8-2019

Subsistence Strategy Tradeoffs in Long-Term Population Stability Over the Past 6,000 Years

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SUBSISTENCE STRATEGY TRADEOFFS IN LONG-TERM POPULATION

STABILITY OVER THE PAST 6,000 YEARS

by

Darcy A. Bird

A thesis submitted in partial fulfillment
of the requirements for the°

of

MASTER OF SCIENCE

in

Archaeology and Cultural Resource Management

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2019

ABSTRACT

Subsistence Strategy Tradeoffs in Long-Term Population Stability Over the Past 6,000 Years

by

Darcy A. Bird, Master of Science

Utah State University, 2019

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I conduct the first analysis of long-term human population stability in North America using large radiocarbon data sets. Questions regarding population stability among animals and plants are fundamental to population ecology, yet no anthropological research has addressed long term human population stability. This is an important knowledge gap, because a species' population stability can have implications for its risk of extinction and for the stability of the ecological community in which it lives. I use archaeological and paleoclimatological data to compare long term population stability with subsistence strategy and climate stability between 6,000 and 300 B.P. I conduct a coarse-grained analysis in order to better understand general trends regarding population stability in North America as a first step that future fine-grained studies may build upon.

To conduct this research, I used radiocarbon dates as representative of relative population change in North America. I gathered almost 40,000 radiocarbon dates within the United States and Canada using the Canadian Archaeological Radiocarbon Database (CARD) and sample this dataset with a 5° latitude/longitude grid. I generated summed probability distributions (SPD's) that I bin at three different scales (50, 100, and 200-years). I calculated the absolute value of the differences between sequential bins, which are averaged to generate the 50-, 100-, and 200-year population stability measurements. I then took the inverse of this measurement to estimate population stability.

My results demonstrate that agricultural sequences have smaller population changes than hunter-gatherer sequences in general, but they also experience rare, extreme population swings not seen among hunter-gatherers. I propose that agriculturalists trade increased population density and stability over most time-scales for greater vulnerability to large population collapses, while hunter-gatherer systems remain flexible and are less vulnerable to large population changes. I found that population stability shows a weak relationship with climate stability. Climate stability may have an indirect effect on long-term population stability, and climate shocks may be buffered by other aspects of subsistence strategies prior to affecting human demography.

(142 pages)

PUBLIC ABSTRACT

Subsistence Strategy Tradeoffs in Long-Term Population Stability Over the Past 6,000 Years

Darcy A. Bird

I conduct the first comparative analysis of long term human population stability in North America. Questions regarding population stability among animals and plants are fundamental to population ecology, yet no anthropological research has addressed human population stability. This is an important knowledge gap, because a species' population stability can have implications for its risk of extinction and for the stability of the ecological community in which it lives. I use archaeological and paleoclimatological data to compare long term population stability with subsistence strategy and climate stability over 6,000 years. I conduct my analysis on a large scale to better understand general trends between population stability, subsistence strategy, and climate stability. I found that agricultural sequences fluctuate less than hunter-gatherer sequences in general, but they also experience rare, extreme population swings not seen among hunter-gatherers. I suggest that agriculturalists are more vulnerable to population collapses because of their increased population densities. I found that population stability shows a weak relationship with climate stability. Climate stability may have an indirect effect on long-term population stability.

ACKNOWLEDGMENTS

I would like to first thank my father, David Bird, and my sister, Bonnie Bird. My older sister gave me someone to look up to and, sometimes, race. You beat me to a Master's, but know I'll get a Ph.D. first. My father provided me with support, as always, and someone to talk to about the struggles of coding, though we know different languages. Thanks for always being the wind at my back.

I would like to thank friends from far away who nevertheless gave their support. Brittany and Adam, thank you for providing needed breaks with video games every few weeks. I want to thank Scott and Greg for listening to my struggles and sending me delivery cookies when it seemed like too much. I especially want to thank Fernando, who has always been one of my biggest cheerleaders. Thanks to all of you for never doubting.

I would like to thank my cohort, or, as we like to say "the Cohorde," my strongest support network while I've been at USU. Thanks to Alicia for feeding us. Thank you, Emily, for your well-timed puns. Thank you, Maggie, for the afternoon chats that we both needed. Thank you Garnet, for knowing that board games are the best study break. Thank you, Makaela, for teaching me how to truly ski and always high-fiving me when I needed to reaffirm our two-year goal. And thank you Audrey and Trista, for editing my papers, for bouncing ideas, and for late nights drinking wine. I love all of you, and I don't think I could have done as well at this program if we weren't supporting each other through all of it.

I would like to thank my lab members, Aaron and Gideon. Both of you are incredibly selfless and good humans. Thank you for helping me with my code, writing, and conversations about life, goals, and really cool projects we want to work on in the future. I want to thank Richard, who provided guidance to everyone in my cohort from Day 1. I would also like to thank the Anthropology staff assistant, McKinley Benson, for always being game

to help with anything we need.

Finally, I would like to thank my committee members, Drs. Patricia Lambert, Erick Robinson, and Judson Finley, and my chair, Dr. Jacob Freeman. Pat, thank you for combing through my drafts and being the easiest to schedule (I seriously appreciate this). Judson, thank you for knowing exactly where the greatest trouble would be in my research. Erick, thank you for giving me data when we barely knew each other and working with me before you were even on my committee. Finally, thank you Jacob, for being an incredibly supportive advisor. Thank you for always being willing to review poster drafts and presentations, even if it's only a few hours before the "due" time. Once you told me, when you were exhausted from all the work you were doing, when you agreed to review my proposal defense presentation only a few hours before I defended, "That's what advisors are for." Not all advisors would do that, and I'm very, very grateful.

Thank you all for your moral support, patience, and endless encouragement during my time at USU. I could not have done it without all of you.

With love and gratitude,
Darcy A. Bird

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Chapter I: Introduction[1]

The stability of animal populations over time – the change in populations from year-to-year, decade-to-decade, or century-to-century – is fundamental to understanding both the risk of local populations to extinction and the health and functioning of ecological communities (e.g., Blaustein et al. 1994; Murdoch 1966; Murdoch and Oaten 1975; Rall et al. 2010). In theory, the stability of human populations over time could also affect the risk of both local population extinctions among small-scale societies, especially mobile foragers with low population density (Hamilton et al. 2009), and the economic performance in larger scale societies. For instance, large irrigation systems rely on a dependable supply of cooperative labor, however mobilized, to clean and maintain canals (Hunt et al. 2005). If populations fluctuated wildly from decade to decade, such a system would be difficult to maintain because a steady supply of labor would be highly uncertain. Agricultural production may then decline over the long term as individuals abandoned large canals in favor of self-reliant strategies to buffer against the risk of labor shortfalls. Yet, few studies have ever attempted to explain the stability of human populations (e.g., Hamilton et al. 2009). In this paper, I make a first attempt to study the long-term stability—fluctuation over decades to centuries—of human populations by pushing the bounds of paleodemography using the dates as data approach.

Dates as data refers to a broad approach to using large samples of radiocarbon dates to study changes in human population over time (Rick 1987). Most dates as data research over the last 20 years has attempted to study the effects of sampling biases, possible biases introduced by taphonomy and preservation, and biases introduced by

[1] This thesis will be submitted to academic journals with co-authors pending minor revisions.

cultural processes to reconstruct trends in human population over thousands of years or correlate episodes of population growth and/or collapse with particular episodes of climate and subsistence change (Bevan et al. 2017; Downey et al. 2016; Freeman et al. 2018b; Jørgensen 2018; Kelly et al. 2013; Kuzmin and Keates 2005; Louderback et al. 2010; Peros et al. 2010; Rick 1987; Riede 2009; Shennan et al. 2013; Smith et al. 2008, 2015; Spangler 2000; Surovell and Brantingham 2007; Surovell et al. 2009; Timpson et al. 2014; Zahid et al. 2016). This paper is part of a growing literature that builds upon previous studies in an attempt to use radiocarbon records to study basic population ecology processes in human societies from a comparative perspective (e.g., Freeman et al. 2018a; Peros et al. 2010; Shennan et al. 2013; Zahid et al. 2016;) and, in particular, the neglected process of population stability.

I treat radiocarbon records as reflective of energy expenditure that correlates positively with population size (Freeman et al. 2018b), and I propose that the more radiocarbon records fluctuate on the decadal to centennial scale, the less stable populations and economies were over time. I specifically hypothesize that locations in which populations eventually adopted agriculture display more population stability than those where populations remained hunter-gatherers, but also agriculturalists experienced large fluctuations (outlier booms and busts) seldom experienced by hunter-gatherers. To evaluate this hypothesis, I study the relationships among climate, population stability, and the presence of agriculture in prehistoric North America over the last 6,000 years. The North American continent provides an excellent opportunity to study such relationships, because much of the continent was populated by both hunter-gatherer and agricultural societies over the last 6,000 years. I conduct a coarse-grained analysis, which zooms out from the particulars of any given location to investigate large-scale patterns (Flack 2013 et al.; Ortman et al. 2018). This does not deny the importance of local variability in any way; coarse graining simply provides an additional perspective for answering difficult questions about complex population processes.

In the remainder of this thesis, I first lay out my hypothesis for the potential effects of subsistence on the stability of human populations over the last roughly 6,000 years. I then go through my methodology in detail, including the process I used to select sampling units, gather and clean radiocarbon data, calculate stability measurements, calculate both temperature and precipitation stability, and assign agriculture values. I then present the results of my analysis, and, finally, I interpret these results in the context of my hypothesis, compare my conclusions to previous studies, and suggest future research.

