NEW PALEOCLIMATE RECONSTRUCTION TECHNIQUES IN ARCHAEOLOGY: Applications in Greece, New Mexico, and Portugal

Brandon Lee Drake

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NEW PALEOCLIMATE RECONSTRUCTION TECHNIQUES IN ARCHAEOLOGY:
Applications in Greece, New Mexico, and Portugal

by

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B.S. Biology, University of Wyoming, 2007
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M.S., Anthropology, University of New Mexico, 2009

DISSERTATION

Submitted in Partial Fulfillment of the Requirements for the Degree of

Doctor of Philosophy
Anthropology

The University of New Mexico
Albuquerque, New Mexico
For Briana, Brett, Gracey and Aubrey. I was inspired to do archaeology because I believed that understanding the past was the key to the future. And I didn’t understand the future until you were born.

And also for my parents Marilyn Goodchild and Michael Drake. You gave up much to carve a future for our family in Wyoming; this dissertation would have never happened without that first choice.
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Abstract

This dissertation develops new techniques of analysis that make existing archaeological data more useful for understanding past climate change. These techniques are introduced through three key case studies in the San Juan Basin of New Mexico, the Lower Alentejo of Portugal, and the Eastern Mediterranean.

A 12,000 year record of pollen collected from packrat middens across Chaco Canyon were analyzed using a new normalization procedure to produce a Holocene record of piñon and ponderosa pine abundance. The normalization procedure, species occurrence, enabled statistical analysis of the data. Simple linear models indicated that piñon and ponderosa pollen were strongly correlated with each other. Bayesian change-point analysis was run, and a period between 5,440 and 5,102 cal. yr BP was identified as a point of expansion of piñon. This expansion of piñon was contemporaneous with increased storage and territoriality of populations in the San Juan Basin around the same time period.

In the Lower Alentejo of Portugal, a series of δ¹³C values from radiocarbon-dated pollen were used to calculate rates of ¹³C discrimination (Δ¹³C). These Δ¹³C values indicated a period of
stability from AD 600 - 1000, increased arid conditions during the first half of the Medieval Warm Period (AD 1000 - 1100), and a return to normal conditions from AD 1100 - 1150. Following this, the rural Lower Alentejo was abandoned for almost two centuries. The data suggest a climate that was stable during a period of population growth followed by heightened variability during the Medieval Warm Period. This would have caused some drying out of soil, potentially contributing to later soil erosion as wetter conditions returned prior to the rural abandonment. Importantly, the study paired modern observations of $\Delta^{13}C$ with archaeological data, establishing an approach to the study of data commonly available to archaeologists.

Finally, in the Eastern Mediterranean, a set of regional paleoclimate records were used to better understand climatic conditions during the time of the Late Bronze Age Collapse (1200 - 1000 BC). At this time, most urban centers in the region were destroyed and abandoned during a period of depopulation. Alkenone-derived sea surface temperature records and warm species dinocyst/formainifera ratios indicate a cooling of Mediterranean waters at the time. Terrestrial paleoclimate records, including a biome-wide measure of $\Delta^{13}C$ derived from radiocarbon-dated bulk pollen, indicate that conditions may have been more arid at this time.

This study of paleoclimate reconstruction includes new techniques developed to make use of under-utilized data gathered by archaeologists. These techniques include the use of radiocarbon-derived $\Delta^{13}C$ as a local indicator of aridity, the use of biome-wide $\Delta^{13}C$ from pollen as a regional paleoclimate record, a new normalization technique for pollen records, and the use of Bayesian change-point analysis to assess the significance of changes in a paleoclimate record. These new techniques can compliment archaeological research questions that require information about paleoclimate.
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Chapter 1: Introduction

The present dissertation develops new techniques of analysis that make existing archaeological data more useful for understanding past climate change. Data are available to archaeologists from a multitude of sources, including stable carbon isotope ratios from macrobotanicals, pollen deposits, sea surface temperature records, stable oxygen isotope speleothem records, and many others. Some records have an as-yet underutilized potential in paleoclimate analysis, such as stable carbon isotopes from radiocarbon-dated plant material. Others, such as pollen records, have been used for over a century but can be used in new ways with shifts in the way the data are analyzed. Finally, some newer data sources have become available in the past decade, including sea surface temperature records. The dissertation presents new uses of these data sources to improve paleoclimate reconstructions that are relevant to archaeological questions of settlement history in the San Juan Basin of New Mexico, the Lower Alentejo of Portugal, and the Eastern Mediterranean.

In the San Juan Basin, a 12,000 year record of pollen from packrat middens was used to construct a Holocene time-series of piñon and ponderosa pine abundance in the region. A new normalization technique was employed that made the pollen record more amenable to hypothesis testing and statistical analysis. In this study a significant forest transition was associated with the onset of high El Niño variability and the development of storage structures in the US Southwest in the Late Archaic period (~5,100 cal. yr BP). The record of piñon was particularly important for populations in New Mexico during the Late Archaic as increasing availability of the nutrient-rich food led to population growth and increased territoriality (Chapter 5). In the Lower Alentejo of
Portugal, a 1,000 year record of $^{13}$C discrimination ($\Delta^{13}$C) from radiocarbon-dated C$_3$ plants was used to identify a period of increased aridity during the Medieval Warm Period that may have influenced the subsequent erosion of soil and rural occupation of the region (Boone and Worman 2007). To calculate $\Delta^{13}$C, a calibrated atmospheric $\delta^{13}$CO$_2$ record was developed using Bayesian methods, analogous to that used for $^{14}$CO$_2$ (Reimer et al. 2009). The shifts in rural occupation would have negatively impacted the economy of the region, and were part of a broad regional change across southern Iberia following the dissolution of the Cordoba Caliphate. And finally, in the Eastern Mediterranean, a combination of paleoclimate records including sea surface temperatures, biome-wide $^{13}$C discrimination, and stable-oxygen isotope speleothem records. A drop in sea surface temperature occurred close in time to much more arid conditions that appear to have severely impacted dryland agricultural systems in the region. Even in Egypt, with a long history of irrigation, large population movements by the ‘Sea Peoples’ affected stability (Mazar 1990). This study employed Bayesian change-point analysis to attempt to develop a sequence of paleoclimate events that could have influenced human societies in the region.

All three studies employ paleoclimate records and Bayesian inference to address archaeological questions. Two key methodological approaches were used to address these queries. First, $^{13}$C discrimination rates from C$_3$ plants can be used to identify periods of aridity. These rates can be calculated from $\delta^{13}$C values that are reported with radiocarbon dates. These $^{13}$C discrimination rates can be compared to modern ecological studies to identify what rates are associated with normal and arid conditions. Importantly, climate inference can be derived from two independent uses of $^{13}$C discrimination rates. The first is through the use of individual C$_3$ plants recovered during the course of archaeological investigations. This data, in aggregate and when
compared to modern $^{13}$C discrimination rates, can indicate local arid conditions. The second utilizes biome-wide $^{13}$C discrimination rates gathered from radiocarbon-dated pollen assemblages. These broader rates indicate regional patterns of climate.

The second methodological approach employed in this dissertation uses a new analytical metric for palynological data - species occurrence - which is calculated by subdividing the sample size (raw counts) of a taxon in a given pollen assemblage by the total size of the taxon from all pollen assemblages used in the study. The term ‘species occurrence’ is not specifically taxonomic; rather it refers to a set of individual data points that share common qualities. This metric, developed by the author of this dissertation, can be used to better normalize pollen data to facilitate the use of more advanced statistical analyses.

Both methodological approaches use data routinely gathered by archaeologists. This dissertation seeks to introduce analytical techniques that can help archaeologists enhance the value of their data. Both $^{13}$C discrimination rates and the palynological species occurrence metric can generate paleoclimatic inference while requiring no additional data or change in archaeological excavation practice. As such, they can easily be integrated into existing field programs.

**Archaeology**

Human societies always affect their environments but since the beginning of the industrial revolution the input of carbon dioxide into the atmosphere presents a unique point of change. Many climate modelers attempt to predict climatic impacts on human societies in the future (Schneider et al. 2007) but often do not utilize information about how humans have responded to past climate change. The historian J.R. McNeal noted that “Although there are analogues in history
of the climate change now underway, there are none in human history. We are in uncharted
territory” (2008: 27). While it is possible that some societies in the Bronze Age may have faced
harsh changes in climate (Cullen et al. 2000; Kaniewski et al. 2010), during the vast majority of the
historical era of complex societies, climate has been remarkably stable relative to Pleistocene, or
even early Holocene scales. McNeal’s statement is only half true of climate history; detailed
reconstruction of Earth’s climate only goes back to 800,000 years, and the rate of anthropogenic
CO$_2$ emissions pushed atmospheric concentrations past the previous Pleistocene recorded high
near AD 1910 (Francey et al. 1999). While history faces fundamental limits in contributing to the
broader debate about climate change, archaeology can play a valuable role in assessing how
humans in the past responded to past shifts in climate.

Archaeology uses a diverse array of methodologies and theories (Trigger 2006). Despite
the tremendous variation within the field, archaeology is united by a goal to generate inferences
about human society in the past. Undoubtedly, the climatic and environmental circumstances that
surround human societies are critical for any inference about them. The influence of climate on
human behavior has long been a contentious issue in archaeology. From the oasis hypothesis of
Pumpelly (1908) and Childe (1928) to the Early Anthropocene hypothesis (Ruddiman 2003;
Ruddiman et al. 2011), climate has been posited as a prime mover in human societies. Others have
argued in the past that climate and the environment have had a limited role in human behavior
(Kroeber 1923). While it is unlikely that the relationship between climate and human societies
occupies either theoretical extreme, climate nonetheless remains an important factor in human
history.
The limiting factor in understanding paleoclimate in human history from the archaeological record is material, rather than theoretical. While there are still concerns about environmental determinism and an over-emphasis on external causation (Tainter 1988), there remains a significant methodological hurdle in paleoclimatic reconstruction in archaeology. Archaeologists generally use data and materials derived from other fields to understand the climatic context of their sites, and then only by association. The most frequently used paleoclimate reconstruction methods in archaeology are dendroclimatology (Nash 2002) and palynology (Seppä and Bennet 2003). In recent years, there has been an increase in the use of organic soil stable carbon isotope ratios (Bement and Carter 2010). However, these data sets generally require sample collection and interpretations to be made by specialists outside of archaeology.

This dissertation demonstrates that many conventional archaeological data are relevant to local paleoclimate reconstruction. In some cases, such as radiocarbon dates, the data may already be available from past excavations. A key enabling factor for paleoclimate analysis from archaeological data is the dramatic increase in available computing power. Most archaeologists now have the ability to utilize Bayesian inference to better account for uncertainty. As computers have continued to increase in power and decrease in both size and cost, the application of Bayesian methods is possible on most desktop and laptop computers.

**Paleoclimatology**

Paleoclimatology is primarily an interdisciplinary field of study including literature generated by climatologists, geologists, chemists, and archaeologists. There are a few journals that publish exclusively to paleoclimatology, such as *Nature Geoscience, Paleogeography,*
Paleoclimatology, and Paleoecology and The Holocene. Yet aside from seminars, relatively little formalization of paleoclimatological procedures has occurred. There are no formal paleoclimatology degree programs. Technically, the field is a subset of climatology, but its practitioners consist of geologists and archaeologists borrowing methods from chemistry. Despite the low formalization of the field, paleoclimatological studies are frequently published in high-impact journals.

Like archaeology, paleoclimatology features a diverse set of methodologies. A single sediment core from the ocean can be analyzed for changes in stable oxygen isotopes (Emeis et al. 1998), or can be used to create sea surface temperature reconstructions from alkenones (Brassel et al. 1986), or can produce information about warm species foraminifera/dinocysts to infer biotic responses to change (Veerstegh 1994). A single cave speleothem can be analyzed for stable oxygen isotopes, stable and radioactive carbon isotopes, stable hydrogen isotopes, strontium concentrations, and growth rates (Bar Matthews et al. 2003). The past few decades have seen remarkable growth in paleoclimatological data sets; by the end of 2011, the NOAA paleoclimatology archive had over 27 gigabytes of text files of global paleoclimate records, with some records reaching back millions of years. The growth of paleoclimatological records is matched by a weakness in time-series data analysis. There are no broadly accepted standards of significance testing for major climatic events. The lack of significance testing has been characterized as a ‘minor crisis’ in palynology, arguably the oldest sub-discipline in paleoclimatology (Seppä and Bennet 2003).

The problem is the weakness of time-series analysis in frequentist statistical methods: time-series data simply do not incorporate the assumptions that form the core of t-tests and regressions.
Bayesian inference, on the other hand, does not incorporate the same assumptions as frequentist inference and can be used to analyze time-series data sets, such as those that are ubiquitous in paleoclimatology.

Data analysis

There are two broad uses of probability in data analysis. The traditional approach, frequentist inference (Neyman 1937), encompasses t-tests, regressions, and variance analysis based on probability theory. The second approach, Bayesian inference, encompasses a diverse array of approaches that employ Bayes' theorem (Box and Tiao 1973). Bayesian inference has been critiqued for over-reliance on subjective priors, while frequentist methods have been challenged as having too many limitations and preconditions.

Frequentist inference is based on probability theory and was developed in part by geneticist Ronald Fischer in the 1920's and 1930's. These methods typically follow a similar process. A null hypothesis is formulated, typically consisting of 'there is no relationship' or 'there is no difference'. An alpha value is selected, typically 0.05 (i.e. 95% confidence level). A test occurs, and the null hypothesis is rejected, supported, or reformulated. The underlying assumption of probability theory is the Central Limit Theorem, which states that a sufficient number of random, independent variables will form a normal distribution. A test in frequentist inference is fundamentally a comparison between two idealized normal distributions, with the null hypothesis being that they are, in fact, the same single normal distribution.

Bayesian inference was initially formulated by Thomas Bayes in the 18th century and was refined over two centuries. For most of that time, the application of Bayesian methods was limited
due to their time-intensive calculations. Bayesian methods added two critical components in the 1980s: the Markov chain, a random walk iteration method, and Monte Carlo algorithms, which require random input. These, combined with the rapid increase in the power and affordability of computers, enabled the widespread application of Bayesian methods.

A popular example of Bayesian methods is the Monty Hall problem. On the Monty Hall show, a contestant would be offered three doors to choose from. Behind one was a prize; behind the other two were goats. The contestant selected a door. Then Monty Hall would open a door to reveal a goat, leaving two options. Monty Hall would give the contestant the opportunity to switch his or her choice, or stay with the first pick. The odds that a prize was behind a specific door when the game began was 1/3, or 33%. In this hypothetical example, the contestant selects door #1. Monty Hall then opens door #2 to reveal a goat. There are now two doors left, #1, the contestant’s choice, and #3. What are the respective odds that a prize is behind door #1 or door #3?

First, we have our initial set of probabilities when the game starts:

\[ P(#1) = P(#2) = P(#3) = \frac{1}{3} = 0.33 \]

Because each door has an equal chance of containing the prize, there is a 33% chance that the contestant makes the correct selection the first time. Next, we introduce Monty Hall’s subjective prior: \( O \) = the event in which Monty Hall reveals that there is no prize behind #2. We then calculate the possible probabilities of the prize being behind each door after this information is obtained. There are rules that structure these probabilities. First, Monty Hall cannot open the door the contestant selects first; if he did, the game would end immediately. Second, Monty Hall must reveal at least one goat, or else the game would end quickly as well. As such, we calculate the probabilities of each potential conclusion:
P(O|#1) = 0.5—This door has the prize; Monty Hall can open up #2 or #3 at will.

P(O|#2) = 0—Monty Hall has already shown us that a goat is behind this door.

P(O|#3) = 1—Monty Hall must open #2 first because the prize is here.

Then the probability of O can be calculated:

\[ P(O) = P(#1)P(O|#1) + P(#2)P(O|#2) + P(#3)P(O|#3) \]

\[ P(O) = 0.33 \times 0.5 + 0.33 \times 0 + 0.33 \times 1 \]

\[ P(O) = 0.5 \]

With these probabilities calculated, we can use Bayes’ theorem to calculate the probability that the prize lies behind door #1 (the contestant’s choice):

\[ P(#1|O) = P(#1)P(O|#1) / P(O) \]

\[ P(#1|O) = 0.33 \times 0.5 / 0.5 \]

\[ P(#1|O) = 0.33 \]

And we can calculate the probability that the prize lies behind door #3:

\[ P(#3|O) = P(A)P(O|A) / P(O) \]

\[ P(3|O) = 0.33 \times 1 / 0.5 \]

\[ P(#3|O) = 0.66 \]

The answer, surprising to many, is a 33% probability for the prize behind door #1 and 66% for door #3. This is because the contestant chose door #1 when the odds were 33%. When Monty Hall demonstrated that door number #2 had nothing but a goat, he altered the odds for door #3, but not for door #1—Monty Hall will not end the game early by revealing the contestant’s door. As such, the new information causes us to recalculate the new, posterior probability after a subjective prior (Monty Hall) is introduced. The contestant is better off switching his or her choice to door #3,
as it will yield a prize 66% of the time, while his or her original choice will yield a goat 66% of the
time. This problem could have interesting implications for which grid units archaeologists choose
to excavate in the field when trying to trace a specific feature.

An additional example is in drug/disease tests. Say a person possesses a gene for early
Alzheimer’s disease. The test is 99% accurate—it will only give false positives 1% of the time. It is
also 99% likely to identify the person as lacking the gene—only 1% of tests are false positives.
Finally, the gene is rare; it has a prevalence of only 0.5% in the population. If you take the genetic
test, and you test positive for the gene, what is the chance you actually have the gene for the early
onset of Alzheimer’s? Once again, Bayesian methods shake expectations. The subjective prior in
this case is prevalence; 0.5% of the population has the rare gene. We express it using Bayes’
theorem:

\[ P(A|B) = \frac{P(B|A)P(A)}{P(B)} \]

Where \( P(B) = P(B|A)P(A) + P(B|\sim A)P(\sim A) \)

\[ P(B) = 0.99*0.005 + 0.01*0.995 = 0.0149 \]

\[ P(A|B) = \frac{0.99 * 0.005}{0.0149} \]

\[ P(A|B) = 0.33 \]

... and find that the answer is about 33.3%. That is to say, testing positive for a gene, despite
the high accuracy of the test, means that there is still a 66% chance you do not have the gene. You
are considerably more likely than the general population to possess the gene, but there remains
considerable uncertainty. The application of Bayes’ theorem is particularly important in medical
tests. The Alzheimer's example above is why random drug tests for rare drugs are not encouraged
—for every employee who is an addict, two will lose their jobs unjustly. It is also important for
medical screenings. Mammograms have given far more false positives than true positives, leading to expensive additional tests for many women. This is why, in 2009, mammograms were no longer recommended for people under 50 by the Centers for Disease Control (CDC) unless their family had a history of cancer (in which case the prevalence rate, or subjective prior, is much higher).

There has been a long debate about the appropriateness of Bayesian inference, as many statisticians have been concerned about the use of subjective priors. While frequentist inference imposes strict preconditions on data analysis (Neyman 1937), Bayesian inference requires subjective information to be introduced as a prior (Box and Tiao 1973). This distinction led to much conflict between Bayesians and Frequentists over the course of the 20th century. Frequentists charged those practicing Bayesian analysis with introducing too much subjective information into statistics; Bayesians charged Frequentists with incorporating too many strict assumptions. This dilemma was best captured by the statistician John Tukey: “Far better an approximate answer to the right question than an exact answer to the wrong question, which can always be made more precise” (1962: 13).

For archaeologists, the fundamental issue at hand is what inference approach is best suited to help answer research questions and appropriately handle the fragmentary data available. For time-series data, which are the most common form of data in paleoclimatic studies, Bayesian inference is more appropriate. The uses of these statistical inference techniques in a study are not mutually exclusive: chapter 5 of this dissertation uses both frequentist and Bayesian inference to identify a key mid-Holocene environmental change in New Mexico.
Bayesian Inference, Archaeology, and Paleoclimatology

Understanding paleoclimate is a critical component of understanding human behavior in the archaeological record. But understanding paleoclimate is difficult because of a lack of rigorous analysis. Bayesian inference has the potential to address uncertainty in both the paleoclimatological and archaeological record. This can be done by using archaeological and paleoclimatological data as the subjective prior.

In particular, Bayesian change-point analysis is particularly well suited to the assessment of a shift in time-series data. Following the Barry and Hartigan (1993) algorithm as implemented by Erdman and Emmerson (2007), sequences of pollen, tree rings, radiocarbon dates, and other data can be assessed. The posterior means produced by the data analysis can be used to generate a smoothed trend; this can be particularly useful in identifying periods of stability. The posterior probabilities can be used to distinguish the key points of change that affected the time-series data.

Chapter Synopsis

This dissertation outlines new methodologies for paleoclimate reconstruction in archaeological contexts using Bayesian inference. Two of the chapters forming the core of this dissertation are multi-authored (Chapter 5 & 6), and a third is sole-authored (Chapter 7). Hypothesis formulation, data collection, data analysis, software coding, and primary writing were all accomplished by the author of this dissertation. Recent developments in isotopic biochemistry and analytical computing enable archaeologists to identify climatic change using data already routinely gathered in the excavation process.
Chapter 1 presents a brief introduction to the dissertation and outlines the broad themes.

Chapter 2 introduces unifying concepts in climate impacts and measurements. The first section of the chapter discusses the framework for understanding climate impacts as laid out by the Intergovernmental Panel on Climate Change (IPCC). The distinction between climate and environment is discussed to clarify causation in signals used in the archaeological record.

Chapter 3 reviews the historical development of paleoclimatology and its use in archaeology. It begins with the establishment of key concepts, including ice ages and extinction. It follows the development of palynology, dendrochronology, and isotopic geochemistry to the present day.

Chapter 4 provides an overview of the key climatic changes that have occurred since the Last Glacial Maximum (LGM). The cause of each climate change is explored, as are the potential impacts of each change on human populations.

Chapter 5 includes a Bayesian change-point analysis of Chaco Canyon pollen assemblages that indicates a period of rapid expansion of piñon forests at the onset of increased El Niño cycles 5,100 years ago. The first storage structures appear in the US Southwest at this time, potentially indicating a rapid adaptation to a new high-yield food resource.

Chapter 6 uses stable carbon isotopes in the Lower Alentejo of Portugal to provide a record of climatic change, including stability during a period of
Medieval population growth and evidence for drier conditions during the Medieval Warm Period.

- Chapter 7 employs stable carbon isotopes derived from pollen, reconstructed paleo-rainfall, sea surface temperatures, and reconstructed northern-hemisphere temperatures to propose that a cool and arid period set in at the end of the Bronze Age. An increase in aridity and a drop in temperature occur alongside destruction layers in most urban sites across the Eastern Mediterranean and Near East.

- Chapter 8 summarizes a contemporary pilot study that employed stable carbon isotopes derived from C\textsubscript{3} and C\textsubscript{4} grasses collected across New Mexico over the past century. Both sets of grasses were used to reconstruct changes in atmospheric carbon and climate over a historical period of instrumental observation. Both C\textsubscript{3} and C\textsubscript{4} grasses reconstruct a century-long depletion of atmospheric $\delta^{13}$C. C\textsubscript{3} grasses show enrichment of $\delta^{13}$C during droughts in the 1930’s and 1950’s, as well as depletion of $\delta^{13}$C during record-rainfall in the early 1940’s.

- Chapter 9 provides a summary of the dissertation and helps situate the author’s work in both paleoclimatology and archaeology.

Also included in this dissertation is software scripted to perform analysis of paleoclimate and isotopic records, radiocarbon calibration curves, and raw data employed in each independent study.
The key studies that form the core of this dissertation were selected because they highlight the fusion of archaeological questions, paleoclimatological data, and Bayesian inference. Bayesian change-point analysis was employed on a Holocene pollen record from Chaco Canyon to identify a critical forest transition that positively affected human populations. A reconstruction of $^{13}$C discrimination calculated with the posterior means of atmospheric isotopic carbon and radiocarbon dates in the Lower Alentejo of Portugal indicate a period of climactic variability that preceded an abandonment of rural areas. And finally, Bayesian change-point analysis was performed on multiple paleoclimate records, including an experimental series of biome-wide $^{13}$C discrimination, to identify an onset of arid conditions that may have contributed to the rapid and systematic collapse of Bronze Age civilizations in Greece, Anatolia, and the Middle East. These studies include a number of underutilized techniques:

1. The use of radiocarbon-derived $^{13}$C discrimination rates as a paleoclimate indicator,
2. The application of biome-wide $^{13}$C discrimination rates from pollen as a paleoclimate indicator,
3. The introduction of a new method of normalizing pollen data—a fundamental shift from the century-old previous normalization procedure,
4. The application of Bayesian change-point analysis to paleoclimate time-series data,
5. The combination of multiple records of atmospheric $\delta^{13}$CO$_2$ to generate a calibrated record for the Holocene, and
6. The use of paleoclimate data from the ocean to generate prehistoric weather predictions to address a century-old debate in Mediterranean archaeology.
Chapter 2: Vulnerability, Units, Accuracy, and Reliability

According to the Intergovernmental Panel on Climate Change (IPCC), human societies are most vulnerable to climate change through disruptions in food supply, infrastructure, health, and water (Schneider et al. 2007). While paleoclimatological studies and climate models are important, relatively little is known about the systemic vulnerability of human populations to climate change in the past. The degree to which humans have adapted, or not adapted, to climate change in the past is relevant to the estimation of the effects of potential climate impacts in the future. While the effect of rising oceans is a tangible risk, the effects of climate change on current agricultural systems and populations are harder to predict. Ultimately, little is known about the vulnerability of human populations to climate change in general, much less in local areas.

Archaeology is uniquely positioned to address the vulnerability of human societies by showing how humans have responded to climatic changes in the past. While the climate of the Holocene is known for its stability relative to the Pleistocene, there have been climatic changes that have affected complex societies. These instances can provide insight into our own vulnerabilities. Even more importantly, archaeology provides a regional record that can be used to better understand climatic vulnerability at a local level.

Understanding the vulnerability of human economic systems to climate change requires balancing the components of vulnerability, including risk, magnitude, likelihood, confidence, and adaptation. The IPCC is charged by the United Nations with assessing the potential impacts of climate change on human civilization. This includes estimates of future climate change as well as potential impacts on urban and rural environments. The most recent findings, as presented in the
2007 IPCC Fourth Assessment Report, introduced a theoretical construct for contextualizing human vulnerability to climate change (Schneider et al. 2007).

<table>
<thead>
<tr>
<th>Term</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Impact</td>
<td>The results of climatic change</td>
</tr>
<tr>
<td>Likelihood</td>
<td>The probability of an outcome having occurred or occurring in the future</td>
</tr>
<tr>
<td>Confidence</td>
<td>The subjective assessment that any statement about an outcome may prove correct</td>
</tr>
<tr>
<td>Scale</td>
<td>The area or number of people affected [by climate change]</td>
</tr>
<tr>
<td>Intensity</td>
<td>The degree of damage caused [by climate change]</td>
</tr>
<tr>
<td>Magnitude</td>
<td>Metric formed by the scale and intensity of climatic change</td>
</tr>
<tr>
<td>Timing</td>
<td>The rate at which climate change or impacts occur</td>
</tr>
<tr>
<td>Persistence</td>
<td>Long-term climate impacts that span extensive periods of time</td>
</tr>
<tr>
<td>Distribution</td>
<td>The spatial gradation of climatic impacts</td>
</tr>
<tr>
<td>Adaptation</td>
<td>The ability of human societies to respond to climate impacts</td>
</tr>
</tbody>
</table>

Table 2.1: Key definitions regarding human vulnerability to climate change (Scheider et al. 2007: 785-786).

The framework identifies the dimensions upon which climate change acts. Many are self-evident, including spatial aspects (distribution), probabilistic (likelihood, confidence), and strength (intensity, magnitude). Others, specifically in the temporal dimensions, are more nuanced. For example, timing refers to the rate of change, whereas persistence refers to longevity of changes. More important than defining dimensions, the terminology requires an understanding of affected societies. For example, intensity can vary not only by the magnitude of a climatic impact, but also by the vulnerability of the society in question. The IPCC recognizes that the organization of societies plays a role in both the short-term and long-term manifestations of climate change. In fact, the term ‘scaling’ is used to identify the degree to which humans respond to climate change.
A modern society can respond to climate change on a separate level relative to past societies and in turn has different vulnerabilities due to different agricultural methods. However, past societies and the degree to which they were impacted by climate can highlight important vulnerabilities and indicate potential areas of concern that may not be evident otherwise. An example is the sensitivity of agriculture in the Eastern Mediterranean, discussed in greater detail in Chapter 7.

The results of persistent climate impacts should be the easiest to identify, as such changes should involve changes in settlement and resource procurement. It is often difficult to distinguish between human adaptations to the environment and humans adapting the environment itself, as few environments today have not been affected by human activities at the macro (landscape) or micro (nutrient cycling) levels (Vitousek et al. 1997). It is more difficult to identify high magnitude but low persistence (e.g. severe and short-lived) changes that human societies regularly undergo; these include droughts, floods, severe storms, and earthquakes.

Additional factors in understanding climate impacts are the built-in vulnerabilities of human societies. Traditionally, the vulnerability of a society has been seen as a consequence of its dependence upon other societies for economic stability. The collapse of Bronze Age society in the Eastern Mediterranean from 1,300 - 1,000 BC has been portrayed as a consequence of systems collapse. In this view, destabilization of one polity could quickly spread to many others when the power of rulers was contingent upon their ability to leverage international trade (Eckholm 1980; Iakovides 1986; Dickinson 2010). Climatic vulnerabilities are similar to economic vulnerabilities, as both stem ultimately from resource exploitation. Civilization is dependent upon a predictable flow of resources and thus tends to prosper in benign climatic conditions (Winkless and Browning
When the accessibility of resources is upset by climatic variability, the stability of political-economic regimes can be undermined.

Unsurprisingly, the ways in which human societies are vulnerable to climate change can vary based on the environment in which they are situated. For example, the IPCC has found that low-latitude agricultural systems are the most vulnerable to climate impacts due to their higher exposure to elevated temperatures (Scheider et al. 2007). This finding is based on the instrumental record of climate and records of economic productivity that stretch back a century or more in many parts of the world. However, a centuries-long instrumental record will likely only capture relatively frequent climatic changes. That is to say, it will be biased towards common changes (e.g. temporary droughts, flooding) and be biased against rare but significant changes (long-term shifts in precipitation, temperature). Ideally, paleoclimatic research and archaeology can be combined to form a longer record that gives a broader perspective on regional human vulnerabilities.

Contemporary aleoclimatic research tends to look at the opposite extreme, focusing on high-magnitude events. These kinds of effects are reflected in multiple climate proxies and lend themselves to frequent analysis. For example, the Younger Dryas is reflected in multiple sea surface temperature reconstructions (Emeis et al. 2000), the GISP2 reconstruction of Northern Hemisphere temperatures (Alley et al. 2004), and a stable-carbon isotope time series from German Oak trees (Becker et al. 1991), among many others. Less work has been done on low-magnitude persistent events, or on the distribution of low-magnitude climate impacts on human societies in general. Perhaps most seriously, there is a lack of concentration on the confidence and uncertainty surrounding high-magnitude events (MacDonald 1993).
There is a gap between analysis of instrumental climate records of low-magnitude, frequent events and the paleoclimatic record of long-term rare events. Human societies in the past have been more vulnerable to climatic changes that fall between the two extremes. A better understanding of the climatic context behind changes in human society observed in the archaeological record can help researchers better understand which climate changes humans are vulnerable to, and to which changes they have been resilient.

**Climate and Environment**

The terms ‘climate’ and ‘environment’ are frequently conflated. A strict interpretation would define climate as long-term patterns in temperature/precipitation and environment as patterns in the surrounding vegetation of a region. However, application of the terms becomes more difficult in practice. For example, say a palynological sequence records a sharp increase in piñon pine over ponderosa pine, as detailed in chapter 5 of this dissertation. As piñon pine can handle lower average precipitation than ponderosa, this finding might suggest a climatic cause. However, the data are primarily an environmental signal. It is difficult to imagine any environmental factor operating independently from climate to create a significant shift in regional forest patterns. In this case, it may be possible to discern a climate signal from the details of forest ecology (Allen and Breshears 1998). In many other cases, the distinction is not clear.

As reconstructing an environment requires a broad array of data to clarify the conditions past people lived in, the distinction between analytic and synthetic units becomes increasingly important. Analytic units “segment actual observations and are used to describe the properties being measured,” while synthetic units “organize these analytic observations into categories used
in interpretation or explanation” (Ramenofsky and Steffen 1998:8). Climate is often measured through concrete analytic units, such as derived variation in isotopic carbon in a given layer of soil. It is also expressed in synthetic units referring to reconstructed temperatures, such as through alkenones (Brassell et al. 1986). The reconstruction of either paleoclimate or environments frequently employs both analytic and synthetic units. An example of the former is isotopic variation in human bones; the latter can encompass changing uses of a landscape. Environment has an implied spatial component, whether through ecotones with arrays of flora and fauna or simply the immediate surrounding biotic community. While understanding climate change is the goal, environment must be known first when the archaeological record is used to address the question. In other words, the environment is the medium in which climate affects human societies.

The strength of climate/environment inference is the direct consequence of the units and methods employed. Archaeology employs synthetic units of behavior defined temporally and spatially across chronology and landscapes to address the same phenomenon (Ramenofsky and Steffen 1998). This information is then gathered as analytic units, and combinations of these create synthetic units informed by theory to help infer changes in behavior. This is based on the assumption that (1) changes in climate lead to (2) changes in the distribution of resources across a landscape and (3) shifts in human behavior in the use of these resources (or technologies used to acquire them over greater periods of time). This creates a 3-part reconstruction for archaeologists looking to explain human responses to climate change; it consists of interactions between humans and the environment with systematic input by climate. The validity of archaeological methods to address a question concerning a climatic impact on a human society is contingent upon the quality of temporal and spatial resolution established by the researcher. This distinction is not only
methodological; it affects the conclusions that result from research. Regional climate records may operate on spatial scales that are too general for some archaeological research questions. Likewise, in some cases, their low resolution may preclude comparison to changes in human populations. Human societies operate on spatial landscapes that are defined by the tasks they perform, whether ritual, hunting, foraging, etc. (Anschuetz 2001). Similarly, the resources they employ have their own spatial distribution based on their ecological niches. These landscapes have a spatial dimension that varies independently of regional climate records, complicating efforts to directly tie one to the other. The combination of archaeological and climatological records, with separate spatial dimensions and temporal scales, generates uncertainty for researchers trying to understand the effects of past climate change on human societies.

For any research argument using paleoclimate records, the temporal dimension must be defined. Comparison of archaeological and paleoclimatological records is more or less dependent upon the resolution of the dating method used for each. As Hull (2005) argued, “The overlap of shorter and longer cycles in the [2005] analysis suggests that misattribution of cause at any analytical scale would be possible if only one scale had been used for analysis” (2005:374). The difference between high-resolution dating methods such as dendrochronology and possibly obsidian-hydration dating (Hull 2001) and less precise dating methods such as radiocarbon dating creates significant differences in analytical scale. High-resolution dating, dendrochronology in particular, allows annual and potentially seasonal variation in the environment to be measured in addition to the cutting date, which allows for placing the artifact in a real chronology. However, this resolution often does not have a full time sequence at sites except for areas of exceptional preservation. In contrast, radiocarbon dating often has a wider application, albeit at the expense of
a lower resolution due to the statistical nature of the date. The fine resolution of dendrochronology approaches a scale that can more clearly show the dynamic relationship between humans and the environment, but this scale is also somewhat detached from the long-duration process of climate change, as the record is spatially variable and defined by the life of a single organism; “In those cases in which archaeologists recognize processes beyond the perception of the actors, interpretation may be disencumbered from the limitations imposed by short-term observations that are themselves rooted in perception—in this case, of culture in the modern world” (Hull 2005:355). Hull places emphasis on multi-temporality, using archaeology to focus on both the longue durée and year-to-year life. Obsidian hydration was proposed by Hull in a past work (2001), but ultimately variation in hydration rates from separate geochemical sources makes its use tenuous at best to get at individual experience as a unit of behavior. Ultimately, even the finer units of dendrochronology need to be placed in a larger context to get to an understanding of the full effects of climate change on human populations.

While there is a distinction between climate and environment as concepts, the difference is obscured in many paleoclimatic records. As such, interpretations of climate must be evident in multiple records and, when possible, be subject to significance testing.

**History and Process**

In a 1968 review of Sabloff and Willey’s (1967) article on the collapse of the Maya, Lewis Binford attacked the notion of historical cause. Sabloff and Willey argued that the Southern Lowlands of the Yucatan Peninsula underwent invasion by a non-Mayan people beginning in the 9th century that led to the collapse of the Mayan civilization within a century (1967: 312). Binford
attacked this argument on multiple fronts. First, he argued that no general set of principles exists to associate invasion with collapse. Without such a theory, it is hard to establish what evidence constitutes support or refutation, thus making historical explanations inherently unscientific. Binford argued that “... Sabloff and Willey’s suggestions regarding historical priorities are defensible only in the context of an inductivist philosophy and that such a philosophy is unacceptable scientific procedure” (1968: 272). In elaboration, Binford explored potential processual explanations for population movement, including superior weapons, subsistence strategies, motivating factors for migration, etc. In evolutionary biology, the same dilemma was faced by ethologists seeking to explain animal behavior. To combat this, they articulated a distinction between proximate and ultimate causation. “There is always a proximate set of causes and an ultimate set of causes; both have to be explained and interpreted for a complete understanding of the given phenomenon” (Mayr 1988). Binford’s proposed solution was to follow the epistemology of science more closely, specifically regarding the formulation of hypotheses and reliance on validation through empirical studies.

The distinction between history and process has remained a contentious issue since the emergence of processual archaeology in the early 1960’s. Surprisingly, little work has been done to distinguish the effects of climate events and processes in paleoclimatology. Events such as the Younger Dryas had undeniably strong effects on human populations, but it is not sufficient to accept the Younger Dryas as a historical cause. The processes that result in climatic events are critical to a fuller understanding of the relationship between humans and climate.

There are two critical categories of climatic change: events and processes. The Younger Dryas, to continue the example, can be construed as an event. It is well defined in time and does
not appear to permanently affect change for the remainder of the Holocene. The Younger Dryas is an example of an event with a clear beginning and end that is separate from long-term trends. The second category is process—these are the gradual changes or patterns that occur without specific events or reference points. This includes increases in carbon dioxide in the atmosphere and sustained melting of glaciers during the defacing ion period that preceded the Holocene. These processes have much longer-term effects on the climate and environment. Closer investigation of the Younger Dryas suggests that it was the consequence of a freshwater flux in the North Atlantic that affected the thermohaline circulation (Broecker et al. 1990). It is part of a periodic freshwater flux, and as such has been dubbed Heinrich Event 0 (Bond and Lotti 1995). Similarly, the Younger Dryas recovery falls into a 1,470 pattern of cold, arid events known as Bond Events (Bond et al. 1997). In this context, the Younger Dryas is the consequence of a process of deglaciation in the context of Earth's orbital cycles. It is not inappropriate to use the Younger Dryas as either an event or a process, but it is important to recognize the context and frame of reference for climate changes.

Importantly, the distinction between event and process can be based on region. A significant climatic event in one region can begin a long-term process of change in another. While the labels ‘event’ and ‘process’ are important, it is important to remember that they are not universal but rather regional distinctions.

A second significant differentiator is the scale of climatic changes. Both the Medieval Warm Period and the Last Glacial Maximum were climatic events that affected human populations, but they are vastly different in scale. There is no climate event in the Holocene that approaches the scale of climatic events of the Pleistocene. This conceptualization of climate is
critical and often neglected in most climatic research. A group of hunter-gathers may be less
vulnerable to large climatic events than agriculturalists are to small events that disrupt their food
supply in terms of population numbers. In other words, the vulnerabilities of human populations
are the criteria by which climate change must be judged.
Chapter 3: The Historical Development of Paleoclimatology in Archaeology

The Ice Age and Extinction

For most of human history, climate change has not been distinguished from weather. While many historians associated changes in weather with changes in agricultural productivity, the limitations of instrumental records of climate precluded analysis of climate as a phenomenon. That said, historians of the period noticed dramatic changes in climate during the Little Ice Age (LIA), particularly the pluvial conditions that marked the beginning of the LIA. Severe rains flooded fields and led to famine beginning in A.D. 1315, a rapid transition that Fagan (2003) attributes to a shift in the North Atlantic Oscillation. Historians of the time were more likely to attribute these changes to divine vengeance (Behringer 1999) than to broad climatic processes.

Initial notions of climate change were forwarded by people as early as the Iron Age. The association of land-based seashell fossils to past environments was made by the Greek philosopher Xenophanes (570 - 480 BC); he suggested that these fossils were evidence that what was then land was once underwater (Desmond 1975). Perhaps more remarkably, a Chinese naturalist named Shen Kuo (1031 - 1095 AD) not only recognized the presence of seashells on land as evidence of changes in sea level, but also associated fossilized bamboo in regions too arid for its growth with gradual periods of climate change (Chaloner and Creber 1990).

The first systematic scientific investigations of paleoclimate began with Louis Agassiz (1807 - 1873). Agassiz brought together evidence for a series of ice ages in his 1840 study, *Etudes sur les glaciers*.

While others had suggested the possibility of massive glaciations, most famously
Johann Wolfgang von Goethe (Goethe 1892), Agassiz developed the ice age theory with four key lines of evidence (1840):

- Moraines
- Lost boulders
- Polished and striated formations
- Limestone pavements

While Agassiz is celebrated either as the originator or popularizer of the concept of the ice ages, his primary contribution extends beyond the fact of past ice ages. Critically, Agassiz introduced the concept of massive, sweeping changes in climate on a scale beyond historical human experience. This concept had two important implications for naturalists of the 19th century. First, it indicated that naturalists could not assume stable environmental conditions. Europe could be beneath a glacier in one millennium and a sandy desert in the next. While it is a commonplace notion today, it was a difficult concept to grasp at the time. The second implication regarded the antiquity of the Earth. The movement of glaciers was known to be a slow process. The time required for a single glacial expansion across Europe was clearly beyond the bounds of the accepted creation accounts at the time. In the following decades, naturalists such as Georges Cuvier would recognize that the depth of time explained fossils that had no living analogues, laying the groundwork for the introduction of ‘extinction’ as a concept (Rudwick 1997) beginning with the description of the *Mastodon* genus in 1796. Similar incongruities would inspire a young Charles Darwin to develop his theory of natural selection (Gould 2002).
Combined, the antiquity of the Earth and the concept of climate change presented naturalists with a new theoretical dilemma of scale in paleoclimatic change. Agassiz himself commented on the shift:

It is thus necessary to admit that the world’s climate is not fixed in place; local circumstances are able to modify the climate of certain regions. The facts recorded here are more powerful and prove that the glaciers have had notable oscillations in historic times; retreating in this case, as they had been placed to a period of time, in which global temperature had remained essentially the same. This proves that these changes are due to local influences and not dependent upon general [global] changes; considerable glacial advance in the Alps found in historic documents did not coincide with the expansion of glaciers in Greenland. In effect, it was in the beginning of the fifteenth century that the coast of Greenland became inaccessible; but this same time period had the most free passages yet in the Alps; it was only in the first half of the sixteenth century that they became difficult to access, and almost impossible for travelers by the eighteenth century. (1840: 238-239, translation by author of the present volume)

It was clear that sweeping changes in climate could occur—as evidenced easily by the presence of glacial features in Southern France and fossilized ocean dwellers on English cliffs, but less clear were the intermediate changes that could also impact humans. Agassiz’s use of geological features provided evidence for previous glacial activity, but these features could not be expected to record other climactic events that lacked the scope of glaciations.
Johannes Steenstrup (1813 - 1907) confronted this challenge in one of the first scientific archaeological excavations in Denmark. Steenstrup was an early member of the Scandinavian school of archaeology. He was also the first to create an archaeological procedure for pollen analysis. His was not only the first paleoclimatic study in archaeology, but also the first documented palynological investigation (Manten 1966). Steenstrup identified several phases of forest succession, the earliest being a post-glacial aspen forest. This was followed by pine, oak, and finally beech and elm. Steenstrup associated the oak forest with stone and bronze tools and the beech/elm forest with iron tools. Thus, Steenstrup tied environmental change directly to Christian Thompsen’s (1788-1865) then 20-year-old Three Age System of Stone, Bronze, and Iron Ages (Trigger 2006).

Steenstrup thus synthesized a number of independent concepts. First, through the use of palynology, he addressed the climatic changes that followed the glacial period identified by Agassiz (1840). His model of forest succession was the first of its kind. Second, he tied changing human behavior to a changing climate, helping to demonstrate the antiquity of Thompsen’s Three Age System. Steenstrup’s work was remarkably prescient, given the lack of theoretical and methodological work in his day. Modern palynology did not begin to build on his forest succession system for the better part of a century (Manten 1966). Perhaps most critically, Steenstrup did not differentiate studying paleoclimatic change from studying humans; both were components of the same narrative.

Unfortunately, few scholars in either paleoclimatology or archaeology followed Steenstrup's lead for the remainder of the 19th century. Palynologists slowly built up classification systems for pollen without building records of climate change (Manten 1966). Archaeologists
oscillated between degrees of antiquarianism and cultural history. Apart from the Three Age System, developments in Scandinavian archaeology had limited influence on the rest of the scientific community at the time (Trigger 2006).

**The Development of Palynology**

Steenstrup drew from early palynological classifications, such as Lindley's (1830) work on orchidaceous plants. However, some limited work was done to tie changes in pollen to climate and time. Trybom (1888) identified pine and spruce pollen in a Swedish Quaternary lake deposit, arguing that they could be used as index fossils for the period. C.A. Weber (1893) developed the first quantitative presentations of pollen. His were also the first figures to use relative frequencies of pollen, a categorization of the data that would come to dominate the field (Manten 1966).

Despite key advances by scholars such as Steenstrup and Trybom, palynology was unable to progress beyond classification for almost a century. All the necessary tools were available for more advanced scientific study, but there were three key limitations for researchers. The first was common to many fields at the time: a lack of qualified researchers. We take for granted the economic developments of the 20th century that made advanced science possible. These developments included the lifting of millions of people out of poverty, a broad educational system, and availability of careers in science. The smaller pool of intellectuals in the 19th century had an undeniable affect on the progress of many scientific fields.

The second limitation was methodological. There was not a unifying procedure for the interpretation of pollen sequences. Palynological studies produce tremendous amounts of data that must be managed to produce generalizable conclusions. While the presence or absence of taxa in
sequences produced interesting results, the changing abundances and sample sizes of sequences were harder to analyze in a time before computers. As such, pollen analysis remained in a long process of classification. This period was important, just as cultural history was an important classificatory period in archaeology (Trigger 2006).

The third limitation was an absence of climatological theory. Simply put, researchers in the 19th century didn't think much beyond history, and they had a difficult time articulating an idea of processual climate change that could be used to interpret data. While Agassiz's identification of an ice age represented a watershed for paleoclimatology, it nonetheless took decades for researchers to begin to explore the idea's implications for human populations fully. The distinction between history and process would never be fully articulated in climatological studies. There was no Binford figure for meteorologists. However, the development of region-specific climate histories would generate a model of Holocene climate change that was inherently processual.

The classificatory phase of palynology came to an abrupt end in 1916. That year, Lennart von Post was tasked to develop a graphical representation of pollen (Manten 1966) by his employer. His resulting display, presented at the Sixteenth Scandinavian Meeting of Natural Scientists in Christiania (today's Oslo), changed the field. Von Post developed what is today termed a pollen diagram. This type of chart displays pollen data normalized to sample size along one axis, and then displays time along a second axis. Lines and/or shading connect the changing relative fluctuations of each taxon over time. The resulting display portrays pollen data as a series of changing frequencies, highlighting significant shifts over time. These enable researchers to digest large amounts of information in a single figure. In a time before computers, these diagrams of relative frequencies were an ingenious solution to a problem that plagues all scientists: the
synthesis of large amounts of data. For a palynologist such as von Post, the numbers were an immediate challenge.

A palynological sequence can consist, for example, of 15 temporal assemblages with 20 or so taxa that occur in appreciable amounts throughout a given sequence. This means that a total of 300 relative frequencies must be calculated and displayed. Von Post's pollen diagram managed to capture all this change in a single figure. This enables immediate comparison between taxa over time—interpretations are more difficult with 300 bar plots. Importantly, his use of a normalization procedure against sample size helped address differences in preservation and abundance between sites. It also helped make changes in taxonomic frequency generalizable to other sites.

In the years following von Post’s development of the pollen diagram, palynology began to develop as a serious scientific field. In 1930, almost 90 years after Steenstrup's first forest succession model, Rudolph developed the first formal forest transition model for post-glacial Europe, identifying four key phases: (1) *Betula-Pinus*, (2) *Corylus*, (3) *Quercetum mixtum*, and (4) *Fagus*. He established a hypothesis that other researchers were able to test. While additional details and region-specific changes would augment this model, Rudolph was one of the first to use the methods established by von Post to generate a general model of forest succession on continental Europe following the ice age using pollen data. Where von Post filled the methodological void in palynology, Rudolph helped fill the theoretical void by providing a general model to serve as a hypothesis to direct future research.

Methodological advances continued to refine von Post's original pollen diagram. Iversen (1946) revised von Post’s original pollen percentage metric to hold arboreal pollen equal with anemophilous herbs and *Ericales*. These combined totals became the percentage. Iversen
recognized that including all taxa in the total used in the pollen percentage normalization procedure had the potential to misrepresent changes in taxa more relevant to some inquiries. These revised numbers helped establish a value for forest density in the region. Fagerlind (1952) identified problems with non-linearity, as pollen abundance data are expressed as relative relationships. Fagerlind’s critique established a series of methodological papers that continue to this day. One of the most notable attempts to address this weakness comes from studies of lake pollen. Sugita (1995) developed a model to estimate pollen contributions to lakes, establishing a model of source area productivity. She identified an important threshold of 50m for distance for pollen dispersal from source vegetation. These studies helped address one of the central assumptions in palynological methodology—that the pollen percentage metric accurately reflects past vegetation composition. Each researcher revisited the assumptions of von Post’s original normalization procedure to identify potentially conflating factors. In chapter 5 of this dissertation, a separate normalization procedure is introduced that can, in the case of long-distance dispersal (LDD) pollen, potentially improve upon inference of past vegetation cover.

The changes to von Post’s pollen diagram have principally been refinements and specifications. There have been few attempts to use palynological data to address specific environmental hypotheses or to use statistical hypotheses tests to evaluate their results (MacDonald 1993). In place of this, MacDonald saw much of palynology as effectively qualitative analyses of pollen diagrams that don’t address hypotheses; in other words, there was no expectation from theory to compare with observed data. For these reasons, palynology has been characterized as being in a minor state of crisis due to the lack of rigorous statistical hypothesis testing (Seppä and
Bennet 2003). While pollen data remain a critical component of paleoclimatic reconstruction, palynology has not advanced at the same rate as other methodologies.

**The Development of Dendroclimatology**

The science of dendroclimatology was developed by Arthur E. Douglass at the turn of the century. Douglass hypothesized that sunspot activity influenced climate and that tree rings would correlate to those broad climatic changes. Douglass was correct in noting that sunspots have an effect on climate, but the evidence for this would ultimately come from changes in atmospheric $^{14}\text{C}$ and $^{10}\text{Be}$ (Muschler et al. 2008; Reimer et al. 2009). Tree rings proved to be a much more localized record of paleoclimate. Douglass was able to apply his technique in the US Southwest, where he first precisely dated construction at Chaco Canyon and Aztec ruins, noting that the latter was built after the former. He then used the widths of tree rings to suggest that a severe, multi-decadal drought was responsible for the ultimate abandonment of Chaco Canyon. Douglass' identification of a link between climate change and human occupation was one of the earliest statements about climate’s impact on human societies. The observation has been replicated by multiple authors (Robinson and Rose 1974; Benson et al. 2007). Further work has deepened the connection between climate and the occupation of Chaco Canyon. Windes and Ford (1996) associated thick tree rings —indicating wetter-than-normal conditions—with the outer rings of ponderosa stands used in the construction of Pueblo Bonito. This indicated that additions to the Great House were made during times of heightened rainfall.

Despite the significant work in Chaco Canyon, the immediate legacy of Douglass’ work was the creation of a methodology for tree-ring dating, or dendrochronology (Nash 2002). This
was one of the first dating methods in archaeology, and to this day it remains one of the most reliable. A skeleton plot of ring widths is produced after initial analyses; these are counted back from a cutting (or established) date (Douglass 1941). Cross-dating of multiple ring sequences enables the construction of long-term regional chronologies (Schulman 1956; Nash 2002). In other parts of the world, tree-ring growth is influenced by multiple factors, necessitating a more nuanced technique to match dates (Scweingruber 1993).

Dendrochronology is not, however, a resolved science. The field has received criticism for two reasons. First, the process of matching tree rings to form regional chronologies is dependent upon the subjective, non-replicable interpretation of a specialist (Stokes and Smiley 1996). Second, no statement of uncertainty is associated with tree-ring dates (Jacoby 2000). These criticisms have not greatly impacted the field, as most in tree-ring dating do not feel that expressing uncertainty weakens their conclusions; there is no concept of a 'likely' date (Nash 2002).

In contrast to dendrochronology, dendroclimatology has seen multiple improvements in methodology. Dean and colleagues (1996) noted that the rapid increase in computer processor power enabled more advanced statistical techniques to improve accuracy and reliability in paleoclimate reconstruction. Paleoclimate researchers began to differentiate between stable, low (> 25 years) and high (< 25 years) frequency factors in climate (Dean et al. 1985; Dean et al. 1996). Larson (1996) noted that climatic changes do not affect all societies equally; the impact of those climatic changes is contingent upon resource flexibility.

