# LANDSCAPE-BASED NULL MODELS FOR ARCHAEOLOGICAL INFERENCE

By

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To the Faculty of Washington State University:

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ARCHAEOLOGICAL INFERENCE

Abstract

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How do we, as humans and as scientists, learn about the world around us? In this dissertation, I explore how models—epistemological tools that connect theory and reality—not only structure scientific inquiry (including the social sciences), but also reflect how humans experience and understand the world. Using this insight enables anthropologists and other social scientists to build more ontologically powerful understandings of human behavior. Here, I focus on how humans experience physical and social *landscapes*—the environments in which they live and with which they interact. The dissertation consists of three studies, each of which build on the previous by adding to the complexity of modeled landscapes. The first concerns *static landscapes*—those that are unchanging over the temporal timescales relevant to human experience. I develop a topographically-derived index of defensibility and use it to infer defensive behavior among prehistoric populations in the Northwest Coast of North America. The second paper introduces *dynamic landscapes*—those that change at scales experienced by humans, but whose changes are primarily driven by external forces. An example relevant to agrarian societies is climate change. I develop a new method for reconstructing past climate landscapes and explore the potential impacts of those changes on Ancestral Pueblo maize farmers in the southwestern United States over the past two millennia. Finally, the third paper grapples with *complex landscapes*—dynamic landscapes in which human behaviors play important and recursive causal roles. I highlight the coevolution of locally-adapted maize varieties and human selection and cultivation strategies as an example of these types of landscapes, and develop frameworks for modeling maize paleoproductivity that can better honor the realities of Pueblo agricultural strategies.

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For Mom and Dad.

*A great deal of intelligence can be invested in ignorance*
*when the need for illusion is deep.*
~ Saul Bellow

# PREFACE

This is not a traditional dissertation. It is a compilation of three academic papers, each of which stands on its own, and all of which are integrated around the theme of using landscapes as null models for archaeological inference. Each paper builds on the last by adding to the complexity of the system being modeled, moving from *static landscapes* for predicting human settlement patterns (Chapter 2), to *dynamic landscapes* predicting both settlement patterns and movement (Chapter 3), to *complex landscapes* that capture feedbacks between human behavior and landscape genesis (Chapter 4). Each chapter begins with a short introduction before moving on to the published or submitted research paper.[1]

Chapter 2 focuses on how archaeologists might use static models of landscapes, such as digital elevation models (DEMs), maps of coastlines, or locations of hydrological resources in generating inferences about human settlement patterns. By analyzing how archaeological sites are situated on a landscape in reference to static landscape features, we should be able to make inferences about what past people found important when making settlement decisions. This line of inference has a long history in archaeology (Jones 2010; Kellogg 1987; Kohler and Parker 1986; Maschner and Stein 1995; Plog and Hill 1971). In my paper, I echo earlier work (Kvamme 1990, 1999; Wheatley 1995) in stating that the use of one-sample statistical tests—comparing archaeological site locations to the population of potential locations on the landscape—allows for stronger and more elegant inferences. I develop such a one-sample methodology to infer defensive behavior among prehistoric populations in the Gulf of Georgia and lower Fraser River valley of British Columbia, in light of the baseline defensibility of the landscape.

Landscapes change, however, due to forces both internal and external to human behavior. Humans and other animals are constantly adapting to changing landscapes; therefore, when trying to interpret human behavior, archaeologists must consider landscape dynamics. Chapter 3 focuses

[1] I have minimized the degree to which the format of each article has adjusted into WSU thesis format, in most cases just changing the in-text citation style and standardizing the formatting of tables and figures.

on landscapes that change due to external forcing. My coauthor and I develop a new method for reconstructing past climate landscapes (also called *spatiotemporal climate fields*) from tree-ring chronologies, retrodict summer accumulated heat and water-year precipitation across two large regions in the southwest United States from AD 1–2000, and reconstruct the rain-fed maize growing niche in each of these regions. We then use these dynamic landscapes to understand the timing and trajectory of the famous Ancestral Pueblo migrations from the Mesa Verde region to the Northern Rio Grande region during the 13th and 14th centuries AD.

Human behavior is bound in coupled natural-human systems at multiple scales. How can we begin to capture the complexity of socio-ecological dynamics? In the introduction to this dissertation, I suggest that a computational complex-systems approach might be our best way forward. In Chapter 4, I develop a proposal for such a study, using the joint evolution of maize landraces—locally adapted maize varieties—and human selective strategies as a case study. The productive capacity of different landraces in the southwest United States represents an evolving landscape in which humans played a central causal role. I propose two approaches to reconstructing maize productivity in the Ancestral Pueblo southwest that are fundamentally different from prior research (Burns 1983; Kohler 2012b; Van West 1994), and demonstrate how these new productivity models may be effective tools in inferring the causal mechanisms of past human behavior.

I start, however, with a series of reflections on model-based social science, and how archaeology—a discipline spanning the social and life sciences—might be uniquely situated to answer longstanding questions in cultural and historical ecology. I take an epistemological approach: How do we go about learning "facts" about the past? I argue that a model-based approach to social science is not only intuitive, but also is among the only approaches that can generate the kinds of material expectations useful to archaeologists. I close by introducing models of conflict and climate that provide important context for the following studies.

## CHAPTER ONE

## SKIPPING OFF THE SURFACE OF HISTORY—A FEW INTRODUCTIONS

The game of skipping stones has gotten a surprising amount of attention in the scientific literature lately (Bocquet 2003; Clanet et al. 2004; Hewitt et al. 2011; Nagahiro and Hayakawa 2005; Rosellini et al. 2005). Researchers in France have described the physics of stone skipping using mathematical models of gravity, resistance, and fluid dynamics, and have derived a theoretical maximum number of skips (38) that may be achieved under just the right circumstances (Bocquet 2003; Clanet et al. 2004).[1] Physicists have performed experiments validating these mathematical models, and have shown that a "perpetual skip" may be achieved if stone velocity can be maintained (Hewitt et al. 2011). NASA engineers have built on skipping theory to describe a type of spaceflight where a ship skips off the surface of earth's atmosphere, saving fuel but undoubtedly leading to a bumpy ride for passengers (Chase 1996). Looking at the research, it seems like we've finally got stone skipping nailed down.

But what if, instead of lab settings and Newtonian principles, we only had a sample of skipping attempts at a professional skipping competition from which we were asked to derive skipping theory? We can imagine having data on the number of skips per throw, personal statistics on each skipper, and perhaps the distance each stone travelled in its recorded number of skips. We might then describe the relationship between the number of skips and the distance traveled, or explore the impact of biophysical metrics of the skippers. But could we reconstruct Newtonian mechanics and fluid dynamics from the these limited observations alone? Or could we predict who is likely to win the tournament? How should we organize our analysis of the tournament data to answer these questions?

[1]Throw the stone at a 20 degree incidence angle with the surface of the water, while also maintaining a leading edge 20 degrees above the trailing edge; throw it at 40 feet per second, and use a flick of the wrist to give it ~14 rotations per second. This, believe it or not, was reported in *Nature* (Bocquet 2003; Clanet et al. 2004).

**Structural versus historical approaches in the social sciences**

The dual challenges of deriving the mechanics of stone skipping while simultaneously attempting to predict the outcome of a stone skipping competition is an apt analog to our task as archaeologists. As recorders of human life in the past, we are interested in exploring the trajectory of history in minute detail; as anthropologists, we seek to understand not only the diversity of the human experience, but also humanity's common heritage (Binford 1962). We strive to know what makes us human. Anthropological observations of repeated patterns of human behavior cross-culturally and throughout time present compelling evidence that there *must* be structuring principles of human behavior (e.g., Keeley 1996). Still, when observing particular instances of human behavior, anthropologists are made acutely aware of the historical contingency of behavior, leading to the suggestion that history itself is the most important structuring principle of all. McAllister (2002) explores the tension between structural and historical approaches in the natural and social sciences. Structural approaches seek unifying explanations for behaviors or observations, and privilege predictive accuracy as a measure of the quality of explanation; historical approaches emphasize contextualization and historical contingency, and value specification and description over prediction. A historian might argue that while it is interesting to explore the causal links between *past* states of a system, prediction of future states of the system is a relatively futile effort.

The distinction between structural and historical approaches mirrors the theoretical development in the social sciences, and in anthropology and archaeology especially. Malinowski and Boas stressed the "situatedness" of human behavior; Clifford Geertz's (1973) "thick description" is an effort to fully contextualize behavior and experience. In archaeology, the *Conjunctive Approach* introduced by Taylor (1948) and the later processual movement brought exploration of structural causes to the fore. Both the processual approach and historical particularism emphasize the context of behavior, but the processualist goal was to distill simplified causal relationships between context and behavior—law-like principles of behavior that have predictive value (this is still the goal of many; e.g., Kohler 2012a; Simon 1990). The historical reaction in the 1980s and 1990s was a direct reaction to this goal; post-processualists found human behavior to be far more interesting in the particular, and argued that explanations invoking structure and making prediction often marginalized the diverse experiences of many actors in a society (Colwell-Chanthaphonh 2012:274). Post-processualists were equally critical of the hagiographic approach to history, with its focus on big men and important actors (this is the foundation of Marxist critique).

There have been several attempts to unify structural and historical approaches in archaeology, especially over the last two decades. Trigger (1991), both an archaeologist and historian of archaeology, argues in *Constraint and Freedom* that archaeologists ought to consider the structural constraints on human behavior—the environmental and social frameworks within which actors behave[2]. Trigger emphasizes that these constraining factors are not determinist, in the adaptive or Darwinian sense, but instead bound a suite of possible behaviors. Trigger abandons the historical/structural dichotomy and instead defines *external* versus *internal* constraints. "External constraints relate to forces that exist independent of human beings; however people perceive them, they impact on behavior independently of human volition" (Trigger 1991:536). Internal constraints are purely cultural constructions. External factors tend to be universal in their application while most internal factors are specific to historically related cultures. "External constraints include ecological and technological factors, and the biophysical limits of the human organism. Internal constraints include knowledge (or lack thereof), beliefs, values, and culturally conditioned habits" (Trigger 1991:537). Trigger concludes with a sketch of a research program whereby the archaeologist models individual human decision making in reference to how an individual might have perceived the world; i.e., with a culturally filtered impression of the external constraints of their behavior. This is an approach that I will expand upon in later in this introduction.

More recently, Barrett (2012) also emphasized biological and cognitive constraints on human agency. Barrett's initial working definition of agency is that *agents do work*: "Doing work requires: a mechanism, something for that mechanism to work on, information to direct its application, and the transference of energy with resulting material consequences" (2012:147). Barrett takes the material world to be the "something" human agents work upon, and considers the way human per-

[2]Practitioners of archaeology do this, by necessity.

ception of that world ends up generating the trajectories of certain culture histories. Like Trigger, Barrett allows that some structural realities are fixed, in the sense that they will be unchanging over the spatiotemporal period of archaeological interest. Barrett challenges the strict materialist notion that objects are a direct reflection of human intentionality, or the Darwinian interpretation (and its progeny, Dual Inheritance Theory; Boyd and Richerson 1985; Shennan 2012) that cultural change may be assessed through archaeological materials as practices are selected through a type of cultural selection. Instead, Barrett focuses on "treating humanity as a way of reproducing life," not only in the biophysical sense, but in the sense of "human agency as the behaviors that treat diverse physical life experiences as the manifestation of a coherent causality and purpose to life" (2012:162). Agency is then not only the act of doing work on the perceived world, but also the act of being worked upon; the developmental process of living life in a particular way. Were it clearly articulated, Barrett's program for archaeological study would be an investigation of the structural aspects of environment and society that stimulate a given agency to arise.

**The surface[s] of history**

I find both Trigger's and Barrett's assessment of the relationship between structure and agency unsatisfying on two counts. First and foremost, both still maintain a duality between structure that is timeless and spaceless and structure that is affected by history (Trigger's distinction between external and internal structure, and Barrett's distinction between "biological realities" and the social and phenomenological considerations of living). This critique extends to McAllister's call for a synthesis as well:

> The universe is the product of two elements: a structural element and a historical element. The structural element determines the set of physically possible worlds within which the actual universe finds itself; the historical element determines which of these physically possible worlds, and in what order of succession, the universe comes to instantiate in its development. (2002:46)

My challenge is not to the laws of physics, which may indeed define the parameters within which the universe develops.[3] Instead, it is the assertion that such static structure constrains the realities of human cultures in any meaningful way (see also Kornet 2002). Physics may be able to describe the interaction between stone and water, but prediction of the skipping system requires knowledge of the state of the stone-pond-wind-world system, a historical contingency that comes to wholly define the physical structure. That is not to say that the system is not constrained, but that historical constraint is endogenous to the system; all structure is internal; all structure is historical. The surface of history is changing with every stone that is thrown (and even when stones are not thrown at all), and we can only attempt to capture the skips as they happen, and induce the cause(s) of their paths from the historical structures upon which they occur.

My second and less extreme concern with Trigger, McAllister, and Barrett's joint formulation is that maintaining a false dichotomy between structure and history reduces incentives for exploring feedbacks between human behavior and structure. If the surface of history shifts with every skip a valid focus of study is the ways in which certain skips or plunks impact the rest of the historical fabric (for a related sentiment concerning systems theory, see Kohler 2012a:95–96). Even where students of social science have allowed that events might have repercussions, these have usually been seen as only locally important. Scalar effects of human behavior are only rarely considered.

### Skipping off the surface of history

What approach to learning about the past can we as archaeologists take that explores human behavior within the structure of history? In what remains of this introduction—and, indeed, in the rest of this dissertation—I argue for a return to a model-based epistemology in archaeological research; but not the positivist approach so witheringly critiqued by postmodernism. Instead, I advocate continued adoption of complex systems (CS) modeling in archaeology, and specifically the use of agent-based simulation. Agent-based CS approaches allow us to explore the interactions between structure and history by imagining families of possible histories, and deriving probable

[3] Though I am reminded of one of my first graduate essays, written in Andrew Duff's *Archaeological Method and Theory* course, where I argued that quantum physics calls even this into question.

ones. They cast agents—simulation components such as human individuals and households—as the fundamental objects of archaeological study, while allowing for the generation (or *emergence*) of higher-level material patterns that are the bread-and-butter of archaeological practice. In the next section (*On models*) I review the development of model-based epistemologies in science, and introduce complexity science as the answer to the postmodern critique. I then take a model-based approach in considering the historical and structural forces that have shaped the development of Americanist archaeological method and theory (*History is behind us*). In the final two sections, I turn towards how the model-based approach may be used to better our understanding of prehistoric warfare on the Northwest Coast and in the Southwest US, in the former by implementing anarchist theory in an agent-based framework (*Models of sociocomplexity and conflict*), and in the latter by generating a more fine-grained understanding of how climate change may have structured large scale patterns of violence (*Reconstructing past climates, understanding lived environments*).

## On models

The basic task of an archaeologist is to connect conceptual ideas about human behavior with the material record of those behaviors, and particularly those that can be recovered archaeologically.[4] Archaeologists have traditionally approached this task *inductively*: we focused on identifying patterns in archaeological data—from a single site, archaeological region, globally, etc.—and inferred processes from those patterns. Kohler and Varien (2012a:8–9) note, however, that as scientists, archaeologists must also work from the opposite direction—deducing patterns from processes.[5] *But what is a process?* I follow Henrickson and McKelvey (2002:7290) and take a description of a process to be a *model*—an independent entity mediating between abstract theory and natural phenomena, or, alternatively, an indirect representation of a target system (Godfrey-Smith 2009:104). In this section, I review the development of a model-based (or "model-centered;" Henrickson and McKelvey 2002) epistemology in the social sciences. I then explore the complex system model-

[4]These "conceptual ideas" have been informed by history, ethnography, economic principles, theory from other fields of science, or even personal experience.

[5]This is of course the basic contrast between inductive and deductive reasoning (Godfrey-Smith 2003:43).

ing paradigm and the agent-based approaches promoted by Henrickson and McKelvey (2002) and McGlade (2014), among others, as isomorphic with postmodernist views of human agents. I highlight and critically assess the implementation of agent-based approaches in archaeology thus far—focusing on the Village Ecodynamics Project simulations—and suggest that while our attempts conform quite nicely to the structure of the *Semantic Conception*, we have a ways to go until we effectively demonstrate multiscalar *ontological adequacy*. I close with recommendations for the development of computational models that focus on a probabilist epistemology instead of our current possibilist approach. The research presented in this dissertation provides the foundation for such computational models.

**What is a model?**

A model is, in its most basic sense, a description of our phenomenology; it is a more or less accurate representation of our perception of the world. Nancy Nersessian describes modeling as "a fundamental form of human reasoning [...] in the analogical sense of a structure intended as isomorphic to some aspect of a physical system [...] the model is the mode of representation between the phenomena and expression in a language (including mathematics) [...] the actual forms of reasoning through which concept formation and change take place" (1999:14–15). The modeler-scientist—Nersessian (1999) stresses that all scientific thought consists initially of conceptual modeling—calls on basic principles and constraints as well as prior knowledge, and uses these as tacit assumptions concerning the behavior of a target system. "Models are mentally constructed and articulated, their expectations generated and tested, and their assumptions adjusted based on those tests" (Bocinsky 2011:4).

There have been several attempts to develop a typology of models, but I will follow Godfrey-Smith (2009) and adopt a quadripartite classification: *math models*, *physical models*, *computer simulations*, and *word models*. Math models (sometimes referred to as *formal* models) are systems expressed in numbers and equations. Math models come in two basic forms (Aldenderfer 1981:15). *Analytical* models are "built" axiomatically, and thus may be reduced to axioms, or basic statements of accepted fact. "The general aim of the axiomatic method is to determine the properties logically entailed by a set of axioms, primitive terms, and definitions. While one might appeal to real-world experience for motivation of one's choice of primitives, axioms, and initial definitions, the connection with the real-world is neither necessary nor a criterion for evaluation of an axiomatic system" (Read 1990:30–31). Analytical models are True in the sense that they are internally coherent. Models that use differential and integral calculus are often considered analytical models. *Numerical* models, in contrast, describe systems by estimating numbers for independent variables and parameters; these are parametric or statistical models (Aldenderfer 1981:15). Numerical models are not True in the same sense that analytical models are; they are approximations of a target system derived directly from that system. Examples of both of these forms of math model as applied to a target system are provided by Bettencourt (2013); using basic geometric axioms, he derives a set of scaling laws relating the size of cities to various economic indicators, and demonstrates that a statistical model calculated from data on a large number of real cities has the same form as the analytical one. Physical models are (usually) scaled-down or simplified versions of a target system; a popular example is a wind-tunnel (Godfrey-Smith 2009:103). Computational models are representations of target systems or intractable math models (analytic models too complicated to solve) usually presented in computer code; they derive their power from *simulation* to generate output data comparable to data from a target system (Aldenderfer 1981:14). Finally, word models (sometimes called informal or heuristic models) "sketch possible processes and mechanisms, perhaps with a flow-chart or similar device" (Godfrey-Smith 2009:104).

**Theory ↔ Model ↔ Phenomena** What makes a model a "good," or even "right?" Intuitively, we might answer that a good model is one that "fits" a target system—a model whose structure is isomorphic to that of the target system and that generates expectations that are met by elements of the target system. But where does that leave analytical math models, which may have no relation to a target system? Henrickson and McKelvey (2002:7290), following the *Semantic Conception* (Suppe 1989), position the model as an independent interlocutor between *theory* and *phenomenon* (see also Read 1990:Figure 1). *Theory* is an idealized statement of principle concerning a set of processes or phenomena. For example, rational choice theory in economics states that, when making a decision, an autonomous agent will seek to maximize benefit and minimize costs over a set of preferences (their *utility function*; Elster 1989). A theory by itself does not seek to specify or describe a given target system. *Phenomena*, on the other hand, *are* the target system, or at least data that derive from such a system. An example might be the decisions from among a set of choices reported by a sample of informants (given that each choice carries a unique set of costs and benefits). This view of phenomena is unbendingly realist; it holds that the world may be experienced and measured in an objective way. Finally, a *model* seeks to connect theory with phenomena. Using our example: given the principle of optimization from rational choice theory, an actor should choose option $x$ from among option set $X$.

This classification of theory, model, and phenomena as being independent entities in scientific reasoning allows for two measures of model adequacy (Henrickson and McKelvey 2002:7290). *Analytical adequacy* relates to how well the model implements the central tenets of the theory; it is a measure of consistency with the theory. Analytical math models and computational models are often defined in such a way to have perfect analytical adequacy; the models "stay true" to the theory within which they reside. In practice, a theory is often at least partially defined by a set of models which are analytically adequate at instantiating it (Henrickson and McKelvey 2002:7291). *Ontological adequacy* describes how well the model represents real-world phenomena. This is the more intuitive sense of the "fit" of a model familiar to archaeologists (Bell 1981; Kohler 2012a:110; Kohler et al. 2012c:24–26). In statistical math models, ontological adequacy might be quantified as the amount of error between prediction and data (e.g., Read 1990:Figure 2). It should be noted that while it is somewhat unclear *how best* to specify (quantitatively or qualitatively) analytical adequacy, it may always be done; however, a model need not make measurable predictions of a real-life phenomenon, in which case one could not comment on ontological adequacy at all. These types of models abound in theoretical physics, and are actually quite common in archaeology.

Henrickson and McKelvey (2002) describe the Semantic Conception not as a normative statement (i.e., a statement about how science *should* operate), but as a description of the way in which modern normal science (*sensu* Kuhn 1962) operates in practice (by which they mean the natural sciences). They note that there is often a division of labor among natural scientists such that some focus on problems of analytical adequacy (describing or defining models that fit theory), while others focus on ontological adequacy (describing or defining models that fit reality); however, they also note that in the social sciences this is not often the case (Henrickson and McKelvey 2002:7291). Furthermore, they criticize social scientists for often attempting direct theory-phenomenon adequacy tests without formalizing a model as interlocutor—although I would follow Nersessian (1999) in countering that a model is always implicit in such attempts, though perhaps not formalized or even well-articulated.[6] Henrickson and McKelvey (2002) stress however that the *types* of models favored in the natural sciences have progressed in a way yet to be acknowledged by social scientists who would be critical of such a model-based approach for trending towards oversimplification and uniformitarianism (the postmodernist critique[7]; Henrickson and McKelvey 2002:7289; Godfrey-Smith 2003:144–148).

**Modeling complexity**

That "progress" noted above is the development of *complex systems* (henceforth, "CS") models in the natural and social sciences (e.g., Barton 2013; Bocinsky and Kohler 2014b; Crabtree and Kohler 2012; Epstein and Axtell 1996; Grimm et al. 2005; Henrickson and McKelvey 2002; Kohler

[6]Brumfiel (1996) presents a good example of how archaeologists have most often navigated the terrain between theory, model, and phenomenon (that is, when they have developed models at all). She works under a theoretical framework that could be broadly termed *resistance theory* and develops a testable hypothesis (model) relating Aztec women's resistance to tribute taking by the Spanish to the quality of the tribute cloth they produce, as proxied by the size of spindle whorls they used in that production. Brumfiel expects that the quality of cloth will decline over time, because "women are not dupes" (Brumfiel 1996:454) and will resist being exploited. Instead, her data demonstrated the opposite; not only did the quality of tribute cloth not decline, it probably improved over time. Brumfiel concludes with an admittedly ad-hoc modification to her model (which she calls a theory): "resistance to exploitation does not occur when activities (such as household-based activities) are vulnerable to supervision and control by the dominant class" (Brumfiel 1996:459).

[7]I should note that the postmodernist critique wasn't only leveled at the social sciences. "Science studies" turned the sociological lens on the practice of doing natural science, and many influenced by postmodernist thought argued (1) that science was just as influenced by historical contingency as history itself, and (2) that the models being used were far too simple, in that they assumed homogeneity and simplicity of components (the mean field approach in physics, the use of point masses, frictionless planes, etc.) in a way that was ontologically impoverished (Godfrey-Smith 2003:144–148). Complexity science is an acceptance of and response to that critique (Henrickson and McKelvey 2002).

2012a; Kohler et al. 2012c; Lansing 2003; McGlade 2014; Miller and Page 2007; Mitchell 2009; Page 2011; Sherrington 2010; Turchin and Gavrilets 2009). CS models have been reviewed thoroughly elsewhere (e.g., Barton 2013; Kohler 2012a; Miller and Page 2007; Mitchell 2009); here, I touch on some of the central concepts to the CS approach, and then follow McGlade (2014) and Henrickson and McKelvey (2002) by highlighting the ontological similarity between postmodern conceptions of agency and the notion of heterogeneous agents typical to CS models.

Kohler (2012a:93) highlights the basic notions underlying CS modeling:

> A complex system, according to Mitchell (2009:13), presents "large networks of components with no central control and simple rules of operation giv[ing] rise to complex collective behavior, sophisticated information processing, and adaptation via learning or evolution." Such systems exhibit emergent and self-organizing behaviors. They commonly exhibit "frustration"—a condition in which it is impossible to satisfy all competing interests within the constraints imposed (Sherrington 2010). They frequently exist in far-from-equilibrium conditions. They are not merely complicated—meaning that they have many "moving parts"—but they also exhibit non-linear interactions involving structural contingencies or positive feedbacks.

CS modeling privileges the *autonomy* of components over top-down coordination, although this is not to suggest that coordinated behavior cannot emerge in such models. Indeed, a central goal of CS approaches is to explore how higher-level order might develop out of the "chaos" of the interactions of lower-level autonomous entities. CS approaches stand in contrast to other modeling approaches in that they implicitly incorporate historic processes and contingencies to a degree that would be difficult if not impossible using other modeling approaches (Peck 2012:2). The concepts of *emergence*, *learning*, and *adaptation*, are themselves dependent on the notion of history.[8] The modeling effort in CS approaches shifts from specifying the dynamics of whole ecosystems to focusing on the particular behaviors of individual components of those systems: how those components receive, process, and react to information about their environments (even if the "environment" is simply the collection of other components spatiotemporally nearby), and by extension

[8]There is some disagreement as to whether these notions apply universally to complex systems. Some would argue that evolutionary mechanisms—such as those that give an organism its current form—are fundamentally different from those that generate an ecosystem (e.g., Peck 2012). Others would suggest that *all* systems are subject to evolutionary (i.e., selective) forces, such that might select for the ability to process information about higher-level environments (Flack et al. 2013; Miller and Page 2007).

how those components interact with one another. System-wide patterns may emerge out of those interactions (or not), but these are not usually defined by the modeler.

Like other models, the creation of CS models can be directed towards achieving both analytical and ontological accuracy. Analytical adequacy is achieved through full specification of component behavior within a CS model and derivation from a body of theory. Ontological adequacy is achieved by not only comparing the component-level behaviors with empirical observations, but also in assessing the emergence of higher-order structures in both the modeled and target systems. Theory-driven CS models are often formalized as computational simulations called *agent-based* simulations.[9] Empirical depictions of complex systems are often represented as networks of connectivity between components of the system, and these network approaches represent one possible point of contact between computer simulations and empirical data.

Henrickson and McKelvey (2002) argue persuasively that the CS approach is isomorphic with postmodern epistemologies in social science that privilege agent autonomy and historic contingency. Their statement on the subject is worth reproducing in full:

> We do need to give relativists and postmodernists credit for reminding us that "We ARE the Brownian Motion!" Most natural scientists are separated from their "agents" by vast size or distance barriers. Social scientists are agents doing their science right at the agent level. Most sciences do not have this luxury. But it also means a fundamental difference. **We are face to face with stochastic heterogeneous agents and their interconnections. Social scientists should want a scientific modeling epistemology designed for studying bottom-up order-creation by agents.** Unfortunately, many postmodernists base their anti-science rhetoric on an abandoned epistemology and ignore a "new" normal science ontological view very much parallel to its own . . . postmodernism zeros in on the web of interconnections among agents that give rise to localized scientific textual meanings. In fact, its ontology parallels that of complexity scientists. The lesson from complexity science is that natural scientists have begun finding ways to practice normal science without assuming away the activities of heterogeneous autonomous agents. There is no reason, now, why social scientists cannot combine "new" normal science epistemology with postmodernist ontology. (Henrickson and McKelvey 2002:7295, bolded emphasis added)

[9] I distinguish between "model" and "simulation" in an agent-based system thusly: a "model" defines an information processing behavior for a given component (agent) of a system; a "simulation" is a collection of components instantiating (i.e., setting in motion) one or several models.

Agent-based simulation and other CS approaches offer social scientists a way to re-engage with the broader scientific community as a "legitimate" scientific endeavor; i.e., by employing the modern agent-based epistemology and model-based methodology of modern normal science. Indeed, these approaches (especially network approaches; c.f., Axtell et al. 2002; Brantingham 2003; Dean et al. 1999; Griffin and Stanish 2007; Hooper et al. 2010; Kohler 2012a; Kohler et al. 2012c; Kohler and Varien 2012b; Powell et al. 2009; Premo and Hublin 2009; Premo and Kuhn 2010; Schwenk and Reimer 2008) are beginning to be employed widely in anthropology and archaeology. Agent-based simulation especially allows for the creation and exploration of "distributions of histories"—what McGlade (2014) calls "narratives" and Godfrey-Smith (2009) terms "fictions." These are the surfaces of history introduced in the last section; given a set of initial parameters and a set of models describing component behavior, what does the set of possible histories look like? What is the probability distribution of those histories? And, to test ontological adequacy, What is the likelihood that a given empirical history (historical phenomenon) derived from the agent-level processes described by the model?

**Modeling [in] the future**

While remaining supportive of its epistemological foundation, McGlade (2014) has critiqued several recent applications of agent-based CS approaches to archaeology. He has two main concerns: (1) that, as with any new methodology, but especially one that requires high technical proficiency not widely shared in the discipline, privilege has been given to technological achievement and sophistication over explanatory power, and (2) modelers may have forgotten that they are constructing a set or family of possible, contingent histories, or narratives, none of which can be "fit" to our empirical picture of the past. McGlade (2014:11) suggests that our focus should more be on the experimental qualities of model building as narrative creation, as opposed to our current focus on modeling as a problem-solving exercise. One potential way of achieving this is the exploration of whether and to what extent certain environmental characteristics structure or constrain human behavior, or the potential paths of history. Although several high-profile archaeological applications of agent-based simulation have attempted this, success has been marginal.[10] McGlade (2014:11) also notes that researchers working under an agent-based framework have found it difficult to validate their models (i.e., to achieve ontological adequacy).

For several years, I have been a collaborator in a long-term research project that employs agent-based simulation as a tool for interpreting the archaeological record of southwest Colorado—the Village Ecodynamics Project (VEP). Building off my experience with the VEP, I would suggest three foci for improvement to address the problems McGlade identifies: a pivot from historical possibilism to historical probabilism; further development of multi-scale measures of ontological adequacy; and the use of "ontological triangulation" to identify most-probable history-spaces.

**Historical probabilism** Researchers in the VEP have implemented several theory-driven, individual level models—primarily derived from rational choice theory—into an ecological agent-based simulation used to explore the population dynamics and settlement distribution in the northern Ancestral Pueblo Southwest (Bocinsky 2011; Bocinsky et al. 2012; Bocinsky and Kohler 2014b; Cockburn et al. 2013; Cowan et al. 2012; Crabtree 2012; Johnson and Kohler 2012; Kobti 2012; Kohler 2012b,c; Kohler et al. 2012c; Kolm and Smith 2012). However, the bulk of VEP ontological adequacy tests (goodness-of-fit tests) thus far have relied on one-off runs of the simulation (albeit under various combinations of parameter settings) and therefore have not adequately explored the history-spaces generated by their models (e.g., Kohler et al. 2012b). In other words, we cannot situate the single-run histories we have created in reference to static or emergent structural constraints, much less the empirical record we and others have painstakingly organized. In running one-off simulations we are not realizing the full potential of the agent-based framework to explore the probability spaces of the systems we are modeling. To rectify this, agent-based simulations should be run many times to generate estimations of the probability fields for archaeologically relevant expectations. Again, using the VEP simulation as an example, we should be able

[10] I would suggest that our work is not very accessible to other archaeologists, or the broader public. This is slowly changing, but our influence has not seen the rapid adoption enjoyed by other technologies in archaeology, such as the widespread use of geographic information systems or remote sensing technologies. One barrier is that computational modeling of the type done by the VEP is still very much an academic pursuit—I am not aware of it currently being used by any professional cultural resource management projects.

to generate a historical set of probability density distributions (where the number of distributions is equal to the number of time-steps of the simulation). Instead of using two-sample statistical tests, we could then take the conceptually and statistically superior approach of using one-sample tests of fit (Kohler and Parker 1986; Kvamme 1990; Chapter 2 of this dissertation): What is the probability that the empirical (archaeological) history could have been "drawn" from the family of simulated histories?

**Multiscalar ontological adequacy** As noted above, agent-based approaches afford us the ability to test ontological adequacy using empirical patterns at multiple scales. VEP research thus far has focused on emergent patterns of settlement and demography, however, to the neglect of agent-level or intermediate (community-level?) test of adequacy. Further exploration of diversity/inequality among agents needs to be undertaken prior to attempts to emphasize or amplify those inequalities, such as by exploring the evolution of leadership (e.g., Kohler et al. 2012c). VEP researchers have begun to explore relationships at the agent-scale by analyzing simulated exchange networks (Crabtree 2012; Crabtree in press), but this work has not been well-connected to the empirical record; further work needs to be done.

**Ontological triangulation** Once one-sample tests of ontological adequacy are developed, further effort needs to be made to expand the set of comparable, multiscalar measures between simulation output and the empirical record, beyond the measures of demography and settlement distribution currently being explored. Potentially productive foci for the VEP include the spatial distribution of faunal frequencies in middens, the diversity of ceramic and lithic assemblages (proxying long-distance exchange and perhaps even GDP), and the relationship between local simulated maize yields, potential productivity, and empirically estimated population. The latter is of particular importance for trying to understand the technological innovations employed by Ancestral Pueblo people to adapt to changing environments through artificial selection of maize landraces (see Butler and Huybers 2013).

The studies presented in the rest of this dissertation provide an important foundation for future model-based research. Chapter 2 considers the possibility that people on the Northwest Coast were homogeneously concerned with defensive posturing on the landscape; I find that they obviously were not, prompting more nuanced models of warfare and defensiveness in the region that consider heterogeneous and historically contingent motivations of corporate groups. The recent theoretical focus on anarchy and heterarchical political and economic structures on the Northwest Coast is particularly conducive to agent-based approaches (e.g., Angelbeck 2007, 2009; Angelbeck and Grier 2012; Angelbeck and McLay 2011; Crumley 1995; Schaepe 2009); however, as I argue below, the empirical data in the region may not yet be up to the task. Chapters 3 and 4 use the rich environmental record in the Southwest US to create a climatological framework for understanding culture change and adaptational strategies in the region. These reconstructions can be used in agent-based simulations to more thoroughly explore the history-space of the region, and especially to deduce the success of Puebloan peoples in developing strategies to deal with climate change. These strategies might have included the creation of locally adapted maize landraces. My reconstructions can potentially also help explain pattens of warfare and conflict in the region, which I also explore later this introduction.

## History is behind us

"Why has the archaeology of the American Southwest been so prominent within the developmental history of Americanist archaeological method and theory?" This was a question posed to me by colleagues recently, and it strikes me as a good example of the type of question that might get asked not only of the history of archaeological practice, but also of the past itself. Given a pattern of history or prehistory, can we explain why that pattern exists? In what way is that pattern constrained by and in dialog with the environmental structure within which it developed? Furthermore, does that pattern provide clues about the future behavior of the system?

Here, I use the model-based approach detailed above to design a meta-analysis of the development of Southwestern archaeological thought and its prominence within Americanist archaeological method and theory. I present this here as a mental exercise demonstrating a model-based approach outside of the domain of archaeology[11]. I first consider the question, How prominent *is* Southwest archaeology though time, really? To assess this, I suggest reconstructing and analyzing the citation network for Americanist archaeology from 1900–2013. I do not only focus on the Southwestern contribution; I simultaneously consider the contributions of all major archaeological regions in Americanist archaeology, and explore publication interactions between them. Influence is not held in a vacuum; an agent can only influence another, so here I explore scales of influence throughout the citation network, from the influence of individual papers to that of whole sub-disciplines. I suggest four mechanisms that might explain patterns in the citation network, develop models to test with explicit expectations for the data; I then assess them. Finally, I make a tentative prediction as to the influence of Southwest archaeology in years to come.

### Conventional wisdom: Models for consideration

What are the processes that have led to the growth and structure of the Americanist archaeology citation network we see today? How does the network appear at different scales? Is any disproportionate influence of Southwestern archaeology due to the influence of single articles or conceptual/methodological developments, or is influence mainly internal to Southwestern archaeology and the appearance of "prominence" simply a reaction to that internal growth? Here, I present four hypothetical reasons—drawn from conventional wisdom (Ortman et al. 2012:18)—for why Southwestern archaeology has enjoyed prominence within the development of Americanist archaeological method and theory: a history of key methodological contributions, high-precision dating from tree rings, superior archaeological preservation due to an arid climate and low human population density during historic times, and a vast trove of data from large, relatively well-organized archaeological investigations.[12] In two of these, I connect the influence of Southwest archaeology to node-level measurements in the Americanist archaeology citation network: *degree* to assess preferential attachment to methodological contributions, and *betweenness centrality* to access con-

[11] Such a study would be a contribution in its own right, though outside the scope of this dissertation.

[12] I generally limit my hypotheses to the northern Southwest—the Four Corners region and the areas south of there occupied by the modern Pueblos. Although my assertions most likely apply to the Hohokam and Mogollon regions, I am admittedly less knowledgable about the history of research in those regions.

nectivity between the Southwest and other regions, and between Americanist archaeology and the broader body of scientific discourse. In the final two analyses, I postulate that data quality and quantity, as well as its organization, have played an important role in the growth and influence of Southwestern archaeology. These two forms of analysis correspond with bottom-up versus top-down influences on the success of regional research programs; or, cast in terms reviewed in above, historical versus structural influences (recognizing that structure is historical as well!).

*Methodology I: Development*

One could certainly look to the history of Southwestern archaeology, especially the early years of its development, as a summary of the development of Americanist archaeology as a whole. Lipe (1999) describes in detail the numerous methodological contributions made by Southwestern archaeologists. Here, I provide a brief overview of those contributions. Because of the high degree of preservation and historically low population densities in the region, Pueblo archaeological sites were immediately apparent to colonial and early American explorers; William H. Holmes and William H. Jackson, members of the Hayden survey of the intermountain west commissioned by the early USGS from 1867–1878, were the first to systematically document numerous Pueblo III sites in the northern San Juan basin (Lipe 1999:53). Gustaf Nordenskiöld, working with the Wetherill brothers, produced arguably the first excavation report in Southwestern archaeology resembling modern report standards (Lipe 1999:56). The period between 1912 and 1927 is considered by Lipe (1999:61) to be the "stratigraphic-chronological" revolution in Southwestern archaeology, a revolution that likely had a profound impact on americanist archaeological method. Nels Nelson pioneered the use of "metrical stratigraphy," or excavation by arbitrary levels in middens and other contexts (Nelson 1916). He, along with A.V. Kidder and Earl Halstead Morris were able to create detailed stratigraphic chronologies of pottery types found in their excavations (Kidder 1915, 1917). A.L. Kroeber's explorations recorded in *Zuñi Potsherds* (1916; see also Spier 1917) were also influential in connecting the concept of cultural evolution to the material record, though in a haphazard way conceptually different from Kidder (Lyman et al. 1998:240–241). Kidder (1924) provided the first regional synthesis in Americanist archaeology, later formalized in the Pecos classification (Lipe 1999:64–65). Gladwin and Gladwin (1934) were pioneers of the use of hierarchical taxonomic classification systems in archaeology. The rate of methodological contributions from the Southwest picked up considerably after the dawn of "new" archaeology in the 1960s. Eddy (1972) presents one of the earliest and most thorough archaeological applications of Julian Steward's cultural ecology (Steward 1937, 1955) in his reanalysis of the results of the Navajo Reservoir project. Lipe (1999:82) notes several important methodological advancements that came out of the Dolores Archaeological Project, including the use of archaeobotanical samples to document how changes in firewood and construction timber use correlate with population growth (Kohler and Matthews 1988); among the first reconstructions of potential agricultural yields (Kohler and Parker 1986; Orcutt et al. 1990); the development of statistical techniques to "unmix" multiple component artifact assemblages (Kohler and Blinman 1987); and the use of comprehensive computer databases for recording project data (Lipe 1999:83). Many of these contributions still resonate today.[13]

**Model: Preferential attachment** *Preferential attachment* is a model from complex network theory stipulating that an agent seeking connections in a social network will prefer to connect with already well-connected individuals; i.e., the "rich-get-richer" (Barabási and Albert 1999).[14] This dynamic, if realized at the dyadic level, will lead to the degree distribution of the network conforming to a power-law. In terms of a citation network, once a paper starts to become cited, it will generally start accumulating citations (influence) at a higher rate. A similar concept is employed by Arthur in his concept of "lock-in by historical events:" "Modern, complex technologies often display increasing returns to adoption in that the more they are adopted, the more experience is gained with them, and the more they are improved" (1989:116). I suggest that the same has happened for key methodological papers from Southwestern archaeology—and the methods described therein—and thus propose that if Southwest archaeology has truly had a prominent role in Americanist

[13]As evidenced by their inclusion in many undergraduate and graduate level archaeological method and theory courses. My sample size is $n = 1$ for the preceding statement.

[14]Barabási and Albert (1999) is actually a *great* example of preferential attachment in citation networks. According to Google Scholar, as of November 2, 2014 the article in *Science* has been cited over **21,000** times!

archaeology, its key papers will appear in the tail of the degree distribution of the Americanist archaeology citation network, and that those key papers will have experienced superlinear growth in their number of citations through time. The influence of Southwestern archaeology is a case of "lock-in by historical events;" key methodological contributions from the past century has ensured its preeminence and permanence.

*Methodology II: Dendrochronology*

A key contribution of Southwestern archaeology not noted above is the development of dendrochronology (Contributors of the International Tree-Ring Data Bank 2014; Dean 1988; Dean and Robinson 1978; Douglass 1929; Fritts 1976; Grissino-Mayer and Fritts 1997; Haury 1935). Dendrochronology, literally telling time from trees, allowed for unprecedented annual (or even seasonal) accuracy in dating wood samples from archaeological sites in the Southwest (or at least in the upland Southwest). This in turn allowed for synchronization of site components across the region, and the systematic development of cultural historical sequences (Lipe 1999:69). The development of dendrochronology also initiated the first reconstructions of ancient climates in the Southwest, and allowed such reconstructions in the absence of a historical record for the first time (Douglass 1929). Douglass (1929) reconstructed a prehistoric precipitation record, and argued that the abandonment of the Four Corners region of the northern Southwest correlated with a "Great Drought" from AD 1276–1299. Douglass' work initiated the development of modern dendroclimatology, and is considered a foundational document of that field.

**Model: Betweenness centrality** There are likely two ways in which the development of dendrochronological methods improved the influence of Southwestern archaeology. First, dendrochronology is not possible everywhere, and only recently has it been applied to species of trees beyond conifers. Its development would have given Southwest archaeology an appreciable "leg-up" over other regions, especially during the first half of the 20th century when archaeological effort was primarily devoted to chronology-making. It is difficult to assess from the citation network data whether this had an appreciable impact, however. On the other hand, the dawn of New Archaeology and its early acceptance and application in the Southwest would almost certainly have had a disproportionate impact on the pace and impact of research in the Southwest.

The second impact of the development of dendrochronology relates to the broader influence of Southwestern archaeology on other scientific fields, including (but not limited to) climate science and cultural geography; indeed, I expect it to be among the only methodological exports from archaeology to the broader scientific community. Douglass (1929) and related papers on dendrochronology should therefore demonstrate high *betweenness centrality* (Freeman 1977) on the larger scientific citation network; they should disproportionately connect archaeology to the broader body of scientific knowledge. I predict that the betweenness centrality scores for Southwestern papers will be higher than other Americanist archaeological regions; Southwestern archaeology will be more central to Americanist archaeology than other regions, and will provide a disproportionate number of links to other fields.

*Data I: Climate and demography*

Much ado has been made over the "superior" archaeological preservation in the Southwest due to an arid climate and low modern population density (Bocinsky and Kohler 2014b; Ortman et al. 2012). Speaking of the Northern San Juan region in particular, Ortman et al. (2012) noted, "the relatively arid climate, alkaline soils, dry alcoves, and relatively shallow time depth of ancestral Pueblo sites all encourage preservation of bone, plant remains, fiber artifacts, and other organic materials, especially in the famous cliff dwellings ... relatively few sites have been destroyed because this landscape has witnessed limited use since the Pueblo exodus" (2012:19). Lipe et al. (1999) temper this notion slightly by noting that "[t]he archaeological record is a rather peculiar record of past activities, and cannot be assumed to represent these activities in a direct or self-evident way" (1999:10); thus, both taphonomy and cultural deposition will impact archaeological visibility and representation. Still, it is reasonable to suggest that the post-depositional physical and demographic environment of an archaeological site likely relates to its preservation, and, by extension, that the degree of archaeological preservation in a region might relate to the research productivity and methodological influence of that region.[15] To my knowledge, there has been no systematic effort to relate large-scale structural influences on archaeological preservation to regional research productivity or growth-rates.

**Model: Growth $\propto$ aridity; growth $\propto$ demography$^{-1}$** There are two expectations that derive from the statements above; each relate the growth of a regional body of archaeological knowledge with archaeological preservation in that region. The (logged) growth rate of each regional citation network should be proportional to the mean aridity of the region; and it should be inversely proportional to the logged growth rate of population. These two factors alone might not be enough to capture the degree of preservation in each region—the character of the archaeological record and of past human lifeways in each region will have a large impact on preservation. For instance, the masonry architecture of the Pueblo periods in the Southwest would likely preserve well independent of what region it appeared in, while the archaeological signature of mobile hunter-gatherers will almost always be cryptic.

*Data II: Big Archaeology*

A final potential benefit to Southwestern archaeology is the vast amount of archaeological data that has been systematically collected in the Southwest. This stems from two historical developments: a "preservation ethic" extant in the region since the early 1900s, and the development and implementation of modern Cultural Resource Management over the course of several large archaeological projects in the region. It was recognized from the late nineteenth century that the Pueblo remains of the northern Southwest were important to the cultural history of the region, and were in danger of being destroyed for commercial purposes. The Colorado Federation of Women's Clubs lobbied for governmental protection of the ruins at Mesa Verde, and in 1906 President Theodore Roosevelt signed the Antiquities Act, allowing the president to declare federally protected National

[15] Though as I argue in the next section, lack of archaeological data has not seemed to prevent useful contributions to archaeological theory in other regions, particularly the Northwest Coast.

Monuments. That same year, the US Congress established Mesa Verde National Park, and in 1923 Hovenweep National Monument was established (Lipe 1999:57,64). In 2000, Canyons of the Ancients National Monument was created by President George W. Bush. Further south, Aztec Ruins National Monument (1923, President Warren Harding; Lister and Lister 1990) and Chaco Culture National Historical Park (established at Chaco Canyon National Monument in 1907 by President Theodore Roosevelt; renamed 1980) were established; and Bandelier National Monument (1916, President Woodrow Wilson) was created on the Pajarito plateau in north-central New Mexico. Each of these areas has received extensive archaeological attention before and after their formal establishment (Hayes 1976; Hayes et al. 1981; Kohler 2004). Other federal land holdings, including millions of acres of National Forest and Bureau of Land Management land, the Valles Caldera National Preserve, and Los Alamos National Laboratories have also received extensive archaeological attention. Each of these federal entities maintains proprietary archaeological databases, and site-level data are aggregated in state databases.

In addition to Federal land holdings, the Southwest has an extensive history of legally-mandated excavation and documentation of archaeological sites that would be damaged or destroyed by the construction of reservoirs or other infrastructure projects. These projects often included full-coverage survey of the impacted areas, extensive excavation, and often major contributions to the knowledge of Southwestern prehistory and to archaeological method more generally. Substantial projects include the Glen Canyon Project (Jennings 1966), the Navajo Reservoir Archaeological Salvage project (Eddy 1966), the Dolores Archaeological Program (Breternitz et al. 1986), the Animas-La Plata Project (Potter 2010), and the Navajo-Gallup Water Supply Project (PaleoWest Archaeology, ongoing). Each of these projects amassed huge amounts of data, and most of it has been fully digitized and curated in state or Federal facilities.

**Model: Growth $\propto$ data** It is possible that the huge amount of data has both helped and hindered archaeological research in the Southwest. On the one hand, it has enabled several regional syntheses and allowed for countless research programs, large and small. We have enough data to satisfy budding MAs and PhDs for years to come. But perhaps this data glut has also stunted our growth, particularly our theoretical development. Fowles puts it this way:

> Whereas a former generation of Southwesternists may have authored and promoted a "behavioral archaeology" or been devotees of an explicitly "processual archaeology," those of the contemporary scene are typically happy to let Europeans keep their post-processual, interpretive, symbolic, symmetrical, etc., archaeologies and the inevitable polemics that accompany them. In the Southwest, the bulk of archaeologists tend to regard themselves as salt-of-the-earth empiricists and stubborn realists who remain hard at work within what Kuhn would describe as a period of normal science: New data are amassed and new methods developed to address core intellectual questions of longstanding concern (see Hegmon 2003). Which is to say that Southwestern archaeologists, unlike their colleagues overseas, still read and cite texts from the 1970s with impunity.[16] (2010:454)

Still, it is reasonable to suggest that Southwestern fortune is somewhat related to the amount of raw material we have to deal with. Estimating the "amount" of archaeological data for a region is difficult, but here I develop an approximate measure by using the amount of data (in megabytes) in the Digital Archaeological Record for each region, recognizing that this is an imperfect measure, and almost certainly subject to bias.[17] An alternative measure might simply be the relationship between the cumulative number of papers published and the growth of citations of those papers.