Chapter II: Literature Review

Few researchers have investigated the stability of human populations over decades to centuries, thus a dearth of anthropological literature exists on the topic. This is partially because it has been difficult to construct datasets useful to estimate changes in human populations over long time-scales (hundreds to thousands of years). The goal of this chapter is to provide a hypothesis to guide my investigation of human population stability. Drawing on a dynamical systems model of foraging and farming, I propose that human societies face a long-term performance–vulnerability tradeoff in their demographic systems generated by the adoption of agriculture. The basic idea is that agriculture increases the potential carrying capacity of environments, which leads to larger population densities and more stable populations most of the time (higher performance) but also increases the vulnerability of agricultural populations to rare, large fluctuations (booms and busts) greater than the rare, large fluctuations experienced by hunter-gatherers.

Given the dearth of literature on the stability of human populations, the literature on the stability of animal populations provides a starting point for creating expectations about the stability of human populations. Research on the population ecology of non-human animals demonstrates two basic results. First, the fluctuation of animal populations forms a highly skewed distribution, often well fit by a power law distribution (e.g., Allen et al. 2001; Halley 1996; Keitt and Stanley 1998; Marquet et al. 2005). This means that most increases and decreases in population are small, but occasionally, populations experience large booms and/or busts. Thus, I expect that human population fluctuations also display similar right skewing, with many small population changes and a few large fluctuations.

Second, the stability of animal populations results from a complex interaction of climate forcing on the resources for a particular species, internal population processes, life history characteristics, and social processes (e.g., Hidalgo et al. 2011; Jenouvrier et al. 2003; Murdoch 1966). Thus, holding human life history constant, I expect complex relationships among climate, technological organization, and the stability of human populations. Because the study of human population stability is nascent, I do not attempt to formally model the interaction of all of these processes. Rather, I develop a qualitative, narrative hypothesis for the stability of human populations using a dynamical systems model developed by Freeman et al. (2015) that contrasts foragers and farmer-foragers.

Freeman et al. (2015) illustrate the consequences of adopting maize for the maximum population density, food supply, and vulnerability of a social-ecological system to environmental change in an idealized forest ecosystem. In this ecosystem, human foragers may either harvest seeds from the trees of the forest, or they invest in maize agriculture by clearing the forest. The main dynamics of the model relevant here are as follows. The adoption of maize first makes the system resilient to environmental change by operating as a buffer, and it drastically increases potential carrying capacity. If one increases the population density parameter of the model, farmer-foragers can maintain an optimal harvest of seeds and maize, but the entire system becomes vulnerable to climate variation that may initiate a transformation of the system into a degraded state. For example, when a drought hits the system, maize and tree seed productivity are depressed. Individuals respond by clearing more forest to grow more maize to stabilize the intake of food in the short run. The newly denuded forest produces fewer seeds, which leads to a greater need to grow more maize (Freeman et al. 2015). This positive feedback loop eventually causes the system to collapse.

Two qualitative insights for population stability follow from the model results described above. First, we should expect agriculture to increase how well individuals produce food, both increasing the productivity and stability of a supply of food most of the time. This may be done by increasing the supply rate of food production (as in the model) or through storage. This expectation fits well with conventional anthropological wisdom that farming provides an opportunity for increasing the productivity of an environment and decreasing the risk of production shortfall—leading to higher carrying capacity (e.g., Freeman 2016, Glassow 1978; Roosevelt 1984). This carrying capacity increase is reflected by population densities recoded in the ethnographic record. The maximum population density among ethnographically documented hunter-gatherers is between 3.39 and 5 people per square kilometer (Binford 2001; Kelly 2013; Roscoe 2009), while small-scale, subsistence agriculturalists can live at population densities of 200-300 people per square kilometer (Netting 1993). Though ethnographically recorded population densities fit this expectation, no one has ever compared the stability of populations among archaeological sequences that become agricultural vs. those that remain hunter-gatherers. I fill this empirical knowledge gap with this study.

Second, though adopting agriculture improves the performance of food production and, thus, should increase population density and stability in the medium term, agriculture also transforms ecosystems and may make ecosystems more vulnerable to climate variation that was once easily absorbed. In fact, this is a key lesson of dynamic systems models of human-resource interactions in general (e.g., Anderies 2006; Barnes et al. 2017; Freeman and Anderies 2012; Freeman et al. 2015; Lima 2014), and is consistent with the idea of a "rigidity trap" from resilience theory. A rigidity trap occurs when a system is "stuck," because individuals must spend all of their time and effort maintaining what they have, which reduces the opportunity to adapt and innovate (Hegmon et al. 2008; Holling et al. 2002; Marston 2015). Thus, although I expect agriculture to stabilize a food supply and, consequently, the populations of agricultural sequences relative to those that remain hunter-gatherers, we should also expect agricultural sequences to display rare larger booms and busts than hunter-gatherer sequences. This is because agriculture suddenly increases the carrying capacity of an environment much more than foraging innovations and, on average, agricultural societies should be more vulnerable to falling into "rigidity traps" that lead to very large collapses.

Several anecdotal lines of evidence are consistent with my second expectation that agriculturalists experience more intense and rare booms and busts than hunter-gatherer sequences. For example, the adoption of agriculture caused several major biological changes in human societies, specifically health decline, physiological stress increase, nutrition decline, and birth rate increase, among others (Lambert 2009; Larsen 1995; Roosevelt 1984). Notably, one change is sudden population growth following the adoption of agriculture (Bocquet-Appel and Bar-Yosef 2008; Gignoux et al. 2011; Lambert 2009; Larsen 1995; Li et al. 2009; Shennan et al. 2013), which may suggest a fitness-health tradeoff wherein populations are larger but less healthy.

Further, researchers using the dates as data approach observe population booms and busts following the adoption of agriculture (Bernabeu Aubán et al. 2016; Shennan et al. 2013; Timpson et al. 2014). For example, with the adoption of agriculture, archaeologists observe one or several population boom and bust cycles in northwestern Europe (Gronenborn et al. 2014; Shennan et al. 2013; Timpson et al. 2014; Warden et al. 2017). Some researchers argue that this boom-bust cycle is a result of climatic effects (Gronenborn et al. 2014; Warden et al. 2017) especially when populations are high (Gronenborn et al. 2014), while others argue for internal social-ecological processes, such as fertility transitions or land cover changes and the degradation of agricultural habitat (Shennan et al. 2013; Timpson et al. 2014). Again, while these studies suggest that agriculture may be related to a particularly large boom or bust episode in population, no one has ever systematically compared the long-term population stability of archaeological regions that become agricultural with those that remained hunter-gatherers.

In sum, research into the long-term stability of human populations is rare, especially on archaeological time-scales. However, insights from animal ecology and a dynamical systems model that contrasts foragers and farmers within the same ecosystem provides a narrative hypothesis useful to guide my analysis. I propose that, like all other known animal populations, human populations experience many small changes and a few large changes in population and economy size. In addition, I expect that most of the time archaeological sequences where agriculture was adopted experience greater stability than hunter-gatherer sequences because, ideally, agriculture improves the productivity and stability of a supply of food, which leads to larger and more stable population densities. Adopting agriculture also suddenly increases the potential carry capacity of an environment, which may lead to population booms, and the increasing reliance on agriculture can also transform ecosystems to such an extent that human populations become vulnerable to a type of rigidity trap and experience very large collapses. Thus, I expect that when rare but large booms and busts occur, these are more intense in agricultural sequences than among hunter-gatherer sequences. I will test this hypothesis in the subsequent chapters.

Chapter III: Data and Methods

Paleodemographic studies have estimated changes in human populations by using tree rings (Berry 1982; Berry and Benson 2010; Bocinsky et al. 2016), human mortality profiles from burials (Bocquet-Appel and Bar-Yosef 2008; Kohler et al. 2008), human fecal stanols (White et al. 2019), site catchment analysis (Li 2015; Roper 1979), changes in house size or number (Brown 1987, Gronenborn et al. 2014; Kolb 1985), and radiocarbon time-series—dates as data (Barton et al. 2017; Bevan et al. 2017; Chaput et al. 2015; Downey et al. 2016; Freeman et al. 2018a; Jorgenson 2018; Kelly et al. 2013; Kuzmin and Keates 2005; Louderback et al. 2010; Peros et al. 2010; Rick 1987; Riede 2009; Robinson et al. 2019; Shennan et al. 2013; Smith et al. 2008; Spangler 2000; Timpson et al. 2014; Zahid et al. 2016; See Chamberlain 2006 for an overview of archaeological paleodemography). The dates as data approach is the most widely applicable of these approaches as radiocarbon data are more widespread and accessible than, for example, burials (restricted to larger societies) and tree-ring cutting dates (restricted to deserts where wood preserves). The basic concept is that each dated archaeological artifact presumably represents past human activity, which allows the archaeologist to assess relative occupation history in a given region (Rick 1987). While these data are not without their faults (see Appendix I section 1), radiocarbon databases provide the opportunity to conduct comparative analyses essential to answer basic population ecology questions about prehistoric North America.

I analyze 5,700 years of calibrated radiocarbon ages from North America to estimate changes in population. Over the past decade there has been an increase in the analysis of radiocarbon date frequencies to estimate changes in human population densities (Kelly et al. 2013; Louderback et al. 2010; Rick 1987; Shennan et al. 2013) and to analyze population growth, decline, and movement (Bevan et al. 2017; Downey et al. 2016; Jørgensen 2018; Kuzmin and Keates 2005; Peros et al. 2010; Rick 1987; Riede 2009; Smith et al. 2008, 2015; Spangler 2000; Timpson et al. 2014; Zahid et al. 2016). Freeman et al. (2018a) argue that radiocarbon ages can be usefully thought of as an estimate of energy consumption, which scales sub-linearly with population size. Energy consumption also has a relationship with economic complexity: as economic complexity increases, additional energy is necessary to coordinate populations via exchange and fund critical infrastructure (Freeman et al. 2018b). Thus, we treat large samples of radiocarbon ages as a proxy for energy consumption and, indirectly, population density and economic activity in a given area.