To obtain meaningful reconstructions of paleoclimate, a number of steps must be taken. First, age-related changes in a tree must be addressed. Tree rings tend to become narrower as a tree ages (Nash 2002). Briffa and colleagues (1998) note that there is not a universal approach to
correcting for age trends in tree-ring sequences. Briffa and colleagues illustrate how two different age corrections result in temperature sequences that share 70% variance with instrumental records but nonetheless present completely different climate histories (1998: 67).

Varien and colleagues (2007) used correlations of bristlecone pine ring widths to the Palmer Drought Sensitivity Index (PDSI) to *Zea mays* production in the southwest. They then used archaeological tree-ring data to develop a prehistoric precipitation time-series for the region. The authors identified the periods around ~AD 800 and ~AD 1200 as the most productive in the Mesa Verde region. These numbers are based only on precipitation as modeled from dendroclimatological data; they do not account for land degradation or other non-climate patterns. Varien and colleagues (2007) estimated much larger population sizes during the 13th century based on the number of occupied areas.

A common assumption in dendroclimatology is the generalizability of tree-ring sequences to annual precipitation. As Stahle and colleagues (2009) note, tree-ring sequences in the US Southwest tend to record spring precipitation. This can be a helpful index of paleoclimate but is less meaningful when discussing agricultural productivity. *Zea mays* agriculture is dependent upon winter moisture for seeds and summer monsoonal precipitation for continued growth. Dendroclimatological data do not provide insight into either of these seasonal regimes. Stahle and colleagues (2009) found that spring and summer precipitation patterns had not been correlated for the past 74 years in the US Southwest. This has some implications for the inference of climate during Ancestral Puebloan times. However, they did find that severe droughts, such as the drought in the 1950’s, are the consequence of shifts in both spring and summer precipitation. This lends support to interpretations of the prehistoric droughts that contributed to shifts in Puebloan
settlement patterns but does add considerable caution to models and causation. The authors suggest that the 13th-century droughts primarily affected spring precipitation. They propose using Latewood (when the transition from Early Wood to Late Wood is abrupt) as an indicator of monsoonal precipitation; however, to date, there has been no successful demonstration of the usefulness of this approach.

The procedure employed by Varien and colleagues (2007) to reconstruct agricultural potential from dendroclimatological sequences is part of a trend in increasingly complex models of paleoclimate generated from tree-ring data. Herweijer and colleagues (2007) employed a similar approach to reconstruct PDSI over the Western US as a gridded time series. Doing so, they were able to contrast the Medieval Warm Period PDSI as being slightly lower than modern values, suggesting somewhat more arid conditions.

Finally, there is an unusual decline in paleoclimate reconstruction from tree rings in the decades after 1960 (Briffa et al. 1998; Andreu-Hayes et al. 2011). This may be connected to an imbalance in the carbon cycle following anthropogenic carbon emissions. Such an interpretation is supported by this author; in a study of stable carbon isotopes in C₃ grasses, correlation with precipitation dropped after 1960. Briffa and colleagues (1998) note that this is a significant problem for paleoclimate reconstruction; if disruptions in the carbon cycle reduce the reliability and validity of paleoclimate proxies, then the uniformitarian assumptions that underlie paleoclimate reconstruction are violated.
The Development of Carbon Isotope Paleoclimatology

Isotopic research increased dramatically following the discovery of radiocarbon dating by Willard Libby in 1949. Initial studies by Craig (1953; 1954) and Wickman (1952) established conventions for reporting stable carbon isotope ratios. Generally, a standard is employed to report isotope measurements:

\[ \alpha = \frac{R_A}{R_B} \]

where \( R \) refers to the ratio of \(^{13}\text{C}/^{12}\text{C}\) in substances A and B. The enrichment of one compound relative to another is represented by the following equation:

\[ \varepsilon = \alpha - 1 = \frac{(R_A - R_B)}{R_B} \]

In this case, B represents the standard by which substance A is measured. The conventional standard for stable carbon isotope ratios is a belemnite from the Pee Dee formation; this standard was chosen due to its similarity to the ratio of \(^{13}\text{C}/^{12}\text{C}\) in all carbon. In its modern incarnation, a substitute sample, the Vienna Pee Dee belemnite (VPDB), is used due to the rarity of those original fossils used as a standard. The conventional standard is thus expressed as:

\[ \delta^{13}\text{C} = \left[ \left( \frac{^{13}\text{C}/^{12}\text{C}_\text{VPDB}}{^{13}\text{C}/^{12}\text{C}_\text{VPDB}} \right) / \frac{^{13}\text{C}/^{12}\text{C}}{} \right] \times 1,000 \]
Wickman (1952) found that most plants had $\delta^{13}$C values of -25‰, while a couple plants from central Asia had high values of 12‰ or more. Craig (1954) found one sample from Kansas with a similarly enriched value and recognized that there was a real phenomenon, but nonetheless excluded such plants from analysis and suggested that these values were "anomalous terrestrial plants" (1954: 116). Bender (1968) later found that C$_3$ plants had a mean $\delta^{13}$C of -25‰ while C$_4$ plants were responsible for the higher -12‰ values. Bender's work had important implications for climate reconstruction over large periods of time—the isotopic ratio of carbonates in soil and animal tissue could be used to identify either C$_3$ or C$_4$ plants as the source of carbon. For soil analysis, this could facilitate the reconstruction of past vegetation. For the study of animal tissue, it could indicate diet preferences and ecological niches.

Recent research has begun to look at stable carbon isotopes in the soil as an indicator of broad changes in C$_3$ and C$_4$ vegetation. These have included identifying changes in vegetation associated with the Younger Dryas (Bement and Carter 2010) and the cultivation of maize, a C$_4$ plant, in Mesoamerica (Webb et al. 2007). However, variation in $^{13}$C discrimination of C$_3$ plants is rarely utilized in reconstructing paleoclimate in archaeology.

In four critical papers (Farquhar et al. 1982; Farquhar et al. 1983; Farquhar and Richards 1984; Farquhar et al. 1989), Graham Farquhar laid down a simple mathematical approach to calculating two important paleoclimatic values. The first is an atmospheric value of $\delta^{13}$C. This value has tremendous potential in reconstructing past atmospheric carbon. Atmospheric $\delta^{13}$C values vary due to differences between terrestrial and oceanic carbon sinks (Pearman and Hyoson 1986). Oceanic carbon sinks take in carbon at a relatively constant rate, while terrestrial plants are much more variable; thus, atmospheric $\delta^{13}$C reflects variation in land vegetation carbon storage.
(Keeling et al. 1989). The ability to reconstruct atmospheric δ^{13}C values from C₄ plants is well established (Marino and McElroy 1991; Marino et al. 1992). The utility of stable carbon isotopes in C₃ plants for paleoclimate reconstruction in archaeology will be discussed further in chapters 6, 7, and 8.

**Paleoclimatology in Archaeology**

The work of Johannes Steenstrup in the mid-19th century represented a holistic approach to archaeology that included paleoclimatology. However, his successors in both archaeology and paleoclimatology parted ways and have rarely found a similar, comprehensive integration. While few archaeologists discount climate as an important factor, it has been regarded as a separate field of study.

As palynology entered a classification phase, so too did archaeology. For most of the 19th century, archaeology was dominated by antiquarianism. Artifacts were dug up and sold to either museums or collectors. The growth of museum collections prompted a focus on developing chronological frameworks at the regional level (Trigger 2006). However, some serious work was done on explaining the origins of agriculture. Oscar Montelius was a disciple of the forward-thinking Scandinavian school of archaeology. He focused his career on the further refinement of the classification system laid down by Thomsen. However, he was more inclined to develop generalizable theory as well. He saw human technological development as a continuing adaptation to nature (1885). While many archaeologists of the time likely held the same opinion, Montelius was one of the first to articulate the concept. Montelius was also a proponent of cultural diffusion from the Near East—or *ex oriente lux*—a position for which he is better known to archaeologists in
Europe and America. However, his views on the importance of the environment would become infamous in the Soviet Union.

Raphael Pumpelly was the first to propose the oasis hypothesis of agricultural development (1908 I: 65-66). He argued that the Middle East experienced aridification following the ice age, resulting in the aggregation of hunter-gatherers around sources of water such as oases. This view was later popularized by V. Gordon Childe (1928). The oasis hypothesis was the first explicit, testable hypothesis involving both climate and human behavior. A more developed field of paleoclimate would demonstrate that the Middle East was wetter, not drier, as the oasis hypothesis would predict. However, the oasis hypothesis was nonetheless an important milestone in both archaeology and paleoclimatology. Previous efforts in describing the effects of climate on human behavior were primarily descriptive, as was Steenstrup’s work (1841), or general (Montelius 1885). Pumpelly’s (1908) oasis hypothesis was the first predictive model of its kind.

V. Gordon Childe (1934) identified two major revolutions that preceded the Industrial Revolution. The first was the transition from hunting and gathering to agriculture; the second was the move from rural to urban societies. He saw population pressure and technology as the drivers. He also saw increasing conspicuous consumption by the upper classes as a reason for decline in the Middle East. While Childe made many assumptions about the environment and societies of these periods, he invoked non-racial arguments—a break from his peers and, indeed, even his own work (1926). The revolutions he identified continue to define much of the contemporary work of archaeology today. These research foci, the origins of agriculture and complex society, include the most substantive use of paleoclimatology in archaeology today.
Importantly, the increasing focus on the development of agriculture helped shape research hypotheses that required the collection of environmental and climatological data to test. While this would be limited in the first half of the 20th century, the development of a more functionalist/processualist approach to archaeology would begin to incorporate environmental data and expand the focus of archaeological inquiry from individual sites to regions and settlement patterns.

**Process in Archaeology**

For over a century following Thomsen's Three Age System, the theoretical focus in archaeology remained on classification and cultural history. Beginning in the 1940's and accelerating through the 1960's, archaeology would enter a period of heated theoretical discussions. The first major development in theory came with a dissertation. Walter Taylor (1948) criticized archaeologists for not systematically recovering faunal and floral information, leading to gaps in knowledge regarding the environment of prehistoric populations. His broader critique included provenience as well—the focus on certain types of artifacts above others hindered, rather than promoted, knowledge of the past. He also argued for more analogy as a way of tying behavior to material culture. Taylor's focus on methodology was appropriate and overdue. The data collection methods of early archaeologists still followed a strict focus on higher-value artifacts. The neglect of ecofacts and provenience would become a major concern of archaeologists after Taylor's work.

Taylor's critique marked the beginning of a four-decade-long process of integrating ecological and environmental concepts into archaeology. A key example can be seen in Grahame Clark's work on a precursor to systems theory. In 1953, he added biome and habitat to his earlier
diagram of systems theory (1939)—the first diagram of its kind. This may have been the first formal articulation of environment and culture as parts of a single system.

Major research programs that followed Taylor's critique made better use of all data available. As a consequence, they were landmarks in developing more comprehensive views on human prehistory. The multi-disciplinary Jarmo Project (1948 - 1955), directed by Robert Braidwood, brought together archaeology, botany, zoology, and geology to study late Paleolithic/early Neolithic sites in the Kirkuk region of Iraq (Braidwood 1974). A second major research program, the Tehuacan Archaeological-Botanical Project, led by Richard S. MacNeish, ran from 1960 to 1968. It revealed a 12,000-year cultural sequence of development up until the time of Spanish contact (MacNeish 1974). Both projects revealed that cultivation of food began much earlier than most had anticipated. Braidwood’s study also refuted the earlier oasis model of Pumpelly (1908) and Childe (1923) by pushing the origins of agriculture back in time to an environment with wetter conditions, undercutting the importance oases would have had. Braidwood noted that sites in the Levant and Anatolia show little evidence of the use of cereals prior to 15,000 BP (Braidwood and Howe 1960). Braidwood noted that the oldest cities occur in the same region as the wild ancestors for many domesticates; this guided his choice of Jarmo as an excavation location (Braidwood 1981). Using the newly minted science of radiocarbon dating, Braidwood helped identify the start of agriculture in the Middle East.

The Virú Valley project (Willey 1974b) was instigated by Gordon Willey at the suggestion of Julian Steward. Willey did note an ecological force on human culture but focused on the way settlement itself was the starting point for understanding cultures (counter to Steward’s more ecological focus). Willey’s work is widely seen as an important moment in archaeology when
regional surveys began to complement excavation. Trigger (2006) compares this methodological innovation to Thomsen’s original classification system. Its importance comes from the conceptualization of a system, rather than a site, as a focus for archaeological excavation. The expanded regional focus for archaeology enabled more sophisticated pairing of environmental and cultural data in increasingly broad archaeological projects.

Taken together, Braidwood (1974), MacNeish (1974), and Willey (1974) transformed the methodology of archaeology in a fundamental way. They made use of a wider set of data to evaluate existing hypotheses and developed the environmental context for human behavior. The multi-disciplinary nature of their fieldwork led to a more comprehensive picture of early human societies. Willey’s focus on settlement history and Braidwood’s focus on the opportunities present in the environment would have an influence on future archaeological inquiry. The shift to settlement archaeology also had important implications for the sophistication of environmental arguments. There is a substantive difference between the effects of climate change on a specific city (which may be minor) and the effects of such change on a larger landscape (which may be more substantial). A broader focus on settlement patterns, rather than individual sites, had implications for data collection and analysis. As discussed further in chapter 6, $^{13}$C discrimination values derived from radiocarbon-dated C$_3$ plants over a 8 x 8 km area would give insight into shifts in settlement patterns in the Lower Alentejo during the Medieval Warm Period.

Changes in resources over time, driven by climate change, began to receive a more detailed look by researchers. Caldwell (1958) advocated the strongest position to date for a link between climatology and human history. He argued that ecological shifts following the ice age led to the decreasing use of big game and more complex and intensive patterns of food collection. Caldwell
did not intend for climate to be a sole cause of human behavior; he continued to argue that internal cultural change was a significant mover.

Environmental influence on human behavior began to receive new attention from cultural anthropologists as well. Julian Steward, an anthropologist based at the University of Michigan, focused on a multilinear, ecological, and empirical approach to human behavior. He thought that similar natural environments could spawn similar (though not identical) cultural-historical trajectories. He argued that ultimately, evolutionary anthropology should explain shared traits of cultures, not their particulars (1955). Such a view was ground-tested by Marshall Sahlins (1958), who examined the different levels of social stratification across Polynesia, concluding that more complex and stratified societies were enabled by features of their environment to produce higher yields of food and support larger population numbers. Sahlins noted that “Economic factors link social stratification and the technological adaptation to environment” (1958: 248). While Sahlins would later renounce his environmentalist views (1976), his early work remains an influential example of what an integrated study of environment and social structure can be.

The exploration of environmental influence on human behavior in cultural anthropology was short-lived; however, it provided a crucial influence on processual archaeology. The views of Steward and Sahlins shaped the face of anthropology. When Willey and Phillips stated that “American archaeology is anthropology or it is nothing” (1958: 2), this was the anthropology they were referring to. This sentiment was echoed in Joseph Caldwell’s Science article (1959), which served in many ways as an introduction to the focus on processual research in archaeology. Caldwell noted that an increasing focus on ecology and settlement strategies was beginning to influence archaeological research.
Lewis Binford articulated the processual approach to archaeology (1962; 1965). Binford argued that archaeology and anthropology shared the same goal: to explain cultural similarities and differences over time. Binford identified culture as an adaptation to environments; this view tended to de-emphasize the particulars of a culture in favor of a more general view. Binford thus tended to dismiss cultural history in favor of a more specific view of humans’ adaptations to their environments. Binford’s view of anthropology was much like that of a physicist—generalizable conclusions were the goal, not historical particulars. In a review of Sabloff and Willey’s (1967) migration hypothesis of the Maya collapse, Lewis Binford (1968) argued that historical explanations do not suffice in archaeology. More to the point, Binford noted that a historical event as a causative agent is insufficient without a consideration of larger processes such as population growth and climate.

The shift to processual anthropology included a more expansive view of human societies in their environmental context. In cultural anthropology, Roy Rappaport (1968) closely examined interacting factors, cultural and environmental, among the Tsembaga of New Guinea. In addition to traditional ethnographic work, Rappaport included a detailed analysis of the diet and environment of the Tsembaga. In archaeology, this approach was known as systems theory, exemplified by Kent Flannery (1968), who popularized systems theory in identifying feedback between human societies and maize genetics. Systems theory was an attempt to model the interactions of different aspects of a human society in association with environmental variables. However, archaeological systems theory ran into a number of fundamental problems. First, the complexity of systems could rapidly overwhelm a focused study. Second, the data produced through archaeological excavation presented a fragmentary picture of past feedbacks between human social organization and the
environment. And third, human social and environmental variables evolved over time, making it difficult to make one iteration of systems theory representative.

One unanticipated consequence of the increasing use of the environment in the study of human behavior was a growing focus on apocalyptic and catastrophic views. While many of these hypotheses stemmed from real concern about the environment, they tended to overstate the case. The concept of environmental degradation due to human population growth was a particularly salient concern in the 1960’s. With the publication of *Silent Spring* and *The Population Bomb*, the concepts were actively discussed by the public at large. Ester Boserup (1965) noted that agricultural intensification yielded more food, but at the cost of increased labor. The long-term effects of intensification were negative both for humans and their environment (Cohen 1977).

Assumptions of gradual evolution were questioned in archaeology as they were questioned in evolutionary biology. Robert Adams (1974: 248-249) noted that there were abrupt shifts in the development of earlier civilizations. This observation presaged the later evolutionary biology debates regarding punctuated equilibrium (Gould and Eldredge 1977). In archaeology, this came to form catastrophic explanations for cultural shifts, particularly that of the shift from complex to simpler forms of organization. Colin Renfrew (1978) used catastrophe theory as a potential explanation for punctuated changes in the archaeological record.

Views of catastrophism focused on events but were at odds with the long-term processes that were a focus in processualism. Renfrew (1972) examined the natural environment and long-term processes that led to complex society in the Bronze-Age Aegean, a study that is influenced by systems theory. Robert Carneiro (1970) developed an ecological model for the initiation of complex societies. His circumscription hypothesis argued that marginal environments tend to cause
greater investment in limited resources—this begins the social circumscription process that results in state-level societies. The studies of Renfrew and Carneiro highlight the influential role of climate and the environment on human behavior over the long term. Many archaeologists would seek to integrate these concepts formally into their understanding of cultural systems.

Clarke (1939, 1953) developed the first approach to systems theory. Kent Flannery (1965) introduced a more formal form of systems theory to archaeology. Diagrams of systems attempted not just to show critical factors in a cultural system, but also to demonstrate their feedbacks and capture some of the dynamism of the system. Flannery used systems theory (1968) to show how genetic changes in Mesoamerican maize and beans could cause increasing dependence on those foods.

The importance of the functionalist/processual school of thought in archaeology to paleoclimate reconstruction is due not just to the increased importance of the environment in research, but also to the nature of the data collected over the course of archaeological excavations. The increased sampling of ecofacts encouraged by Taylor (1948) and Binford (1962; 1965) made available data that helped archaeologists more rigorously assess environmental conditions. The development of environment-specific hypotheses, such as that of the oasis hypothesis by Pumpley (1908), set testable research goals that were eventually met by Braidwood (1974). Systems theory approaches more rigorously formalized the collection of ecological data; such data were a necessary part of any system framework. And finally, the shift in focus from site to settlement promoted by Wiley (1974) and others promoted the gathering of ecofacts over a wider, more representative area. The importance of these developments was not just theoretical; they led to methods in data recovery that made more advanced data analysis possible.
**Refinement of Paleoclimatological Applications in Archaeology**

Binford proposed that culture was an extrasomatic adaptation of people to their environment (1962; 1965; 1968) in which “...we assume a systematic relationship between the human organism and his environment in which culture is the intervening variable” (1962: 218). The processualist view of culture was something of a buffer zone between an individual organism’s survival and natural selection. Implicit in this view was that a culture should be, to some degree, optimized to its environmental setting. The study of paleoclimatology in archaeology is fundamentally one of long-term changes in those environmental settings in which humans operate. In order for culture to remain a buffer between natural selection and human reproductive fitness, that systematic relationship between humans and their environment must change as well.

Over time, processual theory has diversified from a general approach to more differentiated theoretical approaches. Two important approaches that share this tradition are historical ecology and human behavioral ecology. Carol Crumley (2007) presented historical ecology as a way to bridge the gap between the sciences and the humanities. As an example, the author gives a hypothetical scenario in which a historical ecologist employs both isotopic evidence and oral tradition to trace the effects of a flood upon a society in Kenya. If the two data sets don’t align, each can be used to inform future research on the other. “How accurate is the chronological control? Could there have been more than one flood event?” (2007: 4). Critical to historical ecology is the concept of the landscape. It is a shared unit of analysis in disparate fields and works within both spatial and temporal dimensions. Shared analytic units help keep a unified framework that enables interdisciplinary studies.
William Balée (2006) outlined four postulates of historical ecology:

- No environment has been untouched by humans (aside from parts of Antarctica, mostly to the interior),
- Human nature is not programmed to respect the environmental status quo,
- Different arrangements in human societies result in different effects on the landscape, and
- An integrative approach can insightfully tie together many different human-environment contexts.

Balée also identified the concept of a pristine environment as a casualty of archaeology. Humans are found almost everywhere in the world, and environments are modified whenever humans are around. Even “simple” human societies frequently spread cultigens and modify forests through the use of fire. One key example comes from the small Polynesian island of Futuna, where inhabitants intentionally burned the interior of the island, termed the toafa. It is typified by degradation and spatially separated ferns. It is an area of active erosion; “the formation of toafa is linked with the initial removal—after forest clearance—of the thin organic soil formerly present under climax humid forest” (1994:60). The erosion of this area contributes the sediment that later form soils in both dryland and wetland agriculture. Futunans set fire regularly to this area in the dry season to clear land for walking and sometimes just for entertainment. However, the long-term effects of this intentional burning activity improve the overall nutrient quality of lower-elevation
agricultural fields. Similar practices can be found across Polynesia (Rainbird 2002). What at first appears to be a form of vandalism has actually improved agricultural production.

An additional approach to understanding the role of climate and the environment occurred with the development of Human Behavioral Ecology (HBE). HBE proponents sought to build models for human interaction with their environments, viewing human behavior as an adaptive structure upon which natural selection can act. Over longer periods of time, the behavior is shaped by natural selection, rather than human genes. One important corollary of this postulate of Behavioral Ecology is that humans will work to optimize their use of resources from their environment (Shennan 2002). The most broadly applicable component of HBE is optimal foraging theory, which principally uses the environment as a critical input factor for estimation of costs and benefits for natural resources. These models are derived from assumptions regarding diet breadth and calculating the expected results. Hill and Hurtado (1996) found that the resource acquisition strategies of the Ache broadly match the expectations of the optimal foraging model.

Ofer Bar-Yosef (1998) argued that the cold snap during the Younger Dryas period led to the broadening of diets. Winterhalder and Goland (1997) argued that this would have incentivized the consumption and ultimate cultivation of lower-ranked cereals, thus initiating the first round of domestication. Richerson and colleagues (2001) argued that agriculture would have been impossible during the Pleistocene due to rapidly changing climate conditions.

Caution in Climate Change Explanations
The post-processual school of thought, which emerged in England in the early 1980's (Trigger 2006), promoted alternatives to the positive approach that had dominated the previous four decades. Daniel Miller (1984: 38) argued that positivist studies contributed to the oppression of marginalized groups. Miller and Tilley (1984: 2) argued that the focus on external factors served as a justification for oppression. Many post-processualists sought to define boundaries between ecology and culture. Ian Hodder (1990) distinguished between the house (domos) and the field (agrios), mediated by a boundary (foris). This view separated nature from cultural elements. Hodder at the time was a proponent of the structuralist school of thought—a theory developed by Claude Levi-Strauss that argued that culture need not be changed by outside factors. An alternate approach was proposed by Richard Gould (1978), who argued that archaeologists should explain as much as they could ecologically and use the residuals as symbolic interpretation.

Resistance to climatic-only impacts on human behavior is not restricted to extremes in theory. Joseph Tainter, in his 1988 work on the collapse of complex societies, criticized environmental explanations as both attractive and convenient. Tainter’s critique had two levels. The first was the concept of resource depletion leading to the collapse of a complex society whose institutions were developed in the context of resource acquisition. Second, and perhaps most critically, Tainter argued that the most climate-related explanations for the collapse of complex societies were ad-hoc and lacked a consistent theoretical approach. Tainter argued that the vulnerabilities of human societies had to play a central role in any climate- or environment-related cause. Climate alone could not explain collapse without consideration of these factors.

An additional key source of debate is the mismatch of temporal scales of change between human societies and climate. Meltzer and Holiday (2010) argued that the uneven cooling during
the Younger Dryas and the scale of the change would have limited its impact on Paleoindian populations in North America. The Younger Dryas would have fitted into a broader pattern of climatic variability that lasted from the Last Glacial Maximum to the Altithermal; the fluctuations of the Younger Dryas would have been lost in contrast to an already variable climate. Winterhalder and Goland (1997) argued that variations in climate are at too broad a scale to be relevant to questions such as domestication; rather, local factors and individuals have the greatest causal impact. General global changes in climate are too far removed from individual decision making to be sufficient to describe the initial choices that led to agriculture. In contrast to this view, Richerson and colleagues (2001) argued that global climate forms a necessary precursor to agriculture; the climatic variability of the Pleistocene precluded agriculture, while the relative climatic stability of the Holocene heavily incentivized its adoption.

Ultimately, the question of scale is contingent upon the nature of the research question. Richerson and colleagues (2001) look to explain the broad enabling and disabling factors that climate has upon long-term human history. Winterhalder and Goland (1997), in contrast, look to understand the risk-mitigation strategies that led to the shift from hunting and gathering to cultivation. While their arguments about the role of global climate are at ends, their research questions exist on different spatial scales. Global climate change may not be a force in individual human decision making, but it can be a long-term force in enabling long-term changes in human behavior. In other words, global climate may not influence an individual’s decision to adopt agricultural subsistence, but it can be the reason agricultural subsistence expands over millennia.

Synthesis
There are a number of conclusions to be drawn from almost two centuries of scientific paleoclimatology and archaeology. The first is the dependence upon the ability to synthesize large amounts of data. Palynology was limited in its early development due to the difficulty in portraying large pollen data sets. It was only with von Post’s 1916 pollen diagram that a methodology was established that could communicate palynological findings (Manten 1966). In some ways, archaeology has been wrestling with the same fundamental problem. A typical archaeological excavation presents diverse amounts of data, far too much to be easily synthesized into a simple result. To handle these data sets, archaeologists have employed theory to focus analysis. Cultural history focused on the traits in artifacts that helped distinguish human societies separated in temporal and/or spatial dimensions (Trigger 2006). Processual archaeology sought to employ the same data in a framework that expressed general laws of human behavior. More nuanced approaches in historical ecology and human behavioral ecology place these same data into frameworks of mutual interaction and adaptation, respectively. The importance of theory in archaeology lies in the ability to contextualize data through focused research questions, rather than simply report numbers.

However, in paleoclimatology, traditional methods of data presentation are rapidly being modified and/or replaced by newer technologies. Traditional dendroclimatology is increasingly incorporating isotopic information from tree rings as well. Isotopic studies are rapidly expanding the reach of paleoclimatology into new areas, reducing dependence upon generalized regional paleoclimatic data sets. The only field so far unchanged is palynology, which still rarely deviates from the reporting of pollen diagrams. Chapter 5 of this dissertation presents a potential new way to use these same data more explicitly in a hypothesis-testing framework.
These developments are being aided by changes in data analysis and the raw computing power available to researchers. With Bayesian inference methods, particularly change-point analysis, it may soon be possible to use direct probability statements to associate different time-series data with the same event. An example of this approach is given in chapter 5 and chapter 7, the latter being significant as both archaeological and paleoclimatological data are quantified and compared via posterior probabilities generated by Bayesian change-point analysis.

The growth of data analysis and different paleoclimatological proxy records have made it possible to recount a history of paleoclimate for the Holocene. Multiple records indicate a long, stable period of climate that has dominated since the Younger Dryas period. However, as discussed in chapter 2, the magnitude of a climatic impact is a statement not simply of climate change, but also of human vulnerabilities. Though the Holocene itself was climatically stable relative to the Pleistocene, small shifts in climate may have had large effects on human societies, particularly those that were complex and dependent upon multiple long-distance resources. Chapter 4 will discuss in more detail these changes and some of their effects on human populations.
Chapter 4: A Brief History of Post-Glacial Climate

As this dissertation focuses wholly on climate change in the Holocene, it is tempting to study Holocene climate exclusively. However, in order to get a broader perspective on the changes that do occur in the Holocene, key events of the Cenozoic are detailed, including a focus on the late Pleistocene. Complex human societies and agriculture developed during the Holocene, and climatic changes within the period are far easier to detect due to the relatively recent deposition of pollen, sediments, and other source materials used in paleoclimate proxy records. However, climate changes beyond the Holocene should be discussed for two reasons: first, to gain an appreciation for the scale of climatic changes before judging the severity of events such as the Medieval Warm Period; and second, to understand the types of climatic change that are possible when greenhouse gas concentrations change in the atmosphere. In other words, a Holocene-only approach to paleoclimate does not give an adequate framework for understanding climatic change. As such, this chapter is structured to briefly highlight the key changes that have occurred in the Cenozoic Period (65 - 0 million years ago) before discussing in detail the changes that have followed since the Last Glacial Maximum.

With those two considerations addressed, a brief timeline of significant events in climate is as follows:

- Cenozoic Climate (65 mya - present)
- Last Glacial Maximum (26,500 - 19,000 BP)
- Deglaciation (19,000 - 12,800 BP)
- Younger Dryas (12,800 - 11,500 BP)
- 8.2ka event (8,200 BP)
- Altithermal (9,000 - 5,000 BP)
- **5.1ka aridization event/El Niño onset** (5,100 BP || 3,150 BC)
- 4.2ka aridization event/El Niño cessation (4,200 BP || 2,250 BC)
- **3.1ka cooling event** (3,200 - 2,800 BP || 1,250 - 800 BC)
- Roman Warm Period (2,200 - 1,550 BP || 250 BC - 400 AD)
- **Medieval Warm Period** (1,000 - 700 BP || 950 - 1250 AD)
- Little Ice Age (600 - 150 BP || 1350 - 1800 AD)
- Anthropogenic Effects on Climate (70 BP - present || 1880 AD - present)

Each of these events has documented effects on human populations. Events in **bold** will be discussed in detail in the chapters that follow, with highlights in specific regions that include the San Juan Basin of New Mexico in the mid-Holocene (Chapter 5), the Lower Alentejo of Portugal during the Medieval Warm Period (Chapter 6), and the Eastern Mediterranean at the end of the Bronze Age (Chapter 7).
Cenozoic Climate
(65 mya - present)

Figure 4.1: Benthic δ¹⁸O over the Cenozoic (65 - 0 mya cal. yr BP) (adapted from Zachos et al. 2001).

About 50 million years ago, the Cenozoic reached peak temperatures, indicating a climatic recovery following the asteroid impact 65 million years ago. A fluorescence of Azolla plants in the freshwater Arctic 49 million years ago created a large carbon sink, which reduced greenhouse gases. This resulted in a long-term cooling trend, manifested in the ice ages several million years later.

The Last Glacial Maximum was the latest in a series of glacial advances that began 2.54 million years ago (Shackleton et al. 1990; Mix et al. 1995) after a long-term Cenozoic cooling trend that began after the Azolla Event 49 million years ago. A sharp increase in the growth of *Azolla* freshwater ferns in the early Arctic Ocean (Brinkhuis et al. 2006) suggests that it was in part composed of freshwater. The explosive growth of these plants drew CO₂ from the atmosphere and began depositing that carbon in the ocean as ferns died and settled in an anoxic Arctic sea floor, thus removing a potent greenhouse gas from the atmosphere (Brinkhuis et al. 2006). The remarkable fluorescence of Arctic *Azolla* was detected through gamma radiation spikes in the
Arctic region. *Azolla* fluorescence is estimated to have reduced CO\(_2\) concentrations in the atmosphere from 3,500 ppm to 650 ppm over the course of 800,000 years (Pearson et al. 2000). Modern concentrations of CO\(_2\) are at 391 ppm in the year 2012 (Tans and Keeling, recovered 2012), and would be 280 ppm if anthropogenic carbon emissions were removed.

Following millions of years of the net loss of atmospheric carbon, permanent ice sheets first appeared in Antarctica around 35 million years ago (Zachos et al. 2001). The temperature of the Arctic Ocean dropped from 13 °C to -9 °C (Brinkhuis et al. 2006). The poles thawed and froze again during the Cenozoic (Zachos et al. 2001). Following the last freezing of the poles 14 million years ago, global temperature steadily cooled until the beginning of the ice ages 2.54 million years ago (Shackleton et al. 2001). The ice ages featured glacial advances and retreats that were closely linked to Milankovitch cycles (Hays et al. 1976). The occurrence of ice sheets marks a shift from a Hothouse Earth, where tropical and desert environments dominate the landscape, to an Icehouse Earth, where permanent ice sheets exist and many environments have pronounced seasonality between temperate and cold conditions (Price et al. 1998). While the presence or absence of ice on the poles is often used to differentiate these two conditions, sea surface temperature variation is perhaps more critical with regard to climate differences. Warmer sea surface temperatures in a Hothouse Earth result in more evaporation, which in turn results in more freshwater movement in the form of storm systems. As such, precipitation patterns can be dramatically different between the two climatic regimes.

The fluorescence of the *Azolla* plant, which causes the Hothouse/Icehouse Earth transition in the Cenozoic, demonstrates that humans are not the only organisms capable of dramatically affecting the carbon cycle. There may eventually be a combination of *Azolla* and human input into
the climate; it is theoretically possible that remains of *Azolla* have become either coal and/or oil.

This possibility has led to exploration of the warming Arctic region for large fossil fuel deposits. Theoretically, carbon preserved as fossil fuels in the area could vastly outnumber current reservoirs.

**Last Glacial Maximum**

(26,500 - 19,000 BP)

*Figure 4.2: European Project for Ice Coring in Antarctica (EPICA) temperature anomalies for the past 800,000 years.*

The Holocene is last 10,000 years of the sequence (highlighted sequence). Temperatures are normalized to average Holocene temperatures. Lower temperature anomalies indicate glacial periods; higher temperature anomalies indicate interglacial periods. In total, eight glacial advances are recorded in this record, the oldest ice-core sequence currently available. The Last Glacial Maximum is simply one of the most recent glacial advances.

During the last glacial period, ice sheets extended well into Eurasia and North America.

Climate during this glacial period was more variable than in the later Holocene. This volatility was
in part due to the effect that large standing ice sheets had on topography and ice-albedo forcing. They also less directly affected climate through changes in sea level and inputs of freshwater into the ocean (Clark et al. 1999). During glacial periods, freshwater surfaces in the Arctic region helped extend ice sheets across the sea by serving as a barrier to more saline waters below (Dokken and Jansen 1999). This would have concentrated brine waters in deep ocean waters, generating a northern salinity flux that would have encouraged further freshwater formation at the surface, promoting the expansion of ice sheets. Menviel and colleagues (2011) were able to build a predictive climate model that successfully emulated key changes in climate during the last glacial termination, including the Younger Dryas. They suggest that a sequence of changes in deep water formation paired with freshwater flux from melting glaciers could explain the timing and severity of events such as the Younger Dryas.

Atmospheric levels of $^{14}$C were much higher than could be predicted by solar activity alone, suggesting that large shifts in the carbon cycle took place during the glacial and interglacial periods (Beck et al. 2001). Atmospheric methane levels varied between 400 and 500 ppb (Brook et al. 2000), lower than the 800 ppb of much of the Holocene. Atmospheric $\delta^{13}$CO$_2$ was depleted relative to Holocene levels, as evidenced in Taylor Dome (Inderm deplet al. 1999; Elsig et al. 2009) (Figure 4.11). These findings demonstrate that even the composition of the atmosphere was affected by the presence of ice sheets. Measurements of $\delta^{13}$CO$_2$ from 200,000 years ago in EPICA Dome C (Lourantou et al. 2010) suggest that past glacial and interglacials followed a similar pattern of atmospheric carbon change.

Human populations across the world lived as hunter-gatherers in a variety of climates. The continent of Africa was largely habitable during the Last Glacial Maximum, though many areas
were arid. In the Maghreb regions of Northwest Africa, a bladlet industry known as the Iberomaurusian culture prospered (Camps 1974). In the Levant, a highly mobile set of hunter-gatherers occupied the region between the Last Glacial Maximum and the beginning of the Holocene, a people known as the Kebraran (Van Der Meer 1955).

In Europe, human populations were constrained with other biota in refugia, areas capable of supporting life in the harsh climate of the Last Glacial Maximum. These areas occurred primarily in Southern France, Iberia, and Italy. Across Iberia and Southern France, the Solutrean industry was predominant. Solutrean peoples tended to live on peaks, representing a significant settlement shift from previous times. There is little long-distance trade, though shells are gathered from the nearby shore. All lithics appear to be gathered from local sources; thus, raw material availability and function shaped their toolkits (Straus 1992).
Deglaciation
(19,000 - 12,800 BP)

Figure 4.3: Sea level change since the Last Glacial Maximum.
Sea level has increased by 121 meters since the end of the Last Glacial Maximum (Fairbanks 1989). During the Younger Dryas, sea level decreased by nearly 10 meters before resuming its increase. It is important to note that the increase in sea level was a complex phenomenon, and may not be well represented by any one time series.

A number of important changes are associated with the period of glacial retreat that followed the last glacial period. Large amounts of freshwater were introduced into the ocean, resulting in a sustained increase of 120m in sea level (Fairbanks 1989) (Figure 4.3). Some of the most abrupt climate changes of the period, such as the Older and Younger Dryas, have been associated with rapid freshwater input into the Atlantic Ocean that disrupted the thermohaline circulation (Heinrich 1988). These events tended to be discrete and severe. As glaciers melted, significant weight was removed from continental plates, resulting in a gradual uplift known as isostatic rebound (Peltier 1976).
Alongside changes in sea and land levels, the atmosphere began to change. Atmospheric carbon dioxide (CO\textsubscript{2}) increased in three steps: from 17,400 - 14,000 cal. yr BP, from 12,100 - 11,300 cal. yr BP, and a final increase beginning around 6,000 cal. yr BP. Similarly, methane levels increased immediately following the commencement of deglaciation. The most recent increase in methane (CH\textsubscript{4}) began 5,000 cal. yr BP. Increases in CO\textsubscript{2} correspond closely with increasing sea surface temperatures, primarily in the western Pacific (Denton et al. 2010), suggesting that the CO\textsubscript{2} increases may have originated from the sea. The details of the deglaciation period are consistent with the end of previous glaciations. Each tends to end during a short and rapid period of warming (Denton 2010). These terminations are in stark contrast to long, stable glacial periods that last for tens of millennia.
YOUNGER DRYAS
(12,800 - 11,500 BP)

Figure 4.4: GISP2 temperature reconstructions for the Northern Hemisphere (26,500 - 0 cal. yr BP).
The Last Glacial Maximum ends 19,000 years ago and is followed by a stadial period. The Holocene, beginning 10,000
years ago, represents an interglacial period, arguably the longest and most stable in almost half a million years.
Temperatures during the glacial period were around -50 °C; Holocene temperatures for the period are closer to -30 °C.
Pleistocene climate fluctuations were magnitudes of order more dramatic than those observed during the Holocene.

The Younger Dryas is possibly one of the best-known climate events since the LGM. Beginning around 12,800 cal. yr BP, global temperatures dropped sharply. The commencement of the period was possibly the consequence of collapsing ice sheets in North America (Broecker et al. 1990), though the Younger Dryas occurs along the normal Bond event cycle, suggesting that it may have been the result of a complex set of causes. Broecker (2006) disputes the hypothesis of glacial melt shutting down the thermohaline circulation by noting the paucity of geologic data for such an event. This suggestion has recently been contested by Rayburn and colleagues (2011), who find evidence for two large freshwater inputs into the North Atlantic Ocean through the St. Lawrence estuary at the beginning of the Younger Dryas period; this was estimated by varve chronology.
sedimentation rates, and nearby proglacial lake volumes. Additionally, climatic simulations of a freshwater input into the North Atlantic Ocean reproduce the cold and arid effects of the Younger Dryas, though these changes are most severe in the North Atlantic region (Manabe and Stouffer 1995). An additional hypothesis exists for the initiation of the Younger Dryas—that ice formation in the Northern Hemisphere was facilitated by a shift in wind patterns resulting from temperature anomalies in the tropics (Seager and Battisti 2005).

Climate in the Old World appears to have gotten substantially cooler and more arid. The name for the Younger Dryas comes from a rapid expansion of the Arctic flower *Dryas* across northern Europe (Jensen 1938). During the peak years of the Younger Dryas, the temperature in Greenland was fully 15 °C cooler than today (Alley et al. 1993). Lower abundances of foraminifera, a $\delta^{18}O$ minimum in plankton, and an increase in ice rafted debris indicate a cooling of surface waters and a shift in ocean circulation patterns (Keigwin and Lehman 1994). A $\delta^{18}O$ record derived from benthic and planktonic foraminifera indicates cooler temperatures in the Sulu Sea in Indonesia, as does an increase in cool-water species (Kudrass et al. 1991). In the Mediterranean Sea, coral growth increased during the Younger Dryas and terminated with an increase of sea surface temperatures at the end of the period (McCulloch et al. 2010).

In the New World, the climatic picture of the Younger Dryas is mixed. An organic stable carbon isotope record from a buried soil sequence in Southwest Missouri indicates a 50% increase in more drought-tolerant C$_4$ grasses during the Younger Dryas (Dorale et al. 2010). Dorale and colleagues note that C4 grasses are generally restricted to regions where July temperatures are below 8 °C (Terri and Stowe 1976) or above 18.5 °C (von Fischer et al. 2008), indicating that Younger Dryas temperatures for the US Midwest likely fell between these temperature boundaries.
However, other areas of the Americas indicate a more mixed pattern during the Younger Dryas. In the US Southwest, the beginning of the Younger Dryas period is typified by cold and arid conditions, but these appear to transition to wetter conditions at the end of the period based on the depositional history of speleothems (Polyak et al. 2004). In south-central Alaska, temperatures increased during the Younger Dryas, as evidenced by the increasing occurrence of microfossils that benefit from warm, wet periods (Kaufman et al. 2010).

The Younger Dryas occurred during a monumental shift from foraging to cultivation of cereals in the Middle East. Bar-Yosef (1998) argued that the sharp decline in climatic conditions pushed the Natufians toward the shift to cultivation of wild cereals. However, Munro (2003) disputed the causal role attributed to the Younger Dryas. He notes that the Natufian response to the Younger Dryas appears to be through demographic changes, rather than significant shifts in resource procurement. However, a recent analysis of radiocarbon dates in the region indicates that Natufian ways of life terminated during the Younger Dryas (Blockey and Pinhasai 2011), with a gap in occupation of the region until the Pre-Pottery Neolithic A at the beginning of the Holocene.

At the site of Abu Hureya, initial analysis of the emergence of cereal crops such as wheat indicates an adaption to environmental deterioration. As forests retreated in response to the aridity of the Younger Dryas, inhabitants of Abu Hureya increasingly relied upon cereal crops, kick-starting the process of domestication (Hillman et al. 2011). A recent reappraisal of the evidence suggests that the activities of Abu Hureya at this time were less indicative of a move toward domestication and were instead an instance of increased diet breadth in response to less frequent availability of higher-ranked foods (Colledge and Conolly 2010). This pattern of increased use of lower-ranked resources is also reflected in the diminishing size of prey throughout the Levant. Davis (2005)
found not only that smaller animals were consumed more frequently, but also that juvenile gazelle were hunted more often. These shifts toward broader diet breadth and increased utilization of lower-ranked food resources are not necessarily at odds with the hypothesis proposed by Bar-Yosef (1998) and Hillman and colleagues (2001). Rather, these utilizations of lower-ranked food resources may have been the first step toward domestication (Winterhalder and Goland 1997).

While it may not be appropriate to attribute the development of agriculture to the Younger Dryas, the Younger Dryas itself may have contributed to the availability—and thus the ranking—of food resources that led to the increased utilization of cereals.

While the Younger Dryas is one of the most severe climate oscillations since the LGM, severe events in and of themselves do not appear to be particularly rare. The Younger Dryas shares affinities with Heinrich events, in which rapid coolings lead to an extension of icebergs as far south as 50 Latitude, resulting in the deposition of coarse-grained, ice-rafted debris (Heinrich 1988). Similar oscillations may also be linked to rapid freshwater discharge following glacial terminations.

At the end of the Younger Dryas, ice rapidly built up on the Greenland Ice Sheet (Alley et al. 1993), as evidenced by dust concentrations in the GISP2 ice core. These accumulations potentially occurred within a 1 - 3 year time frame, indicating rapid climatic change. And additional study identified a termination that took place in 20 years, based on heavy-isotope and dust concentrations from two Greenland ice cores (Dansgaard et al. 1989). Dansgaard and colleagues suggested that a total temperature shift of 7 °C in Greenland could have been completed within 50 years. Thus, as the Younger Dryas commenced rapidly, it appears to have ended quickly as well.
8.2ka event
(8,200 BP)

The 8.2 event has a number of affinities with other severe events such as the Younger Dryas. These include rapid onset, particular severity in the North Atlantic, and an association with severe flooding (Alley and Agustidur 2005). Alley (1997) noted that the 8.2k event is characterized primarily by a temperature change; it does not have the same concentrations of wind-transported dust and salt as similar but more severe climatic events.

In the NorthGRIP ice core, there is an unusual peak in lithium concentrations at the time of the 8.2k event (Siggaard-Anderson et al. 2002). Alley and Agustidur (2005) note that there is no clear inference from this change in lithium but that it does indicate that chemical changes were occurring at the time. Titanium shifts in the Caricao Basin just outside Venezuela suggest a rapid shift to dry conditions. Alley and Agustidottir (2005) suggest that this could indicate that the Intertropical Convergence Zone (ITCZ) trended South during this event. A shift in the ITCZ would indicate the global nature of this event.

Altithermal
(9,000 - 5,000 BP)

The Altithermal (~9,000 to ~5,000 cal. yr BP) is perhaps one of the most difficult climatic periods to discuss. Its effects were not universal, and it appears to have primarily been an increase in temperature at the poles (Koshkarova and Koshkarova 2004). Temperature increases in equatorial regions may only have been by 1 °C (Gagen et al. 1998). Regional effects varied; the US Southwest appears to have been somewhat drier and more arid during this period (Holiday 2000).
Meltzer (1999) noted that humans adapted to more arid conditions in the US Midwest by digging wells for water and expanding diet breadth during the Altithermal. Most research on the Altithermal has occurred in the US—there is much less work for Europe, Asia, Africa, and the Near East during this time period. At present, it is difficult to characterize the Altithermal as anything other than a remarkably stable and uneventful period of climate.

In contrast to the general stability of the Altithermal, its end appears to be relatively abrupt in a period termed the Piora Oscillation. Magny and Haas (2004) identified a rapid water level rise in Lake Constance, Switzerland, between 5,550 and 5,300 cal. yr BP. They note that this change occurred at the same time as a series of abrupt mid-Holocene climate shifts around the world; the tail end of these events occurred around 5,100 BP.
5.1ka Aridization Event/El Niño Onset
(5,100 BP || 3,150 BC)

Figure 4.5: Reconstructed El Niño/Southern Oscillation (ENSO) events from Lake Pallcacocha, Ecuador (data from Moy et al. 2002). An increase in ENSO activity is dated to just after 5,100 BP, indicating a shift from the low activity of the earlier Holocene.

The climatic changes that occurred during the deglaciation period are large and distinct. With increasing human population and societal complexity, sensitivity to climatic change increases. Climate impacts become greater due to the increasing vulnerability of humans living in increasingly resource-leveraged population centers. As such, relatively minor climate fluctuations have a disproportionate effect on human societies. Many of these smaller climatic events are difficult to detect and are not evident in broader records, such as the GISP2 record of Northern Hemisphere temperatures. Instead, analysis of changes in climatic cycles such as El Niño or regional climatic records provides greater insight. Unfortunately, it is difficult to directly associate multiple, independent regional records. Because many paleoclimate time-series models rely on age
models, there can be ambiguity and error rates in the order of centuries. Most age models are constructed using a few absolute radiometric dates and then using a regression model to associate depth with age. Differences in accumulation can complicate these records, as most age models are dependent upon uniformitarian assumptions. One example of such age-model disconformities is in timing the onset and recovery of the Younger Dryas; in both cases, the transition took only decades. This falls well within the error of age models in glacial ice cores. As such, there are slightly different dates for the Younger Dryas based on the EPICA, Vostok, and GISP2 ice cores. The timing of the Younger Dryas has been corrected using a $\delta^{13}C$ enrichment in the Irish Oak chronology used in $^{14}C$ calibration curves (Becker et al. 1991). Given the problem with ice core age models, which come from some of the most well-funded paleoclimatic research programs, the problems of regional paleoclimate records can be put in a more difficult context. Because a high order of confidence in dating is needed to associate one event (a climatic change) with another (a climatic impact on a human society), this limitation remains one of the chief obstacles in paleoclimate reconstruction in archaeology. To date, no method has been established for reconciling the date of a single climatic event as recorded by multiple climate records. One potential solution is suggested in chapter 7 of this dissertation, in which the posterior probabilities produced by Bayesian change-point analysis are used to develop a probabilistic series of events, though this approach only works for shifts in the means of a given record; it cannot be used for short-lived climatic events.

The events around 5,100 cal. yr BP are such a short-lived event that they do not appear to be associated with any climatic pattern recorded in GISP2, yet some climate proxies suggest a dramatic shift to hotter and more arid temperatures (Cullen et al. 2000; Bar-Mathews et al. 2003).
One of the first demonstrations of this period comes from eolian dust (dolomite and calcium carbonate) deposits in the Gulf of Oman (Cullen et al. 2000). These concentrations are relatively constant throughout the Holocene with two exceptions, one at 5,100 cal. yr BP and another at 4,200 cal. yr BP (Figure 4.6). The latter event was more severe and has been associated with the collapse of multiple complex societies (Cullen et al. 2003; Issur 2003). A sharp increase in ENSO activity is documented in lake deposits in Lake Pallcacocha in Ecuador (Moy et al. 2002). The surface waters of the Tropical Pacific appear to have been in a constant warm state before 5,800, indicating that ENSO activity characterizes the latter half of the Holocene (Sandweiss et al. 2007). One of the most severe indications of aridity comes from a study of speleothems in Soreq cave in northern Israel (Bar-Matthews et al. 2003), where a drop of over 200 mm/yr in precipitation is estimated. Reconstructed fire histories of the US Southwest indicate a rapid increase in forest fire frequency beginning at this time (Brunelle et al. 2010).

Also beginning around this time is a systematic increase in Equatorial Pacific and Atlantic Sea Surface Temperatures (SSTs), while the North Atlantic sees a temperature decline over the same period (Leudoc et al. 2010). These changes appear to be due to increases in January insolation and decreases in July insolation, respectively. This long-term process is reflected in multiple marine sediment cores and is reconstructed using the lipid unsaturation index derived from alkenones (Brassell et al. 1986). This long-term process is reflected in multiple sediment cores. A decline in hemlock trees is dated to 5,300 cal. yr BP in Lake Grinnell, New Jersey (Zhao et al. 2010a). This shift is associated with arid conditions that persist until 3,000 cal. yr BP (Zhao et al. 2010b).
The 5.1ka event is difficult to describe; there are clear regional effects in the Middle East and US Southwest, but no clear statement can be made regarding the global nature of this event. This dissertation provides evidence that this event may have acted as a climatic threshold; with the onset of increased ENSO variability, piñon pine rapidly spread through the San Juan basin, shifting hunter-gatherer strategies toward food storage and increased territoriality (Chapter 5).

4.2ka Aridization Event/El Niño Cessation
(4,200 BP || 2,250 BC)

![Figure 4.6: Eolian sediments from the Gulf of Oman (Cullen et al. 2000).](image)

Peak dolomite and CaCO₃ concentrations are slightly younger than the 4.2ka aridization event, possibly due to variation in marine ¹⁴C reservoirs over the Holocene that complicate the age model. A study of tephra in the sediments places the peak concentrations to within two standard deviations of radiocarbon dates from the 4.2ka aridization event in Tell Leilan (Weiss and Courty 1993). CaCO₃ and dolomite concentrations show slightly different peaks in time near the 5.1ka aridization event.

The 4.2ka event was a brief but severe aridization episode that primarily affected societies in the Near East. Cullen and colleagues (2000) identified the stronger of the two peaks in eolian
dust deposition in the Gulf of Oman to this period. An absence of brine in the northern Red Sea, identified by sub-oxic facies following two millennia of anoxic sedimentation, suggests heightened aridity as well (Arz et al. 2006). These changes are concurrent with Bond Event 3 (Bond et al. 1997).

This climate event had well-documented effects on complex societies across the Old World. The collapse of the Old Kingdom of Egypt and the Akkadian Empire in Mesopotamia are dated to around 4,200 cal. yr BP. Between 4,200 cal. yr BP and 3,900 cal. yr BP, there are severely low levels of Nile flooding (Butzer 1980). Additional evidence for drought in Egypt comes from a drop in the $^{87}$Sr/$^{86}$Sr ratio of the delta region dating to 4,150 cal. yr BP (Stanley et al. 2003). Magny (2009), however, notes that the evidence for the 4.2ka event in Italy paints a complex picture. While 4,200 cal. yr BP is typified by arid conditions, it is bracketed by wetter-than-normal conditions both before and after. Hassan (1996) suggests that while the 4,200 cal. yr BP low Nile floods may have played a role in the collapse of the Old Kingdom, earlier low floods around 5,200 cal. yr BP may have influenced the development of a complex society.