### The fortunes of Southwestern archaeology

What does the future hold for Southwestern archaeology? Southwestern archaeological influence has been increasing since its earliest days, and the trend looks to continue into the future. There is no reason to believe that the trends demonstrated here will change in the foreseeable future. "New data [will be] amassed and new methods developed to address core intellectual questions of longstanding concern" (Fowles 2010:454). These new methods will include innovations in remote sensing and digital recording of archaeological sites, computational modeling of socionatural com-

[16] Fowles (2010) is not actually criticizing Southwestern archaeological thought, nor does he believe that Southwestern archaeology has not "evolved" theoretically. Indeed, he is promoting a "Southwestern School" of landscape archaeology that explicitly invokes Pueblo cosmologies and phenomenologies in its interpretations while maintaining ecologic and systemic perspectives.

[17] tDAR was developed by a team at Arizona State University, and adoption has seemed to be heavily weighted towards Southwest projects.

plex systems, increasing collaboration with native groups, and the marriage of phenomenological perspectives with empirical methodologies.

That being said, the fortunes of Southwestern archaeology are not only tied to internal dynamics of the region or even of Americanist archaeology as a whole. Allow me to speculate for a moment. I forecast that Southwestern archaeology is on the brink of becoming intimately engaged with the broader scientific community in studying the human impacts of global climate change and how archaeological and anthropological insight might guide human adaptation going forward. The Southwest is a global canary of climate change;[18] already, forest ecologists are noting extreme changes occurring in forest structure and drought stress, and resulting wildfire frequency and insect infestation (Williams et al. 2013). Future climate has been predicted to be far more arid than today, a trend that is forecast to be amplified during La Niña climate cycles (Dominguez et al. 2010). Climate over the last two millennia was marginal at best for Pueblo maize agriculturalists, changed through time, and at times stimulated profound societal friction, reorganization, and even collapse (Bellorado and Anderson 2013; Benson and Berry 2009; Cordell et al. 2007; Dean 1988; Kohler et al. 2014; LeBlanc 1999; Lekson 2002; Wright 2010). Pueblo prehistory is therefore a telling narrative when trying to understand adaptive and non-adaptive strategies to changing environments among small-scale agricultural societies. Ancestral Pueblo agricultural strategies deserve continued intensive study, and efforts to understand and manipulate the functional genomics of ancestral maize landraces might prove fruitful for developing new drought resistant strains (Butler and Huybers 2013).[19] Further investment in discussions on global climate change has already been identified as among the future "challenges" for archaeology at a global scale (Kintigh et al. 2014a); Southwestern archaeology stands ready to meet them.

[18]There are a lot of "canaries;" see Berkes and Jolly 2002; Bicknell and McManus 2006; Diaz et al. 2003; Higham and Cohen 2011.

[19]Imagine Hopi corn being the savior of subsistence farmers in Africa. The Pueblo have been developing these hybrids for much longer than Monsanto!

## Models of sociocomplexity and conflict

Studies of prehistoric conflict have enjoyed a renaissance over the last two decades around the world, but especially in North American archaeology. Major treatises on warfare, including Keeley's *War Before Civilization* (1996) and LeBlanc's *Prehistoric Warfare in the American Southwest* (1999), shifted focus from the idea that warfare—"violent and coercive practices conducted in organized means against other autonomous groups" (Angelbeck 2009:43)—was only present in chiefdom and state-level societies. Keeley demonstrated that, quite to the contrary, violence at the group level was widespread among small-scale societies in the past, and persists at high rates among ethnographic non-state societies. His review highlighted the diversity of forms of violence in the past and stimulated several regional treatments. Lambert (2002) performed a more systematic review of the nature of warfare in prehistoric North America that built on a larger body of mortuary data. She found the evidence for prehistoric warfare abundant across North America and through time (2002:228–229).

However, Lambert (2002) noted the diversity in the theoretical frameworks in which warfare has been approached by archaeologists across North America, and in the intensity and duration of those research efforts. She identifies three primary causes for these differences. First, Lambert notes that the initial impressions of colonial ethnohistorians have cast a long shadow over regional perspectives on prehistoric conflict. Early French and English accounts of endemic raiding and warfare on the Northwest Coast of North America (NWC) rendered explorations of violence subject to less scrutiny (Lambert 2002:213), while in regions like the Ancestral Pueblo southwestern United States (SWUS) early portrayals of widespread peace among Pueblo peoples and later ethnographic evidence of the same has long presented barriers to studies of violence (Kohler et al. 2014; Lambert 2002:219; LeBlanc 1999:22). Second, Lambert argues the character of the archaeological record in each region has also shaded archaeological interpretation. For instance, researchers on the NWC and the north Pacific Rim have primarily relied on studies of architecture and defensive posturing on the landscape as indirect evidence of warfare and widespread concerns for defensiveness

(Lambert 2002:211–216; see also Angelbeck 2007, 2009; Angelbeck and McLay 2011; Martindale and Supernant 2009; Maschner and Reedy-Maschner 1998; Maschner and Stein 1995; Moss and Erlandson 1992; Sakaguchi et al. 2010; Schaepe 2006, 2009; Supernant 2011). Although several studies of human remains have been completed (e.g., Cybulski 1992, 1994, 1999), preservation and focus have thus far prevented the accumulation of sizable sample sizes of human remains across the region. In contrast, the relatively good preservation of human remains in the SWUS has led archaeologists to focus on these lines of evidence in recent years, often to the neglect of several of the architectural or landscape based inferences about concerns with defense. Finally, perspectives on the environment, resource abundance, and resource competition have had a major influence on recent explanations of warfare in the SWUS (Kohler 2010; Kohler et al. 2014; Kohler and Varien 2012b; LeBlanc 1999:32–41, and throughout; Lekson 2002). With the exception of Suttles' (1968; 1990) description of the distribution and variability of NWC ecological zones (which, though spatial, is atemporal), little has been done to connect resource abundance with patterns of warfare on the NWC. Notable attempts at ecological reconstruction (though not usually connected to studies of conflict) are Fladmark's (1975) model connecting sea-level stabilization with salmon populations, Croes and Hackenberger's (1992; 1988) models of subsistence changes along the Hoko River, and the recent efforts by Fedje and Christensen (1999) to reconstruct paleo-shorelines in the northern NWC (see discussions in Ames 1994; Campbell and Butler 2010).

### Conflict on the Northwest Coast and Pacific Rim

Maschner and Reedy-Maschner (1998), in their review of evidence for warfare in the north Pacific Rim, highlight the theoretical conflict between "materialist" and "Darwinian" interpretations of conflict. Materialist perspectives, championed by Ferguson (1984), focus on the conflict over material resources such as food, agricultural or hunting/foraging land, water, and access to trade goods. Materialist research has accordingly focused on environmental and demographic reconstructions, and on models for warfare that focus on these elements (e.g., Ember and Ember 1992; Turchin and Korotayev 2006). Darwinian or evolutionary approaches, championed by Chagnon (1988;

1990), have focused on reproductive fitness, prestige, and kin selection. "People participate in conflict because it is in their kin group's self-interest to participate" (Maschner and Reedy-Maschner 1998). Although resources are an obvious component to fitness, evolutionary theorists have tended to downplay environmental or demographic explanations for explanations that focus on political economy, retaliation, mate procurement and the like. An example of the merging of these two approaches is proposed by Coupland (1985; 1989; see also Swadesh 1948). He uses Marxist theory to suggest that the process of claiming and gaining control over important salmon fishing places was both important to the establishment of inequality on the NWC and inevitably led to violent conflict (i.e., conflict over resources). Conflict was then perpetuated by economic and reproductive inequality and retaliation after the entrenchment of elite power and hegemony (Angelbeck 2009).

Angelbeck (2009; see also Angelbeck and Grier 2012) provides the most recent and thorough theoretical perspective on warfare in the Coast Salish region of the southern NWC. He blends materialist and Darwinian perspectives on warfare by shifting focus from *causes of* warfare to multifaceted and multiscalar individual and group *motivations for* conflict. In his review of the archaeological record of warfare on the NWC, Angelbeck (2009:141–167) describes warfare potentially emerging as motivated by resource and territorial competition among kin groups, as in Coupland's model, but concludes that by the Late Pacific period (~AD 500 to contact) and post contact periods warfare was primarily motivated by elite acquisition of capital surpluses, either through direct raiding for goods, or through raiding for slaves to produce such surpluses. Angelbeck emphasizes that the likely shortage was not in the raw materials of surplus (i.e., salmon), but in the labor necessary to harvest it (Angelbeck 2009:166).

One aspect of warfare and conflict that Angelbeck (2009; 2011) focuses on is the development (and dissolution) of alliances for warfare and defense (Angelbeck 2009:59), even in a culture that seems to privilege autonomy. Angelbeck and McLay (2011) use a thorough analysis of ethnohistoric documentation and oral history of the Battle of Maple Bay to highlight the maintenance of autonomy among corporate groups even when cooperating to combat a common foe. Their analysis invokes the multivocality of oral histories to both paint a striking picture of the events of the battle, but also to highlight the inconsistencies of both fact and focus among the histories. They describe leaders from autonomous groups coming together to decide whether or not to ally in battle, and then uniting as one force to defeat the Kwakwaka'wakw Lekwiltok: "The oral histories about this battle illustrate a core principle of Coast Salish political organization, which is that Coast Salish households and local groups to a great extent act autonomously, but they organize together through regional kinship networks to meet mutual goals" (Angelbeck and McLay 2011:381). What they do not highlight, however, is the functional role of leadership in battle that may (and I would argue, must) have existed in its planning and execution. Angelbeck and McLay (2011) emphasize the maintenance of autonomy, but it would be interesting to explore processes by which autonomy may be temporarily (or permanently in certain domains) set aside for cooperative effectiveness (Hooper et al. 2010; Kohler et al. 2012c).

Apart from reviewing data on settlement distribution and defensive structures on the NWC, Angelbeck does not strive to connect alliance formation directly with the archaeological record.[20] Other recent research on the NWC has more directly highlighted the possible material correlates of alliance formation. Schaepe (2006, 2009) uses a GIS analysis of lookout sites and rock fortifications along the Salishan lower Fraser river to support the presence of visual communication networks between villages to facilitate early warning in case of an attack. Maschner and Stein (1995), Sakaguchi et al. (2010), and Martindale and Supernant (2009) present similar arguments, which I detail in Chapter 2.

### Conflict in the prehistoric Southwest United States

Whether we are interested in uncovering structural causes or individual motivations for conflict, a crucial goal should be to connect our models to archaeological and historic structural data. The focus on political explanations of warfare among NWC archaeologists—and their strong commitment to the direct historic approach—may be partially understood as a response to the relative lack of information about prehistoric demography or resource availability/stability on the NWC

[20]Though he does suggest that shared defensive technologies such as underground rooms, trench embankments, or rock-wall fortifications might signal alliances (Angelbeck 2009:219–221).

in general (though see Croes 1992; Croes and Hackenberger 1988; Fedje and Christensen 1999; Fladmark 1975). In contrast, explorations of warfare in the SWUS have focused almost entirely on materialist explanations. As reviewed above, this is most likely due to an abundance of data on prehistoric climate and resource availability as proxied by tree rings, and the long history of research on agricultural productivity, demography, and resource depletion in the region. Lekson (2002) used a model by Ember and Ember (1992) relating population, resource instability, and "socialization for fear" to argue that the two major periods of conflict identified by LeBlanc (1999) in the northern SWUS (the AD 700s–900s, and 1250–1600s) may best be explained by resource unpredictability (as proxied tree rings analyzed by Dean 1988, 1996), while the intervening period (the "Chaco fluorescence", but especially the 1100s during the decline of the centers in Chaco canyon and the rise of the Chacoan center of Aztec) was likely a period when social control was exercised through isolated through extreme acts of violence.[21] He finds that the middle period corresponds with a period of resource predictability (Lekson 2002:616).

Kohler et al. (2014) have recently challenged both the characterization of the middle period as either an "an era of unprecedented peace," (LeBlanc 1999:196) or as a period of resource stability. Building on Cole (2012), they gathered data on human remains from across two large areas of the SWUS (the Central Mesa Verde [CMV] and Northern Rio Grande [NRG] regions; see Chapter 3) and demonstrate that the period of "*Pax with a twist*," and especially the mid-1100s, is a period of the most extreme violence in the SWUS, with nearly 90 percent of human remains showing some evidence of interpersonal violence. Kohler and colleagues do not associate this heightened violence with resource unpredictability per se, but instead suggest that during other periods of heightened resource variability and lower levels of conflict (namely 800–880 and 1180–1260), "polities—communities—were able to override structural tendencies for violence to co-occur with low per-capita resource availability" (Kohler et al. 2014). In the NRG, violence is most prevalent during what would have been a good period for maize productivity (as proxied by precipitation records from tree rings) relative to population (which was low but rapidly growing, presumably

[21] These are the "extreme processing events" including evidence of cannibalism described in great detail by LeBlanc (1999:162-186), Turner and Turner (1999), and Kuckelman et al. (2000).

due to immigration). After the early 1300s however, they find violence decreases dramatically. This pattern may be attributed to two possibilities. First, their sample includes sites from the Gallina region where large amounts of violence occurred in the late 1200s through early 1300s (Chase 1976; Seaman 1976), likely inflating the record of violence during that period. Second, they argue that agricultural, economic, and social innovations likely changed the field for violence; intensification of water management opened new niches for maize and cotton agriculture in the Chama and Rio Grande valleys and likely reduced agricultural uncertainty; larger communal organization culminating in the very large (> 500 people) historic Pueblos likely increased within-group solidarity; and a shift to a market based economic system and shared religious ideology between Pueblos created economic and ritual connections that overcame causes for conflict, and brought the communities together regionally. Their analyses demonstrate that both structural and historical explanation—or materialist and Darwinian explanations, following Ferguson (1984) and Chagnon (1988, 1990)—are necessary to understand the history of warfare in the SWUS and likely elsewhere.

### The environmental context of conflict

In many ways, but primarily to its expansive dataset, the SWUS and particularly Kohler's analysis present a framework for understanding warfare that may lead to a better understanding for the motivations for conflict than the descriptive and ethnohistoric methods being pursued on the NWC. Research in the SWUS has focused on determining the environmental and political *contexts* for conflict—where context and motivation are causally linked—whereas in the NWC contextualization has been limited to unsubstantiated claims of labor shortfalls and tit-for-tat sentiments. This does not reflect a lack of theoretical sophistication among researchers on the NWC (as demonstrated above), but I would argue certainly reflects a lack of solid material evidence for prehistoric violence or for the contexts in which it took place. It is necessary to both provide context for violence in the form of reconstructions of the social and physical environment, as well as middle-range models linking proposed motivations (e.g., labor shortages) to these contexts.

Contextualizing violence is indeed a unifying theme in this dissertation. In Chapter 2, I build on pioneering work by Martindale and Supernant (2009) to challenge the notion of an overwhelming tendency towards defensive posturing on the NWC, especially in the Marpole and Late Pacific periods. I argue that defensive behavior must be inferred in relation to the physical landscape in which those behaviors took place. Although I do not engage in demographic reconstructions around the Salish Sea, I argue that there is little evidence that people were selecting more defensible habitation sites through time, undermining the notion that such considerations were widespread by the late period. In chapters 3 and 4, I further contextualize the physical environment of violence in the SWUS, first by generating high resolution reconstructions of the maize growing niche in the CMV and NRG regions, and then by exploring the impact climate change might have had on actual maize yields. Results presented in chapter 4 demonstrate, with striking effect, that the period of highest amounts of violence in the CMV—the mid 1100s, which LeBlanc (1999), Lekson (2002), and Kohler et al. (2014) attribute to the collapse of Chacoan influence and its repercussions—corresponds with a sudden, dramatic, and long lived constriction of the maize growing niche to its smallest size during the period of Pueblo occupation. While historical and political motivations may indeed have played a role, climate change and its influence on maize production likely had a larger impact on violence during the period than previously thought. I suggest in Chapter 4 that agricultural innovations in the NRG would likely have helped agricultural production outpace population growth, and removed a major impetus for violence in the region. As such a demonstration has barely been attempted on the NWC, this would likely prove a fruitful avenue of research in the future.

## Reconstructing past climates, understanding lived environments

Humans experience, adapt to, and influence climate change at local scales. A drought in California, flooding on the Gulf Coast, a "polar vortex" rendering the American heartland an icebox—these local and regional events are the shared experience through which social understandings of adaptive response and environmental stewardship are negotiated and agreed upon. McIntosh et al. (2000)

suggest shared social memory—the curation of events and experiences across generations—would have been among the primary adaptive strategies at the disposal of past societies. "We are collectively all paleoclimatologists" (McIntosh et al. 2000:24), because it pays to know how people experienced climate in the past when confronting the future.

In the culture of modern Western science, we have tended to externalize and naturalize social memory in an attempt to render experience objective. Accordingly, Western scientists who seek to reconstruct past climates often do so via climate *proxies*, physical archives of local environmental conditions (*paleoenvironment*) that are thought to reflect local to global scale climate patterns (*paleoclimate*).[22] Proxy selection in paleoclimate reconstruction can be no less a subjective social negotiation than the construction of social memory, however; which proxies are "appropriate" for reconstructing a given climate signal is subject to individual and disciplinary biases, and whether or how those proxies ought to be combined is all the more contentious.[23] Anthropologists and archaeologists have a vested interest in paleoclimate research not only because humans adapt to and interact with their local environments, but also because human manipulation of environments undoubtedly changes the nature and availability of the proxy records themselves (McIntosh et al. 2000:8).

Archaeologists have played an integral role in the development of proxy-based paleoclimate research, though that role has diminished with the shift in focus to global climate processes over the past two decades. Tree-ring based reconstruction methods were developed in the Southwestern United States (SWUS) first as a means of relative dating and subsequently as a paleoclimate reconstruction method. Timbers from archaeological sites served as essential to establishing long chronologies, and local and regional reconstructions have been used to "solve" longstanding archaeological problems from their beginning (see Douglass 1929). Sediment cores (including pa-

[22]The spatiotemporal linking processes between local environment and global climate are considered *mesoscale* processes.

[23]As a personal example, I recently had a dendrochronologist express his deep concern about the technique of modulating a high-frequency tree-ring-based temperature reconstruction with a low-frequency pollen-based reconstruction (as Tim Kohler and I suggest in chapter 3). His objection wasn't specific to the method, but that as a member of the tree-ring culture he was highly skeptical about the validity of pollen-based reconstructions. Tellingly, an eminent palynologist seemed to embrace the method.

lynological analyses and fire reconstructions) have also proven essential in linking past climate to the lived environments of past peoples. But while most work undertaken by archaeologists has focused on developing a highly local understanding of paleoenvironment, a vast majority of the recent effort by paleoclimatologists has been directed at establishing global climate signals, especially since the recognition of the human impact on global climate change. As Tingley and Huybers (2010:2766) recently put it, "there seems little point [. . . ] in making estimates at a scale finer than that of the original [i.e., modern climate] data," a sentiment expressed implicitly in the regional or larger-scale focus of most modern paleoclimate work.[24] But anthropologists and especially archaeologists understand that humans fundamentally experience and influence their environments at a local level—through resource procurement and agriculture—and thus that local reconstructions are critical in understanding human behavior. However, because archaeologists generally have very little training in modern paleoclimate reconstruction methods, our recent methodological contributions have been limited.

The extent to which any particular climate proxy is useful for reconstructing local to global paleoclimate remains an open question, and the development of single- and multi-proxy reconstruction methods is an active area of research. In parallel to empirical research on the paleoclimate proxies discussed below, researchers have developed general circulation models (GCMs) that seek to model global-scale external and internal climate forcing including estimates of solar variation, carbon cycles, atmospheric and oceanic circulations, and long-distance climate teleconnections. GCMs may be used as test-beds for exploring the potential global and regional impacts of variation in forcing intensity, such as increased atmospheric $CO_2$ on global temperature. Although the development and calibration of GCMs have been fundamentally informed by paleoclimate proxy research, the models themselves function independent of proxy data and can be used to explore "what if" global climate scenarios. Ensemble runs of GCMs under a range of parameters serve as the principal method of climate forecasting used by scientists on the International Panel on Cli-

[24]Tingley and Huybers (2010:2766) were using the 5°x 5° CRU gridded time series as their training data, a scale far larger than can be considered relevant to human experience. The recent availability of high-resolution gridded products such as PRISM renders my critique somewhat moot, although Tingley and Huybers failed to acknowledge why such high-resolution reconstructions might be of interest.

mate Change (IPCC; see Dominguez et al. 2010). Over the past decade, GCMs have also been used to test the effectiveness of various proxy-based paleoclimate reconstruction techniques. The output of a GCM can be used to create "pseudo-proxies" such as fake tree-ring records or ice-cores with varying amounts of signal noise, and empirical researchers have been challenged to test their reconstruction methods against these fake datasets.

Chapters 3 and 4 of this dissertation deal directly with reconstructing past climates and environments, specifically the climates and environments of the SWUS over the past two millennia. In chapter three, *A 2000-year reconstruction of the rain-fed maize agricultural niche in the US Southwest*, I use networks of tree rings and pollen analysis from sediment cores to create high resolution climate field reconstructions of precipitation and temperature across the two VEP study areas. This allows me to generate baseline estimates of the extent and variability of the maize growing niche in the SWUS through time, and to begin to interpret the Puebloan archaeological record though that lens. Chapter four, *Poshumi and paleoproductivity: Toward biocultural models of ancestral maize diversity*, combines the paleoclimate reconstruction presented in chapter three with regional soils data and a cropping systems model to generate spatial estimates of actual maize yield across each landscape through time.

# CHAPTER TWO
# STATIC LANDSCAPES

**People make decisions in the context of—and in dialogue with—their physical and social environments.** Choices, such as where to build a habitation site, a ritual village, or what to hunt, are necessarily and logically constrained by environments. You choose where to build *on a landscape*; you choose what to hunt *based on the prey available to you*. The constraint of the choice-set can actually help archaeologists make well-reasoned assessments of intentionality and behavior that led to archaeological patterns. We can assess how special or unusual a decision is. In fact, we already do this intuitively: we notice patterns ("people build great houses on prominent places"), but sometimes the patterns we notice can be misleading. Patterns mean very little if counterfactual realities are equally as probable ("that great house would have been equally visible practically anywhere on the mesa"). Decisions are not independent, however; the significance of a choice can also change over time, with replication or environmental constriction. Available space can change. Social structures (such as *social norms*; Bicchieri 2006) can eclipse physical ones.

Cultural ecologists—those who seek to connect environmental structure with culture in a causal fashion—tend to focus on whether and how human behavior is adaptive to environmental conditions at a given place and time. The environment is defined liberally; it includes all relevant aspects of the physical world around an individual, and also the complex network of social relationships, cultural structures, and personal preferences within which decisions are made. Often, researchers will attempt to isolate the influence of one or more of these ecological components when inferring behavioral causality. The research program of *historical ecology* (Balée 2006; Crumley 1993) focuses on how long-term environments—and in particular environmental change—have shaped human cultures, often along divergent historical trajectories (Balée 2006:76). Archaeologists, given their focus on the material record tend to more readily explore environmental explanations for behavior and are well-situated to assess historical trajectories in human/environment interactions (Bocinsky and Kohler 2014b; Varien et al. 2007).

The three papers in this dissertation are each examples of how we might take a cultural/historical ecological approach to archaeology. They build in complexity of human-environment interactions, from humans responding directly to static physical characteristics of their environments to dynamic feedbacks between agriculturalists, cultivars, and physical environments. The paper presented in this chapter—*Extrinsic site defensibility and landscape-based archaeological inference: An example from the Northwest Coast* (Bocinsky 2014b)—is an example of how we may generate inferences from static landscapes. I present a relatively simple index of defensibility constructed entirely from local topographic information, and calculate the index over a very large area of the Gulf of Georgia and lower Fraser River valley of British Columbia. I then use this defensibility landscape to infer the extent to which humans living in the region might have been behaving defensively when choosing where to position their habitations on the landscape.

In order to understand how peoples' physical environments structure their behavior, we must have a way of describing and quantifying those environments. A Geographic Information System (GIS) is a computational tool for describing, quantifying, and visualizing raster and vector landscapes. Modern GISs, such as ESRI ArcGIS, GRASS (GRASS Development Team 2012), and geostatistical packages for *R* (R Core Team 2014), are powerful tools that are capable of complex spatial statistics, network analysis, raster algebra, and many other analyses. Analyses are also able to be scripted—written in computer code—so that they may be performed on many different datasets or iterated on a single dataset. This analysis (along with those presented in Chapters 3 and 4) uses the R statistical framework for quantifying and analyzing landscapes, and all analyses are fully scripted so that they may be scrutinized and reproduced by others (Barnes 2010; Ducke 2012; Mesirov 2010; Peng 2011; Stodden 2010). I describe a novel algorithm—based on matrix algebra—to rapidly calculate a defensibility index across very large landscapes.

The analysis of static landscapes need not be as simple as I present here. In fact, I make no effort to control for other predictors of site location that likely covary with high defensibility, such as access to water, food, and other important resources (Maschner and Stein 1995); nor do I consider the dynamic social landscape (including proximity to others living on the landscape). These are fruitful areas for future research.

# Extrinsic site defensibility and landscape-based archaeological inference: An example from the Northwest Coast

R. Kyle Bocinsky

**Abstract**

People make decisions in the context of their physical and social environments. Therefore, when inferring the choices that people may have made in the past, archaeologists should consider—to the extent possible—the environmental context(s) of decision making. In this paper, I attempt to build stronger inferences about the nature of defensive decision-making by characterizing the defensibility of a given landscape and treating it as a population from which a sample of archaeological sites may be considered. I develop a spatial defensibility index that may be calculated for any and all points on a raster landscape (a digital elevation model). I then calculate the defensibility of a large region in Gulf of Georgia and lower Fraser River valley of British Columbia, and assess the defensibility of a large sample of recorded pre- and post-contact archaeological sites in light of the baseline defensibility of the landscape. I find that while residential sites are generally built in more defensible places on the landscape, previously identified "defensive" sites (trench embankment sites) are not necessarily in *unusually* defensible places. These and similar methods ought to be employed whenever archaeologists attempt to infer defensive decision-making, and are essential for cross-cultural study of warfare and conflict.

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> "I shall not today attempt further to define the kinds of material I understand to be embraced within that shorthand description; and perhaps I could never succeed in intelligibly doing so. But I know it when I see it, and the motion picture involved in this case is not that."
>
> Justice Potter Stewart, concurring opinion in Jacobellis v. Ohio 378 U.S. 184 (1964), regarding whether the film *The Lovers* constituted "hard-core pornography"

The standard by which we as archaeologists have often judged defensiveness is similar to the way in which US Supreme Court Justice Potter Stewart judged hard-core pornography: we know it when we see it. And to a certain extent, we do. Inaccessible places with imposing or enclosing architecture are immediately recognizable as "unusual" to even the most amateur archaeologist; and, based on prior experience and our innate capacity for pattern recognition, we characterize those places as "defensive." What is more, our descriptions and justifications of defensiveness in the literature are not lacking in detail (cf. Maschner and Reedy-Maschner 1998:32–37). We amply describe what we see. But, just as Justice Stewart's phrase is infamous in the context of a Supreme Court opinion (maybe unfairly so; Gewirtz 1996), perhaps intuition should not qualify as the standard by which we make archaeological inference.[1]

Recently, several archaeologists have attempted to better define defensiveness (several in the context of Northwest Coast archaeology; Jones 2010; Lambert 2002; LeBlanc 1999; Martindale and Supernant 2009; Sakaguchi et al. 2010; Schaepe 2006). LeBlanc (1999:55–74), in his volume on warfare in the US Southwest, outlined settlement pattern evidence for warfare[2] (LeBlanc 1999:55–56; see also Lambert 2002:209–210):

[1]A glossarial note: humans may act *defensively* (an adverb), while a place or building is *defensible* (an adjective). An archaeologist sometimes infers *defensiveness*—the degree to which an action is defensive—by discussing the *defensibility* of a place. Places or structures themselves are not defensive, though the act of constructing them may be. This distinction has not been universally recognized, but I will adhere to it here.

[2]LeBlanc (1999:7), following Meggitt (1977), defined warfare as "a state or period of armed hostility existing between politically autonomous communities, which at such times regard the actions (violent or otherwise) of their members against the opponents as legitimate expressions of the sovereign policy of the community." Thus, some of the archaeological indicators of between-group hostility might not apply to smaller-scale feuding.

1. Site configurations

    Evidence for sites being planned and laid out for defense

    Evidence for sites increasing in size over time

    Evidence for smaller sites being abandoned before larger sites

    Evidence for rapid construction of sites

2. Site on defensible landforms

    Evidence that smaller sites are on more defensible landforms than larger sites

    Evidence for sites located to provide secure domestic water supplies

3. Site distributions

    Evidence for clustering with empty zones between clusters

    The sequence of site abandonment within clusters

    The sequence of cluster abandonment among clusters in a region

4. Sites located for line-of-sight communication

    Evidence that line-of-sight links were bounded and so define site alliances

LeBlanc focused on aspects of defensive behavior as among the most archaeologically visible evidence for warfare. Settlements are designed to be defensible spaces and are located in defensible places; both are defensive responses to expected aggression. Furthermore, LeBlanc emphasized temporal trends in defensive behavior over time: sites become larger, settlement clusters become more separated, and sites and clusters are abandoned from least-defensible to most-defensible. Violence and defensiveness of the type that leaves an archaeological signal is not usually a local one-off event but a process of mutually reinforcing actions at a regional level.

Jones (2010) presented a GIS analysis of Iroquois settlement locations in which he operationalized several of the ideas outlined above. Jones (2010:Table 2) quantified the influence of defensibility as a function of site viewshed size, accessibility, and the presence of a palisade. Site viewshed, or the portion of the surrounding landscape visible from within or immediately adjacent to a settlement, is commonly considered an important aspect of landscape defensibility. People inhabiting settlements with large viewsheds are more likely to see an enemy approaching, and may be able to communicate visually with nearby allies to coordinate a defensive response. Viewshed size can be enhanced by constructing tall towers or large buildings. However, Kantner and Hobgood (2003) found that tower kivas at several sites in the US Southwest did not increase long-distance visibility, perhaps limiting peoples' ability to enhance visual communication networks for defense. Jones (2010:7) also defined a binary measure of accessibility: settlement accessibility is "restricted" if over 50 percent of the settlement boundary is at a greater than 45 degree slope. Jones (2010:10) used discriminant function analysis to weigh site defensibility against other geospatial indices and found that, when Iroquois villages were compared to random points on the landscape, defensibility was not a significant factor in village placement.

Several archaeologists working in the Northwest Coast and western sub-Arctic of North America have also assessed the defensibility of archaeological sites. Schaepe (2006) presented a geospatial analysis of rock fortification sites in the lower Fraser River canyon of British Columbia. Schaepe defined four types of rock fortifications that may be differentiated based on construction and geographic position (Schaepe 2006:689). He then tested the hypothesis that rock fortification sites in the lower Fraser River canyon form a defensive network "linked by line of sight communication and functioning to monitor and regulate canoe travel within the canyon" (2006:695). He finds that such a system could indeed have been used to communicate up and down the canyon, but does not comment on whether such a system is probable given alternative site locations. Schaepe implicitly considers viewshed size and particularly line-of-sight to other rock fortifications to characterize defensible sites. Martindale and Supernant (2009) developed multivariate index of site defensiveness as a means of standardizing measures across archaeological sites (discussed at length below); they calculated the index using field and topographic maps, and site visits. Supernant (2011) extended the studies by Schaepe (2006) and Martindale and Supernant (2009) by reconsidering rock fortification sites in the lower Fraser River, calculating the defensiveness index for each site as well as performing a cumulative viewshed analysis of all of the sites to characterize the defended landscape. Supernant (2011:278) found that while the fortification sites on their own are not particularly defensible, the sites are likely distributed with respect to other sites on the landscape, presumably so as to increase their cumulative visual coverage. Furthermore, the rock fortification network may have added to the *perception* of defensibility in the eyes of possible aggressors (Supernant 2011:292). Sakaguchi et al. (2010) similarly used a GIS to develop an index for sites in middle Fraser River on the Canadian Plateau, incorporating viewshed size and proximity to probable pedestrian routes into their analysis. They report that a shift to more defensible site locations correlates positively with increased osteological indicators of violence (Sakaguchi et al. 2010:1182). Defensiveness is argued by all of these authors as being critical to our understanding of the role of conflict in structuring human behavior. Other researchers have presented thorough reviews of the history of warfare and violence on the Northwest Coast, though they are less explicit about defining defensibility (Angelbeck 2007, 2009; Lambert 2002; Maschner and Reedy-Maschner 1998; Moss and Erlandson 1992).

This study joins those mentioned above in further defining and clarifying notions of defensiveness. Specifically, I am interested in how archaeologists may better infer defensiveness from the archaeological record. I argue that we may only judge an action—such as choosing to build *here* and not *there*—to be defensive if such an action is unlikely to have been randomly drawn from the set of potential actions. I will return to this epistemological argument below, but allow me to briefly return to Justice Potter's decision from the epigraph. To "know it when we see it" implies that knowledge is situated within an environmental context (what has been *seen before*); in this case, the set of all movies, pornographic or otherwise, viewed by Justice Potter prior to his opinion. If that set had been primarily pornographic, it would be hard for any potential film to stand out to him as overly-explicit; if it had been primarily puritanical, *The Lovers* might have seemed hardcore indeed. Justice Potter's opinion reflected the backdrop of his prior movie-viewing experience. What is the appropriate backdrop for the archaeological inference of defensive decision-making?

*An index of site defensiveness*

Martindale and Supernant (2009) identified and reviewed a trend prevalent in the literature on archaeological defensive structures: the exclusive use of heuristic models (e.g., "defensive locations are high locations," "defensive locations have escape routes") that are under-specified and therefore not reproducible or easily comparable between case studies. And while heuristic assertions have allowed for the identification of many apparently defensive sites on the NW Coast and elsewhere, they have not allowed these sites to be compared to each other in a standardized fashion. Their goal was to present a formal index of defensiveness that may be applied uniformly across archaeological sites. Martindale and Supernant note that the index they have come up with is imperfect, and ought to be improved against more archaeological and modern data.

Martindale and Supernant's defensiveness index quantifies four different components of site defensibility: visibility, elevation advantage, accessibility, and site area. They argue that these four measures quantify a "syntax of biomechanical control" reflected in site layout (2009:192): the position and structure of a defensible site are actively chosen and shaped to direct where and how human bodies move toward and through them. The components of their index are defined as follows:

**Visibility** Visibility is calculated as the arc length (in degrees) of visibility over approachable land and water in excess of 100 m from the center of the site, divided by the total arc length of approach around the site. This value scales from 0 to 1. Martindale and Supernant define "unapproachable" land as "landforms that cannot be crossed" (2009:195), although they are unclear about how these landforms are judged to be uncrossable.

**Elevation** Elevation advantage is measured as the difference in elevation between the highest point within the site to the access point(s) at the edge of the site, measured radially. This measurement is expressed in degrees/90, and ranges from 0 to 1. Martindale and Supernant do not consider sites sitting at the bottom of basins—i.e., with access points above the site center—and it is not clear how they would calculate elevation advantage were they to consider such a site. It is also not immediately apparent how they measure the extent of a site.

**Accessibility** Accessibility is a "measure of ease of access" (2009:195), and is an architectural measure that considers both the degrees of possible approach around the site—as defined above—and the portion of that approach that is mediated by architectural thresholds, such as breaks in walls. This is again defined as a proportion of the arc of approach, and therefore scales from 0 to 1.

**Area** Martindale and Supernant argue that larger sites hold more people, and that the size of the population is an important aspect of defense. They include site area (divided by the arbitrary but necessary denominator 1,000,000, which again scales area from 0 to 1) as the fourth part of their defensiveness index.

Finally, the defensiveness index itself is simply the sum of visibility, elevation, accessibility, and area, and scales from 0 to 4.

Martindale and Supernant applied their index to 31 sites throughout the Northwest Coast area of North America, and concluded that their results generally met expectations for defensiveness levels at most sites. They asserted, "in those historical situations where conflict is perceived as a threat, the scale of human modification of the landscape towards more defensiveness will be observable, measurable and comparable" using indexes such as the one they defined (2009:203). They also called for a "full accounting of the defensiveness of all sites [...] to locate the presence of wide spread conflict in the past, generate comparative measures of its increase or decline at specific times, and begin to evaluate its causal role in history" (Martindale and Supernant 2009:203).

*Null models for inferring defensiveness*

Their call is warranted, for it speaks to the larger regional questions that Northwest Coast archaeologists and others are keen to address. Furthermore, such a goal is perhaps only achievable given a standardized index like the one they provide. However, we must ask: to what extent do indices allow us, as observers of the past, to infer human intention? Indices such as the one discussed here aim at quantifying some form of human behavior, generally structured as a simple choice. A stone tool user chooses whether to discard her flake tool or make another (Andrefsky 2009; Clarkson 2002; Davis and Shea 1998; Shott 1996); a hunter chooses whether to pursue a low-ranked prey, or forego that prey in hopes of capturing a higher-ranked one (Charnov 1976; Lupo 2007). The (unarticulated) choices at hand in this defensiveness index are similarly structured: Do I build here or someplace else? Do I build architectural features that restrict access? Do I build large enough to potentially enclose many people?

A choice about whether to curate a tool or about whether to pursue a given prey item—at least as these choices are often conceived by archaeologists (Andrefsky 2009; Lupo 2007)—is made in the context of the local physical and social environment. Low curation or expedient reduction technologies are expected to correlate with raw-material abundance; a forager operating under the prey-choice model from optimal foraging theory decides whether to pursue a prey item based on the probability of encountering higher-ranked items. Archaeological inference based on these models is strengthened by and indeed hinges upon an understanding of the environmental context of decision making. We can more strongly infer the relative value of a stone tool if we consider the regional availability of its parent material and the relative availability of other lithic materials (Andrefsky 2009; Bamforth 1990). We can more strongly infer whether a hunter is making an optimal choice to forego a low-ranked prey if we consider the existence and abundance of higher-ranked prey (Driver 2011; Duff et al. 2010; Johnson 2006; Schollmeyer and Driver 2012). We infer the importance of the environment in these choices by (often implicitly) comparing them with choices that would be made in the absence of considering the environment. This alternate model can be considered the null model. The null model postulates no relationship between the behavior *and the environment*.

All components of Martindale and Supernant's index—to the extent that they reflect actual decisions made in the past—can and ought to be assessed in the context of the environment of (potentially defensive) decision making. We can more strongly infer whether someone is making a defensive decision when they choose where to build a site if we consider the defensibility of the surrounding landscape. How defensible are the "other places" that might have been chosen? Are people choosing the most defensible places to live? Similarly, our inferences are made stronger when weighed against information about the social environment, such as population density or the rate of interpersonal violence, although this may be more difficult in practice.

*Using landscapes as null models: Archaeological precedent*

Although this study is the first in this tradition of research to seek to characterize landscapes as null models for inferring defensiveness it has many precedents, most prominently in the settlement pattern and predictive modeling literature (Jones 2010; Kellogg 1987; Kohler and Parker 1986; Maschner and Stein 1995; Plog and Hill 1971). Plog and Hill (1971) noted early on that characterizing the distribution of a given geographic metric over archaeological sites alone reveals nothing about whether site locations were chosen for that particular quality, and Kohler and Parker (1986:415) asserted, "A null model of random site location is absolutely essential to determining the role of environmental factors in location." Kellogg (1987:143) said much the same thing: "A set of observations on a group of archaeological sites is a sample of the environment in which the sites are found. It might be assumed that such a sample shows cultural biases for particular environmental characteristics; but a histogram of site frequency by some variable reveals little about cultural behavior without knowledge of the available natural environment of the region in which the sites are found." Kellogg also noted that describing landscapes as well as sites can be useful in comparing regions to one another, and provides several examples from coastal Maine. Comparing site locations with a random sample of non-site locations has now become common practice in settlement pattern analysis (see Maschner and Stein 1995 and Jones 2010 for an early and more recent example, respectively).

Additionally, several researchers have pointed out the statistical power of one-sample tests rendered possible by modern computational methods (Kvamme 1990, 1999; Wheatley 1995:169–170). A GIS allows the researcher to rapidly compute geospatial metrics for not only a random sample of non-site locations, but for an *entire population* of potential site and non-site locations.

Kvamme (1990:368–369) illustrated the superiority and simplicity of one-sample tests in relation to two-sample tests. Two-sample tests in geospatial situations may suffer from autocorrelation between the site and random samples, especially as the size of each sample increases. Also, as the random sample size increases, the probability of choosing a location with site on it increases. A one-sample testing strategy has also been used widely in cumulative viewshed analysis (Lake et al. 1998; Wheatley 1995). Given a set of $n$ viewsheds (say, from archaeological sites), the cumulative viewshed of a location is simply the number ($n' < n$) of viewsheds that include that location. This can easily and rapidly be calculated for each location (cell) on a raster landscape (Lake et al. 1998). A one-sample test can then be formulated thus (as in Supernant 2011:277):

H0: Sites are distributed irrespective of other sites that are visible

H1: Sites are not are distributed irrespective of other sites that are visible

The extent to which such a test is truly a one-sample situation is potentially complicated by the fact that the population (landscape) distribution is dependent on the locations of the sample sites. A discussion of this potential statistical issue is beyond the scope of this paper, however.

*Intrinsic versus extrinsic defensibility*

In this study, I consider two related but nonetheless discrete classes of potentially defensive decisions individuals or households make. The first action is to select where to construct a building (be it a house, storage area, or redoubt). This decision may by structured by what I term *extrinsic* defensibility: factors that are external to site architecture. These include visibility and elevation advantages over surrounding areas, but may also include anthropogenic aspects of the landscapes at the time of the decision such as trails, the remains of previous sites and architectural enhancements (e.g., old walls), and aspects of the social environment such as proximity to allies or enemies. The second set of actions is to build defensibility into the architecture of a site. These are reflections of *intrinsic* defensibility, and include accessibility, site size, and other potential signals of willfully invoked defensive structure. Intrinsic defensibility evolves over the life-history of a given site, and will be responsive to local contingencies such that it might not even be reasonable to expect regional patterns. Extrinsic defensibility, on the other hand, reflects an in-the-moment decision and therefore is less swayed by a particular site history; the initial decision of where to live may reflect an expectation of violence in the future.

*Generalizing extrinsic defensibility*

My purpose in this study is twofold. First, I present a "rasterization" of the extrinsic components of Martindale and Supernant's defensiveness index, essentially generating a population of defensibility values for the landscape at a given level of granularity. To do so, I further specify Martindale and Supernant's concepts of visibility and elevational advantage, and I adapt their index to a 30 m digital elevation model (DEM) so that defensibility may be computed for any point on a landscape (Section 3.1.3). Second, I seek to realize Martindale and Supernant's call for a "full accounting" of the extrinsic defensibility of locations of recorded pre- and post-contact archaeological sites in the Gulf of Georgia and lower Fraser River valley of British Columbia, and compare these to the baseline defensibility of the landscape (Section 2.1.2). By doing so I am able to consider to what extent the initial decision of where to build is a defensive one, both for particular sites and in the past in general.

I should emphasize what this study is not. It is not an attempt to develop an alternative index to Martindale and Supernant's, even though substantial revisions to it may be warranted, as I shall discuss below. Martindale and Supernant focus on aspects of defensibility that may be considered actively or aggressively defensible: the focus is on seeing a potential aggressor approaching and on having a strategic advantage should a battle ensue. There are certainly other types of defensible places, including passively defensible ones such as refugia. Invisibility may be as important as visibility. Nor is this study an attempt to comment on the current readings of warfare and violence on the Northwest Coast (though its applicability to such will hopefully be apparent). The scale of violence on the Northwest Coast varies spatially and temporally, and it is my hope that future studies will be able to use the methods presented here to describe and interpret peoples' responses to this variation.

*Landscape-based archaeological inference and comparative archaeology*

The comparative vision of archaeology (Drennan and Peterson 2012; Peregrine 2004; Peterson and Drennan 2012) relies on comparability of archaeological datasets, a tall order of which a full discussion is well beyond the scope of this paper. However, the development of empirical *indices* of behavior is a first step in rendering archaeological data comparable. Was warfare a more widespread and consistent reality on the Northwest Coast, than, say, the Pueblo Southwest? As I have already argued, the answer to this question demands more than just calculating a defensibility index across archaeological sites in the two regions. It requires an analysis and comparison of the defensibility of the landscapes of the Northwest Coast and the Pueblo Southwest and how they relate to settlement distribution. The methods detailed in this study are designed to be applicable beyond the Northwest Coast, and, indeed, anywhere moderately high-resolution elevation data is available. Regions enjoying recent archaeological analysis of warfare and conflict—such as the Ancestral Pueblo Southwest (Kohler et al. 2014; LeBlanc 1999; Lekson 2002)—would benefit from analyses such as the one I undertake here.

**Methods**

Here, I characterize the defensibility of an entire landscape by calculating visibility and elevation indices for every position on that landscape (at a 30-meter resolution). Doing so requiresMartindale and Supernant's extrinsic defensibility indices—which were vector-based measures of elevation and visibility reconstructed from original site maps—be adapted to a discontinuous raster landscape. Where possible, I have attempted to retain the central assumptions concerning minimal useful visibility and access from Martindale and Supernant's study (2009:194). In this section, I detail my methods of calculating extrinsic defensibility over raster landscapes.

*Adapting the Martindale and Supernant model to a raster landscape*

Martindale and Supernant use local topological maps and on-the-ground assessments for each site in their study to calculate indices of visibility and elevation, as described above. Topological maps provide a more-or-less continuous (vector-based) surface from which they hand-calculate degrees (angles) of visibility and approach to sites. Digital elevation models (DEMs) translate continuous vector surfaces into discrete raster surfaces that may be analyzed computationally. Raster surfaces present a problem for calculations such as angles and distances, however, due to their grid layout. Thus, it is necessary to recalibrate the Martindale and Supernant (2009) model to a raster landscape.

Table 2.1 presents Martindale and Supernant's calculations and their approximate equivalents on a raster landscape. The critical change is the radius of 100 m, which Martindale and Supernant (2009:194) assert is the minimum distance at which visibility is functional on the Northwest Coast. If visibility is restricted to less than 100 m, a resident would not see an aggressor in time to react defensively; thus, Martindale and Supernant defined their visibility index as the proportion of the visual arc around the site which is visible beyond 100 m. For the present analysis, I use the Moore ("square" or "Queen's case") neighborhood around each focal cell, out to a radius of three cells (the "$r_3$" cells; Figure 2.1). This means that the neighborhood radius on a 30 m resolution DEM, $D$, in the north/south or east/west directions is 90 m, while the diagonal radius is $90 \cdot \sqrt{2}$, or approximately 127 m (as measured from the center of the focal cell to the center of the $r_3$ cells). The distance from the focal cell to any other cell is given by the Cartesian distance equation,

$$D = \sqrt{dx^2 + dy^2} \tag{2.1}$$

where $dx$ and $dy$ are positive distances in the east/west and north/south directions, respectively. The rasterized elevation index is the average angular elevation difference between the focal cell and all $r_3$ cells, and the rasterized visibility index is the proportion of $r_3$ cells visible from the focal cell. I will now consider each of these in turn.

**Table 2.1 | Visibility and elevation indices, as presented in Martindale and Supernant (2009) and in this study, respectively.** $r_3$ cells are cells at a Moore radius of 3 from the focal cell (dark gray cells in Figure 2.1). $\bar{\theta}$ is the average angle of elevation from the focal cell to all $r_3$ cells, as defined in Figure 2.2.

| Index | Martindale and Supernant (2009) (continuous) | This study (rasterized) |
|---|---|---|
| Elevation | $\arccos \frac{\Delta \text{ elevation from site center to boundary}}{\text{distance from site center to boundary}}$ / 90° | ($\bar{\theta}$ of $r_3$ cells + 90°) / 180° |
| Visibility | $\frac{\text{degrees of visibility in excess of 100 m}}{\text{degrees of approach around the site}}$ | $\frac{\text{number of } r_3 \text{ cells visible}}{\text{total number of } r_3 \text{ cells (24 cells)}}$ |

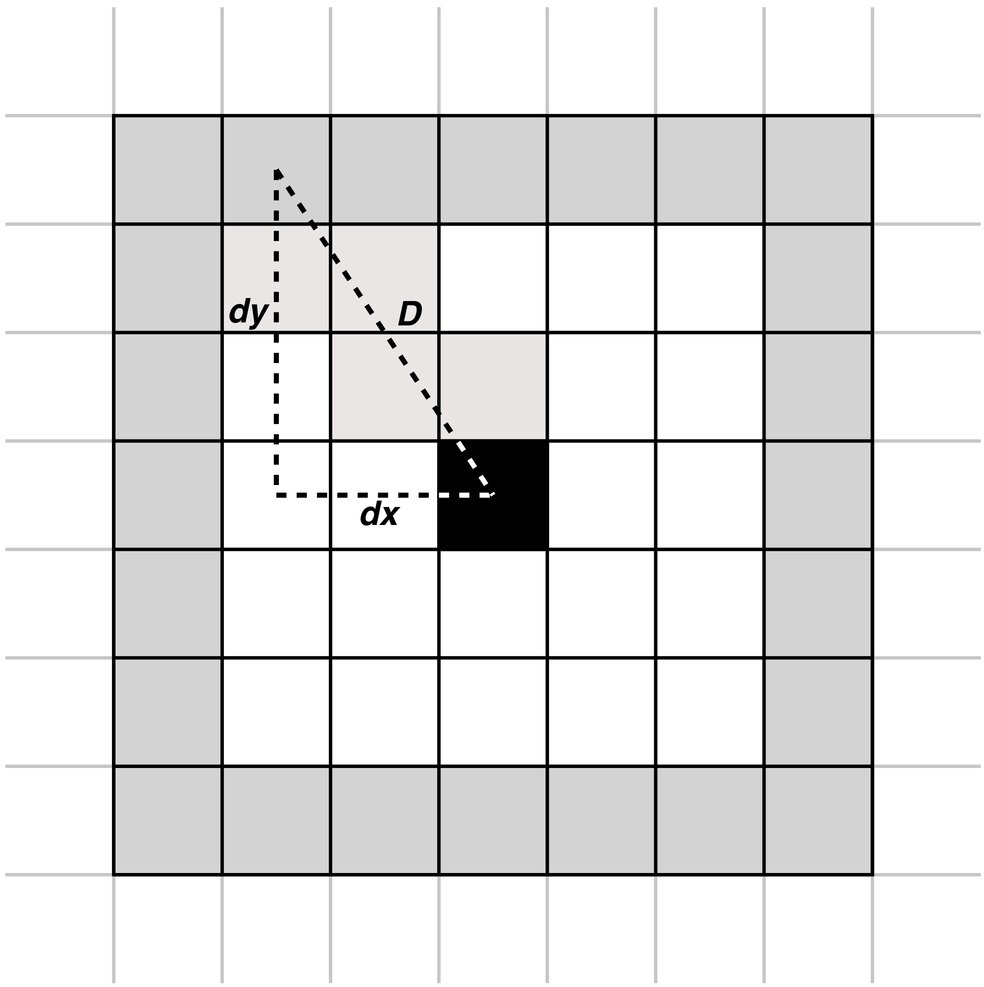


**Figure 2.1 | Plan-view of distance calculation on a grid.** The defensiveness index is calculated for the focal cell (black). Dark gray cells are at a Moore distance $r_3$ from the focal cell. Light gray cells are potentially intersected by the line-of-sight between the focal cell and the $r_3$ cell.

