will constrain its ultimate trajectory. In any given real-world setting, the initial distribution of sites, not to mention the spatial configuration of productive land and physical impediments to travel, will influence the resulting settlement patterns. Future exploration of this model measure the effect of such environmental variability. In particular, this disaggregated modeling framework can help isolate quantitative classes of variability that lead to qualitatively different settlement patterns, such as degrees of spatial or temporal auto-correlation.

Future work should also draw on the extensive toolkit developed in geography and economics for dynamic spatial interaction modeling. Potential methodological innovations include various ways of further disaggregating the "fast" flow dynamics or of incorporating more complex or context-specific models into the "slow" settlement dynamics (Fry and Wilson 2012). For example, how do the costs of transporting resources to settlements interact when the resources include not just food, but other raw materials for energy or craft production that may contribute to a settlement's carrying capacity or attractiveness. Similarly, the migration flows could be disaggregated to explore the interactions between those of different age, ethnic, or social classes (Altaweel 2015).

Given more precise models of the spatial flows, the dynamics of settlement growth and decline can also be elaborated. In the present version of the model, the production of food and the production of migrants at each settlement is assumed to be constant or a fixed proportion of population size, respectively. One might instead model the dynamics of the food producers directly, incorporating feedbacks between producer and consumer populations (Turchin 2003), or allow migration rates to vary based on population size (Curiel et al. 2018) or differences in the levels of *per capita* food consumption (Anderies and Hegmon 2011). Even if these elaborations do little to alter settlement patterns at equilibrium, they will introduce important new behaviors as theses systems approach that equilibrium – the "transient" dynamics – that in concert with variable initial and boundary conditions will be critical for reproducing the complexity visible in the archaeological record.

And it is precisely here, at the interface of archaeological theory and data, where spatial interaction models may contribute most. These models support both dynamical and statistical implementation; the same model can be used as a tool for developing theory from one domain and interpreting data in another. Numerical simulation with these models can help explore the empirical archaeological record, and act as a test bed for the development of new statistical methods. For example, a statistical spatial interaction model estimates only one β value, the coefficient of distance in a log-linear regression. How should one interpret this regression coefficient when it is likely that the pattern at hand arose from the interaction of multiple spatial processes? Disaggregated, dynamic spatial interaction models allow researchers to flexibly explore different dynamical processes interacting to form the stable patterns recorded in the field.

This research highlights dynamics *of* networks, not dynamics *on* networks. The approach implicit in many conceptual and mathematical models of networks, and archaeological networks in particular, treats them as static (if nontrivial) structures on which some dynamic of interest plays out. These structures only change in time to the extent that the researcher intervenes by adding or removing nodes and edges manually. This view is understandable given the fragmentary and time-averaged nature of the archaeological record. Instead, the approach used here treats social networks as dynamical systems with continuous flows of matter, information, and energy in constant interaction with their ecological and social environments (Brughmans and Poblome 2016; Crabtree 2015). Improved representations of social and biophysical dynamics will not only enhance understanding of the empirical settlement patterning in the archaeological record, but will also facilitate future cross-cultural and inter-regional comparisons by providing a shared set of questions and methodological tools for answering them.

Settlement patterns are some of the most basic components of the archaeological record, yet only in recent decades have archaeologists developed the computational expertise and theoretical tools needed to reconstruct the social fabrics binding those settlements together. But the utility of such datasets for addressing questions of societal relevance remains limited. Archaeological settlement pattern data are rarely comprehensible to the researchers, policy advisers, and stakeholders in the developing world most likely to gain meaningful insight from the information they contain. The solution to this problem lies in the fuller integration of theory and data from the broader social sciences. Spatial interaction models can act as a bridge in this respect, allowing archaeologists to leverage decades of accumulated research into the role of space and distance on the societies of the present and the past.