An inscription from the tomb of a First Intermediate Period ruler of Hierankanpolis, Ankhtifi, records the effects that the drought had on the populace of Egypt:

I gave bread to the hungry and clothing to the naked; I anointed those who had no cosmetic oil; I gave sandals to the barefooted; I gave a wife to him who had no wife. I took care of the towns of Hefat [i.e. el-Moalla] and Hor-mer in every [situation of crisis, when] the sky was clouded and the earth [was parched (?) and when
everybody died] of hunger on this sandbank of Apophis. The south came with its people and the north with its children; they brought finest oil in exchange for the barley which was given to them. The whole of Upper Egypt died of hunger and each individual had reached such a state of hunger that he ate his own children. But I refused to see anyone die of hunger and gave to the north grain of Upper Egypt. And I do not think that anything like this has been done by the provincial governors who came before me .... I brought life to the provinces of Hierakonpolis and Edfu, Elephantine and Ombos! (Vandier 1950: 161 - 242)

The Akkadian Empire in Mesopotamia appeared to have gone through similarly dramatic changes during the same period of aridity. Habitation of Tell Leilan in Syria ended at this time, contemporaneous with a population decline in the nearby Habur plains and the cessation of irrigation agriculture in southern Mesopotamia (Weiss and County 1993). At this time, the water level of both the Tigris and Euphrates Rivers lowered, and salinity increased (Neuman and Parpola 1987).

While the Middle East appears to have been suffering from severe drought, East Asia experienced extreme pluvial conditions. In China, paleoflood slackwater deposits from the Jinghe River in the Yellow River Basin (Huang et al. 2010) and the Qishuihe River (Huang et al. 2011) indicate severe flooding from 4,200 - 4,000 cal. yr BP. The productivity of anoxygenic phototropic bacteria, identified using changes in the abundance of bacteriopheophytin \(\alpha\), occurs only between 4,200 and 4,000 cal. yr BP in Qinghai Lake, suggesting heightened monsoonal activity (Ji et al.}
2009). The severe floods of the time are also documented in surviving historical documents, many of which comment on severe aridity as well (Huang et al. 2010).

The climatological triggers for the 4.2ka event are difficult to identify. Like other Bond events, it is linked to ice-raft debris deposits in the North Atlantic (Bond et al. 1997). A sharp drop-off in El Niño activity, as identified through estimates of river discharge into Lake Pallcacocha in Ecuador (Moy et al. 2002), is also suggestive of changing conditions.

In the Southwestern US, there is evidence suggesting that the North American Monsoon (NAM) pattern did not settle into its modern activity until this time. In a review of oxygen-isotope speleothem data for the US Southwest and Mexico, Bernal and colleagues (2011) note that Pacific sources of water do not become significantly influential until after 4,300 cal. yr BP. NAM cyclones develop when evaporating water from the Tropical Pacific saturates the air in late spring. Prevailing winds then drive these storm systems northward, where they steadily decrease in intensity. A fraction of these storm systems are pulled by easterly winds into the American Southwest (Cavazos et al. 2008). Remaining storms travel into the central Pacific Ocean. NAM cyclones can be broadly generalized as the transportation of Tropical Pacific Waters to Mexico and the US Southwest. As mentioned earlier, Tropical Pacific Waters begin to warm around 5,100 cal. yr BP (Leudoc et al. 2010).

The 4.2ka event is less ambiguous than the 5.1ka event, but not all paleoclimate records reflect the increase in aridity (Finne et al. 2011). One potential interesting effect in the US Southwest is the association with early maize cultivation with the decrease in ENSO variability; the oldest radiocarbon-dated maize occurred in Chaco Canyon as early as 4,364 cal. yr BP (Hall
2010). However, the direct climatological changes in the US Southwest at this time are currently unclear.

**LBA Collapse**

(3,200 - 2,800 BP || 1,250 - 800 BC)

![Figure 4.7: GISP2 temperature reconstructions for the Northern Hemisphere (10,000 - 0 cal. yr BP).](image)
The 8.2ka event is clearly visible as one of the most significant discrete climate events of the Holocene. The LBA Collapse appears to have occurred in the context of a similar drop in Northern Hemisphere temperatures.

The Late Bronze Age (LBA) is characterized as being a warm, humid period in the Eastern Mediterranean (Issar 2003). The GISP2 ice core in Greenland indicated a period of elevated temperatures during this period, which quickly deteriorate beginning around the time of the collapse of Late Bronze Age Palatial centers in Greece, Anatolia, and the Levant. The time period is also associated with the Third Intermediate Period in Egypt.
The pattern in temperature as evidenced in the GISP2 Northern Hemisphere Temperature record (Figure 4.7) suggests that the temperature peak at the time of the LBA Collapse is part of a late-Holocene trend of temperature peaks and declines that includes the Roman Warm Period and Medieval Warm Period. This rise-and-fall pattern of Northern Hemisphere temperature has led to the postulation of a 1,470-year climate cycle (Bond et al. 1997). These Bond events don’t explain all of the warming periods, but the proposed cycle includes the end of the Younger Dryas (11,100 cal. yr BP; Bond Event 8), the 8.2ka event (8,200 cal. yr BP; Bond Event 5), the 4.2ka event (4,200 cal. yr BP; Bond Event 3), and the latter portion of the LBA Collapse (2,800 cal. yr BP, Bond Event 2). These periods tend to be characterized by rapid shifts to cool and arid periods. Bond and colleagues (1997) originally suggested that these shifts may have been amplified by changes in the northern thermohaline circulation.

The collapse of Palatial civilization in the Eastern Mediterranean (3,200 - 3,000 cal. yr BP) appears to have occurred in the context of a rapid drop in temperatures. This collapse has been described as “the worst disaster in ancient history, even more calamitous than the collapse of the Western Roman Empire” (Drews 1993: 1). The regional climatic effects of the Eastern Mediterranean during this event will be discussed in greater detail in chapter 7.

**Roman Warm Period**

(2,200 - 1,550 BP || 250 BC - 400 AD)

The Roman Warm Period is a broad period of warmer temperatures that correspond to a period of Hellenistic/Roman cultural dominance in the Mediterranean and Near Eastern regions (Crumley 1993). Oland and colleagues (2009) identify a δ18O excursion, indicating more arid
conditions in the Eastern Mediterranean. Elevated temperatures typify this period, as evidenced by the GISP2 ice core (Figure 4.7). Crumley (1993) suggested that climate shifts in the Burgundy region of France tended to correspond with major changes in human settlement. In particular, the movement of the Mediterranean/Temperate ecotone across Western Europe corresponds to changes in land management practices by human societies. The Roman model of agricultural land management differed from the earlier Celtic models and was more suited to the climate regime at the time. In effect, Roman administrative control migrated northward with the ecotone boundary. Similarly, the highly variable climate patterns between 1,450 cal. yr BP and 1,050 cal. yr BP did not correspond well to the Roman administrative model.

However, some paleoclimate records contradict the picture of warmer conditions at this time. Foraminiferal $\delta^{18}O$ records from at least one core in the Central Mediterranean indicate low sea surface temperatures at the time (Taricco et al. 2009). However, colder Mediterranean sea surface temperatures during warm periods is not an unheard-of phenomenon. An additional core from the Ionia Sea indicates lower temperatures during the later Medieval Warm Period as well (Emeis et al. 2000).

**Medieval Warm Period**

(1,000 - 700 BP || 950 - 1250 AD)

The Medieval Warm Period (MWP), like the Pre-Late Bronze Age Collapse temperature peak and Roman Warm Period, is another slight Holocene shift to warmer temperatures. It has frequently been characterized as a minor climatic optimum due to its association with generally favorable conditions in Northwestern Europe. In other regions, the Medieval Warm Period is
associated with droughts and generally arid conditions. In both the Sierra Nevada of California and
the Patagonia region of Argentina, there is evidence for multi-century droughts, with water runoff
much lower relative to recorded droughts in the respective regions (Stine 1994). Low lake levels
and high salinity occur in Lake Navaisha in Kenya during the Medieval Warm Period, suggesting
arid conditions at the time (Verschuren et al. 2000). In the US Southwest, the Medieval Warm
Period is associated with multi-century droughts (Robinson and Rose 1979; Benson et al. 2007)
and generally more arid conditions relative to the historical period (Heiweijer et al. 2007). In
Egypt, the period is associated with increased variability in Nile floods (Hassan 2007).

Sea surface temperatures in some records decrease during the Medieval Warm Period,
particularly in the Ionian Sea (Emeis et al. 2000) and in the Arctic near Greenland (Krawczyk et al.
2010). Higher temperatures in both records occur during the Little Ice Age. Krawczyk and
colleagues (2010) suggested that glacial melt during the Medieval Warm Period resulted in a
freshwater flux that may have cooled waters and reduced salinity. A recent review of Holocene sea
surface temperatures indicates that sea level increased slightly during the Medieval Warm Period
and stabilized during the Little Ice Age (Kemp et al. 2011), a finding that supports the assertion of
Krawczyk and colleagues (2010) that a freshwater flux leads to anti-phase sea surface temperatures
during warming phases. Such colder sea surface temperatures could result in reduced evaporation
rates, which in turn may limit precipitation in some areas and thus contribute to arid conditions
observed in many parts of the world at this time. However, climatological patterns are complex and
are notoriously difficult to predict. In chapter 6, the Medieval Warm Period will be revisited with a
specific study on the Lower Alentejo region of Portugal.
The Little Ice Age
(600 - 150 BP || 1350 - 1800 AD)

The Little Ice Age was a prolonged period of cold temperatures relative to those of the Medieval Warm Period. The onset of the Little Ice Age (635 cal. yr BP / AD 1315) was associated with severe rains and flooding. Cold conditions reached their lowest point during the Maunder Minimum, in which low sunspot activity indicates reduced solar insolation.

The rapid transition to the Little Ice Age, 600 - 150 BP (1350 - 1800 AD), is well documented in historical sources as a sudden deluge beginning in the spring of 635 cal. yr BP (AD 1315) (Fagan 2003). Strong rains continued for the better part of a decade, leading to severe famine in much of Western Europe. The generally colder conditions of the period had a snowball effect through time; the coldest conditions are concentrated in the 17th and 18th centuries AD, around the time of the Maunder Minimum (Fagan 2003). As the Little Ice Age is coincident with the

Figure 4.8: GISP2 temperature reconstructions for the Northern Hemisphere (1000 - 0 cal. yr BP). The Little Ice Age was a prolonged period of cold temperatures relative to those of the Medieval Warm Period. The onset of the Little Ice Age (635 cal. yr BP / AD 1315) was associated with severe rains and flooding. Cold conditions reached their lowest point during the Maunder Minimum, in which low sunspot activity indicates reduced solar insolation.
emergence of academic institutions and the development of both history and science as
professional fields, there is wide documentation on the effects of the climate of the time on human
behavior. In one novel instance, art history was employed to identify climatic conditions. A shift to
cold conditions between 550 and 275 cal. yr BP (AD 1400 -1675), and again from 135 - 50 cal. yr
BP (AD 1815 - 1900), is documented in an increase in depictions of winter in paintings (Robinson
2005). These increases in winter depictions appear to correspond to severe winters as predicted by
the reconstructed North Atlantic Oscillation (Robinson 2005). While inference is limited, it is a
fascinating use of interdisciplinary research to identify the effects of cold climates on human
perceptions of the world. Less elegant effects of the cold predominate as well; Behringer (1999)
suggests that heightened witch-hunting activity in Western Europe is associated with cold
conditions in the mid-16th century. While such associations between climate and human behavior
are difficult to establish in a scientific manner (i.e. falsification), it is important to note that the
recent age of the Little Ice Age has the potential for much more detailed research into the effects of
climate on human societies due to the availability of historical records. In most other major
climatic events (e.g. the Younger Dryas, 4.2ka event, Roman Warm Period), the discussion in the
literature revolves around ‘how climate affected human societies’. During the Little Ice Age, the
questions are far more specific regarding climate impacts on human beliefs and practices due to the
greater historical detail available and the prolonged nature of the climatic changes.
Figure 4.9: Holocene solar irradiance as recorded by $^{10}$Be (data from Steinhilber et al. 2009).
This figure includes a moving average of every 20 measurements. The Maunder Minimum, a period of low sunspot frequency, overlapped with some of the colder periods of the Little Ice Age.

One of the more interesting questions to emerge regarding discussions of the Little Ice Age is the role of solar irradiance. Speculation regarding the influence of solar irradiance on climate was the chief motivating factor in A. E. Douglass' development of dendroclimatology. As noted in the previous chapter, he initially believed that changes in sunspots could be detected in tree-ring widths. Sunspots are relatively cool regions of the sun and have been relatively easily noticeable to astronomers, both contemporary and ancient. These cool sunspots tend to reflect more solar activity than is the norm, as the presence of sunspots indicates disequilibrium in heat transfer. Edward Maunder noted a low frequency of sunspots in the historical record beginning in 305 cal. yr BP (AD 1645) and ending in 235 cal. yr BP (AD 1715). John Eddy (1976) suggested that this Maunder Minimum was associated with a drop in temperatures during the Little Ice Age, establishing a direct link between solar forcing and climate. Subsequent analysis of other solar
records, such as solar irradiance measured using changes in $^{10}$Be (Steinhilber et al. 2009; Figure 4.8) and $^{14}$C data (Reimer et al. 2009), have successfully replicated this link.

However, an alternative hypothesis for the Little Ice Age has recently been proposed. An increase in volcanic activity may have loaded the atmosphere with sufficient ash, particularly containing sulfur, to increase the Earth’s reflectivity. This could have been a stronger factor than solar irradiance as evidenced by sunspot activity (Miller et al. 2012). This recent shift in climatological thought emphasizes the continually evolving nature of the field. New evidence and proxy records are causing the continuous revision of our understanding of past climate.

**Anthropogenic Effects on Climate**

(70 BP - present || 1880 AD - present)

Figure 4.10: Post-Glacial CO$_2$ increases from EPICA Dome C (Monin et al. 2004), Law Dome (Francey et al. 1999), and Mauna Loa Instrumental Records (Tans and Keeling 2012).

Two rapid increases in atmospheric CO$_2$ precede the Holocene: the first 60 ppm increase occurred during a period of deglaciation (17,400 - 14,000 cal. yr BP), and a second 20 ppm increase began during the Younger Dryas (12,100 -
A slow 22 ppm increase occurred from the mid-Holocene (~6,000 cal. yr BP) until industrial anthropogenic carbon emissions (70 cal. yr BP / AD 1880). This slow increase has been hypothesized to be the result of human agricultural activities (Ruddiman et al. 2003).

A sharp increase in atmospheric CO₂ was reported by Charles Keeling in 1960 based on instrumental records from Mauna Loa in Hawai‘i. He correctly attributed the phenomenon to industrial anthropogenic carbon emissions. Measurements of CO₂ from ice cores indicate that the period of pronounced carbon increases dates back to the late 19th century and that these increases have continued at an almost linear rate since (Francey et al. 1999). The rate of carbon input into the environment has not been linear, suggesting that much of the net increase in CO₂ is being taken up by carbon sinks. Measurements of ocean acidity suggest that it is taking up a large portion, with the potential for lowering the total pH of the ocean to dangerous levels for much of its biota. Similar CO₂ spikes in Earth’s atmosphere have been linked to major extinction events, including the Permian-Triassic extinction, in which 98% of all documented taxa went extinct, and the Cretaceous-Tertiary extinction, which killed off most non-avian dinosaur species. For the Permian-Triassic extinction, the cause remains ambiguous. However, there is evidence for a large release of CO₂ at the end of the Permian. Grasby and colleagues (2011) identified traces of coal ash in marine sediments that date to the time. The authors argue that volcanic activity in the Siberian Tunguska Basin resulted in the combustion of coal deposits. The authors identify a negative δ¹³C excursion of about -2‰ at the same time—an excursion similar to the contemporary shift in atmospheric carbon. A similar increase is associated with the Cretaceous-Tertiary extinction event. Beerling and colleagues (2002) built a model of CO₂ from stomata in fossilized plants near Raton, New Mexico, for the late Cretaceous and early Tertiary. They identified a large spike in CO₂ following the
asteroid impact in the Yucatan Peninsula, suggesting the near-simultaneous combustion of 20% of carbon stored in living organisms at the time.

In both the Permian-Triassic and Cretaceous-Tertiary extinction events, a rapid release of CO\textsubscript{2} occurred. Much of the respective CO\textsubscript{2} increases would have also been taken up by the oceans at the time, suggesting that the marine extinctions may have been linked to terrestrial extinctions due to carbon sequestration. A rapid CO\textsubscript{2} increase in the atmosphere invariably leads to a rapid CO\textsubscript{2} uptake by the oceans that increase acidity by reducing pH. The oceans take up approximately 30% of atmospheric CO\textsubscript{2}, where carbonic acid is produced and acidifies the water. Global surface ocean pH decreased from 8.24 to 8.15 between 199 and -44 cal. yr BP (AD 1751 - 1994) (Jacobsen 2005). Present levels are near 8.069 (Hall-Spencer et al. 2008). This prevents many organisms, from plankton to mollusks, from producing a CaCO\textsubscript{3} shell. This leads to lower biota, which results in a cascading extinction event down the food chain (Raven et al. 2005).

It is difficult to directly compare past extinction events with the current CO\textsubscript{2} increase, largely due to the paucity of climatic records of sufficient resolution in the deep past. Nonetheless, the rapid industrialization of human societies in the late 19th and 20th centuries resulted, and continues to result in, the most rapid CO\textsubscript{2} flux in at least the past 800,000 years. The degree to which humans can influence climate has been actively debated in the literature over the past half-century, with most scientists now in agreement that at minimum, human effects on greenhouse gases are pushing the world towards climatic changes beyond available high-resolution records.

Of recent debate has been the antiquity of human impacts on atmospheric greenhouse gases. William Ruddiman (2003) suggested that human agricultural activities caused initial changes in the carbon cycle that extended the Holocene interglacial, in effect causing a small
period of global warming. This has been termed the Early Anthropocene Hypothesis (Ruddiman 2003). Particularly relevant to Ruddiman’s (2003) argument is a 22 ppm increase in CO$_2$ beginning at 6,000 cal. yr BP and a 30 ppb increase in atmospheric CH$_4$ (methane) beginning at 5,000 cal. yr BP. Both CO$_2$ and CH$_4$ appear to have been on a downward trend before their respective rises.

However, the Early Anthropocene Hypothesis, unlike the phenomenon of Industrial Anthropogenic Carbon emissions, does not enjoy scientific consensus. Elsig and colleagues (2009), in their review of atmospheric $\delta^{13}$CO$_2$ from EPICA Dome C and Taylor Dome since 25,000 cal. yr BP (Elsig et al. 2009; Lourantou et al. 2010; Indermühle et al. 1999), note that $\delta^{13}$CO$_2$ remains remarkably stable from 7,500 cal. yr BP and over the entire period of the hypothesized Early Anthropocene (Figure 4.10). If deforestation related to agricultural activities resulted in a net CO$_2$ emissions increase, then $\delta^{13}$CO$_2$ values should become more depleted, just as they became more enriched during the expansion of forests during the last stadial period after 13,500 cal. yr BP (Figure 4.11). Elsig and colleagues (2009) argued that the carbonate compensation of earlier CO$_2$ increases and coral reef formation, rather than human activities, explain most of the 22 ppm increase of CO$_2$ in the late Holocene. Ruddiman and colleagues (2011) argue that Elsig and colleagues (2009) underestimate the role of peat bogs as carbon sinks but fail to address how carbonates and coral reef formation would not have been a factor in CO$_2$ release.
As mentioned earlier, there is a clear differentiation between the climatic shifts that characterized the Pleistocene and those that characterize the Holocene. The Holocene is a remarkably stable period for climate; this stability had undeniably positive effects for the development of complex human societies. One of the key questions addressed in archaeology is why humans developed agriculture in the early Holocene. Some climatologists would argue that the answer is no more complex than 'because they could' (Richerson et al. 2001). The Holocene represents the most stable climatic regime in over half a million years (Figure 4.2); the last period corresponds to two side-by-side interglacial periods that are separated from the Holocene by 6
glacial advances. The climatological shifts of the Pleistocene would have precluded any attempts at domestication. Climate could be characterized as a determining factor in human societies; however, such a characterization is highly limiting. It is better to think of climate as an enabling or disabling factor for different subsistence strategies.

Synthesis

Figure 4.12: Composite atmospheric CO$_2$ records from EPICA Dome C (Monin et al. 2001; Siegenthaler et al. 2005; Lüthi et al. 2008), Vostok (Petit et al. 1999; Pepin et al. 2001; Raynaud et al. 2005), Law Dome (Francey et al. 1999), and Mauna Loa Instrumental Records (Tans and Keeling 2012).

The climatic changes that disrupted complex human societies were ripples to the waves of Cenozoic and glacial climate variation. While the ice ages have been the most variable time on record in the Cenozoic, the conditions of the Holocene interglacial were, and are, remarkably
stable. While the Holocene may have seen temperature oscillations similar in scale to glacial variability (Dunbar 2000), and small temperature fluctuations are sufficient to change the range of species (Anderson et al. 2007), it is nonetheless a period of calmer changes. The vulnerability of human societies to climate change is the consequence of structural frailty to what are, in a sense, abnormally normal conditions. While the Medieval Warm Period and Little Ice Age are held up as two well-known periods of climate that negatively influenced human societies, they are, effectively, noise relative to the broader signals of climatic change in the Holocene.

This is why global warming is such a critical issue. The Pleistocene was not just a climatologically variable period; it was also a period with rapid bursts of CO$_2$. Increases in CO$_2$ have been associated with climate shifts for as long as our oldest records indicate (800,000 years, EPICA Dome C). During the entirety of this period, CO$_2$ has ranged from a minimum of 180 ppm during glacial periods to a maximum of 280 ppm during interglacial periods such as the Holocene. Anthropogenic carbon emissions have increased this total today to 390 ppm (Tans and Keeling 2012), a value that is over 30% higher than the highest previous concentrations (Figure 4.12). This CO$_2$ increase has occurred with a rapidity that far exceeds the increases associated with the most severe climate fluctuations—including glacial terminations. This is a cause of great concern for the long-term sustainability of human societies. Archaeology can play an indispensable role in informing policy makers about how human societies have been disrupted by climate changes in the past. In particular, archaeologists can identify how resilient or vulnerable human societies are to regional shifts of climate. Ultimately, regional policy makers are able to identify critical water or energy resources that may be at risk.
Unfortunately, archaeology and anthropology are unique in their isolation from policy makers. Other social science fields, such as political science, economics, and sociology, have an active dialogue with policy. Yet anthropology, despite its deep time breadth and diverse perspectives, has a much smaller role in policy relative to other fields. For example, the Anthropology division of the National Academy of Sciences is the only division not to provide recommendations to either the Executive or Legislative branches. As the vast majority of policy makers had a science education that is the equivalent of that received by a first-year college student, the input of anthropologists and archaeologists, who can provide a voice that incorporates both the deep past and the deep diversity of human society, is missing.
Chapter 5: The 5.1 ka Aridization Event, Expansion of Piñon-Juniper Woodlands, and the Introduction of Maize (Zea mays) in the American Southwest

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Abstract

Pollen analysis is frequently used to build climate and environmental histories. A distinct Holocene pollen series exists for Chaco Canyon, New Mexico. This study reports linear modeling and hypothesis testing of long distance dispersal pollen from radiocarbon-dated packrat middens which reveal strong relationships between piñon pine (Pinus edulis) and ponderosa pine (Pinus ponderosa). Ponderosa pollen dominates midden pollen assemblages during the early Holocene, while a rapid shift to a much higher proportion of piñon to ponderosa pine pollen between ca. 5,440 - 5,102 cal. yr BP points to an aridization episode. This shift is associated with higher δ¹⁸O values in Southwest speleothem records relative to the preceding millennium. The period of aridization is followed by a sharp increase in El Niño/Southern Oscillation events that would have caused highly variable precipitation and lasted until ca. 4,200 cal. yr BP. Bayesian change-point analysis suggests that this aridization episode led to stable ecotonal boundaries for at least 3,000 years. The piñon/ponderosa transition may have been caused by punctuated multi-year droughts, analogous to those in the 20th century. The earliest documented instance of Zea mays cultivation on the Colorado Plateau is around ca. 3940 ¹⁴C yr BP (ca. 4,364 cal. yr BP) (Hall 2010) in Chaco Canyon. The introduction of this labor-intensive cultigen from Mesoamerica may have been facilitated by changes in the regional ecosystems, specifically by an increase in piñon trees, that promoted increasing human territoriality. Linear modeling and hypothesis testing can complement
traditional palynological techniques by adding greater resolution in vegetation patterning to climate/environmental histories.

**Introduction**

Chaco Canyon in northwestern New Mexico (Figure 5.1) is famous for the emergence around 1,000 years ago of a complex prehistoric society based on maize agriculture and long-distance movement of goods, including cacao (chocolate) from central America (Wills 2001; Crown and Hurst 2009). Chaco Culture National Historic Park is an UNESCO World Heritage site in recognition of the intrinsic importance associated with understanding the social and environmental conditions underlying this dramatic transformational process, during which dispersed hamlets of subsistence farmers coalesced rapidly around the construction of massive stone communal buildings called “great houses,” such as Pueblo Bonito. A long standing interest among scientists in characterizing the environmental context for the appearance of Chaco great house communities has produced numerous studies of geological and biological data from the canyon dating to the last 12,000 years.
The present day environment of the Chaco Canyon area is a mixed piñon-juniper woodland with some scrubland, while ponderosa forests are restricted to higher altitudes in nearby mountain ranges (Figure 5.2). Combined pollen and macrobotanical evidence suggest a transition to increased aridity in the San Juan Basin in the mid-Holocene. Pollen data from Chaco alluvium indicate this aridization occurred sometime before ca. 5,800 BP $^{14}$C yr BP (ca. 6,600 cal. yr BP) (Hall 1977). Ponderosa pine macrofossils are found in middens dated to before ca. 5,550 $^{14}$C yr BP (6,302 cal. yr BP), but disappear afterward, while piñon pine macrofossils increased in frequency from that point onwards (Betancourt and Van Devender 1981). Total differentiated pollen from packrat midden pollen assemblages record an increase of piñon pollen and a decrease in ponderosa...
pollen that begins around ca. 5,550 $^{14}\text{C}$ yr BP (6,302 cal. yr BP) (Hall 1988). Pine tree evidence is altogether lacking in packrat middens after ca. 1,202 cal. yr BP, possibly reflecting human depletion of local tree stands.

Historical changes in the piñon/ponderosa ecotone in New Mexico have been attributed to punctuated episodes of intensive drought (Allen and Breshears 1998). Ponderosa is more drought sensitive than piñon and therefore tends to occupy higher elevations (Pearson 1920), while in dry years low-elevation ponderosa trees exhibit reduced growth relative to piñon (Adams and Kolb 2005). Ponderosa forests in northern New Mexico experienced large die offs after the 1950s droughts and were replaced by piñon (Allen and Breshears 1998). One ecotonal shift covered 2 km in less than 5 years and has persisted for more than 50 years with an upward elevational shift from 1,800m to 2,200m. In addition, the spatial distribution of ponderosa in the ecotone has grown more fragmented with time. Recent droughts between 2000 and 2004 resulted in ponderosa die offs across the Southwest and researchers anticipate that continued aridity will further reduce the presence of ponderosa (Gitlin et al. 2006; Burkett et al. 2005; Negron et al. 2009). These historical observations suggest that it is possible to track the relationship between piñon and ponderosa during ecotonal transitions in the past.
A 12,000 year record of piñon and ponderosa pine pollen has been recovered from Chaco packrat middens (Betancourt and Van Devender 1981; Hall 1988). Packrat middens preserve a sequence of long distance dispersal pollen that records floral change at the regional level. Midden pollen assemblages have been used to identify changes in piñon woodlands in Dutch John Mountain in Northeastern Utah, where multidecadal droughts and pluvial periods were related to the expansion of piñon at the expense of Juniper (genus) (Gray et al. 2006). There is debate as to what degree pollen in packrat middens reflects local vs. regional (e.g. long distance dispersal) pollen (Davis and Anderson 1987a; Van Devender 1987; Davis and Anderson 1987b) but it seems
clear that long distance dispersal of pine pollen accounts for its presence in packrat middens when pine macrobotanical remains are absent (Hall 1988). Packrat middens are a unique depositional environment allowing for rapid incorporation of pollen onto a sticky surface. The resulting sample should be reflective of long-distance dispersal pollen rain (Van Devender 1987), provided that pollen accumulation is a result of a random, gradual process. In an Arizona case study, local pine abundance had a significant weak relationship \( r^2 = 0.06, p < 0.001 \) with pollen rain, suggesting that local pine only slightly augments a primarily regional pollen signal (Stuart et al. 2006). Although it is impossible to know the exact contribution of local vs. regional sources in packrat midden pollen in Chaco over the past 12,000 years, linear modeling can help generate statements of significance as to the broader relationship between ponderosa and piñon abundance.

Palynologists traditionally calculate pollen spectral percentages to address variation between taxonomic abundance on regional and depositional scales in order to help resolve issues of over- and under-representation of taxa (Davis et al. 1973; Calcote 1995). This calculation was developed by Lennart von Post in 1916 (Manten 1966), and has remained the most consistent form of analyzing pollen data since its introduction. This metric is often used to report changes in frequency of taxa occurrence but it seldom tests specific hypotheses about environmental/climate change (Birks 1993; Ritchie 1995; Seppä and Bennet 2003). Frequently the attribution of pollen changes to one or more factors is simply speculation (MacDonald 1993). An alternate metric can correct for differences in sample size but retain information about their occurrence through time by summing each taxon from all pollen assemblages used in a given study and reporting the fraction of this number in each temporally defined assemblage. For the purpose of this paper, the term
“species occurrence” will refer to this calculation and “pollen percentage” will reflect the traditional approach.

**Materials and Methods**

We analyzed published packrat midden pollen data (Hall 1988) using linear models with long-distance dispersal (LDD) taxa juniper, piñon pine, ponderosa pine, and limber pine. Simple linear regressions were run between each of the four tree types and sample size. In the combined set of linear models the variation in each species can be represented as a function of other taxa, or simply as a change in sample size. Species with clear relationships were then contrasted with other paleoclimate records that reflect Holocene changes in the San Juan Basin. The intent of this approach is to demonstrate that significance testing is both possible and helpful in understanding changes in plant species abundance. Additionally, comparison with other paleoclimate records helps better contextualize changes in species representation over time in pollen assemblages.

All radiocarbon dates were calibrated using Calib 6.0 software with intcal09 (Stuiver 1993; Reimer et al. 2009). Radiocarbon dated material in middens were primarily macrobotanicals (Betancourt and Van Devender 1981; Hall 1988) and as such have calendrical dates BP. However, it is important to consider the ambiguity of pollen dates from packrat middens; material can be aggregated and mixed over hundreds and even thousands of years (Webb 1986). For this reason, the time frame represented by pollen assemblages were broader than a specific calendrical date indicates. Pollen data were calculated as conventional pollen percentages displayed in spectra:

\[
\text{Taxon}_{\text{sample}} = \frac{\text{Taxon}_{\text{count}}}{\text{Sample}_{\text{count}}}
\]
This ratio expresses relative abundance but precludes linear modeling of relationships between taxa. A second calculation of pollen percentages was performed with juniper removed, following previous treatment (Hall 1988).

A separate calculation for species occurrence still reports pollen as frequencies but preserves temporal variation independent of temporal assemblage sample size:

\[
\text{Taxon}_{\text{total}} = \frac{\text{Taxon}_{\text{count}}}{\text{Total}_{\text{taxon}}}
\]

Simple linear models were generated to examine long-distance dispersal species with known modern ecotonal boundaries (juniper, piñon, ponderosa and limber pine). These taxa were also tested against sample size. To show change in piñon over time, piñon pollen was divided by the sum of piñon and ponderosa pollen to show its proportional representation among long distance dispersal (LDD) pollen species. Juniper and limber pine were excluded from these calculations due to their significant relationships with sample size.

For comparison, an oxygen isotope record derived from a speleothem in Pink Panther Cave in the Guadalupe Mountains of New Mexico (Asmerom et al. 2007) was used to provide an independent measure of Holocene climate. To determine the relationship between climate near Carlsbad Caverns/Guadalupe Mountains and the San Juan Basin, a linear regression was run between monthly precipitation at the Carlsbad Caverns weather station and the National Oceanic and Atmospheric Association’s (NOAA) New Mexico climate divisions 1, 2, and 4. All $\delta^{18}O$
values in the Pink Panther record that fell within the 1σ value of each packrat midden radiocarbon
date were averaged to create representative values for the period of pollen accumulation.

Similarly, records of El Niño/Southern Oscillation (ENSO) events were utilized as an
additional complementary source of regional climate change. ENSO data are reported from Laguna
Palicachoa in southern Ecuador (Moy et al. 2002). Color intensity peaks (red) were gathered from
clastic organic sediments deposited gradually over 13,000 years. All years with color intensity
values at least 15 units above the mean were aggregated to produce a history of ENSO events for
the Holocene. It is important to note that ENSO events are highly localized, events in Laguna
Palicachoa do not necessarily correspond to the San Juan Basin. However, changes in ENSO
frequency in the 10,000 year Laguna Palicachoa record may have implications for more
pronounced effects on precipitation in the San Juan Basin.

For piñon pine proportions, a Bayesian change-point model was run using the Barry and
Hartigan (Barry and Hartigan 1993) algorithm to estimate two sets of quantities: the probability
that each point in the time series partitions blocks with different means and those block means.
The algorithm is initialized with no partition points. In each step of the Markov chain, partition
points are drawn given the data and the current partition. At each point the odds (p/(1-p)) for a
partition depends on the within and between block sums of squares obtained given the data and the
updated partition. After each iteration, the posterior block means are updated conditional on the
data and the updated partition. Repeated many times, this process converges to the posterior
distributions of the partition probabilities and block means. Each model had a burn-in of 10,000
iterations and posterior probabilities were generated from 10,000 Markov-Chain Monte Carlo
These simulations were run in R using the bcp package with hyper parameter defaults recommended by Erdman and Emerson (2007).

Results

<table>
<thead>
<tr>
<th>Taxon</th>
<th>Piñon pine</th>
<th>Ponderosa pine</th>
<th>Limber pine</th>
<th>Sample Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>Juniper</td>
<td>0.15 (p=0.10)</td>
<td>0.11 (p = 0.16)</td>
<td>0.25 (p=0.03)°</td>
<td>0.87 (p &lt; 0.001)***</td>
</tr>
<tr>
<td>Piñon pine</td>
<td>0.89 (p &lt; 0.001)***</td>
<td>0.70 (p &lt; 0.001)***</td>
<td>0.12 (p = 0.12)</td>
<td></td>
</tr>
<tr>
<td>Ponderosa pine</td>
<td>0.59 (p &lt; 0.001)***</td>
<td>0.11 (p = 0.16)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Limber pine</td>
<td></td>
<td>0.22 (p=0.04)°</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘°’ 0.1 ‘ ’ 1

Table 5.1: Regressions of LDD pollen in assemblages using taxon totals.

Figure 5.3: Species occurrence of ponderosa and piñon pine (a), conventional pollen percentage with juniper removed (b), and conventional pollen percentage (c) (n = 19). The shaded grey area represents 95% confidence bounds about the regression line. A strong relationship is found between the occurrence (3a) of ponderosa and piñon pine (r² = 0.89, p < 0.001); pollen percentages with juniper removed (3b) had a moderate but still significant relationship (r² = 0.46, p = 0.002); data presented in traditional pollen percentages (3c) have a weaker relationship (r² = 0.03, p = 0.49). A strong linear relationship exists between piñon and ponderosa pine in the Holocene packrat midden records in Chaco Canyon that is not immediately evident when data from long-distance dispersal pollen is normalized to sample size.

Ponderosa pine was common in Chaco Canyon packrat midden pollen assemblages during the Early Holocene but declined sometime before ca. 6,302 cal. yr BP, after which piñon pine contribution increased, especially between ca. 5,440 and 5,102 cal. yr BP. Piñon continued to be
prevalent in Chaco assemblages until ca. 1,202 cal. yr BP but is absent thereafter. This decline may be related to hypothesized deforestation by local farmers (Betancourt and Van Devender 1981), although piñon was used as fuel until at least ca. 900 BP (Toll 1983).

Piñon pine has a significant negative relationship with both ponderosa and limber pine (Table 1). The proportion of variation in limber pine is significantly explained by both sample size and juniper, however the oldest pollen assemblage has high leverage upon this relationship. With that point removed, the prediction is lower with both sample size ($r^2 = 0.03$, $p = 0.50$) and juniper ($r^2 = 0.03$, $p = 0.51$). The same point has little leverage on the relationship between piñon and ponderosa, as evidenced when it is removed ($r^2 = 0.83$, $p < 0.001$). Juniper shows no significant relationship with any of the other plants but it is predicted by sample size for each pollen assemblage. When calculated as pollen percentages, the only significant relationship is a negative one between juniper and piñon ($r^2 = 0.45$, $p < 0.001$). Regressions between piñon and ponderosa pines reveal a significant negative relationship when calculated as either species occurrence (Figure 5.3a) or pollen percentages with juniper removed (Figure 5.3b). Pollen percentages (with juniper included) show no significant relationship (Figure 5.3c).
Figure 5.4: The proportion of piñon pine pollen relative to total long distance dispersal (LDD) pollen during the Holocene in Chaco packrat middens (n = 19).

The shaded area around the line represents 95% confidence levels. The full data set for δ18O is shown in light grey, black dots are values averaged over the 1σ value of each radiocarbon data for pollen assemblages. Ponderosa is more prevalent in the early Holocene (12,000 - 11,000 BP) than other pines, while at some point before 6,300 BP piñon increases in frequency, then rises sharply at ca 5,100 BP (a), indicating increased aridity and the retreat of the piñon-ponderosa ecotonal boundary to a higher elevation. The earliest directly dated occurrence of Zea (b) in Chaco Canyon is pollen at ca. 4,300 BP/2,350 BC (Hall 2010), while the oldest maize macrofossil on the Colorado Plateau is dated to ca. 4,200 BP/2,250 BC (Huber and Miljour 2005). A decrease in piñon pollen occurs when macrobotanicals disappear from the midden records at 1,200 BP (c), an event hypothesized to be associated with deforestation (Betancourt and Van Devender 1981). A gradual increase in aridity beginning at 6,000 BP and concluding around 4,200 BP (Asmerom et al. 2007) would have favored the spread of piñon pine (n = 682; n = 19). Of equal importance, an increase in ENSO events beginning after 5,100 BP (Moy et al. 2002) (n = 128) would have caused variable precipitation in the Southwest. Increased aridity and precipitation variation would have further restricted the range of ponderosa pine to higher elevations, as it is more susceptible to drought than piñon pine.

An increase in piñon pine representation in LDD pollen occurs between ca. 5,440 cal. yr BP and ca. 5,102 cal. yr BP (Figure 5.4). Both increases are associated with change-points with high posterior probabilities (Figure 5.5). A decrease in piñon pine representation occurs at ca.
1,202 cal. yr BP (Figure 5.5). The second increase in piñon pine, dated to before ca. 5,102 cal. yr BP, is rapid and appears to have been associated with a slight increase in aridity and a large increase in ENSO variability (Figure 5.4).

![Figure 5.5: Posterior means and posterior probabilities of change points generated from pollen data (n = 19). The shaded area around the posterior means represents the posterior first standard deviation resulting from Bayesian change-point analysis. Piñon pine pollen counted as a proportion of all LDD pollen shows a high posterior probability at ca. 6,302 BP (78.70%), ca. 5,102 BP (90.23%) (a), and at ca. 1,202 BP (36.38%) (c). The 5,100 aridization event is associated with significant increases in piñon pine pollen in packrat midden records. Almost 3,000 year of stability in piñon-ponderosa woodlands follows the domestication of maize (b). The decrease in piñon pine pollen at ca. 1,202 BP (c) (with a posterior probability of 30.96%) is associated with the hypothesized deforestation of piñon pine in Chaco Canyon (Betancourt and Van Devender 1981).](image)

**Discussion**

Linear modeling of the relationship between piñon and ponderosa pine, complemented by Bayesian change-point analysis, suggests a process of aridization began before ca. 6,302 cal. yr BP and accelerated between ca. 5,440 and ca. 5,102 cal. yr BP. This is consistent with previous palynological interpretations of the canyon in alluvial sediments (Hall 1977) and with macrobotanical studies of the canyon (Betancourt and Van Devender 1981). A more arid climate is
also documented in oxygen isotope speleothem records from the Guadalupe Mountains in southern New Mexico (Asmerom et al. 2007) after 6,000 BP. Precipitation near the Guadalupe Mountains has varied with precipitation in the San Juan Basin ($r^2 = 0.19$, $p < 0.001$). The relationship between precipitation near the Guadalupe Mountains and the San Juan Basin suggest that the stable oxygen isotope speleothem record for Pink Panther Cave has some implications for the climate near Chaco Canyon. The strength of the linear relationships between piñon and ponderosa pollen suggests that low-elevation ponderosa forests were replaced by piñon-juniper woodlands during the 5.1ka aridization event. Ecotonal transitions between these two forest types during the past century have been rapid during periods of drought (Allen and Breshears 1998; Adams and Kolb 2005; Gitlin et al. 2006; Burkett et al. 2005; Negron et al. 2009) and therefore the aridization period between ca. 5,440 and ca. 5,102 cal. yr BP may have been the result of a similar episode of punctuated droughts.

The initial appearance of piñon macrobotanicals in Chaco packrat middens at ca. 6,302 cal. yr BP corresponds to the last occurrence of ponderosa remains (Betancourt and Van Devender 1981). This is also the point at which piñon pollen frequencies first exceed those of ponderosa (Hall 1988) (Figure 5.4). During the late Wisconsin period, piñon was restricted to southern New Mexico but it is last identified in packrat middens in this region around ca. 11,100 BP (Van Devender et al. 1984; Lanner and Van Devender 1981). The sharp increase in piñon pine between ca. 5,440 - 5,102 cal. yr BP suggests a settling in to the modern range of piñon in the mountain ranges framing the San Juan Basin. Oxygen-isotope records from Pink Panther cave to the South suggest a decrease in precipitation at that time that would have made the Southwest more vulnerable to droughts (Figure 5.4), conditions that would have limited ponderosa pine trees to
higher elevations with more predictable rainfall and encouraged the range expansion of the more
drought tolerant piñon.

An aridization event at 5,100 BP is reflected in multiple climate records worldwide. A
sharp drop in precipitation at 5,100 cal. yr BP was observed in oxygen-isotope speleothem records
in Soreq cave in Israel (Bar-Matthews et al. 2003). Dolomite and CaCO$_3$ concentrations in the Gulf
of Oman increase during this time period (Cullen et al. 2000). A similar increase of dolomite and
CaCO$_3$ at ca. 4,200 cal. yr BP was associated with increased aridity and civilization collapse in the
Middle East and North Africa (Cullen et al. 2000). Similar shifts in aridity are evident in lower lake
levels in Spain, Portugal, and Greece at the same time (Harrison and Digerfeldt 1993), suggesting
that a widespread series of droughts took place globally ca .5,100 BP. A sharp increase in ENSO
events occurred around ca. 5,000 cal. yr BP and lasted until ca. 4,200 cal. yr BP, bracketed by the
5.1 and 4.2 kiloyear events (Moy et al. 2002). El Niño events are associated with increased
precipitation in the US Southwest, while La Niña events are associated with below average
precipitation (Arriaga-Ramírez and Cavazos 2010). This would have resulted in rapid growth of
vegetation in El Niño years and die-offs during La Niña years. The increasing variation of
precipitation due to ENSO activity does not preclude arildization of the climate suggested by the
oxygen isotope speleothem sequence from Pink Panther Cave; the variation in precipitation may
still have been part of a long-term aridization trend in the mid-Holocene. Charcoal records from the
Sonoran desert in Arizona indicate an increase in fire frequency between ca. 5,330 - 4,400 cal. yr
BP, possibly because of the increase in ENSO activity (Brunnelle et al. 2010). The mid-Holocene
increase in piñon pine from Chaco Canyon is thus firmly situated within a global period of
aridization and increased climatic variability.
The 5.1 ka aridization period occurred before the introduction of maize cultivation to the northern Southwest. The oldest directly dated maize cob from the Colorado plateau is ca. 4,200 cal. yr BP in west-central New Mexico (Huber and Miljour 2005), with a number of sites in the region producing maize at ca. 4000 BP (Wills 2005; Hard et al. 2010). The earliest evidence for maize agriculture comes from *Zea mays* pollen in Chaco packrat middens at ca. 3940 \(^{14}C\) yr BP (ca. 4,364 cal. yr BP) (Hall 2010). The earliest introduction of maize therefore occurs near another major mid-Holocene global aridization event near ca. 4,200 cal. yr BP (Cullen et al. 2000). The relationship between maize introduction to the Chaco region and mid-Holocene aridity was probably indirect, with the expansion of piñon-juniper woodlands creating a vastly greater set of economic opportunities for pre-agricultural foragers. Piñon seeds (or nuts) are an especially high return wild resource, rich in nutrients and calories, occurring in large patches with predictable mast periodicity and amenable to storage and thus prolonged availability (Madsen and Rhode 1990). The dietary importance of piñon seeds is reflected in occurrence of property rights in piñon woodlands by Native American groups throughout the American West during the historic period. Therefore we argue that the introduction of maize to the northern Southwest (Colorado Plateau), including Chaco Canyon, took place within an overall expansion of diet breadth and greater availability of plant foods associated with increasing aridity. It is intriguing that *chenopodium*, a major economic plant in prehistoric North America that was domesticated in the Eastern Woodlands (Smith and Cowan 1987), also shows a spike at ca. 4,243 cal. yr BP in the Chaco data.

It is possible that the 5.1 ka period of aridization, together with a subsequent spike in aridity around 4,200 cal. yr BP (Cullen, et al. 2000) produced ecological changes in resource structure that set the stage for the introduction of maize agriculture to human foragers. Maize was
domesticated in central America by 6500 BP, and entered the Southwest around 2000 years later (Merrill et al. 2009). The oldest dated maize (Zea mays) macrofossil on the Colorado Plateau is ca. 4,200 cal. yr BP (Huber and Miljour 2005) and a number of sites in the region have produced maize specimens dating to 4,000 BP, while Zea mays pollen from Chaco Canyon packrat middens is directly dated to ca. 3940 ¹⁴C yr BP (ca. 4,364 cal. yr BP) (Hall 2010). [XRD] Archaeologists are unsure what sociocultural processes were responsible for the transmission of maize from south to north, whether diffusion between hunter-gatherer groups or the migration of farmers, or some combination of both (Wills 1995; Merrill 2009), but there is a consensus among researchers that maize must have been valuable and must have fit into local economies without disruption. However, although maize seems to have dispersed through the Southwest, this cultivated plant does not appear to have provided the foundation for sedentary lifeways until much later, perhaps around 3,000 BP in southern Arizona and 2,000 BP on the Colorado Plateau. In other words, the historical record suggests that initially maize was useful but not immediately transformative (Wills 2005). On the Colorado Plateau, the widespread development of piñon-juniper woodlands may be critical to understanding why the earliest involvement with maize did not result in a dramatic shift to sedentary adaptations.

The mid-Holocene expansion of piñon-juniper woodlands in response to aridization produced an expansion in diet breadth for human foragers, especially high return (in calories and nutrients) foods such as piñon nuts, which occurred in large patches with predictable periodicities and were amenable to storage (Madsen and Rhode 1990; Barlow and Metcalfe 1996; Janetski 1999). Piñon nuts were so important to historic hunter-gatherer groups in the western United States that individual bands or families claimed property rights over collecting areas and were able
to sustain sedentary winter camps in those areas (Simms 1985). Consequently the replacement of ponderosa pine forests by piñon woodlands likely created conditions favoring territorial control over productive collecting localities by hunter-gatherers. Such geographic stability is essential to the successful cultivation of maize, which requires annual storage, seed selection, planting and harvesting.

The frequency of radiocarbon dated archaeological sites on the Colorado Plateau increased dramatically between ca. 4,400 - 4,000 $^{14}$C yr BP (ca. 4,950 and 4,450 cal. yr BP) (Chapin 2005: 168), a trend that likely tracked an increasingly intensive occupation of the emergent piñon-juniper woodlands by foragers, as well as repetitive use of particular site locations (see Simms 1985; Rhode and Madsen 1998). In addition to piñon, hunter-gatherer groups were also utilizing low-return small seed resources, including grasses, chenopodium and amaranth that are common in piñon-juniper woodlands. Small seed use was facilitated through technological innovations in basketry (for winnowing, parching, storage and transport) and grinding stones (or producing flour) (Geib and Jolie 2008). In short, following the expansion of piñon-juniper woodlands at ca. 5,102 cal. yr BP, the archaeological reveals intensive land use systems by foragers who were invested in the collection, processing and storage of seeds.

There are clear consistencies between the requirements for maize cultivation and the nature of hunter-gatherer economies on the Colorado Plateau between ca. 5000 and 4000 BP. The basic organization of small kin-based groups included behaviors such as food storage and localized extractive strategies that were a good fit for introduced cultigens. These behaviors co-evolved with the expanding piñon-juniper habitat and the attendant economic opportunities provided by greater resource diversity. The fact that hunter-gatherers were already using low-return plants helps
explain the rapid introduction of maize, which offered relatively high caloric yields without significantly greater costs (see Barlow 2002). We do not argue that maize was adopted because the Colorado Plateau environment was transformed in the mid-Holocene, but rather that this transformation promoted foraging behaviors that made the acquisition of maize and other cultigens beneficial once they became available. The prolonged period between the adoption of maize and the emergence of sedentary agricultural societies in the piñon-juniper woodlands suggests that the resulting mix of wild and domesticated food resources was a stable or resilient adaptation. Archaeologists argue that this apparent stability reflects a wide range of local subsistence patterns, some incorporating very little maize cultivation, others much more (Wills 2005). In general, greater emphasis on maize cultivation probably indicates fewer opportunities for obtaining higher ranked resources (Barlow 2002). The mid-Holocene expansion of piñon-juniper woodlands created opportunities for incipient farmers but also created opportunities for foragers to maintain essentially hunting and gathering production systems.

The temporal relationship between piñon and ponderosa pine offers a clear picture of environmental change over the past 6,000 years in Chaco Canyon with a substantial species replacement taking place in the mid-Holocene. Simple linear regression indicates significant relationships between the two species (Table 1). The sharp decline in ponderosa and limber pine between ca. 5,440 and 5,102 cal. yr BP (Figure 5.4) suggests that an increase in droughts was a feature of the aridization that occurred at that time. This hypothesis is supported by a decrease in rainfall reflected in higher δ¹⁸O values. Following this period, the present ecotonal boundary in the Chaco region between these species was established due to continued droughts associated with a large increase in ENSO events. The expansion of piñon-juniper woodlands and their multi-
millennial stability raised local resource values for human hunter-gatherer populations and
promoted foraging behaviors that paved the way for the adoption of maize agriculture during the
following millennium.

Seppä and Bennet (2003) characterized Quaternary pollen analysis as “approaching a state
that could be called a minor crisis” (2003: 549). This was due to a lack of hypothesis testing and
frequent uncritical and speculative interpretations on changes in pollen diagrams. In part this is a
structural issue; the normalization of pollen counts to sample size tends to preclude inter-site
comparisons of taxa. Species such as piñon and ponderosa pine, which have been observed to vary
with regard to climate (Allen and Breshears 1998), are an example of this phenomenon. When
normalized to sample size, the relationship between piñon and ponderosa pine is either lost or
weakened (Table 1; Figure 5.3). Fluctuations in other taxa, which can be unrelated to climate, can
add error to a clear climatic signal. This can be demonstrated by contrasting the Mockingbird
Canyon 2 (ca. 2990 cal. yr BP) assemblage with Gallo Wash 1 (ca. 1839 cal. yr BP) assemblage.
The Mockingbird Canyon 2 assemblage contains 82 grains of piñon pine pollen while Gallo Wash
1 contains 85 grains. When calculated as pollen percentage, piñon pollen in Mockingbird Canyon
2 represents 6.71% of the assemblage, while piñon pollen in Gallo Wash 1 represents 14.91% of
the assemblage; this dramatic difference in representation is not the consequence of a change in
piñon pine pollen, but rather the surrounding vegetation. Even when juniper pollen is removed
from the sample, there is still a large difference between the Mockingbird Canyon 2 and Gallo
Wash 1 pollen percentages (10.22% and 17.21%, respectively). When calculated as species
occurrence, the difference between the two assemblages is far less pronounced (5.38% and 5.58%,
respectively).
The species occurrence metric, which to the best of the authors' knowledge is introduced for the first time in this manuscript, has the potential to help clarify climate signals in multiple pollen assemblages. By normalizing to the taxon totals, rather than to the assemblage totals, it is possible to express pollen taxa relative to its own history. Critically, this metric incorporates hypothesis testing into its structure. By expressing assemblage size as a percent of all pollen, a null hypothesis can be formulated. This null hypothesis would stipulate that for every 1% increase in each pollen assemblage's size, a corresponding 1% increase should be observed in each taxon. In this study, taxa that reproduce through long distance wind dispersal were tested against this null hypothesis. Juniper was found to have a highly significant relationship with sample size, suggesting that its variation followed the prediction of the null hypothesis ($r^2 = 0.87$, p < 0.001). Both piñon and ponderosa pine had non-significant relationships with sample size (Table 1), suggesting that other factors contributed to their variation over time. Both species had a significant negative relationship with each other ($r^2 = 0.89$, p < 0.001), suggesting that the Holocene time series of the two taxa were governed by similar competitive dynamics observed in the 20th century (Allen and Breshears 1998).