Radiocarbon Data

To study the stability of human demographic systems between 6,000 and 300 years cal. BP, I gathered radiocarbon ages from the Canadian Archaeological Radiocarbon Database (CARD) and from the recent NSF-funded project *Populating a Radiocarbon Database of North America* (PI: Robert L. Kelly). I used the following methods to clean the data. I removed all non-archaeological dates (bulk sediments, charcoal not associated with human deposits from geological test trenches, etc). Despite only studying calibrated ages 6,000-300 BP, I retained all uncalibrated radiocarbon dates 8,000-0 ^{14}C BP to minimize edge effects (see Appendix I section 1 for details). I removed all radiocarbon ages missing latitude and longitude. I verified that each radiocarbon age comes from a listed radiocarbon lab according to a list provided by *Radiocarbon: An International Journal of Cosmogenic Isotope Research* (Radiocarbon 2018). I ensured

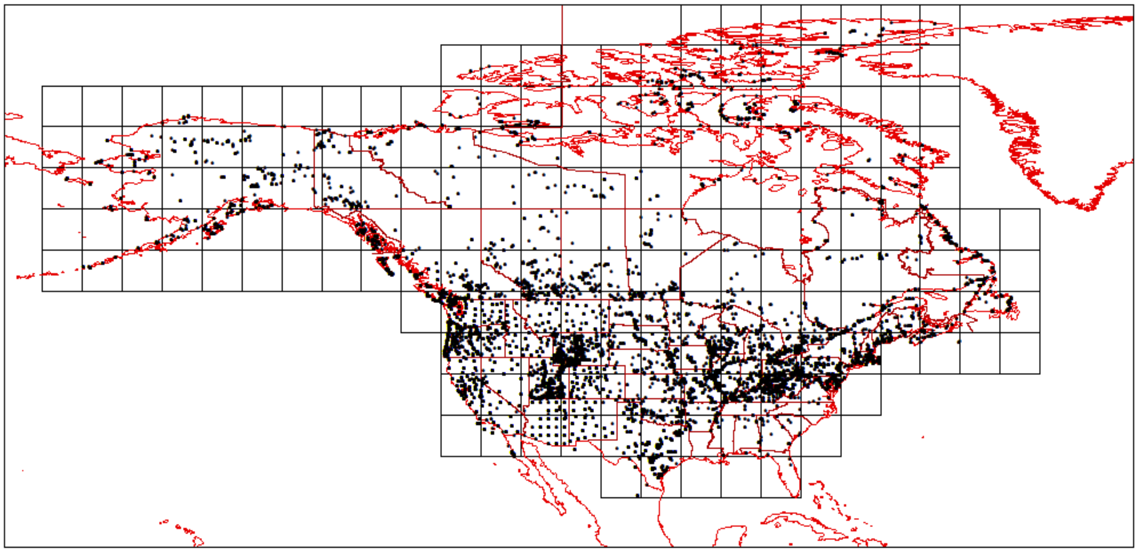

Figure 1: Continental scale with 196 black 5° small boxes and their specific radiocarbon age locations, also in black. Country and state boundaries are delineated in red.

each age was only represented once in the dataset by checking and removing the duplicates. If the locational information was different and the ^{14}C date and standard deviation were the same, but the two duplicates were in the same box, I removed one arbitrarily to count one date within the box. In some cases, the duplicate lab numbers were not in the same sampling unit or they had the same ^{14}C date and/or standard deviation. In this case, I removed both duplicates. After these steps were taken, I had a dataset of 40,017 radiocarbon ages with unique lab numbers within the accepted parameters (Figure 1).

Stability Measurement Methodology

Once I processed the data, I analyze population stability within the United States and Canada by creating 5° grid squares overlaying the continental landmass (Figure 1). This method divided the radiocarbon dataset into sampling units. I used a sampling grid rather than culture areas in order to minimize sampling bias that may be inadvertently introduced by externally defined cultural areas that change in shape and size over time. I chose 5° boxes as this best balanced the need for sample units with sufficient numbers of radiocarbon ages (>199) and developing reasonable sized sampling units to capture variation in climate that may affect population stability. In general, larger sample units smooth out climate variation but lead to larger sample sizes of ages. Smaller sample units allow us to better measure climate differences, but lead to smaller samples of radiocarbon ages that may limit a stability analysis. I selected only boxes with 200 or more radiocarbon ages to ensure each sampling unit had enough dates to produce an SPD with a reasonable spread of ages. In short, this is one step taken to minimize the potential effects of sample size on the stability of an SPD. With 5° boxes, there are 40 sampling units with 200 or more radiocarbon ages. I examine whether the number of radiocarbon ages within each sample unit affects the results and found no bias created by differences in sample size on my results (see Appendix I section 2).

Within each sampling unit, I calibrated the radiocarbon ages using the Intcal13 database (Reimer et al. 2013) then generated a summed probability distribution (SPD) (See Appendix I section 6 for code; Williams 2012). I used the R programming package, 'rcarbon' (Bevan and Crema 2018) and its function, binPrep, to control the aggregation of radiocarbon ages from the same site to control for potential over-sampling (Timpson et al. 2014). I averaged all radiocarbon ages within 100 years of each other from the same site. For each SPD, I summed the annual probabilities into 50, 100, and 200-year bins to study the stability of the records over multiple time-scales (see Appendix 1 section 5 for all SPDs). I chose these three time scales to maintain and study variability in the record. Smaller bin sizes are more likely affected by the calibration curve, while larger bin sizes completely obscure the variability we need to study population and economic stability.

For each of the three time scales, I calculated the first difference values between each bin using the following equation:

$$SPDdiff=SPDt+1-SPDt$$

Where SPDdiff is the difference between the SPD value from one time step in the future (t+1) and the SPD value at time t (Figure 2). This method detrends the SPD's (removes distortions such as a change in the mean over time) and preserves the change in amplitude values around the mean trend of the SPD. Each positive first difference value demonstrates an SPD increase (i.e., boom), while each negative first difference value represents a decrease (i.e., bust). To calculate SPD stability per sampling unit, I took the absolute value of the amplitudes and calculated both average and median values. Taking the inverse of each box's mean or median absolute amplitude value provides a measurement of SPD stability and an estimate for population stability within each box. I also calculated the average increase (or boom) for each box by calculating an average of all positive first difference values and the average decrease (or bust) by averaging all negative first difference values. I assumed these increases and decreases in the first difference values represent increases and decreases in population and economy size within each sampling unit, with the understanding that the calibration curve should affect agriculture and hunter-gatherer systems in the same way. Therefore, any difference between these subsistence strategies' SPD changes should be a result of population change, not an artifact of the calibration curve (but see Bamforth and Grund 2012).

I also considered the entire distribution of amplitude values via density plots to understand the range of variation between the two subsistence strategies. I plotted these

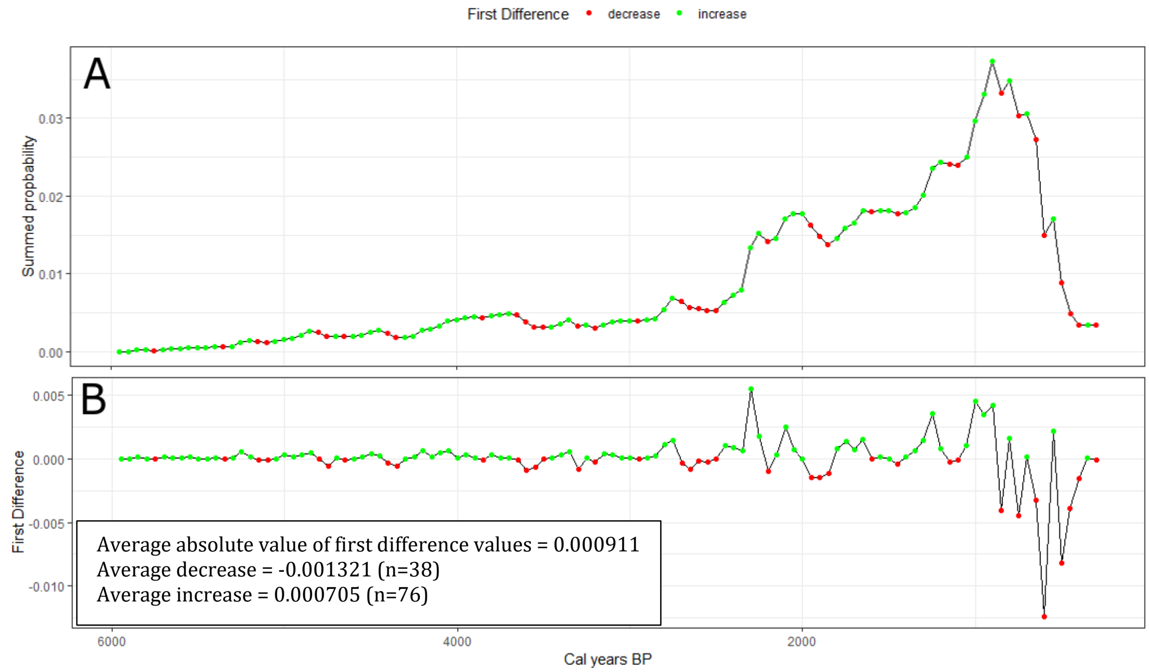

Figure 2: Calculating the first difference values using sampling unit #18. The first difference values are calculated from subtracting the next time step's SPD value from the present time step: the dots are colored red if the SPD value of time step t+1 is less than time step t, representing a decrease in the SPD. Green dots represent first difference values that are positive, so the SPD value at time step t+1 is higher than at time step t. The graph depicts the SPD values for sampling unit #18, located in northern Arizona and southern Utah at the 50-year bin size. A: SPD values graphed against time for one sampling unit with first difference values coded accordingly. Note the exponential trend of increasing SPD values through time. B: First difference values graphed against time. All green dots are positive first difference values while all red dots are negative first difference values. All the green dots are above 0 on the y-axis, while all the red dots are below zero. The average difference (or absolute value of first difference values) is 0.000911, while the average decrease is -0.001321 and the increase is 0.000705.

amplitude values together, taking the absolute value to exclusively view each first difference value, and separately, which allowed me to compare the size of population booms and busts between the two subsistence strategies. I calculated the median and mean amplitude value for the two subsistence strategies to compare their values independently of the sampling units.