**Elevation** Figure 2.2 demonstrates the calculation of the elevation index for a single $r_3$ cell. The rasterized elevation index is computed in a slightly different way than by Martindale and Supernant. Instead of only considering the maximum elevation difference between the center of the site and the site boundary, this rasterized version considers all $r_3$ cells simultaneously by averaging the elevation difference between the focal cell and all $r_3$ cells. As in Martindale and Supernant (2009), the elevation difference, $\theta$, is calculated in degrees, and is

$$\theta = \arctan \frac{\Delta e}{D} \tag{2.2}$$

where $\Delta e$ is the elevation difference in meters, and $D$ is the distance from the focal cell to the $r_3$ cell, as calculated in equation 2.1.

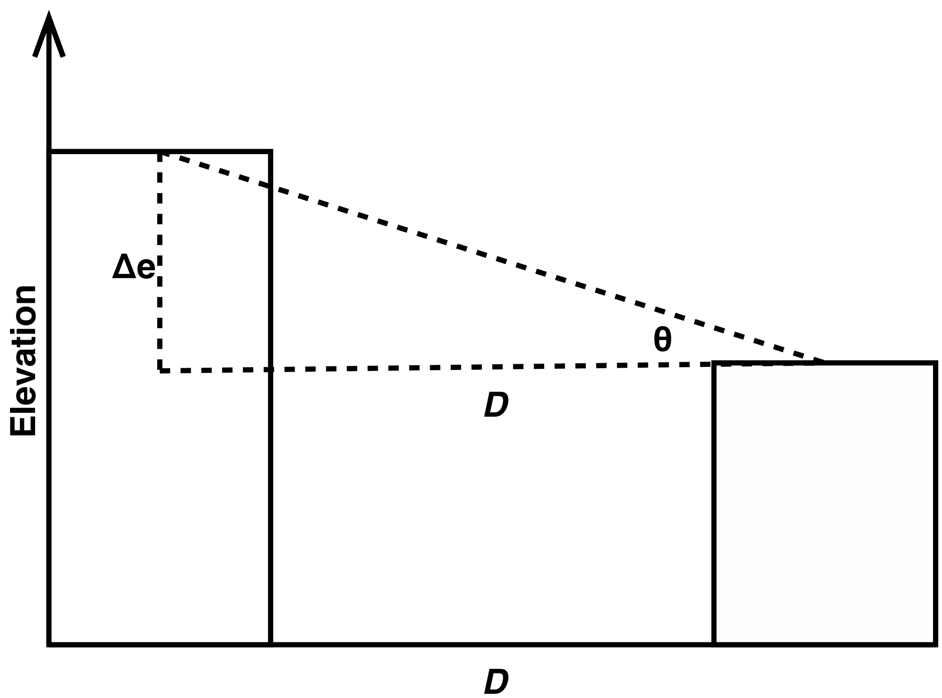


**Figure 2.2 | Profile of elevation calculation between two cells.** The cell centers are a distance $D$ from each other, have a difference in elevation of $\Delta e$. The angle of elevation formed by a right triangle with edge-lengths $D$ and $\Delta e$ is given by $\theta$.

Although I will not change it here, this calculation of elevational advantage—which adheres to Martindale and Supernant (2009:195)—is somewhat problematic. Whereas the value of the visibility index rises linearly with the degrees of visibility, the value of the elevation index is asymptotic to values of 0 and 1. Under most landscapes, this generates an expected probability distribution for elevation of a random landscape that is modal around 0.5 and highly leptokurtic. When combined with the visibility component to derive the defensibility index, the elevation component will effectively act as an upper limit to defensibility. We shall observe this effect in the Section 2.1.2 below.

**Visibility** Figure 2.3 demonstrates the calculation of the visibility index for a single $r_3$ cell. Unlike Martindale and Supernant (2009), who try to estimate the percent of the 100 m arc that is visible from the center of the site, the rasterized Visibility Index is simply the proportion of $r_3$ cells visible from the focal cell. "Visibility" of an $r_3$ cell in this context is defined as that cell having a larger $\theta$ than a $\theta$ calculated for any $r_2$ or $r_1$ cell intersected by the line-of-sight from the center of the focal cell to the center of the $r_3$ cell (see the light gray cells in Figure 2.1). This method echoes now-standard methods for calculating visibility when performing a viewshed analysis on raster landscapes (Lee 1994:453).

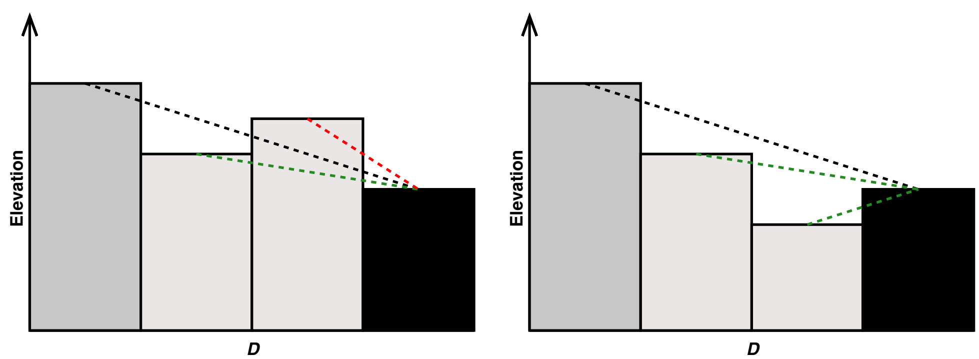


**Figure 2.3 | Profile of elevation and viewshed calculation between the focal cell (black) and the $r_3$ cell (dark gray).** In the left panel, one of the intermediate cells (light gray) intersects the line of sight to the $r_3$ cell, as indicated by the red dashed line. The cells in the right panel do not intersect the line of sight. See Figure 2.3 for a depiction of the elevation calculation.

**Defensibility** As noted above, Martindale and Supernant (2009) define their defensiveness index as the sum of four components, two of which—elevation advantage and visibility—have been rasterized here. In this study, extrinsic defensibility is calculated as the mean of the elevation and visibility indices. This maintains the range of potential defensibility between 0 and 1.

**Results and Discussion**

As a proof-of-concept—and in order to explore the implications of extrinsic defensibility for a well-known archaeological region—here I characterize visibility and elevation in the Gulf of Georgia (or northern Coast Salish) region of the Northwest Coast of North America. In this section, I briefly introduce the study area, and present visibility, elevation, and defensiveness indices for the rasterized landscape. I then compare rasterized index values with the site-based values calculated by Martindale and Supernant (2009:Table 5) for sites in that study that fall inside my study area. I find that the rasterized method captures similar variability in elevation and visibility as Martindale and Supernant's 2009 continuous indices.

This study uses a 30 m DEM developed from the ASTER Global DEM v.2 1/3 arc-second data set, a product of METI and NASA. The DEM was prepared by re-projecting the ASTER GDEM from its native LatLong coordinate system and WGS84 datum to the Universal Transverse Mercator (UTM) Zone 10N projection and NAD83 datum, and resampling it at a 30 m resolution (Figure 2.4; see the online supplementary information for details [and Appendix A of this dissertation][3]). The study area is a rectangle between 5350000 and 5480020 m north, and 435000 and 640020 m east in UTM Zone 10, or a 4334 x 6834 grid of 30 x 30 m cells (approximately 30 million cells). The actual algorithm I developed for efficient calculation of these indices across the landscape is detailed (in code) in the online supplementary information. The R statistical framework (R Core Team 2014) was used for all geographic and statistical processing; see the appendices for specific libraries used.

Figure 2.5 presents the elevation index calculated for each cell on the landscape; Figure 2.6 presents the visibility index; and Figure 2.7 presents the defensibility index, or the mean of the

[3]The online supplementary information consists of the R source code necessary to complete the analyses and compile the figures and tables presented in this paper. The code is provided in an attempt to make this research reproducible (Barnes 2010; Ducke 2012; Mesirov 2010; Peng 2011; Stodden 2010), though the user will have to manually download the ASTER GDEM data and site data from the RAAD database.

visibility and elevation indices. I only consider the landscape in modern-day British Columbia, for reasons that will become apparent later.

*Defensiveness of sites from Martindale and Supernant*

As an initial test of the rasterized defensibility indices, here I compare the continuous indices calculated by Martindale and Supernant (2009:Table 5) with the rasterized indices indices calculated here. Table 2.2 presents this comparison, and Figures 2.8, 2.9, and 2.10 present these results graphically by plotting the Martindale and Supernant indices across the x-axis, and the rasterized indices from this study on the y-axis. The solid line in these figures represents where the points should fall if the continuous and rasterized indices are capturing the same characteristics of site defensibility. If points fall on or near this line, the indices are roughly equivalent. If points fall along a line parallel to the dashed line, the relationship may be rendered equivalent via a simple linear transformation. The dashed line in each plot is the best-fit line through the points, calculated via robust ordinary least squares regression.

Elevation indices generally cluster along the diagonal line, and the trend line through them is nearly parallel to the diagonal (Figure 2.8; robust $R^2 = 0.99$). Martindale and Supernant only considered positive values for their elevation index—they were only concerned with elevation *advantages* and not disadvantages—so all of their values are 0.5 or above; the rasterized index, however, allows for sites to be on average lower than the landscape around them, and thus allows elevation indices less than 0.5. Both the continuous and rasterized indices cluster very close to 0.5, however, so the impact of these differences on the final defensibility index is generally negligible.

With the exception of a few outliers, visibility indices are patterned somewhat linearly and parallel to the diagonal line (Figure 2.9; robust $R^2 = 0.91$). Rasterized index values of five of the nine sites are linearly patterned only 0.1 to 0.2 higher than their continuous counterparts. This is unsurprising, as Martindale and Supernant restricted visibility over land due to approachability and the impact of vegetation, as described above. The rasterized index value considers no such restriction. That the sites are patterned parallel to the diagonal line suggests that these restrictions are fairly consistent across sites. The three outlier sites (Beach Grove, Whalen Farm, and Scowlitz) are each unusual in light of Martindale and Supernant's site sample. The defensiveness index of Beach Grove was calculated from "the most basic of sketch map" (2009:196) enhanced by a satellite photograph (2009:200); they found Beach Grove to have 360 degrees of access but only 90 degrees of visibility (110 degrees in their Figure 4; 2009:Table 5), presumably because of forestation. Visibility at Whalen Farm was similarly highly greatly restricted (180 degrees of visibility for 360 degrees of access). Scowlitz, on the other hand, had an unusually high visibility over water for its accessibility.

Defensiveness indices are the mean of elevation and visibility indices, and thus are patterned similarly to the visibility index, but more towards the center of the plot (Figure 2.10; robust $R^2$ = 0.97).

*The importance of defensibility in choosing site location*

The above data demonstrate that similar variability in elevation and visibility are captured by the rasterized and continuous defensibility indices. I now move towards my second goal of characterizing the general concern with site defensibility in the past. My question here is fairly straightforward: Were people in the past choosing to position themselves on parts of the landscape that were *in general* more defensible than the landscape as a whole? What is novel about the approach taken in this study is that I am able to compare site defensibility to a baseline defensibility of the landscape (or of the landscape relevant to human occupation, defined below).

For this analysis, I focus on prehistoric sites in British Columbia. I obtained detailed site information on 4311 sites within my study area using the *Remote Access to Archaeological Data* (RAAD) service of the Ministry of Forests, Lands and Natural Resource Operations of the province of British Columbia. I took a subset of these sites by querying the "Typology" field—a description of the site—for several terms. First, I only retained sites that included "precontact" or "postcontact" components (as opposed to "historical"). From these, I selected sites for which the "Typology" field included any of the following terms: "house," "pit," "habitation," "shelter," "midden," “mound,” “hearth,” or “embankment.” This left me with a sample of $n = 1914$ sites (see the online supplementary information for details). This is a fairly liberal way to come up with a sample of habitation and defensive sites; a more conservative approach might be to exclude sites known to be non-habitation or defensive sites, such as burial cairns. Sites are generally located in river valleys and along the coast (the black dots in Figure 2.4).

The distribution of defensibility of archaeological sites is significantly different from that of the landscape as a whole, as demonstrated by a one-sample Kolmogorov-Smirnov (K-S) test ($D_{max} = 0.398$, $p < 0.001$). Figure 2.11 displays the cumulative probability distribution of Defensiveness Index values for the landscape (black) and all archaeological sites (red). The short dotted line between the two distributions is the K-S statistic, $D_{max}$, or the largest difference between the two distributions. The dashed line indicates the point in the landscape distribution where defensibility index values are greater than 95% of the landscape, or in this case values greater than 0.63. This demonstrates that, in general, people likely took defensiveness into account when choosing where to build, and that a large portion of sites (nearly 20 percent) are at highly defensible places on the landscape.

*Are “defensive sites” in defensible locations?*

Finally, we can ask, “What sites are located in particularly defensible places?” I take as “particularly defensible” those sites with an extrinsic defensibility greater than 95% of the landscape, or in this case a defensibility index greater than 0.63 (Figure 2.11). In this section, I will briefly consider the sites analyzed by Martindale and Supernant (2009) before analyzing defensible sites in the larger site sample.

**Sites analyzed in Martindale and Supernant (2009)** All but two of the sites considered in this study and analyzed by Martindale and Supernant (2009:Table 5) are characterized as “Village,” and are not considered defensive. Sites DcRu-23 (Finlayson Point) and DeRu-36 (Towner Bay) are “Trench Embankments,” a site form that Martindale and Supernant (2009:193) note has been considered defensive both due to its distribution across the landscape and its associated architecture. Martindale and Supernant (2009:201) found that trench embankments and other site types often considered defensive (such as redoubts and forts) had higher defensiveness index values than other site types. Finlayson Point and Towner Bay are both at particularly defensible locations on the Gulf of Georgia landscape (as defined above; defensibility indices of 0.68 and 0.70, respectively). Two other sites, Shingle Point and Whalen Farm, also have defensibility indices greater than 0.63. Shingle Point lies on a spit of land protruding from the western edge of Valdes Island in the Gulf of Georgia, and thus has well over 180 degrees of unobstructed visibility. The Whalen Farm site is situated on the eastern shore of the Point Roberts peninsula in the Fraser River delta; low elevation gradient gives the site nearly 360 degrees of visibility. The rest of the sites—all villages—have defensibility indices of less than 0.63 (Table 2.2). This suggests that the people who built the Finlayson Point and Towner Bay trench embankment sites, as well as the Shingle Point and Whalen Farm sites purposefully chose highly defensible places on the landscape. Are other trench embankment sites in the Gulf of Georgia region in similarly highly defensible places?

**Trench embankment sites in the Gulf of Georgia region** Here, I compare trench embankment sites drawn from the site sample introduced in Section 2.1.2 to the Gulf of Georgia landscape. I selected sites for which the "Typology" field included "Trench Embankment" ($n = 23$). This subsample does not represent the complete catalog of trench embankment sites in the region, but only sites reported as such in my sample from the RAAD database. Nevertheless, it is useful for the present illustration.

Many of the trench embankment sites (39 percent, or 9/23 sites) are in highly defensible places on the landscape; significantly more when compared to 16.4 percent of non-trench embankment sites (311/1891 sites; $p = 0.008$ using Fisher's exact test) and 5 percent of the landscape. All except four of the trench embankment sites have defensibility greater than the mean defensibility of the landscape ($\bar{x} = 0.47$). This suggests that, in general, people were selecting defensible places on the landscape to build trench embankments. This being said, these data do not support the assertion that all trench embankment sites were built on extrinsically defensible places. Further analysis is needed to determine whether there are differences between highly defensible trench embankment sites and less defensible ones. For the Southwest US, LeBlanc (1999:68) has noted that site size can be a substitute for defensible location; small sites tend to be on more defensible landforms than larger sites. If the trench embankment sites do evidence a concern for defense, those not in defensible locations should be significantly larger than those that are.

## Conclusions

Choosing the location of where to build a residential site is a fundamental household decision, and factors in making this decision are undoubtedly many and complex. However, we may begin parsing the relative importance of each factor by first quantifying spatial population parameters for each and systematically describing where people are choosing to build on their landscape (c.f., Jones 2010; Maschner and Stein 1995). The physical characteristics of a landscape structure and constrain the set of possible decisions an agent can make. We must consider the impacts of the physical environment on human decision making before we are able to consider the much more complex influences of the social environment.

In this paper I have demonstrated a geospatial technique for quantifying the extrinsic defensibility of raster-based landscapes. This technique may be used to compare the defensibility of site locations with a baseline defensibility of the landscape. In the future, this method will allow for meaningful comparisons of site defensiveness to be made between geographic regions and through time. I then applied this technique to the Gulf of Georgia region as a proof-of-concept.

### *Inferring defensiveness on the Northwest Coast*

I performed a "full accounting" not only of the defensibility of archaeological sites in the Gulf of Georgia region of the Northwest Coast, but also of the landscape itself. My findings may be summarized thus:

- **Extrinsic defensibility may successfully be generalized to a raster landscape.** This algorithm is efficient and robust on large landscapes. Its results are comparable to earlier vector-based measures of extrinsic defensiveness, such as those developed by Martindale and Supernant (2009).

- **Site locations in the Gulf of Georgia region are significantly more defensible than the landscape as a whole.** Given the defensibility index I employed, this is primarily due to the selection of sites with higher visibility indices than the surrounding landscape.
- **Among the sites analyzed by Martindale and Supernant (2009) and included in this study, previously identified "defensive sites" (trench embankment sites) are often in highly defensible places on the landscape.** Further analysis is needed to determine whether there are differences between highly defensible trench embankment sites and less defensible ones.

There are several potential extensions to this study in reference to the Northwest Coast:

- Use $^{14}C$ dating data available in the RAAD database and elsewhere to explore changes in extrinsic defensiveness of sites in the Gulf of Georgia region over time. Is the proposed rise in warfare and inter-household violence during the Late period in the Coast Salish region (Angelbeck 2007:262; Burley 1980:65–66; Coupland 1989:212) reflected in where people are choosing to settle?
- Perform a historical analysis that asks, To what extent are people choosing where to live in relation to other sites on the landscape? The statistical distribution of defensibility of available places will change as locations are claimed on the landscape. Are sites freely or despotically distributed (Kennett et al. 2009; Sutherland 1996) on the landscape, based on defensibility?
- Consider more local areas of landscape defensibility. What is the scale of the landscape relevant to human decision making? For instance, if a group of people are deciding where

to build a trench embankment site, they may not consider the entire coastline, but instead a more local area.

- Consider the defensibility of site catchments, as opposed to sites themselves.

*Beyond "I know it when I see it"*

Can be begin to adequately describe the contexts in which we humans make decisions? Can we move beyond the Potterian premise of intuition as an appropriate inferential tool, and begin to contextualize and perhaps minimize our own inferential biases as social scientists? This is a difficult undertaking; social scientists, like Supreme Court justices, are in the peculiar position of having to adjudicate the will and behavior of our fellow humans. We are not separated from our objects of study by vast size, distance, or temporal barriers, as are many natural scientists (Henrickson and McKelvey 2002). And—also like Supreme Court justices—we are seldom completely successful as minimizing or even accounting for our biases. However, we may design tools to help guide our inferences by universalizing and objectifying them.

The methods I present in this paper not only improve archaeological inference by providing landscape-based null models, but also can be used to calculate the defensibility of many places on the landscape with relatively little effort. I am able to compute landscape-based defensibility of a large database of archaeological sites simultaneously, inviting regional and temporal comparisons that are difficult to achieve using non-computational methods. While analyses such as this have been commonplace in the predictive modeling literature (Kellogg 1987; Kohler and Parker 1986; Maschner and Stein 1995), the approach of quantifying landscapes through either sampling or complete coverage (one-sample testing, as I do here) has yet to be used by researchers specifically interested in defensiveness.

Finally, the approach I take here is an initial attempt at developing a "computational phenomenology" that closely emulates how humans experience the world. For the most part, archaeologists have used predictive models to *describe* landscapes, as opposed to training computers to directly interpret how human agents experience, react, and shape those landscapes. Though my focus here is clearly on describing landscapes, my goals are not merely descriptive. We can and should enlist computers in developing culturally specific approaches to space using large architectural or landscape datasets. Promising approaches have been recently employed by Bernardini et al. (2013), who analyzed visual prominence of landforms in the late prehistoric US Southwest, and Lake and Ortega (2013), who interpret the visual setting of Middle Neolithic and Late Bronze Age stone circles in Great Britain. These approaches are less about freeing us from our intuition and biases, but rather about explicating those biases in order to follow them to their logical endpoints. In this framework, Justice Potter Stewart's candor about the scope of pornography *is* useful, in that it is a data point relating his prior movie-watching experience to his decision-making. Our quest as anthropologists is to similarly connect experiences and behaviors in our understanding of the human species.

**Acknowledgements**

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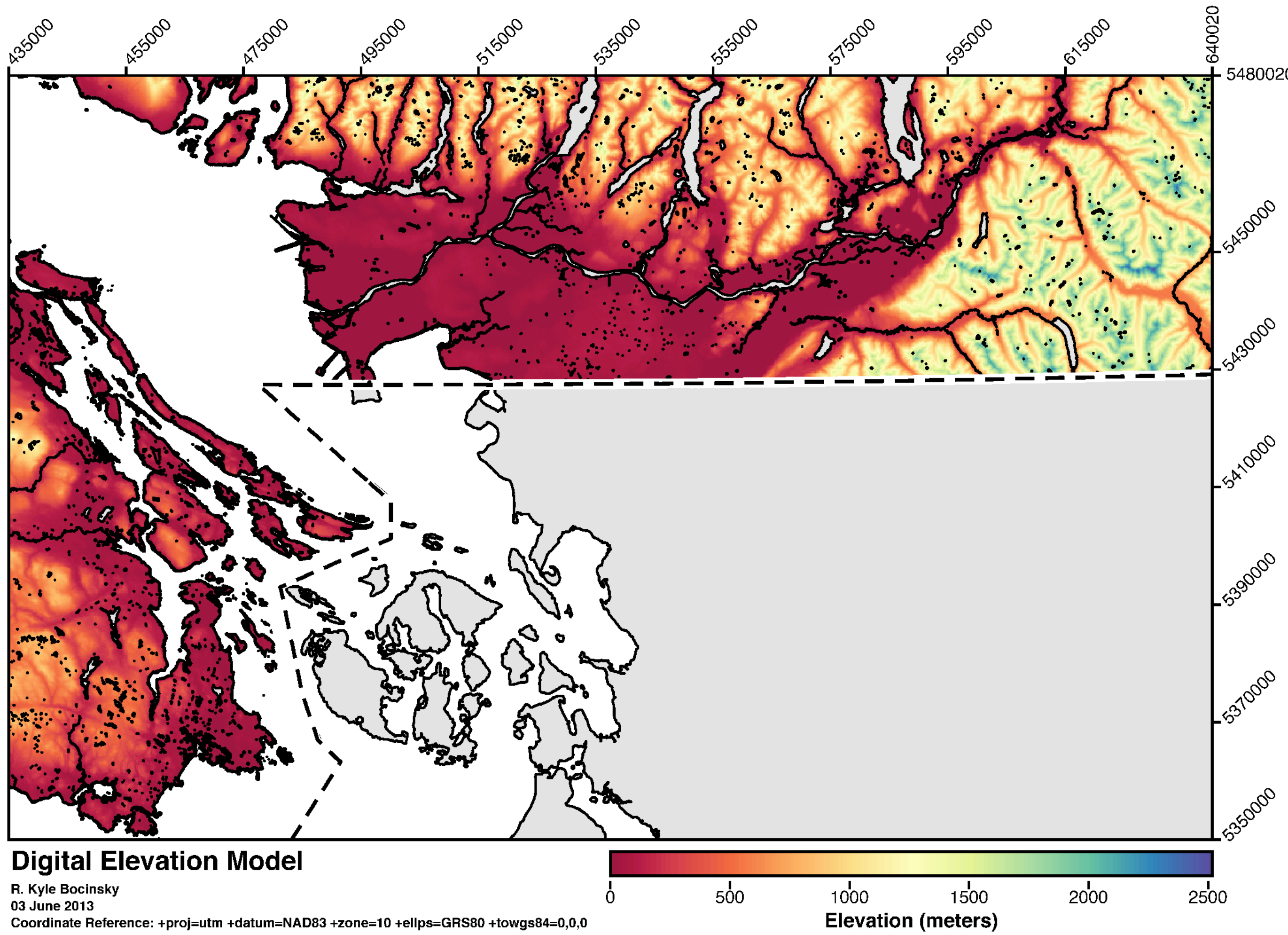


Figure 2.4 | 30 m resolution DEM of the Gulf of Georgia region.

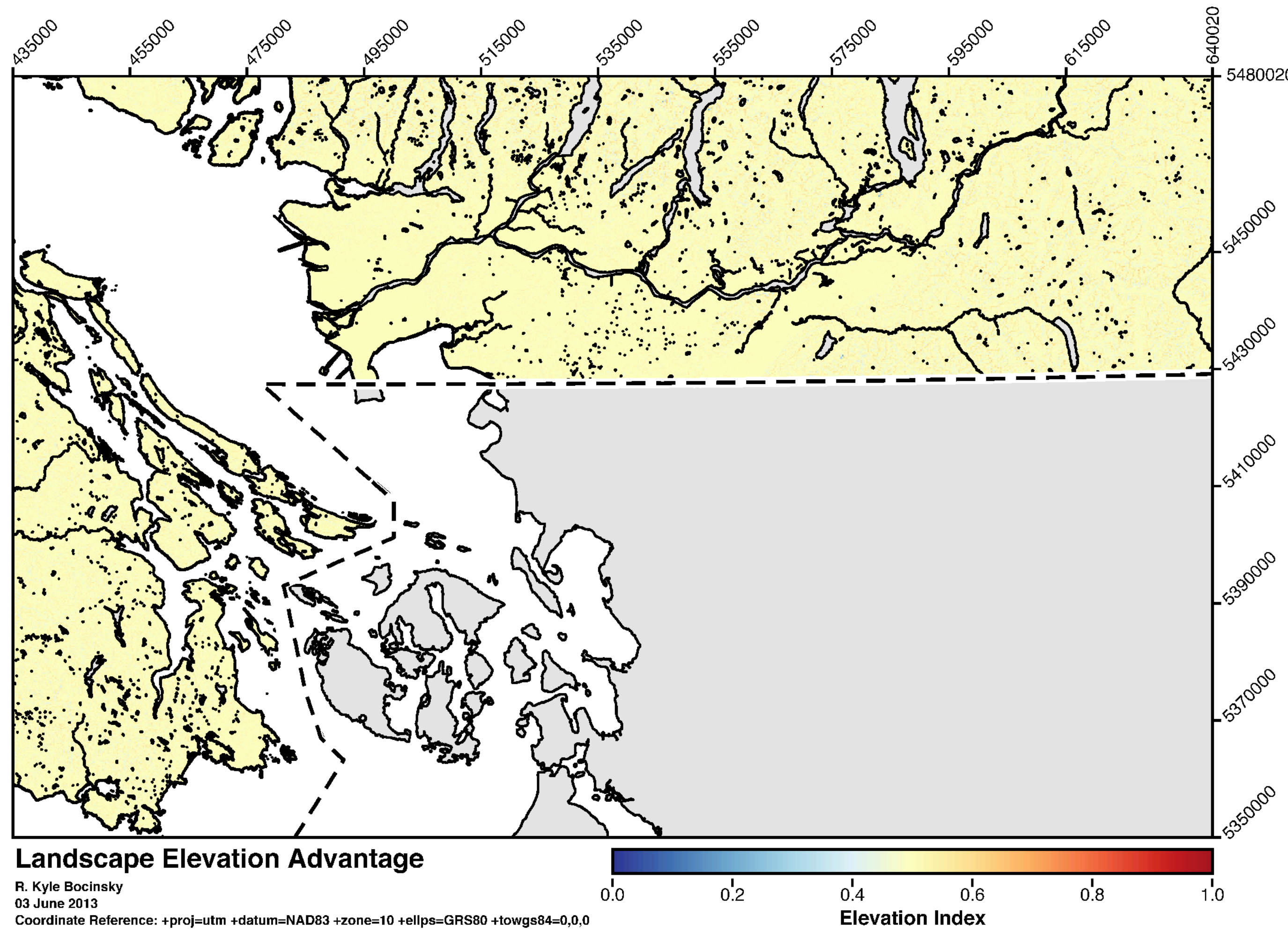


**Figure 2.5 | Elevation index interpolated across the Gulf of Georgia region.** An index of 0 indicates that a site is at the lowest point in the surrounding landscape; 1 indicates the site is at the highest point.

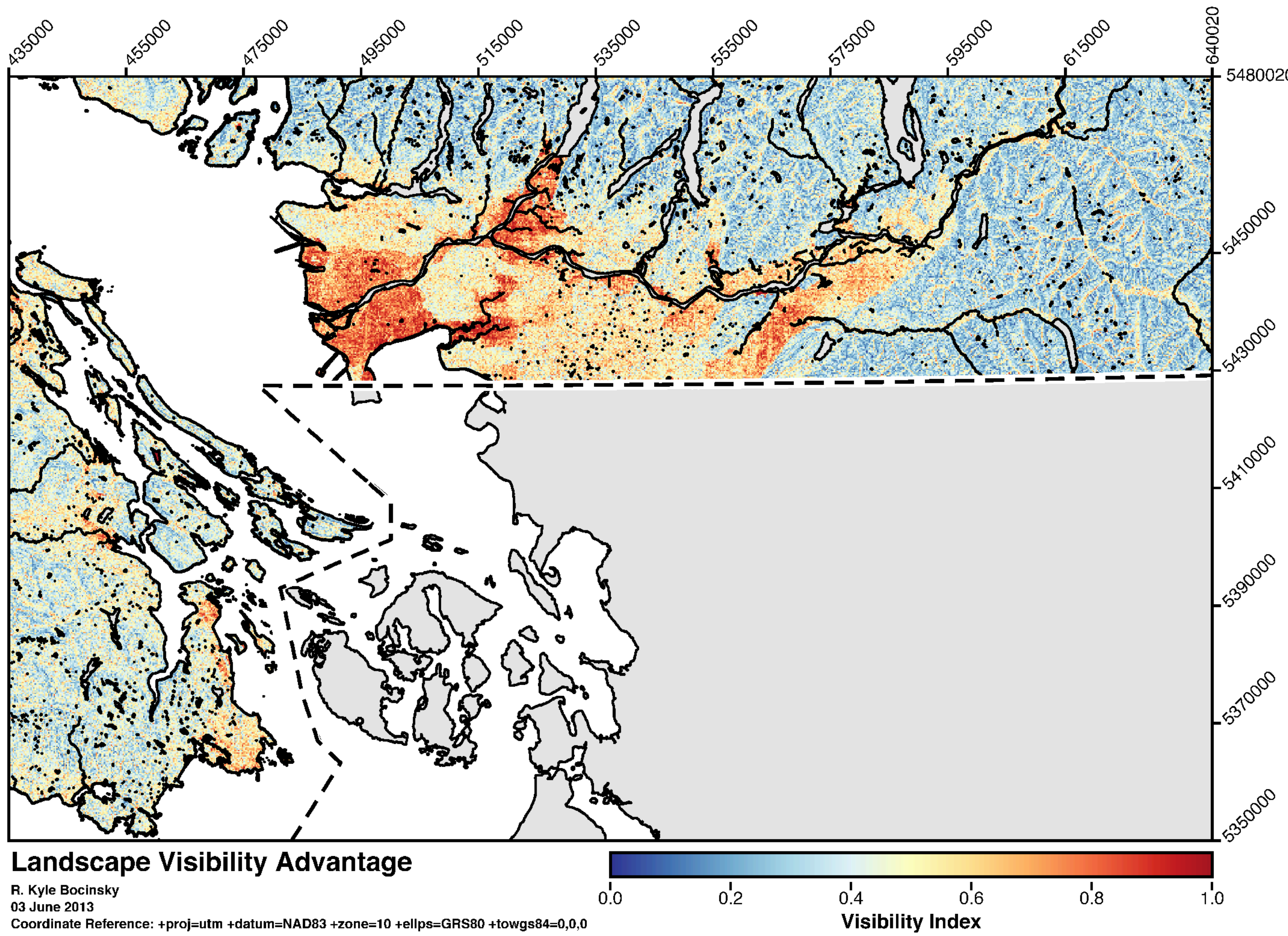


**Figure 2.6 | Visibility index interpolated across the Gulf of Georgia region.** An index of 0 indicates no cells at the Moore radius of 3 are visible from the focal cell; 1 indicates all cells are visible from the focal cell.

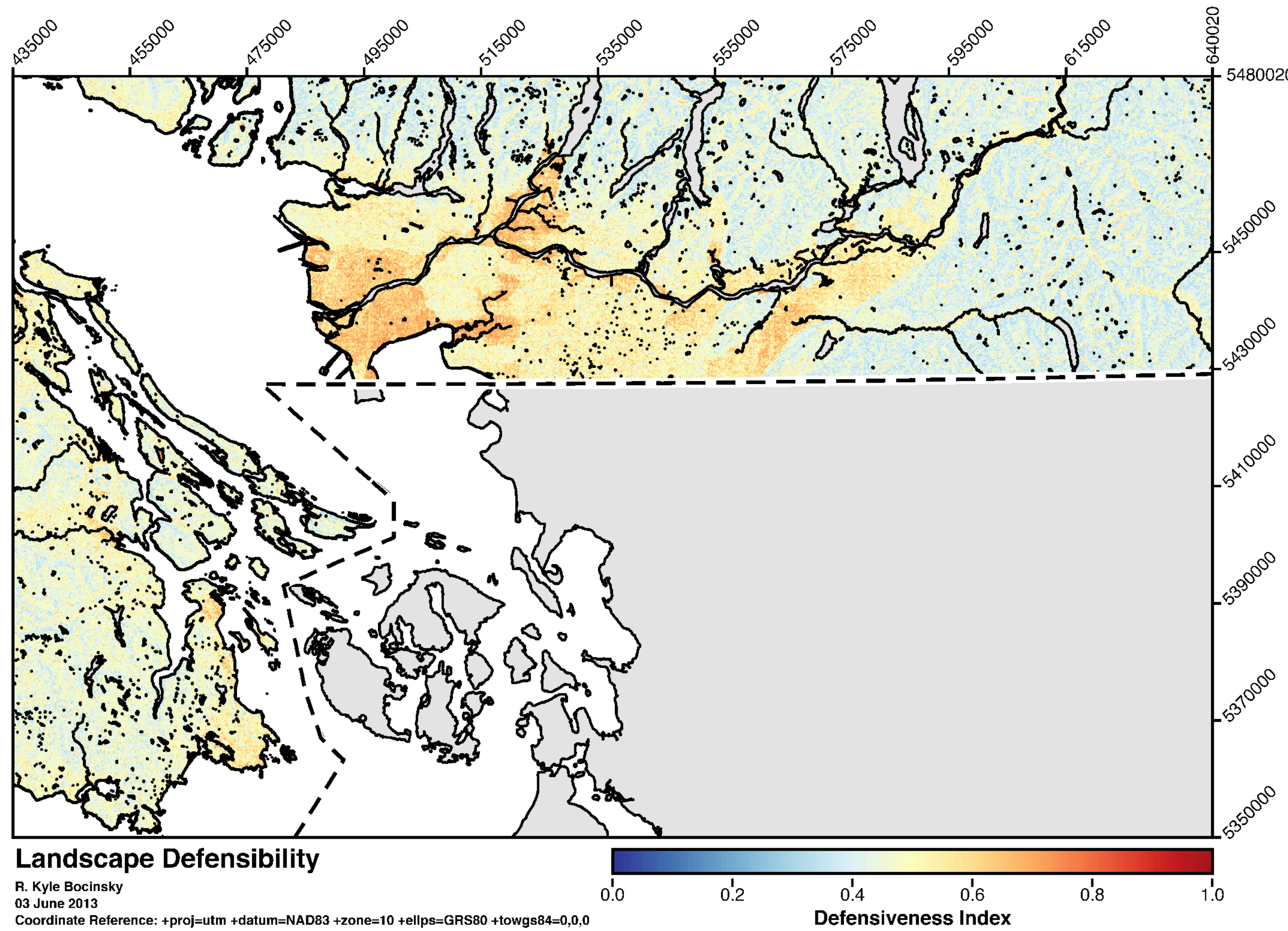


**Figure 2.7 | Defensibility index interpolated across the Gulf of Georgia region.** An index of 0 indicates minimum defensibility; 1 indicates maximum defensibility.

**Table 2.2 | Defensibility, visibility, and elevation indices of Gulf of Georgia archaeological sites, from Martindale and Supernant (2009) and this study.**

| | | | Martindale and Supernant 2009 | | | This study | | |
|---|---|---|---|---|---|---|---|---|
| Site Name | Site Type | Borden Number | Visibility | Elevation | Defensibility | Visibility | Elevation | Defensibility |
| Dionisio Point | Village | DgRv-3 | 0.45 | 0.52 | 0.48 | 0.38 | 0.52 | 0.45 |
| Scowlitz | Village | DhRl-16 | 0.71 | 0.51 | 0.61 | 0.47 | 0.47 | 0.47 |
| Katz | Village | DiRj-1 | 0.31 | 0.52 | 0.42 | 0.45 | 0.51 | 0.48 |
| Beach Grove | Village | DgRs-1 | 0.25 | 0.50 | 0.38 | 0.63 | 0.50 | 0.57 |
| False Narrows | Village | DgRw-4 | 0.56 | 0.50 | 0.53 | 0.73 | 0.49 | 0.61 |
| Shingle Point | Village | DgRv-2 | 0.64 | 0.50 | 0.57 | 0.78 | 0.49 | 0.64 |
| Finlayson Point | Trench Embankment | DcRu-23 | 0.78 | 0.51 | 0.64 | 0.86 | 0.49 | 0.68 |
| Whalen Farm | Village | DgRs-14 | 0.50 | 0.50 | 0.50 | 0.91 | 0.50 | 0.70 |
| Towner Bay | Trench Embankment | DeRu-36 | 0.75 | 0.51 | 0.63 | 0.91 | 0.50 | 0.70 |

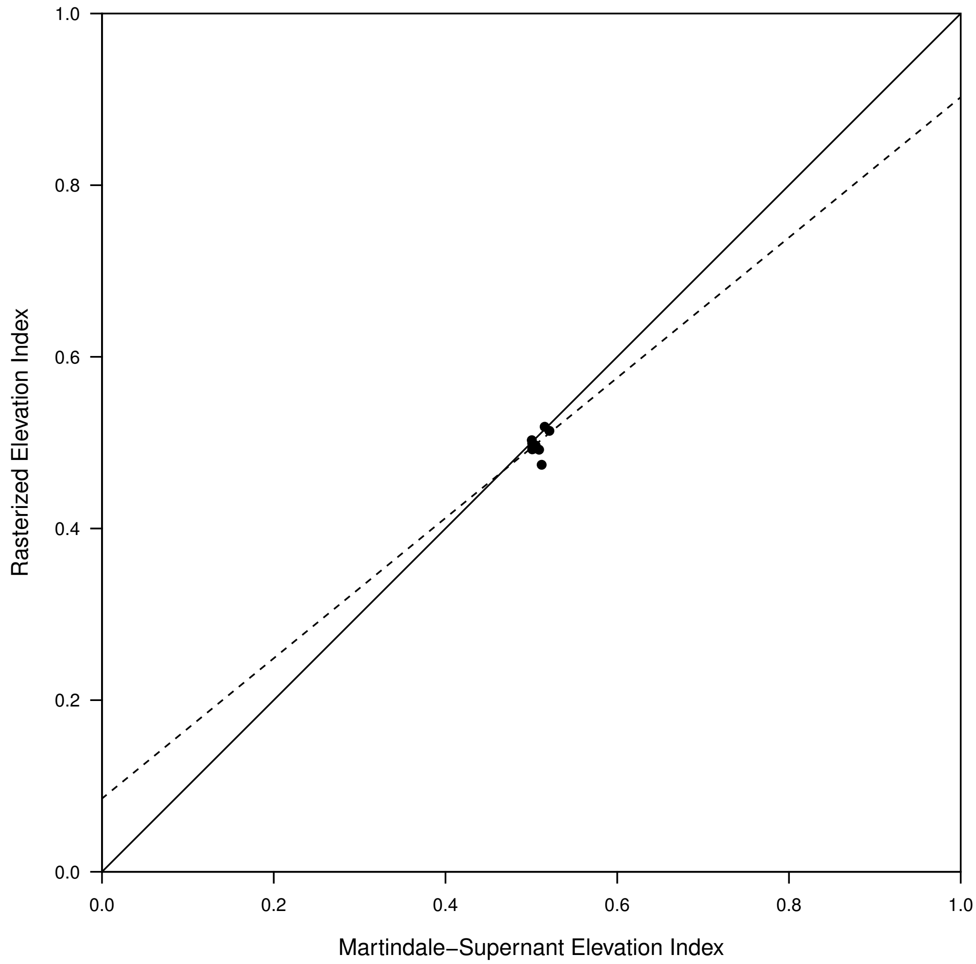


**Figure 2.8 | Elevation indices of sites from Martindale and Supernant (2009) in the Gulf of Georgia region.** The x-axis gives the index as calculated by Martindale and Supernant, while the y-axis the index as computed in this study. The dashed line is the best-fit line through the points, calculated via robust ordinary least squares regression (robust $R^2 = 0.99$).

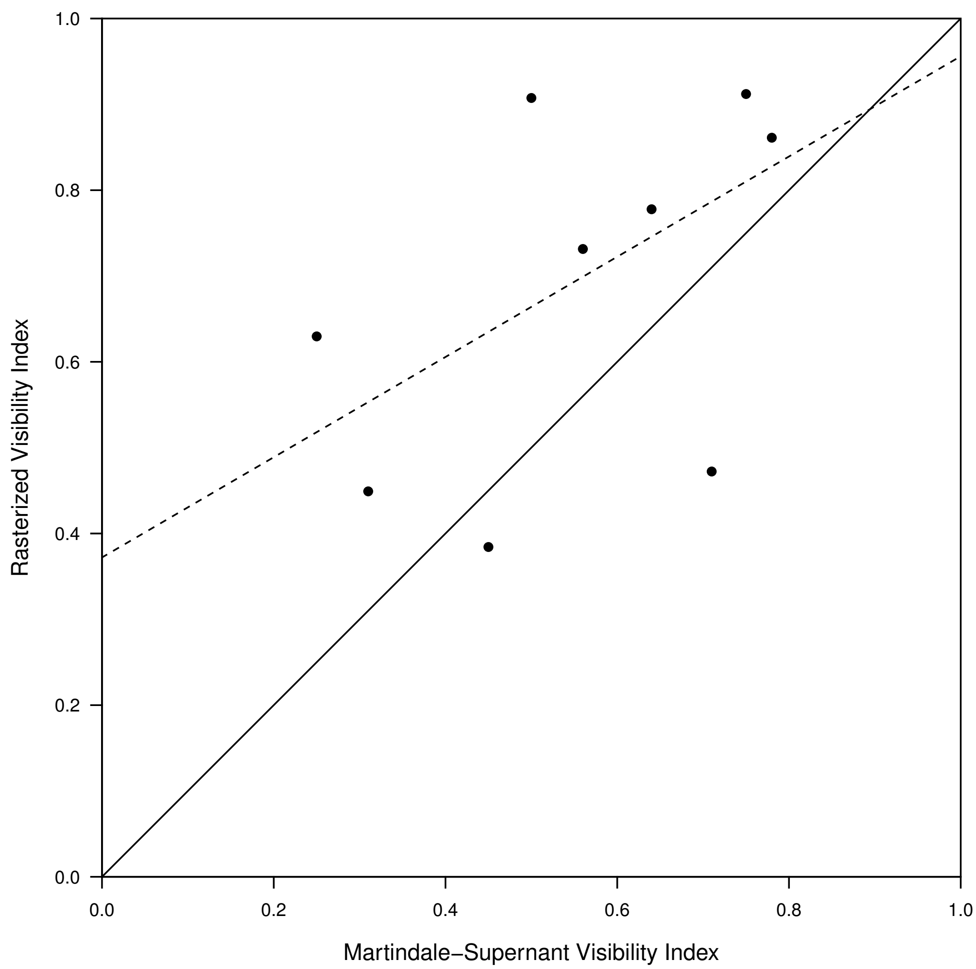


**Figure 2.9 | Visibility indices of sites from Martindale and Supernant (2009) in the Gulf of Georgia region.** The x-axis gives the index as calculated by Martindale and Supernant (2009), while the y-axis the index as computed in this study. The dashed line is the best-fit line through the points, calculated via robust ordinary least squares regression (robust $R^2 = 0.91$).

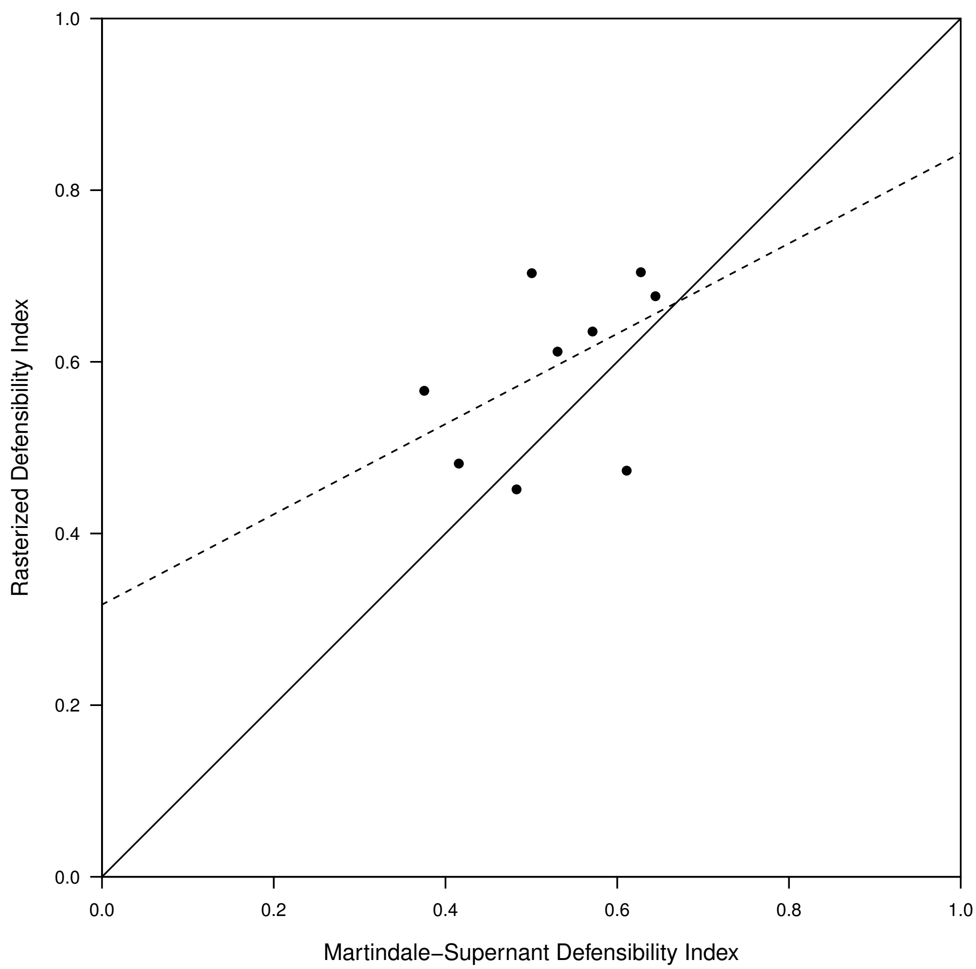


**Figure 2.10 | Defensibility indices of sites from Martindale and Supernant (2009) in the Gulf of Georgia region.** The x-axis gives the index as calculated by Martindale and Supernant (2009), while the y-axis the index as computed in this study. The dashed line is the best-fit line through the points, calculated via robust ordinary least squares regression (robust $R^2 = 0.97$).