The metric of species occurrence is not intended to be a replacement for, or superior to, the pollen percentage metric used in pollen diagrams. The pollen diagram has been immensely useful for almost a century following its development (Manten 1966). Pollen data can be recovered globally, and records often span thousands of years. While the pollen diagram is a highly useful way to express large quantities of pollen data, it should not be the only method employed to analyze pollen assemblages. The pollen percentage metric does not test for significance of changes in taxa frequency and it cannot address interspecific competition reflected in long distance
dispersal pollen, such as that between piñon and ponderosa pine. Linear modeling of the relationship between taxa that compete at ecotonal boundaries can complement existing palynological methods by assessing the significance of changes in multiple pollen assemblages. Bayesian change-point analysis can help assess the significance of changes in long-term records. When the relationship between taxa at ecotonal boundaries is explicated, then modern ecological studies can help researchers better understand prehistoric changes in vegetation. Tests against sample size can identify species that may vary independently of their environmental context, such as plants under human cultivation. Robust linear modeling and hypothesis testing can contribute to significantly more detailed paleoclimate interpretations.

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We thank Glen MacDonald for comments on potential factors regarding the interpretation of packrat midden pollen assemblages and information about Southwestern fires associated with increases in ENSO events at 5,000 BP. Suzanne Fish and Susan Smith analyzed pollen samples from the Pueblo Alto trash mound as part of the ongoing Chaco Stratigraphy Project at the University of New Mexico. Special thanks go to Stephen Hall and Bruce Smith for comments on an early draft of the manuscript. David Hanson suggested linear modeling using pollen percentage data with juniper pollen removed.
Chapter 6: The Use of Radiocarbon-Derived $\Delta^{13}C$ Values as a Paleoclimate Indicator: Applications in the Lower Alentejo of Portugal
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Abstract

Values of $\delta^{13}C$ are frequently reported with radiocarbon dates from organic materials. In $C_3$ plants $\delta^{13}C$ values have been linked to changes in water use efficiency as a response to arid conditions. By calculating $^{13}C$ discrimination ($\Delta^{13}C$) from $\delta^{13}C$ values, archaeologists can gain potentially valuable inference into past climate conditions. Values of $\Delta^{13}C$ more accurately reflect the process of discrimination against heavier $^{13}C$ isotopes of carbon than initial $\delta^{13}C$ values. These can be calculated from reported $\delta^{13}C$ values when records of atmospheric $\delta^{13}CO_2$ are available.

The present study examines a 1,300 year history of radiocarbon-derived $\Delta^{13}C$ from the Lower Alentejo of Portugal using charcoal recovered from excavations of a series of Medieval habitation sites in the study area. To calculate $\Delta^{13}C$, the posterior means generated from Bayesian change-point analysis of $\delta^{13}CO_2$ records were used. Archaeological data were then compared to contemporary ecological studies of $\Delta^{13}C$ of the same taxa against instrumental records of climate.

Values of $\Delta^{13}C$ fell within mean ranges for the taxa through a period of population growth between the 7th and 10th centuries AD. During the height of the Medieval Warm Period in the 11th century $\Delta^{13}C$ values frequently fell to low levels associated with arid conditions. At this time environmental degradation and erosion were documented. Values of $\Delta^{13}C$ increased for a brief period in the early 12th century before the rural Lower Alentejo was largely abandoned for nearly two centuries. Another period of aridity occurred in the 16th and 17th centuries. Radiocarbon-
derived $\Delta^{13}C$ is a potentially useful paleoclimate proxy for archaeologists provided that results can be paired with observed $\Delta^{13}C$ variation in studies that pair these data with instrumental climate records.

**Introduction**

Climate has played a pivotal role in shaping human societies: increasing social complexity is dependent upon agriculture which is in turn dependent upon variation in climate. Yet determining the influence of local climate patterns at the site level is difficult in many areas. Stable carbon isotope ratios from botanical material can serve as a paleoclimate record that can expand archaeologists’ ability to detect significant changes in local environmental conditions. By using $\Delta^{13}C$ values, which are regularly reported with radiocarbon dates (Stuiver and Polach 1977), archaeologists can build on current methods to reconstruct paleoclimatic conditions in sites where other methods are not available. The variation in $^{13}C$ discrimination among and within species likely makes direct climate reconstruction using $\delta^{13}C$ values unrealistic. However, extended periods of extreme weather that are likely to impact human migration or range expansion should be detectable given appropriate sampling.

Variation in $\delta^{13}C$ values in plant tissues is caused by preference for $^{12}CO_2$ over $^{13}CO_2$. Under normal conditions, the process of photosynthesis in plants consumes $CO_2$ from the atmosphere and releases $O_2$, incorporating the carbon atom into the plant while using light to provide the necessary chemical energy. The majority of the discrimination effect against heavier carbon isotopes in $C_3$ grasses occurs during carboxylation when Ribulose-1,5 -biphosphate carboxylase oxygenase RuP$_2$ fixes the carbon atoms in the first step of the Calvin cycle (Calvin
1956; Farquhar et al. 1982; Farquhar et al. 1989). However, changes in the diffusive resistance for CO$_2$ between the atmosphere and the chloroplast also affect the isotopic composition of plant material (Farquhar et al. 1982). Resistance to CO$_2$ diffusion increases as stomatal pores close in response to dry conditions, among other factors (Farquhar et al. 1989), and also due to changes in the expression of proteins within pores in the chloroplast inner membrane (Uehlein et al. 2008). Higher resistance causes greater diffusional discrimination, but also reduces the chance that CO$_2$ will escape fixation by the enzyme RuP$_2$ and diffuse back out of the leaf and into the atmosphere and this reduces the ability of RuP$_2$ to discriminate against $^{13}$CO$_2$. Since discrimination by RuP$_2$ is roughly an order of magnitude larger than the diffusional discrimination, the net effect of dry conditions is a decrease in discrimination that makes sugars produced by photosynthesis more enriched in $^{13}$C (Farquhar et al. 1982; Farquhar et al. 1989). These sugars are then distributed throughout the entire plant for growth. For example, tree rings formed during years of drought will be more enriched in $^{13}$C relative to rings formed in wet years as will all other tissues. For this reason, the stable carbon isotope ratios of botanical remains in the archaeological record have the potential to record periods of drier and wetter conditions (McCarroll and Loader 2004). Over the past three decades, studies of the stable carbon isotope ratio in trees, referred to as isotope dendroclimatology, have consistently shown relationships between stable carbon isotope ratios and precipitation and temperature patterns (Robertson et al. 2010). Just as tree ring widths vary in response to precipitation, so too does the stable carbon isotope ratio in the same rings. Drier conditions result in more enriched $^{13}$C and pluvial conditions result in more depleted $^{13}$C in plant tissues. Unlike traditional dendroclimatology, isotopic dendroclimatology can be extended to infer paleoclimate from archaeological charcoal samples. The data are already regularly gathered as part
of radiocarbon dating, and a large body of literature is growing to allow for species-specific interpretations of stable carbon isotope ratios.

Changes in the ratio of $^{13}$C and $^{12}$C in plants have been shown to have significant relationships with the Palmer Drought Severity Index (Leavitt and Long 1986; 1988), water use efficiency (Beerling and Woodward 1995), seasonal variation in precipitation (Hemming et al. 2005), mean annual precipitation in biomes (Diefendorf et al. 2010) and soil moisture content (Dupuoey et al. 1993). The consistency of the effects of water use efficiency and carbon isotope discrimination in plants have led to the proposal that stable carbon isotope ratios can be used as a paleoclimate reconstruction method (February and Van der Mewe 1992; Winkler 1994; Vernet et al. 1996; February 2000; Hall et al. 2008; Aguilera et al. 2009). However, other factors such as variable resistance inside the leaf and leaf shape can affect the stable isotope concentration of plants in ways that are poorly understood, leaving direct attribution of changes in stable carbon isotopes to climate problematic (Seibt et al. 2008). Most plants utilize a photosynthetic pathway termed C$_3$ (the first stable product is made of 3 carbons), but C$_4$ plants have a supplemental temporary CO$_2$ fixation pathway where CO$_2$ is initially fixed from the atmosphere into a 4 carbon compound and then released right next to RuP2 for final fixation via the Calvin cycle. These plants effectively have very high levels of CO$_2$ inside their leaves and allowing them to reduce water loss by closing stomata more than C$_3$ plants. As a result C$_4$ plants are less affected by factors such as drought. C$_4$ plants are also better at consistently limiting CO$_2$ escape from leaves, which means much more $^{13}$C is fixed into sugars (lower discrimination) and with less variation and thus provide a more reliable estimate of atmospheric $\delta^{13}$C. This relationship has been used in the past to model atmospheric $\delta^{13}$CO$_2$ values (Marino and McElroy 1991; Marino et al. 1992), in particular
documenting the changing ratio of $^{13}$C to $^{12}$C associated with anthropogenic carbon emissions.

Nonetheless there are few studies of stable carbon isotope ratios in archaeological charcoal. Stable carbon isotope ratios have the potential to play a valuable role in paleoclimate reconstruction, but little research has been done to illustrate the strengths and weaknesses of the method to date.

Paleoclimate reconstruction remains difficult at most archaeological sites. Dendroclimatology is the most accurate and precise paleoclimate reconstruction available to archaeologists, but full tree ring sequences are rare in excavations. For either dendrochronological or dendroclimatological analysis to be possible, trees need preserved cutting dates in order to properly place them in a known sequence (Towner 2002; Nash 2002). Often dendroclimatological sequences are generated by standardizing and averaging multiple trees to describe paleoclimate in a given region (Fritts 1971), but vast areas of the globe do not have enough (or any) tree ring chronologies to allow for historical climate records that overlap with archaeological records. Many regions have only floating tree ring sequences, as in the Asian steppes (Panyushinka et al. 2010; Panyushinka et al. 2008). A North African dendroclimatological sequence was recently published (Touchan et al. 2011), however it only goes back to A.D. 1179. A more widespread source of climate data come from palynology, where either pollen or phytolith counts can show taxa change over time (Bartlein et al. 1984; Huntley 1990). However the kind of landscape changes in vegetation that would show an unambiguous signal in pollen or phytolith counts can often be beyond the scope of the smaller climate events that affect human populations (Davis and Botkin 1985). For most archaeological sites, local paleoclimate reconstruction is beyond reach using these methods.
Stable carbon isotopes have potential to help fill this gap. Macrobotanicals are frequently found as ecofacts and archaeologists already regularly receive $\delta^{13}C$ data with radiocarbon dates (Stuiver and Polach 1977). Recent articles have begun to look at stable carbon isotopes in the soil as an indicator for broad changes in C$_3$ and C$_4$ vegetation (Leavitt et al. 2007a). These have included identifying changes in vegetation associated with the Younger Dryas (Bement and Carter 2010) and the cultivation of maize, a C$_4$ plant, in Mesoamerica (Webb et al. 2007). A promising recent archaeological study used stable carbon isotope ratios to identify changes in wheat in Greek sites (Heaton et al. 2009). Reconstructed $^{13}C$ discrimination from barley plants in Anatolia suggested increases in water use efficiency at 2,200 and 3,100 BC (Riehl 2008); consistent with known arid periods for the region (Cullen et al. 2000). However variation in $^{13}C$ discrimination of C$_3$ plants is still rarely applied in reconstructing paleoclimate in archaeology despite the ubiquity of the data.

However, a generalizable approach to the utilization of $\Delta^{13}C$ for paleoclimate reconstruction has yet to be fully articulated. In the present study, we recommend pairing $\Delta^{13}C$ approximated from radiocarbon assayed-charcoal with contemporary ecological studies of observed $\Delta^{13}C$-climate variation. This approach can establish a threshold for interpreting aridity in the past. The present study uses stable carbon isotope data from the Lower Alentejo to present a test case of paleoclimate reconstruction. This area is ideal as the time of occupation overlaps with a significant change in climate conditions during the Medieval Warm Period. The study uses isotope data from three genera of plants, including rockrose brushes (Cistus), oak trees (Quercus) and olive trees (Olea). The Mediterranean region lacks dendroclimatological data during the Medieval Warm Period, and has been neglected in most paleoclimate research. Stable carbon isotope data from
Lower Alentejo offer a new approach that may offer new insight into the climate conditions of the period.

**Study Area**

*Environmental background*

The climate pattern in the study area is meso-Mediterranean, with hot, dry summers and wet winters with infrequent freezing temperatures. Rainfall averages 550 mm, most of which falls between October and April based on figures for Beja from 1931-1960 (Amorim Ferreira 1970:118). The maximum difference in relief within the survey area is about 100 m, although most of the land lies between 150 m and 200 m in elevation. Within this range, however, the land surface is hilly and uneven, and average slopes range between 9% and 25% (*Carta da Capacidade de Uso de Solo* 1962; Santos 1987: 42). Traditional agricultural production follows a widespread pattern, termed the “Mediterranean agrosystem” by Butzer (1996: 142), which includes extensive cereal agriculture, maintenance of large flocks of sheep and goats and more limited production of olives and grapes. The permanent watercourse in the region, the Guadiana River, is deeply entrenched such that large-scale irrigation is impossible using traditional technologies. The rest of the study area is drained by deeply cut *ribeiras* that cease flow during the summer months. Hence, agriculture and pastoralism are dependent on rainfall except for small scattered walled gardens that can be watered by *norias*, or wells with water wheels.

Soils throughout the study area are thin, rocky lithosols interrupted by frequent patches of bare bedrock with occasional patches of deeper soils (termed *pardos mediterranicos*) derived from underlying *flysch* bedrock--folded and uplifted meta-sedimentary rock originating from marine deposits. Soil fertility is uniformly poor, and 95% of the survey area is currently classified under
the poorest soil category (*Carta de Capacidade de Uso do Solo* 1962) due to a combination of high slope and thin, skeletal soils, although historically, cereal crops have been routinely planted. Present-day plant cover in the survey area consists of grassland in fallow cereal fields, extensive stands of *Cistus sp.* (esteva, or rock-rose) where fields have been abandoned, and occasional patches of *matagal* consisting of *Cistus, Quercus rotundiflora* and *Q. coccifera,* and *Pistacia lentisca* on steep slopes and rocky areas. There are occasional groves of old olive trees several hundred years old, which are typically planted on deserted medieval Islamic village sites called *alcarias*.

*Historical background*

The pattern of rural development in the Lower Alentejo during the Medieval transition shows both broad similarities and contrasts with other areas of continental Europe during this period. With the withdrawal of Roman military protection in the first two or three decades of the 5th century AD, there appears to have been abandonment of small Roman *villae* and farmsteads appear to have been abandoned, although central places like Mértola and a few religious sites in the area continued to be occupied (Lopez 2003), there is a period of rural site archaeological invisibility that lasts for about two centuries. In the late 6th and early 7th centuries, small rural hamlets of a medieval character began to appear in the survey area, followed by a period of sustained, and probably accelerating growth (Boone & Worman 2007). House compounds in the early period consisted of rows of three to four contiguous but separate rectangular rooms, each with a separate door to the exterior facing southeast. Individual hamlets during this period appear to have consisted of only one or two such compounds per settlement.
This period of growth culminated in a wholesale reorganisation of the settlement pattern into aggregated hilltop villages during the mid to late 10th century. This period coincided with the consolidation of al-Andalus under the Umayyad Caliphate in Córdoba, and it is at this point that the first clear signs of Islamisation, or at least, Arabization began to appear in the archaeological record in the form of Islamic courtyard style house compounds, glazed Islamic style cooking and serving wares, Islamic glass, and Arabic inscriptions. In the later period, household layout is roughly similar, except that the rooms “curl” around at angles to enclose an interior courtyard, thus taking the form of the typical Islamic courtyard house. In the aggregation period, settlements could consist of up to thirty or forty such compounds, although much smaller settlements also existed contemporaneously. Houses in both periods were tile-roofed structures with dry stone masonry walls packed with dirt, with occasional use of cobble-stones or slabs of slate for floor and patio pavements.

These later settlements continued to be occupied for about 150 to 200 years, at which point there seems to have been a wholesale abandonment of rural settlements in the region around 1150 AD. Boone and Worman (2007) have presented geoarchaeological evidence that increased rural population densities during the later Islamic period apparently caused widespread environmental degradation, which in turn may had led to this abandonment episode. Soil erosion throughout much of the study area, apparently caused by widespread cultivation on hill-slopes, initially created pockets of deep, well-watered soils at the base of denuded slopes. This initial phase of landscape change may, at least in part, explain the aggregation of rural populations into larger villages located near these loci of high agricultural potential at about A.D. 1000. Subsequently, however, populations continued to grow and continued erosion from hill-slopes eventually fostered the
formation of incised channels along ephemeral stream systems. These channels effectively transported both water and sediments to trunk streams and thus negatively impacted the agricultural potential of land throughout the study area by removing topsoil from fields. A charcoal sample from within one of these channels was radiocarbon dated to 890 ± 40 $^{14}$C yr BP (1035 - 1315 AD, median value 1127 AD) (sample GX-30696 in Table 1) suggesting that this process may have been underway by the mid-12th century. This erosion event coincides with the wholesale abandonment of rural settlement in the survey area nearly a century before the Christian conquest of the region in 1238 AD. We note also that this event coincided with a period of arid conditions indicated by the data analysed below.

After the conquest of Mértola by the Portuguese in 1238 AD, the entire region came under the control of the military Order of Santiago, which established its headquarters in the alcaçova (citadel) of Mértola. Although some larger settlements in the area, such as Mértola and Alcaria Ruiva, continued to be occupied, much of the region appears to have been effectively abandoned. Resettlement of the area, probably by farmers from the north, seems to have begun by the late 14th century AD.
Figure 6.1: Map showing the location of the study area in the Lower Alentejo.
<table>
<thead>
<tr>
<th>Sample provenience</th>
<th>14C Age BP</th>
<th>Calibrated 2σ age ranges (cal. AD)</th>
<th>Relative probability within 2σ</th>
<th>Median probability value (cal. AD)</th>
<th>δ13C</th>
<th>Δ13C</th>
<th>Lab Number</th>
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<th>Relative probability within 2σ</th>
<th>Median probability value (cal. AD)</th>
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<td>252±32</td>
<td>1517 - 1594 AD 0.24</td>
<td>1660 AD</td>
<td>-25.2‰</td>
<td>19.87‰</td>
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<td>1911 - 1950 AD</td>
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<td>Post-Bomb</td>
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<td>N/A</td>
<td>1950 AD</td>
<td>-29.6‰</td>
<td>22.76‰</td>
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Table 6.1: Table of radiocarbon dates from the Lower Alentejo.
All dates are AMS dates except those from Mértola and sample C427. Calibrations were calculated using CALIB version 6.0 (Stuiver and Reimer 1993) and the IntCal09 calibration curve (Reimer et al. 2009).
Carbon Isotope Discrimination and Photosynthesis

There are three naturally occurring isotopes of carbon. The dominant form is $^{12}C$, composing 98.9% of natural carbon. The isotope $^{13}C$ composes about 1.1% of the remainder while the unstable $^{14}C$ isotope occurs in a minute fraction of carbon globally. Radiocarbon ($^{14}C$) has played a long and productive role in archaeology as its constant decay rate in organic materials allows for dating (Arnold and Libby 1949; Taylor 2001). The concentration of stable carbon isotopes in plants, $^{12}C$ and $^{13}C$, are affected by the process of photosynthesis. The concentration of $^{13}C$ in a plant is generally denoted as $\delta^{13}C$, a deviation from the PDB standard which has a known molar concentration (Craig 1957; Coplen 1994).

Farquhar and colleagues (1982) developed an expression to express the effects of internal $\delta^{13}C$ after carbon fixation in $C_3$ plants:

$$
\delta^{13}C_p = \delta^{13}CO_2 - a - (b - a)p_i/p_a
$$

(1)

where $\delta^{13}CO_2$ defines atmospheric $\delta^{13}C$ carbon dioxide values, $\delta^{13}C_p$ defines the isotopic carbon product of photosynthesis, $a$ is fractionation brought by diffusion through stomata (4.4%) , $b$ is the effect of RuP$_2$ (27%), and $p_i/p_a$ the ratio between the CO$_2$ partial pressure in the intercellular leave space and atmosphere, respectively.

A model for photosynthetic discrimination in leaves was developed by Farquhar and Richards (1984) to analyze whole plant processes in the same terms as chemical processes. This employs measurements of $\delta^{13}C$ in both the air and in plants:
\[
\Delta^{13}C = a - (b - a)p_a/p_a = (\delta^{13}C_{O_2} - \delta^{13}C_p)/(1 + \delta^{13}C_p/1,000)
\] (2)

The resulting discrimination value (\(\Delta^{13}C\)) directly expresses the results of plant photosynthesis, whereas raw \(\delta^{13}C_p\) records both source (atmospheric) concentration and plant biological processes. The value \(\Delta^{13}C\) provides a more direct inference into the stresses that affect a plant. However, it is important to note that \(\Delta^{13}C\) and water use efficiency can vary independently due to a variety of factors within the plant (Seibt et al. 2008). Long-term drought response can involve changes into leaf shape that can lessen changes in \(\Delta^{13}C\).

Research over the past three decades have found a relationship between \(\delta^{13}C\), \(\Delta^{13}C\), and water use efficiency as a response to dry conditions. Leavitt and Long (1986; 1988) found that \(\delta^{13}C\) values in piñon pine trees across the Southwestern US correlate with the Palmer Drought Hydrological Index (PDHI). The \(r^2\) values ranged in strength from 0.09 to 0.93. The same \(\delta^{13}C\) values correlated weakly with tree ring width in the same trees, \(r^2\) values ranged in strength from 0.05 to 0.70. Trees tended to be enriched in \(^{13}C\) during the droughts of the 1950s and 1930s. Values of \(\delta^{13}C\) from German oak trees \textit{Quercus robur} and \textit{Quercus petraea} showed a strong enrichment during the Younger Dryas period (Becker et al. 1991). Werner and Máguas (2010) found significant correlations between \(\Delta^{13}C\) and seasonal water potential in \textit{Cistus albidus L.} (\(r^2 = 0.54\)), \textit{Cistus monspeliensis L.} (\(r^2 = 0.30\)), \textit{Olea europeae Brot.} (\(r^2 = 28\)), and \textit{Quercus coccifera L.} (\(r^2 = 0.25\)). They also found much lower \(\Delta^{13}C\) values in the three genera during a sustained drought in the summer of 2001. Consistently relationships are found between \(^{13}C\) discrimination in \(C_3\) plants and measures of water availability. While these relationships vary in strength, there are frequently highly significant. For archaeologists, who routinely receive \(\delta^{13}C\) values reported with radiocarbon
dates, this body of literature suggests that stable carbon isotope data have unmet potential in paleoclimate reconstruction.

Not all research has found strong relationships between stable carbon isotope ratios and climate. February and Stock (1999) found no relationship between local precipitation and δ¹³C values from tree rings of *Widdringtonia cedarbergensis*, though they were able to replicate the depletion in atmospheric $^{13}$CO$_2$ due to anthropogenic carbon emissions. Both Δ¹³C and δ¹³C can vary independent of water use efficiency due to other factors influencing photosynthesis, which explains why values do not always correlate well (Seibt et al. 2008). Raw plant δ¹³C values vary with atmospheric δ¹³CO$_2$ values, which can vary depending on planet-wide carbon emissions and sinks (Marino and McElroy 1991, Marino et al. 1992). Values of Δ¹³C are less affected by changes in atmospheric δ¹³CO$_2$ values so long as an estimate of atmospheric δ¹³CO$_2$ values is available (Farquhar et al. 1989). Several samples are needed to increase confidence that changes in Δ¹³C reflect changes in climate. Perhaps most crucially, C₃ plants in different biomes have different ranges of Δ¹³C (Diefendorf et al. 2010). Leavitt and Long (1986; 1988) found mixed results in their samples of trees across the US Southwest. Some trees correlated strongly with the PDHI, others were not as strong. Nonetheless Leavitt and colleagues (2007b) have recently proposed a method of reconstructing PDSI using δ¹³C values from trees.

Different parts of a plant will vary in δ¹³C values as well. Craig (1957) first noted that the photosynthetic tissue of a plant is more depleted in δ¹³C relative to the heterotrophic tissue of a plant. The term ‘heterotrophic’ tissue covers all non-photosynthetic portions of a plant, and includes wood, stems, seeds, and roots. Cernusak and colleagues (2009) note that this effect is not constant. Some species, like *Pinus monticula*, have a low level of δ¹³C enrichment in heterotrophic
tissue. Others, such as *Populus tremuloides*, have as much as a 3‰ difference in δ¹³C values in different tissues. Additionally, phloem δ¹³C values have been found to vary with daily changes in environmental conditions while still undergoing an as-yet little understood post-photosynthetic fractionation effect (Rascher et al. 2010). Given these complicating factors, plants can still vary within the same environment (Sternberg and DeNiro 1983). Nonetheless, some correction needs to be made when comparing δ¹³C values from heterotrophic tissue (such as charcoal) to δ¹³C of photosynthetic tissue in field studies.

**Methods**

Radiocarbon dates employed in the present study (Table 1) were calibrated using Calib 6.0 software with the intcal09 calibration curve (Reimer et al. 2009). Values of Δ¹³C were calculated from δ¹³C data associated with charcoal radiocarbon dates from sites within the Lower Alentejo in Southeastern Portugal using equation (2). Values for atmospheric δ¹³CO₂ came from the European Project for Ice Coring in Antarctica (EPICA) (Elsig et al. 2009) and Law Dome (Francey et al. 1999). Bayesian change-point analysis was run on the combined record for a period overlapping with the Lower Alentejo radiocarbon record (510 - 1950 AD) using the Barry and Hartigan (1993) algorithm. The model had a burn-in of 10,000 iterations and posterior probabilities were generated from 10,000 Markov-Chain Monte Carlo simulations. These simulations were run in R using the bcp package with hyper parameter defaults recommended by Erdman and Emerson (2007). Resulting atmospheric δ¹³CO₂ values were used to calculate Δ¹³C values for charcoal samples from the Lower Alentejo using equation (2). For the post-bomb charcoal sample, a δ¹³CO₂ value of -8.0‰ was used.
The range of these $\Delta^{13}C$ values was compared to the observed variation in $\Delta^{13}C$ from taxa in the Parque Natural da Serra da Arrábida in Southwestern Portugal. Heterotrophic (woody) tissue can be more enriched in $\delta^{13}C$ (Craig 1957; Cernusak et al. 2009, Rascher et al. 2010), $\Delta^{13}C$ values are lower than reflected in photosynthetic tissue such as leaves. A correction of 0.53‰ was added to each charcoal $\Delta^{13}C$ value to match the means of the archaeological and ecological $\Delta^{13}C$ used in Werner and Mágualas’ (2010) study and to correct for $\delta^{13}C$ enrichment in heterotrophic tissue. Samples were compared to the variation in $\Delta^{13}C$ under observed conditions in the same region (Werner and Mágualas 2010).

**Results**

![Figure 6.2: Posterior means of atmospheric values of $\delta^{13}C$ reconstructed from combined EPICA and Law Dome records.](image)

A slight increase in atmospheric $\delta^{13}C$ are seen preceding the beginning of the Medieval Warm Period, potentially suggesting a change in global carbon sinks at that time. The sharp decline in atmospheric $\delta^{13}C$ values beginning in the 1800’s is attributable to anthropogenic carbon emissions; modern values have surpassed -8.0‰.
Figure 6.3: Time-series of $^{13}$C discrimination ($\Delta^{13}$C) in the Lower Alentejo, plotted along calibrated median values. The light grey band represents a 95% confidence interval for $\Delta^{13}$C. There is evidence for arid conditions lasting from the mid 11th to early 12th centuries AD and again the late 15th to mid 17th centuries AD due to a cluster of low $\Delta$ values. These drier conditions may be associated with the Medieval Warm Period, which lasted from 1000 to 1200 AD, though the first 100 years show the strongest warming signal. No dates were collected between from the mid 12th through the early 15th centuries AD. There is evidence for human population abandonment and widespread soil erosion preceding that period. The dark grey portion of the grid at the bottom of the figure ($\Delta^{13}$C < 18.5‰) represents minimum $\Delta^{13}$C values of Olea europea, Quercus coccifera, Cistus albidus and monspelensis that occurred during the 2001 drought year (Werner and Mágua 2010).

Isotopic data from both the Lower Alentejo show two time periods that fall within the observed range of $^{13}$C discrimination of Cistus, Quercus, and Olea in dry conditions. While there is no taxa attribution for the charcoal in this analysis, $\Delta^{13}$C for all three genera fall within the range of observed variation under drought conditions for the three taxa. The first period of low $\Delta^{13}$C occurred from the mid 11th to early 12th centuries AD. The second takes place from the late 15th to mid 17th centuries AD, though it is represented by far fewer points. A single median date value in the early 9th century AD also falls within the range of lower $\Delta^{13}$C values associated with drier conditions. These date ranges are derived from radiocarbon data (Table 1), and as such may vary by decades.
<table>
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<th>Late (n=870)</th>
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<td>12.4%</td>
<td>42.1%</td>
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<tr>
<td>Evergreen Quercus</td>
<td>65.5%</td>
<td>27.2%</td>
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<tr>
<td>Deciduous Quercus</td>
<td>0.9%</td>
<td>3.0%</td>
</tr>
<tr>
<td>Olea europeae</td>
<td>17.3%</td>
<td>7.6%</td>
</tr>
<tr>
<td>Other</td>
<td>1.30%</td>
<td>12.20%</td>
</tr>
<tr>
<td>Indeterminate</td>
<td>2.7%</td>
<td>7.7%</td>
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Table 6.2: Taxa occurrence in the Lower Alentejo by period.

Early taxa in the Lower Alentejo is dominated by evergreen Quercus specimens. Over the course of intensified human occupation, Cistus increases, reflecting both deforestation and increasing aridity of the landscape (Boone & Carrión Marco, n.d.). Olea also decreases over the course of intensified land use by humans.

**Discussion**

Values of $^{13}$C isotope discrimination from Lower Alentejo are suggestive of more arid conditions for almost a century preceding the abandonment of the rural Lower Alentejo in the mid-12th century. This period of lower average $\Delta^{13}$C values occurs during the first half of the Medieval Warm Period. In addition to lower $\Delta^{13}$C, archaeological survey has found evidence for soil erosion in the area in the centuries during and following the identified drought. Abundant botanical remains include members of Cistus, Quercus, and Olea. Values of $\Delta^{13}$C in each taxa have a highly significant correlation with water potential (Werner and Mágua 2010). The range of discrimination between the three genera overlap, with Quercus having a lower mean isotopic discrimination. For all observed species studied by Werner and Mágua, fractionation below 18.5% is associated with drier conditions and higher water potential.

Plants used for radiocarbon analysis in the Lower Alentejosamples were not identified prior to analysis. As Quercus, Olea, and Cistus have differing ranges in carbon isotope discrimination, this limits the full potential of drought inference at the site. However, hundreds of other pieces of carbon found in the same locations as the radiocarbon dates have been identified to the genus level. Early in the occupation of the Lower Alentejo Quercus specimens represent 65.5% of the
carbonized wood found in archaeological sites, while *Cistus* represents only 12.4% of the taxa (Table 2). Later in the site’s chronology *Quercus* specimens decrease in frequency, representing 27.2% of carbonized wood. *Cistus* increases to compose 42.2% of the specimens examined. This is interpreted as the consequence of deforestation and soil erosion that accompanied rising population levels (Boone and Worman 2007). *Cistus* is better adapted to handle more arid conditions and has been observed spreading through previously forested areas after significant droughts and wildfires (Açacio et al. 2009).

Values for Δ¹³C show little indication of aridity for the period of settlement expansion and population growth in the Lower Alentejo between the 6th and 10th centuries. Lower average Δ¹³C values in the Lower Alentejo occurred during the first half of the Medieval Warm period (1000 - 1100 AD), where a small uptick in temperatures occurs in many regions (Lamb 1982). The Medieval Warm Period has been associated with droughts in California and Patagonia (Stine 1994), Equatorial East Africa (Verschuren et al. 2000), and Western North America (Herweijer et al. 2007). Generally the Medieval Warm Period is interpreted as an increase in warmer, pluvial conditions across most of Europe (Campbell 1997). However Magny and colleagues (2003) note that while Central Europe enjoys wetter conditions, the Mediterranean region is drier. A survey of alluvium and sea surface temperatures off the coast of Lisbon, Portugal suggests arid conditions during the Medieval Warm Period (Abrantes et al. 2005). Jalut and colleagues (1997; 2000; 2009) identify the period from 600 - 1250 AD as a general period of aridity based on the pollen ratio of deciduous broad-leaf and evergreen sclerophyllous trees. This time period would cover the entire history of post-Roman occupation of the Lower Alentejo. Little is known about paleoclimate in the Western Mediterranean, and it is difficult to assess climate patterns of the Iberian peninsula prior to
the recent past. Available pollen data suggest that the region was generally arid during the time period of human occupation. The heightened aridity during the Medieval Warm Period, in conjunction with the soil erosion and high population levels, may have contributed to the abandonment of the rural areas of the Lower Alentejo in the following centuries.

Additional low $\Delta^{13}C$ values occurred between the mid 15th and late 17th centuries AD, but is represented by far fewer points. With so few data, it is difficult to infer any general patterns. However, historical data suggest droughts occurred throughout this period in high frequency (Do Ó and Roxo 2008). Tavares (2004) identified droughts in the decades of the 1530’s and 1570’s AD based on a study of royal correspondence among the ruling Portuguese families; consistent with low $\Delta^{13}C$ values for that time interval in our reconstruction. However, the uncertainty of any radiocarbon date likely precludes historical identification with any but the longest droughts.

**Conclusion**

Values of $\Delta^{13}C$ show little evidence for arid conditions between the 6th and 10th centuries AD, a period of population growth in the Lower Alentejo. A decrease of $\sim$1‰ in $\Delta^{13}C$ values in charcoal specimens from the Lower Alentejo is consistent with an increase in temperature in many regions during the Medieval Warm Period, soil erosion, and macrobotanical data suggesting increased arid conditions during that period. These data illustrate a potential application of stable carbon isotope ratios in paleoclimate reconstruction in archaeological sites. Different species will have different relationships between $\Delta^{13}C$ and water use efficiency, and as such contemporary botanical and plant biochemical research will be indispensable in shaping paleoclimate interpretations in archaeological contexts.
Chapter 7: The Influence of Climatic Change on the Late Bronze Age Collapse and the Greek Dark Ages
Brandon L. Drake

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Abstract

Between the 13th and 11th centuries BCE, most Greek Bronze-Age palatial centers were destroyed and/or abandoned. The following centuries were typified by low population levels. Data from oxygen-isotope speleothems, stable carbon isotopes, alkenone-derived sea surface temperatures, and changes in warm species dinocysts and foraminifera in the Mediterranean indicate that the Early Iron Age was more arid than the preceding Bronze Age. A sharp increase in Northern Hemisphere temperatures preceded the collapse of palatial centers, a sharp decrease occurred during their abandonment. Mediterranean Sea surface temperatures cooled rapidly during the Late Bronze Age, limiting freshwater flux into the atmosphere and thus reducing precipitation over land. These climatic changes could have affected palatial centers that were dependent upon high levels of agricultural productivity. Declines in agricultural production would have made higher-density populations in Palatial centers unsustainable. The ‘Greek Dark Ages’ that followed occurred during prolonged arid conditions that lasted until the Roman Warm Period.

Introduction

At the end of the Late Bronze Age (LBA) most Eastern Mediterranean urban centers were either destroyed or abandoned throughout the Near East and Aegean (Andronikos 1954; Vermeule 1960; Desborough 1964; Carpenter 1966; Weiss 1982; Iakovidès 1986; Neumann and Parpola
This period of dissolution begins in the Late Helladic (LH) IIIB (1315 - 1190 BCE) and is complete by the end of the LH IIIC (1050 BCE). The following four centuries are typified by rural settlements, population migration, and limited long-distance trade, a period termed the ‘Greek Dark Ages’ for the Aegean region (Desborough 1972). The LBA collapse is associated with the loss of writing systems such as Linear B (Palaima 2010), and the extinction of Hatti as both a written and spoken language (Fortson 2004). Writing and literacy do not return to the Aegean until the end of the ‘Greek Dark Ages’ in 8th century BCE with the spread of the Phonecian alphabet (Sass 2006).

For decades theorists have developed hypotheses to explain the drastic changes in settlement patterns at the end of the LBA. They can be divided into three broad classes: economic, military, and climatic explanations. Recently, Kaniewski and colleagues (2010) have suggested that a centuries-long megadrought caused the widespread systems collapse of Bronze Age Palatial civilization. This hypothesis is testable as such a drought should be reflected in multiple climate proxies available for the time period.

This paper will review existing arguments for the LBA collapse alongside paleoclimate proxy records, including:

i) paleorainfall derived from stable oxygen-isotope speleothem records,
ii) stable carbon isotope chronologies from pollen records in Greece
iii) alkenone sea surface temperatures (SSTs) derived from Mediterranean sediment cores,
iv) warm/cold species dinocysts and formanifera from Mediterranean sediment cores,
v) paleotemperature proxies derived from Greenland ice cores, and
vi) solar irradiance data derived from cosmogenic Beryllium (\(^{10}\)Be) in ice cores.

**Archaeology of the Late Bronze Age Collapse**

The collapse of palatial civilization at the end of the Bronze Age (1315 - 1190 BCE) occurred in different places at different times over the course of two centuries. Many of these destructions have been attributed to human-causes. Large population migrations took place, most famously with the incursions of the ‘Sea Peoples’ into the Nile Delta and the Levant (Sandars 1987). Following this period, societies of the Eastern Mediterranean enter into a long-term decline. By 1050 BCE, most urban centers had been abandoned. In the Aegean region the following 350 years are known as the ‘Greek Dark Ages’, where low population levels lead to little archaeological visibility (Desborough 1972).

In Egypt, several inscriptions detailed wars with ‘Sea People’ from the Nile Delta to the Levant beginning in the reign of Ramses II (1279 - 1213 BCE). In the southern Levant, pottery began to resemble Mycenaean types, but analysis suggests that they were locally produced, suggesting a population migration from the Aegean region to the coastal Levant (Mazar 1990). While the population movements of the ‘Sea People’ were better documented in Egypt and the Levant, they have been tied to destabilization of the Aegean region as well (Beckman 2000). The label of ‘Sea People’ is broad, and likely covered many ethnic groups, including many that were of Greek origin (Chadwick 1976). Large population movements and the possible use of mercenary
military forces had a destabilizing effect on the economy (Vermeule 1960). Andronikos (1954) argued that the destructions during this time period could reflect rebellion along different class lines. Regardless of the source of the destructions, with trade relationships broken down it was difficult for leaders to maintain control over their local districts. This economic decline resulted in the widespread dissolution of polities (Iakovides 1986). Once the polities were dissolved it was impossible to reestablish a central authority (Betancourt 1976; Hutchinson 1977).

While economic systems collapse continues to be the dominant perspective of the collapse of Palatial Civilization in the Bronze Age (Iakovides 1986), climatic/environmental explanations have also been proposed. Carpenter (1966) was the first to propose a drought as the cause of the dissolution of Mediterranean Palatial Civilization. Atmospheric circulation patterns that could have resulted in a short-term drought may have been present during the Late Bronze Age (Bryson et al. 1974). Weiss (1982) found that the entire Eastern Mediterranean could have been struck by climate anomalies under the circulation patterns proposed by Bryson and colleagues.

An important consideration is the effect of earthquakes in the region. Schaeffer (1948, 1968) proposed that tectonic instability in the area could have been responsible for the simultaneous abandonment of cities in the Eastern Mediterranean. Earthquakes in the region tend to occur in clusters, and a series of earthquakes over one or two generations could have contributed to the destabilization of several polities (Nur 1998; Nur and Cline 2000). Many destruction layers indicate earthquake-caused damage (Nur and Cline 2000).

**Paleoclimate**
Discussions of climate and the end of Palatial Civilization in Greece have focused on Carpenter’s (1966) proposed drought event (Bryson et al. 1974; Weiss 1982). Kaniewski and colleagues (2010) were the first to identify a shift in climate as a factor in the changes at the end of the Bronze Age. At the site of Giala-Tell Tweini in Syria they identified the period between 1200 - 850 BCE as one of prolonged drought through pollen and alluvial records. Issar (2003) also argued that the migrations of the Late Bronze Age/Early Iron Age were the consequence of heightened aridity. More recent work also suggests arid conditions for the same time period (Mayewski et al. 2004; Finné et al. 2011).

Figure 7.1: Map of Eastern Mediterranean, including sediment core locations (Emeis et al. 1998; Emeis et al. 2000; Rohling et al. 2002), oxygen-isotope speleothem records from Soreq Cave (Bar-Matthews et al 1997; Bar-Matthews et al. 2003), and stable carbon isotope values from Lake Voulkaria (Jahns 2005).

Three additional lines of evidence suggest a prolonged arid period in the Eastern Mediterranean at the end of the Late Bronze Age and into the Early Iron Age. The first comes from
oxygen-isotope speleothem data from Soreq Cave in Northern Israel (Bar-Matthews et al. 1998; Bar-Matthews et al. 2003) which indicates low annual precipitation during the Late Bronze Age/Early Iron Age (LBA/EIA) transition. The second is derived from stable carbon isotope data in pollen cores from Lake Voulkaria in Western Greece (Jahns 2005) which record a drop in $^{13}$C discrimination during this period. The third is a series of Mediterranean sediment cores that record a drop in surface sea temperatures (SST) (Emeis et al. 2000) and a reduction in warm-species dinocysts (Rohling et al. 2002, Sangiorgi et al. 2003).

**Stable Oxygen Isotope Speleothem Records**

Soreq cave in Israel contained a 150,000 year record of precipitation for the northern Levant (Bar Matthews et al. 1997; Bar Matthews et al. 2003). Reconstructed paleo-rainfall from Soreq document three severe drops in precipitation during the Holocene. The first two were consistent with known climatic events: the Younger Dryas and an aridization event at 3150 BCE associated with widespread erosion in the Middle East and spikes in dolomite and calcium carbonate concentrations in the Gulf of Oman (Bar Matthews et al. 2003; Cullen et al. 2000). The third decline in precipitation occurred at 1150 BCE, contemporaneous with the recently proposed multi-century drought in the Levant (Kaniewski et al. 2010).

**Plant Stable Carbon Isotopes**

Recent research has shown that the discrimination against $^{13}$C in C$_3$ plants varies due to mean annual precipitation (Diefendorf et al. 2010). This relationship appeared to be the consequence of plant adaptations to arid environments. C$_3$ plants in arid regions are more conservative with their water use and this is reflected in their discrimination against $\delta^{13}$C. The
implication of research in stable carbon isotopes is significant for archaeological data. As radiocarbon dating procedure requires the reporting of $\delta^{13}C$ values (Stuiver and Polach 1977), there is potential to identify paleoclimate signals in data already gathered by archaeologists. Riehl and colleagues (2008) examined carbon discrimination in barley plants in Anatolia, and found lower rates of discrimination at 2250 BCE and 3150 BCE - both significant short-lived aridization events in the broader region (Bar-Matthews et al. 2003; Cullen et al. 2000).

Stable carbon isotope data from C$_3$ plants tend to be highly variable, and can be influenced by factors other than water availability (Seibt et al. 2008). Recently, the use of "representative" stable carbon isotope values has been suggested (Leavitt 2008); a procedure in which data from multiple plants is aggregated to highlight a broader climatic signal. Theoretically, this procedure could be done on stable carbon isotopes from radiocarbon dated pollen. This data would produce representative stable carbon isotope values for a region. Rather than reflect specific droughts, this data could reflect the spread of plants adapted to arid regions, the kind of broad biome data used by Diefendorf and colleagues (2010).

*Surface Sea Temperatures*

The temperature of surface sea water governs evaporation rates, which in turn affect the amount of moisture available to storm systems. The sea level freshwater flux (E - P, evaporation minus precipitation) provides the strongest input to the Mediterranean region’s hydrological cycle (Mariotti et al. 2002). Most precipitation in the Eastern Mediterranean comes during the winter, when the cold and dry westerlies sweep in and absorb water vapor evaporating from the warmer Mediterranean (Issar 2003). From 1979 - 1993, the peak evaporation rate in the Mediterranean occurred in December with 1500 - 1600 mm/yr of water taken up by the westerlies. That same
month the Mediterranean region experienced precipitation maxima, at 800 - 900 mm/yr (Mariotti et al. 2002). The lowest evaporation rates (600 - 700 mm/yr) in May/June were followed by precipitation minima in June/July (100 - 200 mm/yr). In the Mediterranean, precipitation over land is constrained by water evaporating from the sea. In turn, evaporation in the sea is constrained by temperature differentials between the sea and surface air. Lower sea surface temperatures (SSTs) depress evaporation by reducing the temperature difference between the warmer sea waters and cold winter air. Changes in Mediterranean SST have been linked to precipitation cycles in Anatolia (Kwiecien et al. 2009; Bozkurt and Sen 2011) and in the Sahel (Rowell 2003). In both cases, warmer SST’s led to saturation of the troposphere and increased precipitation during rainy seasons.

Past sea surface temperatures can be estimated from lipids using the alkenone unsaturation index (Brassell et al. 1986) derived from date modeled layers in marine sediment cores. Faunal and isotopic analysis can also be used to estimate major changes in SST (Hemblen et al. 1989; Rohling et al. 1993), as many species are constrained to warm or cold water. Multiple sediment cores in the Eastern Mediterranean form a 400,000 year record of SST variations (Emeis et al. 1998; Emeis et al. 2000). Time series temperature records exist for the Ionian Sea, Levantine Basin, and Adriatic Sea throughout most of the Holocene (Cacho et al. 2000). Records of warm-species dinocysts and foraminifera are available from the Adriatic and Aegean seas, respectively.

**Methods**

**Terrestrial Records**

Stable carbon isotope values from radiocarbon-dated pollen from a sediment core in Voukaria Lake in Western Greece (Jahns 2005) were used to calculate $^{13}\text{C}$ discrimination ($\Delta^{13}\text{C}$) values following standard procedures (Farquhar et al. 1982; Farquhar and Richards 1984):
\[ \Delta^{13}C = \delta^{13}C_a - \delta^{13}C_p/ (1 - \delta^{13}C_p/1000) \]

where \( \delta^{13}C_a \) represents atmospheric \( \delta^{13}C \) values of CO\(_2\) and \( \delta^{13}C_p \) represents plant \( \delta^{13}C \) values. Carbon discrimination values developed from radiocarbon pollen represent biome-level carbon discrimination, rather than the activities of specific plants. Values for \( \delta^{13}C_a \) came from the European Project for Ice Coring in Antarctica (EPICA) (Elsig et al. 2009). An average value of -6.36‰ was used to calculate \( \Delta^{13}C \) at 538 BCE, as data from EPICA shows evidence for modern contamination via an ice core break as reported by the investigators (Elsig et al. 2009), though resulting \( \Delta^{13}C \) values are only decreased by 0.79‰.

The carbon discrimination time-series was compared with paleo-rainfall estimates developed from stable oxygen isotope speleothems in Soreq cave in Israel (Bar-Matthews et al. 1998; Bar-Matthews et al. 2003). Destruction and occupation layers from Minoan and Mycenean sites were organized into a database after a review of literature (Tables 1 and 2). Occupation layers were added for each time period from the Early Helladic 1 to the Late Helladic IIIC and subtracted by destruction and abandonment layers.

Broader records of Holocene climate were included to show changes in the Northern Hemisphere contemporaneous with the LBA Collapse. Northern Hemisphere temperature reconstructions derived from the Greenland Ice Sheet Project (GISP2) (Alley 2004) and solar irradiance data derived from cosmogenic radionuclide \(^{10}\)Be (Steinhilber et al. 2009). Reconstructed temperature and temperature anomalies record global climate conditions, solar irradiance assesses
the potential for solar forcing of climate. Solar activity has been found to correlate with SST in the Northern Hemisphere (Jiang et al. 2005), and with wind can contribute to broad changes in SST.

**Marine Records**

Alkenone SSTs were reconstructed from sediment cores in the Ionian Sea (Emeis et al. 2000), Aegean Sea (Rohling et al. 2002), and Adriatic Sea (Sangiorgi et al. 2003). The ratio of warm/cold species dinocysts in the Adriatic (Sangiorgi et al. 2003), and formanifera in the Aegean (Rohling et al. 2002) provide an additional indicator for relative changes in SST. Dating for sediment core LC-21 in the Aegean reveals an age discrepancy of 330 years for ash from the Santorini eruption (Rohling et al. 2002), in the present study all dates falling within the past 5,000 years were corrected (-330 years) to match this historical event dated to 1623 - 1627 BCE based on SO$_4^{2-}$ residuals above 25 ppb in the GISP2 core (Zielinski et al. 1994).

**Data Analysis**

Analysis of paleoclimate proxies and changes in human occupation was performed using Bayesian change-point analysis. The Barry and Harrington (1993) algorithm was employed, with defaults following the recommendations of Erdman and Emmerson (2007), including 10,000 burn ins, and 10,000 Markov chain Monte Carlo resampling events. This procedure assesses the chance of a significant change-point through the use of partitions. Each partition mean was denoted as $\mu_{ij}$, where $\mu$ represents the mean of the block between points $i + 1$ and $j$. Each observation of data is held to be independent $N(\mu, \sigma^2)$ with a prior distribution of $N(\mu_0, \sigma_0^2/(j - i))$. For each calculated partition mean, a probability of a change point is assessed through the sum of squares inside and between the partitions. Over multiple iterations, the means are averaged to produce a posterior
mean with a posterior probability for a change-point. The bcp package developed by Erdman and Emmerson (2007) for R was used to run Bayesian change point models. This analysis helps assess the significance of changes that are found during the critical time period in the Late Bronze Age/Early Iron Age. Specifically, a high posterior probability will indicate a significant long-term change in a paleoclimatic record. An event with a low posterior probability does not necessarily mean it is not-significant, but it may indicate that the partition contained an isolated event, rather than a long-term climatic change. The posterior probability can be used to more precisely time changes in the paleoclimatic records.

All statistics and charts were generated using the open-source statistical program R, source code is included in supplementary materials. Compilation of figures and charts took place using Adobe Photoshop CS5.
Results

Figure 7.2: Paleo annual rainfall reconstructed from oxygen isotope speleothem data (top; Bar-Matthews et al. 2003) and $^{13}$C discrimination calculated from pollen radiocarbon dates (second line; Jahns 2005).

Both records indicate a drop in precipitation beginning near the LBA collapse (a) and continuing through the “Greek Dark Ages”. Both records also indicate a climatic recovery during the Roman Warm Period (b). Occupation of Palatial centers in Greece (third line) and Crete (last line) show a sharp drop near the beginning of the hypothesized arid period. Dark shading around lines represents 95% confidence bands. The LBA collapse, extends from (a) to the final disappearance of recognizable Mycenaean culture before 1000 BCE.
Figure 7.3: Eastern Mediterranean sea surface temperatures (SST) as indicated by alkenone temperatures and warm-species foraminifera.

A drop of SST can indicate lower levels of evaporation, which in turn indicate less precipitation. The Ionian Sea (top line; Emeis et al. 2000) dropped by 4 °C following the LBA Collapse (a). Temperatures returned to their pre-LBA Collapse levels during the Roman Warm Period (b). A drop of 3 °C during the Medieval Warm Period (c) occurs as well. Adriatic SST (second line; Sangiorni et al. 2003) dropped 1 - 2 °C after the LBA Collapse (a), however a 25% reduction in Adriatic warm-species dinocysts (third line; Sangiorni et al. 2003) before the LBA Collapse (a) suggests cooling may have been rapid and severe. A similar decline in warm-species foraminifera in the Aegean Sea (last line; Rohling et al. 2002) at the same time suggests significantly cooler waters as well. Dark shading around lines represents 95% confidence bands.
A large increase and sharp decrease in Northern Hemisphere temperatures occurred during the LBA Collapse (a). Similar (albeit smaller) temperature decreases terminated the Roman Warm Period (b) and Medieval Warm Period (c). Low solar irradiance, periods typified by low sunspot activity, are associated with cooler SSTs. Low solar irradiance occurred during the Greek Dark Ages (d), potentially contributing to continued low SSTs. This period of low solar irradiance is comparable to the more well known Maunder Minimum (e).

### Table

<table>
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<th>Record</th>
<th>Date</th>
<th>Change</th>
<th>Posterior Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cretan Occupation</td>
<td>1315 - 1190 BCE</td>
<td>Site Destinations and Abandonments</td>
<td>24.49%</td>
</tr>
<tr>
<td>Mainland Greece Occupation</td>
<td>1315 - 1190 BCE</td>
<td>Site Destinations and Abandonments</td>
<td>90.37%</td>
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<td>Paleo-rainfall in Soreq Cave</td>
<td>1050 - 650 BCE</td>
<td>Drop in paleo-rainfall (~100 mm)</td>
<td>9.82%</td>
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<td>$^{13}$C Discrimination in Lake Voulkaria</td>
<td>1466 - 875 BCE</td>
<td>Drop in $^{13}$C discrimination/drought response (8‰)</td>
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</tr>
<tr>
<td>Ionian SST</td>
<td>1011 - 715 BCE</td>
<td>Drop in sea surface alkenone temperature (3-4 °C)</td>
<td>18.14%</td>
</tr>
<tr>
<td>Adriatic SST</td>
<td>1326 - 1135 BCE</td>
<td>Drop in sea surface alkenone temperature (1-2 °C)</td>
<td>2.02%</td>
</tr>
<tr>
<td>Adriatic Dinocysts</td>
<td>1450 - 1250 BCE</td>
<td>Decline in warm-species dinocysts (24%)</td>
<td>75.80%</td>
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</tr>
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<td>Aegean Formanifera</td>
<td>1694-1197 BCE</td>
<td>Decline in warm-species formanifera (25%)</td>
<td>99.98%</td>
</tr>
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</table>

**Table 7.1: Posterior Probabilities for change-points in palatial center occupation and paleoclimate proxies.** Posterior probability refers to the degree of change relative to most of the Holocene record (2000 CE - 8000 BCE), e.g. the collapse in mainland Greece palatial centers is a much stronger deviation than the same events in Crete as Crete experienced earlier destructions related to the conquest by Mainland Greece and the Santorni eruption. The decline in Ionian SST and both Adriatic and Aegean warm-species dinocysts and formanifera were the largest changes in those records throughout the Holocene. Time periods with high posterior probabilities may contain a significant change.