Climate Stability Methodology

I used Fordham et al. (2017)'s PaleoView to model climate data for the past 6,000 years within North America. PaleoView's climate data comes from the TRaCE21ka experiment (Liu et al. 2009, 2014; Otto-Bliesner et al. 2014), a Community Climate System Model, version 3 (CCSM3), and a global coupled atmosphere-ocean-sea ice-land general circulation model (AOGCM) with ~3.75° latitude-longitude resolution on land and sea and ~3° resolution over the ocean. PaleoView re-grids the climate data to provide a 2.5° x 2.5° resolution on a global scale 20,050 BC to 1989 AD, and it can be downscaled to smaller resolutions if necessary. PaleoView is currently the only source that provides comparable paleoclimate estimates on a continental scale. The model provides a starting point for making comparisons between projected paleoclimate stability and radiocarbon stability.

I extracted the temperature and precipitation data from PaleoView in the form of 10 year averages for each of the 2.5° raster squares. I then calculated the coefficient of variation (CV) for each raster cell with the following formulas:

$$CV = \frac{\sigma}{\mu}$$

And:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x}_i)^2}{n}}$$

Where μ is the mean of the time series of each raster cell, σ is the standard deviation calculated for each raster cell, and *x* represents each raster cell in the time series. To provide one stability measurement for each sampling unit, I followed a multistep process to convert raw data to temperature or climate stability. First, I average the four contributing 10 year 2.5° climate rasters to generate average 5° sampling unit temperature and precipitation levels on the 10 year scale. I bin these 10 year intervals at three time scales (50-year, 100-year, and 200-year), which I use to calculate the mean and standard deviation and therefore the coefficient of variation. I calculate stability by taking the inverse of the coefficient of variation (1/CV). Finally, I average all of the stability measurements for each sampling unit at each time scale. Each sampling unit has a temperature and precipitation stability measurement at the 50-year, 100-year, and 200-year time scale using this methodology.

Subsistence Strategy Methodology

Finally, I assigned a binary agriculture variable based on presence or absence of agriculture prehistorically within the sampling areas, with a focus on where the radiocarbon samples were coming from (Figure 3; see Appendix 1 section 5). These values were assigned based on documented evidence of the presence of agriculture in the review literature of archaeological records of North America (Jennings 1968; Kopper 1986; Pauketat 2015; Snow 1989; Thomas 1999). Some of the sampling units occur in “border land" areas characterized by a late adoption of agriculture (~800 BP or later) with hunter-gatherers still occupying large portions of the sampling unit. I conducted additional research of these areas to try and parse the extent of agriculture in the area with an emphasis on the effect of agriculture on the daily life of those living there, including hunter-gatherers, as well as comparing when the majority of my radiocarbon sample for these areas came from (see Appendix I section 3 for borderland statements, Appendix I

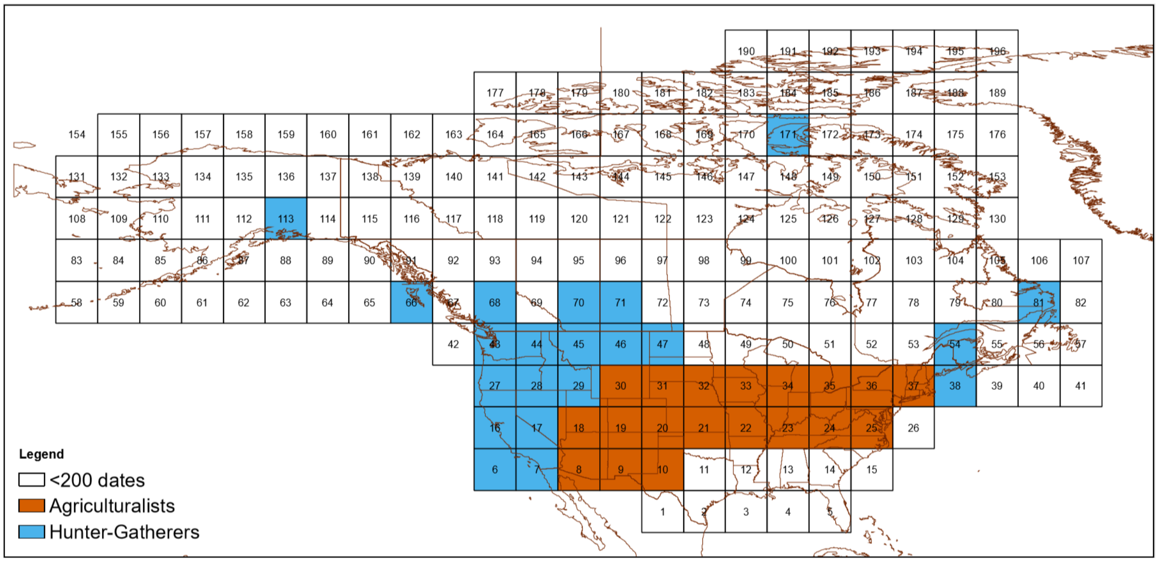

Figure 3: Map demonstrating the locations of the boxes with more than 200 radiocarbon dates and their affiliated subsistence strategy assignation.

section 4 for a false positive check). This coarse-grained approach of assigning a binary agriculture variable allows me to identify general trends in places that adopted agriculture at some point during their occupation versus those locations that barely or never adopted agriculture. Future work finely parsing these areas will depend on the accumulation of more radiocarbon dates to avoid problems associated with very small samples.

I compared the two subsistence strategies across all three time scales in several ways. First, I built box plots of the amplitude means and compared the distributions via a Wilcox rank sum test to evaluate the null hypothesis that the distributions of observations are the same. I then generated density plots of all amplitude values in order to observe the differences in detrended SPD first difference means, medians, standard deviation, and skewness between the two subsistence strategies. I also analyzed the relationship between long-term population stability and climate stability (via temperature and precipitation stability) at three time scales controlling for differences based on subsistence strategy.

Chapter IV: Results

I hypothesized that human societies face a long-term performance—vulnerability tradeoff in their demographic systems generated by the adoption of agriculture relative to societies that remain hunter-gatherers. In other words, I expected both hunter-gatherer and agricultural sequences to display right skewed distributions of changes in radiocarbon (an estimate of population). However, I also expected agricultural sequences to have lower mean population stability than hunter-gatherers because of large outlier booms and busts but a higher median stability than hunter-gatherer sequences because agriculture improves the stability of a food supply most of the time.

I find that sample units where agriculture was adopted display lower mean population stability than the sample units that remained hunter-gatherers throughout the 5,700 year sequences. However, hunter-gatherer sample units have lower median population stability than agricultural sampling units. I note these relationships at all three time scales (50-, 100-, and 200-year) and across different levels of climate stability. The results support my hypothesis that agriculture initiates a performance—vulnerability tradeoff in human–resource systems.

Subsistence Strategy and SPD Stability

Agricultural sequences display a lower mean stability than sequences that remained hunter-gatherers. This indicates that, on average, agriculturalists are less stable than hunter-gatherers. Figure 4 displays box-plots of mean population stability (inverse of average absolute value of the booms and busts), increase (booms), and decrease (busts), as estimated by fluctuations in SPD values. In Figure 4A-C, across the 50-, 100- and 200-year time scales, agricultural sequences display lower mean population stability than