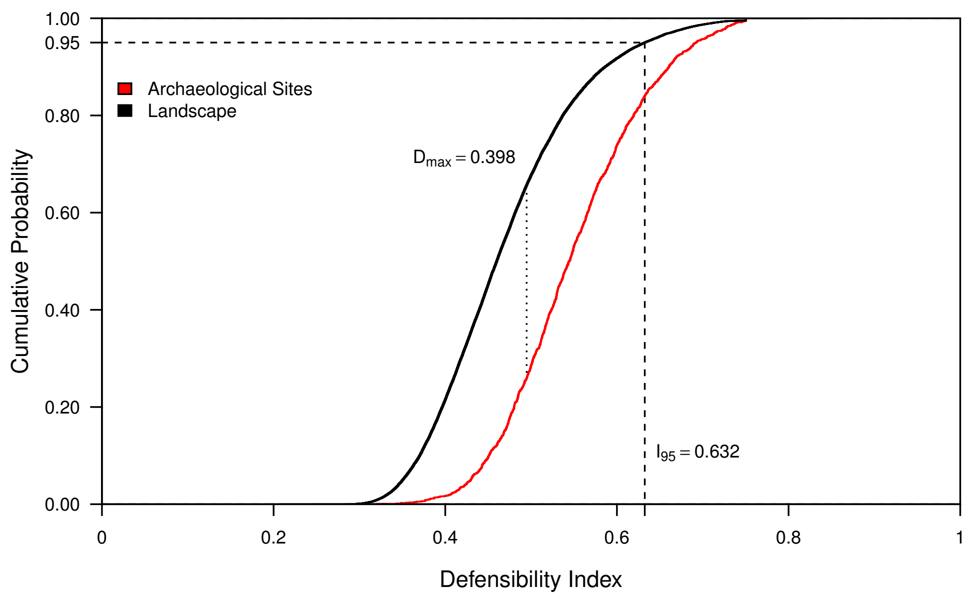


**Figure 2.11 | The empirical distribution functions of defensibility indices of 30 m cells in the Gulf of Georgia region (black) and of archaeological sites in the region (red).** The short dotted line between the two distributions is the K-S statistic, $D_{max}$. The dashed line indicates the point in the landscape distribution where defensibility index values are greater than 95% of the landscape, or in this case values greater than 0.63.

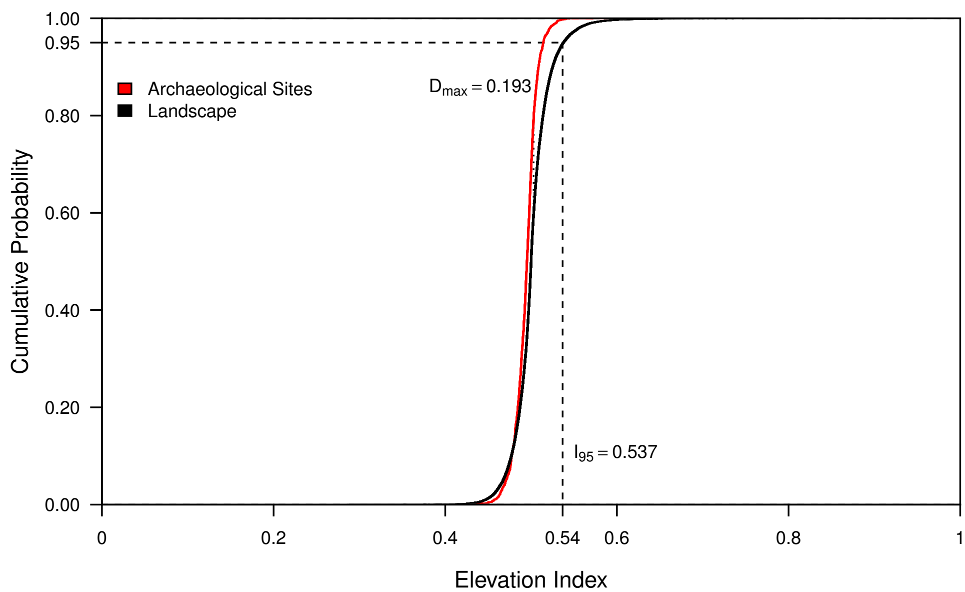


**Figure 2.12 | The empirical distribution functions of elevation indices of 30 m cells in the Gulf of Georgia region (black) and of archaeological sites in the region (red).** The short dotted line between the two distributions is the K-S statistic, $D_{max}$. The dashed line indicates the point in the landscape distribution where elevation index values are greater than 95% of the landscape, or in this case values greater than 0.54.

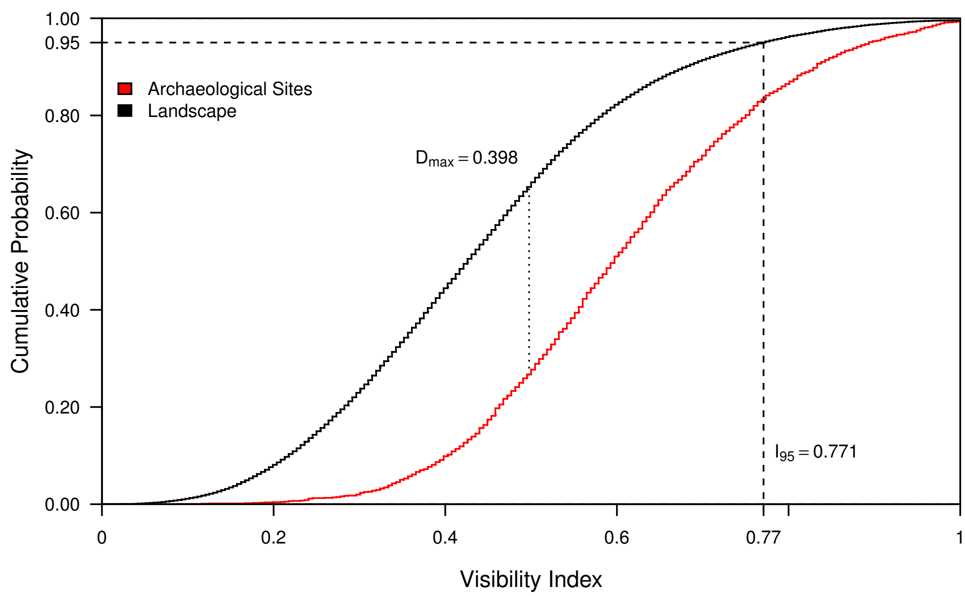


**Figure 2.13 | The empirical distribution functions of visibility indices of 30 m cells in the Gulf of Georgia region (black) and of archaeological sites in the region (red).** The short dotted line between the two distributions is the K-S statistic, $D_{max}$. The dashed line indicates the point in the landscape distribution where visibility index values are greater than 95% of the landscape, or in this case values greater than 0.77.

**Table 2.3 | Defensibility, visibility, and elevation indices of trench embankment sites in the Gulf of Georgia region.**

| Borden Number | Visibility | Elevation | Defensibility |
|---|---|---|---|
| DeRu-36 | 0.91 | 0.50 | 0.70 |
| DcRv-58 | 0.91 | 0.50 | 0.70 |
| DcRu-23 | 0.86 | 0.49 | 0.68 |
| DcRv-5 | 0.87 | 0.48 | 0.67 |
| DhRq-22 | 0.83 | 0.50 | 0.67 |
| DcRv-12 | 0.84 | 0.49 | 0.66 |
| DcRu-22 | 0.81 | 0.49 | 0.65 |
| DcRu-123 | 0.77 | 0.49 | 0.63 |
| DcRu-20 | 0.77 | 0.49 | 0.63 |
| DbRv-13 | 0.69 | 0.49 | 0.59 |
| DcRu-24 | 0.64 | 0.50 | 0.57 |
| DfRv-13 | 0.66 | 0.48 | 0.57 |
| DcRu-11 | 0.62 | 0.51 | 0.57 |
| DhRl-24 | 0.61 | 0.50 | 0.55 |
| DcRu-21 | 0.59 | 0.50 | 0.55 |
| DiRj-30 | 0.61 | 0.47 | 0.54 |
| DcRu-76 | 0.53 | 0.50 | 0.52 |
| DcRw-17 | 0.53 | 0.50 | 0.52 |
| DeRt-41 | 0.53 | 0.49 | 0.51 |
| DcRv-20 | 0.41 | 0.52 | 0.46 |
| DgRv-1 | 0.41 | 0.51 | 0.46 |
| DgRr-5 | 0.38 | 0.51 | 0.44 |
| DgRl-30 | 0.22 | 0.51 | 0.37 |

# CHAPTER THREE

# DYNAMIC LANDSCAPES

The analysis just presented focused on how archaeologists might infer behavior and meaning by treating certain attributes of landscapes as static, and describing the archaeological record in reference to them. The basic assumption is that over the spatiotemporal scales relevant to human behavior these attributes of the landscape do not change, or at least change very little. This assumption applies to surprisingly few landscape attributes. Neglecting for the moment anthropogenic changes to landscapes, our experience tells us that landscapes are changing *constantly*, at multiple time scales, and in ways that intuitively affect human behavior. Rivers and streams change course, forcing people to relocate their fields or homes; animal populations migrate in and out of regions, as do plant communities, affecting foraging patterns; fires reconfigure forestland and invite a succession of new plant life; and events like hurricanes and earthquakes can rapidly render landscapes unrecognizable. When these dynamic landscapes change in ways that affect human life-ways, we can expect that people will change their behavior accordingly.

Perhaps the most direct way in which humans experience dynamic landscapes is through weather and climate. Often, weather is a benign influence on human behavior. Seasonal weather patterns are used to keep time and guide subsistence behavior, such as taking advantage of monsoonal floods or migrating animals to seasonal pastures. Other climate and weather changes can be quite disruptive indeed. Extreme weather events can occur at momentary timescales (e.g., tornadoes, floods, and wind storms) or at seasonal, decadal, and centennial scales (droughts, and climate anomalies such as the Medieval Warm Period and Little Ice Age). Based on the frequency and intensity of these events, human populations will be more or less effective at responding adaptively.

Agriculturalists are particularly sensitive to climate changes that directly affect the productivity of the crops upon which they subsist. In semi-arid regions like the southwestern United States—areas marginal for agriculture—small weather fluctuations can mean the difference between crop booms and busts. If archaeologists aim to understand potentially adaptive responses to risk and abundance on these landscapes, we must first strive to understand their agronomically salient dynamics. This requires modeling climate at spatiotemporal scales relevant to human behavior.

In this paper—*A 2000-year reconstruction of the rain-fed maize agricultural niche in the US Southwest* (Bocinsky and Kohler 2014a)—my coauthor and I focus on these dynamic weather landscapes. We address the need for high resolution climate reconstructions by developing a new method based on CAR regression (Zuber and Strimmer 2011). We use this method to generate ~800 m resolution reconstructions across two large study areas in the US Southwest from AD 1–2000. We use tree-ring chronologies to calibrate our reconstructions, and thus are able to achieve annual-level (and in some cases, seasonal-level) temporal reconstructions. In the supplementary information to this paper, we demonstrate that our reconstructions meet or exceed the prediction skill of other leading climate-field methods, including that employed to construct the North American Drought Atlas (Cook et al. 2014, 1999).

As archaeologists, we are particularly interested in how changing climates influenced human societies in the past. Therefore, we recast our climate reconstructions into the distribution of the growing niche for rain-fed maize on our landscapes and use this reconstruction to help explain both the timing and the trajectory of the famous thirteenth-century Pueblo migration. It is essential—in an era of dramatically shifting climate—to understand the ways in which people in the past adapted to climate change. One potential conclusion from our study is that humans, like other animals, will tend to prefer invading niches that are appropriate to their current behavior over actually changing that behavior. The Ancestral Pueblo people, when choosing where to settle in the Northern Rio Grande region of modern day New Mexico, settled on the Pajarito Plateau, the best place for doing the type of rain-red maize agriculture to which they had become accustomed.

One thing this study does *not* do is consider land use and landscape change from cultivation, and feedbacks these changes might have on local, regional, and perhaps even global climate patterns. Ancestral Pueblo farmers likely dramatically transformed the landscapes upon which they made a living, by clearing (and possibly burning; Herring et al. 2014:860) forests and degrading soils through over-cultivation (Johnson and Kohler 2012; Kohler 2012b). Understanding the impact of these transformations will be fertile ground for future research.

# A 2000-year reconstruction of the rain-fed maize agricultural niche in the US Southwest

R. Kyle Bocinsky & Timothy A. Kohler

## Abstract

Humans experience, adapt to, and influence climate at local scales. Paleoclimate research however tends to focus on continental, hemispheric, or global scales, making it difficult for archaeologists and paleoecologists to study local effects. Here, we introduce a method for high-frequency, local climate-field reconstruction from tree-rings. We reconstruct the rain-fed maize agricultural niche in two regions of the southwestern United States with dense populations of prehispanic farmers. Niche size and stability are highly variable within and between the regions. Prehispanic rain-fed maize farmers tended to live in agricultural refugia—areas most reliably in the niche. The timing and trajectory of the famous thirteenth-century Pueblo migration can be understood in terms of relative niche size and stability. Local reconstructions like these illuminate the spectrum of strategies past humans used to adapt to climate change by recasting climate into the distributions of resources on which they depended.

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Humans experience, adapt to, and influence climate at local scales. Recent paleoclimate research however tends to focus on continental, hemispheric, or global scales, making it difficult for archaeologists and paleoecologists to study local effects of past climate change. Furthermore, studies that have attempted high-resolution climate-field reconstruction (Cook et al. 2014, 1999, 2004; Tingley and Huybers 2010) have generally failed to recast climate into the distributions of resources on which humans depend, such as viable land for agriculture and crop productivity.

Regional- to local-scale paleoclimate reconstructions from tree-ring chronologies typically have been generated using one of two basic methods. Well-known regional (Williams et al. 2013) and climate field Cook et al. (2014, 1999, 2004) reconstructions of drought employ principal component regression (PCR) in an effort to calibrate the joint variance in a set of tree-ring (t-r) chronologies to a given regional or locally interpolated climate signal. In contrast, researchers primarily interested in local climate tend to select one or a few local t-r chronologies for calibration to a local climate signal, either using OLS linear regression (Stahle et al. 2009) or, less commonly, mean-variance matching (Towner and Salzer 2013) or principal component regression on a limited selection of chronologies (Kohler 2012b; Van West 1994). Researchers have long noted that certain species of trees in particular ecological settings are better or worse at predicting a given climate signal (LaMarche 1974), and many methods employ expert knowledge about these proxy/climate relationships (Salzer and Kipfmueller 2005) or else screen potential t-r chronologies using basic correlation statistics (Cook et al. 1999; Franke et al. 2013). State-of-the-art, compute-intensive methods such as BARCAST (Tingley and Huybers 2010) approach paleoclimate reconstruction in a fundamentally different and promising way—by simultaneously endogenizing the spatiotemporal covariance structure of both empirical climate measurements and climate proxy data—but to our knowledge these have not yet been attempted on very high-resolution ($<$ 1 km) spatiotemporal fields.

Both the data-laden principal components techniques and the more selective manual methods illustrate the careful balancing act undertaken by those attempting local paleoclimate reconstruction: We know that such reconstructions require focus on local conditions (which we expect will be proxied by local t-r chronologies), but also we recognize that our paleoclimate inferences are strengthened when patterns are robust across available chronologies. We seek a method that not only emulates well-informed manual selection of t-r chronologies for local climate reconstruction, but also automates the discovery of proxies causally linked to the climate signal which may not have been considered by the researcher. For example, climate teleconnections may make non-local chronologies good proxies for local conditions in some circumstances.

Here, we address both the need for improved climate-field reconstruction methods and the need for reconstructions relevant to human experience and adaptation. We generate 2000-year reconstructions of net water-year precipitation and accumulated heat over the growing season for two large and environmentally heterogeneous areas (the "VEPIIN" and "VEPIIS" study areas; Fig. 3.1) in the southwestern United States (SWUS) with very dense populations of prehispanic maize (*Zea mays*) farmers. We then recast these reconstructions as estimates of the rain-fed maize growing niche across the regions. By doing so, we are able to assess the degree to which significant cultural transitions in the Ancestral Pueblo SWUS can be explained by changes in the spatial distribution of the niche. We find niche size and stability to be highly variable within and between the regions. Prehispanic rain-fed maize farmers in both regions tended to live in agricultural refugia—areas most reliably in the rain-fed agricultural niche. Also, both the timing and trajectory of the famous thirteenth-century Pueblo migration in the region can be understood in terms of the relative niche size and stability in the two regions. Local reconstructions like those presented here illuminate the spectrum of strategies past humans and other organisms used to adapt to climate change by recasting climate into the distributions of resources on which species depend.

### Results

**Climate-field reconstruction** We employ a variable ranking and selection method developed in quantitative genomics called CAR (Correlation-Adjusted corRelation) regression (Zuber and Strimmer 2011). The CAR method was developed as a robust variable ranking method for ill-posed inference problems where the number of variables is much larger than the number of observations.

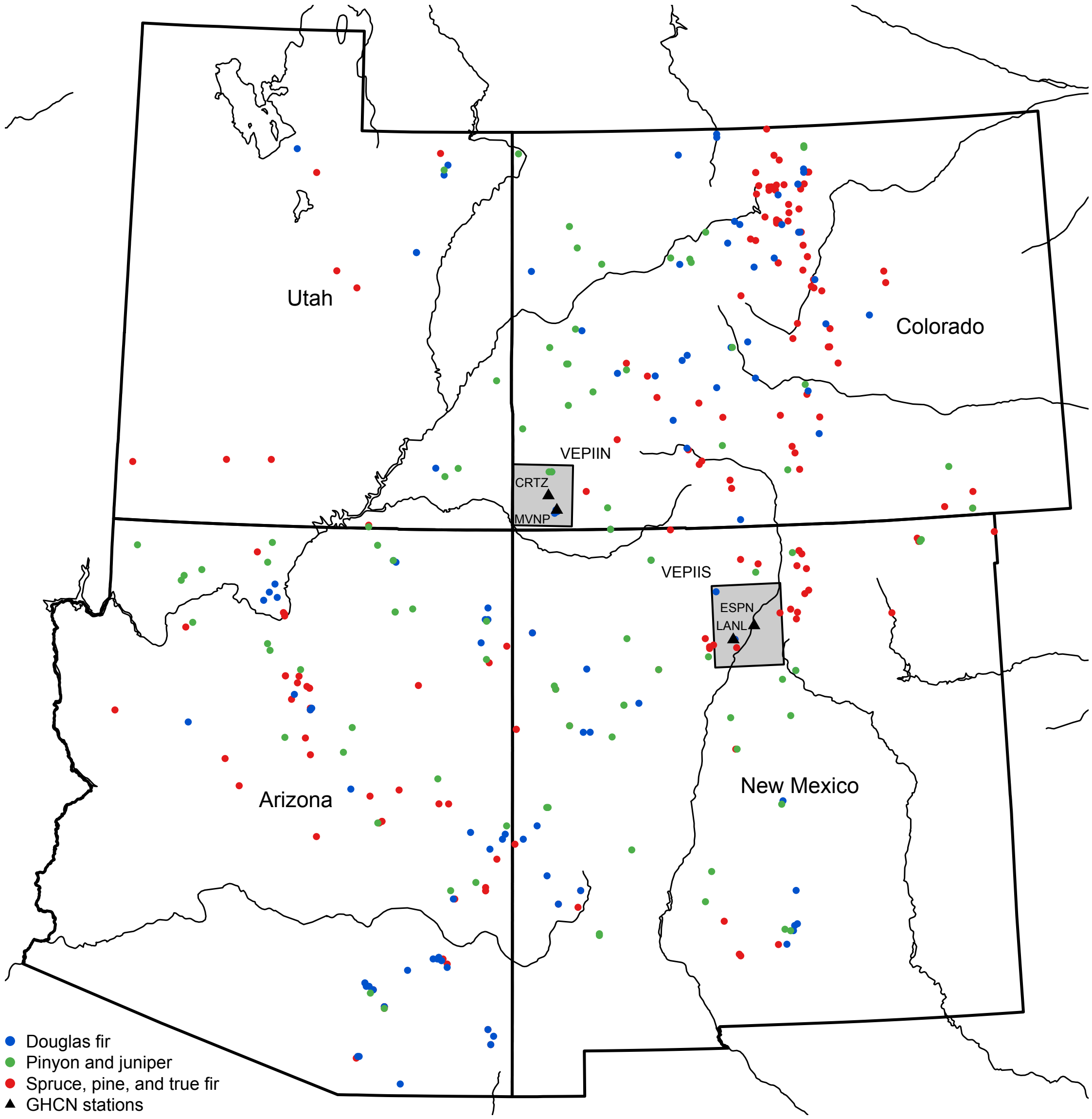


**Figure 3.1 | The Four Corners region of the southwestern United States.** Tree-ring chronologies are colored dots, our two study areas are shown as gray rectangles, and weather stations used for model comparison (Supplementary Methods) are shown as black triangles. MVNP, Mesa Verde National Park, Colorado; CRTZ, Cortez, Colorado; LANL, Los Alamos National Laboratory, New Mexico; ESPN, Española, New Mexico.

Such high-dimensional problems are typical in paleoclimate reconstruction, where the number of available annually resolved climate proxies continues to rapidly expand, but observed climate data are generally limited to the last century or so. The CAR method first orthagonalizes the t-r chronologies over a historic calibration period using the Mahalanobis transform (Zuber and

Strimmer 2011). It then ranks the orthogonal chronologies by their squared correlations with the observed climate signal. Ranked chronologies are then added step-wise into a linear regression until cross-validated root mean squared prediction error (RMSE) is minimized. The CAR method is similar to principal components techniques. Accounting for covariance between predictors (in this case, t-r chronologies), the method determines which linear combination of chronologies best predicts a given climate signal. Unlike PCA, though, the CAR method explicitly ranks and selects chronologies based on the mutual information shared between the t-r chronologies and the climate signal. Using an associated shrinkage regression technique (Opgen-Rhein and Strimmer 2007; Schäfer and Strimmer 2005), we then generate unique and highly accurate reconstructions across a spatiotemporal climate field.

We generate spatiotemporal reconstructions by first performing independent CAR reconstructions for each of 17,554 grid cells in our two study areas (see Methods). Starting with the calibration period (1924–1983), for each cell and each climate signal we use CAR ranking to select the best linear combination of t-r chronologies, then generate a retrodiction using those chronologies extending back in time as far as their joint duration allows. At that point, we calibrate a new model using the remaining available chronologies. We repeat this process until the retrodiction reaches the date of initial interest, AD 1. Finally, to remove spatial artifacts inherent to the discrete nature of the CAR proxy selection procedure, the reconstructions are spatially standardized such that for any given year all cells in a study area are using the union of all the selected sets of t-r chronologies in their reconstructions.

Fig. 3.2 presents a summary of the spatiotemporal paleoclimate reconstructions as the cumulative proportion of the landscape at different climate values, through time; Supplementary Movie 1 presents the actual climate field reconstructions. As is typical of climate in the SWUS, summer precipitation and growing-season GDDs are negatively correlated at most locations. GDD shows less year-to-year variation than does precipitation. Precipitation reconstructions for both study areas show general agreement with other regional reconstructions of drought (Benson and Berry 2009; Cook et al. 2014); major pan-regional drought episodes occurred in the first half of the first century AD, the mid-AD 100s, mid-AD 700s, late AD 1200s, and late AD 1500s. Several major droughts affect the VEPIIS area more strongly than the VEPIIN area, including those around AD 1000, the mid-AD 1100s, and the late AD 1400s.

**Niche reconstruction** Climate change affects human behavior in many ways, but in agrarian societies such as the prehispanic Pueblo peoples inhabiting these two study areas—who derived ~70% of their dietary biomass from maize (Coltrain and Janetski 2013)—its most direct influence is on agricultural productivity. Therefore we convert our paleoclimate reconstructions into estimates of the spatial extent of the rain-fed maize agricultural niche within each landscape. We model agricultural niche—as opposed to modeling productivity directly for a particular landrace of maize (Kohler 2012b; Van West 1994)—as an acknowledgement of the phenotypic plasticity of maize that allows for rapid adaptation to changing local conditions (Butler and Huybers 2013). We seek to answer the question: Given ample time and human effort, where on the landscape could we reasonably expect locally adapted maize landraces to flourish? Accordingly, we threshold the niche at the 30-cm isohyet for the net water-year precipitation reconstruction, which Shaw (1988) and others (Benson 2011a) take as the lower bound for rain-fed maize cultivation; and we threshold the niche at 1800 GDD (measured in Fahrenheit GDDs) for the growing-season GDD reconstruction, following experimental estimates for ancestral landraces (Adams et al. 2006; Bellorado 2010) and previous reconstructions (Benson 2011a). For each year, we define the rain-fed maize agricultural niche as the portion of the landscape that satisfies both of these thresholds (Fig. 3.3).

Niche size and stability are highly variable within and between the two regions (Figs. 3.2 and 3.3). The niche reconstructions are primarily driven by high-amplitude changes in the size of the precipitation niche in both areas, and although cold periods do impact higher-elevation locations they usually co-occur with an increase in precipitation across the landscape (Supplementary Movie 1). The proportion of the landscape available for rain-fed maize cultivation is generally much less in the VEPIIS study area than in the VEPIIN, primarily due to elevation differences in the two regions.

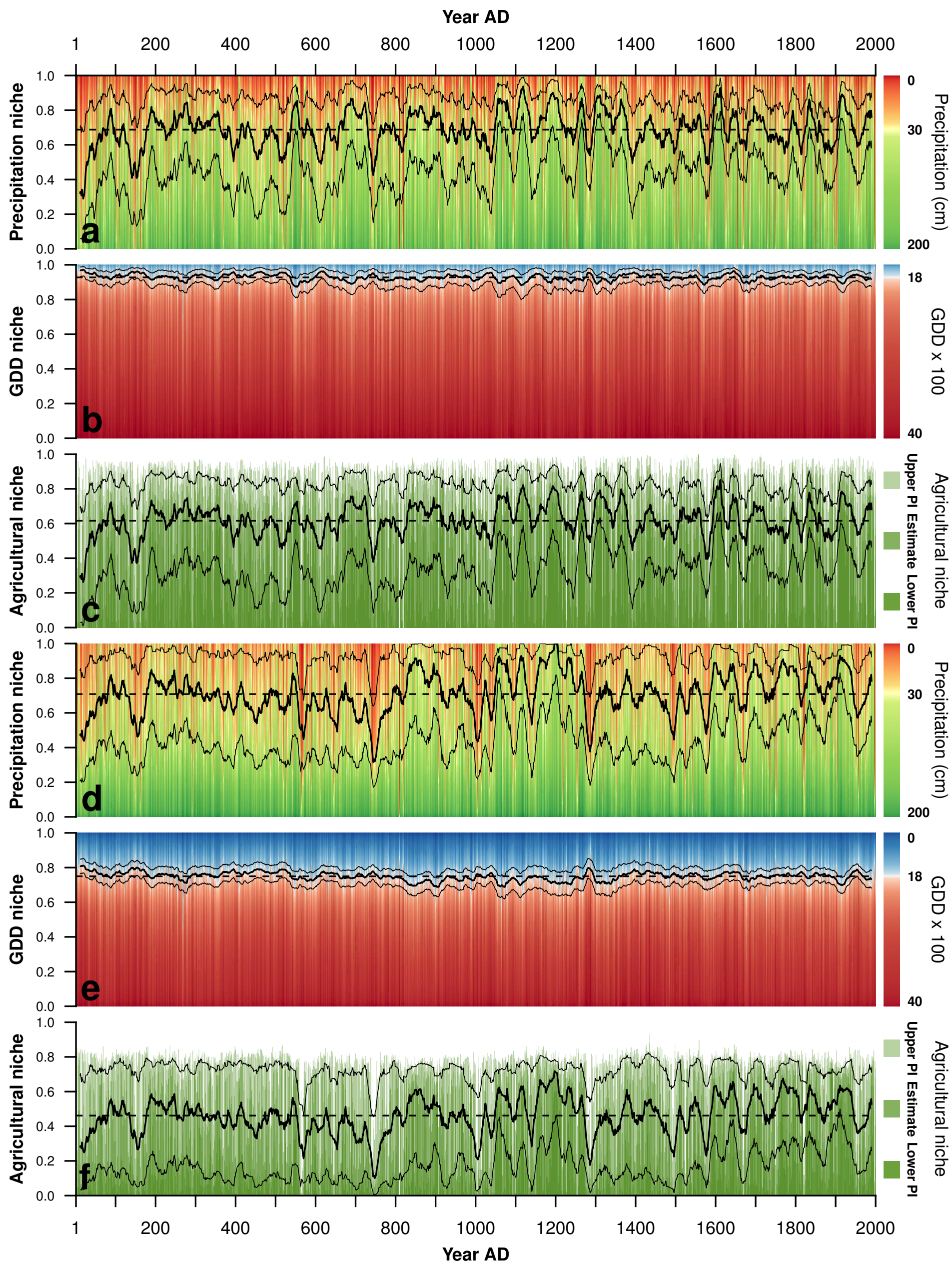


**Figure 3.2 | The rain-fed maize agricultural niche through time.** Each year is represented by the cumulative proportion of the landscape at different values, represented by color gradients defined in the right margin. The color gradient of each panel breaks at the extent of that signal's agricultural niche. The thick solid line in each panel is a 21 year running mean of the estimated proportion in each niche; the thin solid lines are the upper and lower prediction intervals (see Methods); the dashed line is the mean estimated proportion in the niche over the entire reconstruction. **a**, VEPIIN net water-year precipitation, green portion in niche. **b**, VEPIIN growing-season growing degree days (GDDs), red portion in niche. **c**, VEPIIN rain-fed maize agricultural niche, light green in niche upper PI, medium green in niche estimate, dark green in niche lower PI. **d–f**, The same as **a–c** for the VEPIIS study area.

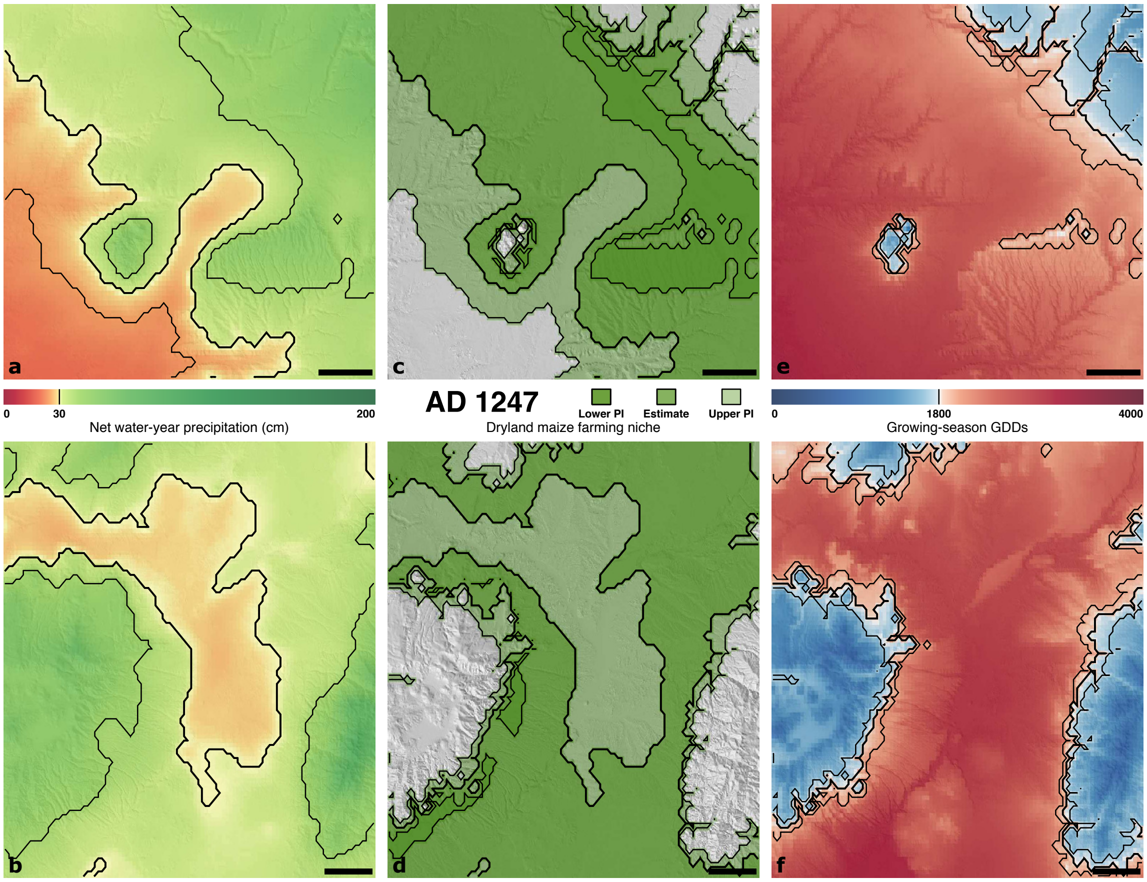


**Figure 3.3 | The rain-fed maize agricultural niche in AD 1247.** The upper panels represent the VEPIIN study area; the lower panels represent VEPIIS. Each panel's color gradient breaks at the extent of that signal's agricultural niche. Thin black lines are at the upper and lower prediction intervals. Scale bar: 10 km. **a,b**, Net water-year precipitation, green portion in niche. **e,f**, Growing-season GDDs, red portion in niche. **c,d**, The rain-fed maize agricultural niche, light green portion in upper PI, medium green portion in niche, dark green portion in lower PI. Supplementary Movie 1 presents the full 2000-year reconstruction.

**Ancestral Pueblo demographic transitions** We can more directly compare the two regions by analyzing the deviation of each niche-series from its 2000-year mean and thus assessing push- and pull-factors that might have stimulated population flows between the regions (Fig. 3.4). Here, we focus on the period salient to the Prehispanic Pueblos (AD 500–AD 1500). The VEPIIN study area outperforms the VEPIIS study area for much of the initial settlement of maize agriculturalists in VEPIIN (AD 600–AD 750; Ortman et al. 2012). The pan-regional drought in the mid-AD 700s is substantially worse and occurs over a longer duration in the southern area than in the north, and may partially explain the relatively late expansion of maize farmers in the northern Rio Grande, which accelerates after AD 750 (Post 2013). In contrast, the VEPIIS study area outperforms the VEPIIN area from just after the mid-AD 1100s drought through the mid-AD 1200s. During this same time Pueblo emigration began from the northern SWUS in general, and likely from VEPIIN in particular (Duff and Wilshusen 2000), with the northern Rio Grande one of the most important destinations (Ortman 2012).

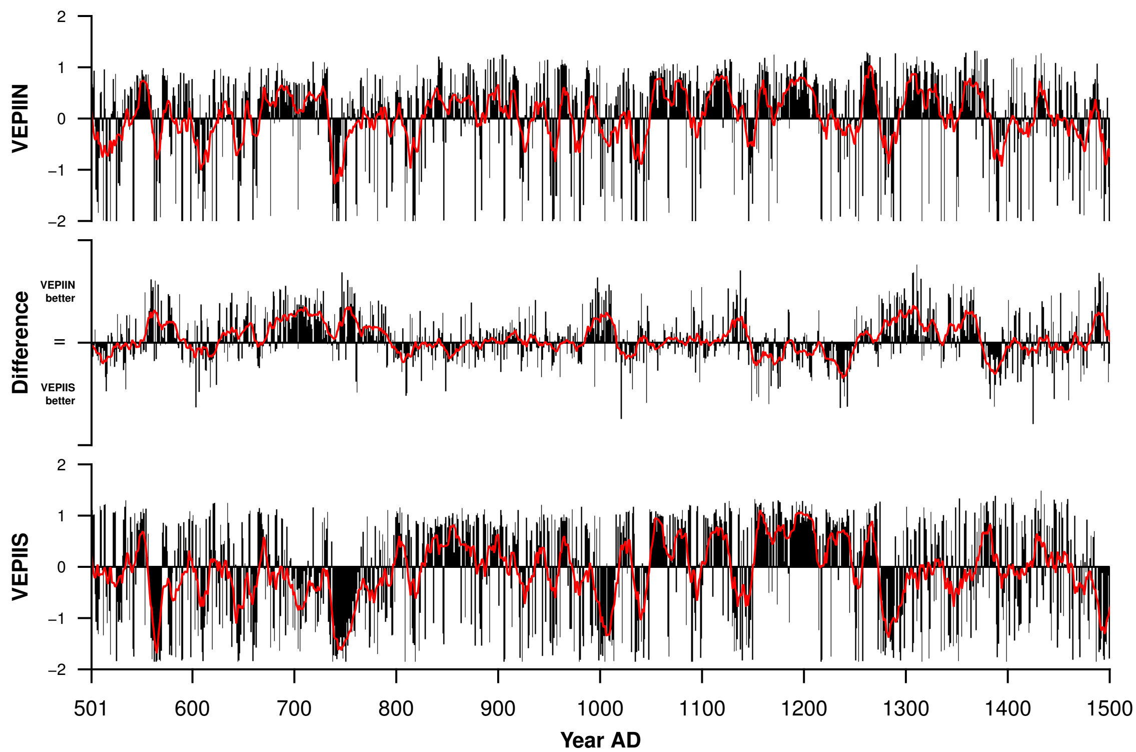


**Figure 3.4 | The difference in niche size between the study areas.** The top and bottom plots present the standardized proportion of each landscape in the niche and the center plot presents the difference between the two study areas during AD 501–AD 1500. The red line in each panel is a 11 year running mean of the series. The center plot takes the difference of the upper and lower plots.

**Locating Ancestral Pueblo agricultural refugia** Spatial analysis of niche stability reveals the location of refugia during agricultural downturns (Fig. 3.5). In the VEPIIN study area, much of the Mesa Verde cuesta is in the niche more than 90% of years over the last two millennia, and the northeast half of the Montezuma Valley—the region of modern rain-fed bean farming—is in the niche more than 80% of years. The region of the McElmo Dome surrounding Sand Canyon and Goodman Point, two of the largest villages during the late AD 1200s (Glowacki and Ortman 2012), is also in the niche more than 80% of years. In the VEPIIS study area, much of the Pajarito Plateau on the eastern flanks of the Jemez mountains is in the niche more than 90% of years. This portion of the VEPIIS study area experienced more immigration in the AD 1200s and early AD 1300s than any other part of VEPIIS (Ortman 2012). Rain-fed maize agriculturalists apparently settled first on the portion of the landscape most suitable to rain-fed maize agriculture; only later did they start developing and adopting the water management technology and mobility strategies required to farm elsewhere in the region (Duwe and Anschuetz 2013; Towner and Salzer 2013). Our reconstruction of the maize niche in VEPIIS differs from other reconstructions of precipitation for northern Rio Grande (Cordell et al. 2007) in that ours identifies the late 1200s as a period of significant drought in the region. As a refugium in times of drought, the Pajarito Plateau would therefore have been particularly attractive for people arriving from the north at that time.

**Discussion**

The reconstruction presented here suggests where Pueblo people may have been able to practice rain-fed maize agriculture, but not how productive their efforts may have been. More nuanced analyses of CAR-based paleoclimate reconstructions—such as cropping system models accounting for adaptation of maize landraces to local conditions (Butler and Huybers 2013) and integrating soils data (Benson 2011a) and killing degree days (Butler and Huybers 2013)—will improve our understanding of how humans and their domesticates adapted to changing climate conditions. Our paleoclimate reconstructions can also be improved by better accounting for low-frequency temperature change, perhaps via a regionalized application of wavelet modulation with pollen and speleothem data (Moberg et al. 2005; Viau et al. 2006). Temperature anomalies of the scale of the Medieval Warm Period and Little Ice Age in North America (each within ± one degree Celsius from the long-term average; Viau et al. 2006) may have had a substantial impact on GDD in our region. A one-degree-Celsius decrease in average growing-season temperature would result in an approximately 275 GDD decrease (in Fahrenheit GDDs), effectively shutting down high-elevation

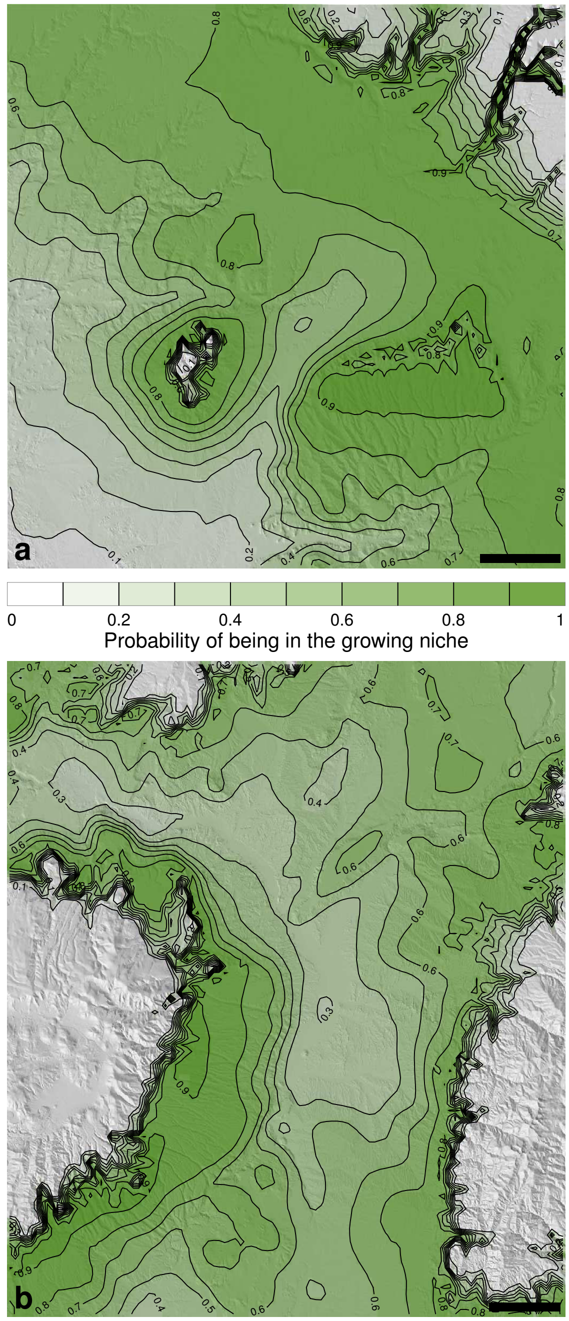


**Figure 3.5 | Ancestral Pueblo agricultural refugia.** These maps show the proportion of years (AD 1–2000) each location is in the rain-fed maize agricultural niche. More shaded areas are in the niche more often. In the VEPIIN study area (**a**), the Mesa Verde cuesta (lower-right quadrant) is in the niche more than 90% of the years in the last two millennia. In the VEPIIS area (**b**), portions of the Pajarito Plateau (lower-left quadrant) are also in the niche more than 90% of the years. Scale bar: 10 km.

maize production in areas like the Mesa Verde cuesta. Local, low-frequency temperature reconstructions have not yet been attempted at the scale of our subregions, however, so it is an open question as to whether the effects of regional climate anomalies were consistent across regions. From our high-frequency results, neither of these major climate anomalies appears to have had a substantial impact on precipitation.

Compute-intensive methods like the one presented here may be used to discover new ecological knowledge, both about landscapes themselves and about causal connections between climate and climate proxies. A complete exploration of the ecological ramifications of our paleoenvironmental reconstruction is beyond the scope of this study, but several initial observations may be made. Water-year precipitation in VEPIIN is best reconstructed using pinyon, juniper, and Douglas fir chronologies from the western slope of the Colorado Rocky Mountains. In contrast, the precipitation system in VEPIIS is dominated by the summer-arriving North American Monsoon which is connected to precipitation intensity in southern Arizona and throughout southern and central New Mexico (Adams and Comrie 1997; Cordell et al. 2001; Dean 1988). The majority of chronologies selected for precipitation reconstruction in VEPIIS are low- and mid-elevation chronologies from southern Arizona and New Mexico. Tree-ring chronologies selected for growing-season GDD reconstructions are much more similar between the landscapes; chronologies are generally selected from among higher-elevation spruces, pines, true firs, and Douglas firs, and the chronologies selected are often more distant than for precipitation. Future research might focus on identifying ecological zones by their common selected proxies, and the temporal consistency of relationships between proxies.

The archaeological and paleoecological record provide important information about how humans and other organisms have adapted to past climate change, and how they might adapt in the future. Regardless of contemporary technological innovations, humans and other species struggle to adapt to climate change on the time scales and amplitudes present in both our reconstructions and contemporary projections. The rate and scale of contemporary climate change is unprecedented at a hemispheric level; however, past agrarian populations have had to adapt to rapid, dramatic changes in their local environments. Archaeological knowledge—analyzed in the context of reconstructed environments—is essential in understanding the dynamics and operation of coupled human and natural systems (Kintigh et al. 2014b). The experience in the Ancestral Pueblo SWUS suggests that, when faced with changing environments, humans will first seek alternative habitats that do not require them to change behavior—such as the Pajarito Plateau—and only once those are unavailable will they develop or adopt alternative strategies. Generalizing to modern times, when confronted with rapidly changing environmental conditions, we should (1) identify those environmental niches that will remain open or even improve due to rapid climate change, and (2) identify regions where contemporary strategies simply will not work given climate predictions, so that alternative strategies may be more rapidly adopted. Assessing either of these requires accurate, precise, and local reconstructions of how resource distributions change in response to climate change.

## Methods

**Study areas** The study areas in this analysis are drawn from the Village Ecodynamics Project (VEP), a research initiative investigating long-term relationships between humans and the environment in the SWUSKohler et al. (2012a); Kohler and Varien (2012b) (Fig. 3.1). The first study area (VEPIIN) is a 4600 $km^2$ region in southwestern Colorado encompassing Mesa Verde National Park, Canyons of the Ancients National Monument, the Montezuma Valley, portions of the Ute and La Plata piedmonts, and the contemporary towns of Cortez, Dolores, and Mancos, Colorado. The area is defined in NAD83, Zone 12 Universal Transverse Mercator (UTM) grid units; it extends from 672800 m E to 740000 m E, and 4102000 m N to 4170000 m N. The second area (VEPIIS) is a 6955 $km^2$ region in north-central New Mexico encompassing Pajarito Plateau, Bandelier National Monument, the Rio Grande and Chama river valleys, and the contemporary cities of Santa Fe, Los Alamos, and Española, New Mexico. It extends from 359200 m E to 435800 m E, and 3939600 m N to 4030400 m N in NAD83, Zone 13 UTM coordinates. The climate reconstructions presented here were calculated on slightly larger areas than these study regions to account for spatial projection and resolution differences between the VEP regions and the PRISM interpolated climate data presented below.

**Tree-ring chronologies** We used publicly available, standardized, pre-processed tree-ring chronologies in the International Tree-Ring Data Bank (ITRDB) as of January 2014 (i.e., those without a trailing "A" or "R" in their file name; Contributors of the International Tree-Ring Data Bank 2014; Grissino-Mayer and Fritts 1997). We downloaded all available chronologies and imported *.crn files into *R* using the *dplR* library (Bunn et al. 2014). We only retained chronologies that are from the US states of Arizona, Colorado, New Mexico, and Utah, and that fully overlapped our calibration/validation period of 1924–1983 ($n$ = 205); many long chronologies in the Southwest US only extend to the early 1980s. Fig. 3.1 shows the location and species information for the chronologies used in this study, and Fig. 3.6 shows the number of chronologies available through time. The length and availability of tree-ring chronologies is quite variable across records and species. Inclusion of chronologies updated more recently (but not yet in the ITRDB) would undoubtedly improve the skill of these reconstructions.

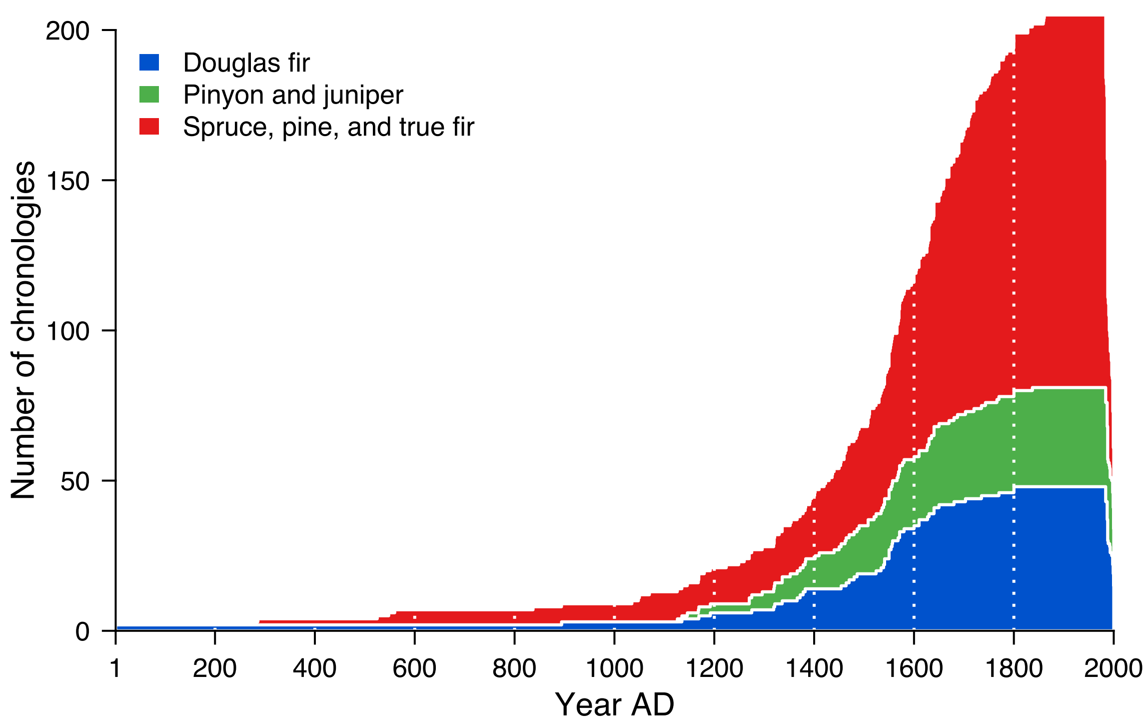


**Figure 3.6 | Tree-ring chronology availability.** Colors represent species classification. During the 1924–1983 calibration period 205 chronologies available.