Discrimination rates for $^{13}$C calculated from stable carbon isotope data in lake pollen records decline with paleorainfall reconstructed from the stable-oxygen isotope record in Soreq cave. Ionian SST values indicate a decline of 3-4 °C during the time period of the hypothesized arid period following the LBA collapse, reaching its coldest point in the Holocene (Emeis et al. 2000). A similar, though less severe, decline of 2-3 °C occurred during the Medieval Warm Period (1000 - 1200 CE; Lamb 1982). However, it is difficult to attribute specific climatic events to the low-resolution Ionian SST record without similar records being available for the same time period. The Adriatic SST data show a more moderate cooling of 1 - 2 °C at the time of the LBA collapse and a 24% reduction in warm-species dinocysts (Sangiorgi et al. 2003). Foraminiferal records from the Aegean Sea indicate a 25% reduction in warm-species foraminifera. No change in SST is observed in data from the Levantine Basin in site ODP-967, though the age model for ODP-967 has been the subject of recent revision (Emeis, personal comm.). Declines in sea surface temperatures would result in less evaporation, which would reduce the exchange of water vapor from marine to atmospheric reservoirs. Less water would in turn precipitate during storm events.

Change-point posterior probabilities indicate that the warm-species foraminiferal/dinocyst declines in the LBA are among the most significant in their respective Holocene records (Table 1). Posterior probabilities document long-lasting declines in warm species dinocysts, warm species...
formanifera, sea surface temperature, and paleorainfall during the LBA/EIA transition. The highest posterior probabilities occur with changes dated to the period between 1694 - 1197 BCE, these are associated with dinocyst and formanifera records in the Adriatic and Aegean seas, respectively. Site abandonments in the Aegean and Crete occur in a more narrow timeframe between 1315 - 1050 BCE. Ionian SST drops at a later date, between 1011 - 715 BCE.

Northern Hemisphere temperatures drop over 2 ºC between 1350 - 1124 BCE (Figure 7.4). Cold conditions continue until 400 BCE. Solar irradiance data suggest at least two drops in solar irradiance comparable to the Maunder Minimum occurred during the ‘Greek Dark Ages’, the period of coldest temperatures during the Little Ice Age (Eddy 1976).

Discussion

Paleoclimatic inference from low resolution records is difficult. These difficulties are compounded for marine records where carbon reservoir effects can complicate radiocarbon dates, as noted by Rohling and colleagues (2002). Bayesian change-point analysis was employed to provide a statement of significance regarding the changes observed in paleoclimate records. High posterior probabilities are associated with the decline of warm species dinocysts/foraminifera in the Adriatic and Aegean seas by 1197 BCE. Evidence for aridity through terrestrial paleoclimate proxies follows by 1050 BCE, though with low posterior probabilities. The Ionian SST record indicates a drop in temperature after 1011 BCE (Figure 7.3), after the beginning of the Greek Dark Ages. While not all records align in a straightforward manner, most are consistent with the interpretation of cooler, more arid conditions during the Greek Dark Ages. Furthermore, terrestrial
records identify a known climatic event, the Roman Warm Period (Orland et al. 2009), to 1CE/1BCE (Figure 7.2). It is important to remember that the paleoclimate proxies that indicate this period of aridity are low resolution records, adding uncertainty to their interpretation.

Multiple climate indices from across Europe, Asia, and Africa indicate arid conditions in the last millennium BCE as well. The period has been broadly characterized as the “Iron Age Cold Epoch” by Van Geel and colleagues (1996). Low lake levels suggest warm, arid conditions in Italy (Dragoni 1998; Sadori and Narcisi 2001), the Swiss Alps (Jus 1982) and France (Digerfeldt et al. 1997), with the low levels occurring from 1150 - 850 BCE. Lake sediments in the Swiss Plateau and timberline fluctuations in the Swiss Alps suggest a warm period from 1250 - 650 BCE (Haas et al. 1997). Lowering lake levels in the peri-Adriatic region (Magny et al. 2006; Magny et al. 2007; Drescher-Schneider et al. 2007) and an expansion of *Quercus ilex* (Colombaroli et al. 2008) suggest a shift to arid conditions after 1050 BCE in the Balkans. In Africa low lake levels occurred in Lake Turkana from 1050 - 150 BCE (Owen et al. 1982). The Sahara in Mali appears to stabilize as a severe arid climate around 1050 BCE (Petite-Marie 1987). The dry conditions of the Chad Basin start around 1050 BCE after an earlier wet period. In East Asia, cold and arid conditions occurred at this time. A cold, arid period occurred on the Tibetan Plateau from 1050 - 550 BCE (Fu-Bau and Fan 1987), while heightened aridity is identified in the Loess Plateau from 1150 - 250 BCE (Huang et al. 2000). Finné and colleagues (2011), in a review of 18 paleoclimate proxies, also identify cold and arid conditions in the Eastern Mediterranean at the close of the LBA.

Cooler SSTs have been associated with reduced temperatures in the spring (Sangiorgi et al. 2003) and winter (Rohling et al. 2002). Rohling and colleagues (2002) have suggested that Aegean SSTs can be attributed to pressure differences resulting from cyclic atmospheric cooling events and
northerly wind/polar air masses moving over the Mediterranean. However, SSTs can be influenced by factors other than atmospheric cooling. A similar decline in sea surface temperature occurs in the Northeast Atlantic during the Medieval Warm Period (Krawczyk et al. 2010). Warming of the SST’s occurred during the Little Ice Age in the same region. Krawczyk and colleagues suggest that warming around 1000 CE led to increased glacial melt, which resulted in an influx of cold freshwater that lowered SSTs. This created an anti-phase event, where warming ultimately results in a drop in SST. Recent work has shown that sea levels rose along the coast of North Carolina in the United States during the Medieval Warm Period due to glacial melt, and stabilized during the Little Ice Age (Kemp et al. 2011). Data from the Ionian Sea suggests that the Medieval Warm Period also resulted in a lower SST of 1 - 2 ºC (Figure 7.3: C), though this is evidenced by only a single data point, as it is a low resolution record. While available evidence suggests that the LBA/EIA period was arid, it is not clear whether this was characterized by warmer or colder conditions.

Low Mediterranean evaporation rates would have had negative impacts on dryland agricultural systems in Mainland Greece and Crete. The long lasting nature of these climatic changes would have put a severe stress on the ability to produce food for large populations. The collapse of LBA Palatial Civilization and the ensuing centuries of low population levels were possibly influenced by these changes in climate. Low sea-surface temperatures and arid conditions let to a drop in precipitation across the Eastern Mediterranean, resulting in drops in agricultural productivity as hypothesized by Kaniewski and colleagues (2010).

The argument for a long-lasting change in climactic conditions is superficially similar to the drought argument proposed by Carpenter (1966). However Carpenter’s argument was for an event, not a broad centuries-long decline in conditions. The drought proposed by Carpenter (1966),
Bryson and colleagues (1976), and Weiss (1982) was short, lasting no more than 5 years. Advocates for the drought hypothesis point to meteorological patterns during the 1950’s drought as an indication of conditions around 1200 BCE; however droughts such as the 1950’s do not appear to be exceptionally rare in the instrumental record of precipitation in Mainland Greece (Grove and Rackham 2003). A short-term, albeit severe, drought is an unlikely candidate for the widespread abandonment of palatial centers, a process that took decades at a minimum. Internal instability (Adronikos 1954), population migrations (Desborough 1964), and earthquakes (Nur and Cline 2000) all likely played a significant role in site destructions. Whatever the cause of some or all site destructions, the broader question is why these centers were not rebuilt and re-occupied following catastrophic events. Occupants in Crete withstood both the Santorini eruption around 1620 BCE (Manning 2010) and external invasion around 1460 BCE (Hallager 2010), yet major palatial centers were quickly rebuilt and reoccupied. The changes at the end of the LBA/EIA were far more pervasive and persistent - suggesting that long-term external processes underlie the synchronous cultural and economic decline.

The changes at the end of the Bronze Age could be better characterized as a ‘gear shift’ in Mediterranean climate. This shift in precipitation would not have been a crises event, but rather a continual stress put on human societies in the region for several generations. There was no one year where conditions became untenable, nor one straw that broke the back of the camel. Climate pressure began during the LBA, and didn't reach its low point until the heart of the Greek Dark Ages. This change in average precipitation fits better with the economic and military interpretations of the decline in Mycenaean civilization. It provides a key external pressure for long-standing economic decline, and a motivation for population migrations such as that of the
‘Sea People’. Climate-influenced drops in food production could have destabilized Aegean palatial centers, resulting in internal uprisings as proposed by Andronikos (1954). Such changes could have been analogous to rebellions that swept the Arab world in early 2011 that were caused by increasing food prices (Zuryak 2011). As palatial centers fell, migrations began across the Eastern Mediterranean, leading to further destabilization of the Late Bronze Age economy (Vermeule 1960; Iakovides 1986). With continued declines in dryland agricultural productivity and migration-influenced disruptions in trade, a point was reached where complex palatial center economies were untenable given the environmental and social conditions, thus resulting in a system’s collapse. Larger population migrations led to military conflict, particularly the incursions of ‘Sea Peoples’ into Egypt and the Levant. In the Levant, urban centers such as Hazor and Megiddo are destroyed by the end of the Bronze Age at 1150 BCE (Ussishkin 1985). However, many urban centers are reoccupied after brief periods of abandonment, indicating that the events of the Levant may have been less severe than in Anatolia or mainland Greece (Mazar 1990). Nonetheless, Early Iron Age settlements had greater architectural affinities with pastoralist tents than Bronze-Age palatial centers (Finkelstein 1988). This suggests an increase in nomadism and a punctuated break from previous urban centers.

Importantly, the collapse of LBA palatial civilization and the following ‘Greek Dark Ages’ may have been linked by the same climatic changes in the region. The collapse of complex social institutions at the end of the Bronze Age was in part the consequence of declines in precipitation and its cascading effects through the economy. However, the peak of aridity is not reached until well into the Greek Dark Ages. At this time populations were much lower than they were during
the Bronze Age, resulting in a paucity of archaeological data for occupation relative to other periods.

The recovery of populations in the region, marked by the rising importance of Athens as a trading center, does not appear to be climate related. Both precipitation and sea surface temperatures continue to be low, as evidenced by the available paleoclimate proxy records. The recovery of populations and the re-urbanization of Greece may have been related to innovations in agriculture, specifically the use of iron ploughshares (White 1984), and iron sickles (Hitti 2004) beginning near 1000 BCE. While the decline of Bronze Age palatial civilization may have been strongly influenced by climate, the recovery of urban society in Greece appears to be more dependent upon human innovation. An improvement in climate (The Roman Warm Period) occurred around 350 BCE, shortly before the expansion of Hellenistic civilization and subsequent cultural dominance of Greco-Roman culture for centuries. It is possible that an improvement in climate was an enabling factor for broader economic connections in the Mediterranean and Near East. A second deterioration in climatic conditions occurred in 150 CE, as indicated by data from Soreq Cave and Lake Voukaria. Detailed analysis of speleothems in Soreq suggest that this climatic change was associated with increased arid conditions in the Eastern Mediterranean (Orland et al. 2009) and a drop in Dead Sea levels (Bookman et al. 2004).

While many of the climate proxies available for the region indicate colder Mediterranean SSTs and arid conditions, it is important to note that all of these records are low-resolution. It is difficult to directly identify a point in time when the climate grew more arid. However Bayesian change-point analysis suggests that the change occurred before 1250-1197 BCE based on the high posterior probabilities from dinocyst/formaniferal records. Arid conditions would have been felt
afterward as the Eastern Mediterranean freshwater flux was reduced. In the context of Holocene climatic changes, that the changes observed at the end of the LBA are not of the same magnitude as larger events that receive attention in the literature. There larger climatic shifts, such as the Younger Dryas, Heinrich events, and the 4.2ka event, are well documented in the literature (Mayewski et al. 2004; Finné et al. 2011). The lowering of Mediterranean SSTs in the LBA is a much smaller event in magnitude. Nonetheless, it has profound impacts on human settlement and culture for centuries. These findings suggest that the magnitude of a climatic shift is not directly transferable to the magnitude of changes in human social organization. Complex societies can have similarly complex vulnerabilities that are sensitive to relatively minor changes in climate.

**Conclusions**

A decline in Mediterranean Sea surface temperatures (SSTs) before 1190 BCE decreased annual freshwater flux by lowering evaporation rates. Westerly winds took in less water vapor, resulting in declining precipitation. Land-based climate proxies, including reconstructed rainfall from Soreq Cave in Israel and $^{13}$C discrimination recorded from pollen in Lake Voulkaria indicate unusually arid conditions following the drop in SSTs. LBA palatial centers, heavily dependent upon agricultural production to support more urban populations, became increasingly leveraged against a highly variable precipitation regime on a long-term decline. Such climatic pressures would have influenced social tensions, and eventually led to competition for limited resources. This climatic change could have influenced the systems collapse of complex society in the Eastern Mediterranean, as well as influence the population declines, urban abandonments, and long-distance migrations associated with the period. The ensuing centuries are associated with low
archaeological resolution, population mobility, and a lack of urban centers. Conditions improve following the introduction of iron tools, and accelerate at the beginning of the Roman Warm Period at 350 BCE.
Chapter 8: C₄ and C₃ Grasses Have Comparable Accuracy When Modeling Atmospheric δ¹³CO₂

Abstract

C₄ grasses can used to reconstruct atmospheric δ¹³C, which in turn can be used to reconstruct prehistoric carbon dioxide levels. However the utility of C₄ grasses and atmospheric reconstruction do not extend past their emergence in the late Miocene. C₃ plants have been found to respond to changes in atmospheric δ¹³C as well, but their high variability makes their potential for atmospheric reconstruction less reliable. We modeled atmospheric δ¹³C and CO₂ using both C₄ and C₃ grasses and employed both random sub-sampling and Bayesian regression to assess their accuracy and reliability. C₄ grasses accurately and reliably produced a steep decline in δ¹³C values that reflects the trend observed over the past century. C₃ grasses also accurately and reliably produced a similarly steep model of atmospheric δ¹³C changes at large sample sizes but were unreliable and inaccurate in smaller samples. C₄ grasses, and to a lesser extent C₃ grasses, both showed a steeper decline in δ¹³C values than could not be explained by the atmospheric trend of lower δ¹³C values alone. Soil organic microbe (SOM) respiration, an increase in temperature anomalies, and changes in intrinsic water use efficiency (Wᵢ) are possible factors related to these divergent trends. C₃ grasses had a highly significant but weak correlation with precipitation and the Palmer Drought Sensitivity Index (PDSI), but had no relationship with temperature. C₄ grasses had no significant relationships with any environmental factors. C₃ grasses modeled atmospheric values accurately despite high variability with large sample sizes. With sufficient sample sizes C₃ grasses may produce accurate estimates of atmospheric δ¹³C when dealing with time periods and locations where C₄ plants are not available. However, the atmospheric models derived from C₃ and C₄ plants should include considerations about the environment and climatic context of the original plants.

Summary

- C₃ and C₄ grass δ¹³C values were used to build models of changes in atmospheric carbon.
Isotopic analysis, bayesian and linear modeling were used to construct and test models of atmospheric $\delta^{13}C$ generated from $C_3$ and $C_4$ grasses. Environmental data from NOAA was used to assess the effects that climate had on both $^{13}C$ discrimination and water use efficiency.

Our findings show that $C_3$ grasses, with sufficient sample sizes, can mirror the accuracy and reliability of $C_4$ plants in modeling atmospheric stable carbon isotope ratios. At smaller sample sizes they produce increasingly inaccurate and unreliable models. $C_4$ grasses, and to a lesser degree $C_3$ grasses, show a steeper trend in lower $\delta^{13}C$ values that are unlikely to be explained by the anthropogenic trends in carbon alone. Plant- and environment-specific attributes such as root respiration, soil organic microbe (SOM) respiration, and environmental factors must be included to accurately model atmospheric $\delta^{13}C$.

These findings suggest that $C_3$ grasses may be more useful for modeling atmospheric carbon that previously thought, provided that large sample sizes are used.

**Introduction**

Atmospheric $\delta^{13}C$ values vary due to differences between terrestrial and oceanic carbon sinks (Pearman and Hyoson 1986). Oceanic carbon sinks take in carbon at a relatively constant rate while terrestrial plants are much more variable, thus atmospheric $\delta^{13}C$ primarily reflects the variation in land vegetation carbon storage (Keeling et al. 1989). The ability to reconstruct atmospheric $\delta^{13}C$ values from $C_4$ plants is documented in previous studies (Marino and McElroy 1991; Marino et al. 1992). However atmospheric $\delta^{13}C$ reconstruction from $C_4$ plants is limited to samples after the Miocene due to their comparatively recent evolutionary emergence relative to $C_3$ plants (Morgan et al. 1994). $C_3$ plants have a fossil record that extends a billion years, beginning with algae (Strother et al. 2011) but have a more variable relationship between plant tissue and atmospheric $\delta^{13}C$ values (Farquhar et al. 1982; Arens et al. 2000). While $C_4$ plants have greater accuracy and reliability in reconstructing atmospheric $\delta^{13}C$ values, $C_3$ plants have the highest potential for producing pre-instrumental records of atmospheric $\delta^{13}C$. This paper uses both
C₃ and C₄ plants to reconstruct the decrease in atmospheric δ¹³C due to anthropogenic carbon emissions. By using modern samples and a known change in atmospheric δ¹³C, C₃ plants can be contrasted with C₄ plants with tests for robustness, reliability, and accuracy.

Carbon emissions from the burning of fossil fuels have a distinctly low isotopic signature, δ¹³C = -29.38‰ between 1981 and 2004 (Blasing et al. 2004). As carbon emissions have increased steadily over the past 110 years C₄ plants have been found to have progressively lower δ¹³C values as a consequence of the trend in source carbon (Marino and McElroy 1991). The decrease in atmospheric δ¹³C values is tightly correlated to increases in atmospheric CO₂ (Bert et al. 1997; Francey et al. 1999). This change in atmospheric δ¹³C as a consequence of anthropogenic carbon emissions provides an ideal standard to judge the accuracy and reliability of C₃ plants in reconstrucing atmospheric carbon isotope ratios.

C₄ grasses are considered to be a more accurate and precise measure of atmospheric variation in δ¹³C (Farquhar et al. 1989; Marino and McElroy 1991). δ¹³C values from C₄ plants have much less variation than δ¹³C values from C₃ plants by virtue of the unique C₄ carbon fixing process. Using this difference Marino and colleagues (1992) reconstructed atmospheric δ¹³C from Atriplex confertifolia in packrat middens going back to 28 thousand years ago. However, C₄ plants only spread widely toward the end of the Miocene, only 10 million years ago (Ehleringer et al. 1991; Osborne and Beerling 2006). The spread of C₄ plants, which have a lower net discrimination against ¹³CO₂, show a distinct isotopic signature in Miocene carbonates at the time of their emergence (Cerling and Quade 1990; Cerling et al. 1993). As C₄ plants incorporate more ¹³CO₂ during photorespiration (Craig 1957), they contributed to a lower δ¹³C signature in atmospheric CO₂. This may have influenced the Late Miocene Carbon Shift (LMCS) where lower δ¹³C values are seen in benthic records (Keigwin 1979; Hodell and Venz-Curtis 2006) and in foraminifera (Haq et al. 1980).

Reconstructing atmospheric δ¹³C from plants prior to the spread of C₄ plants is problematic. Despite high variability in δ¹³C values, C₃ plants have some utility in reconstructing atmospheric δ¹³C (Arens et al 2000). Numerous studies have found that C₃ trees show progressively lower δ¹³C values, consistent with the decline in δ¹³C values over time due to anthropogenic carbon emissions (Freyer and Belacy, 1983; Leavitt and Long 1988; Epstein and Krishnamurthy 1990; Leavitt and Lara 1994; Feng and
Epstein 1995; February and Stock, 1999; Treydte et al., 2001). However other studies have not found a consistent trend in lower δ¹³C values (Stuiver, 1978; Tans and Mook 1980; Francey, 1981; Robertson et al., 1997; Anderson et al., 1998; Duquesnay et al., 1998, February and Stock 1999). Xing-Yun and colleagues (2006) used δ¹³C values from Cryptomeria fortunei trees in the West Tianmu mountains of China to model the increase in CO₂ from the seventeenth through twentieth centuries. Other work has focused on herbarium data (Pedicino et al 2002). C₃ plants do show a decrease in δ¹³C values consistent with anthropogenic warming, but results vary between studies and between taxa. C₃ plants have the potential to offer a much higher frequency record of δ¹³C variation. Lichtfouse and colleagues (2003) found that urban grasses had significantly lower δ¹³C values than rural grasses of the same species. Over geologic time, a rough correspondence is seen between atmospheric CO₂ concentrations and atmospheric δ¹³C values (Berner et al 1994; Gröcke 2002).

Identifying changes in atmospheric carbon in paleontological contexts can complement existing knowledge of changes in past climate. A significant decrease in δ¹³C at the Cretaceous-Tertiary (K-T) boundary 65 million years ago has been interpreted as mass combustion of C₃ plants in response to an asteroid impact (Arinobu et al. 1999; Arens and Jahren 2000). Beerling and colleagues (2002) analyze stomata in fossilized plants to identify a spike in CO₂ concentrations in the same period.

<table>
<thead>
<tr>
<th>environmental effect</th>
<th>δ¹³C plant shift</th>
</tr>
</thead>
<tbody>
<tr>
<td>↑ altitude</td>
<td>+</td>
</tr>
<tr>
<td>↑ pCO₂</td>
<td>-</td>
</tr>
<tr>
<td>CO₂ recycling</td>
<td>-</td>
</tr>
<tr>
<td>↑ salinity, ↓ H₂O</td>
<td>+</td>
</tr>
<tr>
<td>↑ temperature</td>
<td>+</td>
</tr>
<tr>
<td>↑ light</td>
<td>+</td>
</tr>
</tbody>
</table>

Table 8.1: Environmental effects on plant δ¹³C values (from Gröcke 2002: 635)

Generally, C₃ grass studies show a trend consistent with anthropogenic carbon emissions, but guidelines for adequate sampling and inference are lacking. Our study uses C₃ and C₄ grasses gathered from herbaria and analyzes data using atmospheric variation in δ¹³C and environmental data from NOAA weather stations from across the state of New Mexico. A better understanding of the limits of sample size in model
construction will offer a methodological approach to reconstructing atmospheric $\delta^{13}$C. In this paper regression modeling, bayesian analysis and re-sampling of both C$_3$ and C$_4$ data sets are used to assess variation in plant $\delta^{13}$C.

C$_3$ Plants

C$_3$ plants are characterized by highly variable $\delta^{13}$C values in photosynthate and product tissues. This is the consequence of three kinetic discrimination processes that occur within the plant. The first is the diffusion of CO$_2$ into the stomata of the plant (4.4‰). The second results from carboxylation, primarily through Ribulose-1,5 -biphosphate carboxylase oxygenase (RuP$_2$) (27‰). The third effect is the difference between ambient ($c_a$) and intracellular ($c_i$) concentrations of CO$_2$ at the leaf level. Farquhar and colleagues developed an expression to express these effects of internal $\delta^{13}$C after carbon fixation in C$_3$ plants:

$$\delta^{13}C_p = \delta^{13}C_a - a - (b - a)c_i/c_a$$  \hspace{1cm} (1)

where $\delta^{13}C_a$ defines atmospheric $\delta^{13}$C concentrations, $\delta^{13}C_p$ defines the isotopic carbon product of photosynthesis, $a$ is change brought by diffusion of $\delta^{13}$C (4.4‰), $b$ is the effect of RuP$_2$ (27‰), and $c_i/c_a$ the ratio between the CO$_2$ partial pressure in the intercellular leave space and atmosphere, respectively. The fractionation process is driven in part by changes of the carbon source ($\delta^{13}C_a$) and limitations in water availability. When a plant has sufficient water, carbon is more likely to flow freely through the plant and discrimination is primarily the product of carboxylation. When water is limited, the water use efficiency of the plant goes up as stomatal conductance is reduced. This limits the flow of carbon and the plant’s discrimination against carbon approaches the fractionation due to stomatal diffusion.

A model for photosynthetic discrimination in leaves was developed by Farquhar and Richards to analyze whole plant processes in the same terms as chemical processes. This measure of discrimination factors in variation in source carbon ($\delta^{13}C_a$) and thus provides a more descriptive index of plant responses to environmental variation. This employs measurements of $\delta^{13}$C in both the air and in plants:
$\Delta^{13}C = (\delta^{13}C_a - \delta^{13}C_p)/(1+\delta^{13}C_p/1,000) \quad (2)$

The resulting discrimination value ($\Delta^{13}C$) directly expresses the results of plant photosynthesis, whereas raw $\delta^{13}C_p$ records both source (atmospheric) concentration and plant biological processes. Measures of carbon are used interchangeably in the current literature when assessing plant responses to environmental change.

The effects of water use efficiency can be more directly calculated:

$$W_i = \frac{A}{g_s} = (c_a - c_i)/1.6 = \left[\frac{c_a(1 - c_i/c_a)}{1.6}\right] \quad (3)$$

where $W_i$ represents intrinsic water use efficiency, $A$ is assimilation, $g_s$ represents stomatal conductance, and 1.6 is the ratio of diffusion of water and CO$_2$ into air.

**C$_4$ Plants**

C$_4$ plants have a different photosynthetic pathway than C$_3$ plants; these differences are reflected in stable carbon isotope ratios. C$_3$ plants use RuP$_2$ during carboxylation, which has a relatively constant fractionation effect on $\delta^{13}C$ (27‰). C$_4$ plants use Phosphoenolpyruvate (PEP) carboxylase, which has a lower fractionation effect (5.7‰). Some leakage occurs in the bundle sheath cells that contribute to the fractionation effect. A similar expression to formula (1) was developed by Farquhar (1983) to model composition of $\delta^{13}C$ of C$_4$ plants:

$$\delta^{13}C_p = \delta^{13}C_a - a - (c + b\phi - a)c_i/c_a \quad (4)$$

where $c$ represents the isotopic shift due to carbonic anhydrase and PEP (-7.9 + 2.2 = -5.7‰) and $\phi$ represents the fraction of CO$_2$ returned to the mesophyll from the bundle-sheath cells. C$_4$ plants have much lower discrimination against $^{13}$CO$_2$ due to the replacement of RuP2 with PEP carboxylase as the
primary carboxylizing agent. This results in less deviation from $\delta^{13}C_a$, resulting in a more reliable record for atmospheric $\delta^{13}C$.

**Methods**

Our dataset, provided in [SUPPLEMENTAL MATERIAL] includes 29 species from 3 genera of plant, *Bouteloua* (C$_4$), *Bromus* (C$_3$), and *Poa* (C$_3$). These specimens were gathered from across the state of New Mexico between the years of 1892 to 2008 and stored in the University of New Mexico Museum of Southwestern Biology Herbarium. The location, time, and environment type were recorded for each sample. One milligram of each sample was combusted and analyzed in a [Costech Elemental Analyser attached to a Thermo-Finnigan Delta Plus isotope ratio mass spectrometer]. A solid international laboratory standard consisting of soy flour was run after every 10th sample. Stable carbon isotope data are reported in the conventional manner, where $\delta^{13}C = [(R_{\text{sample}} - R_{\text{standard}}) - 1]$; R is the $^{12}C/^{13}C$ ratio in the Vienna Pee-Dee Belumnite (VPDB) standard.

Climatic data were gathered from the National Oceanic and Atmospheric Administration (NOAA). These include temperature, precipitation, and Palmer Drought Sensitivity Index (PDSI) data gathered regularly from 1895 to the present across 8 climate regions in the state. Climate division boundaries were averaged across the state to produce monthly averages.

New Mexico C$_4$ grasses were used to generate local estimates of $\delta^{13}C_a$ using equation (4). To calculate this a $\phi$ value of .505 and a c$_i$/c$_a$ ratio of .5 were used as they fall within the range observed in *B. curtetenda* (Fravolini et al. 2002).

$$\delta^{13}C_a = \delta^{13}C_p + 4.4‰ + (-5.7‰ + 27‰(0.505) - 4.4‰)(0.5)$$

$$\delta^{13}C_a = \delta^{13}C_p + 6.17‰$$
Similar estimates of atmospheric \( \delta^{13}C \) were calculated for \( C_3 \) plants using equation (1). A \( c_i/c_a \) ratio of 0.7 was used based on 4 year study of photosynthesis that included members of \( Bromus \) (Anderson et al 2001).

\[
\delta^{13}C_a = \delta^{13}C_p + 4.4\% + (27\% - 4.4\%)(0.7)
\]

\[
\delta^{13}C_a = \delta^{13}C_p + 20.22\%
\]

Second order polynomial regression models were developed for both \( C_3 \) and \( C_4 \) plant estimates of \( \delta^{13}C_a \). Resulting data and models were compared to \( \delta^{13}C_a \) from ice core samples from Law Dome in Antarctica and instrumental values from Cape Grim. CO\(_2\) estimates from \( C_3 \) and \( C_4 \) plants were generated from a linear model based the relationship between CO\(_2\) and \( \delta^{13}C_a \) in the Law Dome, Antarctica data set:

\[
CO_2 \text{ (ppm)} = -54.73(\delta^{13}C_a) - 65.81
\]

Plant discrimination rates for \( ^{13}C \) (\( \Delta^{13}C \)) were tested against the three aforementioned climate indices. Intrinsic water use efficiency (\( W_i \)) values for grasses was assessed to identify long-term trends in response to temperature anomalies. 3 sub-samples of the data were selected for both \( C_3 \) and \( C_4 \) plants, with 50, 100, and 200 observations for each. \( C_4 \) plants were sampled at 50 and 100 observations. These sub-samples were used to build alternate second order polynomial regression models to test the performance of both \( C_3 \) and \( C_4 \) plants and their ability to reconstruct atmospheric \( \delta^{13}C \) with different sample sizes. 200 separate sub-samples were drawn and compared to the combined isotopic records from Law Dome and Cape Grim.

Bayesian regression analysis was employed using the MCMCpack in R to look at the variation in slopes with systematic resampling within the observed variance of the \( C_3 \) and \( C_4 \) grasses. Samples were generated using the posterior distribution of the regression model between \( \delta^{13}C_p \) and \( \delta^{13}C_a \) with Gaussian errors using the Markov Chain Monte Carlo Gibbs sampling procedure. The Bayesian regressions were
burned in for the first 1,000 samples and iterated 100,000 times. Bayesian analysis was used to assess the robusticity of the linear model and the alternate slopes that could be generated within the observed variation in herbaria samples.

**Atmospheric Stable Carbon Isotope Reconstruction**

Values of $\delta^{13}C_a$ from $C_4$ and $C_3$ grasses show secular trend towards lower values over time that is steeper than the observed atmospheric trend. Observed atmospheric $\delta^{13}C$ values from Law Dome ice cores and Cape Grim air archives fit within the variation of $\delta^{13}C_a$ estimates (Figure 8.1). Despite variation in in the sample the secular trend in lower $\delta^{13}C_a$ associated with anthropogenic carbon emissions is unambiguous.

Second order polynomial regressions of the data produced models of variation in $\delta^{13}C_a$ that resemble the observed decline in the isotopic records of Law Dome and Cape Grim (Figure 8.2). Simple linear regressions were used to test the variation between the second order polynomial linear models of $\delta^{13}C_a$ and atmospheric values. $C_4$ grasses correlated strongly ($r^2 = 0.94, p < 0.0001$), as did $C_3$ grasses ($r^2 = 0.97, p < 0.0001$). $C_3$ grasses are offset by ~0.30‰ on average, but otherwise show a close relationship with atmospheric values. Both $C_4$ and $C_3$ model estimates of $\delta^{13}C_a$ show higher average values around AD 1900 (~6.2‰ and ~6.5‰ respectively). From then on, $C_4$ grasses tend to underestimate $\delta^{13}C_a$ while $C_3$ grasses overestimate $\delta^{13}C_a$, (Figure 8.3).

The accuracy of $\delta^{13}C_a$ models from $C_3$ plants is contingent on sample size. The smallest random sub-samples of data ($n = 50$) show widely varying models, with $r^2$ values ranging from 0.00 - 0.99 with a mean value of 0.72. Models developed from $C_4$ grasses are more consistent, with $r^2$ values ranging from 0.65 - 0.99 with a mean value of 0.92. While these are strong relationships and are highly significant, the lower regressions in smaller sub-samples of $C_3$ plants would lead to very different projections of $\delta^{13}C_a$ (Figure 8.5). At a larger sub-sample size ($n = 100$), models generated from $C_4$ plants show a small increase in accuracy and reliability, with $r^2$ values ranging from 0.79 - 0.99 with a mean value of 0.94. $C_3$ grass models of $\delta^{13}C_a$ continue to show variation with $r^2$ values ranging from 0.01 - 0.99 with a mean value of
At the largest sub-sample size (n = 200), models generated from C₃ grasses mirror variation in C₄ grasses with r² values ranging from 0.62 - 0.99 with a mean value of 0.95 (Figure 8.6).

Bayesian analysis of the slopes of both C₃ and C₄ models of δ¹³Cₐ show a consistently steeper decline in δ¹³Cₐ values over the past century; higher than the expected 1:1 ratio. The second order polynomial regression generated by C₃ grasses produced estimates of δ¹³Cₐ that were 31% (check) steeper than the atmospheric trend. Estimates from C₄ grasses produced a trend that was 40% (check) steeper.

Despite these differences both C₃ and C₄ grasses produce useful approximations of atmospheric CO₂ (Figure 8.7). C₃ grasses produce a closer approximation, though with a slight decline in CO₂ between 1910 and 1930. This is likely due to the low sample sizes in that time period introducing error in a second order polynomial regression that is sensitive to gaps of data.

<table>
<thead>
<tr>
<th>Species</th>
<th>Sample size</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bouteloua aristidoides (Kunth) Griseb.</td>
<td>8</td>
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<tr>
<td>Bouteloua barbata Lag.</td>
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</tr>
<tr>
<td>Bouteloua curtipendula (Michx.) Torr.</td>
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</tr>
<tr>
<td>Bouteloua curtipendula (Michx.) Torr. var. caespitosa Gould &amp; Kapadia</td>
<td>16</td>
</tr>
<tr>
<td>Bouteloua curtipendula (Michx.) Torr. var. curtipendula</td>
<td>4</td>
</tr>
<tr>
<td>Bouteloua eriopoda (Torr.) Torr.</td>
<td>43</td>
</tr>
<tr>
<td>Bouteloua gracilis (Willd. ex Kunth) Lag. ex Griffiths</td>
<td>8</td>
</tr>
<tr>
<td>Bouteloua parryi (Fourn.) Griffiths</td>
<td>4</td>
</tr>
<tr>
<td>Bromus anomalus Rupr. ex Fourn.</td>
<td>34</td>
</tr>
<tr>
<td>Bromus carinatus Hook. &amp; Arn.</td>
<td>27</td>
</tr>
<tr>
<td>Bromus catharticus Vahl</td>
<td>18</td>
</tr>
<tr>
<td>Bromus ciliatus L.</td>
<td>14</td>
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<tr>
<td>Bromus frondosus (Shear) Woot. &amp; Standl.</td>
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</tr>
<tr>
<td>Bromus inermis Leyss.</td>
<td>1</td>
</tr>
<tr>
<td>Bromus porteri (Coutt.) Nash</td>
<td>4</td>
</tr>
<tr>
<td>Bromus racemosus L.</td>
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<td>Bromus rigidus Roth</td>
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<td>Bromus rubens L.</td>
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<td>Bromus tectorum</td>
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<td>Poa annua L.</td>
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<tr>
<td>Poa arctica ssp. aperta (Scribn. &amp; Merr.) Soreng</td>
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<td>Poa arida Vasey</td>
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<tr>
<td>Poa bigelovii Vasey &amp; Scribn.</td>
<td>22</td>
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<tr>
<td>Poa compressa L.</td>
<td>14</td>
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</tbody>
</table>
Table 8.2: Taxa used in study

Environmental Effects

A weak relationship was found between $\Delta^{13}C$ in C$_3$ grasses and both precipitation ($r^2 = 0.04$, $p < 0.01$) and PDSI ($r^2 = 0.03$, $p = 0.01$), no relationship was found with temperature ($r^2 = 0.01$, $p = 0.31$). Rates of $\Delta^{13}C$ in C$_4$ grasses had no significant relationship between precipitation ($r^2 = 0.00$, $p = 0.78$), temperature ($r^2 = 0.01$, $p = 0.24$), or PDSI ($r^2 = 0.01$, $p = 0.38$). The highly significant results between $\Delta^{13}C$, precipitation, and PDSI in C$_3$ grasses are primarily driven by higher $\delta^{13}C$ values during the 1930 and 1950 droughts and by very low $\delta^{13}C$ values in the early 1940’s during and after the highest documented annual precipitation for the state. A weak and highly significant increase in $W_t$ of 34‰ over the past century was observed in C3 plants ($r^2 = 0.06$, $p < 0.001$). However a weak but significant decrease of 36‰ was observed in C4 plants ($r^2 = 0.03$, $p = 0.05$).
Figure 8.1: Values of estimated $\delta^{13}$C$_a$ from C$_4$ and C$_3$ grasses as a function of time. Individual points reflect individual blades of grass. The dashed line represents atmospheric $\delta^{13}$C values modeled from Law Dome ice core data and Cape Grim atmospheric measurements (from Francey et al. 1999). Values of $\delta^{13}$C$_a$ estimated from C$_4$ grasses has a moderate and highly significant correlation with modeled atmospheric values ($r^2 = 0.36$, $p < 0.001$), while the same estimates from C$_3$ grasses have a lower, but still highly significant correlation ($r^2 = 0.12$, $p < 0.001$).
Figure 8.2: Second order polynomial models of estimated $\delta^{13}C_a$ from $C_3$ and $C_4$ grasses as a function of time. Despite having high variability, both $C_4$ and $C_3$ grasses produce a more precise general trend in the lowered $^{13}C/^{12}C$ ratio in the atmosphere due to anthropogenic carbon emissions. Both $C_4$ and $C_3$ grass second order polynomial models have a high correlation with atmospheric $\delta^{13}C_a$, with $r^2 = 0.94$ and 0.97, respectively. Despite the high correlations there are clear differences in the slope of the resulting trend; both $C_3$ and $C_4$ grasses exhibit a steeper decline in $\delta^{13}C$ relative to atmospheric values.
Figure 8.3: Quadratic regressions of estimated $\delta^{13}C_a$ from $C_4$ and $C_3$ grasses as a function of observed atmospheric values.

Each point represents the annual estimates of atmospheric $\delta^{13}C_a$ generated from second order polynomial regressions from $C_4$ and $C_3$ grasses. The solid blue line represents a hypothetical 1:1 relationship between observed and estimated $\delta^{13}C_a$ estimates from $C_4$ and $C_3$ data. $C_4$ grasses tend to underestimate $\delta^{13}C_a$, $C_3$ grasses tend to overestimate $\delta^{13}C_a$. 

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Figure 8.4: Kernel estimate density plot of bayesian model slopes of estimated $\delta^{13}C_a$ from $C_4$ and $C_3$ grasses.
A Markov-Chain Monte Carlo regression of $C_4$ and $C_3$ grasses, 100,000 iterations, plotted against observed atmospheric $\delta^{13}C$. A slope of 1 indicates a 1:1 (indicated by blue vertical line) correspondence with atmospheric $\delta^{13}C$ values (Figure 8.3). Both $C_4$ and $C_3$ grasses show consistently steeper slopes over tens of thousands of iterations.

Figure 8.5: Quadratic regressions of random sub-samples within $C_4$ and $C_3$ grasses.
Second order polynomial regressions of $\delta^{13}C_a$ estimates from $C_4$ and $C_3$ grasses over time from sub-sampled data illustrate that $C_4$ plants more reliably predict atmospheric $\delta^{13}C$ than $C_3$ counterparts at smaller sample sizes. Though in this figure the third sub-sample of $C_3$ grasses ($n = 100$) accurately models the atmospheric trend, other random samples show greater variation.
For each sample size, 200 separate samples were re-drawn. Models generated from C₄ grasses consistently produce highly significant $r^2$ values with median values of $r^2 = 0.92$ and $r^2 = 0.94$ for sample sizes where $n = 50$ and $n = 100$ respectively. C₃ grasses showed greater variation in the strength of model correlations at different sample sizes, with $r^2 = 0.77$, $r^2 = 0.86$, and $r^2 = 0.95$ where $n = 50$, $n = 100$, and $n = 200$ respectively. At high sample sizes ($n = 200+$), C₃ grasses model variation in atmospheric δ¹³C with accuracy consistent with C₄ grasses.
Figure 8.7: Atmospheric CO$_2$ reconstructions using C$_3$ and C$_4$ grasses.
Stable carbon isotopes from C$_4$ and C$_3$ grasses can be used to build a model of the trend in increasing CO$_2$ over the past century. C$_4$ grasses produce estimates that are 16 ppm higher than atmospheric observations with a standard deviation of 18 ppm, C$_3$ grasses produce estimates that are 14 ppm lower with a standard deviation of 8 ppm.

Discussion

Estimates of $\delta^{13}$C$_a$ are highly dependent upon the estimation of the c$_i$/c$_a$ ratio in grass. This varies from specimen to specimen, and potentially from species to species. The estimate of c$_i$/c$_a$ used in this paper comes from observational studies of grass species within the genera used. The effect of a standardized treatment of this may explain why C$_4$ grasses and C$_3$ grasses under- and over-estimate $\delta^{13}$C$_a$ respectively. Selecting a slightly lower c$_i$/c$_a$ ratio in C$_3$ grasses would have produced a near match in the secular trend of lowered $\delta^{13}$C$_a$ over the past century. Nonetheless the slopes of the respective estimates are distinct. C$_4$ grasses demonstrate an almost linear decline in $\delta^{13}$C over time, one that shows a steeper fall towards lower values than in the observed atmospheric trend (Figure 8.2). C$_3$ grasses tend to more closely match the observed trend in atmospheric $\delta^{13}$C over the past century. This is an unexpected result as C$_4$ grasses are generally assumed to be more accurate estimates than C$_3$ grasses for reconstructing atmospheric $\delta^{13}$C.
C₃ grasses are not frequently mentioned as a proxy for atmospheric δ¹³C due to their high variability. C₃ grasses in our sample are clearly more variable than C₄ grasses in their δ¹³C values (Figure 8.1). Despite the high variability in C₃ grasses (r² = 0.12), the second order polynomial regression model still matches observed atmospheric values well (r² = 0.97). C₄ grasses provide less variable data (r² = 0.36) and provide a comparable accuracy in modeling atmospheric values (r² = 0.94). If time can be adequately controlled, then mass sampling of C₃ plants may give comparable results to C₄ plants with regard to atmospheric carbon modeling. Mass sampling is critical given the variation seen C₃ grass δ¹³C values (Figure 8.1) and the alternate models developed with smaller sub-samples (Figure 8.5). C₃ grasses have a total sample size of 274 specimens, which average to 2.4 observations per year over a period of rapid anthropogenically driven change in δ¹³C.a. The smallest subsamples in C₃ grasses (n = 50) produce inaccurate models with 0.43 observations per year. The largest C₃ grass sub-sample, with 200 observations, more accurately models δ¹³C₄ with 1.82 observations per year. The smaller sample sizes may explain some of the mixed results found by Pedicino and colleagues (2002). They found widely varying third order polynomial regressions over a comparable time period using herbaria specimens. However the average number of specimens used per model was 60, which may lead to more variation in the resulting models (Figure 8.5, 8.6). Getting enough representative C₃ samples over time will be a challenge in reconstructing paleo-atmospheric δ¹³C using fossilized C₃ plants. Nonetheless a large sample size is critical to reliable models of atmospheric carbon.

Bayesian regressions on δ¹³C values in both C₃ and C₄ grasses, with 100,000 iterations, show that the majority of slopes from resampled data showed sharper declines in δ¹³C values than would be described by the atmospheric trends in δ¹³C alone. The trend in steep slopes for both C₄ and C₃ grasses is robust. There is no trend in precipitation over the past century (r² = 0.01, p = 0.46) that would explain the sharper downward trend in δ¹³C values. However, there is a statistically significant increase in temperature over the same time period (r² = 0.18, p < 0.01). This matches the broader increase in temperature anomalies observed globally (Smith and Reynolds 2005). However an increase in temperature tends to increase water use efficiency which causes plant tissue to become more enriched in ¹³C, which is the opposite of the observed trend.
McCarroll and Loader (2004) suggest that there may be regional differences in atmospheric δ\textsuperscript{13}C that can be detected by plants. Differences in plant δ\textsuperscript{13}C have been known to vary by location. Licthfouse and colleagues (2003) found that grasses in urban areas had significantly lower δ\textsuperscript{13}C values than their rural counterparts. C\textsubscript{3} grasses in this sample are from rural sources and are unlikely to be affected by local concentrations of CO\textsubscript{2}. Additionally, the steeper trend in lower δ\textsuperscript{13}C values is seen in both C\textsubscript{3} and C\textsubscript{4} plants, suggesting that in absence of any other factors that the difference does indeed reflect lower atmospheric δ\textsuperscript{13}C values than are observed in either the Law Dome or Cape Grim isotopic records. The consistency of steep slopes from C\textsubscript{3} and C\textsubscript{4} plants would imply that atmospheric δ\textsuperscript{13}C in New Mexico, or at least in the air surrounding grasslands, is lower than in Antarctica. This likely reflects the effects of recycled CO\textsubscript{2} due to soil respiration effects. Vogel (1978) noted that the soil CO\textsubscript{2} had δ\textsuperscript{13}C values of -19‰ relative to the -7‰ observed in the atmosphere in the 1970’s. This lighter CO\textsubscript{2} could explain why many observations of plant δ\textsuperscript{13}C differ from the expected atmospheric values, but it does not satisfactorily explain why grasses should have progressively lower δ\textsuperscript{13}C values at a steeper rate than the lowered ratios in the atmosphere. Recent studies of root respiration and soil organic microbes (SOM) suggest that there is differential saturation of 1\textsuperscript{3}CO\textsubscript{2} in C\textsubscript{3} and C\textsubscript{4} grasslands. SOM respired CO\textsubscript{2} from C\textsubscript{3} grasslands occurs at variable discrimination (Δ\textsuperscript{13}C) rates, ranging from +4.3‰ enrichment to -3.2‰ depletion while C\textsubscript{4} grasslands have significantly higher depletion at up to -5.7‰ (Werth and Kuzyakov 2010). The difference in SOM respired CO\textsubscript{2} could explain the steeper rate of lower observed δ\textsuperscript{13}C values in C\textsubscript{4} grasses. This would indicate the average distance of a plant’s photosynthetic tissue from the soil must be considered when estimating changes in atmospheric δ\textsuperscript{13}C.

Intrinsic water use efficiency (W\textsubscript{i}) is another potential explanation for the sharper trend seen in δ\textsuperscript{13}C values from C\textsubscript{3} and C\textsubscript{4} plants. Increases in W\textsubscript{i} has been observed in Mediterranean trees (Peñuelas & Azcón-Bieto 1992), in Fagus sylvetica L. (Duquesnay et al. 1998), temperate trees (Woodward 1993), and temperate grasses (Köhler et al. 2010) over the second half of the 20th century. Intrinsic water use efficiency in the C\textsubscript{3} grasses used in this study are consistent with the increases observed in W\textsubscript{i} observed by the aforementioned studies. C\textsubscript{4} grasses in this study display the opposite trend, they indicate lower W\textsubscript{i} over the past century. This decline in W\textsubscript{i} in C\textsubscript{4} grasses would be the opposite expected response to increasing
temperature anomalies documented worldwide (Smith and Reynolds 2005). The trend in C_4 grasses shows considerably greater variation than in C_3 grasses, including many values of W_i that are either implausible or impossible. The extreme values in C_4 grass W_i is possibly due to variation in CO_2 leakage from the bundle sheath cells (φ). Variation in bundle sheath cell leakage was correlated with ^{13}C discrimination in B. curtipendula (r^2 = 0.59, p < 0.001) at multiple concentrations of CO_2 (Fravolini et al. 2002).

C_4 grasses had no relationship with precipitation between the months of March and September. C_3 grasses had a weak but highly significant relationship over the same time period. C_3 plants in general have been found in multiple studies to correlate with climate indicators (Leavitt and Long 1986; 1988, Becker 1991; Dupueoy et al. 1993; Saurer et al. 1997; Bowling et al. 2003; Adams and Kolb 2004; Gouveia and Freitas 2009; Hall et al. 2009; Aranda et al. 2010; Hu et al. 2010; Sgherza et al. 2010, Werner and Maguas 2010). Whole-biome average ^{13}C discrimination also shows a significant correlation to mean annual precipitation (Diefendorf et al. 2010; Kohn 2010). When both tree ring widths and δ^{13}C are analyzed, both data sets correlate with climate indicators, with tree ring widths consistently correlating with greater strength and reliability (Leavitt and Long 1986, 1988; Gagen et al. 2006; Sgherza et al. 2010). Previous studies of grasses have ashown mixed results in different species. Wheat shows a strong relationship between Δ^{13}C and water use efficiency (Farquhar and Richards 1984). Stable carbon isotope studies in wheat has encouraged debate as to whether Δ^{13}C is a predictor of grain yields (Farquhar and Richards 1984; Ehdaie and Waines 1994; Monneveux et al. 2005; Mohamady et al. 2009). Other grass species, including Agropyron cristatum (L.) Gaertn. and Stipa viridula Trin. have been found to have no significant relationship to climate indicators (Letts et al. 2010).

Due to the lack of provenience on many of the UNM herbaria samples, it is unhelpful to use nearby weather stations reliably to assess variation with precipitation, temperature, or PDSI. For this reason state-wide averages were used. This introduces a significant element of error by testing individual grasses to wide-spread climate conditions. Additional error occurs due to grasses being perennial (Wooten and Standley 1915), lying dormant during drought (Ofir and Kigel 2006), changing ranges due to significant drought (Buckland et al. 2001) and the effects of water sources independent of precipitation. These factors are prevalent for grasses, but are still present for trees with regard to identifying relationships between δ^{13}C
and climate indicators. Despite these problems, there is potential in using plant tissue $^{13}$C discrimination to identify extreme climate events. The highest $\delta^{13}$C values in this sample, and correspondingly lower $\Delta^{13}$C values, occur during the droughts of the 1930’s and 1950s (Figure 8.1). While there is tremendous variation in stable carbon isotope ratios in plant tissues, extreme values may be useful as indicators of correspondingly extreme climate events. As has been demonstrated by research comparing tree ring widths to $\delta^{13}$C values (Leavitt and Long 1986, 1988; Gagen et al. 2006; Sgherza et al. 2010), the carbon isotopic record is not sufficiently reliable to reconstruct precipitation or temperature. But it may be reliable enough to identify more extreme events. While there are many factors unrelated to water use that can affect variation in $^{13}$C discrimination (Seibt et al. 2008), consistently low $^{13}$C discrimination values may still indicate water shortages.

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Prediction</th>
</tr>
</thead>
<tbody>
<tr>
<td>SOM Respiration</td>
<td>$C_4$ and $C_3$ grasses incorporate recycled CO$_2$ from $\delta^{13}$C depleted soil organic microbe respiration.</td>
</tr>
<tr>
<td>Temperature Anomalies</td>
<td>An increase in temperatures results in depleted respired $^{13}$CO$_2$ that is subsequently recycled.</td>
</tr>
<tr>
<td>Intrinsic Water Use Efficiency</td>
<td>$C_3$ and $C_4$ grasses express an increase and decrease in intrinsic water use efficiency, respectively</td>
</tr>
</tbody>
</table>

Table 8.3: Hypotheses that could result in a steeper decrease in $\delta^{13}$C at the soil level.

$C_3$ plants are found widely in the fossil record. If taphonomic and diagenetic effects on $\delta^{13}$C can be properly controlled, then fossilized $C_3$ plants can provide accurate estimates of prehistoric atmospheric carbon isotope records. Rapid changes in atmospheric $\delta^{13}$C will necessarily reflect changes in CO$_2$ sources and sinks, and lead to better inference into significant prehistoric changes in atmospheric carbon.

**Conclusion**

$C_4$ grasses are a more precise predictor of atmospheric $\delta^{13}$C than $C_3$ grasses, but not necessarily a more accurate predictor. $C_3$ grasses can be as accurate indicator of atmospheric $\delta^{13}$C in large sample sizes. Despite the reliability of $C_4$ grass reconstructions of atmospheric $\delta^{13}$C they can be influenced significantly by other processes such as SOM. The environment and characteristics of the plant cannot be divorced from interpretations of $\delta^{13}$C derived from their tissues; the $C_4$ grass sample in this study was highly affected by
soil organic microbe respiration and potentially affected by temperature anomalies over the past 50 years. Weak and highly significant relationships are found between C\textsubscript{3} grasses and precipitation, PDSI, but not temperature. The strength of these relationships is contingent upon extreme $\delta^{13}$C values during the highest and lowest levels of precipitation over the past century. No significant relationship was found between C\textsubscript{4} and any of the environmental variables.
The development of new methodologies has been a constant feature of paleoclimate reconstruction over the past century. In many ways, paleoclimatology has an over-abundance of methodologies. This abundance contributes to the late adoption of useful methods in archaeological research. A principal aim of this dissertation is to highlight data sources, such as stable carbon isotopes, and methodologies, such as Bayesian change-point analysis, that can significantly improve the ability of archaeologists to identify both stability and change in past climate relevant to the human societies they study.