Chapter 5

CONCLUSION

Together, these studies define a unified approach to modeling regional social-ecological systems in the past. They are a first step towards addressing the paucity of formal quantitative theory that can account for the complexity of human-environment interactions and the fragmentary nature of the archaeological record. In general, these studies explicitly tie environmental variability to population growth and food production and present a set of methodological approaches flexible enough to represent patterns and processes on multiple scales:

Chapter 2 First, I used a statistical model to analyze a database of 7.5 million artifacts collected from nearly 500 archaeological sites in the Southwest and found that sites located in different climatic zones were more likely to interact with one another than a sites occupying the same zone. This research extended previous findings by using objective, physically-consistent measures of climate variability and a large regional database of archaeological social network proxies. It highlights the importance of distinguishing between different types of drought and flood events when considering their potential social impacts.

Chapter 3 Next, I developed a computational model of demography and food production in ancient agrarian societies. Using North Africa as a motivating example, I showed how the concrete actions and interactions of millions of individual people lead to emergent patterns of population growth and stability. This hierarchical simulation approach was better able to close the feedback loop between demography and food production while simulating the nested organization of human societies often overlooked in models of food-limited demography. Going forward, bottom-up simulations rooted in first principles of human behavior will be crucial for understanding the coevolution of preindustrial societies and their natural environments wherever the archaeological record is so fragmentary as to restrict precise empirical analysis.

Chapter 4 Finally, I built a simple mathematical model of trade and migration among agricultural settlements to determine how the relative costs and benefits of social interaction drive population growth and shape long-term settlement patterns. I found that the costs of moving food to people was the primary constraint on the number, size, and spacing of settlements, but the movement of people to food had important influences on enhancing or diminishing existing hierarchies. This model illustrates how the broad toolkit for spatial interaction modeling developed in geography and economics can aid the precision of quantitative theory building in archaeology, and provides a road-map for connecting mechanistic models to the empirical archaeological record.

5.1 Addressing Grand Challenges

In Chapter 1, I framed this dissertation in the context of four "grand challenges" for archaeology (Kintigh et al. 2014). These challenges are pressing questions that our discipline is well-placed to address, but solid answers are to date lacking due to the rarity of interregional synthesis projects and advanced modeling studies. How well have the above studies addressed these questions?

How do humans respond to abrupt environmental change? In the short run, abrupt environmental changes can lead to catastrophic mortality in vulnerable populations, but these responses are temporary as birth rates will increase once population pressure is reduced (Chapter 4). For those who leave their settlements during an abrupt event, their choice of destination is informed by social institutions that reflect in part underlying environmental structure (Chapter 2).

How does the organization of human communities at varying scales emerge from and constrain the actions of their members? Households make decisions about the production and consumption of food based on the food requirements and labor availability derived from the age structures of their individual inhabitants (Chapter 3). The size and organization of settlements on the landscape reflects a feedback between slow processes of population growth and fast processes of spatial interaction (Chapter 4).

What factors drive or constrain population growth in prehistory and history? On a local scale, the age structure of a population determines its relative need for food versus labor, which constrains population growth (Chapter 3). On a regional scale, the movement of food and people between settlements can lead to zones of temporarily high "carrying capacity."

What are the relationships among environment, population dynamics, settlement structure, and human mobility? The environment constrains the size, location, and mutual accessibility of population centers, as well as underlying spatial and temporal variability of resources (Chapter 2). Given these external constraints, people will trade and migrate among settlements according to their relative sizes and importance (Chapter 4). The ease with which trade and migrant flows move over space constrains shapes settlement structure and by extension the size of local populations and their impact on the local environment (Chapter 3 and 4).

A key factor in addressing these questions was the use of an integrated modeling framework capable of representing nonlinearity, scale, and emergence. Dissemination of this framework will be necessary to enable extensions that further address these and other pressing questions in archaeology. To facilitate reuse by archaeologists and members of the climate-change impact-assessment community working outside of academia, all analyses have used free and open-source software, all results will be published in open-access journals, and all computer code and data will be fully documented and and preserved in a persistent, discoverable, and accessible public archive. Raw and post-processed data from all simulations will also be hosted publicly, allowing parties without access to high-performance computing facilities to acquire and modify those data for further study. Finally, to enable broader public engagement with the concepts and tools underlying this research program, the core components of this framework will be distributed as an R package and interactive web application using the Shiny platform for R.