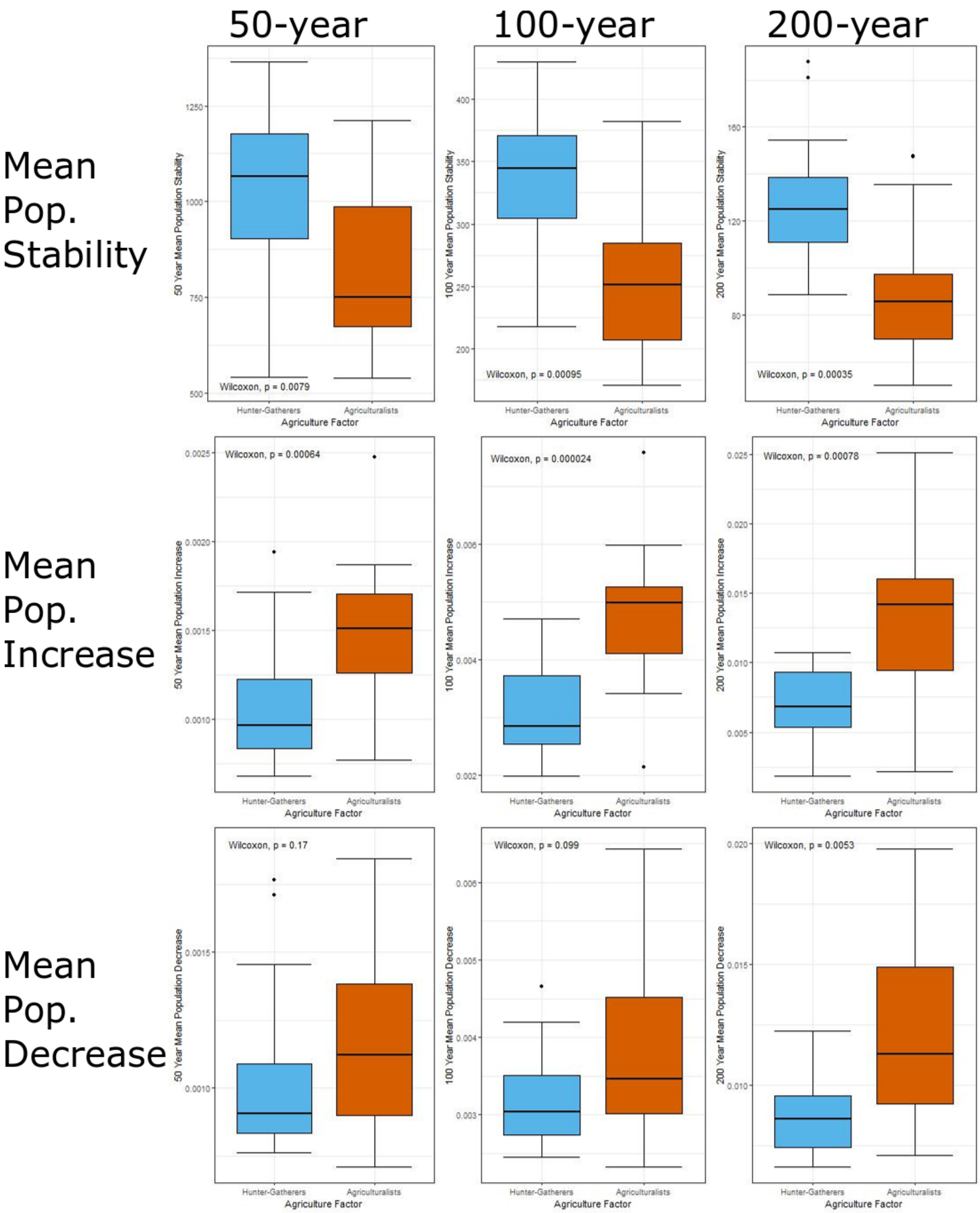

Figure 4: These box-plots demonstrate the mean values for each sampling unit. A-C: Mean population stability distribution. D-F: The mean boom distributions. H-J: The mean bust distributions.

sequences where populations remained hunter-gatherers. The difference in mean population stability is statistically significant at all three time scales.

When comparing the means of SPD increases and decreases separately, I find that mean population booms are significantly higher among agricultural sequences at all three time scales (Figure 4D-F). Similarly, agricultural sequences display larger mean busts than hunter-gatherer sequences at all three time scales (though only statistically significant at $p<0.05$ at the 200 year time scale, Figure 4G-I).

It is important to recall that the plots in Figure 4 compare the mean amplitudes of each given sequence within each sampling unit. While agricultural sequences display less stability on average than hunter-gatherer sequences, hunter-gatherer sequences actually have lower median population stability estimates than agricultural sequences. For instance, Figure 5 compares the distribution of SPD fluctuations from agriculturalist Sampling Unit #32 (SU#32 located in southeast South Dakota, northeast Nebraska, and western Iowa) and hunter-gatherer Sampling Unit #17 (SU#17 located in southwest Nevada and southeast California). Both distributions display right skewing. Most of the time, SPD changes are very small, and sequences experience infrequent large changes (either positive or negative). In this case, the SU#32 density plot is more right-skewed and has more outliers. The greater degree of skewing and longer tail in SU#32 leads to a greater mean value of amplitude of change than SU#17. However, SU#17 has a larger median amplitude of SPD fluctuation. This is consistent with my proposal that hunter-gatherer sequences are less stable than agricultural sequences most of the time, but agricultural sequences display rare, extreme population changes not observed among hunter-gatherer sequences that inflate the means of these sequences.

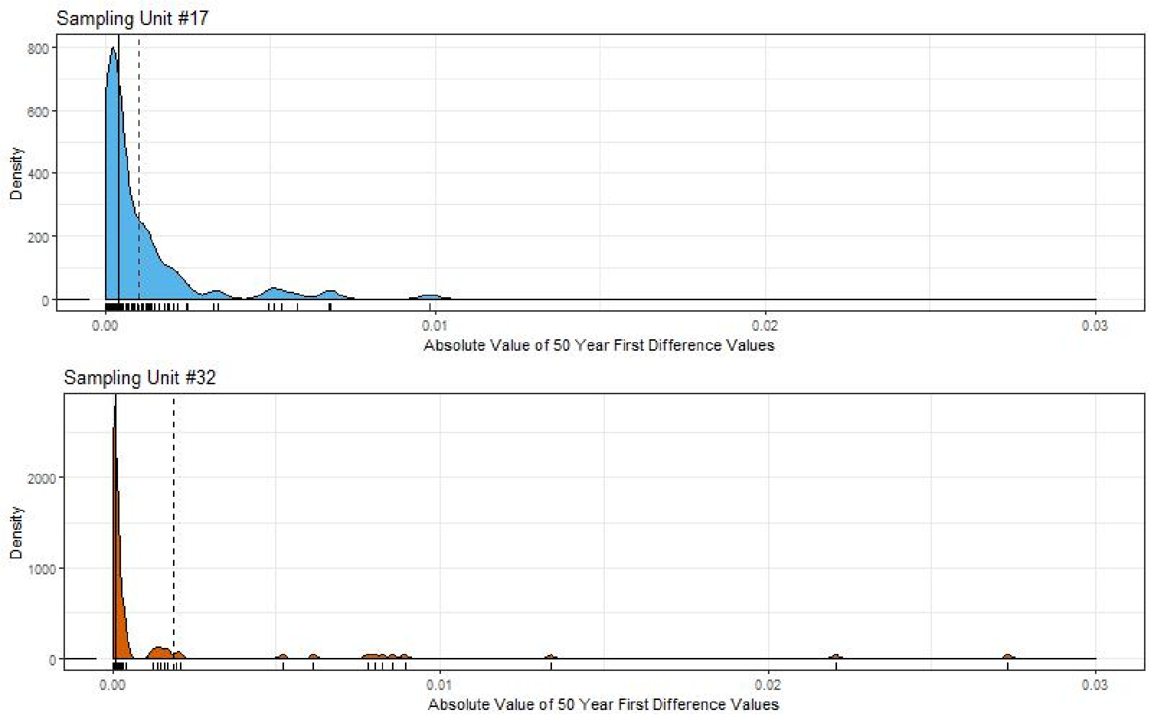

Figure 5: Density plots of two sampling units, #17 (located in southwest Nevada and southeast California) on top and #32 (located in southeast South Dakota, northeast Nebraska, and western Iowa) on bottom. #17 was occupied by hunter-gatherers between 6,000 and 300 cal BP, while people living in #32 adopted agriculture at some point. The solid line represents the median and the dashed line the mean. #32 is more skewed by outlier population changes than #17, pulling the mean to the right.

Table 1 and Figure 6 illustrate this pattern in general. Note, in Table 1 hunter-gatherer sequences have larger median amplitudes of change, but agricultural sequences have larger mean amplitudes and standard deviations. Agriculturalists also have more positive first difference values suggesting that they experience more long-term growth and fewer population declines than hunter-gatherer sequences. This pattern holds across all three time scales (Table 1).

Figure 6 displays the distributions of SPD fluctuations among all hunter-gatherer and agriculturalist sequences at 50, 100, and 200-year time scales (see Appendix I, section 5 for graphs and skewness tables for just SPD increases and decreases). Figure 6