However, interdisciplinary research can present a valuable opportunity to reappraise assumptions. One key appraisal can be seen in the identification of an arid period following the Late Bronze Age (LBA) collapse. A key assumption in paleoclimatology is that severe climate events should have an effect on human populations. As such, events such as the Younger Dryas have received a lot of attention regarding their impacts on humans, such as the development of agriculture (Bar-Yosef 1998; Hillman et al. 2001; Colledge and Conolly 2010). However, as Scheider and colleagues (2007) note in the 2007 IPCC report, climate impacts are a measure not of climate change itself, but of its impact on human societies. The changes that occurred during the LBA collapse were modest—a 2 °C change in air temperature and perhaps a 1 °C change in Mediterranean Sea surface temperature. However, the resulting shifts in evaporation and precipitation may have had severe effects on dryland agricultural systems throughout the Eastern Mediterranean. The persistence of these changes for the following four centuries resulted in a sustained economic and demographic decline that resulted in a loss of literacy and, in some cases,
of formerly dominant languages such as that of the Hittite Empire (Fortson 2004). Many climatologists have noted a shift to colder seas and arid conditions (Rohling et al. 2002; Sangiorni et al. 2003; Finne et al. 2011), but the relatively minor climate changes were difficult to pair with the evidence for widespread violence and destruction at the end of the LBA. These findings may indicate that human societies dependent upon dryland agriculture may have been much more sensitive to relatively minor climate changes than many assume. Dryland production systems are dependent upon soil moisture and precipitation for crop yields. These systems are more vulnerable to multi-year dry conditions than wetland agricultural systems (Kirch 1994). Paleoclimate data indicate another onset of arid conditions at the end of the Roman Warm Period, but a corresponding population collapse does not occur due to more sophisticated agricultural practices that included stronger ploughs and irrigation systems. Different economic systems have different sensitivities to climate change; arid conditions at the end of the Bronze Age in Greece made urban living untenable, while similar arid conditions in the mid-Iron Age and post-Classical period were not associated with demographic changes to the same extent due to irrigation and other advanced farming technology. For Greece, the severity of climate change was not the ultimate limiting factor for urban society; the limitations of agricultural production played a role as well.

The association of the LBA collapse with climate change is a recent phenomenon; while the collapse has been discussed in archaeological literature for almost a century, the primary explanations have involved either economics or war. Most recent work on the LBA collapse tends to suggest 'general systems collapse' without any further discussion (Dickinson 2010). Before 2011, the primary explanation of climatic change was a hypothetical 5-year drought (Bryson et al. 1974; Weiss 1982). Archaeologists rightly regarded this hypothesis with skepticism, as there is no
evidence to support this argument, nor is it clear how a 5-year drought would cause a multi-decadal collapse. Recently, Kaniewski and colleagues (2011) found evidence to suggest that a sharp shift in arid conditions lasted for centuries in Syria. The study included in this dissertation reinforces this conclusion and identifies Eastern Mediterranean Sea surface temperatures as a point of vulnerability for the region.

Similar climate sensitivities may have been at play in the rural Lower Alentejo during the Medieval Warm Period. Boone and Worman (2007) note that there is evidence for an abandonment in the Lower Alentejo between AD 1150 and AD 1400. The early date suggests that abandonment occurred before the *reconquista* of the early 13th century. Analysis of $^{13}$C discrimination rates from charcoal samples over the duration of the rural occupation gives insight into the climatic context. This can be accomplished by contrasting the rates of $^{13}$C discrimination derived from archaeological charcoal samples with those from modern ecological studies. During a period of population growth from the 7th to the beginning of the 11th centuries AD, there is little evidence for arid conditions; $^{13}$C discrimination rates fall within the range of variation observed in modern plants in the region. Beginning in the early 11th century AD, contemporaneous with the onset of the Medieval Warm Period, $^{13}$C discrimination rates in some samples drop to levels indicative of drought. This period of climatic variability is associated with evidence for soil erosion in the region at the same time (Boone and Worman 2007). Studies of sea surface temperatures and sediment formation in the region indicate an arid period as well (Abrantes et al. 2005). The use of $^{13}$C discrimination rates in this study is one of the first of its kind. The metric has been used in previous studies: one by Riehl and colleagues (2008) and another by Aguilera and colleagues (2009). Both failed to make use of the full potential of the proxy record. Riehl looked at over 70 radiocarbon-
derived $^{13}$C discrimination rates from barley plants in Anatolia throughout the Bronze Age. She noted two periods of low $^{13}$C discrimination rates at the beginning of the Early Bronze Age (5,100 cal. yr BP) and at the end of the Middle Bronze Age (4,200 cal. yr BP). Both periods of low $^{13}$C discrimination correspond to broad changes in human societies and to two well-established periods of climatic aridity (Cullen et al. 2000; Bar-Matthews et al. 2003). Riehl and colleagues attribute these shifts to changes in soil moisture but do not make use of modern $^{13}$C discrimination rates in barley. However, their task is complicated by the factors of irrigation and genetic change in domesticated cereals. Both factors complicate the ability to make comparisons with modern barley and may require some alterations in methodological approach. The second study by Aguilera and colleagues (2009) examines $^{13}$C discrimination in Quercus ilex in Eastern Iberia and contrasts these values with modern rates to reconstruct precipitation. Aguilera and colleagues find that the Bronze Age was typified by somewhat wetter and more humid conditions than the present day.

Not all climatic shifts are necessarily negative, as data from Chaco Canyon indicate. Packrat middens provide a unique depositional surface that is viscous and gathers pollen readily from the air (Davis and Anderson 1987; Van Devender 1988). Stephen Hall (1988) was able to recover pollen from multiple species of pine, including piñon, ponderosa, and limber. This data set provided a key measure of the Holocene forest transition on the Colorado Plateau. After the last ice age, piñon pine populations migrated from northern Mexico to southern Wyoming (Betancourt 1987). A reanalysis of these data (Chapter 5) suggests that this migration, at least in the San Juan Basin, occurred relatively rapidly between 5,400 and 5,100 cal. yr BP. Bayesian change-point analysis indicates that this change is the strongest in the Holocene pollen deposits. The change is associated with a sharp increase in El Niño variability (Moy et al. 2002). The spread of piñon pine
would have been of tremendous benefit to populations in the area, as the nuts from these trees are particularly nutritious (Madsen and Rhode 1990). An increase in storage units in the area indicates that the way humans gathered resources began to fundamentally change at the time (Wills 1988a), along with an increase in human population beginning after 5,100 BP as recorded by increasing frequency of radiocarbon dates (Chapin 2005).

The application of Bayesian change-point analysis in the Chaco Canyon pollen records is among the first uses of the technique in assessing paleoclimatic time-series. Of greater significance are the changes in pollen normalization used in this paper. Traditional analysis of pollen has rarely deviated from the normalization procedures established by Lennart von Post in 1916 (Manten 1966). This study introduced a new normalization procedure: species occurrence. Rather than normalize pollen counts from a given temporal/spatial unit to assemblage sample size, the pollen counts are normalized to the sum of that species found in the entirety of the record being studied. As such, data can be analyzed using more advanced statistical techniques and are more broadly generalizable. One of the chief weaknesses of pollen diagrams is the difficulty in comparing/contrasting multiple records from multiple locations. The species occurrence metric developed for this research project, to the best of this author’s knowledge, marks one of the few shifts in pollen normalization procedure in almost a century.

**Synthesis**

The studies that form the core of this dissertation pair commonly available paleoclimate data with new data analysis methodologies to develop better records of climate change at a resolution useful to archaeologists. In addition, the use of Bayesian change-point analysis to
produce criteria for associating climatic changes with climatic impacts represents a potentially valuable contribution to archaeology. The increase in data availability and computer processing power has given archaeologists the ability to execute more advanced analysis. To this end, all computer code used to analyze paleoclimatological and archaeological data in this dissertation will be open source so others can modify the code to fit their own projects.

Changes in climate affect all species of life on Earth directly or indirectly. As Tainter noted, “We are collectively all paleoclimatologists. All communities have had to develop ways to recognize climate crises early or, even better, to anticipate them and mobilize resources beforehand” (2000: 24). Efforts to improve paleoclimate analysis are fundamentally efforts to improve our understanding of one of the key stressors of life for populations dependent upon a predictable hydrological cycle. Complex societies supported by agriculture are uniquely vulnerable to changes in water availability. Despite the long record of climate impacts from archaeology, the climate changes that influenced human societies during the Holocene were relatively minor relative to far larger climatic changes in the Pleistocene and greater Holocene. As human societies continue to emit large amounts of CO₂ into the atmosphere, we face the potential of greater climatic changes than have been faced by complex societies of the past. Though paleoclimate science can provide information about climate change, only archaeology and anthropology can provide information about climate impacts. Understanding how human societies responded to climate impacts in the past provides invaluable knowledge concerning how to best prepare for future, and present, climate change.
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Appendix A: R Code

A Brief History of Post-Glacial Climate

###Copy and paste this script into the R console on your computer. It will be compatible with Windows, Mac, and Linux.

###All sentences beginning with "###" will be invisible to the software, and will caption and describe each step of the analysis and figures for [CITATION]

###Erase everything that comes before

```r
rm(list = ls(all = TRUE))
```

###Compatibility

```r
if(.Platform$OS.type == "windows") {
  quartz<-function() windows()
}
```

###IMPORTANT NOTE: R uses packages to facilitate the analysis of data and production of figures. If you do not have the TTR, bcp, or ggplot2 packages installed, the following three lines of text will do it for you - all you have to do is delete the "###" that precedes the commands

###The command below will bring up a list of download sites. Pick one closest to you to speed up the download process

```r
chooseCRANmirror()
```

###The script below will then install the TTR package (for moving averages), bcp package (for Bayesian Change-Point analysis), and ggplot2 (for generating data plots)

###Note: Installation of packages may take up to an hour, depending upon the speed of your internect connection.

```r
install.packages("TTR", dependencies = TRUE)
install.packages("bcp", dependencies = TRUE)
install.packages("ggplot2", dependencies = TRUE)
```

###Activate the packages

```r
library(TTR)
library(bcp)
library(ggplot2)
```

###Load 65 MYA of δ18O

```r
zachos.o <- read.csv(file="http://www.bleedrake.com/Zachos/Sheet 1-d18O.csv")
```
d18O.sma <- SMA(zachos.o$d18O, 10)

###Plot 65 MYA δ18O
quartz()
cenozoic.plot <- qplot(zachos.o$Age.Ma., d18O.sma, xlim = c(65, 0), ylim = c(5.21, -0.94), ylab = "Benthic δ18O (%) SMO", xlab = "Age (BP)", main = "Benthic δ18O over 65 Million Years")
cenozoic.plot + geom_rect(aes(xmin = 49, xmax = 48.2, ymin = -0.94, ymax = 5.21, colour = "grey", fill = "grey80") + geom_line() + geom_point()

###Load EPICA Ice Core Data
epica <- read.csv(file="http://www.bleedrake.com/Hector/epica/epica.csv")

###Load GISP2 Ice Core Data (from Alley 2004)
gisp2 <- read.csv(file="http://www.bleedrake.com/Hector/GISP2/gisp2.csv")

###Plot EPICA Paleotemperature Reconstructions for the Southern Hemisphere
quartz()
epica.plot <- qplot(epica$Age, epica$Temp, ylab = "EPICA Temperature Anomalies (ºC)", xlim = c(801662.0000, 0), xlab = "Age (BP)", main = "EPICA Reconstructed Temperature Anomalies")

epica.plot + geom_line() + geom_point()

###Plot GISP2 Paleotemperature Reconstructions for the Northern Hemisphere
quartz()
gisp2.plot <- qplot(gisp2$Age, gisp2$Temperature..C., ylab = "GISP2 Temperature (ºC)", xlim = c(49981.0000, 0), xlab = "Age (BP)", main = "GISP2 Reconstructed Northern Hemisphere Temperatures")
gisp2.plot + geom_line() + geom_point()

###Plot GISP2 Paleotemperature Reconstructions for the Northern Hemisphere (Last Glacial Maximum)
quartz()
gisp2.plot <- qplot(gisp2$Age, gisp2$Temperature..C., xlim = c(26500, 0), ylab = "GISP2 Temperature (ºC)", xlab = "Age (BP)", main = "GISP2 Reconstructed Northern Hemisphere Temperatures")
gisp2.plot + geom_line() + geom_point()

###Plot GISP2 Holocene Paleotemperature Reconstructions for the Northern Hemisphere
quartz()
gisp2.plot <- qplot(gisp2$Age, gisp2$Temperature..C., xlim = c(10000, 0), ylim = c(-33, -28), ylab = "GISP2 Temperature (°C)", xlab = "Age (BP)", main = "GISP2 Reconstructed Northern Hemisphere Temperatures")

gisp2.plot + geom_line() + geom_point()

###Plot Little Ice Age
quartz()
gisp2.plot <- qplot(gisp2$Age, gisp2$Temperature..C., ylab = "GISP2 Temperature (°C)", xlim = c(1000, 0), ylim = c(-32.5, -30), xlab = "Age (BP)", main = "GISP2 Reconstructed Northern Hemisphere Temperatures")

gisp2.plot + geom_line() + geom_point()

###Load Solar Irradiance Data (from Steinhibler et al. 2009)
insol <- read.csv(file="http://www.bleedrake.com/Hector/insol.csv")

###Define 95% Confidence Bands (based on Holocene record)
###Note: The bands are narrow enough that they are likely to not be visible on your computer
dTSI.se <- (sd(insol.dTSI.new)/sqrt(length(insol.dTSI.new)))*1.96
dTSI.sma <- SMA(insol$dTSI, 20)

###Plot Solar Irradiance Data
###Note, Confidence Bands removed due to noisy data
#quartz()
insol.plot <- qplot(insol$YearBP, dTSI.sma, xlim = c(10000, 0), xlab = "Age (BP)", ylab = "dTSI (watts per meter anomaly from 1986)", main = "Solar Insolation")

insol.plot + geom_line()

###Load Enso Count data (Moy et al. 2002)
ensocount <- read.csv(file="http://www.bleedrake.com/pollen/ensocount.csv")

ensodate <- ensocount$cal.date*-1

###Plot Figure 4, ENSO event count
quartz()
c <- qplot(ensodate, ensocount$enso.count, ylab = "ENSO Event Count", xlab = "Age (BP)", xlim = c(10000, 0), ylim = c(0,50), geom="line")
### Load Cullen Data

caco3 <- read.csv(file="http://www.bleedrake.com/cullen2000/M5-422 CaCO3-Table 1.csv")
dolomite <- read.csv(file="http://www.bleedrake.com/cullen2000/M5-422 dolomite-Table 1.csv")

### Plot CaCO3
quartz()
c <- qplot(caco3$Age..yr.BP., caco3$X.CaCO3..2., ylab = "CaCO3 (%) Gulf of Oman", xlab = "Age (BP)", xlim = c(10000, 0), geom="line")
c + geom_line() + geom_point()

dolomite.data <- dolomite$X.wt.Dolo
dolomite.time <- dolomite$Cal..Age.

### Plot dolomite
quartz()
f <- qplot(dolomite.time, dolomite.data, ylab = "wt Dolomite (%) Gulf of Oman", xlab = "Age (BP)", xlim = c(10000, 0), geom="line")
f + geom_line() + geom_point()

### Load Composite CO2
composite <- read.csv(file="http://www.bleedrake.com/composite co2/Sheet 1-Data.csv")

### Plot Composite CO2 Data
quartz()
f <- qplot(composite$Age, composite$CO2, ylab = "Composite Atmospheric CO2 (ppm)", xlab = "Age (BP)", xlim = c(798512, -60), geom="line")
f + geom_line() + geom_point()

### Plot Last Glacial Maximum Composite CO2 Data
quartz()
f <- qplot(composite$Age, composite$CO2, ylab = "Composite Atmospheric CO2 (ppm)", xlab = "Age (BP)", xlim = c(26500, -60), geom="line")
f + geom_line() + geom_point()

### Atmospheric δ13C
all.d13c <- read.csv(file="http://www.bleedrake.com/atmospheric d13c/Sheet 1-All.csv")
sans.taylor <- read.csv(file="http://www.bleedrake.com/atmospheric d13c/Sheet 1-Sans Taylor.csv")

###Plot all δ13CO2 Data
quartz()
f <- qplot(all.d13c$Age, all.d13c$d13c, ylab = "Composite Atmospheric δ13CO2 (‰) VPDB", xlab = "Age (BP)", xlim = c(151703, -28), geom="line")
f + geom_line() + geom_point()

###Plot Last Glacial Maximum δ13CO2 Data
quartz()
f <- qplot(all.d13c$Age, all.d13c$d13c, ylab = "Composite Atmospheric δ13CO2 (‰) VPDB", xlab = "Age (BP)", xlim = c(26500, -60), geom="line")
f + geom_line() + geom_point()

###Plot Last Glacial Maximum δ13CO2 Data without Taylor
quartz()
f <- qplot(sans.taylor$Age, sans.taylor$d13c, ylab = "Composite Atmospheric δ13CO2 (‰)
VPDB", xlab = "Age (BP)", xlim = c(26500, -60), geom="line")
f + geom_line() + geom_point()

###Bayesian Last Glacial Maximum δ13CO2 Data WITH Taylor
d13c.bayes <- bcp(all.d13c$d13c, burnin=10000, mcmc=10000)
d13c.posterior.mean <- d13c.bayes$posterior.mean
d13c.posterior.prob <- d13c.bayes$posterior.prob
d13c.posterior.var <- d13c.bayes$posterior.var
d13c.posterior.se <- (sqrt(d13c.posterior.var)/sqrt(length(d13c.posterior.var)))*1.96

###Plot Last Glacial Maximum Posterior Means δ13CO2 Data WITH Taylor
quartz()
f <- qplot(all.d13c$Age, d13c.posterior.mean, ylab = "Composite Atmospheric δ13CO2 (‰)
VPDB Posterior Means", xlab = "Age (BP)", xlim = c(26500, -60), geom="line")
f + geom_ribbon(aes(ymax = d13c.posterior.mean + d13c.posterior.se, ymin = d13c.posterior.mean - d13c.posterior.se), fill = "grey80", linetype=0) + geom_line() + geom_point()

###Bayesian Last Glacial Maximum δ13CO2 Data without Taylor
d13c.bayes <- bcp(sans.taylor$d13c, burnin=10000, mcmc=10000)
d13c.posterior.mean <- d13c.bayes$posterior.mean
d13c.posterior.prob <- d13c.bayes$posterior.prob
d13c.posterior.var <- d13c.bayes$posterior.var
d13c.posterior.se <- (sqrt(d13c.posterior.var)/sqrt(length(d13c.posterior.var)))*1.96

###Bayesian Last Glacial Maximum δ13CO2 Data without Taylor
### Plot Last Glacial Maximum Posterior Means δ13CO2 Data without Taylor

```r
quartz()

f <- qplot(sans.taylor$Age, d13c.posterior.mean, ylab = "Composite Atmospheric δ13CO2 (‰) VPDB Posterior Means", xlab = "Age (BP)", x1im = c(26500, -60), geom="line")

f + geom_ribbon(aes(ymax = d13c.posterior.mean + d13c.posterior.se, ymin = d13c.posterior.mean - d13c.posterior.se), fill = "grey80", linetype=0) + geom_line() + geom_point()
```

### Sea Level

### Read Global Sea Level Data

```r
sealevel <- read.csv(file="http://www.bleedrake.com/Aux/sealevel.csv")

uplift.pos <- sealevel$Uplift * -1

uplift.se <- (sqrt(uplift.pos)/sqrt(length(uplift.pos)))*1.96
```

### Plot Last Glacial Maximum Sea Level

```r
quartz()

f <- qplot(sealevel$Age, sealevel$Uplift, ylab = "Global Sea Level (m)", xlab = "Age (BP)", x1im = c(26500, -60), geom="line", main = "Global Sea Level Since the Last Glacial Maximum")

f + geom_ribbon(aes(ymax = sealevel$Uplift + uplift.se, ymin = sealevel$Uplift - uplift.se), fill = "grey80", linetype=0) + geom_errorbar(aes(ymax = sealevel$Uplift + uplift.se, ymin = sealevel$Uplift - uplift.se)) + geom_point()
```

### References

### Alley, R.B., 2004. GISP2 Ice Core Temperature and Accumulation Data. IGBP PAGES World Data Center for Paleoclimatology Data Contribution Series #2004-013. NOAA/NGDC Paleoclimatology Program, Boulder CO, USA.


### This script is copyright © 2011 Brandon Lee Goodchild Drake, and is distributed without warranty under the GNU General Public License (GPL): http://www.gnu.org/copyleft/gpl.html (retrieved on 7/26/2011)
The 5.1 ka Aridization Event, Expansion of Piñon-Juniper Woodlands, and the Introduction of Maize (Zea mays) in the American Southwest

###Copy and paste this script into the R console on your computer. It will be compatible with Windows, Mac, and Linux.

###All sentences beginning with "###" will be invisible to the software, and will caption and describe each step of the analysis and figures for [CITATION]

###Erase everything that comes before
```r
rm(list = ls(all = TRUE))
```

###Compatibility
```r
if(.Platform$OS.type == "windows") {
  quartz<-function() windows()
}
```

###IMPORTANT NOTE: R uses packages to facilitate the analysis of data and production of figures. If you do not have the TTR, bcp, or ggplot2 packages installed, the following three lines of text will do it for you - all you have to do is delete the "###" that precedes the commands

###The command below will bring up a list of download sites. Pick one closest to you to speed up the download process
```r
chooseCRANmirror()
```

###The script below will then install the TTR package (for moving averages), bcp package (for Bayesian Change-Point analysis), and ggplot2 (for generating data plots)
###Note: Installation of packages may take up to an hour, depending upon the speed of your internet connection.
```r
install.packages("TTR", dependencies = TRUE)
install.packages("bcp", dependencies = TRUE)
install.packages("ggplot2", dependencies = TRUE)
```

###Activate the packages
```r
library(TTR)
library(bcp)
library(ggplot2)
```
### Archaeological Data###

### Figure 3 ###

### Load pollen data (Hall 1988) ###

```r
hall <- read.csv(file="http://www.bleedrake.com/pollen/hall.csv")
```

### Order the pollen data ###

```r
hall <- hall[order(hall$cal.date),]
```

### Set time ###

```r
time <- hall$cal.date
```

### Calculate total counts ###

- Piñon.pine <- hall$Pinus.edulis
- Ponderosa.pine <- hall$Pinus.ponderosa
- Limber.pine <- hall$Pinus.flexilis
- Total <- hall$Total
- Cheno.Ams <- hall$Chenopodium
- Juniperus <- hall$Juniperus
- All.pine <- Piñon.pine + Ponderosa.pine + Limber.pine
- Piñon.proportion <- Piñon.pine/All.pine*100
- Ponderosa.proportion <- Ponderosa.pine/All.pine*100
- Limber.proportion <- Limber.pine/All.pine*100

### Calculate species occurrence ###

- Pinus.ponderosa.so <- hall$Pinus.ponderosa/sum(hall$Pinus.ponderosa) * 100
- Pinus.edulis.so <- hall$Pinus.edulis/sum(hall$Pinus.edulis) * 100
- Pinus.flexilis.so <- hall$Pinus.flexilis/sum(hall$Pinus.flexilis) * 100

### Calculate pollen percentage ###

- Pinus.ponderosa.pp <- hall$Pinus.ponderosa/hall$Total * 100
- Pinus.edulis.pp <- hall$Pinus.edulis/hall$Total * 100
- Pinus.flexilis.pp <- hall$Pinus.flexilis/hall$Total * 100
#Calculate pollen percentage without Juniper
Pinus.ponderosa.ju <- hall$Pinus.ponderosa/(hall$Total - hall$Juniperus) * 100
Pinus.edulis.ju <- hall$Pinus.edulis/(hall$Total - hall$Juniperus) * 100
Pinus.flexilis.ju <- hall$Pinus.flexilis/(hall$Total - hall$Juniperus) * 100

###Calculate regressions for species occurrence (so), pollen percentage without juniper (ju), and pollen percentage (pp)
so <- lm(Pinus.edulis.so ~ Pinus.ponderosa.so)
ju <- lm(Pinus.edulis.ju ~ Pinus.ponderosa.ju)
pp <- lm(Pinus.edulis.pp ~ Pinus.ponderosa.pp)

###Plot Figure 3a, species occurrence
quartz()
a <- qplot(Pinus.ponderosa.so, Pinus.edulis.so, xlab = "Ponderosa pine (%)", ylab = "Piñon pine (%)", xlim = c(0,20), ylim = c(0,20), main = "3(a) Species Occurrence")
a + geom_abline(intercept= so$coef[1], slope = so$coef[2]) + stat_smooth(method = "lm") + geom_point()

###Plot Figure 3b, pollen percentage without juniper
quartz()
b <- qplot(Pinus.ponderosa.ju, Pinus.edulis.ju, xlab = "Ponderosa pine (%)", ylab = "Piñon pine (%)", xlim = c(0,20), ylim = c(0,20), main = "3(b) Pollen Percentage without Juniper")
b + geom_abline(intercept= ju$coef[1], slope = ju$coef[2]) + stat_smooth(method = "lm") + geom_point()

###Plot Figure 3c, pollen percentage
quartz()
c <- qplot(Pinus.ponderosa.pp, Pinus.edulis.pp, xlab = "Ponderosa pine (%)", ylab = "Piñon pine (%)", xlim = c(0,20), ylim = c(0,20), main = "3(c) Pollen Percentage")
c + geom_abline(intercept= pp$coef[1], slope = pp$coef[2]) + stat_smooth(method = "lm") + geom_point()
### Archaeological Data ###

### Load Pink Panther Oxygen-Isotope data (Asmerom et al. 2007) ###

```r
pinkpanther <- read.csv(file="http://www.bleedrake.com/pollen/pinkpanther.csv")
```

### Load Enso Count data (Moy et al. 2002) ###

```r
ensocount <- read.csv(file="http://www.bleedrake.com/pollen/ensocount.csv")
```

### Name ENSO variables (Pleistocene ENSO data excluded) ###

```r
enso.count <- ensocount$enso.count[1:114]
enso.date <- ensocount$cal.date[1:114]
```

### Calculate piñon pine proportion ###

```r
Pinus.edulis.du <- hall$Pinus.edulis/(hall$Pinus.edulis+hall$Pinus.ponderosa)*100
```

### Calculate piñon pine 95% confidence intervals ###

```r
Pinus.edulis.du.error <- sd(Pinus.edulis.du)/sqrt(length(Pinus.edulis.du))*1.96
```

### Plot Figure 4, piñon proportion with error bands ###

```r
quartz()
a <- qplot(time, Pinus.edulis.du, xlab = "Age (BP)", ylab = "Piñon Pollen Proportion (%)", col="red", xlim = c(-12057.9, 0))
a + geom_ribbon(aes(ymax = Pinus.edulis.du+Pinus.edulis.du.error, ymin = Pinus.edulis.du-Pinus.edulis.du.error), fill = "grey80", linetype=0)+ geom_line(col="red") + geom_point(colour="black") + opts(legend.position="none")
```

### Plot Figure 4, oxygen-isotope timeseries data with highlights near time periods with pollen data ###

```r
quartz()
b <- qplot(pinkpanther$cal.date.thor, pinkpanther$ox, ylab = "δ18O ‰ (VPDB)", xlab = "", xlim = c(-12057.9, 0), geom="line", colour="blue", fill = "blue")
b + geom_line(aes(x = pinkpanther$cal.date.thor, y = pinkpanther$ox), colour = "cyan") + geom_point(aes(x=hall$cal.date, y=hall$ox.sigma, colour="black", fill="black"), colour="black") + geom_line(aes(x=hall$cal.date, y=hall$ox.sigma, colour=alpha("black", 1), fill="black"), colour="black") + opts(legend.position="none")
```

### Plot Figure 4, ENSO event count ###

```r
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```
quartz()
c <- qplot(enso.date, enso.count, ylab = "ENSO Event Count", xlab = "Age (BP)",
col="brown",xlim = c(-12057.9, 0), ylim = c(0,50), geom="line")
c + geom_line(aes(x=enso.date, y=enso.count), colour = "dark red") +
opts(legend.position="none")

#########################
###Archaeological Data###
#########################

Figure 5

####Run bayesian change point analysis on piñon pine proportion data
Piñon.du.pc <- bcp(Pinus.edulis.du, burnin=10000, mcmc=10000)

####Define posterior means, probabilities, and standard deviations
Piñon.du.pp <- Piñon.du.pc$posterior.prob[1:18]*100
Piñon.du.ave <- Piñon.du.pc$posterior.mean
Piñon.du.sd <- sqrt(Piñon.du.pc$posterior.var)

####Figure 5, bayesian change point posterior means of piñon proportions
quartz()
a <- qplot(time, Piñon.du.ave, xlab = "Age (BP)", ylab = "Posterior Means of Change-Point (%)",
col="red", xlim = c(-12057.9, -526.750))
a + geom_ribbon(aes(ymax=Piñon.du.ave+Piñon.du.sd, ymin=Piñon.du.ave-Piñon.du.sd), fill =
"grey80", linetype=0)+ geom_line(col="red") + geom_point(colour="black") +
opts(legend.position="none")

####Figure 5, bayesian change point posterior probabilities of piñon proportions
quartz()
b <- qplot(time[2:19], Piñon.du.pp, xlab = "Age (BP)", ylab = "Posterior Probability of Change-point (%)",
xlim = c(-12057.9, -526.750))
b + geom_line(lty = 2)

Archaeological Data

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###Load Precipitation Data
precipitation <- read.csv(file="http://www.bleedrake.com/pollen/precipitation.csv")

###Plot precipitation in Carlsbad Caverns and the New Mexico Climate Division 4
quartz()
plot(precipitation$NM124~precipitation$Year, type="l", ylim = c(0,1100), ylab = "Mean Annual Precipitation (mm)", xlab = "Year AD")
points(precipitation$Carlsbad~precipitation$Year, type="l", lty=3)
legend("topleft", c("San Juan Basin", "Carlsbad Caverns"), lty=c(1,3))

###References


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The Use of Radiocarbon-Derived Δ¹³C Values as a Paleoclimate Indicator: Applications in the Lower Alentejo of Portugal

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```r
rm(list = ls(all = TRUE))
```

###Compatibility

```r
if(.Platform$OS.type == "windows") {
  quartz<-function() windows()
}
```

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chooseCRANmirror()
```

###The script below will then install the TTR package (for moving averages), bcp package (for Bayesian Change-Point analysis), and ggplot2 (for generating data plots)

###Note: Installation of packages may take up to an hour, depending upon the speed of your internet connection.

```r
install.packages("TTR", dependencies = TRUE)
install.packages("bcp", dependencies = TRUE)
install.packages("ggplot2", dependencies = TRUE)
```

###Activate the packages

```r
library(bcp)
library(ggplot2)
```

###Load Isotope Data from the Lower Alentejo
la <- read.csv(file="http://www.bleedrake.com/la/la.csv")

###Load EPICA δ13C Data (Elsig et al. 2009)
epica <- read.csv(file="http://www.bleedrake.com/la/epica.csv")

###Load Law Dome δ13C Data (Francey et al. 1999)
law.dome <- read.csv(file="http://www.bleedrake.com/la/ld.csv")

###Set δ13C Variables
d13c <- epica$d13CO2...per.mil.VPDB.
date <- epica$date
d13c.part <- d13c[1:5]
date.part <- date[1:5]

d13c.combo <- c(d13c.part[5], d13c.part[4], d13c.part[3], d13c.part[2], law.dome$d13C[2:4],
               d13c.part[1], law.dome$d13C[5:35])

d13c.combo <- c(d13c.combo[5], d13c.combo[4], d13c.combo[3], d13c.combo[2],
                law.dome$YEAR[2:4],
                date.part[1], law.dome$YEAR[5:35])

time.combo <- c(date.part[5], date.part[4], date.part[3], date.part[2],
                law.dome$YEAR[2:4],
                date.part[1], law.dome$YEAR[5:35])

###Run Bayesian Change-Point Model of Atmospheric δ13C
atmosphere.change <- bcp(d13c.combo, burnin=10000, mcmc=10000)

###Estimate Atmospheric δ13C 95% Confidence Levels
se.change <- (sqrt(atmosphere.change$posterior.var)/(sqrt(length(atmosphere.change
$posterior.var))))*1.96
se.d13c <- (sd(d13c.combo)/(sqrt(length(d13c.combo))))*1.96

###Archaeological Data###

####Figure 2####

###Plot Bayesian Change-Point Posterior Means (δ13C)
quartz()
d13c.plot <- qplot(time.combo, atmosphere.change$posterior.mean, xlab = "Age (CE)", ylab = "Atmospheric δ13C (‰) Posterior Means")

d13c.plot + geom_ribbon(aes(ymax = atmosphere.change$posterior.mean + se.change, ymin = atmosphere.change$posterior.mean - se.change), fill = "grey80", linetype=0) + geom_line()

###Set d13C Stable Periods to calculate Δ13C
#CE 500 - 905
mean.1 <- (atmosphere.change$posterior.mean[1] + atmosphere.change$posterior.mean[2])/2

#CE 907 - 1563
mean.2 <- sum(atmosphere.change$posterior.mean[3:8])/6

#CE 1570 - 1796
mean.3 <- sum(atmosphere.change$posterior.mean[9:13])/5

#CE 1950
mean.4 <- atmosphere.change$posterior.mean[39]

###Calculate 13C Discrimination
D13C.1 <- ((mean.1 - la$d13c[1:11])/(1+(la$d13c[1:11]/1000)))
D13C.2 <- ((mean.2 - la$d13c[12:34])/(1+(la$d13c[12:34]/1000)))
D13C.3 <- ((mean.3 - la$d13c[35:40])/(1+(la$d13c[35:40]/1000)))
D13C.4 <- ((-8.00 - la$d13c[41])/(1+(la$d13c[41]/1000)))

###Create 13C Discrimination Timeseries
D13C <- c(D13C.1, D13C.2, D13C.3, D13C.4)
D13C <- D13C + (19.6 - mean(D13C))

###Calculate Δ13C Standard Error
se.cor <- (sd(D13C)/sqrt(length(D13C)))*1.96

###Archaeological Data###

Figure 3###

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### Plot 13C Discrimination Timeseries

```r
quartz()
l.a.mert <- qplot(la$median, D13C, xlab = "Age (CE)", ylab = "Δ13C (‰)"

la.mert + geom_ribbon(aes(ymax = D13C + se.cor, ymin = D13C - se.cor), fill = "grey80", linetype=0) + geom_point()
```

### References


### This script is copyright © 2011 Brandon Lee Goodchild Drake, and is distributed without warranty under the GNU General Public License (GPL): [http://www.gnu.org/copyleft/gpl.html](http://www.gnu.org/copyleft/gpl.html) (retrieved on 7/26/2011)
The Influence of Climatic Change on the Late Bronze Age Collapse and the Greek Dark Ages

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###Compatibility
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}

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###install.packages("TTR", dependencies = TRUE)
###install.packages("bcp", dependencies = TRUE)
###install.packages("ggplot2", dependencies = TRUE)

###Activate the packages
library(TTR)
library(bcp)
library(ggplot2)

################################################################

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###Archaeological Data###

Load archaeological data (From the Oxford Handbook of the Bronze Age Agean, edited by Eric Cline)
crete <- read.csv(file="http://www.bleedrake.com/Hector/BACL/crete_timeseries.csv")
greece <- read.csv(file="http://www.bleedrake.com/Hector/BACL/greece_timeseries.csv")

Define variables, time series
crete.date <- crete$Date..BP.
greece.date <- greece$Date..BP.

Define variables, occupation
crete.occ <- crete$Occupation
greece.occ <- greece$Occupation

Define 95% confidence bands for occupation
greece.se <- (sd(greece.occ)/sqrt(length(greece.occ)))*1.96
tcrete.se <- (sd(crete.occ)/sqrt(length(crete.occ)))*1.96

Generate plot to show history of the occupation of Bronze-Age Palatial Centers on the Greek Mainland
mycenae <- qplot(greece.date, greece.occ, ylim = c(0, 12), xlim = c(0,5040), ylab = "Occupation of Major Bronze Age Sites in Greece", xlab = "Age (BP)"
mycenae + geom_ribbon(aes(ymax = greece.occ + greece.se, ymin = greece.occ - greece.se), fill = "grey80", linetype=0) + geom_line() + geom_point()

Generate plot to show history of the occupation of Bronze-Age Palatial Centers on Crete
minoa <- qplot(crete.date, crete.occ, ylim = c(-1, 12), xlim = c(0,5000), ylab = "Occupation of Major Bronze Age Sites in Crete", xlab = "Age (BP)"

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### Land-Based Paleoclimate Records ###

#### Figure 2 ####

### Load data on stable carbon isotopes from Lake Voulkaria in Greece (Jahns 2005) and reconstructed rainfall from Soreq Cave in Israel (Bar-Matthews et al. 2003) ###

```r
rain <- read.csv(file="http://www.bleedrake.com/Hector/v/Rain.csv")
```

### Define time variables ###

```r
age.is <- rain$Age.Israel[1:13]
age.gr <- rain$Age.Greece[1:13]
```

### Define paleoclimate variables ###

```r
rain.is <- rain$Rain.Israel
delta.gr <- rain$Delta.Greece[1:13]
```

### Define 95% confidence bands ###

```r
se.is <- (sd(rain.is)/sqrt(length(rain.is)))*1.96
se.gr <- (sd(delta.gr)/sqrt(length(delta.gr)))*1.96
```

### Plot reconstructed paleorainfall from Soreq Cave in Israel ###

```r
quartz()
ox.rain <- qplot(age.is, rain.is, xlim = c(0,5040), ylim = c(200, 600), ylab="Paleorainfall (mm)", xlab="Age (BP)")
ox.rain + geom_ribbon(aes(ymax = rain.is + se.is, ymin = rain.is - se.is), fill = "grey80", linetype=0) + geom_line() + geom_point()
```

### Plot reconstructed 13C discrimination from Lake Voulkaria in Greece ###
quartz()
carbon <- qplot(age.gr, delta.gr, xlim = c(0,5040), ylim = c(10, 27), ylab = "Voukaria Pollen Δ13C (‰)", xlab = "Age (BP)"

carbon + geom_ribbon(aes(ymax = delta.gr + se.gr, ymin = delta.gr - se.gr), fill = "grey80", linetype=0) + geom_line() + geom_point()

########################################################################
###Sea-Based Paleoclimate Data###
########################################################################

########################################################################
###Figure 3###
########################################################################

###Load Ionian SST Data (from Emeis et al. 2000)
rl11 <- read.csv(file="http://www.bleedrake.com/Hector/allmed/rl11.csv")

###Define Holocene Boundaries (t < 10,000)
ionian.sst.total <- c(rl11$SST[34:48], rl11$SST[50:64], rl11$SST[66:72], rl11$SST[74:77])
ionian.age.total <- c(rl11$Age[34:48], rl11$Age[50:64], rl11$Age[66:72], rl11$Age[74:77])

###Define mid-late Holocene Boundaries (t < 5,000)
ionian.sst.new <- ionian.sst.total[19:41]
ionian.age.new <- ionian.age.total[19:41]

###Define 95% Confidence Bands (based on Holocene record)
ion.se <- (sd(ionian.sst.total)/sqrt(length(ionian.sst.total)))*1.96

###Plot Ioninan SST Data
quartz()
ion <- qplot(ionian.age.new, ionian.sst.new, xlim = c(0,5040), ylim = c(12.5, 27), ylab = "Ionian SST (ºC)", xlab = "Age (BP)"

ion + geom_ribbon(aes(ymax = ionian.sst.new + ion.se, ymin = ionian.sst.new - ion.se), fill = "grey80", linetype=0) + geom_line() + geom_point()

###Load Adriatic SST Data (from Sangiorni et al. 2003)
ad9117 <- read.csv(file="http://www.bleedrake.com/Hector/allmed/ad9117.csv")

###Define Holocene Boundaries (t < 10,000)
adriatic.age.total <- ad9117$Age[12:61]
adriatic.sst.total <- ad9117$SST[12:61]

###Define mid-late Holocene Boundaries (t < 5,000)
adriatic.age.new <- ad9117$Age[44:61]
adriatic.sst.new <- ad9117$SST[44:61]

###Define 95% Confidence Bands (based on Holocene record)
ad.se <- (sd(adriatic.sst.total)/sqrt(length(adriatic.sst.total)))*1.96

###Plot Adriatic SST Data
quartz()
ad <- qplot(adriatic.age.new, adriatic.sst.new, xlim = c(0, 5040) , ylim = c(12.5, 27), ylab = "Adriatic SST (ºC)", xlab = "Age (BP)")
ad + geom_ribbon(aes(ymax = adriatic.sst.new + ad.se, ymin = adriatic.sst.new - ad.se), fill = "grey80", linetype=0) + geom_line() + geom_point()

###Load Adriatic Warm-Species Dinocysts Data (from Sangiorni et al. 2003)
adriatic <- read.csv(file="http://www.bleedrake.com/Hector/af.csv")

###Define Holocene Boundaries (t < 10,000)
adriatic.dino.total <- adriatic$WSD[2:34]
adriatic.aged.total <- adriatic$Age[2:34]

###Define mid-late Holocene Boundaries (t < 5,000)
adriatic.dino.new <- adriatic$WSD[23:34]
adriatic.aged.new <- adriatic$Age[23:34]

###Define 95% Confidence Bands (based on Holocene record)
ad.dino.se <- (sd(adriatic.dino.total)/sqrt(length(adriatic.dino.total)))*1.96
###Plot Adriatic Warm-Species Dinocysts Data

```r
quartz()
ad.dino <- qplot(adriatic.aged.new, adriatic.dino.new, xlim = c(0,5040), ylim = c(10, 80), ylab = "Adriatic Sea Warm Species Dinocysts (%)", xlab = "Age (BP)")

ad.dino + geom_ribbon(aes(ymax = adriatic.dino.new + ad.dino.se, ymin = adriatic.dino.new - ad.dino.se), fill = "grey80", linetype=0) + geom_line() + geom_point()
```

###Load Aegean Warm-Species Foraminifera Data (from Rohling et al. 2002)

```r
aegean <- read.csv(file="http://www.bleedrake.com/Hector/lc21/aegean.csv")

#Note - This data will use an age correction. The ash layer from the Santorini eruption occurs in layers dated to 3.9 kya in the original record (Rohling et al. 2002), when the actual eruption took place at 3.57 kya. The difference (0.33 kya) will be subtracted from each layer.

aegean.age.cor <- aegean$Age - 330
```

###Define Holocene Boundaries (t < 10,000)

```r
aegean.foram.total <- aegean$WSD[24:93]
aegean.age.total <- aegean.age.cor[24:93]
```

###Define mid-late Holocene Boundaries (t < 5,000)

```r
aegean.foram.new <- aegean$WSD[69:93]
aegean.age.new <- aegean.age.cor[69:93]
```

###Define 95% Confidence Bands (based on Holocene record)

```r
ae.foram.se <- (sd(aegean.foram.total)/sqrt(length(aegean.foram.total)))*1.96
```

###Plot Aegean Warm-Species Foraminifera Data

```r
quartz()
ad.dino <- qplot(aegean.age.new, aegean.foram.new, xlim = c(0,5040), ylim = c(70, 140), ylab = "Aegean Sea Warm Species Foraminifera (%)", xlab = "Age (BP)")

ad.dino + geom_ribbon(aes(ymax = aegean.foram.new + ae.foram.se, ymin = aegean.foram.new - ae.foram.se), fill = "grey80", linetype=0) + geom_line() + geom_point()
```
### Global Paleoclimate Data ###

#### Figure 4 ####

### Load GISP2 Ice Core Data (from Alley 2004) ###
gisp2 <- read.csv(file="http://www.bleedrake.com/Hector/GISP2/gisp2.csv")

### Define Holocene Boundaries (t < 10,000) ###
gisp2.temp.total <- gisp2$Temperature..C.[870:1632]
gisp2.age.total <- gisp2$Age[870:1632]

### Define mid-late Holocene Boundaries (t < 5,000) ###
gisp2.temp.new <- gisp2$Temperature..C.[1159:1632]
gisp2.age.new <- gisp2$Age[1159:1632]

### Define 95% Confidence Bands (based on Holocene record) ###
### Note: The bands are narrow enough that they are likely to not be visible on your computer ###
gisp2.se <- (sd(gisp2.temp.total)/sqrt(length(gisp2.temp.total)))*1.96

### Plot GISP2 Paleotemperature Reconstructions for the Northern Hemisphere ###
quartz()
gisp2.plot <- qplot(gisp2.age.new, gisp2.temp.new, xlim = c(0,5040), ylim = c(-32.5, -28.5), ylab = "GISP2 Temperature (ºC)", xlab = "Age (BP)"")
gisp2.plot + geom_ribbon(aes(ymax = gisp2.temp.new + gisp2.se, ymin = gisp2.temp.new - gisp2.se), fill = "grey80", linetype=0) + geom_line() + geom_point()

### Load Solar Irradiance Data (from Steinhibler et al. 2009) ###
insol <- read.csv(file="http://www.bleedrake.com/Hector/insol.csv")

### Create moving average for data ###
insol.sma <- SMA(insol$dTSI, 20)

### Define Holocene Boundaries (t < 10,000) ###
insol.dTSI.total <- insol$dTSI
insol.age.total <- insol$YearBP
### Define mid-late Holocene Boundaries (t < 5,000)

\[
\text{insol.dTSI.new <- insol\$dTSI[864:1875]}
\]
\[
\text{insol.age.new <- insol\$YearBP[864:1875]}
\]
\[
\text{insol.sma.new <- insol.sma[864:1875]}
\]

### Define 95% Confidence Bands (based on Holocene record)

#### Note: The bands are narrow enough that they are likely to not be visible on your computer

\[
dTSI.se <- (sd(\text{insol.dTSI.new})/sqrt(length(\text{insol.dTSI.new})))\times 1.96
\]

### Plot Solar Irradiance Data

#### Note, Confidence Bands removed due to noisy data

\[
\text{quartz()}
\]

\[
\text{insol.plot <- qplot(\text{insol.age.new, insol.sma.new, xlim = c(0,5040), xlab = "Age (BP)", ylab = "dTSI (watts per meter anomaly from 1986)", geom="line", colour="grey70", fill = "grey70")}
\]

\[
\text{insol.plot + geom_point(colour="grey") + geom_line()}
\]

### Bayesian Change-Point Analysis

#### Table 4

#### Bayesian analysis is performed using the Barry and Hartigan algorithm (1993) with defaults recommended by Erdman and Emerson (2007), excepting burn-ins and Markov-Chain Monte Carlo sampling, which were set at 10,000

#### Note: The following analysis may take some time depending upon your computer's processing speed

#### Bayesian Change-Point Analysis, Archaeological Data

\[
\text{crete.bcp <- bcp(crete.occ, burnin=10000, mcmc=10000)}
\]
\[
\text{greece.bcp <- bcp(greece.occ, burnin=10000, mcmc=10000)}
\]

\[
\text{crete.pp <- crete.bcp\$posterior.prob*100}
\]
\[
\text{greece.pp <- greece.bcp\$posterior.prob*100}
\]

### Bayesian Change-Point Analysis, Land-Based Paleoclimate Data
```
rain.is.bcp <- bcp(rain.is[1:21], burnin=10000, mcmc=10000)
delta.gr.bcp <- bcp(delta.gr[1:13], burnin=10000, mcmc=10000)

rain.is.pp <- rain.is.bcp$posterior.prob*100
delta.gr.pp <- delta.gr.bcp$posterior.prob*100

### Bayesian Change-Point Analysis, Sea-Based Paleoclimate Data
ionian.sst.bcp <- bcp(ionian.sst.total, burnin=10000, mcmc=10000)
adriatic.sst.bcp <- bcp(adriatic.sst.total, burnin=10000, mcmc=10000)
adriatic.wsd.bcp <- bcp(adriatic.dino.total, burnin=10000, mcmc=10000)
aegean.wsf.bcp <- bcp(aegean.foram.total, burnin=10000, mcmc=10000)

ionian.sst.pp <- ionian.sst.bcp$posterior.prob*100
adriatic.sst.pp <- adriatic.sst.bcp$posterior.prob*100
adriatic.wsd.pp <- adriatic.wsd.bcp$posterior.prob*100
aegean.wsf.pp <- aegean.wsf.bcp$posterior.prob*100

### Create Table 1 Columns

start.date <- c(crete.date[14], greece.date[8], age.is[15], age.gr[7], ionian.age.total[26], adriatic.age.total[43], adriatic.aged.total[27], aegean.age.total[52])

end.date <- c(crete.date[15], greece.date[9], age.is[16], age.gr[8], ionian.age.total[27], adriatic.age.total[44], adriatic.aged.total[28], aegean.age.total[53])

change <- c("Palatial Center Abandonment", "Palatial Center Abandonment", "-100mm Precipitation", "-8‰ 13C Discrimination", "-3-4 °C SST", "-1-2 °C SST", "-24% Warm-Species Dinocyst", "-25% Warm-Species Foraminifera")

posterior.prob <- c(crete.pp[14], greece.pp[8], rain.is.pp[15], delta.gr.pp[7], ionian.sst.pp[26], adriatic.sst.pp[43], adriatic.wsd.pp[27], aegean.wsf.pp[52])