5.2 Limits to Generalization

A subtle but important concern limiting the generalization of these studies is the question of parameterization. Parameters define the nature of the modeled system: the rates, thresholds, and fractions that make the system do what it does. How many parameters should a model have, and at what values should they be set? There is a tradeoff between simplicity and generality on the one hand, and complexity and specificity on the other. This tradeoff has different implications for different classes of model. In statistics this problem is known as the bias/variance tradeoff. One must choose between models that perform well in one case but have varying performance in other cases, or models that perform well across cases but that are biased in any one case. Modelers can try to strike an optimal balance between model complexity and goodness-of-fit using measures from information theory or techniques like regularization, as was the case in Chapter 2. However, this process is not so simple in archaeological simulation studies where qualitative comparisons to proxy data are the norm and quantitative goodness-of-fit is harder to assess.

In numerical simulation models there is an inherent tradeoff in the number of free parameters that mirrors the bias/variance tradeoff. A model can have several free parameters, which result in a complex model that can be tuned to fit increasingly specific contexts. Or, a model can have few parameters and capture quite general properties of a system that are likely to be hidden within the complexities of any given case. It is important to distinguish between mechanistic parameters that represent some physical phenomenon such as distance deterrence and those that represent more abstract properties such as the attractiveness of different climate zones to potential migrants. One example of this distinction is the notion of carrying capacity. Chapter 4 uses an abstract notion of carrying capacity, manipulating the units so they reflect "food needed to feed one person per year". This abstraction allows for a potentially more rigorous analytical analysis. In Chapter 3, on the other hand, "carrying capacity" was not a single value but instead an emergent property of several parameters including the maximum potential crop yield, the caloric needs of different age classes, and the taxation rate. In some cases these values were known in advance, either from existing empirical work or because they represent mechanistic physical quantities, and it was simple to tune the model to fit the real world. But this flexibility comes at the cost of true understanding. Any uncertainty in one part magnifies the uncertainty of the whole.

This concern with parameterization is especially important to climate modellers who attempt to simulate the entire Earth system, and there are many design lessons to be learned from their experience. Climate models rely on many free parameters to resolve phenomena that lack solid mechanistic models or that operate on different time scales, like cloud formation in the atmosphere (Gettelman and Rood 2016). Although the general dynamics of the Earth's climate system can be described in a minimal set of equations, more complex numerical simulations are required to make predictions about specific times and places in the future or past.

One design lesson from these types of models is modularity. We should build self-contained submodels for the important parts of the system, isolating sets of closely-interacting parameters and state variables. Then we can work to understand the parts in isolation using more computationally intensive methods such as sensitivity analysis and selective parameters sweeps for each of the sub-components. We thus ratchet up our understanding of the whole system by systematically analyzing the actions and interactions of each part in turn. Climate models, for example, have many interacting sub-components such as the atmosphere and the ocean which can be run in any number of combinations. An atmospheric model can be run independently, driven by observations or previously simulated data, or connected to a fully interactive ocean model (Gettelman and Rood 2016). Simulations of human dynamics must be similarly modular.

Earth system scientists also employ sophisticated tools for empirical calibration. This approach works only for archaeology if we have observations or proxies for the key parameters, like historical records of Roman tax rates, allowing us to fix those parameters to empirical values. But what happens if the parameters are more abstract quantities that cannot be inferred directly from the data? Another promising tool from climate modeling and numerical weather prediction is data assimilation (Tardif, Hakim, and Snyder 2013; Matsikaris, Widmann, and Jungclaus 2015). Data assimilation involves the fusion of models and data. An ensemble of simulations serve as prior information about the possible states of the system, and the observed data provide information about the time evolution of those states. In this way, the model itself does the work of connecting simulated dynamics to their expected empirical outcomes. Archaeological data assimilation would be a model-based hindcast optimally constrained by archaeological observations. This method accomplishes this by building "forward models" of the data into the simulation, thus creating a virtual archaeological record *in silico*. In this way, the uncertainty in the data can be directly compared to the structure of the model's outputs.