**Historic climate data** We use the ~800 m-resolution Parameter-elevation Relationships on Independent Slopes Model (PRISM) interpolated monthly data grids (the "LT81m" dataset) available from the Oregon State University (Daly et al. 2008; PRISM Climate Group 2014) to calibrate annual reconstructions of water-year precipitation and growing-season growing degree days (GDD). We calibrate our reconstruction to years 1924–1983. We follow Stahle and colleagues (2009) in defining the water-year in the US Southwest as the previous October–current September, and we define the growing season as May–September of the current year. Monthly precipitation totals were summed over the water year. Growing season GDD was estimated by first calculating monthly GDD from monthly mean maximum and minimum temperatures using Equation 3.1 (below), summed over the number of days for each month. May–September monthly GDD estimates were then summed to estimate net GDD for the growing season. All GDD results reported here are in Fahrenheit heat units; GDDs were converted from Celcius heat units to Fahrenheit heat units by multiplying by a factor of 1.8.

The equation for daily GDD is:

$$\text{GDD} = \frac{T_{\text{MAX}} + T_{\text{MIN}}}{2} - T_{\text{BASE}} \tag{3.1}$$

where $T_{\text{MAX}}$ is the maximum daily temperature, $T_{\text{MIN}}$ is the minimum daily temperature, and $T_{\text{BASE}}$ is the temperature below which plant growth ceases, which we take to be 10°C for maize.

Here, we use a series of corrections to equation (3.1) typically applied for calculating maize GDD (McMaster and Wilhelm 1997), which down-corrects $T_{\text{MAX}}$ and $T_{\text{MIN}}$ to an upper threshold ($T_{\text{UT}}$, here 30°C) above which corn growth does not appreciably increase, and up-corrects $T_{\text{MAX}}$ and $T_{\text{MIN}}$ if they fall below $T_{\text{BASE}}$ (here 10°C). To summarize:

$$\text{if } T_{MAX} > T_{UT}, \quad T_{MAX} = T_{UT}$$

$$\text{if } T_{MIN} > T_{UT}, \quad T_{MIN} = T_{UT}$$

$$\text{if } T_{MAX} < T_{BASE}, \quad T_{MAX} = T_{BASE}$$

$$\text{if } T_{MIN} < T_{BASE}, \quad T_{MIN} = T_{BASE}$$

Net water-year precipitation and GDD grids were calculated for each of our two study areas. The VEPIIN study area includes 7144 grid cells at 30 arc-second (~800 m) resolution. The VEPIIS study area includes 10,400 cells at the same resolution.

Mean temperature in the Northern Hemisphere has trended dramatically upward over the 20th century, potentially confounding reconstructions due to non-stationarity in the PRISM-based GDD calibration data (Rutherford et al. 2003). We therefore tested whether these data show similar trends. Local to our study areas, the seasonal PRISM data for GDD are second-order stationary over the 1924–1983 period (although GDD trend higher post-1983). We performed the Priestley-Subba Rao (PSR) test of non-stationarity (Constantine and Percival 2014; Priestley and Rao 1969) on each of the grid cells in each landscape (Supplementary Fig. 1). None of the cells in either landscape have PSR p-values low-enough to reject the null hypothesis of stationarity at the $p < 0.05$ level. This does not remove the possibility that past climate was non-stationary. Rutherford and colleagues found that reconstructions of non-stationary (forced) climate using a stationary calibration signal tend to underestimate reconstructed trends (Rutherford et al. 2003). We attempt to compensate for this by performing mean and variance matching over the calibration period (below); however, our reconstructions should be considered conservative estimates of past low-frequency climate variability.

**Local reconstruction overview** For each location (cell) in the PRISM data and each climate signal (water-year precipitation and growing-season GDD), we de-correlate the matrix of tree-ring chronologies by applying the Mahalanobis transform, using a Stein-type shrinkage approximation of the covariance matrix following (Zuber and Strimmer 2011, 2014); generate estimates of the marginal correlations between the training data and each decorrelated tree-ring chronology (the CAR scores); rank the tree-ring chronologies by their squared CAR scores; select the optimal set of tree-ring chronologies for use in a linear model by minimizing average root mean squared prediction error over a three-fold consecutive cross-validation, and estimate linear regression coefficients; standardize the set of chronologies to the union of the selected chronologies across all cells in each study area; retrodict the signal over the joint duration of the selected tree-ring chronologies; transform and scale the retrodiction such that the mean and variance of the retrodiction over the calibration period matches the mean and variance of the climate signal over the same period; repeat the preceding steps, going back through time as fewer tree-ring chronologies become available (see Fig. 3.6).

**Variable ranking by CAR score** The CAR score is defined as the correlation between the outcome variable (in this case, water-year precipitation or growing-season GDD) and the Mahalanobis de-correlated predictors (the tree-ring chronologies; Zuber and Strimmer 2011:p. 11). The Mahalanobis transform is similar to other matrix orthogonalization methods, however Zuber and Strimmer note that it is particularly desirable for variable selection in that it generates orthogonal variables that are nearest to and informative of the original standardized variables (2011:pp. 9–10). CAR scores reduce to raw correlations between the outcome and predictor variables as correlation among predictor variables vanishes (2011:p. 8). Furthermore, predictors that are highly correlated will have nearly identical CAR scores, leading to their co-selection (or co-rejection) when CAR scores are used in variable ranking and selection (2011:p. 13).

Here, we calculated CAR scores using the *carscore* method in the *care* package for *R*, developed by Zuber and Strimmer (Zuber and Strimmer 2014). Because the number of available tree-ring chronologies (predictor variables) is larger than the number of observations (years in our calibration period, 1924–1983), we use estimate the correlation and covariance matrices using Stein-type shrinkage estimators (Schäfer and Strimmer 2005; Zuber and Strimmer 2014). The shrinkage intensity variables $\lambda_c$ and $\lambda_v$—the shrinkage intensities of the correlation and covariance matrices, respectively—were estimated for each cell using the complete set of 205 available tree-ring chronologies. Once CAR scores are calculated for each cell and each climate signal, tree-ring chronologies are ranked by their squared CAR scores.

**Variable selection by minimized RMSE** There are many ways one could select variables once they are ranked, including removing null variables using an adaptive threshold (Zuber et al. 2012), optimized selection using compute-intensive cross-validation, or classic model selection using information criteria such as Akaike's Information Criterion (*AIC*; Akaike 1974). Here, we follow the suggestion of Zuber and Strimmer (2011) and use three-fold consecutive cross-validation over the 1924–1983 period to choose the set of tree-ring chronologies that minimizes root mean squared prediction error, as well as to provide estimates of prediction error along our reconstructions.

**Spatial artifacts and chronology standardization** The CAR reconstruction method—like all tree-ring-based paleoclimate reconstructions—assumes covariance relationships between the tree-ring chronologies in the calibration period remain consistent as the chronologies extend back in time. This "uniformitarian principle" underlies all paleoclimate proxy research. Random signal noise in each tree-ring chronology causes these relationships to weaken at short time scales. This reality has required a variety of complex accommodations by paleoclimate researchers, from standardization using principal components as in the North American Drought Atlas (Cook et al. 2014, 1999, 2004) to explicitly accounting for inconsistencies in both the proxy and instrumental data using compute-intensive estimation of the spatial covariance and temporal evolution of the climate field in a hierarchical Bayesian framework (Tingley and Huybers 2010).

Our reconstructions—when done with unique spatiotemporal combinations of locally CAR-selected chronologies—are affected by these issues as well. Locations on the landscape that are proximate to one another tend to select the same chronologies, and thus consistent spatial covariance between the locations is maintained. However, sometimes adjacent grid locations select a slightly different set of chronologies. When the covariance between the uniquely selected sets of chronologies breaks down, spatial artifacts occur such that usually smooth temperature and precipitation gradients become coarse and step-like. Panels (a) and (b) in Fig. 3.7 shows this effect for the net water-year precipitation reconstruction in the VEPIIN and VEPIIS study areas respectively, in year AD 1400. Spatial artifacts tend to be less extreme in the GDD reconstruction, as temperature is a far less local phenomenon than precipitation in our study areas. Still, such artifacts impact the size and extent of the maize growing niche reconstruction at annual timescales, and often lead to unlikely spatial configurations of the maize niche (though these artifacts generally disappear when the reconstruction is averaged over larger timescales).

In order to remove the visible spurious spatial artifacts prior to modeling the maize growing niche, we perform data standardization across both study areas on an annual basis. For each year (AD 1–2000), we first take the union of all sets of cell-wise selected tree-ring chronologies across the landscape. Doing this for each year creates a new sequence of selected chronologies that is the spatiotemporal union of each of the unique reconstructions. We then calibrate new sequences of shrinkage linear models for each cell on the landscape, using these union sets of t-r chronologies and the original shrinkage intensities calculated above. This smooths our spatiotemporal reconstructions at a slight loss to model performance across the landscapes. Reduction in model performance generally increases through time, as locations across the landscapes begin selecting a larger union set of t-r chronologies, thus slightly overfitting models across the landscape.

This solution—annual chronology standardization across each landscape by taking the union of selected proxy signals—is obviously somewhat ad hoc, and its negative impact on reconstruction skill will increase with the size or heterogeneity of the landscape. We offer it as a solution intermediate between the *a priori* selection of proxies common in spatial paleoclimate reconstruction today, and not correcting spatial artifacts at all.

**Shrinkage estimation of regression coefficients** Once the RMSE-optimized and annually unioned set of tree-ring chronologies has been selected, we calculate regression coefficients by least squares regression of climate signal in each cell on the selected tree-ring chronologies over

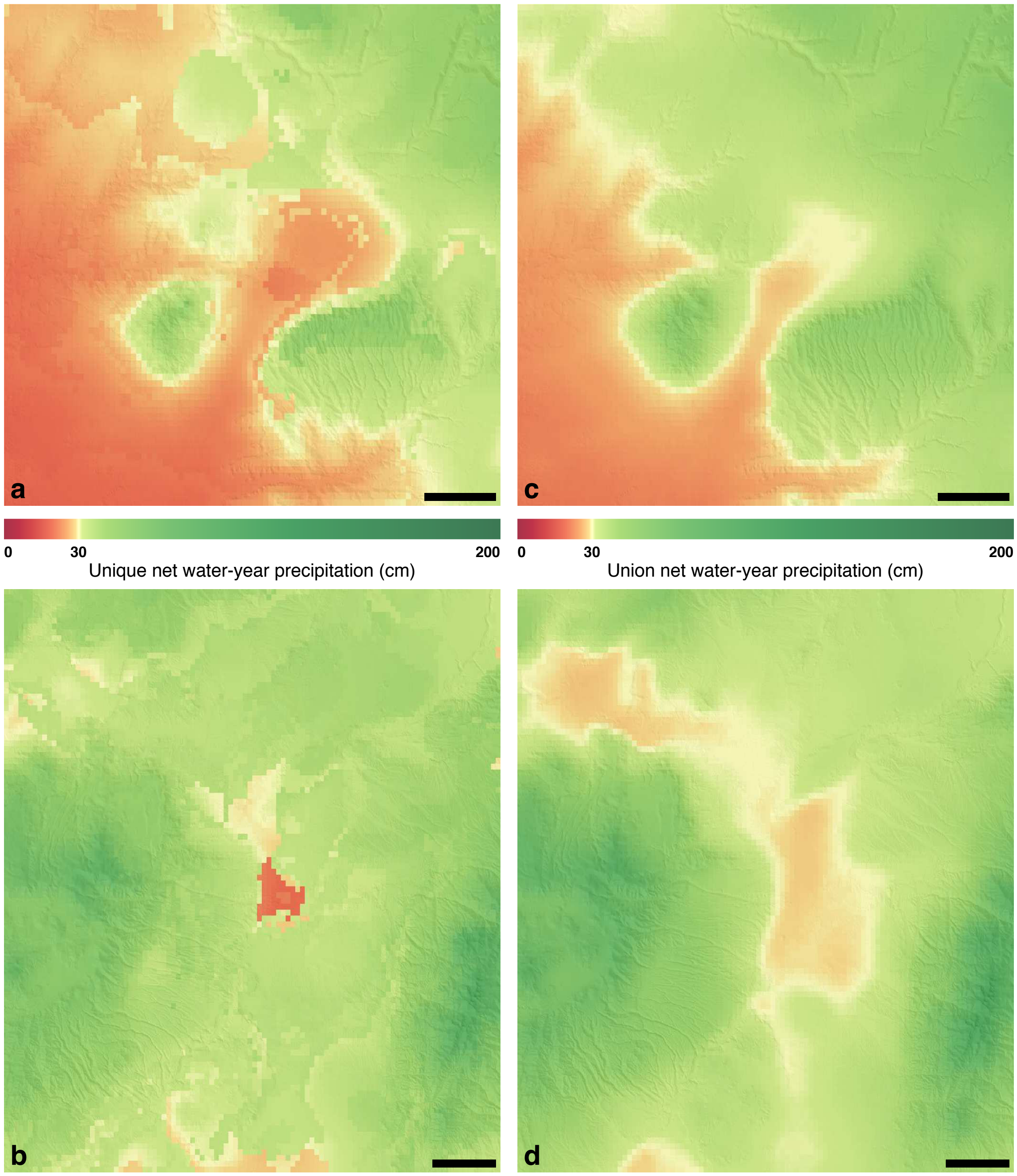


**Figure 3.7 | Spatial artifacts and chronology standardization.** These maps present spatial net water-year precipitation reconstructions in AD 1400 using cell-wise unique CAR selection (left panels) and the union of selected chronologies (right panels) across each study area. The cell-wise unique reconstructions show spatial artifacts due to inconsistencies between regional tree-ring chronologies. Using the union of all sets of selected tree rings ameliorates these inconsistencies, though at a slight loss of cell-wise model performance. Scale bar: 10 km. **a**, VEPIIN, unique reconstructions. **b**, VEPIIS, unique reconstructions. **c**, VEPIIN, union reconstructions. **d**, VEPIIS, union reconstructions.

the 1924–1983 period, again using the shrinkage estimates of the covariance and correlation matrices calculated previously (applying $\lambda_v$ and $\lambda_c$).

**Mean and variance matching over the calibration period** By design, prediction using multiple linear regression reduces the variance of a reconstructed signal to the proportion of the variance in the calibration signal explained by the predictors. This has the effect of shrinking the variance over the reconstruction and, in the case of climate reconstructions where the number of available predictor variables decreases as you go farther back in time, creates a reconstruction with [generally] monotonically increasing variance. To correct for this we transform and scale each reconstruction such that the mean and variance of the reconstruction over the calibration period matches the mean and variance of the calibration dataset. The transformation (mean-matching) and scaling (variance-matching) parameters are thus calculated only over the calibration period, then applied over the whole of the reconstruction.

Let $\mathbf{X_c}$ be the vector of calibration values over the calibration period, $\mathbf{X_r}$ be the vector of reconstructed values over the calibration period, $\mathbf{A_r}$ be the vector of all reconstructed values (of which $\mathbf{X_r}$ is a part), and $\mathbf{A_r^*}$ vector of all reconstructed values after mean and variance matching. Then,

$$\mathbf{A_r^*} = (\alpha \times \mathbf{A_r}) + \boldsymbol{\beta} \tag{3.2}$$

where,

$$\alpha = \frac{\sigma_{\mathbf{X_c}}}{\sigma_{\mathbf{X_r}}}$$

or a scalar that is the ratio of the standard deviations of the calibration and reconstructed vectors over the calibration period, and,

$$\boldsymbol{\beta} = \overline{\mathbf{X_c}} - (\alpha \times \overline{\mathbf{X_r}})$$

or a transformation to the mean of the calibration vector corrected by the scaled mean of the reconstructed data over the calibration period. Thus, every reconstruction for a particular cell will have the same mean and variance over the calibration period.

**Retrodiction over all available data** Our reconstruction process proceeds in a stepwise fashion backwards, starting with the calibration period and ending at the first year of the reconstruction period (here, AD 1). At each step, a reconstruction is made that extends as far back in time as all selected tree-ring chronologies will allow. At the year when one of the selected chronologies drops out of the sequence, RMSE selection, landscape-wide chronology standardization, and shrinkage estimation of the regression coefficients are repeated with the remaining available chronologies, but still using the original CAR ranking of chronologies. Thus, a new reconstruction is not completed at every change in the tree-ring chronology set (see Fig. 3.6), but only when tree-ring chronologies deemed important by the ranking and selection process are no longer available. This retrodiction process yields an optimized (in terms of computational time) set of sequential reconstructions; each reconstruction begins at the earliest year when all its selected tree-ring chronologies are available, and ends at the beginning of the subsequent reconstruction.

**Model performance through time** We used 3-fold consecutive (adjacent) cross-validation over the 1924–1983 period to generate fit statistics for each RMSE-minimized model. This differs from the 2-fold sequential cross-validation usually performed in paleoclimate research (Cook et al. 1999, 2010), which generate reconstructions over a calibration dataset and withhold a portion of historic data for model validation. Although the PRISM dataset extends back to 1895, it has a well-documented increase in uncertainty prior to 1924 that makes the use of the 1895–1923 data as a validation dataset inappropriate. The statistics presented here are averaged over the three-folds; each fold calibrates with 40 years of data, and validates with the remaining 20 (for example, calibrating with 1944–1983, and validating with 1924–1943).

**Reconstruction skill** Model performance is measured on an annually resolved cell-wise basis using three important performance statistics: The validation $R^2$ ($R^2_v$), the normalized root mean squared prediction error ($RMSE_n$), and the coefficient of efficiency ($CE$) (Cook et al. 2014, 1999) (see Supplementary Methods for descriptions of each measure). Fig. 3.8 shows these averaged over the entire 2000-year net water-year precipitation reconstruction, and Fig. 3.9 shows the same for the growing-season GDD reconstruction. It should be noted that due to the non-linear trend in tree-ring chronology availability (Fig. 3.6), these temporally averaged measures are a poor reflection of model performance, especially for reconstructions during the last millennium (see Supplementary Movies 2 and 3 for maps of reconstruction skill through time). Still, we can make several observations. Precipitation reconstructions (Fig. 3.8) generally perform better for high-elevation (and thus higher-precipitation) locations; reconstructions at these locations are not only better-correlated with withheld cross-validation data, but also generate reconstructions with lower proportional prediction error. A somewhat different pattern exists in the GDD reconstructions (Fig. 3.9); $R_v^2$ and $RMSE_n$ are highest in mid-elevations on portions of the landscape with consistent gradients. Drainages, including the major river valleys of the Rio Grande and Chama rivers in the VEPIIS study area, perform well, as does the Mesa Verde cuesta.

Aggregating model performance spatially presents a somewhat more useful assessment of model fit. Fig. 3.10 presents time series of model performance for the net water-year precipitation and growing-season GDD reconstructions, respectively. Model performance generally improves through time in both reconstructions, especially after AD 1200. That being said, neither study area achieves average $CE$ values $> 0$ during the GDD reconstructions, though this measure could very well be influenced by the skewed nature of the $CE$ metric.

The CAR method is highly effective in selecting t-r chronologies appropriate to each location and climate signal and that reflect well-documented regional climate patterns and medium-range teleconnections (Supplementary Methods; Supplementary Figs. 4 and 5). Furthermore, CAR reconstructions over the historic period show prediction skill comparable to or better than the PCR method used in the North American Drought Atlas (Cook et al. 2014, 1999, 2004), and greatly outperform reconstructions that use the marginal correlation for variable ranking (Supplementary Methods; Supplementary Table 17).

**Uncertainty estimation** Uncertainty in the size of the rain-fed maize agricultural niche is a function of the compound error in the PRISM weather interpolations, tree-ring measurement and signal

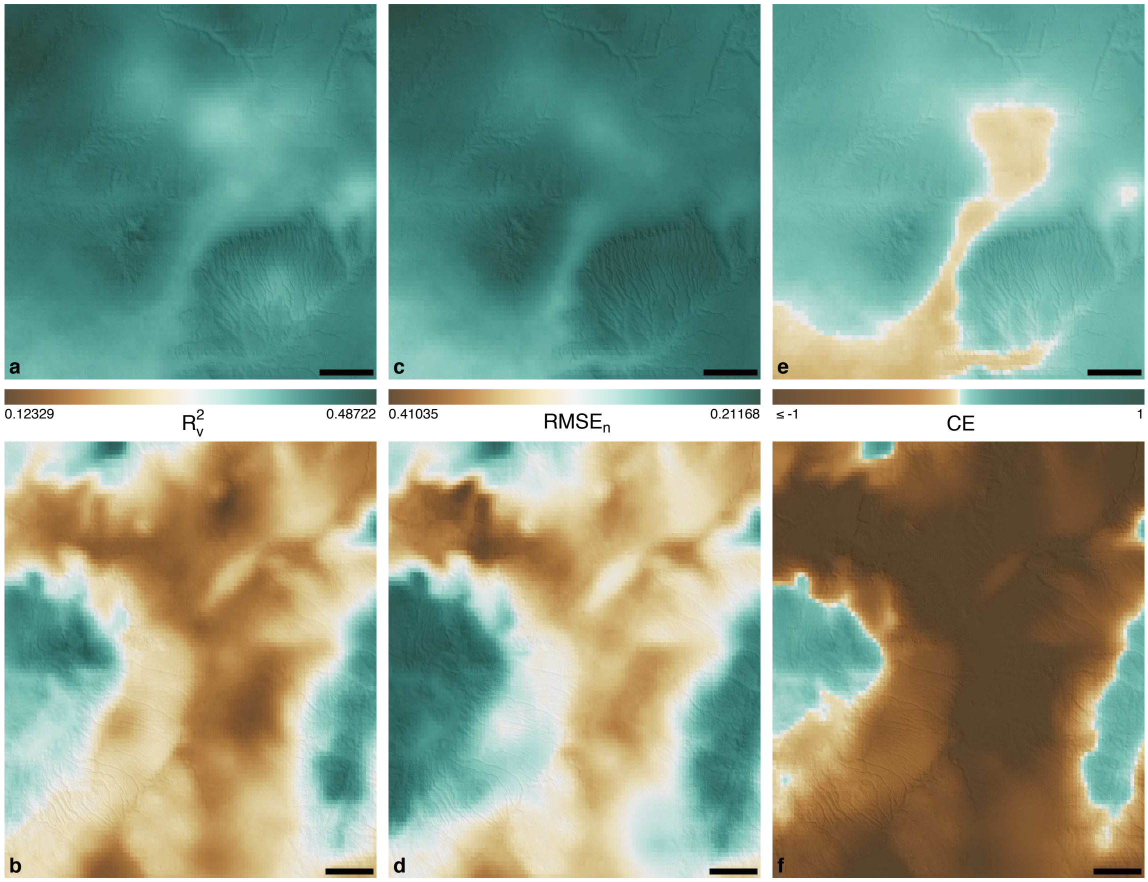


**Figure 3.8 | Model skill in reconstructing net water-year precipitation.** Values shown are averaged over the entire 2000-year reconstruction. $R_v^2$, validation $R^2$; $RMSE_n$, normalized root mean squared prediction error; $CE$, coefficient of efficiency. Each performance statistic has its own legend and color-scale. Scale bar: 10 km. **a**, VEPIIN $R_v^2$. **b**, VEPIIS $R_v^2$. **c**, VEPIIN $RMSE_n$. **d**, VEPIIS $RMSE_n$. **e**, VEPIIN $CE$. **f**, VEPIIS $CE$.

noise, and cell-wise CAR reconstructions. A full description and quantification of each of these sources of uncertainty is beyond the scope of this paper. However, to aid in interpretation we define a first-order approximation of the prediction interval $PI$ for each cell $i$ in each year $t$ as,

$$\mathbf{PI_{i,t}} = x_{i,t} \pm RMSE_{i,t} \tag{3.3}$$

where $x$ is the predicted value, and $RMSE$ is the cross-validated root mean squared prediction error for the cell's linear model. This generates annual prediction intervals for each cell for both the precipitation and GDD reconstructions. We derive prediction intervals for the spatial extent of

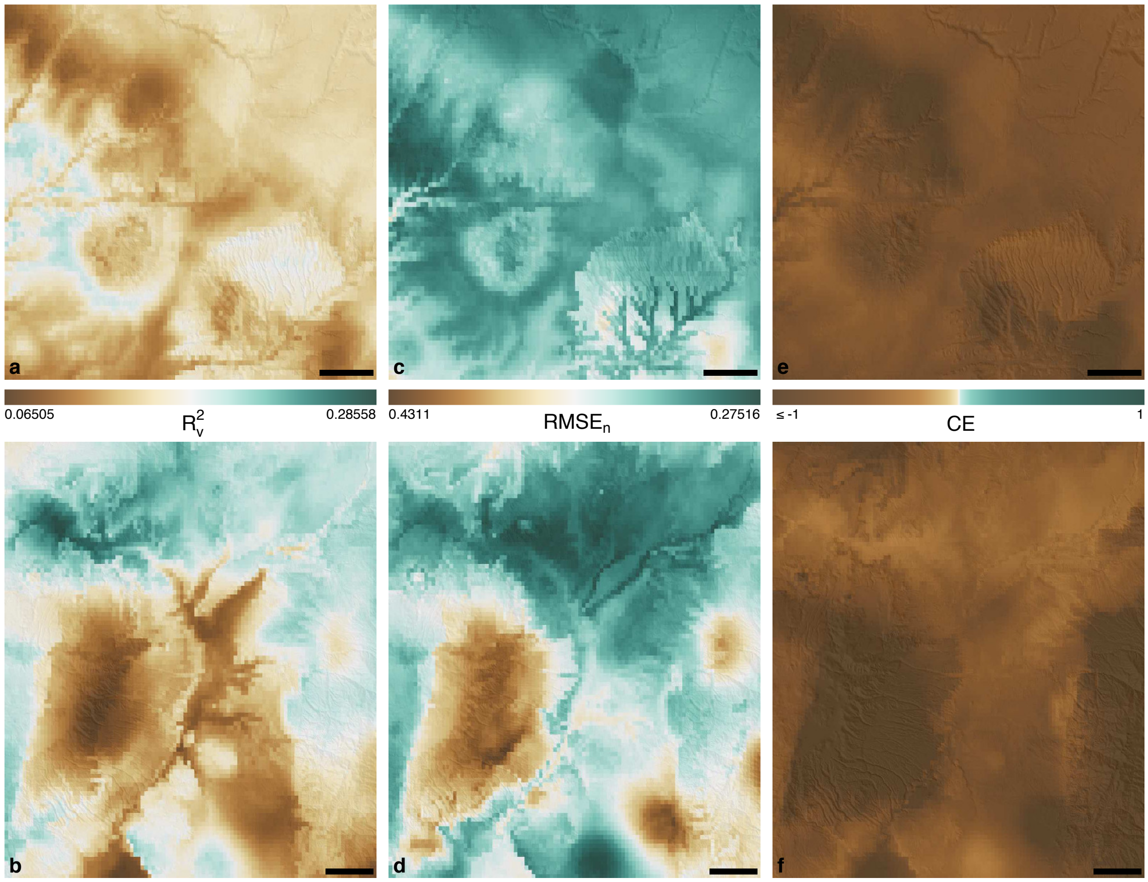


**Figure 3.9 | Model skill in reconstructing growing-season growing degree days.** Values shown are averaged over the entire 2000-year reconstruction. $R_v^2$, validation $R^2$; $RMSE_n$, normalized root mean squared prediction error; $CE$, coefficient of efficiency. Each performance statistic has its own legend and color-scale. Scale bar: 10 km. **a**, VEPIIN $R_v^2$. **b**, VEPIIS $R_v^2$. **c**, VEPIIN $RMSE_n$. **d**, VEPIIS $RMSE_n$. **e**, VEPIIN $CE$. **f**, VEPIIS $CE$.

the rain-fed maize agricultural niche by overlaying the lower and upper intervals for each climate signal (Fig. 3.3, Supplementary Movie 1). These prediction intervals do not incorporate uncertainty in the PRISM weather interpolations or uncertainties stemming from tree-ring measurement and signal noise. Spatial uncertainty estimates for the LT81m PRISM dataset used in this study have not been published; estimates for an earlier version of the PRISM dataset ("LT71m") are presented by Daly and colleagues (2008).

**Examples and model comparison** The online supplementary information presents local paleoclimate reconstructions at four weather stations across the SWUS as an example of the CAR method (Supplementary Methods; Supplementary Figs. 2–5; Supplementary Tables 1–17). These four reconstructions are then compared with those produced using the PPR method from the North American Drought Atlas (Cook et al. 2014, 1999, 2010, 2004) and those produced by ranking chronologies by their marginal correlations with the local climate signal.

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### Author contributions

R.K.B. and T.A.K. designed the analysis and wrote the paper. R.K.B. implemented the analysis.

### Additional information

Supplementary information is available in the online version of the paper. Raw data and all computer code are archived at `http://village.anth.wsu.edu/MAIZE_NICHE/` [and in Appendix B of this dissertation]. Reprints and permissions information are available online at www.nature.com/reprints. Correspondence and requests for materials should be addressed to R.K.B.

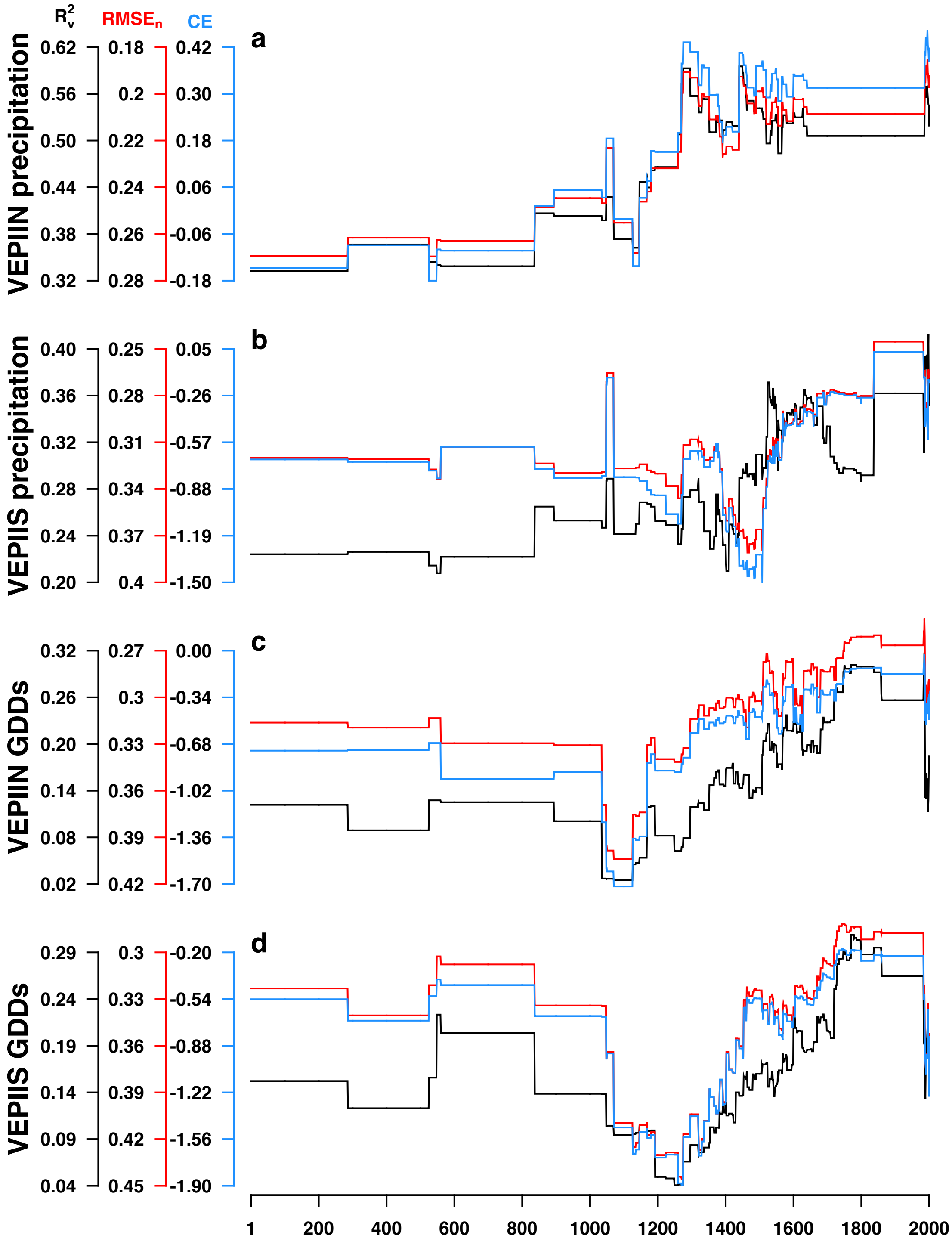


**Figure 3.10 | Reconstruction skill through time.** $R_v^2$, validation $R^2$; $RMSE_n$, normalized root mean squared prediction error; $CE$, coefficient of efficiency; GDDs, growing-season growing degree days. Note the inverted scale for $RMSE_n$. **a**, VEPIIN precipitation. **b**, VEPIIS precipitation. **c**, VEPIIN GDDs. **d**, VEPIIS GDDs.

# Supplementary Information

## Supplementary Figures

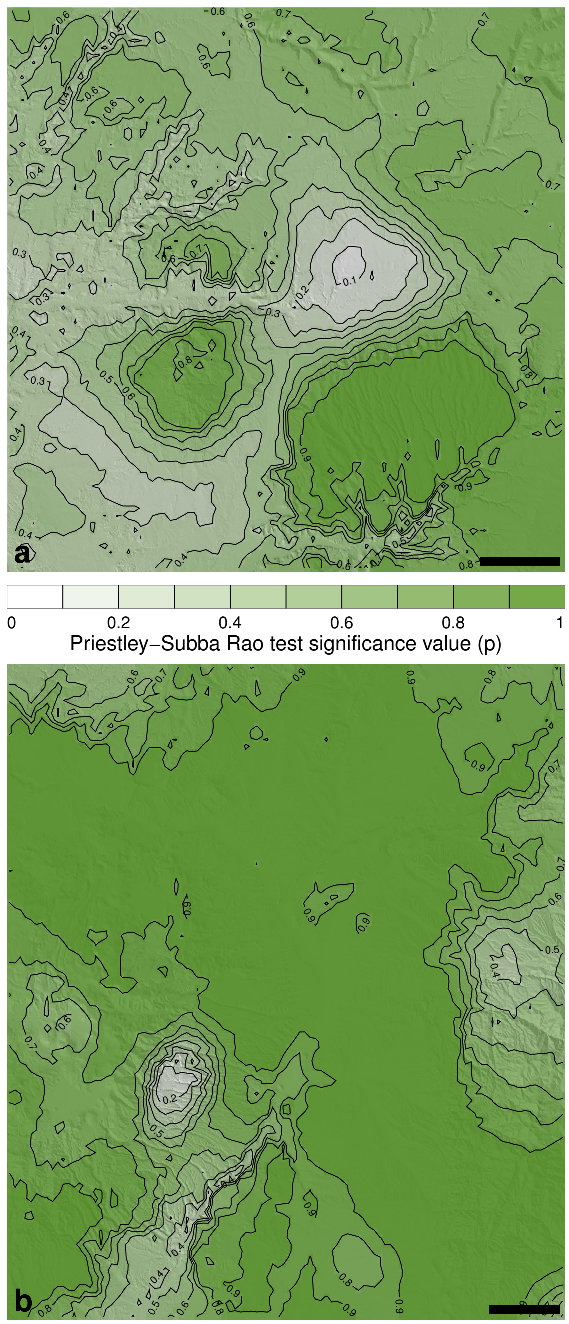


**Figure 3.11 | Significance of the Priestley-Subba Rao test of non-stationarity (p).** More shaded areas have higher *p*-values; they are less likely to be non-stationary. Scale bar: 10 km. **a**, VEPIIN. **b**, VEPIIS.

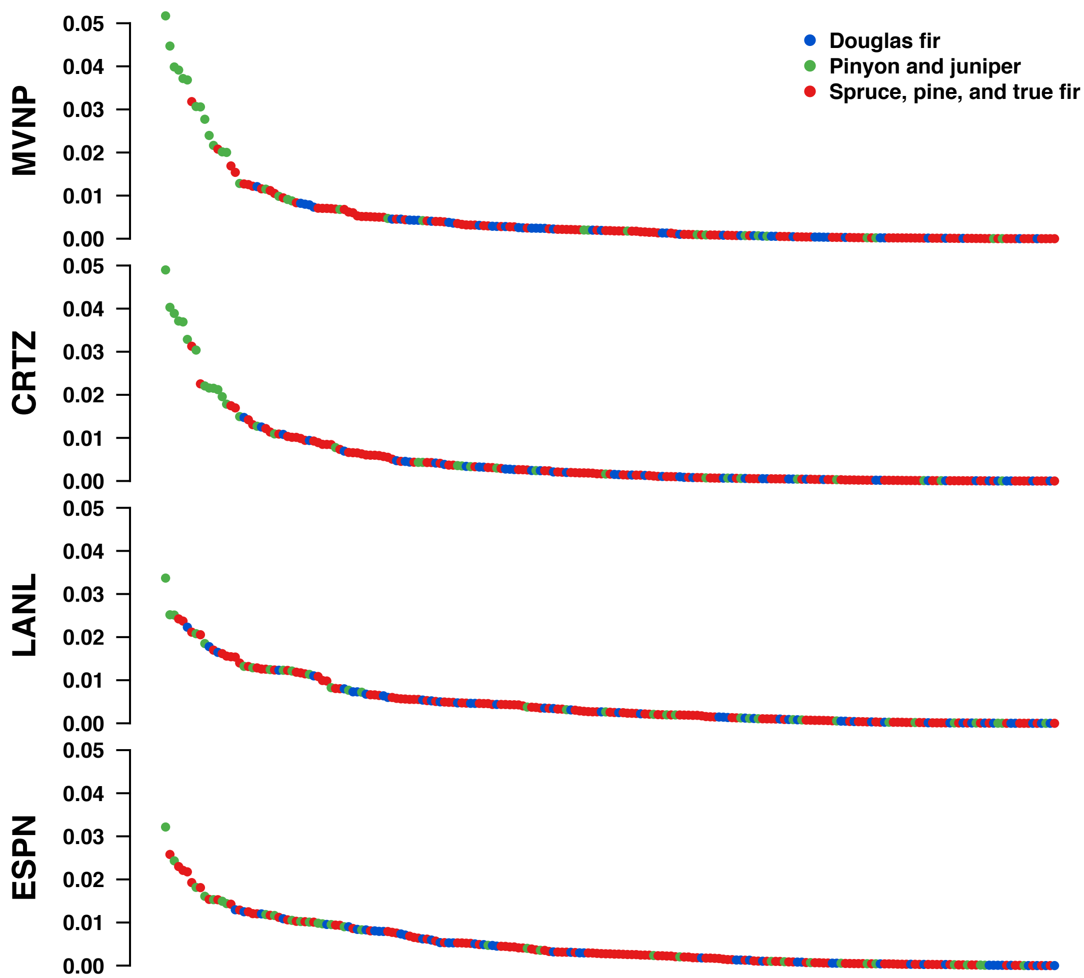


**Figure 3.12 | Correlation-adjusted correlation (CAR) score rank-distribution of tree-ring chronologies for reconstructing net water-year precipitation at each weather station location.** The value on each y-axis is the proportion of the sum of the squared CAR scores. MVNP, Mesa Verde National Park, Colorado; CRTZ, Cortez, Colorado; LANL, Los Alamos National Laboratory, New Mexico; ESPN, Española, New Mexico.

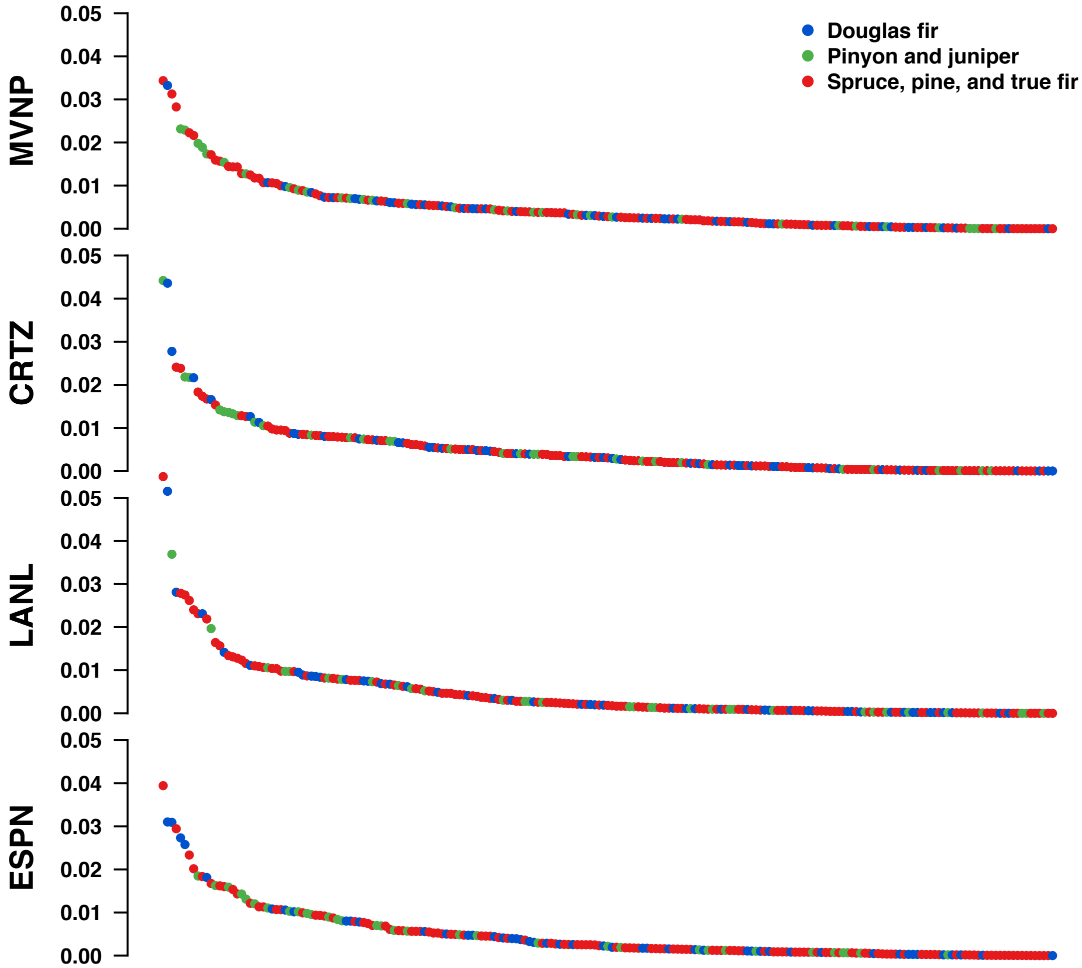


**Figure 3.13 | Correlation-adjusted correlation (CAR) score rank-distribution of tree-ring chronologies for reconstructing growing-season GDDs at each weather station location.** The value on each y-axis is the proportion of the sum of the squared CAR scores. MVNP, Mesa Verde National Park, Colorado; CRTZ, Cortez, Colorado; LANL, Los Alamos National Laboratory, New Mexico; ESPN, Española, New Mexico.

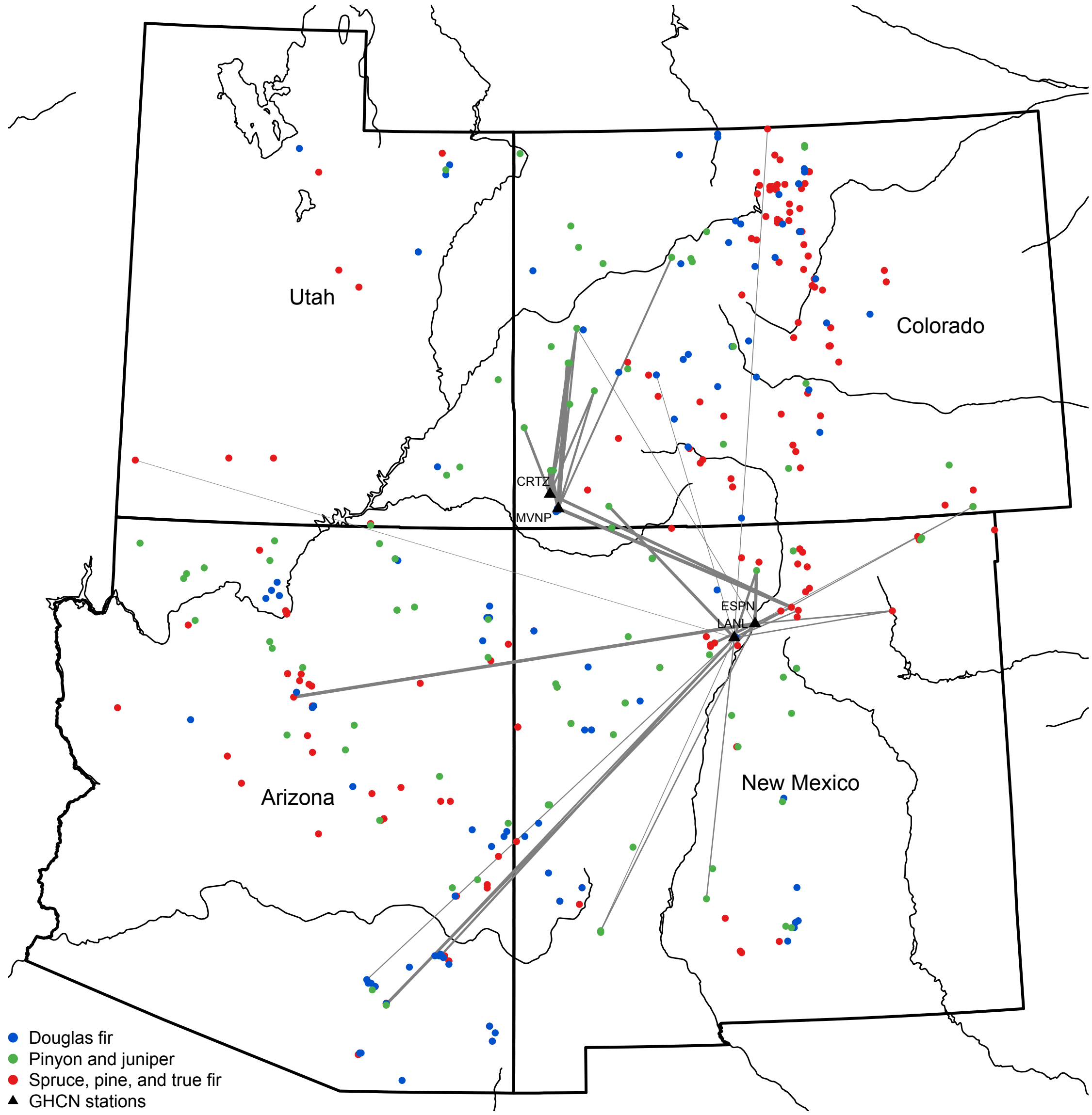


**Figure 3.14 | Correlation-adjusted correlation (CAR) regression variable selection results predicting net water-year precipitation at each weather station.** Gray lines show the tree-ring chronologies used in each reconstruction; the thicker the line, the more variance in the climate signal is explained by that chronology. MVNP, Mesa Verde National Park, Colorado; CRTZ, Cortez, Colorado; LANL, Los Alamos National Laboratory, New Mexico; ESPN, Española, New Mexico; GHCN, Global Historical Climate Network.