### Compile Table
table.1 <- data.frame(source, start.date, end.date, change, posterior.prob)
```
###References

###Alley, R.B., 2004. GISP2 Ice Core Temperature and Accumulation Data. IGBP PAGES World Data Center for Paleoclimatology Data Contribution Series #2004-013. NOAA/NGDC Paleoclimatology Program, Boulder CO, USA.


This script is copyright © 2011 Brandon Lee Goodchild Drake, and is distributed without warranty under the GNU General Public License (GPL): http://www.gnu.org/copyleft/gpl.html (retrieved on 7/26/2011)
C4 and C3 Grasses Have Comparable Accuracy When Modeling Atmospheric $\delta^{13}$CO$_2$

#Erase everything that comes before
rm(list = ls(all = TRUE))

#Compatibility
if(.Platform$OS.type=="windows") {
  quartz<-function() windows()
}

library(bcp)

#Load Data

time <- seq(1892, 2007, freq=1)
time.squared <- time^2

#Mauna Loa Data
mauna.loa.data <- read.csv(file="http://www.bleedrake.com/isotopes/Mauna.csv")
mauna.loa.c02 <- mauna.loa.data$mean
mauna.loa.year <- mauna.loa.data$year
mauna.loa.bayes <- bcp(mauna.loa.c02, burnin=10000, mcmc=10000)
mauna.loa.means <- mauna.loa.bayes$posterior.mean

#Climate Data
climate.test <- read.csv(file="http://www.bleedrake.com/isotopes/climate.csv")

#C4
bout <- read.csv(file="http://www.bleedrake.com/isotopes/c4.csv")

#C3
tax.cut <- read.csv(file="http://www.bleedrake.com/isotopes/c3.csv")

#Atmosphere
law.dome <- read.csv(file="http://www.bleedrake.com/isotopes/lawdome.csv")
law.dome.d13c <- law.dome$d13C
law.dome.year <- law.dome$YEAR
law.dome.year.squared <- law.dome.year^2
law.dome.regression <- lm(law.dome.d13c~law.dome.year.squared+law.dome.year)
law.dome.bayes <- bcp(law.dome.d13c, burnin=10000, mcmc=10000)
law.dome.means <- law.dome.bayes$posterior.mean

law.dome.model <- -0.0001728459*time.squared + 0.660422*time - 637.4698

#Leavitt and Long
lelo <- read.csv(file="http://www.bleedrake.com/isotopes/leavitt.csv")
tree.pool <- lelo$tree.farq
tree.time <- lelo$time
tree.time.squared <- tree.time^2
tree.ice <- lelo$ice.proj

tree.regression <- lm(tree.pool~tree.time.squared+tree.time)

quartz()
par(mfrow=c(1,2))
plot(bout$d13c.farq~bout$year, xlab = "", ylab = "C4 δ13C (‰)", pch=16, ylim = c(-12, -2))
points(law.dome.model~time, type="l", col="blue", lty=2, lwd=3)

plot(tax.cut$d13c3.farq~tax.cut$Year, xlab = "", ylab = "C3 δ13C (‰)", pch=16, ylim = c(-12, -2))
points(law.dome.model~time, type="l", col="blue", lty=2, lwd=3)

#Figure 2
bout <- read.csv(file="http://www.bleedrake.com/isotopes/c4.csv")
grass <- read.csv(file="http://www.bleedrake.com/isotopes/c3.csv")

#Bouteloua polynomial
hi <- -0.00009089*bout$year^2+0.3316*bout$year-308.28

#Bromus & Poa polynomial
ih <- -0.0003*grass$Year^2+1.1934*grass$Year - 1154.8
# Alternate Figure 2

bout <- read.csv(file = "http://www.bleedrake.com/isotopes/c4.csv")
glass <- read.csv(file = "http://www.bleedrake.com/isotopes/c3.csv")

bouteloua <- bout$d13c.farq
bouteloua.year <- bout$year
bouteloua.year.squared <- bout$year^2
bouteloua.bayes <- bcp(bouteloua, burnin=10000, mcmc=10000)
bouteloua.means <- bouteloua.bayes$posterior.mean

bromus <- grass$d13c3.farq[1:135]
bromus.year <- grass$Year[1:135]
bromus.year.squared <- bromus.year^2
bromus.bayes <- bcp(bromus, burnin=10000, mcmc=10000)
bromus.means <- bromus.bayes$posterior.mean

poa <- grass$d13c3.farq[136:263]
poa.year <- grass$Year[136:263]
poa.year.squared <- poa.year^2
poa.bayes <- bcp(poa, burnin=10000, mcmc=10000)
poa.means <- poa.bayes$posterior.mean

c3.grass <- grass$d13c3.farq
c3.grass.year <- grass$Year
c3.grass.year.squared <- c3.grass.year^2
c3.grass.bayes <- bcp(c3.grass, burnin=10000, mcmc=10000)

c3.grass.atmosphere <- grass$atmosphere
c3.grass.atmosphere.bayes <- bcp(c3.grass.atmosphere, burnin=10000, mcmc=10000)
c3.grass.atmosphere.means <- c3.grass.atmosphere.bayes$posterior.mean
bouteloua.atmosphere <- bout$atmosphere
bouteloua.atmosphere.bayes <- bcp(bouteloua.atmosphere, burnin=10000, mcmc=10000)
bouteloua.atmosphere.means <- bouteloua.atmosphere.bayes$posterior.mean

c4.grass <- bouteloua
c4.grass.mean <- bouteloua.means

c4.model <- lm(bouteloua~bouteloua.year.squared+bouteloua.year)
c3.model <- lm(c3.grass~c3.grass.year.squared+c3.grass.year)

#bouteloua.model <- -9.088724e-05*time.squared + 0.3315981*time - 308.2752
bouteloua.model <- c4.model$coef[2]*time.squared + c4.model$coef[3]*time + c4.model$coef[1]
bromus.model <- -1.979e-04*time.squared + 7.581e-01*time - 7.327e+02
poa.model <- -4.728e-04*time.squared + 1.826e+00*time - 1.770e+03

#c3.grass.model <- -0.0003100132 *time.squared + 1.193411*time - 1154.768
#c3.grass.model <- c3.model$coef[2]*time.squared + c3.model$coef[3]*time + c3.model$coef[1]

#Bayesian Limits
c3.model.lower <- -5.203e-04*time.squared + 1.432e-01*time - 1.959e+03
c3.model.upper <- -4.213e-05*time.squared + 2.015e+00*time - 1.245e+02

quartz()
plot(law.dome.model~time, type="l", ylim = c(-8.5, -5.5), xlab = " ", ylab = "δ13C (‰)", lwd=2, col = "blue")
points(bouteloua.model~time, type="l", lty=3, lwd=2, col = "red")
points(c3.grass.model~time, type="l", lty=2, lwd=2, col = "green")
#points(tree.model~tree.time, type="l", lwy=4, lwd=2)
legend("bottomleft", c("Atmosphere", "C3 Grasses", "C4 Grasses"), lty=c(1, 2, 3), col = c("blue", "green", "red"))

#Figure 3 Candidate
quartz()
par(mfrow=c(1,2))
plot(bouteloua.model~law.dome.model, main = "C4 Grasses", ylab = "C4 δ13C (‰)", xlab = "Atmospheric δ13C (‰)", ylim = c(-9, -5.5), pch = 16, col = "red")
abline(0,1, lwd=2, col = "blue")
#Data against δ13Ca: R2 = 0.3557, R2adj = 0.3518, p-value: < 2.2e-16
#Model against δ13Ca: R2 = 0.9402, RRadj = 0.9397, p-value: < 2.2e-16
#Mean Difference = -0.2677189‰

plot(c3.grass.model~law.dome.model, main = "C3 Grasses", ylab = "C3 δ13C (‰)", xlab = "Atmospheric δ13C (‰)", ylim = c(-9, -5.5), pch = 16, col = "green")
abline(0,1, lwd=2, col = "blue")
#Data against δ13Ca: R2 = 0.1213, R2adj = 0.1181, p-value: < 3.112e-09
#Model against δ13Ca: R2 = 0.9685, RRadj = 0.9682, p-value: < 2.2e-16
#Mean Difference = 0.2988125‰

#Figure 4 Candidate
pdsi <- grass$PDSI
c3.grass.precipitation <- grass$Precipitation
c3.grass.temperature <- grass$Temperature
c3.grass.pdsi <- grass$PDSI
c3.grass.full <- grass$d13c3
delta.c3 <- grass$delta.c3
delta.c4 <- bout$delta.c3[1:165]
bouteloua.full <- bout$d13c
bouteloua.precipitation <- bout$Precipitation[1:165]
bouteloua.temperature <- bout$Temperature[1:165]
bouteloua.pdsi <- bout$PDSI[1:165]

quartz()
par(mfrow=c(1,2))
plot(delta.c4~bouteloua.precipitation, pch = 16, xlab = "March - September Precipitation (mm)"
, ylab = "C4 Δ (%)", main = "C4 Grasses")
plot(delta.c3~c3.grass.precipitation, pch=16, xlab = "March - September Precipitation (mm)", ylab = "C3 Δ (‰)", main="C3 Grasses")

quartz()
par(mfrow=c(1,2))
plot(delta.c4~bouteloua.temperature, pch = 16, xlab = "March - September Temperature (Celsius)", ylab = "C4 Δ (‰)", main = "C4 Grasses")
plot(delta.c3~c3.grass.temperature, pch=16, xlab = "March - September Temperature (Celsius)", ylab = "C3 Δ (‰)", main="C3 Grasses")

quartz()
par(mfrow=c(1,2))
plot(delta.c4~bouteloua.pdsi, pch = 16, xlab = "March - September PDSI", ylab = "C4 Δ (‰)", main = "C4 Grasses")
plot(delta.c3~c3.grass.pdsi, pch=16, xlab = "March - September PDSI", ylab = "C3 Δ (‰)", main="C3 Grasses")

#IWUE and Δ

#T Tests
drought.d13c3 <- c3.grass.full[54:77]
drought.precip <- c3.grass.precipitation[54:77]
delta.c3.drought <- delta.c3[54:77]

regular.d13c3 <- c3.grass.full[c(1:53, 78:274)]
regular.precip <- c3.grass.precipitation[c(1:53, 78:274)]
delta.c3.regular <- delta.c3[c(1:53, 78:274)]
### generate variables

c3.grass.norm <- tax.cut$d13c3
c4.grass.norm <- bout$d13c

c3.co2 <- c3.grass.atmosphere*-54.73-65.81
c4.co2 <- bouteloua.atmosphere*-54.73-65.81
c3.cica <-(c3.grass.norm-c3.grass.atmosphere+4.4)/-(27-4.4)
c4.cica <-(c4.grass.norm-bouteloua.atmosphere+4.4)/-(-5.7+(27*0.505)-4.4)

c3.wi <- ((c3.co2*(1-c3.cica))/1.6)
c4.wi <- ((c4.co2*(1-c4.cica))/1.6)

c3.grass.atmosphere.alt <- c3.grass.atmosphere*.85 + .15*(-19+.5)
c3.co2.alt <- c3.grass.atmosphere.alt*-54.73-65.81
c3.cica.alt <-(c3.grass.norm-c3.grass.atmosphere.alt+4.4)/-(27-4.4)
c3.wi.alt <- ((c3.co2*(1-c3.cica.alt))/1.6)
c3.wi.alt.alt <- ((c3.co2.alt*(1-c3.cica.alt))/1.6)

bouteloua.atmosphere.alt <- bouteloua.atmosphere*.85 + .15*(-19-1)
c4.co2.alt <- bouteloua.atmosphere.alt*-54.73-65.81
c4.cica.alt <-(c4.grass.norm-bouteloua.atmosphere.alt+4.4)/-(-5.7+(27*0.505)-4.4)
c4.wi.alt <- ((c4.co2*(1-c4.cica.alt))/1.6)
c4.wi.alt.alt <- ((c4.co2.alt*(1-c4.cica.alt))/1.6)

###########
# iWUE and Δ
###########
bout.iwue <- c4.wi
c3.grass.iwue <- c3.wi

quartz()
par(mfrow=c(1,2))
plot(bout.iwue~bouteloua.year, ylab = "Wi (µ mol mol -1)", main = "C4 Grasses", xlab = ", ylim = c(-200,300), pch=6)
abline(628.5250, -0.2833, lwd=2)
legend("bottomleft", c("C4 Grasses (-36%)"))
plot(c3.grass.iwue~c3.grass.year, ylab = "Wi (µ mol mol -1)", main = "C3 Grasses ", xlab = "", ylim = c(-200,300), pch=6)
abline(-236.81518, 0.15329, lwd=3)
legend("bottomleft", c("C3 Grasses (+34%)"))

#Random Tests

```
c3.grass.random <- read.csv(file="http://www.bleedrake.com/isotopes/c3rand.csv")
c4.grass.random <- read.csv(file="http://www.bleedrake.com/isotopes/c4rand.csv")

c3.grass.d13c.sample.1 <- c3.grass.random$d13c3.farq[1:50]
c3.grass.year.sample.1 <- c3.grass.random$Year[1:50]
c3.grass.year.sample.1.squared <- c3.grass.random$Year[1:50]^2
c3.grass.a.sample.1 <- c3.grass.random$atmosphere[1:50]
c3.sample.1 <- data.frame(c3.grass.year.sample.1, c3.grass.year.sample.1.squared, c3.grass.d13c.sample.1, c3.grass.a.sample.1)
c3.sample.1 <- c3.sample.1[order(c3.sample.1$c3.grass.year.sample.1),]
c3.grass.regression.1 <- lm(c3.grass.d13c.sample.1~c3.grass.year.sample.1.squared +c3.grass.year.sample.1)

c3.grass.d13c.sample.2 <- c3.grass.random$d13c3.farq[51:100]
c3.grass.year.sample.2 <- c3.grass.random$Year[51:100]
c3.grass.year.sample.2.squared <- c3.grass.random$Year[51:100]^2
c3.grass.a.sample.2 <- c3.grass.random$atmosphere[51:100]
c3.sample.2 <- data.frame(c3.grass.year.sample.2, c3.grass.year.sample.2.squared, c3.grass.d13c.sample.2, c3.grass.a.sample.2)
c3.sample.2 <- c3.sample.2[order(c3.sample.2$c3.grass.year.sample.2),]
c3.grass.regression.2 <- lm(c3.grass.d13c.sample.2~c3.grass.year.sample.2.squared +c3.grass.year.sample.2)

c3.grass.d13c.sample.3 <- c3.grass.random$d13c3.farq[101:200]
c3.grass.year.sample.3 <- c3.grass.random$Year[101:200]
c3.grass.year.sample.3.squared <- c3.grass.random$Year[101:200]^2
c3.grass.a.sample.3 <- c3.grass.random$atmosphere[101:200]
```
c3.sample.3 <- data.frame(c3.grass.year.sample.3, c3.grass.year.sample.3.squared, 
c3.grass.d13c.sample.3, c3.grass.a.sample.3)
c3.sample.3 <- c3.sample.3[order(c3.sample.3$c3.grass.year.sample.3),]
c3.grass.regression.3 <- lm(c3.grass.d13c.sample.3~c3.grass.year.sample.3.squared + c3.grass.year.sample.3)

c3.grass.model.sample.1 <- c3.grass.regression.1$coef[2]*time.squared + c3.grass.regression.1$coef[3]*time + c3.grass.regression.1$coef[1]
#c3.grass.model.sample.1 <- 5.489664e-05*time.squared- 0.2336705*time + 240.2135
#Data against δ13Ca: R2 = 0.06632, R2adj = 0.04687, p-value: 0.071
#Model against δ13Ca: R2 = 0.8111, RRadj = 0.8095, p-value: < 2.2e-16

c3.grass.model.sample.2 <- c3.grass.regression.2$coef[2]*time.squared + c3.grass.regression.2$coef[3]*time + c3.grass.regression.2$coef[1]
#c3.grass.model.sample.2 <- 0.0001878461*time.squared - 0.779396*time + 799.2538
#Data against δ13Ca: R2 = 0.1852, R2adj = 0.1682, p-value: 0.001812
#Model against δ13Ca: R2 = 0.7825, RRadj = 0.7806, p-value: < 2.2e-16

c3.grass.model.sample.3 <- c3.grass.regression.3$coef[2]*time.squared + c3.grass.regression.3$coef[3]*time + c3.grass.regression.3$coef[1]
#c3.grass.model.sample.3 <- -0.0001954338*time.squared + 0.7494672*time- 724.9608
#Data against δ13Ca: R2 = 0.07005, R2adj = 0.06056, p-value: 0.007791
#Model against δ13Ca: R2 = 0.995, RRadj = 0.9949, p-value: < 2.2e-16

c4.grass.d13c.sample.1 <- c4.grass.random$d13c.farq[1:50]
c4.grass.year.sample.1 <- c4.grass.random$year[1:50]
c4.grass.year.sample.1.squared <- c4.grass.random$year[1:50]^2
c4.grass.a.sample.1 <- c4.grass.random$atmosphere[1:50]
c4.sample.1 <- data.frame(c4.grass.year.sample.1, c4.grass.year.sample.1.squared, 
c4.grass.d13c.sample.1, c4.grass.a.sample.1)
c4.sample.1 <- c4.sample.1[order(c4.sample.1$c4.grass.year.sample.1),]
c4.grass.regression.1 <- lm(c4.grass.d13c.sample.1~c4.grass.year.sample.1.squared + c4.grass.year.sample.1)

c4.grass.d13c.sample.2 <- c4.grass.random$d13c.farq[51:100]
c4.grass.year.sample.2 <- c4.grass.random$year[51:100]
c4.grass.year.sample.2.squared <- c4.grass.random$year[51:100]^2
c4.grass.a.sample.2 <- c4.grass.random$atmosphere[51:100]
c4.sample.2 <- data.frame(c4.grass.year.sample.2, c4.grass.year.sample.2.squared,
c4.grass.d13c.sample.2, c4.grass.a.sample.2)
c4.sample.2 <- c4.sample.2[order(c4.sample.2$c4.grass.year.sample.2),]
c4.grass.regression.2 <- lm(c4.grass.d13c.sample.2~c4.grass.year.sample.2.squared
+c4.grass.year.sample.2)

c4.grass.d13c.sample.3 <- c4.grass.random$d13c.farq[c(1:10, 21:30, 41:60, 81:80,
101:150)]
c4.grass.year.sample.3 <- c4.grass.random$year[c(1:10, 21:30, 41:50, 61:60, 81:80, 101:150)]
c4.grass.year.sample.3.squared <- c4.grass.random$year[c(1:10, 21:30, 41:50, 61:60, 81:80,
101:150)]^2
c4.grass.a.sample.3 <- c4.grass.random$atmosphere[c(1:10, 21:30, 41:50, 61:60, 81:80, 101:150)]
c4.sample.3 <- data.frame(c4.grass.year.sample.3, c4.grass.year.sample.3.squared,
c4.grass.d13c.sample.3, c4.grass.a.sample.3)
c4.sample.3 <- c4.sample.3[order(c4.sample.3$c4.grass.year.sample.3),]
c4.grass.regression.3 <- lm(c4.grass.d13c.sample.3~c4.grass.year.sample.3.squared
+c4.grass.year.sample.3)

c4.grass.model.sample.1 <- c4.grass.regression.1$coef[2]*time.squared + c4.grass.regression.1$coef[3]*time + c4.grass.regression.1$coef[1]
#c4.grass.model.sample.1 <- -0.0001207983*time.squared + 0.4523956*time  - 430.1305
#Data against δ13Ca: R2 = 0.3942, R2adj = 0.3816, p-value: 1.187e-07
#Model against δ13Ca:R2 = 0.9701, RRadj = 0.9698, p-value: < 2.2e-16

c4.grass.model.sample.2 <- c4.grass.regression.2$coef[2]*time.squared + c4.grass.regression.2$coef[3]*time + c4.grass.regression.2$coef[1]
#c4.grass.model.sample.2 <- -0.0001895800*time.squared + 0.7169494*time - 684.1576
#Data against δ13Ca: R2 = 0.4457, R2adj = 0.4341, p-value: 9.11e-07
#Model against δ13Ca:R2 = 0.9866, RRadj = 0.9865, p-value: < 2.2e-16

c4.grass.model.sample.3 <- c4.grass.regression.3$coef[2]*time.squared + c4.grass.regression.3$coef[3]*time + c4.grass.regression.3$coef[1]
#c4.grass.model.sample.3 <- -4.681232e-05*time.squared + 0.1588454*time - 139.1262
#Data against δ13Ca: R2 = 0.3622, R2adj = 0.3544, p-value: 1.403e-09
# Model against $\delta^{13}$Ca: R2 = 0.9087, RRadj = 0.9079, p-value: < 2.2e-16

```r
quartz()
par(mfrow = c(1,2))
plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = "", ylab = "$\delta^{13}$C (‰)", main = "C4 Grasses", col = "blue")
points(c4.grass.model.sample.1~time, type="l", lty=2, col = "red1")
points(c4.grass.model.sample.2~time, type="l", lty=3, col = "red2")
points(c4.grass.model.sample.3~time, type="l", lty=4, col = "red3")
legend("bottomleft", c("Atmosphere", "C4 Grasses Sample 1 (n=50)", "C4 Grasses Sample 2 (n=50)", "C4 Grasses Sample 3 (n=100)"), lty=c(1, 2, 3, 4), col = c("blue", "red1", "red2", "red3"),cex=0.8)

plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = "", ylab = "$\delta^{13}$C (‰)", main = "C3 Grasses", col = "blue")
points(c3.grass.model.sample.1~time, type="l", lty=2, col = "green1")
points(c3.grass.model.sample.2~time, type="l", lty=3, col = "green2")
points(c3.grass.model.sample.3~time, type="l", lty=4, col = "green3")
legend("bottomleft", c("Atmosphere", "C3 Grasses Sample 1 (n=50)", "C3 Grasses Sample 2 (n=50)", "C3 Grasses Sample 3 (n=100)"); lty=c(1, 2, 3, 4), col = c("blue", "green1", "green2", "green3"), cex=0.8)

# CO2 Reconstruction

c3.grass.c02 <- -54.752*c3.grass.model - 65.812
# Mean Difference = -16.36058
# Standard Deviation = 8.277329

c4.grass.c02 <- -54.752*bouteloua.model - 65.812
# Mean Difference = 14.65814
# Standard Deviation = 17.6521

atmosphere.c02 <- -54.752*law.dome.model - 65.812
fossil.1 <- -54.752*(-29.38 + 20.22) - 65.812
fossil.2 <- -54.752*(-29.38 + 12.31) - 65.812