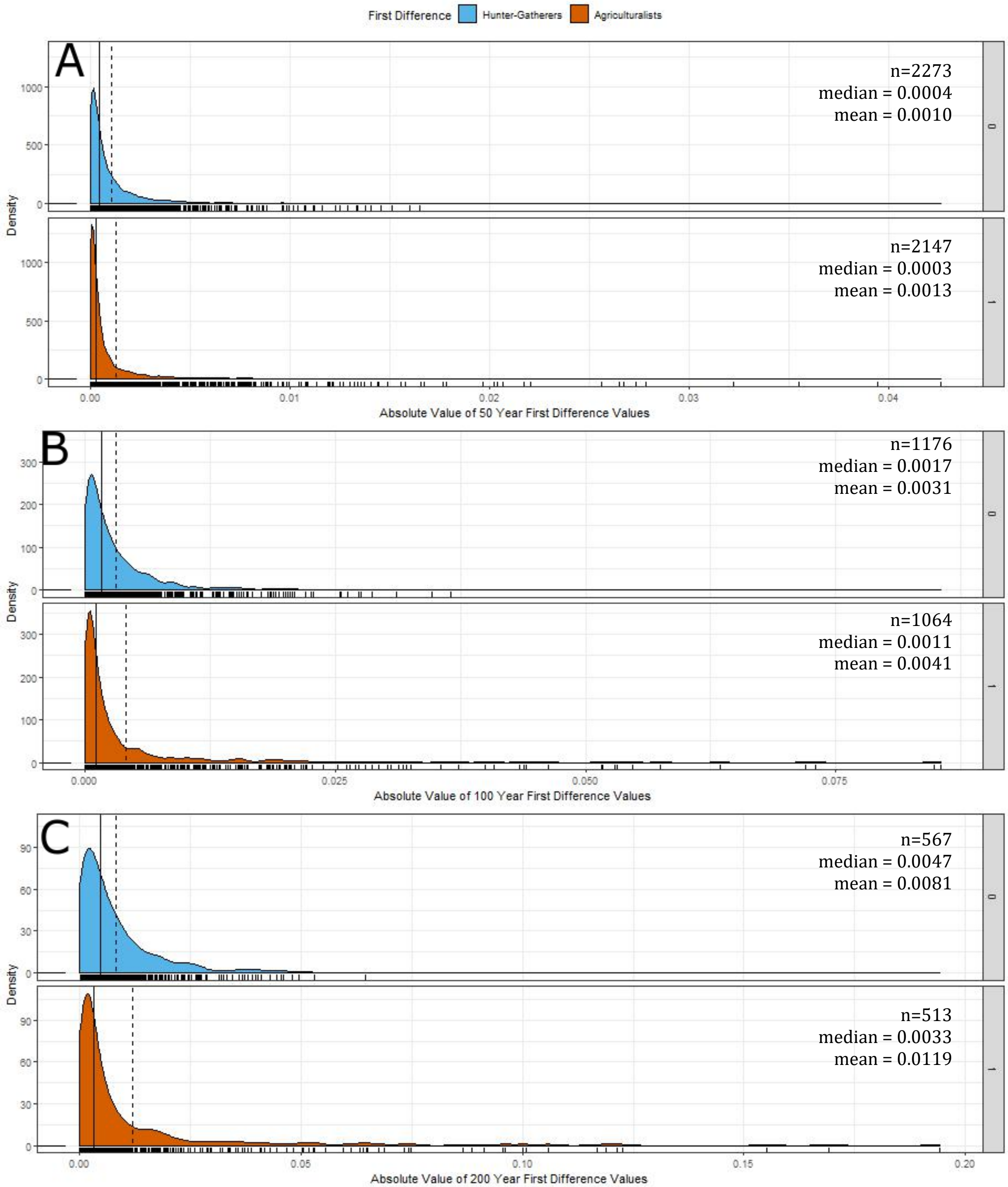

Figure 6: Density plots displaying absolute value of first difference values at the (A) 50-year, (B) 100-year, and (C) 200-year time scales. Sampling units that remained hunter-gatherers for the entire 6,000-year sequence have amplitudes in light blue, while orange represents sampling units that adopted agriculture at some point during the 6,000 years. Solid vertical lines mark the median value while the dashed lines mark the mean. At all three time scales, hunter-gatherers (blue) have a higher median and lower mean than agriculturalists (orange).

illustrates that agricultural sequences have a longer tail that stretches out to the right more than hunter-gatherer sequences. The long tail of the agricultural sequences pulls the mean to the right. At the same time, the distribution of SPD fluctuations is more steeply peaked at very small values among agriculture sequences than among hunter-gatherer sequences. This pulls the median value of agricultural sequences more to the left of the distribution than among hunter-gatherer sequences. In short, most of the time agricultural sequences display more stability than hunter-gatherer sequences, but the agricultural sequences experience very large changes in outlier populations and in the economy that are rarely observed in the hunter-gatherer sequences.

Table 1. Statistical properties for absolute value of first difference SPD trends for each of the subsistence strategies at all three time scales.

Hunter-gather results						
Time-scale	n	% boom	Median	Mean	SD	Skewness
50-year bins	2373	55.3	0.0004	0.0012	0.0023	3.948
100-year bins	1176	54.1	0.0017	0.0037	0.0059	3.219
200-year bins	567	59.1	0.0050	0.0109	0.0182	2.256
Agriculturalist results						
Time-scale	n	% boom	Median	Mean	SD	Skewness
50-year bins	2147	59.4	0.0002	0.0013	0.0035	5.936
100-year bins	1176	59.6	0.0012	0.0044	0.0095	4.656
200-year bins	513	64.1	0.0038	0.0148	0.0029	3.840

Climate Stability and SPD Stability

Figure 7 illustrates the relationship between climate stability (i.e., temperature and precipitation stabilities) and mean radiocarbon stability among hunter-gatherer and agricultural sequences. In general, there are weak relationships between measures of climate stability and the stability of radiocarbon records over time. There are two exceptions. (1) Among hunter-gatherer sequences, radiocarbon stability has a humped relationship with temperature stability (Figure 7A, C, and E). This suggests that in both

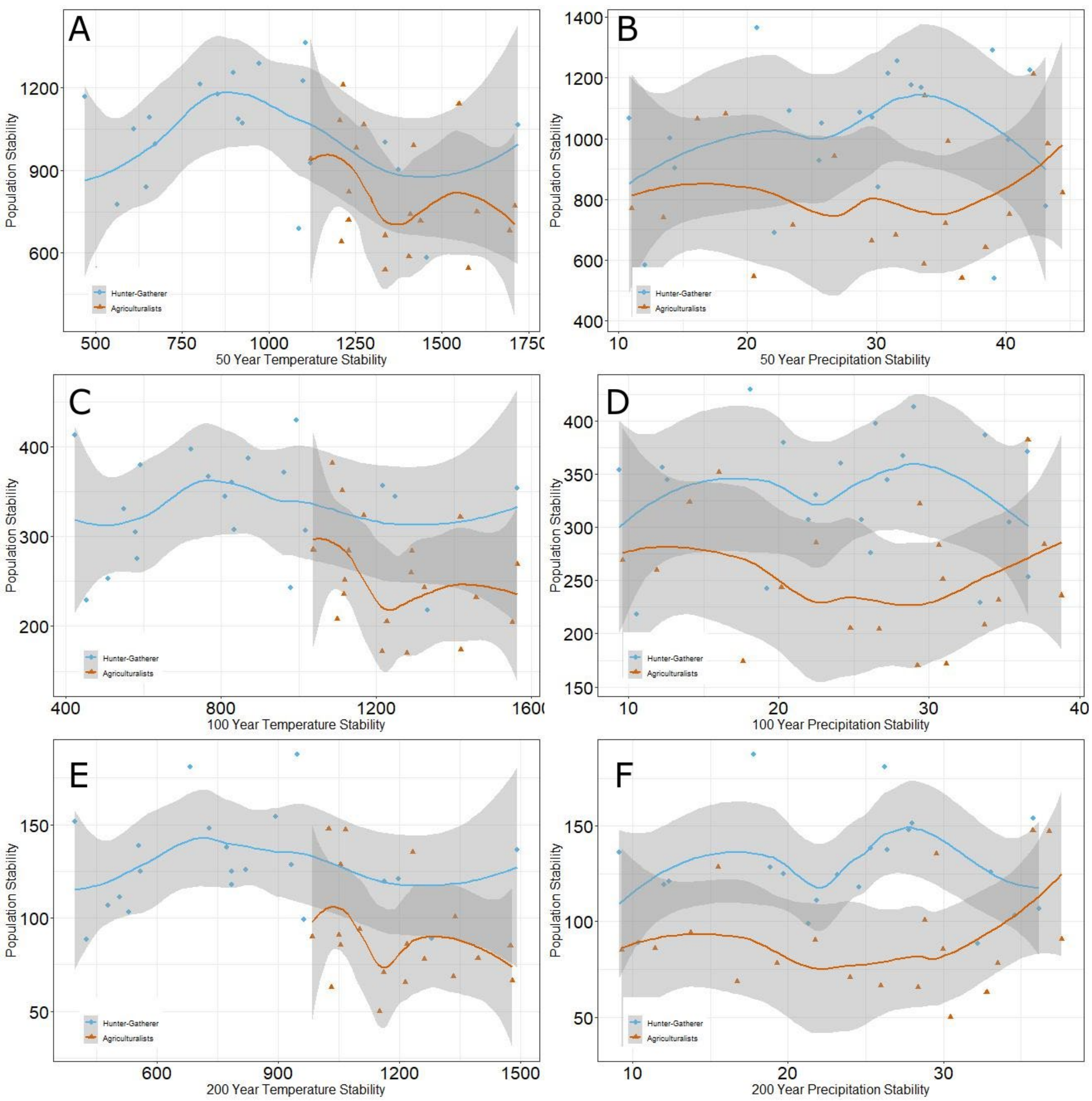

Figure 7: The left column (A, C, E) displays the relationship at all three time scales between precipitation stability and respective mean population stability (i.e. 50-year population stability compared with 50-year precipitation stability) while the right column shows the relationship between temperature stability and mean population stability.

extreme environments where temperatures fluctuate wildly from decade to decade, and in locations where temperature is relatively predictable over long periods of time, hunter-gatherer radiocarbon records also vary more over time. Radiocarbon stability peaks in climates with moderate temperature stability among hunter-gatherer sequences. (2) Agricultural sequences only exist above a temperature stability threshold (Figure 7A, C, and E).

Agriculturalists and hunter-gatherers occupy the same range of precipitation stabilities (Figure 7B, D, and F). Both subsistence strategies display very weak relationships with precipitation stability: as precipitation stability increases, radiocarbon stability appears to vary randomly.

In sum, relationships between climate stability and SPD stability are weak, overall, and most pronounced between hunter-gatherer sequences and temperature stability, especially at the 50-year scale. Most importantly, the differences in mean SPD stability between hunter-gatherer and agricultural sequences remain consistent even when controlling for climate stability (the blue dots are, on average, below the red triangles in Figure 7). The same goes for median values of SPD stability; agricultural sequences have lower values than hunter-gatherer sequences regardless of climate stability (see Appendix I section 5).

Chapter V: Discussion and Conclusions

In this paper, I have attempted to study the basic process of population stability among human societies. Population stability is widely studied among non-human animals because population stability can have important implications for the stability of ecological communities and the risk of extinction for the animals themselves. The stability of human populations may also have significant consequences for humans, both for the long-term growth of our economies and the risk of population collapse in certain regions. Thus, investigating the ecological dynamics that underlie the stability of human populations is an important topic of research. As a first attempt to study human population stability, I have pushed the bounds of the dates-as-data approach to human population reconstruction. I used radiocarbon data to represent population and economic change in the past. If radiocarbon is representative of energy consumption in the past and energy consumption has a relationship with population size (Freeman et al. 2018b), fluctuations in the radiocarbon SPD should represent, all else equal, fluctuations in past populations and/or economies.

My results reveal patterns consistent with the idea that the adoption of agriculture generates a demographic performance–vulnerability tradeoff among human societies. (1) Most of the time, agricultural areas display more stability than hunter-gatherer regions. This suggests that human populations who adopt agriculture experience more stable populations and economies most of the time (higher performance). (2) However, agriculturalist radiocarbon sequences experience large, outlier booms and busts in their economies and populations. Such extreme outliers are rare among populations that remained hunter-gatherers, and this is consistent with the idea that agriculturalists transform landscapes in such a way that they are more vulnerable to a kind of rigidity trap.