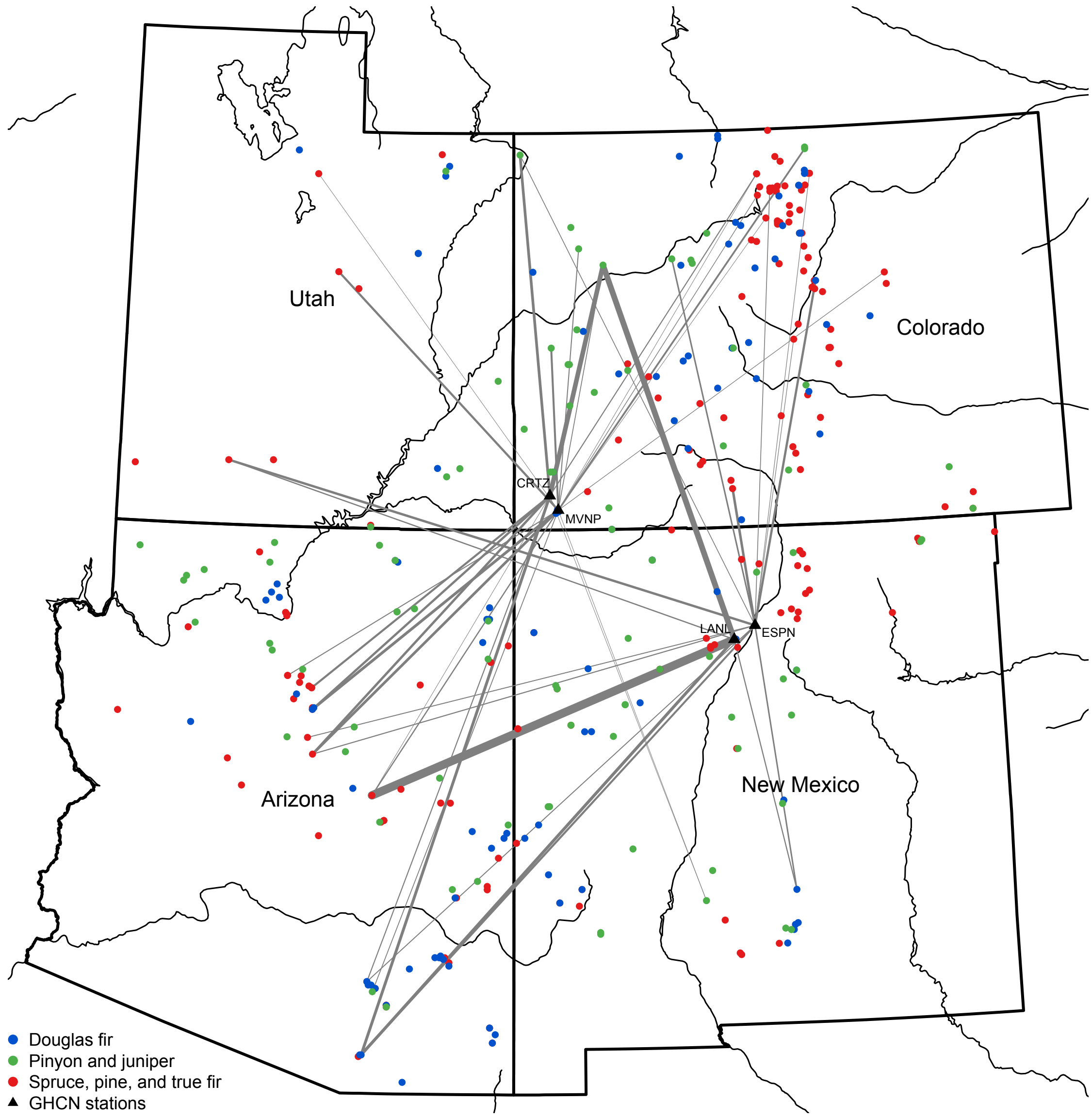


**Figure 3.15 | Correlation-adjusted correlation (CAR) regression variable selection results predicting growing-season growing degree days at each weather station.** Gray lines show the tree-ring chronologies used in each reconstruction; the thicker the line, the more variance in the climate signal is explained by that chronology. MVNP, Mesa Verde National Park, Colorado; CRTZ, Cortez, Colorado; LANL, Los Alamos National Laboratory, New Mexico; ESPN, Española, New Mexico; GHCN, Global Historical Climate Network.

## Supplementary Tables

**Table 3.1 | Correlation-adjusted correlation (CAR) regression results for predicting net water-year precipitation at the Mesa Verde National Park weather station over the calibration period.** n = 7 chronologies were selected by minimizing RMSE. Summed $CAR^2 = 0.503$. Species codes conform to (Grissino-Mayer 1993:Table 3).

| Series | Name | Species | Elevation (m) | $CAR^2$ | $\beta$ |
|---|---|---|---|---|---|
| CO582 | ESCALANTE FORKS UPDATE | PIED | 1737 | 0.105 | 0.206 |
| CO610 | MCPHEE | PIED | 2195 | 0.092 | 0.176 |
| NM557 | RIO PUEBLO | PIPO | 2469 | 0.087 | 0.194 |
| CO612 | MONTROSE | PIED | 2286 | 0.062 | 0.131 |
| CO631 | WILD ROSE | PIED | 2636 | 0.060 | 0.115 |
| CO583 | TRAIL GULCH | PIED | 2210 | 0.057 | 0.108 |
| CO600 | DRY PARK | PIED | 1996 | 0.041 | 0.002 |

**Table 3.2 | Correlation-adjusted correlation (CAR) regression results for predicting net water-year precipitation at the Cortez weather station over the calibration period.** n = 7 chronologies were selected by minimizing RMSE. Summed $CAR^2 = 0.459$. Species codes conform to (Grissino-Mayer 1993:Table 3).

| Series | Name | Species | Elevation (m) | $CAR^2$ | $\beta$ |
|---|---|---|---|---|---|
| CO610 | MCPHEE | PIED | 2195 | 0.096 | 0.205 |
| NM557 | RIO PUEBLO | PIPO | 2469 | 0.071 | 0.162 |
| CO631 | WILD ROSE | PIED | 2636 | 0.067 | 0.140 |
| CO626 | SLICKROCK | PIED | 2000 | 0.065 | 0.098 |
| CO582 | ESCALANTE FORKS UPDATE | PIED | 1737 | 0.057 | 0.094 |
| CO612 | MONTROSE | PIED | 2286 | 0.055 | 0.126 |
| CO600 | DRY PARK | PIED | 1996 | 0.048 | 0.043 |

**Table 3.3 | Correlation-adjusted correlation (CAR) regression results for predicting net water-year precipitation at the Los Alamos National Laboratory weather station over the calibration period.** n = 14 chronologies were selected by minimizing RMSE. Summed $CAR^2$ = 0.493. Species codes conform to (Grissino-Mayer 1993:Table 3).

| Series | Name | Species | Elevation (m) | $CAR^2$ | $\beta$ |
|---|---|---|---|---|---|
| CO638 | GRAND VIEW RIDGE | PIED | 2012 | 0.060 | 0.167 |
| NM581 | LAS TABLAS | PIED | 2300 | 0.053 | 0.088 |
| AZ558 | WEBB PEAK | PSME | 3025 | 0.049 | 0.132 |
| AZ545 | TUCSON SIDE | PIPO | 2362 | 0.044 | 0.163 |
| NM557 | RIO PUEBLO | PIPO | 2469 | 0.038 | 0.074 |
| NM554 | MOUTH OF LA JUNTA | PIPO | 2713 | 0.037 | 0.056 |
| NM577 | MILL CANYON | PIPO | 1710 | 0.036 | 0.141 |
| NM547 | SALINAS PEAK | PIED | 2438 | 0.034 | 0.104 |
| CO571 | SHEEP PEN CANYON | PIED | 1580 | 0.030 | 0.130 |
| AZ557 | REEF OF ROCKS | PSME | 2550 | 0.030 | 0.054 |
| CO591 | BOULDER RIDGE ROAD | PIPO | 2650 | 0.025 | 0.156 |
| NM568 | MIMBRES JUNCTION | PIED | 1950 | 0.024 | 0.038 |
| CO620 | RED CREEK | PSME | 2835 | 0.022 | −0.258 |
| UT511 | CEDAR BREAKS | PCEN | 3120 | 0.011 | 0.081 |

**Table 3.4 | Correlation-adjusted correlation (CAR) regression results for predicting net water-year precipitation at the Española weather station over the calibration period.** n = 10 chronologies were selected by minimizing RMSE. Summed $CAR^2$ = 0.453. Species codes conform to (Grissino-Mayer 1993:Table 3).

| Series | Name | Species | Elevation (m) | $CAR^2$ | $\beta$ |
|---|---|---|---|---|---|
| AZ521 | GUS PEARSON | PIPO | 2255 | 0.068 | 0.194 |
| NM581 | LAS TABLAS | PIED | 2300 | 0.065 | 0.140 |
| NM555 | ABOUSELMAN SPRING | PIPO | 2438 | 0.057 | 0.135 |
| NM557 | RIO PUEBLO | PIPO | 2469 | 0.048 | 0.060 |
| AZ545 | TUCSON SIDE | PIPO | 2362 | 0.047 | 0.139 |
| AZ524 | HELEN’S DOME | PIPO | 2535 | 0.043 | 0.080 |
| NM577 | MILL CANYON | PIPO | 1710 | 0.040 | 0.091 |
| NM568 | MIMBRES JUNCTION | PIED | 1950 | 0.038 | 0.082 |
| CO571 | SHEEP PEN CANYON | PIED | 1580 | 0.024 | 0.138 |
| CO631 | WILD ROSE | PIED | 2636 | 0.023 | 0.022 |

**Table 3.5 | Correlation-adjusted correlation (CAR) regression results for predicting growing-season growing degree days (GDD) at the Mesa Verde National Park weather station over the calibration period.** n = 17 chronologies were selected by minimizing RMSE. Summed $CAR^2 = 0.509$. Species codes conform to (Grissino-Mayer 1993:Table 3).

| Series | Name | Species | Elevation (m) | $CAR^2$ | $\beta$ |
|---|---|---|---|---|---|
| AZ548 | WALNUT CANYON | PSME | 2026 | 0.057 | −0.155 |
| AZ538 | ROCKY GULCH | PIPO | 1965 | 0.055 | −0.117 |
| UT510 | ELECTRIC LAKE | PCEN | 2970 | 0.048 | 0.214 |
| CO629 | UNAWEEP CANYON | PIED | 2225 | 0.046 | −0.127 |
| CO614 | OWL CANYON UPDATE | PIED | 1874 | 0.042 | −0.172 |
| AZ527 | MULETANK | PIPO | 2362 | 0.033 | −0.100 |
| CO595 | COLLINS GULCH | PIED | 2050 | 0.029 | −0.053 |
| AZ543 | SLATE MOUNTAIN | PIPO | 2194 | 0.029 | −0.062 |
| AZ506 | CHERRY CANYON | PICM | 1645 | 0.026 | −0.136 |
| CO621 | RIFLE | PIED | 2073 | 0.026 | −0.017 |
| CO546 | ONAHU CREEK | PICO | 2804 | 0.023 | −0.068 |
| CO627 | SOAP CREEK | PIPO | 2417 | 0.022 | −0.098 |
| CO564 | BLACK FOREST EAST | PIPO | 1800 | 0.022 | −0.018 |
| CO634 | CAMERON PASS | PICO | 3100 | 0.018 | −0.072 |
| UT512 | HIDDEN PEAK | PCEN | 3150 | 0.013 | 0.048 |
| NM547 | SALINAS PEAK | PIED | 2438 | 0.012 | 0.157 |
| CO544 | MONARCH LAKE | PIPO | 2621 | 0.009 | −0.002 |

**Table 3.6 | Correlation-adjusted correlation (CAR) regression results for predicting growing-season growing degree days (GDD) at the Cortez weather station over the calibration period.** n = 10 chronologies were selected by minimizing RMSE. Summed $CAR^2 = 0.423$. Species codes conform to (Grissino-Mayer 1993:Table 3).

| Series | Name | Species | Elevation (m) | $CAR^2$ | $\beta$ |
|---|---|---|---|---|---|
| CO621 | RIFLE | PIED | 2073 | 0.080 | −0.156 |
| AZ544 | SANTA RITA | PSME | 2407 | 0.058 | −0.216 |
| CO616 | PLUG HAT BUTTE | PIED | 2133 | 0.056 | −0.139 |
| AZ538 | ROCKY GULCH | PIPO | 1965 | 0.052 | −0.116 |
| AZ548 | WALNUT CANYON | PSME | 2026 | 0.050 | −0.096 |
| AZ539 | ROBINSON MOUNTAIN | PIPO | 2225 | 0.047 | −0.210 |
| CO634 | CAMERON PASS | PICO | 3100 | 0.030 | −0.122 |
| AZ555 | MT. LEMON | PSME | 2700 | 0.030 | −0.081 |
| AZ527 | MULETANK | PIPO | 2362 | 0.014 | −0.028 |
| NM547 | SALINAS PEAK | PIED | 2438 | 0.007 | 0.156 |

**Table 3.7 | Correlation-adjusted correlation (CAR) regression results for predicting growing-season growing degree days (GDD) at the Los Alamos National Laboratory weather station over the calibration period.** n = 5 chronologies were selected by minimizing RMSE. Summed $CAR^2$ = 0.373. Species codes conform to (Grissino-Mayer 1993:Table 3).

| Series | Name | Species | Elevation (m) | $CAR^2$ | $\beta$ |
|---|---|---|---|---|---|
| AZ527 | MULETANK | PIPO | 2362 | 0.132 | −0.300 |
| CO621 | RIFLE | PIED | 2073 | 0.102 | −0.234 |
| AZ544 | SANTA RITA | PSME | 2407 | 0.066 | −0.176 |
| UT509 | MAMMOTH CREEK | PILO | 2590 | 0.037 | −0.100 |
| NM570 | SIERRA BLANCA | PSME | 3120 | 0.035 | −0.149 |

**Table 3.8 | Correlation-adjusted correlation (CAR) regression results for predicting growing-season growing degree days (GDD) at the Española weather station over the calibration period.** n = 15 chronologies were selected by minimizing RMSE. Summed $CAR^2$ = 0.483. Species codes conform to (Grissino-Mayer 1993:Table 3).

| Series | Name | Species | Elevation (m) | $CAR^2$ | $\beta$ |
|---|---|---|---|---|---|
| CO559 | TERRACE LAKE PINES | PIPO | 2658 | 0.051 | −0.152 |
| UT509 | MAMMOTH CREEK | PILO | 2590 | 0.050 | −0.141 |
| CO540 | KASSLER | PSME | 1828 | 0.048 | −0.164 |
| AZ544 | SANTA RITA | PSME | 2407 | 0.043 | −0.150 |
| CO583 | TRAIL GULCH | PIED | 2210 | 0.037 | −0.073 |
| NM570 | SIERRA BLANCA | PSME | 3120 | 0.036 | −0.130 |
| AZ526 | MOUNT HOPKIN'S | PIPO | 2133 | 0.031 | 0.273 |
| AZ538 | ROCKY GULCH | PIPO | 1965 | 0.029 | −0.071 |
| AZ509 | BEAVER CREEK WATERSHED | PIPO | 2050 | 0.027 | −0.115 |
| AZ555 | MT. LEMON | PSME | 2700 | 0.027 | −0.132 |
| CO547 | RAINBOW CURVE | PIFL | 3352 | 0.024 | 0.181 |
| CO616 | PLUG HAT BUTTE | PIED | 2133 | 0.024 | −0.059 |
| CO602 | ELEVENMILE RESERVOIR | PIPO | 2743 | 0.020 | −0.057 |
| CO538 | HORSETOOTH RESERVOIR | PIPO | 1706 | 0.020 | −0.070 |
| AZ557 | REEF OF ROCKS | PSME | 2550 | 0.015 | 0.006 |

**Table 3.9 | Model fits for predicting net water-year precipitation at the Mesa Verde National Park weather station.** Fits were generates using 3-fold consecutive cross-validation over the calibration period, 1924–1983. $R_c^2$, calibration $R^2$; $R_v^2$, validation $R^2$; $RMSE_n$, normalized root mean squared prediction error; $RE$, reduction of error; $CE$, coefficient of efficiency.

| Start year (AD) | $R_c^2$ | $R_v^2$ | $RMSE_n$ | RE | CE |
|---|---|---|---|---|---|
| 1 | 0.268 | 0.283 | 0.262 | −0.031 | −0.128 |
| 286 | 0.338 | 0.313 | 0.259 | −0.022 | −0.135 |
| 548 | 0.373 | 0.301 | 0.256 | 0.006 | −0.102 |
| 837 | 0.387 | 0.391 | 0.238 | 0.153 | 0.068 |
| 894 | 0.437 | 0.388 | 0.236 | 0.167 | 0.087 |
| 1146 | 0.521 | 0.489 | 0.204 | 0.351 | 0.273 |
| 1169 | 0.570 | 0.453 | 0.208 | 0.346 | 0.279 |
| 1180 | 0.583 | 0.460 | 0.203 | 0.379 | 0.314 |
| 1192 | 0.607 | 0.482 | 0.198 | 0.409 | 0.348 |
| 1270 | 0.580 | 0.554 | 0.182 | 0.500 | 0.448 |
| 1296 | 0.597 | 0.559 | 0.181 | 0.496 | 0.440 |
| 1402 | 0.833 | 0.548 | 0.184 | 0.486 | 0.430 |
| 1440 | 0.642 | 0.560 | 0.176 | 0.522 | 0.467 |
| 1490 | 0.653 | 0.565 | 0.174 | 0.533 | 0.481 |
| 1520 | 0.661 | 0.561 | 0.175 | 0.526 | 0.472 |
| 1536 | 0.660 | 0.559 | 0.176 | 0.524 | 0.470 |
| 1555 | 0.652 | 0.580 | 0.173 | 0.538 | 0.487 |
| 1566 | 0.674 | 0.597 | 0.169 | 0.560 | 0.510 |
| 1569 | 0.664 | 0.601 | 0.165 | 0.578 | 0.531 |
| 1987 | 0.630 | 0.567 | 0.171 | 0.549 | 0.499 |
| 2000 | 0.866 | 0.567 | 0.173 | 0.541 | 0.490 |

**Table 3.10 | Model fits for predicting net water-year precipitation at the Cortez weather station.** Fits were generates using 3-fold consecutive cross-validation over the calibration period, 1924–1983. $R_c^2$, calibration $R^2$; $R_v^2$, validation $R^2$; $RMSE_n$, normalized root mean squared prediction error; $RE$, reduction of error; $CE$, coefficient of efficiency.

| Start year (AD) | $R_c^2$ | $R_v^2$ | $RMSE_n$ | RE | CE |
|---|---|---|---|---|---|
| 1 | 0.263 | 0.289 | 0.270 | −0.104 | −0.208 |
| 286 | 0.321 | 0.319 | 0.267 | −0.089 | −0.204 |
| 525 | 0.312 | 0.298 | 0.267 | −0.080 | −0.189 |
| 560 | 0.376 | 0.302 | 0.266 | −0.082 | −0.199 |
| 837 | 0.415 | 0.400 | 0.246 | 0.075 | −0.021 |
| 1048 | 0.507 | 0.399 | 0.214 | 0.287 | 0.202 |
| 1070 | 0.456 | 0.380 | 0.235 | 0.155 | 0.074 |
| 1146 | 0.516 | 0.491 | 0.209 | 0.310 | 0.232 |
| 1260 | 0.674 | 0.518 | 0.199 | 0.395 | 0.335 |
| 1270 | 0.536 | 0.515 | 0.190 | 0.453 | 0.392 |
| 1391 | 0.763 | 0.547 | 0.187 | 0.461 | 0.399 |
| 1392 | 0.789 | 0.597 | 0.185 | 0.480 | 0.429 |
| 1402 | 0.788 | 0.598 | 0.185 | 0.482 | 0.432 |
| 1440 | 0.593 | 0.553 | 0.178 | 0.519 | 0.466 |
| 1490 | 0.600 | 0.551 | 0.178 | 0.518 | 0.464 |
| 1536 | 0.600 | 0.544 | 0.179 | 0.513 | 0.458 |
| 1555 | 0.599 | 0.544 | 0.176 | 0.526 | 0.470 |
| 1569 | 0.603 | 0.535 | 0.179 | 0.512 | 0.456 |
| 1987 | 0.560 | 0.522 | 0.183 | 0.488 | 0.429 |

**Table 3.11 | Model fits for predicting net water-year precipitation at the Los Alamos National Laboratory weather station.** Fits were generates using 3-fold consecutive cross-validation over the calibration period, 1924–1983. $R_c^2$, calibration $R^2$; $R_v^2$, validation $R^2$; $RMSE_n$, normalized root mean squared prediction error; $RE$, reduction of error; $CE$, coefficient of efficiency.

| Start year (AD) | $R_c^2$ | $R_v^2$ | $RMSE_n$ | RE | CE |
|---|---|---|---|---|---|
| 1 | 0.242 | 0.256 | 0.273 | −0.236 | −0.291 |
| 286 | 0.253 | 0.262 | 0.267 | −0.179 | −0.235 |
| 560 | 0.335 | 0.271 | 0.261 | −0.120 | −0.176 |
| 837 | 0.353 | 0.301 | 0.257 | −0.073 | −0.126 |
| 1180 | 0.424 | 0.260 | 0.252 | −0.030 | −0.079 |
| 1192 | 0.407 | 0.254 | 0.255 | −0.063 | −0.116 |
| 1321 | 0.485 | 0.274 | 0.258 | −0.079 | −0.124 |
| 1423 | 0.614 | 0.315 | 0.259 | −0.082 | −0.127 |
| 1436 | 0.620 | 0.306 | 0.262 | −0.104 | −0.151 |
| 1440 | 0.472 | 0.367 | 0.263 | −0.123 | −0.168 |
| 1460 | 0.478 | 0.347 | 0.262 | −0.112 | −0.158 |
| 1464 | 0.494 | 0.389 | 0.232 | 0.132 | 0.091 |
| 1484 | 0.501 | 0.392 | 0.231 | 0.140 | 0.100 |
| 1490 | 0.468 | 0.397 | 0.230 | 0.147 | 0.112 |
| 1508 | 0.484 | 0.399 | 0.218 | 0.237 | 0.205 |
| 1520 | 0.532 | 0.392 | 0.218 | 0.232 | 0.199 |
| 1524 | 0.591 | 0.469 | 0.204 | 0.326 | 0.300 |
| 1545 | 0.622 | 0.481 | 0.200 | 0.352 | 0.325 |
| 1555 | 0.646 | 0.452 | 0.200 | 0.352 | 0.323 |
| 1566 | 0.666 | 0.476 | 0.195 | 0.387 | 0.357 |
| 1575 | 0.676 | 0.466 | 0.196 | 0.378 | 0.348 |
| 1581 | 0.684 | 0.472 | 0.200 | 0.354 | 0.322 |
| 1595 | 0.645 | 0.553 | 0.195 | 0.381 | 0.357 |
| 1660 | 0.656 | 0.562 | 0.194 | 0.387 | 0.362 |
| 1670 | 0.663 | 0.530 | 0.200 | 0.350 | 0.325 |
| 1687 | 0.671 | 0.521 | 0.196 | 0.377 | 0.352 |
| 1690 | 0.691 | 0.465 | 0.210 | 0.289 | 0.257 |
| 1837 | 0.711 | 0.507 | 0.209 | 0.295 | 0.264 |
| 1984 | 0.699 | 0.497 | 0.204 | 0.329 | 0.299 |
| 1987 | 0.674 | 0.594 | 0.182 | 0.465 | 0.443 |
| 1988 | 0.656 | 0.532 | 0.196 | 0.381 | 0.354 |
| 1991 | 0.706 | 0.525 | 0.189 | 0.420 | 0.393 |
| 1995 | 0.648 | 0.544 | 0.196 | 0.378 | 0.352 |
| 1999 | 0.607 | 0.500 | 0.200 | 0.349 | 0.321 |
| 2000 | 0.641 | 0.429 | 0.209 | 0.298 | 0.265 |

**Table 3.12 | Model fits for predicting net water-year precipitation at the Española weather station.** Fits were generates using 3-fold consecutive cross-validation over the calibration period, 1924–1983. $R_c^2$, calibration $R^2$; $R_v^2$, validation $R^2$; $RMSE_n$, normalized root mean squared prediction error; $RE$, reduction of error; $CE$, coefficient of efficiency.

| Start year (AD) | $R_c^2$ | $R_v^2$ | $RMSE_n$ | RE | CE |
|---|---|---|---|---|---|
| 1 | 0.229 | 0.207 | 0.336 | −0.494 | −1.057 |
| 560 | 0.262 | 0.236 | 0.328 | −0.349 | −0.905 |
| 837 | 0.311 | 0.320 | 0.349 | −0.754 | −1.388 |
| 1048 | 0.471 | 0.362 | 0.243 | 0.295 | −0.007 |
| 1070 | 0.443 | 0.282 | 0.300 | −0.275 | −0.731 |
| 1146 | 0.425 | 0.303 | 0.301 | −0.315 | −0.777 |
| 1169 | 0.436 | 0.272 | 0.311 | −0.367 | −0.861 |
| 1270 | 0.463 | 0.269 | 0.305 | −0.271 | −0.742 |
| 1275 | 0.602 | 0.344 | 0.293 | −0.224 | −0.672 |
| 1296 | 0.640 | 0.324 | 0.298 | −0.294 | −0.755 |
| 1320 | 0.647 | 0.319 | 0.298 | −0.297 | −0.758 |
| 1321 | 0.696 | 0.344 | 0.294 | −0.221 | −0.670 |
| 1336 | 0.662 | 0.318 | 0.300 | −0.295 | −0.762 |
| 1372 | 0.718 | 0.383 | 0.297 | −0.211 | −0.666 |
| 1378 | 0.727 | 0.381 | 0.302 | −0.281 | −0.753 |
| 1383 | 0.600 | 0.317 | 0.308 | −0.325 | −0.805 |
| 1440 | 0.603 | 0.311 | 0.309 | −0.317 | −0.802 |
| 1460 | 0.621 | 0.370 | 0.292 | −0.095 | −0.526 |
| 1490 | 0.622 | 0.370 | 0.291 | −0.071 | −0.498 |
| 1508 | 0.308 | 0.245 | 0.281 | 0.069 | −0.334 |
| 1520 | 0.448 | 0.402 | 0.277 | 0.018 | −0.375 |
| 1550 | 0.520 | 0.399 | 0.240 | 0.302 | 0.012 |
| 1555 | 0.524 | 0.390 | 0.238 | 0.310 | 0.023 |
| 1595 | 0.518 | 0.377 | 0.248 | 0.212 | −0.093 |
| 1660 | 0.573 | 0.413 | 0.225 | 0.391 | 0.136 |
| 1670 | 0.578 | 0.415 | 0.227 | 0.383 | 0.123 |
| 1690 | 0.580 | 0.402 | 0.230 | 0.371 | 0.105 |
| 1837 | 0.596 | 0.448 | 0.229 | 0.375 | 0.109 |
| 1987 | 0.580 | 0.455 | 0.217 | 0.463 | 0.218 |
| 1988 | 0.392 | 0.410 | 0.298 | −0.236 | −0.707 |

**Table 3.13 | Model fits for predicting growing-season growing degree days (GDD) at the Mesa Verde National Park weather station.** Fits were generates using 3-fold consecutive cross-validation over the calibration period, 1924–1983. $R_c^2$, calibration $R^2$; $R_v^2$, validation $R^2$; $RMSE_n$, normalized root mean squared prediction error; $RE$, reduction of error; $CE$, coefficient of efficiency.

| Start year (AD) | $R_c^2$ | $R_v^2$ | $RMSE_n$ | RE | CE |
|---|---|---|---|---|---|
| 1 | 0.086 | 0.027 | 0.357 | −0.633 | −0.969 |
| 286 | 0.161 | 0.067 | 0.342 | −0.499 | −0.780 |
| 525 | 0.040 | 0.051 | 0.368 | −0.733 | −1.057 |
| 1126 | 0.253 | 0.125 | 0.296 | −0.133 | −0.325 |
| 1146 | 0.297 | 0.195 | 0.276 | 0.007 | −0.151 |
| 1168 | 0.289 | 0.289 | 0.278 | 0.009 | −0.165 |
| 1296 | 0.377 | 0.358 | 0.255 | 0.158 | 0.008 |
| 1352 | 0.377 | 0.338 | 0.254 | 0.165 | 0.022 |
| 1401 | 0.506 | 0.389 | 0.255 | 0.156 | 0.009 |
| 1420 | 0.518 | 0.418 | 0.243 | 0.230 | 0.098 |
| 1430 | 0.562 | 0.439 | 0.222 | 0.364 | 0.253 |
| 1453 | 0.568 | 0.451 | 0.215 | 0.407 | 0.304 |
| 1486 | 0.626 | 0.496 | 0.209 | 0.439 | 0.334 |
| 1490 | 0.628 | 0.487 | 0.210 | 0.432 | 0.326 |
| 1508 | 0.699 | 0.546 | 0.192 | 0.520 | 0.413 |
| 1511 | 0.714 | 0.556 | 0.186 | 0.550 | 0.445 |
| 1524 | 0.724 | 0.543 | 0.190 | 0.532 | 0.428 |
| 1530 | 0.723 | 0.541 | 0.191 | 0.524 | 0.419 |
| 1541 | 0.728 | 0.541 | 0.191 | 0.527 | 0.422 |
| 1542 | 0.742 | 0.556 | 0.194 | 0.518 | 0.416 |
| 1568 | 0.771 | 0.542 | 0.189 | 0.542 | 0.442 |
| 1569 | 0.773 | 0.537 | 0.190 | 0.534 | 0.433 |
| 1570 | 0.762 | 0.541 | 0.194 | 0.516 | 0.416 |
| 1577 | 0.782 | 0.539 | 0.193 | 0.520 | 0.422 |
| 1600 | 0.798 | 0.557 | 0.191 | 0.533 | 0.439 |
| 1626 | 0.806 | 0.556 | 0.196 | 0.506 | 0.410 |
| 1630 | 0.800 | 0.540 | 0.189 | 0.543 | 0.452 |
| 1670 | 0.806 | 0.568 | 0.188 | 0.542 | 0.455 |
| 1680 | 0.809 | 0.565 | 0.195 | 0.497 | 0.409 |
| 1687 | 0.656 | 0.530 | 0.195 | 0.507 | 0.413 |
| 1747 | 0.661 | 0.530 | 0.195 | 0.505 | 0.410 |
| 1766 | 0.701 | 0.481 | 0.194 | 0.513 | 0.407 |
| 1770 | 0.704 | 0.494 | 0.190 | 0.529 | 0.428 |
| 1984 | 0.610 | 0.469 | 0.201 | 0.482 | 0.382 |
| 1987 | 0.521 | 0.402 | 0.227 | 0.335 | 0.207 |
| 1988 | 0.777 | 0.451 | 0.212 | 0.422 | 0.310 |
| 1989 | 0.766 | 0.469 | 0.212 | 0.424 | 0.316 |
| 1991 | 0.460 | 0.333 | 0.240 | 0.258 | 0.116 |
| 1998 | 0.449 | 0.320 | 0.250 | 0.200 | 0.034 |
| 1999 | 0.423 | 0.318 | 0.252 | 0.190 | 0.032 |

**Table 3.14 | Model fits for predicting growing-season growing degree days (GDD) at the Cortez weather station.** Fits were generates using 3-fold consecutive cross-validation over the calibration period, 1924–1983. $R_c^2$, calibration $R^2$; $R_v^2$, validation $R^2$; $RMSE_n$, normalized root mean squared prediction error; $RE$, reduction of error; $CE$, coefficient of efficiency.

| Start year (AD) | $R_c^2$ | $R_v^2$ | $RMSE_n$ | RE | CE |
|---|---|---|---|---|---|
| 1 | 0.188 | 0.137 | 0.299 | −0.074 | −0.577 |
| 286 | 0.217 | 0.116 | 0.305 | −0.090 | −0.607 |
| 525 | 0.251 | 0.163 | 0.292 | −0.009 | −0.491 |
| 1126 | 0.317 | 0.169 | 0.294 | 0.006 | −0.462 |
| 1146 | 0.331 | 0.187 | 0.294 | 0.006 | −0.469 |
| 1168 | 0.235 | 0.245 | 0.280 | 0.059 | −0.295 |
| 1270 | 0.233 | 0.223 | 0.283 | 0.055 | −0.346 |
| 1275 | 0.384 | 0.205 | 0.282 | 0.072 | −0.329 |
| 1296 | 0.319 | 0.292 | 0.266 | 0.178 | −0.188 |
| 1352 | 0.363 | 0.333 | 0.234 | 0.328 | 0.099 |
| 1630 | 0.490 | 0.370 | 0.230 | 0.346 | 0.122 |
| 1670 | 0.502 | 0.392 | 0.223 | 0.409 | 0.180 |
| 1680 | 0.504 | 0.397 | 0.219 | 0.436 | 0.208 |
| 1687 | 0.560 | 0.442 | 0.212 | 0.449 | 0.253 |
| 1747 | 0.581 | 0.458 | 0.204 | 0.493 | 0.307 |
| 1984 | 0.578 | 0.466 | 0.202 | 0.491 | 0.320 |
| 1987 | 0.415 | 0.344 | 0.231 | 0.343 | 0.122 |

**Table 3.15 | Model fits for predicting growing-season growing degree days (GDD) at the Los Alamos National Laboratory weather station.** Fits were generates using 3-fold consecutive cross-validation over the calibration period, 1924–1983. $R_c^2$, calibration $R^2$; $R_v^2$, validation $R^2$; $RMSE_n$, normalized root mean squared prediction error; $RE$, reduction of error; $CE$, coefficient of efficiency.

| Start year (AD) | $R_c^2$ | $R_v^2$ | $RMSE_n$ | RE | CE |
|---|---|---|---|---|---|
| 1 | 0.145 | 0.128 | 0.354 | −0.117 | −0.769 |
| 1330 | 0.224 | 0.150 | 0.338 | −0.065 | −0.619 |
| 1352 | 0.280 | 0.244 | 0.290 | 0.195 | −0.272 |
| 1554 | 0.495 | 0.316 | 0.273 | 0.333 | −0.111 |
| 1600 | 0.504 | 0.339 | 0.266 | 0.371 | −0.029 |
| 1630 | 0.504 | 0.392 | 0.231 | 0.485 | 0.216 |
| 1984 | 0.526 | 0.360 | 0.236 | 0.464 | 0.186 |
| 1986 | 0.570 | 0.376 | 0.234 | 0.477 | 0.199 |
| 1987 | 0.642 | 0.364 | 0.248 | 0.435 | 0.130 |
| 1988 | 0.280 | 0.244 | 0.290 | 0.195 | −0.272 |

**Table 3.16 | Model fits for predicting growing-season growing degree days (GDD) at the Española weather station.** Fits were generates using 3-fold consecutive cross-validation over the calibration period, 1924–1983. $R_c^2$, calibration $R^2$; $R_v^2$, validation $R^2$; $RMSE_n$, normalized root mean squared prediction error; $RE$, reduction of error; $CE$, coefficient of efficiency.

| Start year (AD) | $R_c^2$ | $R_v^2$ | $RMSE_n$ | RE | CE |
|---|---|---|---|---|---|
| 1 | 0.250 | 0.247 | 0.284 | −0.021 | −0.178 |
| 1402 | 0.350 | 0.316 | 0.260 | 0.149 | 0.032 |
| 1507 | 0.405 | 0.329 | 0.256 | 0.155 | 0.053 |
| 1554 | 0.394 | 0.380 | 0.245 | 0.237 | 0.136 |
| 1568 | 0.437 | 0.371 | 0.246 | 0.216 | 0.124 |
| 1600 | 0.463 | 0.405 | 0.231 | 0.321 | 0.233 |
| 1670 | 0.503 | 0.404 | 0.236 | 0.297 | 0.199 |
| 1728 | 0.673 | 0.452 | 0.231 | 0.291 | 0.214 |
| 1800 | 0.693 | 0.485 | 0.225 | 0.332 | 0.256 |
| 1984 | 0.445 | 0.367 | 0.242 | 0.264 | 0.160 |
| 1986 | 0.478 | 0.407 | 0.245 | 0.247 | 0.128 |
| 1987 | 0.581 | 0.412 | 0.233 | 0.318 | 0.222 |
| 1988 | 0.433 | 0.385 | 0.249 | 0.225 | 0.098 |
| 1989 | 0.400 | 0.341 | 0.252 | 0.204 | 0.082 |
| 1990 | 0.388 | 0.352 | 0.244 | 0.236 | 0.141 |
| 1998 | 0.338 | 0.286 | 0.263 | 0.117 | 0.003 |
| 1999 | 0.286 | 0.254 | 0.273 | 0.062 | −0.067 |

**Table 3.17 | Model comparison of different reconstruction techniques.** Values given are validation r-squared ($R_v^2$) and normalized root mean squared prediction error ($RMSE_n$; in parentheses). Red type indicates the technique that minimizes $RMSE_n$; blue type indicates the second-ranked model. Each of the six reconstruction techniques are characterized by a variable ranking method, a model classification, and a model selection method. Statistics reported are the mean of all cross-validated runs. CAR, correlation-adjusted correlation method; MCOR, marginal correlation method; PPR, point-by-point regression method; $AIC_c$, corrected Akaike's Information Criterion; $RMSE$, root mean squared prediction error.

| | | $CAR^2$ Zuber and Strimmer (2011, 2014)<br>Shrinkage Regression<br>Min. RMSE | $CAR^2$ Zuber and Strimmer (2011, 2014)<br>Shrinkage Regression<br>Min. $AIC_c$ | $MCOR^2$<br>OLS Regression<br>Min. RMSE | $MCOR^2$<br>OLS Regression<br>Min. $AIC_c$ | PPR Cook et al. (1999, 2004)<br>PC Regression<br>Min. RMSE | PPR Cook et al. (1999, 2004)<br>PC Regression<br>Min. $AIC_c$ |
|---|---|---|---|---|---|---|---|
| | | $R_v^2$ ($RMSE_n$) | $R_v^2$ ($RMSE_n$) | $R_v^2$ ($RMSE_n$) | $R_v^2$ ($RMSE_n$) | $R_v^2$ ($RMSE_n$) | $R_v^2$ ($RMSE_n$) |
| MVNP | PRCP | **0.601 (0.165)** | 0.559 (0.185) | 0.535 (0.184) | 0.542 (0.189) | **0.584 (0.164)** | 0.560 (0.167) |
| | GDD | **0.494 (0.190)** | **0.518 (0.198)** | 0.404 (0.259) | 0.393 (0.279) | 0.374 (0.212) | 0.255 (0.235) |
| CRTZ | PRCP | **0.535 (0.179)** | 0.522 (0.183) | 0.515 (0.188) | 0.515 (0.188) | **0.499 (0.180)** | 0.459 (0.185) |
| | GDD | **0.458 (0.204)** | 0.348 (0.262) | 0.333 (0.234) | 0.346 (0.245) | **0.296 (0.216)** | 0.296 (0.216) |
| LANL | PRCP | 0.507 (0.209) | 0.452 (0.228) | 0.392 (0.241) | 0.290 (0.248) | **0.423 (0.185)** | **0.419 (0.186)** |
| | GDD | **0.392 (0.231)** | **0.385 (0.235)** | 0.291 (0.267) | 0.291 (0.267) | 0.189 (0.258) | 0.216 (0.264) |
| ESPN | PRCP | 0.448 (0.229) | 0.328 (0.309) | 0.375 (0.277) | 0.363 (0.291) | **0.423 (0.207)** | **0.399 (0.212)** |
| | GDD | **0.283 (0.228)** | 0.317 (0.251) | 0.355 (0.254) | 0.331 (0.255) | **0.283 (0.228)** | 0.227 (0.242) |

**Supplementary Methods**

Here, we evaluate model performance using the locations of four ecologically distinct Global Historical Climate Network (GHCN) climate stations (GHCN stations USC00055531: Mesa Verde National Park, Colorado; USC00051886: Cortez, Colorado; USC00295084: Los Alamos National Laboratory, New Mexico; and USC00293031: Española, New Mexico; see Figure 3.1 in the main text).

**Tree-ring chronology ranking by CAR score** Once CAR scores are calculated for each cell and each climate signal, tree-ring chronologies are ranked by their squared CAR scores. The panels in Supplementary Figures 3.12 and 3.13 show the rank-distribution of tree species for reconstructing net water-year precipitation and growing-season GDDs, respectively, at each weather station location. Net water-year precipitation is best reconstructed from pinyons and junipers (green) and Douglas firs (blue). High-elevation spruces, pines, and true firs (red) present the best record of growing-season GDDs. Chronology selection is also influenced by spatial proximity and regional climate patterns.

**The spatial distribution of selected tree-ring chronologies** The spatial distribution of selected tree-ring chronologies for each weather station and climate signal is informative about the climatological processes that affect living trees as well as about the utility of those trees in reconstructing local paleoclimate. Supplementary Figures 3.14 and 3.15 present the selected chronologies for net water-year precipitation and growing-season GDD, respectively. The selected chronologies are in accord with well-documented climate patterns in the SWUS (see discussion in the main text) Adams and Comrie (1997); Cordell et al. (2001); Dean (1988).

**Shrinkage estimation of regression coefficients** Supplementary Tables 3.1–3.4 present the standardized regression coefficients ($\beta$) for the water-year precipitation reconstruction during the calibration period, and Supplementary Tables 3.5–3.8 present the same for the growing-season GDD reconstruction. The squared CAR scores of the predictor variables provide a measure of relative variable importance—they may be interpreted as reflecting the contribution of the tree-ring chronology to the explained variance in the linear model—and the sum of squared CAR scores approximates Pearson's $R^2$.

**Model performance through time** We follow Cook et al. Cook et al. (2014, 1999) by calculating five fit statistics: The squared Pearson correlation over the calibration dataset ($R_c^2$) and the validation dataset ($R_v^2$), the normalized root mean squared prediction error ($RMSE_n$), the reduction of error ($RE$), and the coefficient of efficiency ($CE$). Supplementary Tables 3.9–3.12 present the fit statistics for the water-year precipitation reconstructions, and Supplementary Tables 3.13–3.16 present the same for the growing-season GDD reconstructions.

$\mathbf{R_c^2}$ **and** $\mathbf{R_v^2}$ Calibration ($R_c^2$) and validation ($R_v^2$) $R^2$ are the squared Pearson correlation coefficients relating the reconstruction over the calibration and validation periods to the observed data. These statistics describe the covariance between the predicted and observed values; they summarize the proportion of variance in either the calibration or validation dataset explained by each linear model. $R_c^2$ increases monotonically with the number of predictor variables included in the model, while $R_v^2$ will first improve then degrade as predictors are added and the model becomes "over-fit" to the calibration period. In all reconstructions, $R_v^2$ tends to peak around the calibration period and degrade for older reconstructions as well as for reconstructions after the 1924–1983 calibration period.

$\mathbf{RMSE_n}$ The root mean squared prediction error provides an estimate of how well a model tuned with a calibration dataset can predict observed values in a withheld dataset; however—unlike validation $R_v^2$, which only describes the pattern similarity between the time series—the comparison is based on the magnitude of the pairwise differences between predicted and observed values. Because $RMSE$ is reported in the units of the observed data, we standardize $RMSE$ by calculating a "normalized" $RMSE_n$, where $RMSE_n = RMSE/\Delta X_v$ and $\Delta X_v$ is the absolute difference between the minimum and maximum observed values over the cross-validation validation period. This can be thought of as the proportional error of the reconstruction.

**RE** The reduction of error over the validation period is

$$RE = 1 - \frac{\sum (\mathbf{X} - \mathbf{X_v})^2}{\sum (\mathbf{X} - \overline{\mathbf{X_c}})^2} \tag{3.4}$$

where $X$ is the vector of predicted values over the cross-validation validation period, $X_v$ is the vector of observed values over the validation period, and $\bar{X}_c$ is the mean of the observed values over the calibration period. The $RE$ has a theoretical range from $-\infty$ to 1, though in practice is is most often in the range of $-1$ to 1; an $RE$ value greater than zero indicates a skilled reconstruction Cook et al. (2014, 1999), i.e., one that performs better than simply using the mean of the observed values over the calibration period to estimate the observed validation dataset.

**CE** The coefficient of efficiency over the validation period is

$$CE = 1 - \frac{\sum (\mathbf{X} - \mathbf{X_v})^2}{\sum (\mathbf{X} - \overline{\mathbf{X_v}})^2} \tag{3.5}$$

where, again, $X$ is the vector of predicted values over the cross-validation validation period, $X_v$ is the vector of observed values over the validation period, and $\bar{X}_v$ is the mean of the observed values over the *validation* period. The form and logic of the $CE$ is very similar to that of the $RE$ except that the $CE$ tests whether the model is better at predicting the observed validation data than the mean of the validation dataset; $CE$ scales from $-\infty$ to 1. As the mean of the observed validation data is naturally better at predicting the observed validation data than the mean of the observed calibration data, a positive $CE$-value is a tougher benchmark than a positive $RE$ value. Needless to say, if the mean of the observed calibration data and the observed validation data are the same, $CE$ will be equal to $RE$. Of course, the degree to which either the calibration or validation data adequately describe the mean and variance over the reconstruction period is unknown.

**Comparison with other reconstruction techniques** Here, we demonstrate the effectiveness of the CAR reconstruction technique relative to two other reconstruction techniques: Stepwise insertion of tree-ring chronologies ranked by marginal correlations into an ordinary least squares regression model (the "MCOR" method), and principal components regression, also known as the "Point-by-Point Regression" method used in the North American Drought Atlas (the "NADA" method; Cook et al. (2014, 1999, 2004)). Additionally, for each of these we assess two model selection methods, either minimizing the cross-validated, corrected Akaike's Information Criterion ($AIC_c$; Akaike (1974)) or the cross-validated RMSE. $AIC_c$ privileges parsimony, while RMSE selects the model that generated predictions closest to the validation dataset. As our comparison metrics, we calculate the squared Pearson correlation over the validation dataset ($R_v^2$) and the normalized root mean squared prediction error ($RMSE_n$) using three-fold consecutive cross-validation, as described above. We present our results first, followed by brief descriptions of how we implemented each of these methods. Each method was coded in *R* and all source code is available in online supplementary materials.

Supplementary Table 3.17 presents the results of the model comparison tests for each weather station and climate signal. Red type indicates the technique that minimizes $RMSE_n$; blue type indicates the second-ranked model by this metric. The CAR regression technique outperforms all competing methods on many of the reconstructions. The MCOR method always performed worst. The CAR method outperforms the NADA method in the GDD reconstructions; it also always generates reconstructions with higher $R_v^2$ than the NADA method (and usually every other method). This is likely due to the mean-variance matching discussed above, and suggests that the CAR reconstructions are indeed superior: they better capture the year-to-year variation in the withheld cross-validation data. Model selection using minimized $RMSE$ always out-performs selection using minimized $AIC_c$. This is unsurprising, as it is unclear why one should privilege parsimony over reconstruction accuracy in paleoclimate reconstruction, especially using a static measure such as $AIC_c$ Tingley (2011).

**$\mathbf{MCOR^2}$ ranking and OLS regression (the "MCOR" method)** The CAR reconstruction method gains a lot from its use of shrinkage estimators of the correlation and covariance matrices Schäfer and Strimmer (2005). As in many climate reconstructions (and many other real-data situations) paleoclimate reconstruction from tree-ring chronologies is often a "high-dimensional" problem, with more variables (chronologies) than observations (years with historical climate data) and highly correlated predictors over the calibration period. In the case of orthogonal predictors, however, it is generally agreed that the marginal correlations between the predictors and the response variable provide an optimal ranking of predictors Fan and Lv (2008). Here, we use the squared marginal correlations ($MCOR^2$) as our variable ranking method, and enter the ranked chronologies stepwise into an ordinary least squares multiple linear regression. Resulting predictions over the calibration and validation periods are scaled and transformed using mean-variance matching prior to cross-validation, as described above.

**Principal components regression (the "NADA" method)** The North American Drought Atlas Cook et al. (2014, 1999, 2010, 2004) is a gridded reconstruction of Palmer Drought Severity Indices across North America. The latest version of the NADA (alternatively referred to as the Living Blended Drought Atlas, or LBDA; Cook et al. (2014, 2010)) presents a reconstruction on an 0.5°grid back to AD 1, using the "point-by-point" regression method developed in Cook et al. (1999). The NADA method, in its most basic form, uses a principal components analysis of a set of tree-ring chronologies to generate a new set of orthogonal predictors (the principal component scores), which are then ranked based on their marginal correlations with an observed climate variable and entered into a stepwise OLS multiple regression until $AIC_c$ is minimized. In order to reduce the uncertainty and dimensionality of the reconstruction, the NADA method also employs a multi-step screening process, first restricting the set of chronologies entered into the principal component analysis, and then the set of principal components entered stepwise into the multiple regression.

Here, we follow the detailed description of the NADA method provided in Cook et al. (1999)

to generate NADA-style reconstructions of net water-year precipitation and growing-season GDDs at each of our four climate stations. We start with the same set of 205 chronologies used in the CAR and MCOR methods described above, complete the screening processes described in Cook et al. (1999), and finally enter the resulting principal components into a stepwise OLS multiple regression model. As with our reconstructions using CAR and MCOR, we minimize both the $AIC_c$ and $RMSE$ of the models, and calculate estimates of $R_v^2$ and $RMSE_n$ using three-fold consecutive cross-validation. Here, we detail the screening method (Cook et al. (1999) call this "pooling") employed here. The screening process is performed using the entire 1924–1983 calibration period, and cross-validation is only performed on the final stepwise linear models. Resulting predictions over the calibration and validation periods are scaled and transformed using mean-variance matching prior to cross-validation, as described above.

It should be noted that many of the parameters of the NADA method (the search radius and $\alpha$ cutoff, in particular) were "tuned" by Cook and colleagues using computer simulations, and standardized across their reconstruction grids. Here, we rather naively use their parameters tuned for the North American PDSI reconstructions ($\alpha = 0.10$), while acknowledging that results with better fits might be gleaned by performing our own tuning. Also, the utility of the NADA method depends entirely on the success of the first two levels of screening in reducing the set of potential predictors $p$ to less than the length of the calibration dataset $n$, if only because orthogonalization via PCA cannot be performed if $p > n$. This presents a problem for the NADA method as more high-quality chronologies become available; at some point in the future, $p > n$ predictors will pass the level-1 and level-2 screenings. This did not occur in our analyses, however. The use of the CAR method with shrinkage estimators obviates this issue.

**Level-1 pool: Chronologies within 450 km** For each gridded reconstruction, Cook et al. (2014, 1999, 2010, 2004) select only those chronologies within a 450 km radius of the grid point. Our pool of the 205 chronologies in the Four Corners states already imposes a similar spatial restriction on the reconstruction. Thus, we impose no such restriction; our level-1 pool is the complete set of Four Corners tree-ring chronologies described above.

**Level-2 pool: Significance of raw correlation ($\alpha = 0.10$ cutoff)** The second screening removes any chronologies that fail to be significantly correlated with the observed calibration data at the $\alpha = 0.10$ level. Following Cook et al. (1999), we use a two-tailed hypothesis test of the Pearson correlation coefficient with with $n - 2$ degrees of freedom (here, 58 degrees of freedom). Chronologies that are significantly correlated with the observed calibration data are retained and entered into a principal components analysis.

**Level-3 pool: Kaiser-Guttman eigenvalue-1 criterion** Once the set of principal components has been computed, it is further reduced by removing components that account for very little joint variance in the predictors by employing the Kaiser-Guttman eigenvalue-1 criterion Guttman (1954); Kaiser (1960). Eigenvalues are computed as the squared standard deviations of the eigenvectors (principal components), and only principal components with eigenvalues $\geq 1$ are retained. This guards against spurious correlation between the observed calibration data and uninformative principal components.