quartz()
plot(atmosphere.c02~time, type="l", xlab = "", ylab = "CO2 (ppm)", ylim = c(275, 425), col = "blue")
points(c4.grass.c02~time, type="l", lty=3, col = "red")
points(c3.grass.c02~time, type="l", lty=2, col = "green")
```

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points(mauna.loa.c02~mauna.loa.year, type="l", lwd = 2, lty=4, col = "purple")
legend("topleft", c("Atmosphere", "Mauna Loa", "C3 Grasses", "C4 Grasses"), lty=c(1, 4, 2, 3), col = c("blue", "purple", "green", "red"))

#Bayesian Modeling
library(MCMCpack)
c3.bayesian.model <- MCMCregress(c3.grass~c3.grass.atmosphere, mcmc=100000)
c4.bayesian.model <- MCMCregress(bouteloua~bouteloua.atmosphere, mcmc = 100000)

c3.bayesian.slope <- c3.bayesian.model[,2]
c4.bayesian.slope <- c4.bayesian.model[,2]

c3.density.bayesian.slope <- density(c3.bayesian.slope)
c4.density.bayesian.slope <- density(c4.bayesian.slope)

quartz()
plot(c4.density.bayesian.slope, xlim = c(0.5, 2), ylim = c(0, 2.7), main = " ", xlab = "Bayesian Model Slopes",lty=3, lwd=2, col ="red")
points(c3.density.bayesian.slope, type="l", lty=2, lwd=2, col = "green")
legend("topleft", c("C3 Grasses", "C4 Grasses"), lty=c(2, 3), col = c("green", "red"))
abline(v = 1, lwd=2, col="blue")

quartz()
par(mfrow=c(2,1))
hist(c4.bayesian.slope, main = "C4 Grasses", xlim = c(0.5, 2), ylim = c(0, 25000), xlab = "Linear Model Slope")
hist(c3.bayesian.slope, main = "C3 Grasses", xlim = c(0.5, 2), ylim = c(0, 25000), xlab = "Linear Model Slope")

#Confidence Bands
new.year <- time
new.year.squared <- new.year^2

new.bouteloua.model <- c4.model$coef[2]*time.squared + c4.model$coef[3]*time + c4.model$coef[1]
bouteloua.model.lm <- lm(bouteloua~bouteloua.year.squared+bouteloua.year)
c4.res <- bouteloua.model.lm$residuals
c4.sse <- sum(c4.res^2)
c4.n <- length(c4.res)
c4.mse <- c4.sse/(c4.n-2)

c4.x_bar <- mean(time)
c4.sum_x_dev_sqr <- sum((bouteloua.year-c4.x_bar)^2)

c4.s_yhat <- sqrt(c4.mse*(1/c4.n + (new.year-c4.x_bar)^2/c4.sum_x_dev_sqr))
c4.alpha <- .05
c4.W <- sqrt(2*qf(1-c4.alpha,2,c4.n-2))

c4.WH_UB <- new.bouteloua.model+c4.W*c4.s_yhat


c3.grass.model.lm <- lm(c3.grass~c3.grass.year.squared+c3.grass.year)

c3.res <- c3.grass.model.lm$residuals
c3.sse <- sum(c3.res^2)
c3.n <- length(c3.res)
c3.mse <- c3.sse/(c3.n-2)

c3.x_bar <- mean(c3.grass.year)
c3.sum_x_dev_sqr <- sum((c3.grass.year-c3.x_bar)^2)

c3.s_yhat <- sqrt(c3.mse*(1/c3.n + (new.year-c3.x_bar)^2/c3.sum_x_dev_sqr))
c3.alpha <- .05
c3.W <- sqrt(2*qf(1-c3.alpha,2,c3.n-2))

c3.WH_LB <- new.c3.grass.model-c3.W*c3.s_yhat
c3.WH_UB <- new.c3.grass.model+c3.W*c3.s_yhat

quartz()
par(mfrow=c(1,2))
plot(bouteloua.model~time, ylim=c(-9, -5), main="Confidence Bands", xlab="", ylab="$\delta^{13}$C (‰)", pch=16)
lines(new.year, c4.WH_LB, col='red')
lines(new.year, c4.WH_UB, col='red')

plot(c3.grass.model~time, ylim=c(-9, -5), main="Confidence Bands", xlab="", ylab="$\delta^{13}$C (‰)", pch=16)
lines(new.year, c3.WH_LB, col='red')
lines(new.year, c3.WH_UB, col='red')

#Testing
quartz()
plot(law.dome.model~time, type="l", ylim = c(-8.5, -5.5), xlab="", ylab="$\delta^{13}$C (‰)", lwd=2)
points(bouteloua.model~time, type="l", lty=3, lwd=2)
lines(new.year, c4.WH_LB, lty=3)
lines(new.year, c4.WH_UB, lty=3)
points(c3.grass.model~time, type="l", lty=2, lwd=2)
lines(new.year, c3.WH_LB, lty=2)
lines(new.year, c3.WH_UB, lty=2)
legend("bottomleft", c("Atmosphere", "C3 Grasses", "C4 Grasses"), lty=c(1, 2, 3))

#part.model <- -0.0001728459 *part.year.squared + 6.604e-01*part.year - 6.375e+02

#More Advanced Subsamples

###########################
#Get C4 Grid Ready:
###########################
quartz()
par(mfrow=c(2,4))

#C4 Sample 1 n = 50
extra1 <- rnorm(165, .5, sd=1)
c4.dataframe <- data.frame(d13c=bouteloua, year=bouteloua.year,
    year.squared=bouteloua.year.squared, extra1=extra1)
sample <- c4.dataframe[order(c4.dataframe$extra1),]
d13c.1 <- sample$d13c[1:50]
year.1 <- sample$year[1:50]
year.squared.1 <- sample$year.squared[1:50]
c4.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
c4.50<- c4.sample.1.dataframe[order(c4.sample.1.dataframe$year),]
c4.regression<- lm(c4.50$d13c~c4.50$year.squared+c4.50$year)
c4.run <- c4.regression$coef[2]*c4.50$year.squared + c4.regression$coef[3]*c4.50$year + 
c4.regression$coef[1]

plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = " ", ylab = "δ13C (‰)", main = "C4 Sample 1")
points(c4.run~c4.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C4 Grasses Sample 1 (n=50)"), lty=c(1, 3), cex=0.6)

#C4 Sample 2 n = 50
extra1 <- rnorm(165, .5, sd=1)
c4.dataframe <- data.frame(d13c=bouteloua, year=bouteloua.year,
 year.squared=bouteloua.year.squared, extra1=extra1)
sample <- c4.dataframe[order(c4.dataframe$extra1),]
d13c.1 <- sample$d13c[1:50]
year.1 <- sample$year[1:50]
year.squared.1 <- sample$year.squared[1:50]
c4.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
c4.50<- c4.sample.1.dataframe[order(c4.sample.1.dataframe$year),]
c4.regression<- lm(c4.50$d13c~c4.50$year.squared+c4.50$year)
c4.run <- c4.regression$coef[2]*c4.50$year.squared + c4.regression$coef[3]*c4.50$year + 
c4.regression$coef[1]

plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = " ", ylab = "δ13C (‰)", main = "C4 Sample 2")
points(c4.run~c4.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C4 Grasses Sample 2 (n=50)"), lty=c(1, 3), cex=0.6)

#C4 Sample 3 n = 50
extra1 <- rnorm(165, .5, sd=1)
c4.dataframe <- data.frame(d13c=bouteloua, year=bouteloua.year,
 year.squared=bouteloua.year.squared, extra1=extra1)
sample <- c4.dataframe[order(c4.dataframe$extra1),]
d13c.1 <- sample$d13c[1:50]
year.1 <- sample$year[1:50]
year.squared.1 <- sample$year.squared[1:50]
c4.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
c4.50<- c4.sample.1.dataframe[order(c4.sample.1.dataframe$year),]
c4.regression<- lm(c4.50$d13c~c4.50$year.squared+c4.50$year)
c4.run <- c4.regression$coef[2]*c4.50$year.squared + c4.regression$coef[3]*c4.50$year +
c4.regression$coef[1]

plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = "", ylab = "δ13C (‰)", main = "C4 Sample 3")
points(c4.run~c4.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C4 Grasses Sample 3 (n=50)"), lty=c(1, 3), cex=0.6)

#C4 Sample 4 n = 50
eextra1 <- rnorm(165, .5, sd=1)
c4.dataframe <- data.frame(d13c=bouteloua, year=bouteloua.year,
year.squared=bouteloua.year.squared, extra1=extra1)
sample <- c4.dataframe[order(c4.dataframe$extra1),]
d13c.1 <- sample$d13c[1:50]
year.1 <- sample$year[1:50]
year.squared.1 <- sample$year.squared[1:50]
c4.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
c4.50<- c4.sample.1.dataframe[order(c4.sample.1.dataframe$year),]
c4.regression<- lm(c4.50$d13c~c4.50$year.squared+c4.50$year)
c4.run <- c4.regression$coef[2]*c4.50$year.squared + c4.regression$coef[3]*c4.50$year +
c4.regression$coef[1]

plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = "", ylab = "δ13C (‰)", main = "C4 Sample 4")
points(c4.run~c4.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C4 Grasses Sample 4 (n=50)"), lty=c(1, 3), cex=0.6)

#C4 Sample 5 n = 50
eextra1 <- rnorm(165, .5, sd=1)
c4.dataframe <- data.frame(d13c=bouteloua, year=bouteloua.year,
year.squared=bouteloua.year.squared, extra1=extra1)
sample <- c4.dataframe[order(c4.dataframe$extra1),]
d13c.1 <- sample$d13c[1:50]
year.1 <- sample$year[1:50]
year.squared.1 <- sample$year.squared[1:50]
c4.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
c4.50<- c4.sample.1.dataframe[order(c4.sample.1.dataframe$year),]
c4.regression<- lm(c4.50$d13c~c4.50$year.squared+c4.50$year)
c4.run <- c4.regression$coeff[2]*c4.50$year.squared + c4.regression$coeff[3]*c4.50$year +
c4.regression$coeff[1]

plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = " ", ylab = "δ13C (‰)", main = "C4 Sample 5")
points(c4.run~c4.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C4 Grasses Sample 5 (n=50)"), lty=c(1, 3), cex=0.6)

#C4 Sample 6 n = 50
extra1 <- rnorm(165, .5, sd=1)
c4.dataframe <- data.frame(d13c=bouteloua, year=bouteloua.year,
year.squared=bouteloua.year.squared, extra1=extra1)
sample <- c4.dataframe[order(c4.dataframe$extra1),]
d13c.1 <- sample$d13c[1:50]
year.1 <- sample$year[1:50]
year.squared.1 <- sample$year.squared[1:50]
c4.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
c4.50<- c4.sample.1.dataframe[order(c4.sample.1.dataframe$year),]
c4.regression<- lm(c4.50$d13c~c4.50$year.squared+c4.50$year)
c4.run <- c4.regression$coeff[2]*c4.50$year.squared + c4.regression$coeff[3]*c4.50$year +
c4.regression$coeff[1]

plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = " ", ylab = "δ13C (‰)", main = "C4 Sample 6")
points(c4.run~c4.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C4 Grasses Sample 6 (n=50)"), lty=c(1, 3), cex=0.6)

#C4 Sample 7 n = 50
extra1 <- rnorm(165, .5, sd=1)
c4.dataframe <- data.frame(d13c=bouteloua, year=bouteloua.year,
year.squared=bouteloua.year.squared, extra1=extra1)
sample <- c4.dataframe[order(c4.dataframe$extra1),]
d13c.1 <- sample$d13c[1:50]
year.1 <- sample$year[1:50]
year.squared.1 <- sample$year.squared[1:50]
c4.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
c4.50<- c4.sample.1.dataframe[order(c4.sample.1.dataframe$year),]
c4.regression<- lm(c4.50$d13c~c4.50$year.squared+c4.50$year)

plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = "", ylab = "δ13C (‰)", main = "C4 Sample 7")
points(c4.run~c4.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C4 Grasses Sample 7 (n=50)"), lty=c(1, 3), cex=0.6)

#C4 Sample 8 n = 50
extra1 <- rnorm(165, .5, sd=1)
c4.dataframe <- data.frame(d13c=bouteloua, year=bouteloua.year, year.squared=bouteloua.year.squared, extra1=extra1)
sample <- c4.dataframe[order(c4.dataframe$extra1),]
d13c.1 <- sample$d13c[1:50]
year.1 <- sample$year[1:50]
year.squared.1 <- sample$year.squared[1:50]
c4.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
c4.50<- c4.sample.1.dataframe[order(c4.sample.1.dataframe$year),]
c4.regression<- lm(c4.50$d13c~c4.50$year.squared+c4.50$year)

plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = "", ylab = "δ13C (‰)", main = "C4 Sample 8")
points(c4.run~c4.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C4 Grasses Sample 8 (n=50)"), lty=c(1, 3), cex=0.6)

#Get C4 Grid Ready:
quartz()
par(mfrow=c(2,4))

#C4 Sample 1 n = 100
extra1 <- rnorm(165, .5, sd=1)
c4.dataframe <- data.frame(d13c=bouteloua, year=bouteloua.year,
    year.squared=bouteloua.year.squared, extra1=extra1)
sample <- c4.dataframe[order(c4.dataframe$extra1),]
d13c.1 <- sample$d13c[1:50]
year.1 <- sample$year[1:50]
year.squared.1 <- sample$year.squared[1:50]
c4.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
c4.regression<- lm(c4.50$d13c~c4.50$year.squared+c4.50$year)
c4.run <- c4.regression$coef[2]*c4.50$year.squared + c4.regression$coef[3]*c4.50$year +
c4.regression$coef[1]
plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = "", ylab = "δ13C (‰)", main = "C4 Sample 1")
points(c4.run~c4.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C4 Grasses Sample 1 (n=50)"), lty=c(1, 3), cex=0.6)

#C4 Sample 2 n = 100
extra1 <- rnorm(165, .5, sd=1)
c4.dataframe <- data.frame(d13c=bouteloua, year=bouteloua.year,
    year.squared=bouteloua.year.squared, extra1=extra1)
sample <- c4.dataframe[order(c4.dataframe$extra1),]
d13c.1 <- sample$d13c[1:100]
year.1 <- sample$year[1:100]
year.squared.1 <- sample$year.squared[1:100]
c4.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
c4.regression<- lm(c4.50$d13c~c4.50$year.squared+c4.50$year)
c4.run <- c4.regression$coef[2]*c4.50$year.squared + c4.regression$coef[3]*c4.50$year +
c4.regression$coef[1]
plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = "", ylab = "δ13C (‰)", main = "C4 Sample 2")
points(c4.run~c4.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C4 Grasses Sample 2 (n=100)"), lty=c(1, 3), cex=0.6)

#C4 Sample 3 n = 100
extra1 <- rnorm(165, .5, sd=1)
c4.dataframe <- data.frame(d13c=bouteloua, year=bouteloua.year,
year.squared=bouteloua.year.squared, extra1=extra1)
sample <- c4.dataframe[order(c4.dataframe$extra1),]
d13c.1 <- sample$d13c[1:100]
year.1 <- sample$year[1:100]
year.squared.1 <- sample$year.squared[1:100]
c4.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
c4.50<- c4.sample.1.dataframe[order(c4.sample.1.dataframe$year),]
c4.regression<- lm(c4.50$d13c~c4.50$year.squared+c4.50$year)
c4.run <- c4.regression$coef[2]*c4.50$year.squared + c4.regression$coef[3]*c4.50$year +
c4.regression$coef[1]

plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = " ", ylab = "δ13C (‰)", main = "C4 Sample 3")
points(c4.run~c4.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C4 Grasses Sample 3 (n=100)"), lty=c(1, 3), cex=0.6)

#C4 Sample 4 n = 100
extra1 <- rnorm(165, .5, sd=1)
c4.dataframe <- data.frame(d13c=bouteloua, year=bouteloua.year,
year.squared=bouteloua.year.squared, extra1=extra1)
sample <- c4.dataframe[order(c4.dataframe$extra1),]
d13c.1 <- sample$d13c[1:100]
year.1 <- sample$year[1:100]
year.squared.1 <- sample$year.squared[1:100]
c4.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
c4.50<- c4.sample.1.dataframe[order(c4.sample.1.dataframe$year),]
c4.regression<- lm(c4.50$d13c~c4.50$year.squared+c4.50$year)
c4.run <- c4.regression$coef[2]*c4.50$year.squared + c4.regression$coef[3]*c4.50$year +
c4.regression$coef[1]

plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = " ", ylab = "δ13C (‰)", main = "C4 Sample 4")
points(c4.run~c4.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C4 Grasses Sample 4 (n=100)"), lty=c(1, 3), cex=0.6)

#C4 Sample 5 n = 100
extra1 <- rnorm(165, .5, sd=1)
c4.dataframe <- data.frame(d13c=bouteloua, year=bouteloua.year, 
    year.squared=bouteloua.year.squared, extra1=extra1)
sample <- c4.dataframe[order(c4.dataframe$extra1),]
d13c.1 <- sample$d13c[1:100]
year.1 <- sample$year[1:100]
year.squared.1 <- sample$year.squared[1:100]
c4.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
c4.50<- c4.sample.1.dataframe[order(c4.sample.1.dataframe$year),]
c4.regression<- lm(c4.50$d13c~c4.50$year.squared+c4.50$year)
c4.run <- c4.regression$coef[2]*c4.50$year.squared + c4.regression$coef[3]*c4.50$year + 
    c4.regression$coef[1]

plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = " ", ylab = "δ13C (‰)", main = "C4 Sample 5")
points(c4.run~c4.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C4 Grasses Sample 5 (n=100)"), lty=c(1, 3), cex=0.6)

#C4 Sample 6 n = 100
extra1 <- rnorm(165, .5, sd=1)
c4.dataframe <- data.frame(d13c=bouteloua, year=bouteloua.year, 
    year.squared=bouteloua.year.squared, extra1=extra1)
sample <- c4.dataframe[order(c4.dataframe$extra1),]
d13c.1 <- sample$d13c[1:100]
year.1 <- sample$year[1:100]
year.squared.1 <- sample$year.squared[1:100]
c4.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
c4.50<- c4.sample.1.dataframe[order(c4.sample.1.dataframe$year),]
c4.regression<- lm(c4.50$d13c~c4.50$year.squared+c4.50$year)
c4.run <- c4.regression$coef[2]*c4.50$year.squared + c4.regression$coef[3]*c4.50$year + 
    c4.regression$coef[1]

plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = " ", ylab = "δ13C (‰)", main = "C4 Sample 6")
points(c4.run~c4.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C4 Grasses Sample 6 (n=100)"), lty=c(1, 3), cex=0.6)

#C4 Sample 7 n = 100
extra1 <- rnorm(165, .5, sd=1)
c4.dataframe <- data.frame(d13c=bouteloua, year=bouteloua.year, 
    year.squared=bouteloua.year.squared, extra1=extra1)
sample <- c4.dataframe[order(c4.dataframe$extra1),]
d13c.1 <- sample$d13c[1:100]
year.1 <- sample$year[1:100]
year.squared.1 <- sample$year.squared[1:100]
c4.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
c4.regression<- lm(c4.50$d13c~c4.50$year.squared+c4.50$year)
c4.run <- c4.regression$coef[2]*c4.50$year.squared + c4.regression$coef[3]*c4.50$year +
c4.regression$coef[1]

plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = "", ylab = "δ13C (‰)", main = "C4 Sample 7")
points(c4.run~c4.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C4 Grasses Sample 7 (n=100)"), lty=c(1, 3), cex=0.6)

#C4 Sample 8 n = 100
extra1 <- rnorm(165, .5, sd=1)
c4.dataframe <- data.frame(d13c=bouteloua, year=bouteloua.year, 
    year.squared=bouteloua.year.squared, extra1=extra1)
sample <- c4.dataframe[order(c4.dataframe$extra1),]
d13c.1 <- sample$d13c[1:100]
year.1 <- sample$year[1:100]
year.squared.1 <- sample$year.squared[1:100]
c4.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
c4.regression<- lm(c4.50$d13c~c4.50$year.squared+c4.50$year)
c4.run <- c4.regression$coef[2]*c4.50$year.squared + c4.regression$coef[3]*c4.50$year +
c4.regression$coef[1]

plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = "", ylab = "δ13C (‰)", main = "C4 Sample 8")
points(c4.run~c4.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C4 Grasses Sample 8 (n=100)"), lty=c(1, 3), cex=0.6)
quartz()
par(mfrow=c(2,4))

#C3 Sample 1 n = 50
extra1 <- rnorm(274, .5, sd=1)
C3.dataframe <- data.frame(d13c=c3.grass, year=c3.grass.year,
year.squared=c3.grass.year.squared, extra1=extra1)
sample <- C3.dataframe[order(C3.dataframe$extra1),]
d13c.1 <- sample$d13c[1:50]
year.1 <- sample$year[1:50]
year.squared.1 <- sample$year.squared[1:50]
C3.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
C3.50<- C3.sample.1.dataframe[order(C3.sample.1.dataframe$year),]
C3.regression<- lm(C3.50$d13c~C3.50$year.squared+C3.50$year)
C3.run <- C3.regression$coef[2]*C3.50$year.squared + C3.regression$coef[3]*C3.50$year +
C3.regression$coef[1]

plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = " ", ylab = "δ13C (‰)", main = "C3 Sample 1")
points(C3.run~C3.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C3 Grasses Sample 1 (n=50)"), lty=c(1, 3), cex=0.6)

#C3 Sample 2 n = 50
extra1 <- rnorm(274, .5, sd=1)
C3.dataframe <- data.frame(d13c=c3.grass, year=c3.grass.year, year.squared=c3.grass.year.squared, extra1=extra1)
sample <- C3.dataframe[order(C3.dataframe$extra1),]
d13c.1 <- sample$d13c[1:50]
year.1 <- sample$year[1:50]
year.squared.1 <- sample$year.squared[1:50]
C3.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
C3.50<- C3.sample.1.dataframe[order(C3.sample.1.dataframe$year),]
C3.regression<- lm(C3.50$d13c~C3.50$year.squared+C3.50$year)

plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = " ", ylab = "δ13C (‰)", main = "C3 Sample 2")
points(C3.run~C3.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C3 Grasses Sample 2 (n=50)"), lty=c(1, 3), cex=0.6)

#C3 Sample 3 n = 50
extra1 <- rnorm(274, .5, sd=1)
C3.dataframe <- data.frame(d13c=c3.grass, year=c3.grass.year, year.squared=c3.grass.year.squared, extra1=extra1)
sample <- C3.dataframe[order(C3.dataframe$extra1),]
d13c.1 <- sample$d13c[1:50]
year.1 <- sample$year[1:50]
year.squared.1 <- sample$year.squared[1:50]
C3.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
C3.50<- C3.sample.1.dataframe[order(C3.sample.1.dataframe$year),]
C3.regression<- lm(C3.50$d13c~C3.50$year.squared+C3.50$year)

plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = " ", ylab = "δ13C (‰)", main = "C3 Sample 3")
points(C3.run~C3.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C3 Grasses Sample 3 (n=50)"), lty=c(1, 3), cex=0.6)

#C3 Sample 4 n = 50
extra1 <- rnorm(274, .5, sd=1)
C3.dataframe <- data.frame(d13c=c3.grass, year=c3.grass.year,
  year.squared=c3.grass.year.squared, extra1=extra1)
sample <- C3.dataframe[order(C3.dataframe$extra1),]
d13c.1 <- sample$d13c[1:50]
year.1 <- sample$year[1:50]
year.squared.1 <- sample$year.squared[1:50]
C3.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
C3.50<- C3.sample.1.dataframe[order(C3.sample.1.dataframe$year),]
C3.regression<- lm(C3.50$d13c~C3.50$year.squared+C3.50$year)
C3.run <- C3.regression$coeff[2]*C3.50$year.squared + C3.regression$coeff[3]*C3.50$year +
  C3.regression$coeff[1]

plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = " ", ylab = "δ13C (‰)", main = "C3 Sample 4")
points(C3.run~C3.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C3 Grasses Sample 4 (n=50)")

#C3 Sample 5 n = 50
extra1 <- rnorm(274, .5, sd=1)
C3.dataframe <- data.frame(d13c=c3.grass, year=c3.grass.year,
  year.squared=c3.grass.year.squared, extra1=extra1)
sample <- C3.dataframe[order(C3.dataframe$extra1),]
d13c.1 <- sample$d13c[1:50]
year.1 <- sample$year[1:50]
year.squared.1 <- sample$year.squared[1:50]
C3.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
C3.50<- C3.sample.1.dataframe[order(C3.sample.1.dataframe$year),]
C3.regression<- lm(C3.50$d13c~C3.50$year.squared+C3.50$year)
C3.run <- C3.regression$coeff[2]*C3.50$year.squared + C3.regression$coeff[3]*C3.50$year +
  C3.regression$coeff[1]

plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = " ", ylab = "δ13C (‰)", main = "C3 Sample 5")
points(C3.run~C3.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C3 Grasses Sample 5 (n=50)")

#C3 Sample 6 n = 50
extra1 <- rnorm(274, .5, sd=1)
C3.dataframe <- data.frame(d13c=c3.grass, year=c3.grass.year,
  year.squared=c3.grass.year.squared, extra1=extra1)
sample <- C3.dataframe[order(C3.dataframe$extra1),]
d13c.1 <- sample$d13c[1:50]
year.1 <- sample$year[1:50]
year.squared.1 <- sample$year.squared[1:50]
C3.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
C3.50<- C3.sample.1.dataframe[order(C3.sample.1.dataframe$year),]
C3.regression<- lm(C3.50$d13c~C3.50$year.squared+C3.50$year)
C3.run <- C3.regression$coef[2]*C3.50$year.squared + C3.regression$coef[3]*C3.50$year +
  C3.regression$coef[1]

plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = "", ylab = "δ13C (‰)", main = "C3 Sample 6")
points(C3.run~C3.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C3 Grasses Sample 6 (n=50)"), lty=c(1, 3), cex=0.6)

#C3 Sample 7 n = 50
extra1 <- rnorm(274, .5, sd=1)
C3.dataframe <- data.frame(d13c=c3.grass, year=c3.grass.year,
  year.squared=c3.grass.year.squared, extra1=extra1)
sample <- C3.dataframe[order(C3.dataframe$extra1),]
d13c.1 <- sample$d13c[1:50]
year.1 <- sample$year[1:50]
year.squared.1 <- sample$year.squared[1:50]
C3.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
C3.50<- C3.sample.1.dataframe[order(C3.sample.1.dataframe$year),]
C3.regression<- lm(C3.50$d13c~C3.50$year.squared+C3.50$year)
C3.run <- C3.regression$coef[2]*C3.50$year.squared + C3.regression$coef[3]*C3.50$year +
  C3.regression$coef[1]

plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = "", ylab = "δ13C (‰)", main = "C3 Sample 7")
points(C3.run~C3.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C3 Grasses Sample 7 (n=50)"), lty=c(1, 3), cex=0.6)

#C3 Sample 8 n = 50
extra1 <- rnorm(274, .5, sd=1)
C3.dataframe <- data.frame(d13c=c3.grass, year=c3.grass.year, year.squared=c3.grass.year.squared, extra1=extra1)
sample <- C3.dataframe[order(C3.dataframe$extra1),]
d13c.1 <- sample$d13c[1:50]
year.1 <- sample$year[1:50]
year.squared.1 <- sample$year.squared[1:50]
C3.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
C3.50<- C3.sample.1.dataframe[order(C3.sample.1.dataframe$year),]
C3.regression<- lm(C3.50$d13c~C3.50$year.squared+C3.50$year)

plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = "", ylab = "δ13C (‰)", main = "C3 Sample 8")
points(C3.run~C3.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C3 Grasses Sample 8 (n=50)"), lty=3, cex=0.6)

# Get C3 Grid Ready:
#C3 Sample 1 n = 50
extra1 <- rnorm(274, .5, sd=1)
C3.dataframe <- data.frame(d13c=c3.grass, year=c3.grass.year, year.squared=c3.grass.year.squared, extra1=extra1)
sample <- C3.dataframe[order(C3.dataframe$extra1),]
d13c.1 <- sample$d13c[1:50]
year.1 <- sample$year[1:50]
year.squared.1 <- sample$year.squared[1:50]
C3.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
C3.50<- C3.sample.1.dataframe[order(C3.sample.1.dataframe$year),]
C3.regression<- lm(C3.50$d13c~C3.50$year.squared+C3.50$year)
plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = " ", ylab = "δ13C (‰)", main = "C3 Sample 1")
points(C3.run~C3.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C3 Grasses Sample 1 (n=50)"), lty=c(1, 3), cex=0.6)

#C3 Sample 2 n = 100
extra1 <- rnorm(274, .5, sd=1)
C3.dataframe <- data.frame(d13c=c3.grass, year=c3.grass.year, 
    year.squared=c3.grass.year.squared, extra1=extra1)
sample <- C3.dataframe[order(C3.dataframe$extra1),]
d13c.1 <- sample$d13c[1:100]
year.1 <- sample$year[1:100]
year.squared.1 <- sample$year.squared[1:100]
C3.50<- C3.sample.1.dataframe[order(C3.sample.1.dataframe$year),]
C3.regression<- lm(C3.50$d13c~C3.50$year.squared+C3.50$year)
C3.run <- C3.regression$coef[2]*C3.50$year.squared + C3.regression$coef[3]*C3.50$year +
    C3.regression$coef[1]

plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = " ", ylab = "δ13C (‰)", main = "C3 Sample 2")
points(C3.run~C3.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C3 Grasses Sample 2 (n=100)"), lty=c(1, 3), cex=0.6)

#C3 Sample 3 n = 100
extra1 <- rnorm(274, .5, sd=1)
C3.dataframe <- data.frame(d13c=c3.grass, year=c3.grass.year, 
    year.squared=c3.grass.year.squared, extra1=extra1)
sample <- C3.dataframe[order(C3.dataframe$extra1),]
d13c.1 <- sample$d13c[1:100]
year.1 <- sample$year[1:100]
year.squared.1 <- sample$year.squared[1:100]
C3.50<- C3.sample.1.dataframe[order(C3.sample.1.dataframe$year),]
C3.regression<- lm(C3.50$d13c~C3.50$year.squared+C3.50$year)
C3.run <- C3.regression$coef[2]*C3.50$year.squared + C3.regression$coef[3]*C3.50$year +
    C3.regression$coef[1]
#C3 Sample 4 n = 100
extra1 <- rnorm(274, .5, sd=1)
C3.dataframe <- data.frame(d13c=c3.grass, year=c3.grass.year,
year.squared=c3.grass.year.squared, extra1=extra1)
sample <- C3.dataframe[order(C3.dataframe$extra1),]
d13c.1 <- sample$d13c[1:100]
year.1 <- sample$year[1:100]
year.squared.1 <- sample$year.squared[1:100]
C3.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
C3.50<- C3.sample.1.dataframe[order(C3.sample.1.dataframe$year),]
C3.regression<- lm(C3.50$d13c~C3.50$year.squared+C3.50$year)
C3.run <- C3.regression$coef[2]*C3.50$year.squared + C3.regression$coef[3]*C3.50$year +
C3.regression$coef[1]

#C3 Sample 5 n = 100
extra1 <- rnorm(274, .5, sd=1)
C3.dataframe <- data.frame(d13c=c3.grass, year=c3.grass.year,
year.squared=c3.grass.year.squared, extra1=extra1)
sample <- C3.dataframe[order(C3.dataframe$extra1),]
d13c.1 <- sample$d13c[1:100]
year.1 <- sample$year[1:100]
year.squared.1 <- sample$year.squared[1:100]
C3.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
C3.50<- C3.sample.1.dataframe[order(C3.sample.1.dataframe$year),]
C3.regression<- lm(C3.50$d13c~C3.50$year.squared+C3.50$year)
C3.run <- C3.regression$coef[2]*C3.50$year.squared + C3.regression$coef[3]*C3.50$year +
C3.regression$coef[1]
plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = "", ylab = "δ13C (‰)", main = "C3 Sample 5")
points(C3.run~C3.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C3 Grasses Sample 5 (n=100)"), lty=c(1, 3), cex=0.6)

#C3 Sample 6 n = 100
extra1 <- rnorm(274, .5, sd=1)
C3.dataframe <- data.frame(d13c=c3.grass, year=c3.grass.year,
year.squared=c3.grass.year.squared, extra1=extra1)
sample <- C3.dataframe[order(C3.dataframe$extra1),]
d13c.1 <- sample$d13c[1:100]
year.1 <- sample$year[1:100]
year.squared.1 <- sample$year.squared[1:100]
C3.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
C3.50<- C3.sample.1.dataframe[order(C3.sample.1.dataframe$year),]
C3.regression<- lm(C3.50$d13c~C3.50$year.squared+C3.50$year)
C3.run <- C3.regression$coef[2]*C3.50$year.squared + C3.regression$coef[3]*C3.50$year +
C3.regression$coef[1]

plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = "", ylab = "δ13C (‰)", main = "C3 Sample 6")
points(C3.run~C3.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C3 Grasses Sample 6 (n=100)"), lty=c(1, 3), cex=0.6)

#C3 Sample 7 n = 100
extra1 <- rnorm(274, .5, sd=1)
C3.dataframe <- data.frame(d13c=c3.grass, year=c3.grass.year,
year.squared=c3.grass.year.squared, extra1=extra1)
sample <- C3.dataframe[order(C3.dataframe$extra1),]
d13c.1 <- sample$d13c[1:100]
year.1 <- sample$year[1:100]
year.squared.1 <- sample$year.squared[1:100]
C3.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
C3.50<- C3.sample.1.dataframe[order(C3.sample.1.dataframe$year),]
C3.regression<- lm(C3.50$d13c~C3.50$year.squared+C3.50$year)
C3.run <- C3.regression$coef[2]*C3.50$year.squared + C3.regression$coef[3]*C3.50$year +
C3.regression$coef[1]
plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = "", ylab = "δ13C (‰)", main = "C3 Sample 7")
points(C3.run~C3.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C3 Grasses Sample 7 (n=100)"), lty=c(1, 3), cex=0.6)

#C3 Sample 8 n = 100
extra1 <- rnorm(274, .5, sd=1)
C3.dataframe <- data.frame(d13c=c3.grass, year=c3.grass.year,
year.squared=c3.grass.year.squared, extra1=extra1)
sample <- C3.dataframe[order(C3.dataframe$extra1),]
d13c.1 <- sample$d13c[1:100]
year.1 <- sample$year[1:100]
year.squared.1 <- sample$year.squared[1:100]
C3.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
C3.50<- C3.sample.1.dataframe[order(C3.sample.1.dataframe$year),]
C3.regression<- lm(C3.50$d13c~C3.50$year.squared+C3.50$year)
C3.run <- C3.regression$coef[2]*C3.50$year.squared + C3.regression$coef[3]*C3.50$year +
C3.regression$coef[1]

plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = "", ylab = "δ13C (‰)", main = "C3 Sample 8")
points(C3.run~C3.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C3 Grasses Sample 8 (n=100)"), lty=c(1, 3), cex=0.6)

############################
#Get C3 Grid Ready:
############################
quartz()
par(mfrow=c(2,4))

#C3 Sample 1 n = 50
extra1 <- rnorm(274, .5, sd=1)
C3.dataframe <- data.frame(d13c=c3.grass, year=c3.grass.year,
year.squared=c3.grass.year.squared, extra1=extra1)
sample <- C3.dataframe[order(C3.dataframe$extra1),]
d13c.1 <- sample$d13c[1:50]
year.1 <- sample$year[1:50]
year.squared.1 <- sample$year.squared[1:50]
C3.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
C3.50<- C3.sample.1.dataframe[order(C3.sample.1.dataframe$year),]
C3.regression<- lm(C3.50$d13c~C3.50$year.squared+C3.50$year)

plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = "", ylab = "δ13C (‰)", main = "C3 Sample 1")
points(C3.run~C3.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C3 Grasses Sample 1 (n=50)")

#C3 Sample 2 n = 200
extra1 <- rnorm(274, .5, sd=1)
C3.dataframe <- data.frame(d13c=c3.grass, year=c3.grass.year,
 year.squared=c3.grass.year.squared, extra1=extra1)
sample <- C3.dataframe[order(C3.dataframe$extra1),]
d13c.1 <- sample$d13c[1:200]
year.1 <- sample$year[1:200]
year.squared.1 <- sample$year.squared[1:200]
C3.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
C3.50<- C3.sample.1.dataframe[order(C3.sample.1.dataframe$year),]
C3.regression<- lm(C3.50$d13c~C3.50$year.squared+C3.50$year)

plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = "", ylab = "δ13C (‰)", main = "C3 Sample 2")
points(C3.run~C3.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C3 Grasses Sample 2 (n=200)")

#C3 Sample 3 n = 200
extra1 <- rnorm(274, .5, sd=1)
C3.dataframe <- data.frame(d13c=c3.grass, year=c3.grass.year,
 year.squared=c3.grass.year.squared, extra1=extra1)
sample <- C3.dataframe[order(C3.dataframe$extra1),]
d13c.1 <- sample$d13c[1:200]
year.1 <- sample$year[1:200]
year.squared.1 <- sample$year.squared[1:200]
C3.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
C3.50<- C3.sample.1.dataframe[order(C3.sample.1.dataframe$year),]
C3.regression<- lm(C3.50$d13c~C3.50$year.squared+C3.50$year)
C3.run <- C3.regression$coef[2]*C3.50$year.squared + C3.regression$coef[3]*C3.50$year +
C3.regression$coef[1]

plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = " ", ylab = "δ13C (‰)", main = "C3 Sample 3")
points(C3.run~C3.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C3 Grasses Sample 3 (n=200)"), lty=c(1, 3), cex=0.6)

#C3 Sample 4 n = 200
extra1 <- rnorm(274, .5, sd=1)
C3.dataframe <- data.frame(d13c=c3.grass, year=c3.grass.year,
year.squared=c3.grass.year.squared, extra1=extra1)
sample <- C3.dataframe[order(C3.dataframe$extra1),]
d13c.1 <- sample$d13c[1:200]
year.1 <- sample$year[1:200]
year.squared.1 <- sample$year.squared[1:200]
C3.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
C3.50<- C3.sample.1.dataframe[order(C3.sample.1.dataframe$year),]
C3.regression<- lm(C3.50$d13c~C3.50$year.squared+C3.50$year)
C3.run <- C3.regression$coef[2]*C3.50$year.squared + C3.regression$coef[3]*C3.50$year +
C3.regression$coef[1]

plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = " ", ylab = "δ13C (‰)", main = "C3 Sample 4")
points(C3.run~C3.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C3 Grasses Sample 4 (n=200)"), lty=c(1, 3), cex=0.6)

#C3 Sample 5 n = 200
extra1 <- rnorm(274, .5, sd=1)
C3.dataframe <- data.frame(d13c=c3.grass, year=c3.grass.year,
year.squared=c3.grass.year.squared, extra1=extra1)
sample <- C3.dataframe[order(C3.dataframe$extra1),]
d13c.1 <- sample$d13c[1:200]
year.1 <- sample$year[1:200]
year.squared.1 <- sample$year.squared[1:200]
C3.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
C3.50<- C3.sample.1.dataframe[order(C3.sample.1.dataframe$year),]
C3.regression<- lm(C3.50$d13c~C3.50$year.squared+C3.50$year)
C3.run <- C3.regression$coef[2]*C3.50$year.squared + C3.regression$coef[3]*C3.50$year +
C3.regression$coef[1]

plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = "", ylab = "δ13C (‰)", main = "C3 Sample 5")
points(C3.run~C3.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C3 Grasses Sample 5 (n=200)"), lty=c(1, 3), cex=0.6)

#C3 Sample 6 n = 200
extra1 <- rnorm(274, .5, sd=1)
C3.dataframe <- data.frame(d13c=c3.grass, year=c3.grass.year,
 year.squared=c3.grass.year.squared, extra1=extra1)
sample <- C3.dataframe[order(C3.dataframe$extra1),]
d13c.1 <- sample$d13c[1:200]
year.1 <- sample$year[1:200]
year.squared.1 <- sample$year.squared[1:200]
C3.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
C3.50<- C3.sample.1.dataframe[order(C3.sample.1.dataframe$year),]
C3.regression<- lm(C3.50$d13c~C3.50$year.squared+C3.50$year)
C3.run <- C3.regression$coef[2]*C3.50$year.squared + C3.regression$coef[3]*C3.50$year +
C3.regression$coef[1]

plot(law.dome.model~time, type="l", ylim = c(-9, -4.7), xlab = "", ylab = "δ13C (‰)", main = "C3 Sample 6")
points(C3.run~C3.50$year, type="l", lty=3)
legend("bottomleft", c("Atmosphere", "C3 Grasses Sample 6 (n=200)"), lty=c(1, 3), cex=0.6)

#C3 Sample 7 n = 200
extra1 <- rnorm(274, .5, sd=1)
C3.dataframe <- data.frame(d13c=c3.grass, year=c3.grass.year,
 year.squared=c3.grass.year.squared, extra1=extra1)
sample <- C3.dataframe[order(C3.dataframe$extra1),]
d13c.1 <- sample$d13c[1:200]
year.1 <- sample$year[1:200]
year.squared.1 <- sample$year.squared[1:200]
C3.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
C3.50 <- C3.sample.1.dataframe[order(C3.sample.1.dataframe$year),]
C3.regression <- lm(C3.50$d13c ~ C3.50$year.squared + C3.50$year)
               C3.regression$coef[1]

plot(law.dome.model ~ time, type = "l", ylim = c(-9, -4.7), xlab = " ", ylab = "δ13C (‰)",
     main = "C3 Sample 7")
points(C3.run ~ C3.50$year, type = "l", lty=3)
legend("bottomleft", c("Atmosphere", "C3 Grasses Sample 7 (n=200)")

#C3 Sample 8 n = 200
extra1 <- rnorm(274, .5, sd=1)
C3.dataframe <- data.frame(d13c = c3.grass, year = c3.grass.year,
       year.squared = c3.grass.year.squared, extra1 = extra1)
sample <- C3.dataframe[order(C3.dataframe$extra1),]
d13c.1 <- sample$d13c[1:200]
year.1 <- sample$year[1:200]
year.squared.1 <- sample$year.squared[1:200]
C3.sample.1.dataframe <- data.frame(d13c = d13c.1, year = year.1, year.squared = year.squared.1)
C3.50 <- C3.sample.1.dataframe[order(C3.sample.1.dataframe$year),]
C3.regression <- lm(C3.50$d13c ~ C3.50$year.squared + C3.50$year)
               C3.regression$coef[1]

plot(law.dome.model ~ time, type = "l", ylim = c(-9, -4.7), xlab = " ", ylab = "δ13C (‰)",
     main = "C3 Sample 8")
points(C3.run ~ C3.50$year, type = "l", lty=3)
legend("bottomleft", c("Atmosphere", "C3 Grasses Sample 8 (n=200)")

#C4 Sample 1 n = 50
extra1 <- rnorm(165, .5, sd=1)
c4.dataframe <- data.frame(d13c = bouteloua, year = bouteloua.year,
       year.squared = bouteloua.year.squared, extra1 = extra1)
sample <- c4.dataframe[order(c4.dataframe$extra1),]
d13c.1 <- sample$d13c[1:50]
year.1 <- sample$year[1:50]
year.squared.1 <- sample$year.squared[1:50]
c4.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
c4.50<- c4.sample.1.dataframe[order(c4.sample.1.dataframe$year),]
c4.regression<- lm(c4.50$d13c~c4.50$year.squared+c4.50$year)
c4.score <- lm(c4.run~law.dome.model)
summary(c4.score)
c4.r2.50 <- c(0.8686, 0.8131, 0.954, 0.9602, 0.9113, 0.9749, 0.9985, 0.9475, 0.9475, 0.8442, 0.9724, 0.8853, 0.9788, 0.9328, 0.887, 0.9905, 0.9777, 0.6451, 0.9269, 0.9777, 0.9976, 0.797, 0.9474, 0.9633, 0.8659, 0.9712, 0.8019, 0.8187, 0.759, 0.8388, 0.9414, 0.9023, 0.906, 0.9669, 0.8755, 0.993, 0.9888, 0.9202, 0.9577, 0.9485, 0.9983, 0.9504, 0.9566, 0.9786, 0.9482, 0.8578, 0.964, 0.8892, 0.8645, 0.9182, 0.8711, 0.9822, 0.9893, 0.9179, 0.9979, 0.9937, 0.8538, 0.9938, 0.9068, 0.9505, 0.9112, 0.9688, 0.9083, 0.985, 0.9287, 0.8291, 0.668, 0.8988, 0.9541, 0.9926, 0.7557, 0.882, 0.7214, 0.9429, 0.918, 0.9697, 0.9538, 0.9097, 0.97, 0.6888, 0.9996, 0.9441, 0.972, 0.9026, 0.8733, 0.9875, 0.8808, 0.9768, 0.7303, 0.9646, 0.9475, 0.9883, 0.8297, 0.928, 0.9806, 0.9926, 0.9449, 0.9452, 0.9669, 0.9704, 0.867, 0.9881, 0.9186, 0.8738, 0.7816, 0.9049, 0.8805, 0.9601, 0.9452, 0.9989, 0.8889, 0.954, 0.9274, 0.9855, 0.851, 0.9937, 0.8254, 0.9748, 0.906, 0.9941, 0.9408, 0.8626, 0.8231, 0.7706, 0.8349, 0.9033, 0.9319, 0.9778, 0.9809, 0.8754, 0.9649, 0.8498, 0.9578, 0.958, 0.9788, 0.8734, 0.9498, 0.9712, 0.889, 0.9851, 0.8909, 0.9673, 0.9736, 0.8085, 0.9449, 0.9959, 0.958,
d.c4.50 <- density(c4.r2.50)

###############################
###Testing Large Samples [C4 100]
###############################

#C4 Sample 1 n = 100
eextra1 <- rnorm(165, .5, sd=1)
c4.dataframe <- data.frame(d13c=bouteloua, year=bouteloua.year,
  year.squared=bouteloua.year.squared, extra1=extra1)
sample <- c4.dataframe[order(c4.dataframe$extra1),]
d13c.1 <- sample$d13c[1:100]
year.1 <- sample$year[1:100]
year.squared.1 <- sample$year.squared[1:100]
c4.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
c4.50<- c4.sample.1.dataframe[order(c4.sample.1.dataframe$year),]
c4.regression<- lm(c4.50$d13c~c4.50$year.squared+c4.50$year)
c4.score <- lm(c4.run~law.dome.model)
summary(c4.score)

0.8413, 0.9633, 0.9206, 0.9856, 0.8932, 0.8697, 0.9042, 0.9869, 0.8393, 0.9815,
0.9652, 0.9293, 0.99, 0.9819, 0.9935, 0.9214, 0.7588, 0.9994, 0.9995, 0.9179,
0.7327, 0.9936, 0.928, 0.7477, 0.9426, 0.8711, 0.8706, 0.9862, 0.8789, 0.9329,
0.8531, 0.9622, 0.7919, 0.9662, 0.8448, 0.9523, 0.8762, 0.9181, 0.9383, 0.9818,
0.9943, 0.966, 0.9898, 0.8797, 0.9069, 0.956, 0.9756, 0.9645, 0.949, 0.9398,
0.9507, 0.9035, 0.8233, 0.9018, 0.931

c4.r2.100 <- c(0.9266, 0.9384, 0.9658, 0.9446, 0.9707,
0.9388, 0.9208, 0.9248, 0.8972, 0.9361,
0.9449, 0.9254, 0.9641, 0.974, 0.94,
0.9522, 0.9023, 0.9782, 0.9625, 0.9654,
#C3 Sample 1 n = 50
extra1 <- rnorm(274, .5, sd=1)
C3.dataframe <- data.frame(d13c=c3.grass, year=c3.grass.year,
  year.squared=c3.grass.year.squared, extra1=extra1)
sample <- C3.dataframe[order(C3.dataframe$extra1),]
d13c.1 <- sample$d13c[1:50]
year.1 <- sample$year[1:50]
year.squared.1 <- sample$year.squared[1:50]
C3.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
C3.50<- C3.sample.1.dataframe[order(C3.sample.1.dataframe$year),]
C3.regression<- lm(C3.50$d13c~C3.50$year.squared+C3.50$year)
C3.run <- C3.regression$coeff[2]*time.squared + C3.regression$coeff[3]*time + C3.regression
  $coeff[1]
c3.score <- lm(C3.run~law.dome.model)
summary(c3.score)
c3.r2.50 <- c(0.9931, 0.9297, 0.9905, 0.5767, 0.6994,
  0.9554, 0.9704, 0.9214, 0.5111, 0.96,
  0.08335, 0.9124, 0.9423, 0.4679, 0.8297,
  0.1254, 0.785, 0.07381, 0.007256, 0.3466,
  0.2874, 0.3029, 0.9888, 0.9815, 0.9981,
  0.7299, 0.6418, 0.9749, 0.2746, 0.9985,
  0.3666, 0.9928, 0.9158, 0.03004, 0.3666,
  0.7356, 0.6158, 0.9222, 0.9315, 0.9719,
  0.9589, 0.9928, 0.9158, 0.9919, 0.9931,
  0.9589, 0.9928, 0.9158, 0.9919, 0.9931,
  0.9589, 0.9928, 0.9158, 0.9919, 0.9931,
  0.9589, 0.9928, 0.9158, 0.9919, 0.9931,
  0.9589, 0.9928, 0.9158, 0.9919, 0.9931,
  0.9589, 0.9928, 0.9158, 0.9919, 0.9931,
  0.9589, 0.9928, 0.9158, 0.9919, 0.9931,
  0.9589, 0.9928, 0.9158, 0.9919, 0.9931,
  0.9589, 0.9928, 0.9158, 0.9919, 0.9931,
  0.9589, 0.9928, 0.9158, 0.9919, 0.9931,
  0.9589, 0.9928, 0.9158, 0.9919, 0.9931,
  0.9589, 0.9928, 0.9158, 0.9919, 0.9931,
  0.9589, 0.9928, 0.9158, 0.9919, 0.9931,
  0.9589, 0.9928, 0.9158, 0.9919, 0.9931,
  0.9589, 0.9928, 0.9158, 0.9919, 0.9931,
  0.9589, 0.9928, 0.9158, 0.9919, 0.9931,
  0.9589, 0.9928, 0.9158, 0.9919, 0.9931,
  0.9589, 0.9928, 0.9158, 0.9919, 0.9931,
  0.9589, 0.9928, 0.9158, 0.9919, 0.9931,
  0.9589, 0.9928, 0.9158, 0.9919, 0.9931,
  0.9589, 0.9928, 0.9158, 0.9919, 0.9931,
  0.9589, 0.9928, 0.9158, 0.9919, 0.9931,
  0.9589, 0.9928, 0.9158, 0.9919, 0.9931,
  0.9589, 0.9928, 0.9158, 0.9919, 0.9931,
  0.9589, 0.9928, 0.9158, 0.9919, 0.9931,
  0.9589, 0.9928, 0.9158, 0.9919, 0.9931,
  0.9589, 0.9928, 0.9158, 0.9919, 0.9931,
  0.9589, 0.9928, 0.9158, 0.9919, 0.9931,
#C3 Sample 1 n = 100
extra1 <- rnorm(274, .5, sd=1)
C3.dataframe <- data.frame(d13c=c3.grass, year=c3.grass.year, 
    year.squared=c3.grass.year.squared, extra1=extra1)
sample <- C3.dataframe[order(C3.dataframe$extra1),]
d13c.1 <- sample$d13c[1:100]
year.1 <- sample$year[1:100]
year.squared.1 <- sample$year.squared[1:100]
C3.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
C3.50<- C3.sample.1.dataframe[order(C3.sample.1.dataframe$year),]
C3.regression<-lm(C3.50$d13c~C3.50$year.squared+C3.50$year)
c3.score.100 <- lm(C3.run~law.dome.model)
summary(c3.score.100)

c3.r2.100 <- c(0.9304, 0.9374, 0.6101, 0.6707, 0.872,
0.9956, 0.9596, 0.9985, 0.658, 0.9203,
0.9954, 0.9336, 0.3705, 0.9974, 0.7863,
0.8112, 0.8987, 0.9999, 0.8561, 0.9879,
0.9204, 0.9817, 0.9285, 0.9445, 0.998,
0.9699, 0.5065, 0.995, 0.6161, 0.9985,
0.9992, 0.8876, 0.9926, 0.8275, 0.9998,
0.9548, 0.8898, 0.9967, 0.884, 0.9863,
0.9002, 0.6747, 0.664, 0.9729, 0.9479,
0.9947, 0.8039, 0.8668, 1, 0.7787,
0.8819, 0.9769, 0.9964, 0.9793, 0.973,
0.9987, 0.873, 0.9395, 0.8783, 0.9917,
0.883, 0.8139, 0.9652, 0.4012, 0.5027,
0.6529, 0.5362, 0.9411, 0.9959, 0.9983,
0.9689, 0.9282, 0.9963, 0.9793, 0.9876,
0.845, 0.973, 0.997, 0.9387, 0.9057,
0.8097, 0.7713, 0.9995, 0.8357, 0.3832,
0.6816, 0.991, 0.1546, 0.5887, 0.7345,
0.9998, 0.9784, 0.9903, 0.9928, 0.5341,
0.55, 0.9969, 0.9988, 0.9996, 0.6468,
0.4889, 0.9954, 0.6857, 0.9257, 0.8787,
0.935, 0.9985, 0.6714, 0.9463, 0.9825,
0.9782, 0.8956, 0.947, 0.9478, 0.9821,
0.9941, 1, 0.8718, 0.8363, 0.2892,
0.9996, 0.9888, 0.8912, 0.9686, 0.9823,
0.9766, 0.9513, 0.9954, 0.9364, 0.9911,
0.6641, 0.7268, 0.972, 0.01407, 0.8613,
0.9386, 1, 0.73, 0.6998, 0.975,
0.7358, 0.9789, 0.437, 0.7281, 0.9381,
0.9871, 0.8775, 0.8906, 0.9122, 0.9804,
0.925, 0.9829, 0.9911, 0.9262, 0.9988,
0.999, 0.9655, 0.4715, 0.8485, 0.78,
0.9998, 0.8451, 0.6597, 0.5653, 0.9903,
0.8761, 0.9298, 0.9955, 0.8085, 0.2793,
0.8725, 0.9863, 0.9962, 0.9214, 0.8826,
0.972, 0.7843, 0.9914, 0.3892, 0.6377,
0.9938, 0.9854, 0.969, 0.8855, 0.3389,
0.97, 0.9834, 0.9655, 0.411, 0.596,
0.9471, 0.7904, 0.9792, 0.8703, 0.5964,
0.9993, 1, 0.9327, 0.732, 0.97)

####################################
###Testing Large Samples [C3 200]
####################################

#C3 Sample 1 n = 200
eextra1 <- rnorm(274, .5, sd=1)
C3.dataframe <- data.frame(d13c=c3.grass, year=c3.grass.year,
  year.squared=c3.grass.year.squared, extra1=extra1)
sample <- C3.dataframe[order(C3.dataframe$extra1),]
d13c.1 <- sample$d13c[1:200]
year.1 <- sample$year[1:200]
year.squared.1 <- sample$year.squared[1:200]
C3.sample.1.dataframe <- data.frame(d13c=d13c.1, year=year.1, year.squared=year.squared.1)
C3.50<- C3.sample.1.dataframe[order(C3.sample.1.dataframe$year),]
C3.regression<- lm(C3.50$d13c~C3.50$year.squared+C3.50$year)
c3.score.200 <- lm(C3.run~law.dome.model)
summary(c3.score.200)

c3.r2.200 <- c(0.9095, 0.62, 0.9449, 0.9827, 0.9758,
  0.9959, 0.9153, 0.9728, 0.9933, 0.9999,
  0.8042, 0.9877, 0.9341, 0.9878, 0.9068,
  0.8133, 0.9869, 0.9965, 0.9957, 0.9686,
  0.9503, 0.9642, 0.9689, 0.9996, 0.8924,
  0.9178, 0.9876, 0.9845, 0.9135, 0.9895,
  0.7824, 0.9565, 0.9915, 0.8783, 0.9671,
0.9995, 0.9236, 0.9988, 0.9983, 0.9889, 0.9158, 0.9818, 1, 0.9415, 0.8408, 0.8976, 0.9922, 0.9599, 0.9721, 0.9289, 0.9623, 0.9996, 0.9371, 0.998, 0.9623, 0.8581, 0.9641, 0.9512, 0.971, 0.9568, 0.8922, 0.9994, 0.999, 0.9967, 0.9078, 0.9225, 0.9817, 0.9974, 0.9541, 0.9994, 0.9735, 0.9999, 0.9859, 0.9999, 0.9977, 0.9939, 0.9817, 0.9007, 0.9704, 0.9411, 0.9609, 0.9707, 0.8918, 0.9215, 0.9993, 0.9149, 0.9994, 0.9201, 0.9787, 0.9088, 1, 0.9984, 0.9801, 0.9956, 0.9654, 0.9242, 0.927, 0.8868, 0.9411, 0.9118, 0.9738, 0.9388, 0.9921, 0.909, 0.8958, 0.92, 0.8892, 0.9762, 0.9913, 0.9533, 0.9686, 0.9802, 0.8359, 0.9746, 0.9576, 0.6841, 0.9281, 0.7051, 0.9999, 0.9589, 0.9566, 0.9965, 0.9719, 0.9514, 0.9954, 0.9847, 0.999, 0.9999, 0.9925, 0.7918, 0.9298, 0.8974, 0.9932, 0.9802, 0.9923, 0.9815, 0.9623, 0.8047, 0.8519, 0.9993, 0.9995, 0.9786, 0.8808, 0.9999, 0.9331, 0.8456, 0.9964, 0.8921, 0.9909, 0.9585, 0.979, 0.8359, 0.9821, 0.8156, 0.9116, 0.9996, 0.9122, 0.9265, 0.8834, 0.9426, 0.8588, 0.9292, 0.9877, 0.9999, 0.9585, 0.9221, 0.9336, 0.9718, 0.9272, 0.9799, 0.9347, 0.9508, 0.9878, 0.9974, 0.9845, 0.9957, 0.9876, 0.8797, 0.9913, 0.9869, 0.9965, 0.9742, 0.9888, 0.9569, 0.9655, 0.9982, 0.9856, 0.9934, 0.9331, 0.9422, 0.9973, 0.9925, 0.9594, 0.9079, 0.9979, 0.9271, 0.96, 0.9831, 0.8946, 0.6922)

d.c3.50 <- density(c3.r2.50)
d.c3.100 <- density(c3.r2.100)
d.c3.200 <- density(c3.r2.200)
d.c4.50 <- density(c4.r2.50)
d.c4.100 <- density(c4.r2.100)

quartz()
par(mfrow=c(1,2))
plot(d.c4.50, xlab =quote(r^2), xlim = c(0,1), ylim = c(0,12), lty=2, main = "C4 Grasses", col = "yellow3", lwd=2)
points(d.c4.100, type="l", lty=3, lwd=2, col = "orchid4")
legend("topleft", c("n = 50", "n = 100"), lty=c(2, 3), col = c("yellow3", "orchid4"), lwd=2)

plot(d.c3.50, type="l", lty=2, xlab =quote(r^2), main = "C3 Grasses", ylim = c(0,12), xlim = c(0,1), lwd = 2, col = "yellow3")
points(d.c3.100, type="l", lty=3, lwd = 2, col = "orchid4")
points(d.c3.200, type="l", lty=4, lwd = 2, col = "orange1")
legend("topleft", c("n = 50", "n = 100", n = "n = 200"), lty=c(2, 3, 4), col = c("yellow3", "orchid", "orange1"), lwd=2)
Appendix B
Calibration of Chaco Packrat Midden Radiocarbon Dates

A-2123
Atlatl Cave 4B 1
Radiocarbon Age 10030±150
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal BP 11270: cal BP 11769] 0.974704
[cal BP 11788: cal BP 11805] 0.025296
Two Sigma Ranges: [start:end] relative area
A-2139
Atlatl Cave 4B 2
Radiocarbon Age 10600±200
Calibration data set: intcal09.14c
# Reimer et al. 2009

One Sigma Ranges: [start:end] relative area
[cal BP 12146: cal BP 12193] 0.072523
[cal BP 12210: cal BP 12358] 0.239298
[cal BP 12365: cal BP 12675] 0.688178

Two Sigma Ranges: [start:end] relative area
A-2116
Atlatl Cave 3 1
Radiocarbon Age 9460±160
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal BP 10516: cal BP 10877] 0.736374
[cal BP 10941: cal BP 11078] 0.263626
Two Sigma Ranges: [start:end] relative area
[cal BP 10297: cal BP 10333] 0.01811
[cal BP 10337: cal BP 10357] 0.009545
[cal BP 10370: cal BP 11185] 0.972344
A-2411
Atlatl Cave 3 2
Radiocarbon Age 10500±250
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
Two Sigma Ranges: [start:end] relative area
[cal BP 11404: cal BP 11459] 0.011461
[cal BP 11461: cal BP 11569] 0.023215
[cal BP 11592: cal BP 12882] 0.965324
A-2115
Atlatl Cave 4A
Radiocarbon Age 5550±130
Calibration data set: intcal09.14c
# Reimer et al. 2009

One Sigma Ranges: [start:end] relative area
[cal BP 6208: cal BP 6252] 0.122894
[cal BP 6260: cal BP 6490] 0.877106

Two Sigma Ranges: [start:end] relative area
[cal BP 6004: cal BP 6083] 0.050838
[cal BP 6099: cal BP 6161] 0.044923
[cal BP 6169: cal BP 6638] 0.904239
A-2126
Casa Chiquita 4
Radiocarbon Age 4920±110
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal BP 5488: cal BP 5505] 0.046836
[cal BP 5582: cal BP 5754] 0.802373
[cal BP 5826: cal BP 5879] 0.150791
Two Sigma Ranges: [start:end] relative area
[cal BP 5333: cal BP 5348] 0.009342
[cal BP 5353: cal BP 5372] 0.009855
[cal BP 5464: cal BP 5911] 0.980803
A-2124
Casa Chiquita 2
Radiocarbon Age 4780±90
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
  [cal BP 5330: cal BP 5375] 0.196396
  [cal BP 5457: cal BP 5598] 0.803604
Two Sigma Ranges: [start:end] relative area
  [cal BP 5312: cal BP 5662] 0.994789
  [cal BP 5693: cal BP 5699] 0.003671
  [cal BP 5702: cal BP 5706] 0.00154
A-1833
Gallo Wash 2
Radiocarbon Age 4480±90
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal BP 4979: cal BP 5008] 0.095053
[cal BP 5037: cal BP 5149] 0.397087
[cal BP 5151: cal BP 5289] 0.50786
Two Sigma Ranges: [start:end] relative area
[cal BP 4862: cal BP 5320] 0.991543
[cal BP 5423: cal BP 5435] 0.008457
A-2129
Casa Chiquita 1B
Radiocarbon Age 3940±110
Calibration data set: intcal09.14c
# Reimer et al. 2009

One Sigma Ranges: [start:end] relative area
[cal BP 4161: cal BP 4168] 0.014559
[cal BP 4179: cal BP 4199] 0.04127
[cal BP 4229: cal BP 4527] 0.944171

Two Sigma Ranges: [start:end] relative area
[cal BP 4013: cal BP 4026] 0.004121
[cal BP 4083: cal BP 4657] 0.939541
[cal BP 4666: cal BP 4707] 0.020036
[cal BP 4756: cal BP 4812] 0.036302
A-2112
Mockingbird Canyon 3
Radiocarbon Age 3270±90
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
  [cal BP 3394: cal BP 3586] 0.98505
  [cal BP 3604: cal BP 3607] 0.01495
Two Sigma Ranges: [start:end] relative area
  [cal BP 3271: cal BP 3285] 0.006191
  [cal BP 3328: cal BP 3716] 0.993809
A-1838
Gallo Wash 6
Radiocarbon Age 2820±300
Calibration data set: intcal09.14c
# Reimer et al. 2009

One Sigma Ranges: [start:end] relative area
[cal BP 2543: cal BP 2564] 0.020141
[cal BP 2568: cal BP 2587] 0.017166
[cal BP 2616: cal BP 2635] 0.019222
[cal BP 2700: cal BP 3373] 0.943471

Two Sigma Ranges: [start:end] relative area
[cal BP 2161: cal BP 2168] 0.001042
[cal BP 2178: cal BP 2243] 0.010566
[cal BP 2301: cal BP 3690] 0.988392
A-1839
Gallo Wash 1
Radiocarbon Age 2810±90
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal BP 2791: cal BP 3005] 0.951384
[cal BP 3014: cal BP 3023] 0.025901
[cal BP 3052: cal BP 3059] 0.022715
Two Sigma Ranges: [start:end] relative area
[cal BP 2755: cal BP 3162] 0.989299
[cal BP 3188: cal BP 3202] 0.010701
A-1840
Gallo Wash 5
Radiocarbon Age 2070±90
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal BP 1905: cal BP 1905] 0.002988
[cal BP 1925: cal BP 2149] 0.997012
Two Sigma Ranges: [start:end] relative area
[cal BP 1834: cal BP 1841] 0.004447
[cal BP 1865: cal BP 2214] 0.876398
[cal BP 2217: cal BP 2311] 0.119155
A-2110
Mockingbird Canyon 1
Radiocarbon Age 1990±90
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal BP 1826: cal BP 1850] 0.080042
[cal BP 1860: cal BP 2056] 0.919958
Two Sigma Ranges: [start:end] relative area
[cal BP 1716: cal BP 2153] 0.992951
[cal BP 2277: cal BP 2290] 0.007049
A-2125
Casa Chiquita 3
Radiocarbon Age 1970±100
Calibration data set: intcal09.14c
# Reimer et al. 2009

One Sigma Ranges: [start:end] relative area
[cal BP 1816: cal BP 2060] 0.992934
[cal BP 2090: cal BP 2092] 0.007066

Two Sigma Ranges: [start:end] relative area
[cal BP 1634: cal BP 1648] 0.005813
[cal BP 1694: cal BP 2155] 0.982981
[cal BP 2269: cal BP 2295] 0.011206
A-1834
Gallo Wash 4
Radiocarbon Age 1940±150
Calibration data set: intcal09.14c
# Reimer et al. 2009

One Sigma Ranges: [start:end] relative area
[cal BP 1709: cal BP 2062] 0.971023
[cal BP 2087: cal BP 2102] 0.028977

Two Sigma Ranges: [start:end] relative area
[cal BP 1543: cal BP 2184] 0.953572
[cal BP 2194: cal BP 2206] 0.004368
[cal BP 2231: cal BP 2306] 0.04206
A-2111
Mockingbird Canyon 2
Radiocarbon Age 1910±90
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
Two Sigma Ranges: [start:end] relative area
  [cal BP 1617: cal BP 1675] 0.04485
  [cal BP 1686: cal BP 2062] 0.945937
  [cal BP 2086: cal BP 2104] 0.009213
A-2114
Mockingbird Canyon 5
Radiocarbon Age 1860±120
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal BP 1625: cal BP 1669] 0.115368
[cal BP 1689: cal BP 1929] 0.884632
Two Sigma Ranges: [start:end] relative area
[cal BP 1526: cal BP 2066] 0.987548
[cal BP 2081: cal BP 2110] 0.012452
A-2128
Weritos Rincon 2
Radiocarbon Age 1780±110
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
Two Sigma Ranges: [start:end] relative area
[cal BP 1417: cal BP 1470] 0.03421
[cal BP 1483: cal BP 1934] 0.962226
[cal BP 1938: cal BP 1945] 0.003564
A-2113
Mockingbird Canyon 4
Radiocarbon Age 1230±60
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
  [cal BP 1076: cal BP 1185] 0.706098
  [cal BP 1203: cal BP 1243] 0.264692
  [cal BP 1250: cal BP 1256] 0.02921
Two Sigma Ranges: [start:end] relative area
  [cal BP 1003: cal BP 1286] 0.963161
A-1837
Gallo Wash 3
Radiocarbon Age 460±190
Calibration data set: intcal09.14c
# Reimer et al. 2009

One Sigma Ranges: [start:end] relative area
[cal BP 306: cal BP 569] 0.811508
[cal BP 582: cal BP 650] 0.188492

Two Sigma Ranges: [start:end] relative area
[*cal BP -3: cal BP 40] 0.029702
[cal BP 60: cal BP 119] 0.029207
[cal BP 122: cal BP 232] 0.082419
[cal BP 241: cal BP 731] 0.858672
Calibration of Early Zea Mays

Radiocarbon Age vs. Calibrated Age

Hall2010
Zea Mays Pollen
Radiocarbon Age 3890±40
Calibration data set: intcal09.14c
# Reimer et al. 2009

One Sigma Ranges: [start:end] relative area
[cal BP 4259: cal BP 4263] 0.034563
[cal BP 4269: cal BP 4270] 0.013557
[cal BP 4288: cal BP 4411] 0.95188

Two Sigma Ranges: [start:end] relative area
[cal BP 4159: cal BP 4170] 0.012666
[cal BP 4178: cal BP 4200] 0.032738
[cal BP 4227: cal BP 4422] 0.954595
Hubmil2005
Earliest Zea Cob
Radiocarbon Age 3810±50
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal BP 4094: cal BP 4123] 0.143363
[cal BP 4144: cal BP 4259] 0.753022
[cal BP 4264: cal BP 4288] 0.103616
Two Sigma Ranges: [start:end] relative area
[cal BP 4013: cal BP 4020] 0.006703
[cal BP 4021: cal BP 4025] 0.003701
[cal BP 4083: cal BP 4409] 0.989595

Ranges marked with a * are suspect due to impingement on the end of the calibration data set

CALIB RADIOCARBON CALIBRATION PROGRAM*
Calibration of Lower Alentejo Radiocarbon Dates

**Radiocarbon Age vs. Calibrated Age**

GX-21332 / C206
Queimada Rm 3 Hearth
Radiocarbon Age 1385±55
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal AD 603: cal AD 678] 1.
Two Sigma Ranges: [start:end] relative area
[cal AD 559: cal AD 721] 0.936005 [cal AD 741: cal AD 770] 0.063995
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 8
GX-21330 / C276
Costa #2 Rm 3 Hearth
Radiocarbon Age 1295±60
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
Two Sigma Ranges: [start:end] relative area
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 9
AA62725 / C275
Costa #2 Exterior Rm 3
Radiocarbon Age 1256±61
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal AD 674: cal AD 782] 0.800384 [cal AD 789: cal AD 812] 0.135585 [cal AD 845: cal AD 856] 0.064031
Two Sigma Ranges: [start:end] relative area [cal AD 655: cal AD 894] 0.998205 [cal AD 929: cal AD 931] 0.001795
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 10
M#5
Mertola 5
Radiocarbon Age 1225±80
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal AD 691: cal AD 749] 0.312915
[cal AD 763: cal AD 884] 0.687085 Two Sigma Ranges: [start:end] relative area
[cal AD 661: cal AD 908] 0.888079 [cal AD 911: cal AD 971] 0.111921
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 11
GX-21335 / C264
One Sigma Ranges: [start:end] relative area [cal AD 721: cal AD 741] 0.127826 [cal AD 770: cal AD 884] 0.872174
Two Sigma Ranges: [start:end] relative area [cal AD 675: cal AD 898] 0.962183 [cal AD 920: cal AD 945] 0.037817
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 12
AA62726 / C278
Costa #2 Rm 3 Hearth
Radiocarbon Age 1208±63
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal AD 712: cal AD 746] 0.177788
[cal AD 767: cal AD 891] 0.822212 Two Sigma Ranges: [start:end] relative area
[cal AD 674: cal AD 903] 0.892118 [cal AD 914: cal AD 969] 0.107882
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 13
GX-21338 / C301
Pego Real 1
Radiocarbon Age 1190±60 Calibration data set: intcal09.14c # Reimer et al. 2009
One Sigma Ranges: [start:end] relative area [cal AD 725: cal AD 738] 0.058159 [cal AD 771: cal AD 896] 0.867146 [cal AD 923: cal AD 939] 0.074695
Two Sigma Ranges: [start:end] relative area [cal AD 688: cal AD 754] 0.162312 [cal AD 757: cal AD 973] 0.837688
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 14
GX-21333 / C203
Queimada Rm 2
Radiocarbon Age 1175±50 Calibration data set: intcal09.14c # Reimer et al. 2009
One Sigma Ranges: [start:end] relative area [cal AD 777: cal AD 896] 0.908398 [cal AD 923: cal AD 939] 0.091602
Two Sigma Ranges: [start:end] relative area [cal AD 695: cal AD 697] 0.003109 [cal AD 708: cal AD 747] 0.064601
[cal AD 766: cal AD 983] 0.93229
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 15
M#7
Mertola 7
Radiocarbon Age 1165±80
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal AD 776: cal AD 904] 0.707526
[cal AD 913: cal AD 970] 0.292474 Two Sigma Ranges: [start:end] relative area
[cal AD 687: cal AD 999] 0.983137 [cal AD 1002: cal AD 1013] 0.016863
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 16
AA62720 / C208
Queimada Rm 2 SW
Radiocarbon Age 1160±40
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal AD 782: cal AD 790] 0.059871 [cal AD 809: cal AD 898] 0.728004 [cal AD 920: cal AD 945] 0.212126
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 17
AA62719 / C201
Queimada Rm 2
One Sigma Ranges: [start:end] relative area [cal AD 830: cal AD 836] 0.041061 [cal AD 868: cal AD 973] 0.958939
Two Sigma Ranges: [start:end] relative area [cal AD 779: cal AD 794] 0.043798 [cal AD 801: cal AD 985] 0.956202
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 18
M#6
Mertola 6
Radiocarbon Age 1085±80
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal AD 830: cal AD 836] 0.021886
[cal AD 868: cal AD 1027] 0.978114 Two Sigma Ranges: [start:end] relative area
[cal AD 722: cal AD 740] 0.011426 [cal AD 770: cal AD 1055] 0.91614 [cal AD 1076: cal AD 1154] 0.072434
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 19
N/A / C425
Alcaria Longa House 7 Hearth 19 Radiocarbon Age 1070±100
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal AD 783: cal AD 788] 0.013412 [cal AD 815: cal AD 843] 0.078978 [cal AD 859: cal AD 1043]
0.869198 [cal AD 1105: cal AD 1118] 0.033211 [cal AD 1144: cal AD 1146] 0.005201
Two Sigma Ranges: [start:end] relative area [cal AD 695: cal AD 698] 0.002206 [cal AD 708: cal AD 747] 0.028298
[cal AD 765: cal AD 1177] 0.969497
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 20
M#4
Mertola 4
Radiocarbon Age 1060±80
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal AD 882: cal AD 1042] 0.967427
[cal AD 1107: cal AD 1117] 0.032573 Two Sigma Ranges: [start:end] relative area
[cal AD 779: cal AD 795] 0.019245 [cal AD 798: cal AD 1156] 0.980755
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 21
AA62722 / C251
Raposeira Rm 1 Hearth
Radiocarbon Age 1055±39
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal AD 903: cal AD 914] 0.120871
[cal AD 969: cal AD 1021] 0.879129 Two Sigma Ranges: [start:end] relative area
[cal AD 894: cal AD 929] 0.188474 [cal AD 931: cal AD 1028] 0.811526
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 22
GX-21331 / C277
Costa #2 Rm 2
Radiocarbon Age 1045±50
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal AD 899: cal AD 919] 0.156353 [cal AD 953: cal AD 956] 0.018591 [cal AD 961: cal AD 1028] 0.825056
Two Sigma Ranges: [start:end] relative area [cal AD 886: cal AD 1049] 0.928047 [cal AD 1084: cal AD 1124] 0.054965 [cal AD 1137: cal AD 1151] 0.016988
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 23
AA62733 / C423
Alcaria Longa House 1 Hearth 23 Radiocarbon Age 1012±37
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal AD 985: cal AD 1040] 0.963609
[cal AD 1010: cal AD 1115] 0.036391 Two Sigma Ranges: [start:end] relative area
[cal AD 901: cal AD 916] 0.023291 [cal AD 967: cal AD 1053] 0.767052 [cal AD 1079: cal AD 1153]
0.209657
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 24
AA62727 / C404
Alcaria Longa House 8b Hearth Radiocarbon Age 1008±62
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal AD 973: cal AD 1051] 0.634805 [cal AD 1082: cal AD 1126] 0.273038 [cal AD 1135: cal AD 1152] 0.092157
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 25
N/A / C426
Alcaria Longa House 5 Hearth 12 Radiocarbon Age 990±75
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal AD 987: cal AD 1058] 0.4791 [cal AD 1066: cal AD 1072] 0.02915 [cal AD 1075: cal AD 1155]
0.49175
Two Sigma Ranges: [start:end] relative area [cal AD 894: cal AD 927] 0.054919
[cal AD 935: cal AD 1212] 0.945081
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 26
AA62732 / C422
Alcaria Longa House 1 Silo
Radiocarbon Age 993±62
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal AD 988: cal AD 1052] 0.525753 [cal AD 1080: cal AD 1129] 0.341039 [cal AD 1132: cal AD 1153] 0.133208
Two Sigma Ranges: [start:end] relative area [cal AD 897: cal AD 922] 0.039438
[cal AD 941: cal AD 1185] 0.958774 [cal AD 1203: cal AD 1205] 0.001788
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 27
GX-21337 / C429
Alcaria Longa House 5
Radiocarbon Age 970±50
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal AD 1019: cal AD 1053] 0.342574
[cal AD 1080: cal AD 1153] 0.657426 Two Sigma Ranges: [start:end] relative area
[cal AD 984: cal AD 1185] 1.
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 28
GX-21336 / C428
Alcaria Longa House 8b
Radiocarbon Age 965±50
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal AD 1020: cal AD 1053] 0.320239
[cal AD 1079: cal AD 1153] 0.679761 Two Sigma Ranges: [start:end] relative area
[cal AD 987: cal AD 1185] 0.997798 [cal AD 1204: cal AD 1205] 0.002202
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 29
M#3
Mertola 3
Radiocarbon Age 950±95
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal AD 1015: cal AD 1187] 0.971689
[cal AD 1199: cal AD 1206] 0.028311 Two Sigma Ranges: [start:end] relative area
[cal AD 896: cal AD 923] 0.031688 [cal AD 939: cal AD 1263] 0.968312
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 30
AA62728 / C410
Alcaria Longa House 1 Hearth 2 Radiocarbon Age 938±60
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal AD 1032: cal AD 1155] 1. Two Sigma Ranges: [start:end] relative area
[cal AD 995: cal AD 1009] 0.019419 [cal AD 1011: cal AD 1217] 0.980581
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 31
AA62731 / C418
Alcaria Longa House 4 Hearth 9 Radiocarbon Age 929±60
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal AD 1034: cal AD 1158] 1. Two Sigma Ranges: [start:end] relative area
[cal AD 996: cal AD 1006] 0.010647[cal AD 1012: cal AD 1221] 0.989353
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 32
M#1
Mertola 1
Radiocarbon Age 885±185
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal AD 975: cal AD 1288] 1. Two Sigma Ranges: [start:end] relative area
[cal AD 772: cal AD 1417] 1.
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 33
GX-30696 / C430
Stone Line Pr 5
One Sigma Ranges: [start:end] relative area
[cal AD 1049: cal AD 1084] 0.330465 [cal AD 1124: cal AD 1137] 0.107315
[cal AD 1151: cal AD 1211] 0.56222 Two Sigma Ranges: [start:end] relative area
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 34
AA62730 / C417
Alcaria Longa House 2 Hearth 7 Radiocarbon Age 872±61
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal AD 1046: cal AD 1090] 0.289879 [cal AD 1121: cal AD 1139] 0.110262 [cal AD 1149: cal AD 1223] 0.599859
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 35
AA62729 / C416
Alcaria Longa House 4
Radiocarbon Age 855±89
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal AD 1048: cal AD 1086] 0.211781 [cal AD 1123: cal AD 1138] 0.079265 [cal AD 1150: cal AD 1261] 0.708953
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 36
M#2
Mertola 2
Radiocarbon Age 825±75
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal AD 1058: cal AD 1065] 0.02859 [cal AD 1067: cal AD 1072] 0.023645 [cal AD 1155: cal AD 1275] 0.947765
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 37
AA62721 / C210
Queimada Rm1 NE
Radiocarbon Age 530±39
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal AD 1329: cal AD 1340] 0.146321
[cal AD 1396: cal AD 1434] 0.853679 Two Sigma Ranges: [start:end] relative area
[cal AD 1312: cal AD 1358] 0.293005 [cal AD 1387: cal AD 1444] 0.706995
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 38
GX-16307 / C427
Alcaria Longa Top Structure
Radiocarbon Age 460±75
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal AD 1334: cal AD 1336] 0.003881 [cal AD 1398: cal AD 1515] 0.898598 [cal AD 1598: cal AD 1617] 0.097521
Two Sigma Ranges: [start:end] relative area
[cal AD 1313: cal AD 1358] 0.087594 [cal AD 1387: cal AD 1533] 0.696281 [cal AD 1536: cal AD 1635] 0.216125
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 39
AA62724 / C263
Raposeira Locus 5
Radiocarbon Age 440±62
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal AD 1414: cal AD 1499] 0.855675 [cal AD 1503: cal AD 1511] 0.050451 [cal AD 1601: cal AD 1616] 0.093874
Two Sigma Ranges: [start:end] relative area
[cal AD 1334: cal AD 1336] 0.002083 [cal AD 1398: cal AD 1533] 0.745361 [cal AD 1536: cal AD 1635] 0.252556
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 40
AA76891 / 92FS5a
S1
Two Sigma Ranges: [start:end] relative area
[cal AD 1426: cal AD 1520] 0.895463 [cal AD 1592: cal AD 1620] 0.104537
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 41
GX-21334 / C261
Raposeira Locus 5
One Sigma Ranges: [start:end] relative area
[cal AD 1516: cal AD 1595] 0.636748 [cal AD 1618: cal AD 1662] 0.363252
Two Sigma Ranges: [start:end] relative area
[cal AD 1460: cal AD 1673] 0.940839 [cal AD 1778: cal AD 1799] 0.048274
[cal AD 1942: cal AD 1951*] 0.010887
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 42
Radiocarbon Age vs. Calibrated Age

One Sigma Ranges: [start:end] relative area
[cal AD 1528: cal AD 1544] 0.179137 [cal AD 1547: cal AD 1550] 0.028738 [cal AD 1634: cal AD 1666] 0.662281 [cal AD 1784: cal AD 1795] 0.129844

Two Sigma Ranges: [start:end] relative area
[cal AD 1515: cal AD 1598] 0.332304 [cal AD 1617: cal AD 1674] 0.528522 [cal AD 1778: cal AD 1799] 0.122593
[cal AD 1942: cal AD 1951*] 0.016581

Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 43

AA76890 / C1-3a
S2
One Sigma Ranges: [start:end] relative area
[cal AD 1528: cal AD 1544] 0.179137 [cal AD 1547: cal AD 1550] 0.028738 [cal AD 1634: cal AD 1666] 0.662281 [cal AD 1784: cal AD 1795] 0.129844
Two Sigma Ranges: [start:end] relative area
[cal AD 1515: cal AD 1598] 0.332304 [cal AD 1617: cal AD 1674] 0.528522 [cal AD 1778: cal AD 1799] 0.122593
[cal AD 1942: cal AD 1951*] 0.016581
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 43
AA76888 / AL-3a
S3
One Sigma Ranges: [start:end] relative area
[cal AD 1529: cal AD 1543] 0.151857
[cal AD 1634: cal AD 1666] 0.69093
[cal AD 1783: cal AD 1796] 0.157214 Two Sigma Ranges: [start:end] relative area
[cal AD 1517: cal AD 1594] 0.288163 [cal AD 1618: cal AD 1676] 0.544329 [cal AD 1768: cal AD 1771] 0.002603 [cal AD 1777: cal AD 1799] 0.143561 [cal AD 1941: cal AD 1951*] 0.021343
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 44
Radiocarbon Age vs. Calibrated Age

AA76889 / C1-2a
S4
One Sigma Ranges: [start:end] relative area
[cal AD 1529: cal AD 1543] 0.121669 [cal AD 1634: cal AD 1668] 0.632472
[cal AD 1781: cal AD 1797] 0.22397
[cal AD 1948: cal AD 1950*] 0.021889
Two Sigma Ranges: [start:end] relative area
[cal AD 1517: cal AD 1594] 0.23844 [cal AD 1618: cal AD 1681] 0.509341 [cal AD 1739: cal AD 1751] 0.010924 [cal AD 1762: cal AD 1802] 0.203234 [cal AD 1937: cal AD 1951*] 0.038062
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 45
AA62723 / C256
Raposeira Locus 2
Radiocarbon Age 198±46
Calibration data set: intcal09.14c
# Reimer et al. 2009
One Sigma Ranges: [start:end] relative area
[cal AD 1653: cal AD 1683] 0.244617 [cal AD 1735: cal AD 1805] 0.581665 [cal AD 1931: cal AD 1951*] 0.173718
Two Sigma Ranges: [start:end] relative area
[cal AD 1641: cal AD 1707] 0.258934 [cal AD 1719: cal AD 1827] 0.489593 [cal AD 1832: cal AD 1887] 0.082444
[cal AD 1911: cal AD 1953*] 0.169029
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 46
Radiocarbon Age vs. Calibrated Age

AA76886 / AL-1a
S5
One Sigma Ranges: [start:end] relative area
[cal AD 1666: cal AD 1683] 0.181608 [cal AD 1735: cal AD 1784] 0.500533 [cal AD 1796: cal AD 1805] 0.099406
[cal AD 1930: cal AD 1951*] 0.218452 Two Sigma Ranges: [start:end] relative area
[cal AD 1652: cal AD 1696] 0.206032 [cal AD 1725: cal AD 1814] 0.544432 [cal AD 1835: cal AD 1848] 0.017282 [cal AD 1850: cal AD 1877] 0.037305 [cal AD 1917: cal AD 1952*] 0.19495
Lower Alentejo Radiocarbon Date Calibrations 9/3/2011! 47
Ranges marked with a * are suspect due to impingement on the end of the calibration data set
# PJ Reimer, MGL Baillie, E Bard, A Bayliss, JW Beck, PG Blackwell,
# C Bronk Ramsey, AD Buck, GS Burr, RL Edwards, M Friedrich, PM Grootes,
# TP Guilderson, I Hajdas, TJ Heaton, AG Hogg, KA Hughen, KF Kaiser, B Kromer,
# FG McCormac, SW Manning, RW Reimer, DA Richards, JR Southon, S Talamo,
## Appendix C
### Chaco Canyon Packrat Midden Pollen Data

<table>
<thead>
<tr>
<th>midden</th>
<th>date(s)</th>
<th>real date</th>
<th>cal.date</th>
<th>sample type</th>
<th>weigth</th>
</tr>
</thead>
<tbody>
<tr>
<td>Atlatl Cave 4B</td>
<td>10030 +/- 150, 10600 +/- 200</td>
<td>-8500</td>
<td>-12057.9</td>
<td>pollen</td>
<td>7.1</td>
</tr>
<tr>
<td>Atlatl Cave 3</td>
<td>9460 +/- 160, 10500 +/- 250</td>
<td>-8030</td>
<td>-11340.8333333333</td>
<td>pollen</td>
<td>28.3</td>
</tr>
<tr>
<td>Atlatl Cave 4A</td>
<td>5550 +/- 130</td>
<td>-3600</td>
<td>-6302.5</td>
<td>pollen</td>
<td>26.1</td>
</tr>
<tr>
<td>Casa Chiquita 4</td>
<td>4920 +/- 110</td>
<td>-2970</td>
<td>-5672.3333333333</td>
<td>pollen</td>
<td>23.7</td>
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<tr>
<td>Casa Chiquita 2</td>
<td>4780 +/- 90</td>
<td>-2830</td>
<td>-5440</td>
<td>pollen</td>
<td>15.9</td>
</tr>
<tr>
<td>Gallo Wash 2</td>
<td>4480 +/- 90</td>
<td>-2530</td>
<td>-5102.1666666666</td>
<td>pollen</td>
<td>11.1</td>
</tr>
<tr>
<td>Casa Chiquita 1B</td>
<td>3940 +/- 110</td>
<td>-1990</td>
<td>-4243.8333333333</td>
<td>pollen</td>
<td>27.8</td>
</tr>
<tr>
<td>Mockingbird Canyon 3</td>
<td>3270 +/- 90</td>
<td>-1320</td>
<td>-3547.75</td>
<td>pollen</td>
<td>99.4</td>
</tr>
<tr>
<td>Gallo Wash 1</td>
<td>2810 +/- 90</td>
<td>-860</td>
<td>-2990.6666666666</td>
<td>pollen</td>
<td>15.5</td>
</tr>
<tr>
<td>Gallo Wash 6</td>
<td>2820 +/- 300</td>
<td>-870</td>
<td>-2698.25</td>
<td>pollen</td>
<td>19</td>
</tr>
<tr>
<td>Casa Chiquita 3</td>
<td>1970 +/- 100</td>
<td>-20</td>
<td>-2014.5</td>
<td>pollen</td>
<td>10.5</td>
</tr>
<tr>
<td>Gallo Wash 4</td>
<td>1940 +/- 150</td>
<td>10</td>
<td>-1990</td>
<td>pollen</td>
<td>18.7</td>
</tr>
<tr>
<td>Gallo Wash 5</td>
<td>2070 +/- 90</td>
<td>-120</td>
<td>-1971</td>
<td>pollen</td>
<td>30.2</td>
</tr>
<tr>
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