A rigidity trap occurs when individuals within socio-environmental systems are so locked into their current strategies that innovation cannot occur fast enough to keep up with environmental change. Societies in such a situation continue investing in their current strategies even when these strategies are no longer profitable or even appropriate given the environmental conditions. The end of a rigidity trap is marked by a collapse. The extreme agriculturalist busts may be reflective of a post-rigidity trap collapse. The population of these areas may collapse through emigration and/or mortality.

Shennan et al. (2013) suggest that, contemporaneous with the adoption of agriculture, populations in northwestern Europe experienced sudden population booms followed by population busts, or population instability. My results suggest that the relationship between agriculture and long-term population stability is perhaps more general. Agricultural sequences in North America have smaller population changes and are therefore more stable than hunter-gatherer sequences, but agricultural sequences also experience infrequent and extreme population booms and busts on a scale never experienced by hunter-gatherer sequences. This may occur immediately following the adoption of agriculture, or the outlier booms and busts may occur millennia after the adoption of agriculture. It may be locally variable when agricultural populations experience the rare outlier booms and, especially, busts, but they will experience these at some point.

Finally, I calculated average temperature stability and precipitation stability for each sampling unit over three time scales and compared these values to the mean and median values of SPD stability over the same time scale. Hunter-gatherer population stability has a humped relationship with temperature stability: population increasingly stabilizes as temperature stability increases until a point after which population stability decreases. This suggests that there may be an optimal temperature stability environment for hunter-gatherer populations that maximizes the stability of hunter-gatherer demography and economy. However, as demonstrated in this study, climate stability does not swamp out the effects of subsistence strategy on the stability of hunter-gatherer and agricultural sequences. Evidence of the performance-vulnerability tradeoffs is evident across different climates.

External factors such as climate variability are not to be ignored, but their role in affecting population stability should probably be understood through the lens of internal social factors. Temperature variability may contribute to the selection of subsistence strategy, but the subsistence strategy appears to have a more important role in long-term population stability. Based on the coarse-grained scale of analysis used in this study, precipitation variability does not contribute to subsistence strategy selection, but fine-grained studies may find different results.

Internal and external factors therefore likely work interdependently within the system. Humans occupy a space with a set resource base initially able to absorb external shocks (such as climate shifts). As their population increases, however, they put increasing strain on their resource base, which increases their vulnerability to external shocks. When an adequately large external shock hits a sufficiently vulnerable human system, the system can no longer absorb these shocks and instead collapses (Anderies 2006; Barnes et al. 2017; Freeman and Anderies 2012; Freeman et al. 2015; Lima 2014).

In this way, a large population with a strained resource base may be less capable of dealing with external shocks than one less intensively exploiting their ecosystem.

Much research has gone into understanding the changes within a system once human societies adopted agriculture, but little research has directly compared the large-scale paleodemographic variation between agriculturalists and hunter-gatherers (but see Zahid et al. 2016 for a comparison of growth rates between subsistence strategies). We suggest that the relationship between these three variables is complex and interdependent.

Future directions for this research may focus on change over time in population stability after the adoption of agriculture: for example, a study focusing on the severity of population booms and busts relative to how long populations have practiced agriculture. Agriculturalists may experience increasing population stability following the adoption of agriculture, but at the same time become increasingly susceptible to large outlier busts through time as the agricultural system accumulates landscape capital vulnerable to unexpected climate changes. Similarly, social factors may drive population stability more than subsistence strategy. Socially stratified and sedentary coastal hunter-gatherer-fishers may, for example, have population sizes and stability levels more similar to those of agriculturalists than to mobile hunter-gatherers in xeric regions.

I also suggest further research placing population stability within a resilience theory framework. An analysis comparing the synchrony of external shocks and population busts may focus on systematic changes contemporaneous with the population bust (see Gronenborn et al. 2014 for an example among the LBK culture in western central Europe). A systematic subsistence intensification contemporaneous with a population bust may result in a reduced ability to deal with external shocks in the future.

Quantification of external shocks relative to internal rigidity may help us to understand the size characteristics of population collapse (see Hegmon et al. 2008 for a comparison of society rigidity to social transformation and collapse).

Future studies may also use a similar coarse-grained analysis on a larger (i.e., global) or smaller scale. Changing the scale will allow different analyses of the relationship between past human populations and external factors, including biodiversity and vegetation regimes, pathogen stress, and small-scale social stress. Similarly, modifying the coarse-grained methodology to reflect ecological and geographic zones may reveal more about local patterns of movement and the effect of migration and fission/fusion on population stability (see Freeman et al. 2017 for a look at biogeography and social connectedness on the Texas Coastal Plain).

Pairing paleodemographic methodologies may reveal more about past populations than using one method alone. Radiocarbon by itself reveals information about radiocarbon ages associated with archaeological remains on the landscape. Site count analysis, dendrochronology, and ceramic typologies can be linked to radiocarbon to reveal more about social change. Site count analysis may, for instance, reveal increased population density where the number of sites decreased but radiocarbon calibration curves increase. Dendrochronology of structures reveals economic expansion that, coupled with radiocarbon, may reveal periods of social expansion. Similarly, ceramic typologies reveal information about individuality and inter-societal trade.

Finally, more nuanced estimates of commitment to agriculture may improve our understanding of the stages of agricultural investment relative to population stability. Assigning an ordinal variable that ranks levels of investment in agriculture on different portions of a time series would refine the relationship between the stability of societies and agriculture. This research focuses on the eventuality of agriculture adoption, rather than the moment and intensity of agriculture adoption, which may obscure the change in patterns as agriculture was adopted.

Conclusion

I hypothesized that in locations where populations adopted agriculture, those populations unknowingly initiated a performance-vulnerability tradeoff. To evaluate this hypothesis, I analyzed the relationship between climate, long-term population stability, and subsistence strategy in North America between 6,000 and 300 cal BP. Consistent with a performance-vulnerability tradeoff, I found that agriculturalists are more stable than hunter-gatherers in general, but experience extreme unprecedented population changes unseen by hunter-gatherer societies. This study is the first attempt to investigate long-term human population stability on a large scale and pushes the boundaries of radiocarbon dates-as-data analysis. This research contributes to the growing literature that uses the dates-as-data approach to study basic population ecology processes among human societies. Investigating population ecology processes via archaeological data can inform researchers about the ways in which humans are similar and different to other species and improve our understanding of the consequences of key changes in human ecology over the millennia.

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APPENDICES

Appendix I: Supplemental Information

In this supplemental document, I provide additional analyses that support the main conclusions of the manuscript. First, I address the potential relevance of taphonomic correction and other biases possible in radiocarbon analyses. Then I investigate the potential effects of radiocarbon sample size on my results. Third, I provide a summary of my borderland binary agriculture variables. Fourth, I quantify the likelihood that the mean differences in SPD stability observed between agricultural and hunter-gatherer sequences are due to chance. Finally, I present additional analyses that demonstrate that agricultural sequences have larger SPD busts than hunter-gatherer sequences.

In total, I find buttressing support for the conclusion that agricultural sequences display more stability most of the time, but larger, infrequent booms and busts.

1. Radiocarbon Interpretations and Taphonomy

A current debate within archaeology focuses on the representativeness of radiocarbon dates (or dendrochronology dates) of prehistoric populations and economic activity. I argued in this paper that radiocarbon does not need to directly represent population: in fact, I use Freeman et al.'s (2018b) argument that radiocarbon data represents energy expenditure, which has a relationship with people.

Additional concerns about the use of radiocarbon data to represent past populations focus on several types of bias: taphonomic bias and sampling bias are two major concerns with a dataset as large as ours. Taphonomic bias is defined as "biases introduced by processes which destroy the archaeological and/or geological record" (Surovell and Brantingham 2007:1869). Essentially, older archaeological remains are more likely to be destroyed than younger archaeological remains, as they have had more time to be exposed to destructive processes. While an equation exists to correct for taphonomic bias (Surovell et al. 2009), the authors of the study warned against using this equation thoughtlessly. The equation is more likely to over-correct dates in the past 1,000 years, of which 10,471 dates of our 40,017 (26.2%) total dates are 1,000 years ^{14}C BP or younger. We also have no reason to suspect that taphonomic destruction is occurring uniformly across our data set, especially as many of our sampling units cover large swathes of depositional and erosional environment. Finally, transforming our SPD's using this transformative equation will not change the results: by adjusting all SPD's in the same way, we would only be over-emphasizing some time periods and under-emphasizing others in a way that further removes our data from their original contexts.

As mentioned in the paper itself, we attempted to minimize the effect of over-sampling by averaging all dates within 100 years of each other within the same site using rcarbon's binPrep function. We also attempted to minimize the effect of undersampling. Undersampling is most common during the historic period (post-1650 AD) in North America. I completed my analysis on dates from 6,000 – 300 cal BP or 4050 BC – 1650 AD, to minimize this issue.

Edge effects are also a potential problem in the analysis of summed probability distributions (SPDs). Edge effects are artificial probability drop-off's at the edge of an SPD caused by where the dates aren't calibrating to. A common way to remove edge effects to ensure the SPD values analyzed is simply to remove the edges of the SPD. I gathered uncalibrated radiocarbon dates from 8,000 – 0 14 C^{14} and conducted analysis on calibrated dates between 6,000 and 300 cal BP.

To check for both edge effects and undersampling, which is more common in recent years, I removed more recent bins at the 50-year time scale and graphed the absolute value of the first differences between the two subsistence strategies until the results changed. Trimming recent dates until 650 cal BP (1300 AD) gives hunter-gatherers and agriculturalists comparable means (0.00093 vs 0.00094 respectively), but agriculturalists still had lower medians (0.00042 vs 0.00026). This demonstrates that undersampling and edge effects are likely not issues for my study.