**Level-4 pool: Stepwise multiple regression and minimization of $\mathbf{AIC_c/RMSE}$** Finally, the reduced set of principal component scores are ranked via their squared marginal correlations with the observed calibration data, and then entered stepwise into an OLS multiple regression. For each model, we calculate estimates of $AIC_c$ and $RMSE$ using three-fold consecutive cross-validation, and choose the model that minimizes either $AIC_c$ or $RMSE$. As Supplementary Table 3.17 clearly shows, better fits between the predictions and validation datasets are achieved when minimizing $RMSE$ than when minimizing $AIC_c$.

# CHAPTER FOUR

# COMPLEX LANDSCAPES

Humans are never passive inhabitants of static or dynamic landscapes—we are actively engaged in directly and indirectly transforming landscapes, often in quite apparent ways. Foragers pressure regional flora and fauna, sometimes leading to resource depression and subsistence shifts (Bocinsky 2011; Bocinsky et al. 2012; Bocinsky and Kohler 2014b; Driver 2011; Schollmeyer and Driver 2012). Farmers further clear land of wild resources, altering the distribution of faunal habitats (Cowan et al. 2012). People build large structures, potentially enhancing visibility (Johnson 2003), visual connectedness (Van Dyke et al. 2014), or restricting access (Martindale and Supernant 2009). Access to space and resources may become sources of conflict (Kohler et al. 2012c).

The studies presented in this dissertation have thus far focused exclusively on human adaptations to static and dynamic landscapes, and not on socioecological feedbacks (even neglecting the rather fundamental impact of human population size). However, both of these studies invite the consideration of human-environment feedbacks. Defensiveness requires not only the defensibility of place, but *aggressiveness* by other regional actors (or at least the potential of aggression); population dynamics on the NWC landscape are then critical for inferring defensive behavior on that landscape. Similarly, the expansion and contraction of the rain-fed maize growing niche in the SWUS is of little importance unless there is a large population of maize farmers in that region, large enough to restrict local flexibility in farming location. If people are unable to "follow" the maize growing niche, they must turn to alternative strategies for resource procurement, such as intensification of foraged resources (Freeman 2012, 2014; Freeman et al. 2014; Upham 1984), development of regional exchange systems (Crabtree 2012), resource specialization (Cockburn et al. 2013), and even conflict (Kohler et al. 2012c, 2014).

In the following paper—*Poshumi and paleoproductivity: Biocultural models for the development of ancestral maize landraces* (Bocinsky 2014c)—I develop a research program to study the coevolution of maize landraces and agricultural selection strategies. I introduce *biocultural* models of past maize production: models that simultaneously incorporate the phenological constraints of maize development, the environmental impacts of land use and soil degradation, and the social landscape of ritual and economic needs of human societies. I review past efforts at modeling potential maize productivity, and suggest current efforts be directed at developing either general growing niche models as in Chapter 3, or dynamic productivity models that incorporate a range of maize phenotypes and cultivation strategies. These latter models incorporate all three types of landscapes explored in this dissertation: static landscapes like elevation that generate orographic effects such as cold-air drainage; dynamic climate landscapes; and coevolving human social landscapes, genetic and phenotypic landscapes of the maize they cultivate, and the physical and chemical changes to soils resulting from land use changes.

Agent-based complex-systems approaches represent a natural framework within which to explore the types of complex human-environment interactions introduced in this paper. An agent-based simulation would be able not only to incorporate models for potential paleoproductivity of different populations of maize landraces (via integration with cropping systems models, introduced below), but also models of how Ancestral Pueblo people may have selected which maize to plant in any given year, models of where people choose to farm on a landscape, and models of intensification strategies, such as gravel mulching or implementation of water management technologies. Such simulations incorporate processes as multiple spatiotemporal resolutions, from annual agricultural returns to seed stock population changes over decades and centuries.

As I argue in the conclusion to this paper, the approach presented here has the potential to make long-sought advances in cultural and historical ecology. One way it does this is by clearly describing how both ritual and economic needs of a community might serve to shape genetic diversity in their future maize stock, and by proposing a mechanism for productivity successes and failures to feed back into ritual needs and behaviors. I adopt an historical perspective on the development of social norms (in which I include selecting of ritual poshumi), whereby behaviors that are routinely economically *good* are transformed into those that are deemed ritually *right*. As we shall see, this provides a mechanism for maintaining diversity in seed stock populations over long timescales that would otherwise be bred out of populations given strict economic selection.

# Poshumi and paleoproductivity:

# Toward biocultural models of ancestral maize diversity

R. Kyle Bocinsky

**Abstract**

The development of ancestral maize (*Zea mays*) landraces occurred not only in the context of subsistence need, but in an functional and ritual milieu. Feedbacks between subsistence and ritual needs of maize farmers simultaneously shaped population genetics of maize, as well as the selective strategies of its human cultivators. In this paper, I present a framework for how we may begin to integrate cultural practices into our models of past maize productivity. I review past and contemporary efforts to model potential maize yield, including a recent pivot towards models that more accurately reflect maize phenology. I detail the cultural and physical processes that affect the diversity of local populations of maize, and suggest that ritual needs and maize trade likely served to maintain diversity in seed stock. Maize paleoproductivity modeling should proceed in two complementary directions: modeling maize growing niches where productive landraces were likely to have been developed, and directly modeling potential yield of specific landraces using state-of-the-art cropping systems models coupled with sophisticated reconstructions of environmental data. I illustrate the potential of these types of models by exploring two high-resolution reconstructions of maize paleoproductivity in the central Mesa Verde region of southwest Colorado: a 2000-year reconstruction of the rain-fed maize growing niche and a model of productivity for the Tohono O'odam maize variety.

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### *Poshumi* for ritual and resource

*It's the women who do the selection.* They carefully sort through their seed stock, not necessarily selecting the tallest or healthiest cobs, but the ones whose "kernels look hard," the most robust ones and the best for grinding (Wall and Masayesva 2004:443). The women select for a diverse harvest—they are responsible for ensuring that, upon harvest, the correct types of corn will be available for the coming year's dances, initiation feasts, and other ritual gatherings. In consultation with the men (who are responsible for planting, cultivating, and harvesting the corn; Wall and Masayesva 2004), they also select the seed stock to ensure a bountiful harvest given soil moisture and predictions for the coming growing season—in Hopi, *poshumi* (Nicholas 2008:319). Through a combination of traditional ecological knowledge and attention to ritual necessity—not to mention hard work and prayer (Wall and Masayesva 2004:435)—the Hopi are among the most successful traditional agrarian societies in existence. For the Hopi, corn is not merely a means to living, it is life itself.

Over centuries, the Hopi have developed a form of rain-fed maize agriculture on an arid, sandy landscape that by the standards of the Midwestern corporate farmer is marginal at best. They have developed a portfolio of at least 17 landraces of corn (Soleri and Cleveland 1993:213–214)—locally-adapted folk crop varieties—through a suite of selective strategies. Many of their maize varieties are demonstrably drought resistant (Cleveland et al. 1994; Nabhan 1989:71), a phenotypic trait becoming ever more important in the increasingly arid southwestern United States (Seager et al. 2007). Hopi corn has also been selected for quite deep planting (often greater than 25 cm; Soleri and Cleveland 1993:211) as a means to gain access to soil moisture that recedes quickly during the late spring winds and rising summer heat. The Hopi have been successful corn farmers for centuries. By measures of agricultural productivity and cultural persistence, they have developed resilient subsistence strategies. But to what extent are their selection and cultivation practices—for ritual and resource—*adapted* to the environment in which they make a living?

The dynamic, agency-driven reality of Pueblo farming presents a sobering reality for researchers who seek to model maize paleoproductivity in the Pueblo world and connect those estimates with cultural and behavioral changes apparent in the archaeological record (Benson 2011a,b; Benson et al. 2013; Bocinsky and Kohler 2014a; Burns 1983; Kohler 2010, 2012b; Kohler et al. 2014; Lekson et al. 2002; Therrell et al. 2006; Van West 1994; Wright 2006). Pueblo people are not passive recipients of weather and landscape, simply planting the same corn year after year and accepting whatever yields they can muster. Yet this is how we have tended to model Pueblo farming: as a (usually linear) response to climate signals, irrespective of the adaptive capacity of traditional agricultural practice.

In this paper, I present a framework for how we may begin to integrate cultural practices into our models of past maize productivity. I review past and contemporary efforts to model potential paleoproductivity, including a recent shift towards models that more accurately reflect maize phenology. I detail the cultural and physical processes that affect the diversity of local populations of maize, and suggest that ritual needs likely served to maintain diversity in seed stock. I argue that maize paleoproductivity modeling should proceed in two complementary directions: modeling maize growing niches where productive landraces were likely to have been developed, and directly modeling paleoproductivity of specific landraces using state-of-the-art cropping systems models (CSMs) coupled with sophisticated reconstructions of environmental data. I illustrate the potential of these types of models by exploring two high-resolution reconstructions of maize paleoproductivity in the central Mesa Verde region of southwest Colorado: a 2000-year reconstruction of the rain-fed maize growing niche (Bocinsky and Kohler 2014a), and a model of productivity for the Tohono O'odham maize variety (presented here for the first time). The first offer powerful explanations for patterns of demography (Schwindt et al. 2014) and violence (Kohler et al. 2014) in the region by illuminating spatiotemporal aspects of risk and abundance on the central Mesa Verde landscape. The second demonstrates the feasibility and utility of modeling landrace-specific potential yields using CSMs.

### Maize paleoproductivity modeling in Southwestern archaeology

Archaeologists in the southwestern United States (SWUS) have been interested in the effects of climate on agricultural productivity for almost a century (Douglass 1929). Early dendroclimatologists focused on identifying periods of drought in tree-ring chronologies and connecting them with cultural shifts in the archaeological record, such as the "Great Drought" of AD 1276–1299 and the depopulation of the central Mesa Verde (CMV) region by Ancestral Pueblo farmers during that period (Douglass 1929:766). Dean and colleagues (Cordell et al. 2007; Dean 1988, 1996; Dean and Van West 2002) continued to explore evidence for the impact of regional droughts on Ancestral Pueblo populations. Benson et al. corroborate these claims, and suggest that large droughts in the mid-12th and late-13th centuries were primarily characterized by reductions in summer monsoonal moisture that would have had devastating effects on crop yields (2007:205). All of these studies note that joint reconstructions of potential maize yields and demography are crucial for connecting drought to human behavior (Kohler 2010:103).

#### *Correlation-based yield reconstructions*

The tree-ring-based studies introduced above are founded on the hypothesis that reductions in precipitation generally resulted in low maize yields regionally, though studies are not specific in where or to what extent those reductions might have impacted maize-farming populations. Over the last three decades, archaeologists have begun developing methods for directly modeling potential maize yield in the past via correlation-based analyses relating contemporary production records to modern climate and tree-ring chronologies (Burns 1983; Kohler 2010, 2012b; Van West 1994). Here, I summarize these primary efforts, and pay particular attention to changes in model sophistication and complexity through time (Figs. 4.1–4.4). Kohler (2010:105–109) provides a thorough technical review of efforts by Burns (1983), Van West (1994), and the Village Ecodynamics Project (VEP; see also, Kohler 2012b).

Burns (1983) presented the first annual-scale reconstruction for southwestern Colorado that directly correlated historic maize yields with several regional tree-ring chronologies (Fig. 4.1).

He painstakingly analyzed historic maize yield data from Archuleta, Montezuma, La Plata, San Miguel, and Dolores counties, Colorado, collected during AD 1926–1968 (Burns 1983:307–311)[1]. He first removed a "technology trend" from the historic yield data by controlling for pounds of fertilizer per harvested acre as a proxy for all technological innovation (using linear regression to remove the trend), then experimented with regressing the corrected maize-yield data on several regional tree-ring chronologies, including lagged versions of the series. After settling on five regional series, Burns generated a productivity reconstruction from AD 652–1968. Because of the relatively short calibration period used, Burns was unable to validate his predictions against any withheld productivity data.

Van West (1994) spatialized Burns' reconstruction by correlating a trend-adjusted version of Burns' modern yields (from AD 1931–1960 for Montezuma county, only; Van West 1994:97–102) with a spatial reconstruction of regional Palmer Drought Severity Index (PDSI) values calculated from contemporary regional soils data (Van West 1994:55–94; Fig. 4.2). The PDSI is a monthly measure of stored soil moisture available for plant growth; it is a function of soil texture, precipitation history, and changes in evapotranspiration due to temperature. To reconstruct spatial PDSI, Van West calibrated historic June PDSI values against a principal components analysis of seven regional tree-ring chronologies (called SWOLD7, for SouthWest Old 7), using AD 1922–1970 as a calibration period. The June PDSI values were calculated across 11 regional soil types using historical climate data from five regional weather stations. Van West's spatial model used soil productivity estimates from the soil conservation service (Ramsey 2003) and generated independent productivity reconstructions for each of the 55 soil types and weather station combinations from AD 901–1960. Van West's major innovation was using a geographic information system (GIS) to generate the first spatial paleoproductivity reconstruction (Fig. 4.2); she found that the CMV region could have supported thousands of people, even during the droughts in the 12th and 13th centuries (1994:Fig. 5.2).

Kohler and others (Kohler 2010, 2012b) expanded on Van West's work as part of the VEP

[1]Burns had to estimate data from 1944–1947 for which no yields were published.

TABLE 5-3. RECONSTRUCTED CROP YIELDS PER HARVESTED ACRE.

| YEAR | UNADJUSTED CORN (BUSHELS) | ADJUSTED CORN (BUSHELS) | UNADJUSTED DRY BEANS (POUNDS) | ADJUSTED DRY BEANS (POUNDS) |
|---|---|---|---|---|
| 652 | 8.3 | 11.5 | 494.8 | 422.9 |
| 653 | 10.3 | 15.0 | 436.4 | 393.6 |
| 654 | 13.7 | 19.7 | 533.3 | 698.6 |
| 655 | 15.8 | 13.9 | 227.8 | 646.2 |
| 656 | 17.5 | 17.3 | 14.5 | 365.0 |
| 657 | 17.7 | 16.0 | 262.3 | 349.2 |
| 658 | 14.4 | 11.8 | 531.0 | 424.3 |
| 659 | 18.6 | 12.6 | 418.6 | 352.0 |
| 660 | 16.9 | 9.9 | 379.3 | 342.5 |
| 661 | 13.2 | 9.2 | 197.5 | 90.3 |
| 662 | 14.6 | 10.4 | 442.6 | 210.7 |
| 663 | 15.7 | 11.9 | 590.6 | 152.6 |
| 664 | 13.0 | 10.7 | 232.4 | 210.5 |
| 665 | 14.9 | 11.0 | 511.8 | 420.7 |
| 666 | 18.5 | 13.9 | 482.8 | 450.2 |
| 667 | 11.8 | 12.5 | 358.0 | 569.4 |
| 668 | 10.3 | 10.8 | 116.6 | 232.6 |
| 669 | 9.7 | 14.7 | 417.5 | 377.6 |
| 670 | 6.4 | 14.4 | 579.5 | 408.8 |
| 671 | 12.0 | 12.7 | 302.1 | 675.9 |
| 672 | 12.7 | 16.1 | 258.7 | 494.8 |
| 673 | 14.1 | 13.6 | .1 | 428.0 |
| 674 | 11.9 | 13.9 | 242.0 | 389.5 |
| 675 | 12.2 | 13.8 | 672.8 | 600.1 |
| 676 | 18.7 | 15.5 | 363.6 | 404.2 |
| 677 | 16.7 | 10.1 | 242.5 | 386.3 |
| 678 | 15.9 | 11.4 | 336.6 | 348.0 |
| 679 | 16.9 | 14.3 | 638.6 | 528.8 |
| 680 | 16.9 | 9.8 | 362.8 | 462.0 |
| 681 | 10.5 | 8.0 | 299.6 | 432.2 |
| 682 | 10.8 | 11.3 | 433.0 | 362.6 |
| 683 | 10.7 | 14.2 | 285.4 | 300.8 |
| 684 | 11.7 | 12.9 | 529.6 | 242.7 |
| 685 | 13.9 | 12.4 | 490.3 | 314.0 |
| 686 | 9.5 | 10.9 | 321.6 | 334.4 |
| 687 | 3.7 | 6.5 | 133.1 | 428.2 |
| 688 | 9.7 | 18.1 | 15.7 | .1 |
| 689 | 14.3 | 18.0 | 754.1 | 479.6 |
| 690 | 14.0 | 12.6 | 316.3 | 137.6 |
| 691 | 20.3 | 18.2 | 481.1 | 528.9 |
| 692 | 12.9 | 11.1 | 482.0 | 520.0 |
| 693 | 16.5 | 10.6 | 174.7 | 354.2 |
| 694 | 16.0 | 12.9 | 462.0 | 443.8 |
| 695 | 10.9 | 12.6 | 252.2 | 405.6 |

**Figure 4.1 | Paleoproductivity data as presented in Burns 1983.** Burns, working in the late 1970s and early 1980s, did not have the capacity to easily represent his reconstructions graphically. In fact, there were three figures in his entire 805-page dissertation. All of his statistical calculations were coded in Fortran 77 and were run on paper punch cards at the University of Arizona. Burns and Malcolm Cleaveland wrote the computer program "FOOD," which is fully reproduced as Appendix 8 in Burns' dissertation. This figure is a scan of Burns 1983:Table 5.3.

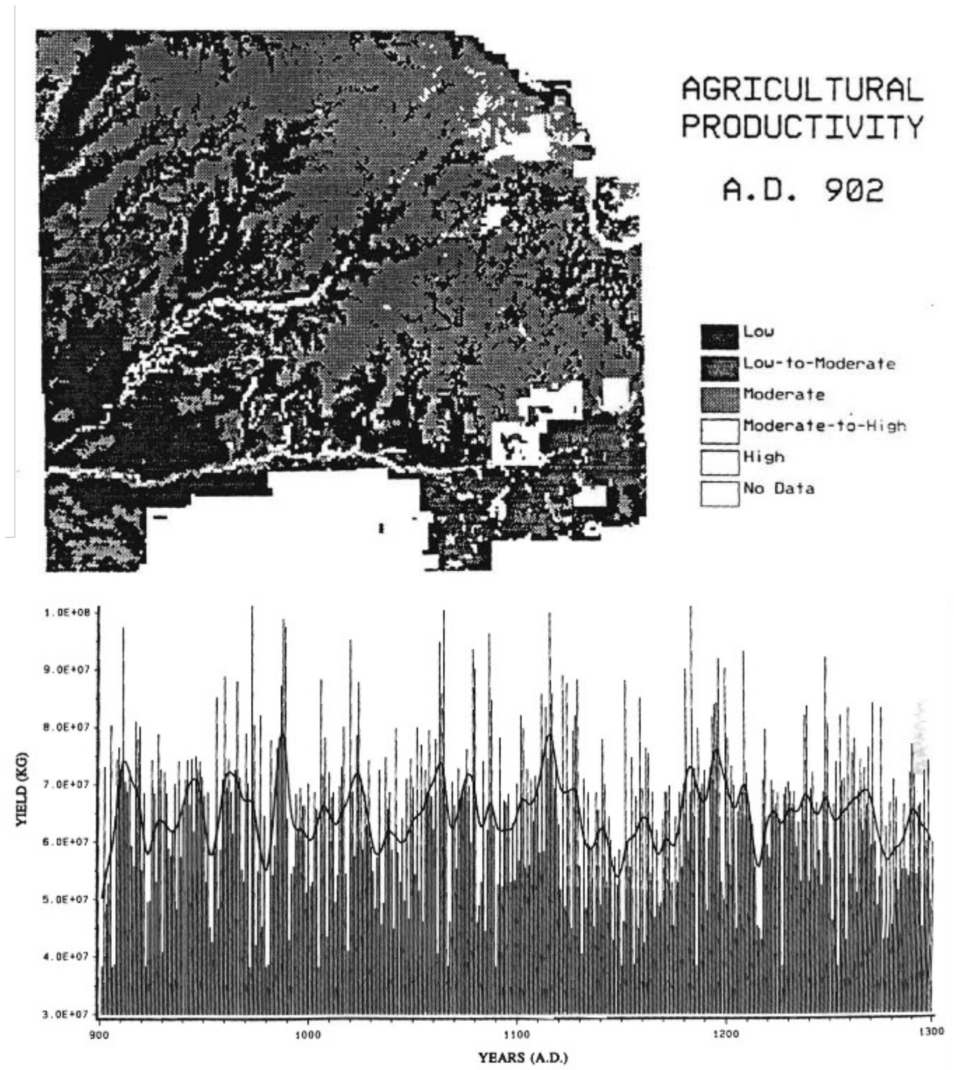


**Figure 4.2 | Paleoproductivity data as presented in Van West 1994.** Van West, working at Washington State University, had access to state-of-the-art computing facilities for the time, including the early geographic information systems VICAR/IBIS (which operated on a mainframe) and EPPL7 (which was on a desktop computer, then called a "microcomputer"). VICAR continues to be developed, maintained, and used at NASA's Jet Propulsion Laboratory. EPPL7 is a raster GIS back-end still used in the EPIC GIS system developed by the state of Minnesota. Van West created color graphics that could at that time only be presented on computer screens; all the figures in her dissertation and subsequent publication (Van West 1994) were formatted for b/w dot-matrix printers. Adapted from Van West 1994:Figs. 4.3 and 5.1.

(Fig. 4.3). Like Van West (1994), the VEP model calculated June PDSI over a large number of regional soil types using historical climate data from four regional weather stations (corresponding to four elevation bands). These regional PDSI values were then correlated with a single tree-ring chronology (the Mesa Verde Douglas Fir [MVDF] chronology), and retrodicted to AD 600.

Kohler and colleagues also account for high-frequency temperature change in their reconstruction by including two high-elevation bristlecone pine series—one from the San Francisco Peaks near Flagstaff, Arizona, and the other from Almagre Mountain, Colorado (Kohler 2012b:88)[2]. Their final reconstruction (Kohler 2012b:100) regresses historic maize yield on three series—reconstructed June PDSI, high-elevation temperature series, and year (to remove the technology trend)—to create paleoproduction estimates for AD 600–1300 (using 1931–1960 as the calibration period). Finally, (Kohler 2012b:100–108) down-adjusted their estimates for hand-planting and high-elevation cold; these estimates may be further degraded dynamically by computational agents in the Village agent-based simulation, depending on their density and continuity of field use. Due to the inclusion of the production-suppression variables, the VEP model generated substantially lower production estimates than the Van West (1994) model, though the VEP also found that substantial populations could have been supported in the region, even during the worst droughts. Recently, I reworked the VEP analysis to generate PDSI reconstructions using highly-local temperature and precipitation records over a larger study area (the ~800 m PRISM climate dataset; Bocinsky 2014a; Fig. 4.4).

Little effort has been made to directly model maize production outside of the Northern San Juan (NSJ) basin in the SWUS, presumably due to unavailability of local high-resolution climate proxies like tree-rings. Therrell et al. (2006) calibrate contemporary maize productivity (AD 1980–2001) to a single latewood Douglas fir tree-ring chronology in central Mexico, which they use to reconstruct maize yield from AD 1474–2001. Their reconstruction is effective at capturing well-documented regional famines and droughts (Therrell et al. 2006:500). PDSI has been reconstructed across the contiguous United States extending back to AD 1000 (Cook et al. 2014, 1999, 2010), but to my knowledge these retrodictions have yet to be transformed into paleoproductivity estimates.

In summary, the strategy of Burns, Van West, and the VEP thus far has been to take modern, highly local maize production data, correlate it with some derived measure of local growing conditions (such as PDSI and temperature), correlate the growing conditions with long-term den-

[2] They also used the first principal component of these two series to construct a joint series (the Prin1 series).

drochronological reconstruction(s), and finally retrodict maize production using these relationships. Apart from relying on contemporary yield data that is of limited spatial extent and not readily available[3], this method has several shortcomings. First, it can only be applied in regions where maize farming occurred during the last century or so. The use of linear models, even with multiple independent variables, will generate predictions that are not very sensitive to local conditions outside of the contemporary agricultural area. For instance in the VEP study area, the contemporary maize data is assumed to come from the "bean fields", the area of present-day direct rain-fed bean farming. These bean fields have very little variation in topography or soil quality (both variables which factor heavily into the VEP model) and therefore are not a representative sample of growing conditions across the landscape. Also, linear models by definition make the assumption that maize production scales linearly with environmental variables, while in reality maize has specific environmental thresholds that must be met at several points during its growth cycle; maize production does not increase linearly above those thresholds (McMaster and Wilhelm 1997). For many variables its response is curvilinear: high near optima, and low on both sides (Jones et al. 1986; Van West 1994:99–101). Furthermore, correlation models effectively reduce variance in predicted values; a series of chained, interdependent regressions reduces variance even further. This can lead to the entirely unrealistic expectation that, even in environments that are extremely unfavorable for agriculture, modest yields might still be achieved[4].

*Experimental studies: Toward phenological models of maize productivity*

Research efforts have recently pivoted towards a focus on the phenology of ancestral maize landraces, or directly modeling the influences conditioning maize growth and development through experimental maize field trials and observational studies (Adams et al. 1999, 2006; Bellorado 2007, 2010; Bellorado and Anderson 2013; Muenchrath 1995), local analysis of soil nutrient availability

[3]Had it not been for Burns aggregating historic production data from Montezuma County, Colorado, neither Van West's nor the VEP reconstruction would exist.

[4]This is the case with the VEP productivity model. The regression relationship is not forced to have an intercept at zero; there is always at least *some* potential productivity, except where the cold-correction is applied. In theory the opposite effect could occur, given the right training data: the model could create expectations of *negative* yield.

(Benson 2011a,b; Homburg and Sandor 2011; Muenchrath et al. 2000), and other factors impacting maize growth (Adams 1979). Ancestral maize field trials have been thoroughly reviewed by Adams (2014), so I will only briefly summarize those efforts here. Other research not reviewed here has focused on the development and use of water and heat management technologies in maize cultivation, including cobble mulch gardens (Anschuetz 1995; Periman 1995), strategy diversification (Herhahn and Hill 1998), dry-farming in pumice soils (Gauthier et al. 2007), and the use of check dams (Doolittle 1985) and terraces (Sandor et al. 1990)[5].

Muenchrath, Adams, and others have been steadily building a portfolio of experimentally derived growth data on ancestral maize landraces using maize field trials (Adams et al. 1999, 2006; Muenchrath 1995; Muenchrath et al. 2000). In a series of field trials under variable precipitation, Muenchrath (1995) characterized the phenological and phenotypic responses of Tohono O'odham (Pima) maize. She found that kernel weight and grain-filling were little affected by precipitation amounts, especially when compared to other traits. More recently, Muenchrath, Werth, and Adams designed and executed a multi-year analysis of over 150 accessions of indigenous maize (the MAÍS project; Adams et al. 2006; Werth 2007) near Farmington, NM on the Colorado Plateau. The plants were kept well irrigated and fertilized (Adams et al. 2006:26–27), so the MAÍS trials primarily report growth and yield under optimal or temperature-limited conditions. Researchers collected data on the timing of planting and seedling emergence, flowering, and maturity, as well as weather data including accumulated heat (growing degree days, GDD) and growing season length. Based on physical characteristics of the harvested maize, Adams et al. (2006) were able to partition the 150 accessions into four primary groups that corresponded well with known geographical and cultural distributions (Adams et al. 2006:43–44).

In related research, Bellorado and others (Adams et al. 2008; Anderson 2008; Bellorado 2007, 2010; Bellorado and Anderson 2013) performed a small field trial in four garden plots in 2003 and 2004 using eight seed varieties (Adams et al. 2008:162). Maize was hand-pollinated, but otherwise left untreated (Adams et al. 2008:165). The relatively high-elevation setting of these

[5]While these methods were apparently widely-used in other areas of the SWUS, they were less-used in the central Mesa Verde region.

field trials—between 6,807 and 6,896 ft in elevation—and their position along the flanks of a broad basin generated good information on the importance of temperature for maize varieties. Bellorado (2007:185–193) reports topographic variation substantially affected the length of the frost-free growing season, which likely affected maize growth. Bellorado also tracked GDDs at the garden plots, and was able to get reasonable yield of Hopi Red corn with as little as 1600 GDDs over the growing season (Bellorado 2007:205), a figure substantially lower than the heat requirements of contemporary varieties grown in the Midwestern United States (~2400–3200 GDD; Adams 2014).

Several researchers have focused on the suitability of soils for various types of indigenous maize agriculture (Benson 2011a,b; Homburg and Sandor 2011; Muenchrath et al. 2000). Muenchrath, Sandor, and Homburg have a long-standing research project on soil genesis and cropping systems in the Zuni region of central New Mexico. Recently, Benson (2011a,b) published a large study of soil nutrients (particularly nitrogen and phosphorus) across the Colorado Plateau and into the Rio Grande region. He found that the central San Juan basin—the area around Chaco Canyon—has some of the least favorable soils for maize agriculture in the SWUS. Conversely, soils in Morefield Canyon on the Mesa Verde cuesta and on the Pajarito Plateau in northern New Mexico are among the most favorable places for maize agriculture (Benson 2011b:101–102). In these studies, Benson also used modern climate data to further establish the temperature and precipitation growth requirements for indigenous maize that I use later in this paper.

These initiatives—and especially the MAÍS project (Adams et al. 2006)—have highlighted the great phenotypic and phenological variation among extant ancestral maize varieties in the SWUS, and provided important growth-data that may be used in more mechanistic reconstructions of maize yield, such as those discussed below. Present-day traditional farmers utilize the diversity of their maize to minimize risk and fulfill ritual needs—a one-size-fits-all model of maize cannot guide archaeologists towards better understandings of these ritual and practical cultivation strategies in the past. Furthermore, growth and yield data from field trials and soil analyses will help us to more accurately estimate potential maize yields in the past across a variety of landscapes.

### Biocultural models of maize agriculture

The efforts at estimating potential maize yields presented above, while groundbreaking and often truly insightful, have been limited in that most assume (by definition in the case of correlation-based analyses) a static relationship between climate (most often proxied by tree rings) and maize productivity. They cannot possibly begin to capture the complexity and long- and short-term adaptability of Pueblo farming. We need a new strategy, one that does not abandon spatiotemporally explicit paleoproductivity modeling altogether, but also one that permits the integration of modern agronomic knowledge with traditional farming practices.

Figure 4.5 presents a heuristic model of the traditional Pueblo agricultural system, integrating biophysical and cultural forcings[6] on maize populations. The *ritual and subsistence needs* of a community are important in selecting the *poshumi* for the coming growing season, and *traditional ecological knowledge* guides variety selection, field selection, and cropping strategies such as tilling and planting depth. Those cultivation strategies (*behavioral forcing*) combine with *environmental* (climate, weather, and soils) and *ritual* (prayer) forcings to determine maize growth and eventual maturity and grain yield. Harvested maize is a naturally-selected subset of the initial planted population. Maize leaves the system to be used for food, ritual, feasting, and trade; it also enters the system from the remains of past harvests and through trade. Trade and the integration of current and previous grain-stores play crucial roles in maintaining diversity in seed stock, as does the annual replenishing of that diverse stock by grow-outs of ritually-important varieties (even though they might not provide “optimal” grain yields).

This model reinforces the idea that selection and cultivation strategies coevolve with the cultivars upon which they act—at every step in the system, ritual, behavioral, and environmental forcings act to shape maize population size and structure. Without robust trade of seed corn and the inclusion of ritually-important varieties in *poshumi*, strong natural selection at a local-level could dramatically reduce phenotypic and genetic diversity within the seed population (Butler and

[6] A *forcing* is any factor external to a given system that influences the state of that system. In this case, behavioral, ritual, and environmental forcings affect maize landrace growth, selection, and eventual grain yield.

Huybers 2013). This is the true definition of a *landrace*—a highly locally-adapted variety. That such diversity is maintained in Pueblo seed populations suggests that Pueblo corn represents not landraces per se, but something more enduring over the long-term: *ecoraces*. Pueblo maize diversity represents the outcome of an evolved socioecological system adapted to maintain that diversity for ritual and subsistence needs. The development of ecoraces may in fact be a long-term resilience strategy, maintaining crop diversity such that when environmental change does occur—as it does in the SWUS with some regularity (Bocinsky and Kohler 2014a)—grain yields are maintained. The intensity of trade and relative importance of ritual needs (as opposed to subsistence needs) become critical factors in the development of ecoraces (Doebley and Bohrer 1983:20). These processes are also of great interest to contemporary SWUS archaeologists (e.g., Fowles 2013; Mills et al. 2013). It is also important to note that while trade has often been cast in terms of supporting communities in times of subsistence stress (Cordell et al. 2007; Crabtree 2012; Kohler et al. 2012a:4–5), the model I am proposing here is a more indirect though perhaps more sustainable form of maize exchange. Instead of trade of grain to meet immediate caloric need, it serves to mix regional ecoraces and maintain diversity in many local populations of maize seed-stock, ensuring that local communities have the best opportunity to meet those needs themselves.

So, how do we move from heuristic models such as this to an understanding of the development of indigenous maize ecoraces? And how do we connect grain yield within this framework to other archaeological visible cultural sequences, such as demography and violence through time? Part of what is required is a re-assessment of now-commonplace questions in environmental archaeology; we need to ask new styles of questions. For instance, we should not only be asking, *Do declines in maize productivity help explain patterns of violence?* We should also ask, *In what ways were the agricultural and social strategies of Pueblo people capable of dealing peacefully with certain climatic conditions—or not?* Previous work by Kohler and colleagues (2014) speaks to this: they found it was not declines in productivity that correlated with a rise in conflict in the northern SWUS, but *increased variability in productivity*, suggesting that Ancestral Pueblo people did not have effective conflict-amelioration strategies in place during those more variable periods. Lekson

(2002) has also made a similar argument, following Ember and Ember (1992), and I explore this idea more rigorously below. Often, answering important and interesting archaeological questions like those posed here does not require modeling maize productivity at all. As productivity is the dynamic result of environment and agricultural practice, many questions may only require a model of agronomically important climate variables, as Dean and others have done regionally. Here, I demonstrate how highly local reconstructions of these variables can lead to profound insights about local and regional adaptive strategies.

### Exemplars: Models of niche and production

In the remainder of this paper, I present two related strategies for better representing Ancestral Pueblo maize paleoproductivity. The first is to model the spatiotemporal extent of environments in which maize landraces may be developed. The question here is: *Given ample time and effort, where on a landscape should we expect locally adapted landraces to flourish?* In other words, where is the maize growing niche? This strategy is in the tradition of work by Benson and colleagues, as well as Dean, Cordell, Bellorado, Stahle, and others. My second strategy is to ask, *How would a particular maize variety "perform" in a given place and time?* Both of these strategies shift focus from yield-reconstruction approaches towards direct reconstruction of the paleoenvironment in which agricultural development would take place[7].

#### *Modeling the agricultural niche in the central Mesa Verde region*

Tim Kohler and I developed a new method for very high-resolution spatiotemporal climate reconstruction from tree-ring chronologies (Bocinsky and Kohler 2014a). Our method has two primary components. First, we used an approach developed in quantitative genomics called Correlation-Adjusted corRelation (CAR) for automated climate proxy selection. Basically, the CAR method ranks a set of tree-ring chronologies by how well they can predict a target climate signal (summer

[7]Kohler (2012b:86, footnote 1) called this a "radical" yet "attractive" strategy, and a major goal in maize paleoproductivity research. The cropping systems model I employ here overcomes both of the potential problems mentioned by Kohler—they account for local soil variability and generate annual estimates maize yield.

precipitation, for example), while accounting for the covariance structure among the chronologies themselves. These ranked chronologies may then be entered into a stepwise regression until some optimality threshold is reached, such as Akaike's Information Criterion (Akaike 1974) or the minimization of cross-validated error. The second component of our method is to repeat this process of tree-ring chronology selection and stepwise regression across an interpolated historical climate field. We used the ~800 m PRISM climate dataset (Daly et al. 2008, 2002; PRISM Climate Group 2014), which is effective at reconstructing topographic patterns in temperature, such as the effects of cold-air drainage. Our method selects appropriate tree-rings given well-documented regional climate patterns and the growth sensitivities of local and regional tree species. Furthermore, our method performs as well or better than several alternative reconstruction methods (Bocinsky and Kohler 2014a:Supplementary Methods).

In order to estimate the extent of the rain-fed maize niche, we first reconstructed net water-year precipitation (October–September) and growing-season GDDs (May–September) across two large and ecologically heterogenous regions in the SWUS using the CAR method (Bocinsky and Kohler 2014a:Fig. 1). Our study areas were drawn from the VEP; the first study area (VEPIIN) is a 4600 $km^2$ region in southwestern Colorado encompassing Mesa Verde National Park, Canyons of the Ancients National Monument, the Montezuma Valley, portions of the Ute and La Plata piedmonts, and the contemporary towns of Cortez, Dolores, and Mancos, Colorado[8]. The second area (VEPIIS) is a 6955 $km^2$ region in north-central New Mexico encompassing Pajarito Plateau, Bandelier National Monument, the Rio Grande and Chama river valleys, and the contemporary cities of Santa Fe, Los Alamos, and Española, New Mexico.[9] We defined the rain-fed maize growing niche as the portions of the landscape receiving more than 30 cm of annual precipitation and greater than 1800 growing-season GDDs (measured in Fahrenheit heat units), following Benson (2011a:13) and Bellorado (2007:263).

In our previous study, Kohler and I demonstrated that these niche reconstructions—or, more precisely, the proportion of each landscape within the maize growing niche, through time—are

[8]VEPIIN is defined in NAD83, UTM Zone 12: 672800 m E to 740000 m E, and 4102000 m N to 4170000 m N.
[9]VEPIIS is defined in NAD83, UTM Zone 13: 359200 m E to 435800 m E, and 3939600 m N to 4030400 m N.

useful in explaining both the timing and trajectory of the 13th century Pueblo migrations (Bocinsky and Kohler 2014a). Here, I take our niche reconstruction for the VEPIIN study area and compare it to two published cultural sequences for the same region: a demographic reconstruction (Schwindt et al. 2014) and a reconstruction the intensity of interpersonal violence on the landscape (Kohler et al. 2014). For this analysis, I summarize the niche data over 14 modeling periods used by the VEP in both the demographic and conflict reconstructions (the periods range in length from 20–125 years; Table 4.1). This allows me to explore how the expansion and contraction of the maize niche through time—proxying agricultural productivity—might have influenced trends in demography and violence. The graphs in Figs. 4.6–4.9 show these sequences, binned over the VEP modeling periods (the vertices are at the midpoints of the periods); Table 4.1 provides the data for the modeling periods.

**Table 4.1** | Periodic niche size, demographic, and conflict data.

| Period | Years (AD) | Population[1] | Conflict[2] | Percent in niche[3] | SD[4] | SI[5] | ISI[6] |
|---|---|---|---|---|---|---|---|
| 6 | 600–725 | 2931 | 0.182 | 61.3 | 0.366 | 5.301 | 3.587 |
| 7 | 725–800 | 3537 | 0.100 | 58.6 | 0.382 | 5.385 | 3.893 |
| 8 | 800–840 | 10523 | 0.000 | 57.3 | 0.385 | 4.114 | 4.061 |
| 9 | 840–880 | 11518 | 0.055 | 68.3 | 0.330 | 7.616 | 2.939 |
| 10 | 880–920 | 4731 | 0.333 | 68.0 | 0.360 | 5.900 | 2.509 |
| 11 | 920–980 | 4158 | 0.000 | 61.6 | 0.405 | 4.626 | 3.093 |
| 12 | 980–1020 | 8589 | 0.250 | 59.8 | 0.415 | 3.889 | 3.151 |
| 13 | 1020–1060 | 9382 | 0.243 | 54.9 | 0.401 | 3.538 | 4.402 |
| 14 | 1060–1100 | 14634 | 0.533 | 70.4 | 0.372 | 6.374 | 2.821 |
| 15 | 1100–1140 | 20741 | 0.407 | 70.8 | 0.327 | 7.775 | 3.172 |
| 16 | 1140–1180 | 20998 | 0.857 | 64.8 | 0.381 | 5.390 | 3.155 |
| 17 | 1180–1225 | 19178 | 0.118 | 74.1 | 0.306 | 10.172 | 2.386 |
| 18 | 1225–1260 | 26695 | 0.080 | 61.0 | 0.375 | 4.334 | 4.110 |
| 19 | 1260–1280 | 21792 | 0.422 | 65.2 | 0.407 | 4.085 | 3.290 |

[1] Estimated total number of individuals in the VEPIIN study area. Data from Schwindt et al. 2014:Table 3.
[2] The proportion of sets of human remains demonstrating violent trauma among all sets of human remains. Data from Kohler et al. 2014:Supplemental Table 2.
[3] The percent of the VEPIIN landscape in the maize growing niche, by area.
[4] The 30-year lagged running standard deviation of the mean niche size.
[5] The 30-year lagged running mean spike interval.
[6] The 30-year lagged running mean inter-spike interval.

Figure 4.6 presents the proportion of the VEPIIN landscape in the maize niche, through time (the "percent in niche"), compared to the other two cultural sequences. The demographic reconstruction shows the now familiar two cycle pattern of the Neolithic Demographic Transition in the region—each NDT cycle has an expansion phase followed by either a contraction or a stability phase (Kohler and Reese 2014; Varien et al. 2007)[10]. As noted by Kohler et al. (2014), the population and conflict curves follow a model in which population booms in a relatively stable landscape are followed by cycles of violence which serve to suppress population (the "Turchin" model; Turchin and Korotayev 2006). Niche size is generally above its 700-year mean during this period, then drops well below the mean for much of the 10th and early 11th centuries. Interesting changes occur during the second population cycle in the 11th–13th centuries. By the early 1100s niche size increases to levels unprecedented during occupation in the VEPIIN region, and population and conflict follow suit. It is likely that increasingly good agricultural conditions allowed population to outpace deaths from warfare, and thus break out of the Turchin cycle. However, after nearly a century of improving conditions, average niche size suddenly constricts dramatically during the mid-1100s drought. Conflict spikes to unprecedented levels, and population flattens out in response[11]. Note that the average niche size is no smaller than in earlier centuries, yet given the size of human populations on the landscape, subsistence stress was likely unavoidable. However, soon thereafter niche size increases again; conflict subsides and populations continue their upward trajectory. Interestingly, an even worse downturn in the mid-1200s does not cause the same violent response. During the early 1200s, Ancestral Pueblo people in the region began adopting new social and residential structures (Glowacki and Ortman 2012), aggregating into large villages scattered across the landscape, and likely pooling labor. It is possible that this new social and residential arrangement ameliorated potential conflict during much of the 13th century.

The 1100s are also a period of rapidly shifting climate regimes. Figure 4.7 presents the 30-year lagged running standard deviation of the mean niche size, though time (the "running SD"). When

[10]Shennan et al. (2013) have found this boom and bust cycle to be common among Neolithic transitions globally.

[11]Population does not decline, however, possibly due to demographic inertia. Estimates of birth rates would clarify this (Kohler and Reese 2014).

this number is high, the niche size is relatively more variable during the period; when it is low, the niche size is more stable. The early-to-mid 1100s are characterized by a more stable landscape than had been experienced in over 200 years, followed by a rapid transition to above-average instability in the mid 1100s. Thus, the mid-1100s period was a perfect combination of small niches and niche unpredictability, especially relative to the preceding period. It likely would have been very difficult for people to transform their selection, production, and storage practices in such a short amount of time.

Two other metrics provide us additional information about the storage potential experienced by people living in the VEPIIN region. Figure 4.8 presents the running average mean spike interval across the landscape. Imagine any place on the landscape flickering in and out of the maize growing niche. The mean spike interval is the average count of consecutive years that place is *in* the niche before it has a year *out* of the niche. Put another way, this is the average number of years people farming that location would be able to store surplus maize before having to deplete that storage. I calculated a 30-year lagged running mean spike interval for each location on the landscape, then averaged across the whole landscape (the "running SI"). People in 1100–1140 enjoyed longer average running SIs than had been experienced in the preceding two centuries and likely adapted their behavior accordingly, but in 1140–1180 that pattern breaks down rapidly.

The inter-spike interval—the average number of years out of the niche before a year in the niche—tells a complementary story ("running ISI"). Not only did good spells get shorter during the mid-1100s, but bad spells got quite longer. The running ISI may be considered an estimate of how many years of storage would be needed to weather a bad spell. Ancestral Puebloans living during the early-to-mid 1100s may have developed strategies to store only enough maize to make it through short periods, relative to those they encountered during the mid-1100s. Other peaks of the running ISI, such as that in the mid-1000s, tend to correspond with stagnant population growth or even population decline.

The bottom line here is that the period of highest conflict in VEPIIN region coincides with some of the highest inter-annual variability and lowest storage capability Ancestral Pueblo people would have experienced in their lifetimes, following a period of great stability and storage potential. The 12th century was a period of shifting climate regimes and growing populations in the Northern San Juan, shifts which had a dramatic and violent impact on Pueblo life.

This discussion of fluctuations in the maize-growing niche illustrates that nuanced interpretations of the cultural record need not depend on reconstructions of actual agricultural yields. Instead, one can model the places on the landscape where agriculture would likely be successful, then analyze changes in the distribution and stability of those places. Furthermore, reconstructions of the spatiotemporal maize growing niche can provide insight into subregional changes that are not possible in non-spatial reconstructions from a single tree-ring chronology. The analyses presented in Bocinsky and Kohler (2014a) suggest that the Mesa Verde cuesta in southwest Colorado and the Pajarito Plateau in the Northern Rio Grande region were the places most consistently in the maize niche in the VEP study areas; they were also the places with the highest population densities of rain-fed maize farmers (Ortman 2012, 2014; Schwindt et al. 2014). In the VEPIIN area, Mesa Verde also stands out as having the longest average running SIs and shortest average running ISIs in the region (Fig. 4.10). People living on Mesa Verde proper would have enjoyed the greatest capacity for maize storage in the central Mesa Verde region—but, ironically, would have had the least need for storage in support of subsistence. Instead, this capacity for storage may have enabled the development of resilient and diverse ecoraces in support of the complex ritual and long-term adaptive needs of Mesa Verde communities.

### *Maize growth requirements and potential productivity*

I started this paper with an acknowledgement of the sophistication of phenotypic selective strategies among contemporary Pueblo women and men, and I would like to now return to our initial question: How do we model maize yield in such a way as to track the development and outcomes of Pueblo farming practice? Here, I use a cutting-edge cropping systems model (CSM) to estimate potential maize yield for a single variety of corn across the VEPIIN study area. CSMs allow agronomists to specify growing conditions—basically temperature, precipitation, soil characteristics, and cropping techniques—and predict yield of any maize variety, given its growth requirements. Figure 4.11 presents the elements of such a reconstruction for the area around Crow Canyon Archaeological Center in Cortez, Colorado (panel a); I combine soil characteristics from the USGS soil surveys (panel b) with modern precipitation (panel c) and temperature (panel d) data from PRISM, and attempt to "grow," in a computer, the Tohono O'odham (Pima, or Ancestral Hohokam) maize variety. These data are available at different spatial resolutions, so I spatially overlay all data types to take unique combinations of soils, temperature, and precipitation (panel e). Each combination has its own independent reconstruction for every year (panel f).

To the best of my knowledge, CSMs have only been used by one other archaeologist to reconstruct prehistoric maize productivity. Michael Pool used similar methods in his dissertation (Pool 2002), though without a spatial weather component. I use his calibration for the Tohono O'odham variety, developed from the aforementioned experimental study by Muenchrath (1995; Adams et al. 1999)[12]. Where our methods differ, though, is that I can now run the CSM using the paleoclimate reconstructions detailed above as input. I first performed independent reconstructions of net winter precipitation, net growing-season precipitation, and growing-season mean temperature using the CAR method. I then used delta transformation to downgrade my seasonal reconstructions to estimates of daily precipitation and temperature. The delta method takes daily data from a "typical" year and modulates those data up or down to meet the mean of a seasonal reconstruction[13]. I created a direct mapping between the USGS soils data and the required data for the CERES-Maize CSM (CERES stands for Crop Environment Resource Synthesis; Jones et al. 1986), which is part of the DSSAT agronomic modeling system (Decision Support System for Agrotechnology Transfer; Jones et al. 2003). Finally, once all the data were in place, I ran the CERES-Maize model for every unique combination of soil and climate in the VEPIIN study area,

[12] Very few other traditional varieties have been calibrated for the CERES-Maize crop models, and Pool's Tohono O'odham calibration is the only one I know of for a SWUS variety.

[13] A superior method for downgrading seasonal or monthly data to daily values is to use a stochastic weather generator, which creates a random daily pattern by analyzing statistical regularities between contemporary instrumental data and the reconstructed coarse-resolution norms. Weather generators are generally used in Monte Carlo simulations of weather scenarios. Unfortunately, to perform such simulations at the spatiotemporal resolution presented, one would need access to quite substantial computing facilities.

for every year from AD 1–2000. Although presenting more detail is beyond the scope of this paper, I completely scripted this analysis in the *R* computer language, and all code is available online at `http://village.anth.wsu.edu/MAIZE_DSSAT/`.