5.3 Iterative Model-Building

Ultimately, there is no right answer to the optimal degree of simplicity or complexity of a model. The answer depends on the research question and the contexts in which it is asked. Statistical models provide insights into the parameters driving the formation of patterns in the empirical record. Computational models, and computational agent-based models in particular, provide insights into the higher-level properties that emerge from heterogeneity at lower levels. Equation-based "mean-field" models, on the other hand, provide a parsimonious middle-ground for capturing the average behavior of a system. Each of these approaches have their unique strengths and weaknesses, and using them in tandem is a powerful strategy for building knowledge.

Indeed, in order to build solid quantitative theory we must use models at *all* levels of complexity in a systematic, iterative fashion. Agent-based computational models are justified when the heterogeneity of a system's constituent parts is central to its behavior, or when the assumption of infinite, well-mixed populations common in many equation-based "mean field" models fails to hold. Iterative comparison of computational and mathematical models of the same system will highlight precisely those domains where such latent assumptions of uniformity or heterogeneity are more or less influential. A complex agent-based model could provide estimates of the range of variability in a sub-domain of the system, which can in turn inform the choice of one or more simpler, mean-field approximations. Likewise, sensitivity analysis of an analytical, equation-based model will help isolate the components of a system where more intricate numerical simulations are needed most.

This dissertation illustrates the potential for such an iterative approach. I first found an empirical relationship between climate patterns and social interaction, but the relationships were not causal because of the mediating role of population growth and food production. I then built a detailed simulation of population growth and food production to explore this connection more fully. Finally, I synthesized the two approaches using a simple equation-based population growth model that approximated the average behavior of the computational simulations, and combined it with the same mathematical models of social interaction used in the statistical analysis. A further iteration of this process might then return to the statistical analysis to ask a more nuanced question about how different forms of social interaction each respond to recurring climate patterns.

5.4 Next Steps

This work focused primarily on the human side of these regional social-ecological systems, investigating the emergent consequences of environmental variability on population growth, food production, and social interaction. A potentially powerful extension of this research program is to close this feedback loop by allowing social dynamics to influence environmental variability. Potential mechanisms of this feedback include land-use changes such as deforestation and irrigation that alter the flux of moisture from the land to the atmosphere. Changes in land use that alter local evapotranspiration rates can propagate downwind to considerably alter region-wide rainfall and, by extension, feed back to impact regional agricultural productivity and population growth (Gordon, Peterson, and Bennett 2008; Mahalov, Li, and Hyde 2016; Wang-Erlandsson et al. 2017; Zemp et al. 2017). The potential for this cascading dynamic is especially marked in arid and semiarid environments, where water availability limits ecological dynamics and the evaporative demand of the atmosphere for moisture is high (Dominguez, Kumar, and Vivoni 2008). Incorporating such two-way feedbacks will have the effect of increasing the overall variance and unpredictability of the system as a whole, a necessary quality for predicting the range of possibility in the modeled system (Robinson et al. 2018).

This theoretical approach to dryland agriculture as a complex, adaptive, social-ecological system and the associated methods for dealing with nonlinearity, scale, and emergence will enable archaeologists to move beyond the dichotomy between environmental and social determinism. By combining theory and methods from ecology, geography, and climate science, archaeologists can better leverage insights from diverse times and places to fill critical knowledge gaps in the study of food security and sustainability in the drylands of today. As the present-day refugee crisis in southwest Asia demonstrates so clearly, climate change, food security, and migration are tightly interwoven components of the same complex system. To anticipate the trajectory of the world's drylands in the coming century, societies must also look back to the lessons learned by those that have come before. Yet archaeological data are rarely comprehensible to the researchers, policy advisors, and stakeholders in the developing world most likely to gain meaningful insight from the information they contain. The solution to this problem lies in the fuller integration of theory and data from the social and Earth system sciences, and a commitment to open data, open methods, and open access. The integrated social-ecological modeling approach pursued in this project is a first step toward addressing this gap.

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