Panel (a) in Fig. 4.12 presents the temporal average of potential paleoproductivity for the VEPIIN study area from AD 600–1300, calibrated to the Tohono O'odham variety of maize, and using uniform cropping strategies through time. This reconstruction was performed at 30-m resolution; I have coarsened it to 200-m resolution here. Panel (b) in the same figure shows the temporal sequence of potential productivity, averaged over the entire landscape; the now-familiar droughts in the mid-700s, mid-1100s and late-1200s are again prominent. What is immediately apparent in the spatial reconstruction is that lower elevation areas in the Montezuma Valley and even the arid southwestern region of the study area seem to perform better than the higher-elevation regions on Mesa Verde and in the northeast part of the landscape. This illustrates the central point of this paper: Tohono O'odham maize is but one maize variety, and in fact an ecorace developed in an physical and cultural environment (presumably southern Arizona) very different from the relatively cool, moist, higher-elevation, and environmentally-stable Mesa Verde. We would not expect the Ancestral Pueblo inhabitants of Mesa Verde to be growing a variety like Tohono O'odham—at least, not on its own. CSMs like this one may be used, however, to predict the types of corn that would have flourished during the Pueblo occupation of Mesa Verde, perhaps by modeling the potential productivity of other varieties for which we have growth-requirement data.

**Conclusion/Commencement**

Humans are embedded in complex socio-ecological systems that included both external environmental forcings and internal, dynamic feedbacks. In agricultural systems, cultural behaviors such as cropping strategies and selection for ritual and resource are potentially important drivers of long-term change in both landscapes and cultivars (Barton et al. 2004; Doebley et al. 2006; Purugganan and Fuller 2009; Smith 2001; Varien et al. 2007). The work presented here blends theory from cultural and historical ecology: selection and cropping strategies may be taken not only as potential adaptive solutions to a physical present, but also as adaptive memory—shadows of an adaptive past. Ritual and social norms of behavior, in this sense, serve in part to ensure long-term resilience by encoding what were once *good* strategies as what are now culturally *right* behaviors. The extent to which this is the case may be explored by testing the efficacy of modern cropping and selection strategies (including ritual strategies) on long-duration simulated past landscapes. The transmission of ritual and ecological knowledge is of obvious importance as a connected field of study.

I hope that this paper will encourage interest in and engagement with paleoproductivity modeling among archaeologists. Using reconstructions like the ones presented above, I suggest four basic questions or directions for future research. **(1)** *What are the ranges of phenological requirements of maize varieties that may grow in different places across the SWUS, through time?* This may be explored by using CSMs to model potential productivity of a suite of theoretical maize varieties with varying growth requirements. Realistic ranges for the phenological parameters of these theoretical landraces may initially be taken from the growth-requirements of extant landraces (Adams et al. 2006). Such computational experiments would provide baseline expectations for the growth requirements of landraces prehistorically across the SWUS. In unstable periods or areas of the landscape, what combinations of varieties/traits offer the most resilient maize package for achieving consistent yields? **(2)** *Where would extant ecoraces, given their phenological needs, have performed well in the past and present? What potential returns would they provide?* Maize grow-outs and more formal field trials have allowed us to estimate the growth requirements for many indigenous varieties of maize (Adams et al. 2006). On what portions of the SWUS, and during what time periods, do each of these ecoraces perform well? Such a study may reveal connections between contemporary cultivars and past landscapes, potentially connecting contemporary agricultural communities to ancestral homelands through their maize. Perhaps ritually important but relatively non-productive contemporary ecoraces reflect past origins on the landscapes where they were in fact productive. **(3)** *Given a suite of maize varieties—and assuming minimal phenotypic plasticity and cross-pollination—how would different selective strategies and cultivation techniques serve to* *maintain diversity within populations?* Theoretical models of selective pressure and genetic bottlenecks are prevalent in the population genetics literature on plant domestication (Abbo et al. 2003; Eyre-Walker et al. 1998; Ross-Ibarra et al. 2007). However, little work has been done to explore the potential downstream effects of post-domestication cultural selective strategies—such as those for selecting *poshumi* among the contemporary Hopi—to creating and maintaining population of seed stock. Do indigenous cultural selection strategies serve to buffer against natural over-selection and bottlenecking? **(4)** *Given more refined understandings of artificial selection methods as well as knowledge about phenotypic plasticity and selectability of ancestral maize varieties, how would we expect particular maize varieties to evolve?* What are the theoretical populations of ecoraces that could have led to the formation of contemporary varieties? How rapidly could people in the past adapt to changing environments via selection alone? This final question requires more nuanced understanding of the genetic malleability of ancestral maize, but such understanding is currently an active area of research (Romay et al. 2013).

The work developed here aims to paint a more vivid picture of ancient agricultural practices, and perhaps yield fruitful insights into the cultural-historical questions of central importance to people today. But it does not stop there; studying past human-environment interactions and feedbacks is a central "Grand Challenge" facing archaeologists today (Kintigh et al. 2014a). Agricultural reconstructions that incorporate selection and cultivation strategies allow researchers to explore the ways in which past peoples remained resilient in the face of changing environments—or not. Furthermore, shifting environments around the globe demand (perhaps-unknown) drought resistant crop varieties (McCouch et al. 2013), especially in parts of the world still dependent on subsistence agriculture—the regions most susceptible to the negative effects of climate change (The International Panel on Climate Change 2014). Unfortunately, we cannot afford to re-develop the cultivation and selection strategies adaptive to these new climate regimes, at least not without considerable human suffering in the interim. Therefore, we ought to consider the diversity of past and present responses when planning future responses. By studying cases of local cultivation strategies we illuminate the ways in which traditional ecological knowledge may be encoded in social norms and ritual practice. This will in turn enable us to conduct our search for adaptive strategies more efficiently.

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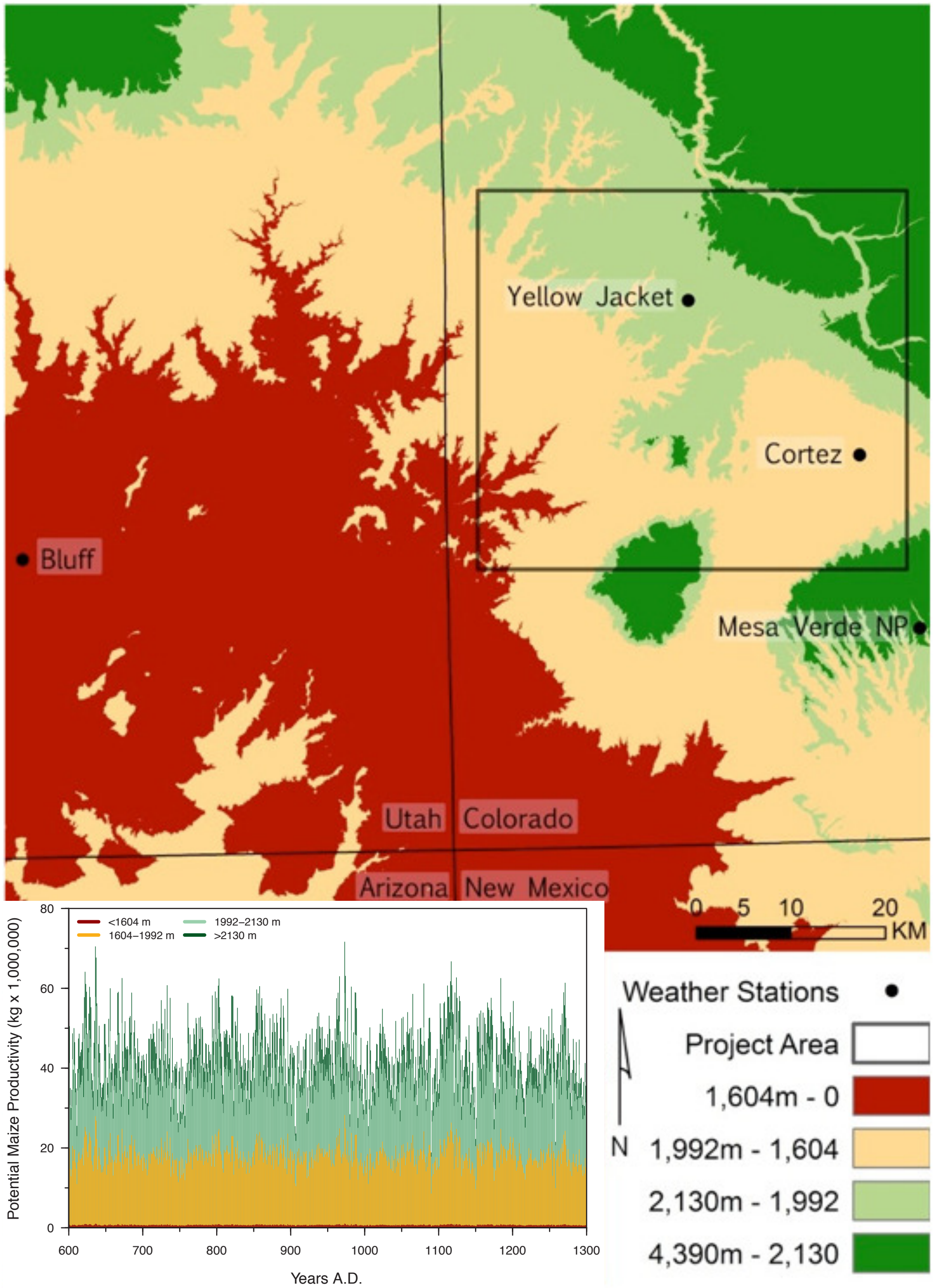


**Figure 4.3 | Paleoproductivity data as presented in VEP I.** Researchers during the first stage of the VEP ("VEP I", 2001–2007) had access to contemporary GIS, statistics, and database technology. All analyses were done using Microsoft Excel for data-entry and tabulation, ESRI ArcGIS for geospatial organization and extraction of soils and elevation data, and the SAS statistical package for paleoclimate reconstructions. This map shows the four elevation bands used to estimate temperature for the PDSI calculation. The inset graph shows the potential maize yield in each of the four elevation bands. The VEP I study area, which conforms to Van West's (1994), is outlined in black. Adapted from Kohler 2012b:Plates 6.3 and 6.6, *University of California Press*.

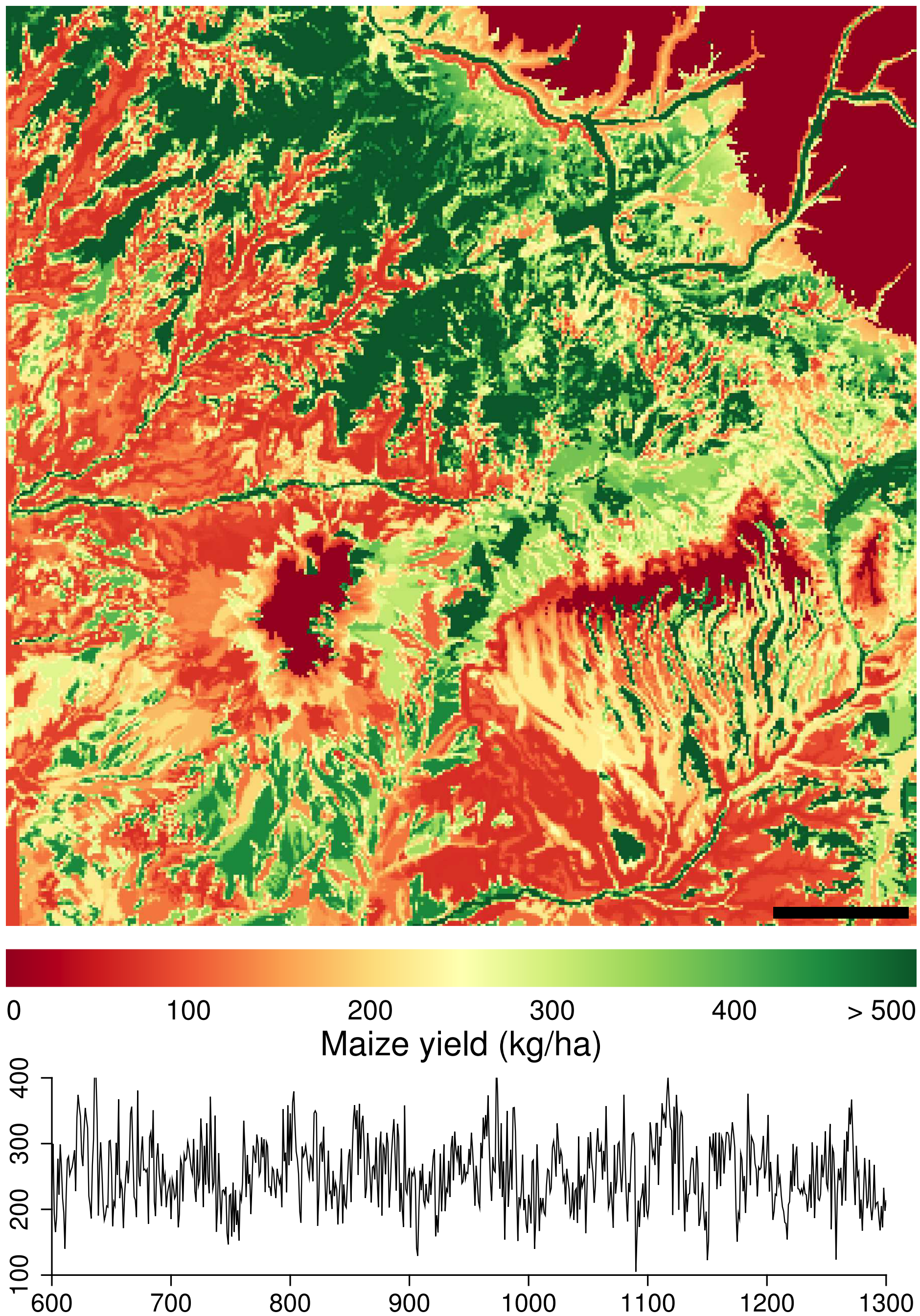


**Figure 4.4 | Paleoproductivity data as presented in Bocinsky 2014a** Bocinsky automated the VEP I paleoproductivity reconstruction method (Kohler 2012b) by scripting it in the *R* programming language. All steps of the reconstruction from extracting raw data from federal databases in the United States to exporting reconstructed production data-planes for use in the Village simulation are now completely automatic. The entire process (with the exception of the PDSI reconstruction) may be run on a personal computer in under an hour for the VEPIIN study area. Scale bar: 10 km.

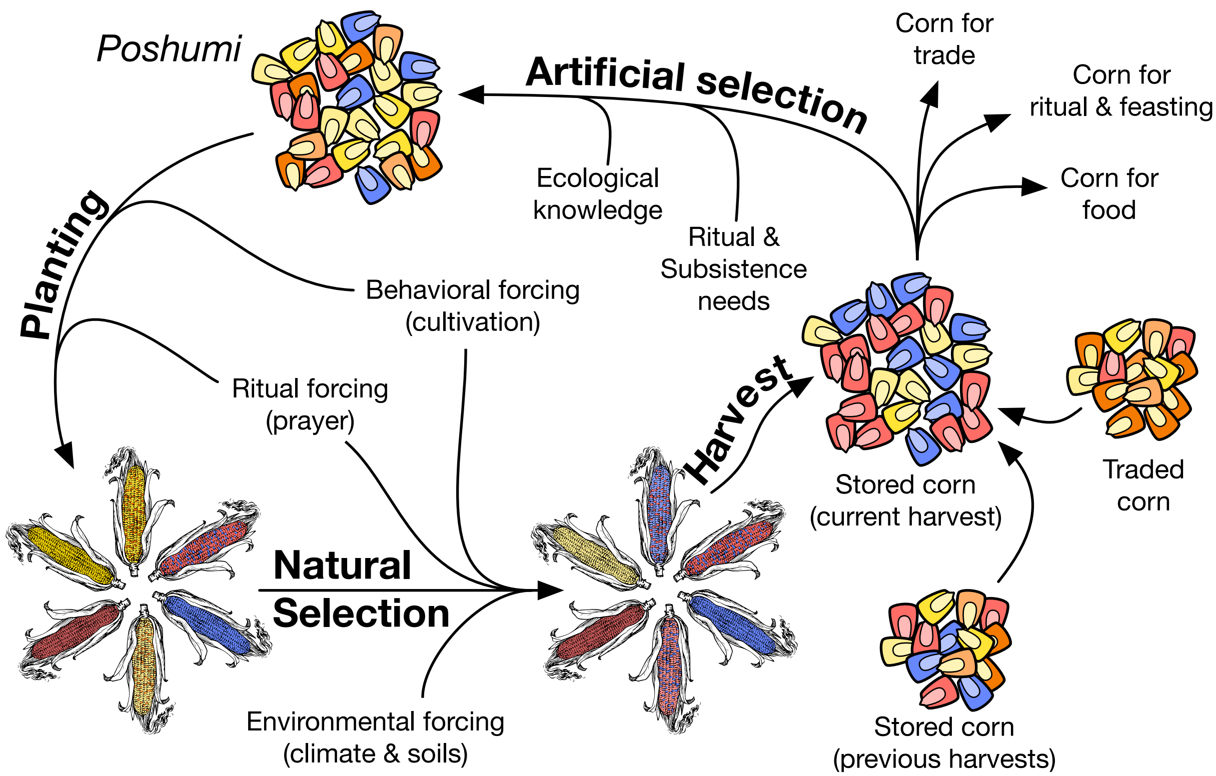


**Figure 4.5 | A heuristic biocultural model of the traditional Pueblo agricultural system.** Many biophysical and cultural processes affect the population size and diversity of maize slated for consumption, storage, and seed. Essential to maintaining diversity in the system are the integration of traded and previously stored maize into the seed population, and the inclusion of ritually-important varieties in *poshumi*.

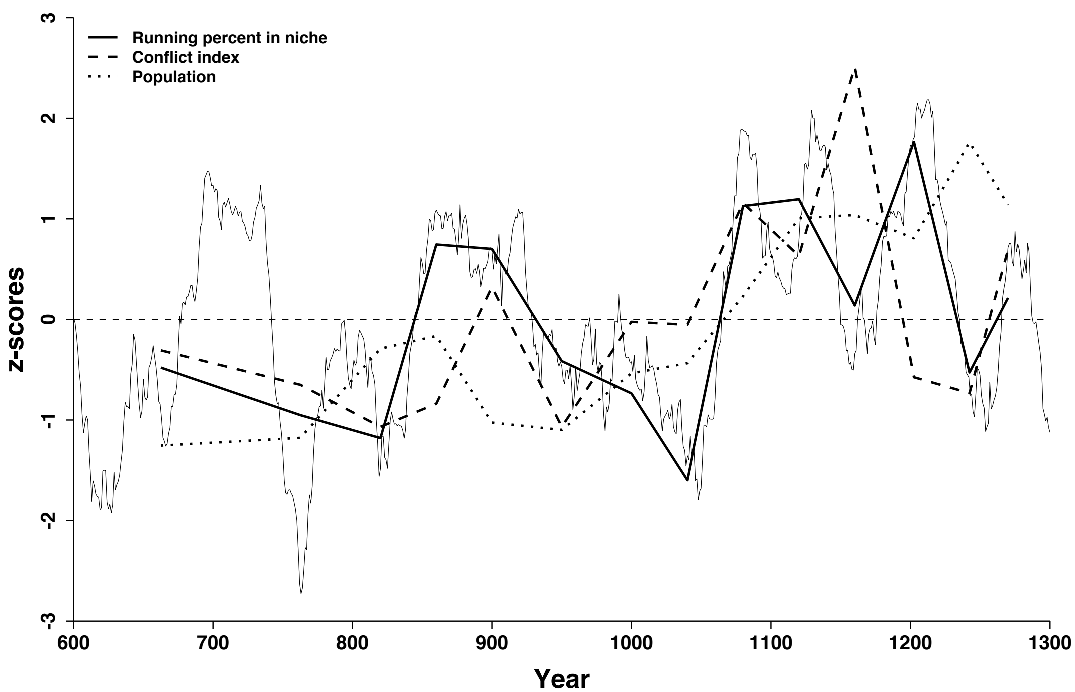


**Figure 4.6 | The proportion of the landscape in the rain-fed maize growing niche through time.** All series are scaled. The thin black line represents the 30-year lagged running mean niche size, and the solid black line is the mean of the running means binned over each modeling period.

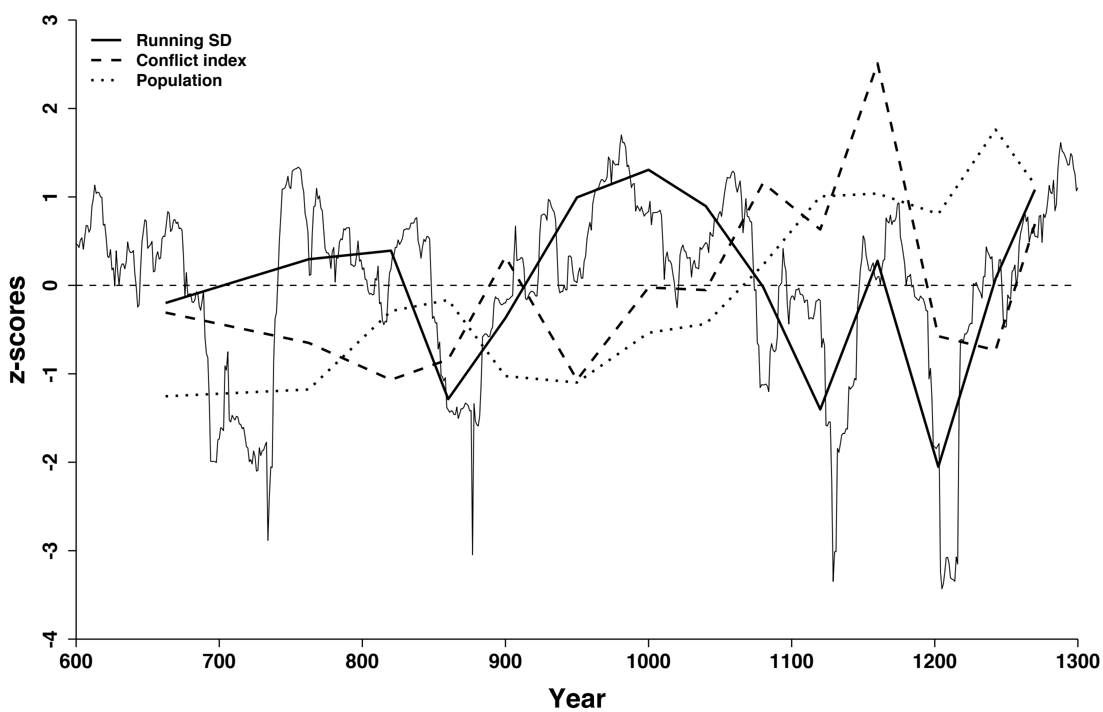


**Figure 4.7 | The running standard deviation of the proportion of the landscape in the rain-fed maize growing niche through time.** All series are scaled. The thin black line represents the 30-year lagged running standard deviation of niche size, and the solid black line is the mean of the running SDs binned over each modeling period.

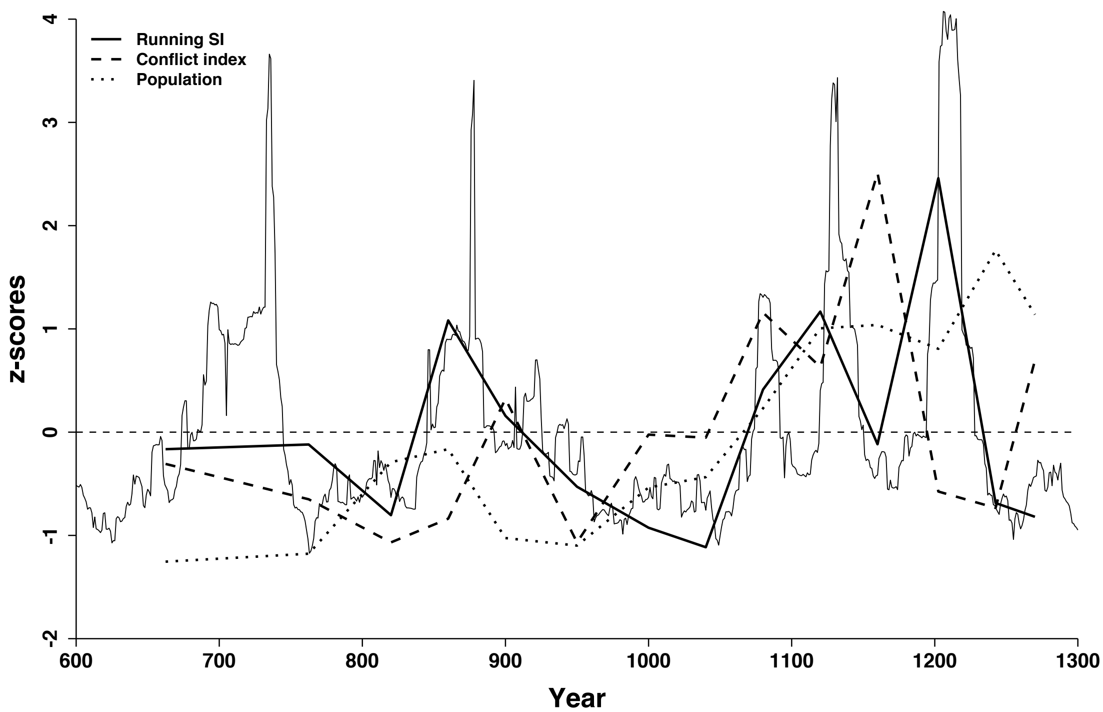


**Figure 4.8 | The running average spike interval of the rain-fed maize growing niche through time.** All series are scaled. The thin black line represents the 30-year lagged running SI of the niche, and the solid black line is the mean of the running SIs binned over each modeling period.

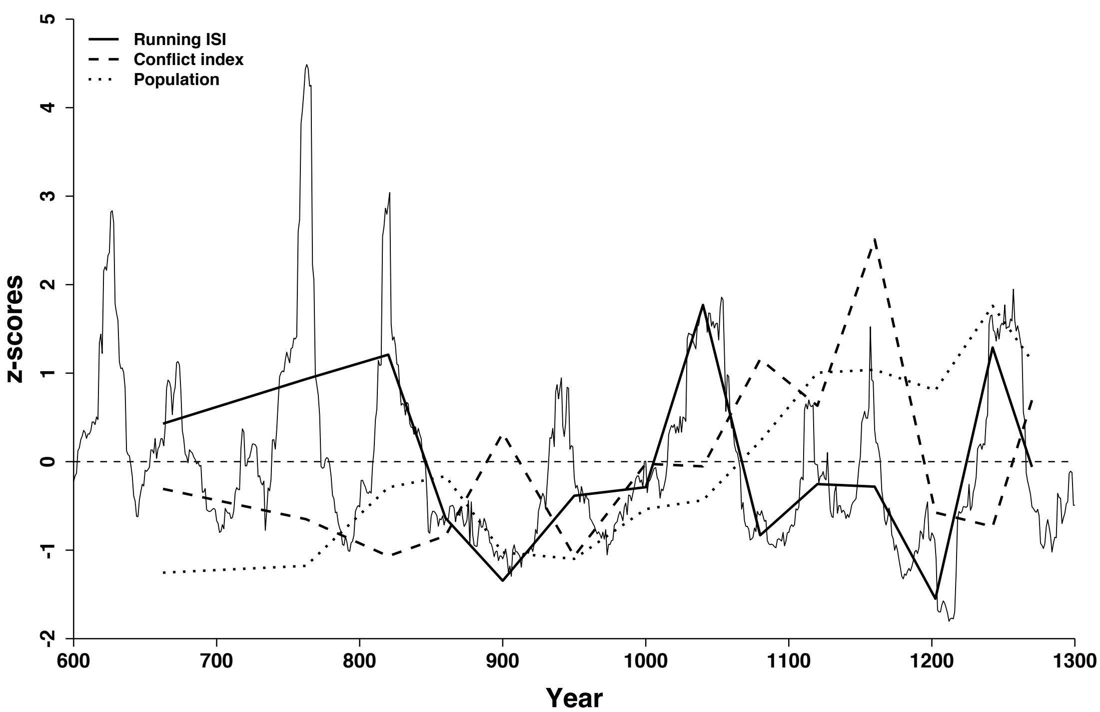


**Figure 4.9 | The running average inter-spike interval of the rain-fed maize growing niche through time.** All series are scaled. The thin black line represents the 30-year lagged running ISI of the niche, and the solid black line is the mean of the running ISIs binned over each modeling period.

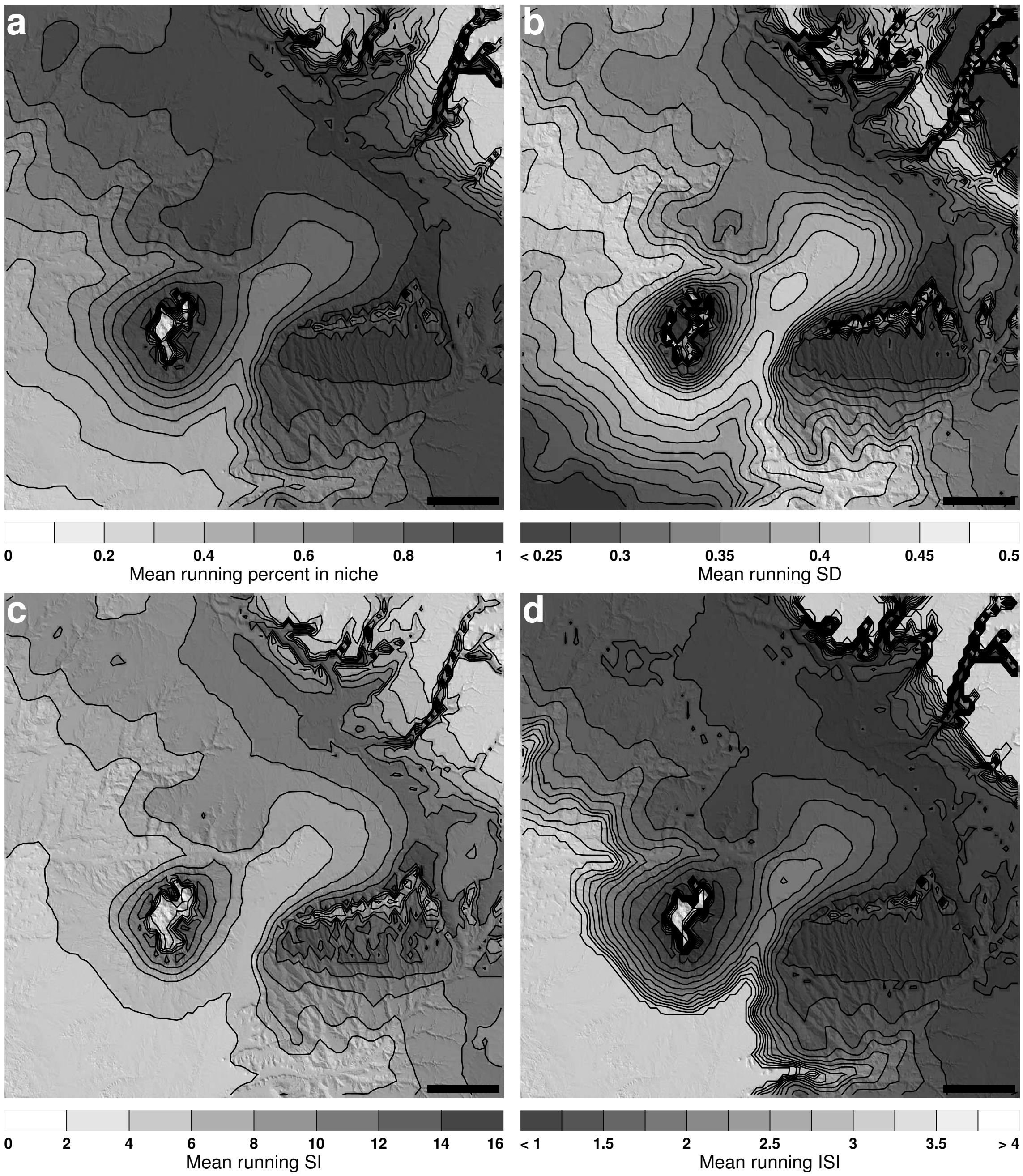


**Figure 4.10 | Average qualities of the maize growing niche across the VEPIIN landscape from AD 600–1300.** In all maps, darker shading generally indicates better potential for maize agriculture. The Mesa Verde cuesta clearly stands out as having more years in the growing niche, less inter-annual variation, and substantially greater storage capability than the surrounding landscape. Scale bar: 10 km. **a**, the percent of years in the maize growing niche, AD 600–1300. **b**, the mean running SD. **c**, the mean running SI, in years. **d**, the mean running ISI, in years.

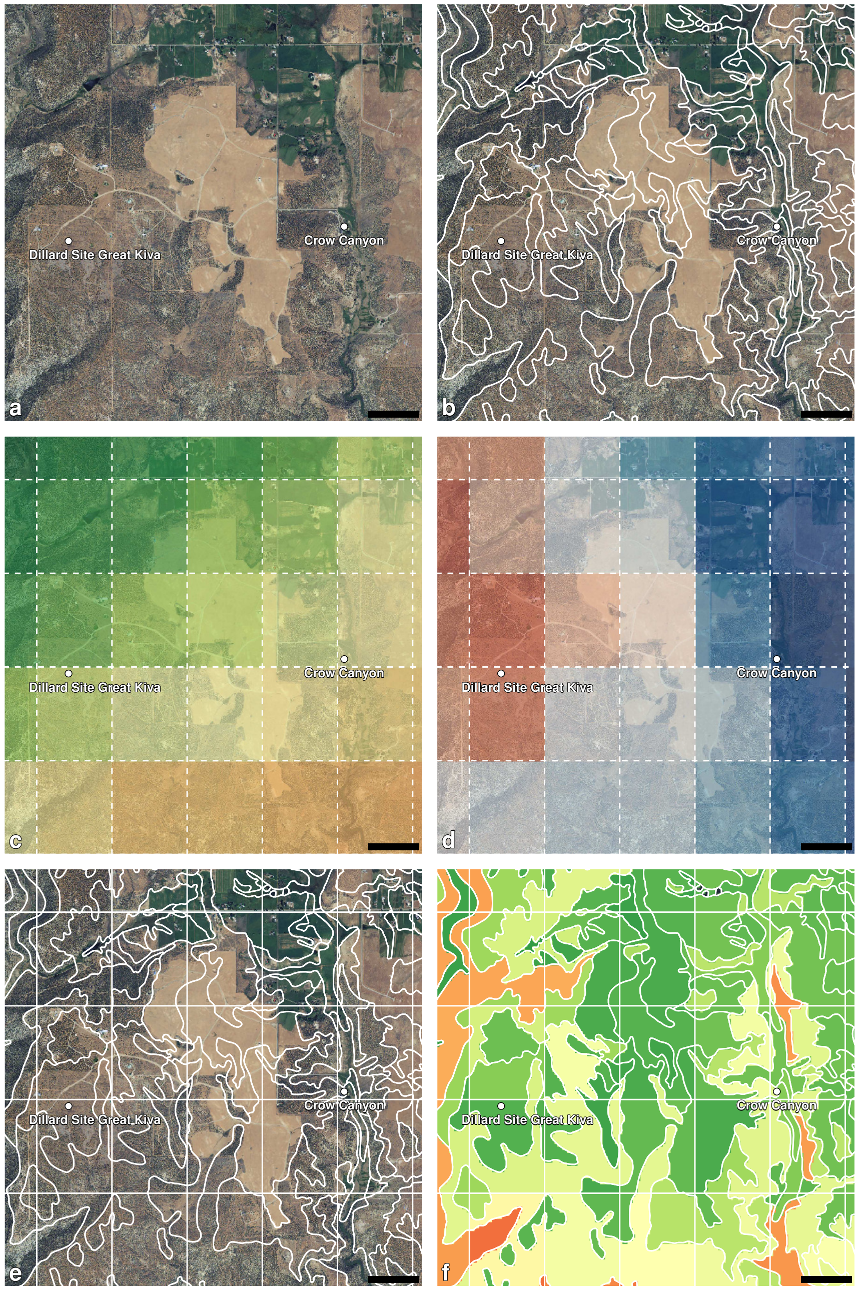


**Figure 4.11 | DSSAT implementation around Crow Canyon Archaeological Center, Cortez, Colorado.** Scale bar: 0.5 km. **a**, orthoimage of the area around Crow Canyon Archaeological Center (CCAC), with white dots at CCAC and the Dillard Site, a Basketmaker III ritual community. **b**, soil type boundary polygons defined by the USGS soil surveys. **c**, modern net precipitation gradient (green is wetter, red is drier); the dotted lines separate PRISM cells. **d**, modern mean temperature gradient (blue is cooler, red is warmer); the dotted lines separate PRISM cells. **e**, spatial overlay all data types to generate unique combinations of soils, temperature, and precipitation. **f**, independent reconstructions across the landscape.

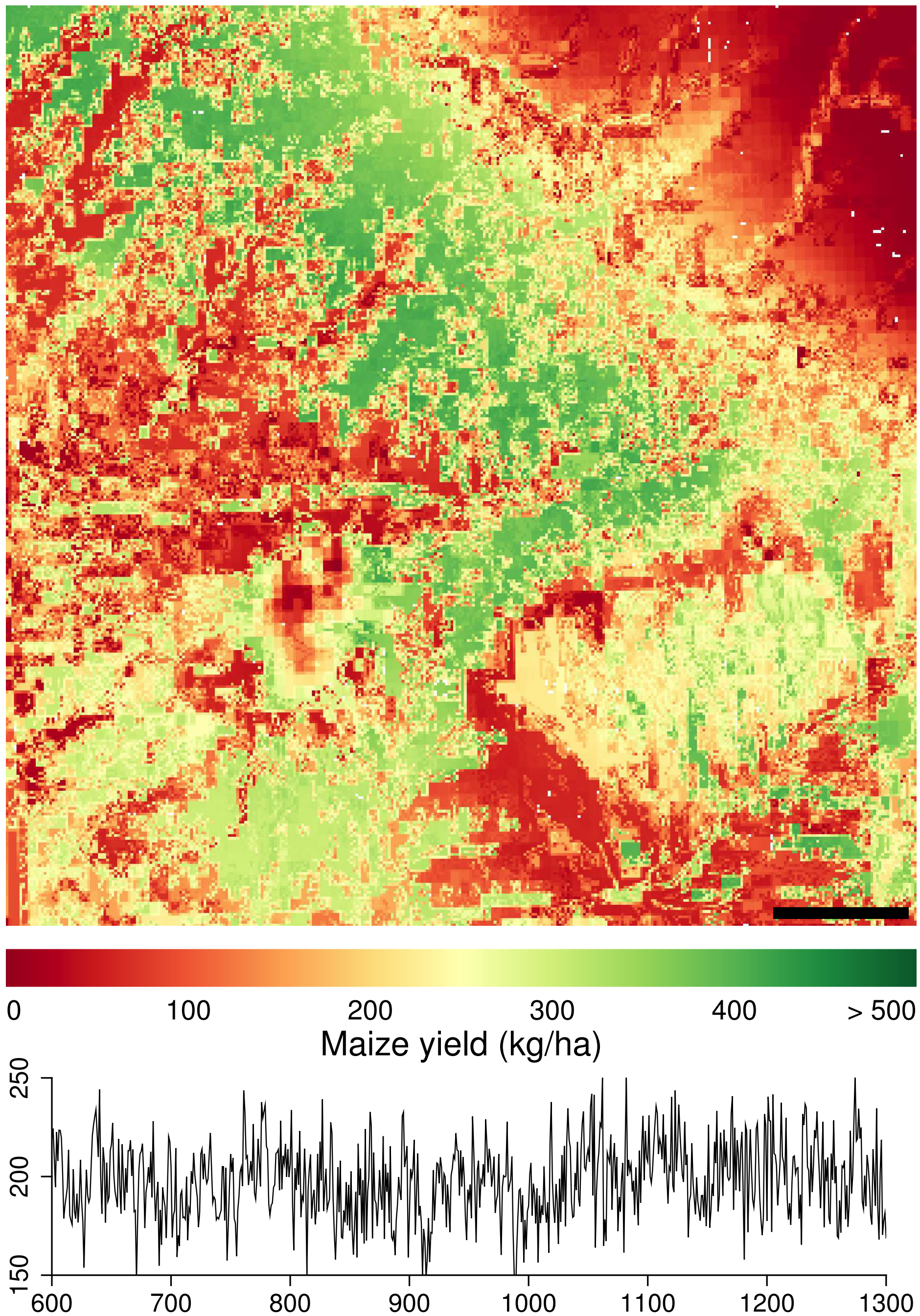


**Figure 4.12 | A reconstruction of Tohono O'odham potential productivity across the VEPIIN study area, AD 600–1300.** The map displays the temporal average of potential paleoproductivity for the VEPIIN study area averaged across the reconstruction period. The graph shows the temporal evolution of potential productivity, averaged over the entire landscape. Scale bar: 10 km.

# CHAPTER FIVE

# THE VALIDITY OF MODELS—A FEW CONCLUSIONS

This dissertation began with a discussion of model-based archaeology and the ways in which models of landscapes may be used to enhance archaeological inference. This concept is not new in archaeological thought! As I describe in Chapter 2, archaeologists have long used the distribution of resources on landscapes to understand human settlement patterns, and more recent researchers in historical ecology have considered the impacts of dynamic landscapes on human populations and have accounted for how humans actively shape these landscapes. What is novel about the studies presented here, however, is the demonstration of how contemporary computational tools enable us to model socio-natural dynamics rapidly, accurately, and at scales previously unattainable to archaeologists. While I hope the studies presented here stand apart from their methodological contributions, one of my primary goals has been the promotion of the use of these computational tools, as well as the development of additional tools that do not require specialist knowledge in computational modeling (i.e., programming skills). In this concluding chapter, I briefly review each of the three studiesI close with a few comments on the analytical and ontological adequacy of each model.

In Chapter 2 I defined *static landscapes*: landscapes or their attributes that may be considered unchanging over spatiotemporal scales relevant to past human experience. I note that these static attributes may readily be mapped at high resolutions across large regions. Whereas in the past researchers used two-sample statistical tests to compare archaeological and landscape patterns (suggesting that both the archaeological and landscape attributes are drawn from the same population), I advocate one-sample tests that *treat the landscape as the population*, and the archaeology as a sample drawn from that population. This is a more intuitive and less assumption-burdened approach than a two sample test (Kvamme 1990:169–170). I then calculate extrinsic defensibility—as indexed by (Martindale and Supernant 2009)—across a large region of the Gulf of Georgia and lower Fraser River valley in British Columbia, and use this static defensibility landscape to interpret settlement distribution in the region.

Humans very rarely experience static landscapes. Rather, landscapes change over time and across space, and how these *dynamic landscapes* impacted human societies is an active area of archaeological research (Kintigh et al. 2014a,b). In Chapter 3, my coauthor and I suggest that climate change is perhaps the most important landscape dynamic affecting agrarian societies. We develop a new method for the reconstruction of high-resolution spatiotemporal climate fields using regional tree ring chronologies—the CAR method—which we then use to reconstruct net water-year precipitation and growing-season growing degree days across two large regions of the SWUS. We use these reconstructions to generate annual estimates of the rain-fed maize growing niche across the regions.

Chapter 4 introduces *complex landscapes*: landscapes whose dynamics are actively shaped by human behavior. The spatiotemporal distribution of potential maize yield is an example of a complex landscape; yield is not only a function of static (soil texture, perhaps) and dynamic (climate/weather) landscape attributes, but also is an historical outcome of Ancestral Pueblo selection and cultivation practices that generated shifting populations of indigenous maize varieties and impacted local environmental conditions. I argue that this complex reality demands models of potential yield that can cope with its complexity, and suggest potentially useful new directions: either a generous approach of modeling the maximal extent of the growing niche or a hyper-specific approach of modeling potential yield of individual landraces.

This paper is the most speculative and theoretical of the three, and is therefore the hardest to critique in a precise way; it also is the most clear about defining a way forward for the paleoproductivity modeling effort. The relationships I identify between niche size, population size, and levels of violence on the landscape are generally qualitative, and the suggestion that aggregation into villages played a role in conflict mitigation is speculative. That being said, it *is* the case that period with the highest degree of population aggregation coincides with relatively low levels of violence and constricted niche sizes. *Something* had to have enabled people to generate enough food for a large, densely settled population, and it is likely that new social mechanisms controlling pooled labor and food sharing were developed during this period.

The use of cropping systems models by archaeologists is in its very earliest stages of development, and thus very little weight should be put on the initial yield estimates I generate for Tohono O'odam maize. Of particular concern is the best way to downgrade monthly or seasonal-level climate data to daily weather patterns. In a footnote in Chapter 4, I suggest that stochastic weather generators are superior to the delta transformation method I performed here. Weather—and in particular summer monsoonal precipitation patterns in the SWUS—may be highly local, and our instrumental record of weather likely does not capture all of the variation that occurred over the last 2000+ years. Stochastic weather generators, in conjunction with Monte Carlo simulation methods, may be used to simultaneously generate yield estimates and their uncertainty distributions.

Additionally, cropping systems models such as CERES-Maize depend on highly accurate local soil data, usually determined by a soil scientist making direct field observations. Direct observation of this type of high-resolution data across large areas is unrealistic. The yield reconstruction I present in Chapter 4 instead uses soils data from the Natural Resource Conservation Service soil surveys. NRCS soil scientists perform local-scale soil analyses, but then interpolate those analyses across large areas with the aid of elevation and geology data, and satellite imagery. The scale at which different soil types are differentiated from one another is generally no higher than 1:24,000; therefore, high-resolution reconstructions like in Chapter 4 include the additional step of interpolating soil qualities (and, therefore, yield estimates) across the landscape. This adds uncertainty to the yield estimates. Still, modeling potential yield opens the door for more interesting models of how past humans might have increased those yields at local levels via cropping, water, and heat management strategies.

Are the models I present in this dissertation *valid*? Or, cast in terms explored in the introduction, do they achieve analytical and ontological adequacy? Recall that analytical adequacy refers to how well a model implements the central tenets of a theory, or how consistent it is with theory. Ontological adequacy refers to how well a model implements reality. The models presented in the three papers above illustrate a progression from analytical adequacy towards ontological adequacy, in that they are based on increasingly complicated (and, finally, complex) visions of human-environment interactions. The defensibility model in Chapter 2 achieves great analytical accuracy; it was built from a precise description of extrinsic measures of defensibility (really, a theory of defensibility). However, it is fairly unrealistic: as noted above, it does not account for social factors influencing defensive behavior, nor is it at all a complete theory describing the multitudinous environmental impacts on human settlement patterns.

The niche model developed in Chapter 3 spans the divide between analytical and ontological adequacy. At its foundation is a phenological theory of maize development, which it instantiates as minimal precipitation and temperature requirements for maize growth; it implements this theoretical framework directly through computer code. Ontologically, the niche model generates somewhat realistic expectations of the spatiotemporal extent of the maize growing niche on the modeled landscapes. Still, it lacks several essential parameters for maize growth, such as soil characteristics. Also, the climate model that serves the niche model demonstrated greater ontological adequacy than several other leading dendroclimatological models by achieving lower prediction errors in cross-validation exercises and by selecting climatologically-expected tree-ring chronologies, and greater analytical adequacy by doing so without the influence of expert knowledge; the CAR method is fully automated.

The heuristic model presented in Chapter 4 is by far the most ontologically adequate in terms of an attempt at capturing the historical, cultural contingency of past maize production. The combination of agent-based simulation and cropping systems models has great potential to enhance ontological and analytical adequacy by (1) being simultaneously more realistic and explicit about causal connections between the environment, cultigens, and human behavior, and (2) by having the potential to generate direct, quantitative expectations about the archaeological and even the contemporary material record. For instance, a future research question might be, *What are the cultivation and selection behaviors that could possibly have led to the diversity and relative abundance of the 17 extant landraces farmed by the Hopi today?* Such a question is akin to those addressed by now commonplace population genetics methods like Bayesian coalescent inference of past population sizes from extant genetic diversity (Drummond and Rambaut 2007; Drummond et al. 2005). We ought to be able to develop similar models that generate expectations of the material record, through time, that are more nuanced than raw demography or settlement pattern. It will be through these new expectations that ontological adequacy can finally be measured, while analytical adequacy is simultaneously maintained.

In Chapter 4, I also posit a new explanation for the role of maize trade in the Ancestral Pueblo SWUS. I employ trade for exotic maize varieties directly in service of the ritual needs of local communities, and indirectly in service of the maintenance of diversity of local seed-stock populations. Trade and long-term storage provide regular infusions of genetic and phenotypic diversity into local maize populations, which serve to ensure that a well-adapted variety will produce even in years when locally- and recently-adapted ecoraces would wither. Although I do not note it explicitly in the article, this model is analogous to several models in cultural transmission theory. A cultivation system where seed is only drawn from last-seasons yield is akin to *vertical transmission*; genetic and phenotypic variation is drawn only from the parent population. Integration of stored grain represents trans-generational vertical transmission; long-term storage allows for genetic variation to leap over cropping seasons that might have selected it out of the population. Finally, trade of seed-stock is a form of oblique transmission under migration; novel variation enters into local populations from previous generations of exotic populations. McElreath and Strimling (2008) have systematically explored the environmental conditions that favor each of these types of transmission. They found that stable environments favor vertical transmission, as it is the least costly and generally the most accurate form of learning; oblique learning pays when environments are highly unstable. Using these findings, we would expect that periods with high climatic variability in the SWUS, such as the AD 1100s, would show evidence for higher-levels of regional exchange and greater amounts of storage—but again, to support diversity rather than direct subsistence. The material correlates of these two classes of storage behavior—diversity versus subsistence—can be quite different. Storing subsistence grain for several years would require large amounts of storage space, whereas only storing seed-grain for long periods would require far less. Also, the labor requirements of trading seed (as opposed to trading food) are also far less, a crucial factor for people living on a rugged landscape with no beasts of burden.

The models presented here are each starting points in redefining an archaeological science that seeks to quantitatively account for the *impacts* of social and cultural behaviors, and maybe even for their origins and genesis. They do so by explicitly incorporating the dynamics of the physical, social, and genetic landscapes within which humans behave, and upon which they act. As archaeologists, we have spent a century counting stones skipping off the surface of history; now it's time we dive below the surface.

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