2. Sample Size

There is only a very weak relationship between the mean and median values of radiocarbon stability from sampling units and the number of radiocarbon ages within in respective unit. Radiocarbon age sample size, thus, does not appear to impact our mean and median stability measures, and my results are not likely simply a function of radiocarbon sample size.

As discussed in the body of the paper, for a sampling unit to be considered, it had to have at least 200 radiocarbon dates within it. Forty sampling units met this criterion. The minimum number of dates within a sampling unit is 205 (SU#113, southeast Alaska), maximum is 3,111 (SU#30, central Wyoming), with a mean of 871 radiocarbon dates per box and a median of 574 radiocarbon dates per box. The sample size data are right-skewed, so we logged them prior to graphing (Figure A1).

I investigated whether the sample size of radiocarbon ages within the 40 sample units impacted the mean and median stability measurement by graphing the logged number of radiocarbon dates within each sampling unit against the mean and the median radiocarbon stability value of each sample box. I ran linear regression models of the number of ages on radiocarbon stability measures. Table A1 illustrates the regression coefficients of the number of ages regressed on mean and median stability measures. In each case, the slope of the relationship between number of ages and stability measures is NOT significantly different from 0.

Table A1. Regression analysis results for Figure A1A-F, demonstrating the relationship between the logged number of ages and stability (mean and median) at all three time scales.

Scale	Independent Variable	Coefficient	SE	t-value	p-value
50-year mean	Log number of ages	44.94	49.17	0.94	0.37
100-year mean	Log number of ages	15.37	14.77	1.04	0.31
200-year mean	Log number of ages	6.64	6.85	0.97	0.34
50-year median	Log number of ages	116.7	323.9	0.36	0.72
100-year median	Log number of ages	42.52	85.37	0.50	0.62
200-year median	Log number of ages	18.46	22.58	0.82	0.42

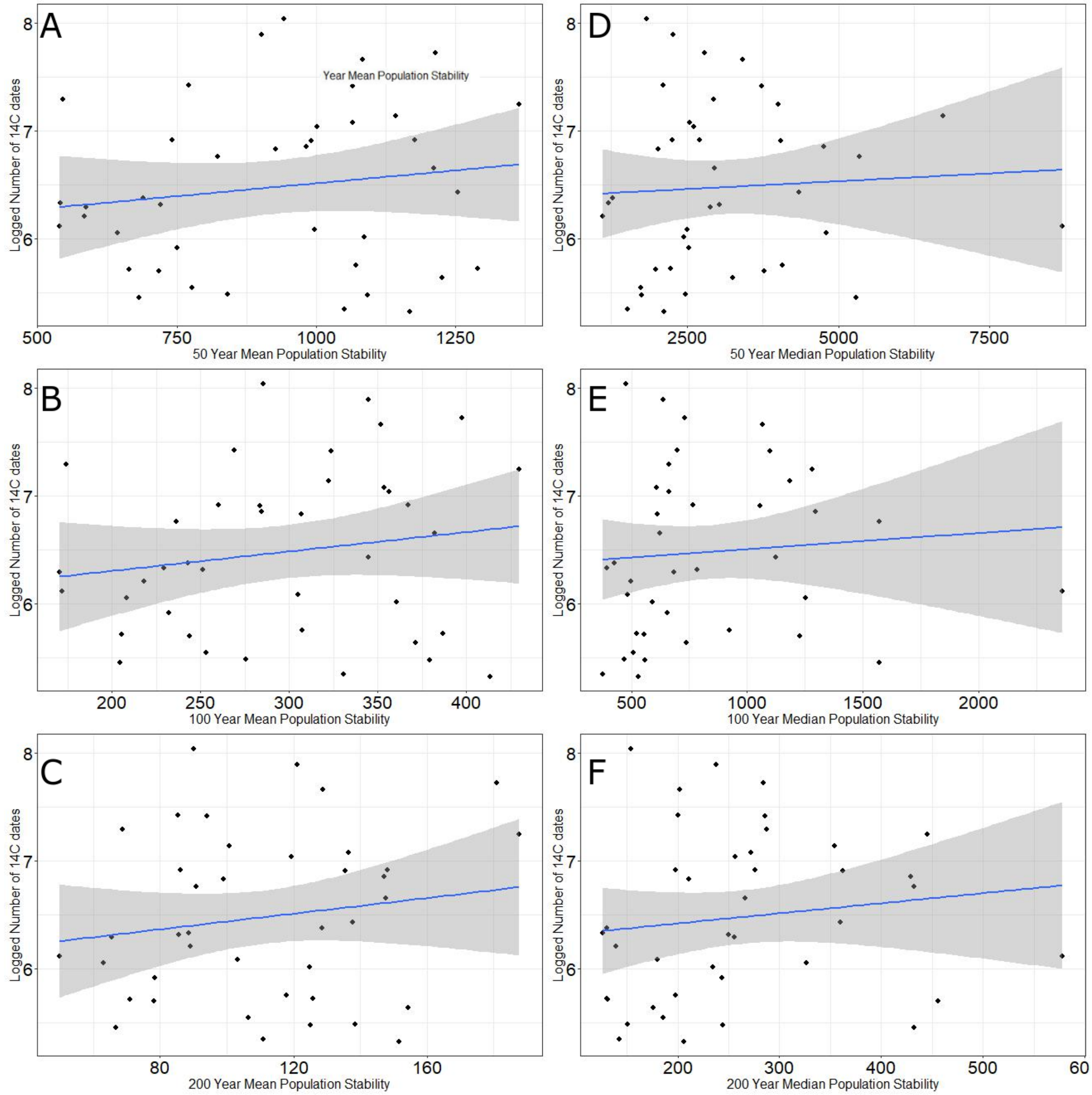


Figure A1: This figure demonstrates the relationship between logged radiocarbon stability (mean A-C, median D-F) and logged number of radiocarbon dates within each box at all three time scales (50-year A, D; 100-year D, E; and 200-year C, F. All three figures show very weak positive relationships between number of dates and population stability within each box. As Table 1 demonstrates, the modelled line is not statistically different from a line with a zero slope.

3. Assignment of Agriculture ID Variable

I assigned a binary agriculture variable based on presence or absence of agriculture prehistorically within the sampling areas (Figure A2), with a focus on where the radiocarbon samples were coming from, based on documented evidence of the presence or absence of agriculture in the review literature of archaeological records of North America (Jennings 1968; Kopper 1986; Pauketat 2015; Snow 1989; Thomas 1999). Some locations, such as those in the American Southwest and the Adena culture core in Ohio, were easily assigned "1" for containing agriculture. Others, such as the entirety of California, Oregon, Washington, Idaho, and Nevada, were just as easily assigned "0" for absence of agriculture. Others were not so easily assigned. SU#10, #25, #29, #30, #31, and #37 all occupy a distinct "border land" zone.

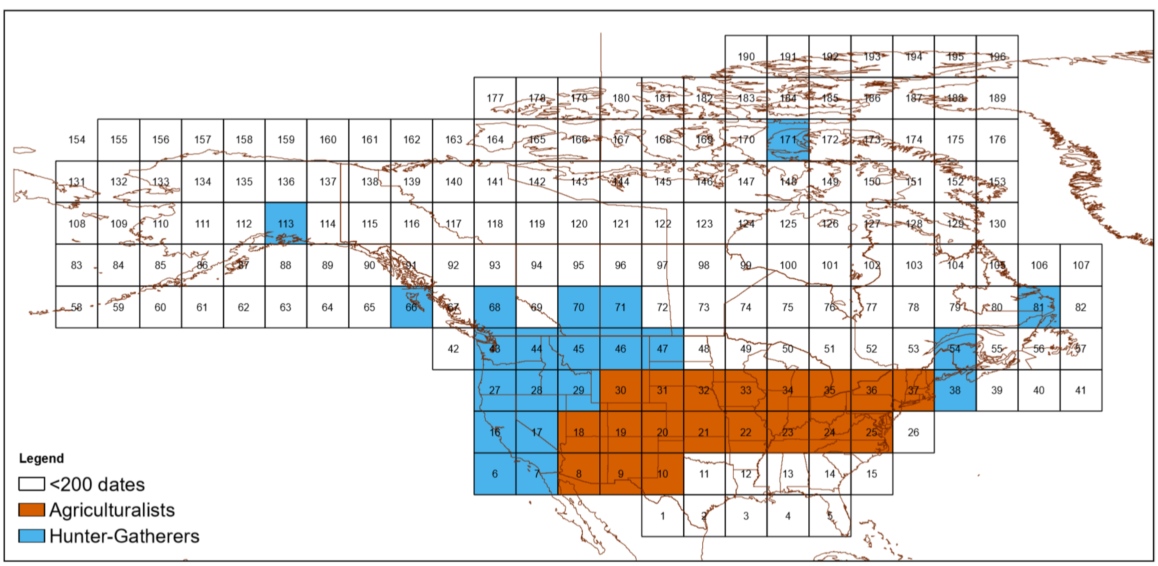


Figure A2: Map demonstrating the locations of the boxes with more than 200 radiocarbon dates and their affiliated subsistence strategy assignation. Reprinted here for ease of viewing.

In order to verify my results regardless of the assignation of these 6 sampling units, I removed them entirely from my study to see if their assignations drastically changed the results at the 50-year scale. The results are relatively identical (Table A2): agriculturalists have a larger percentage their total 50-year bins as population increases ("booms"), and agriculturalists also have a lower median, higher mean, higher standard deviation, and higher skewness. Removing the 6 borderlands sampling units did decrease the hunter-gatherer standard deviation and increase the agriculturalist %boom and decrease agriculturalist skewness. This suggests that the addition of the borderlands may have made our results slightly less distinct from one another, but the results are still the same regardless. The false positive test in Appendix I section 4 also confirms that these results are unlikely due to change.

SU #10 occupies west Texas, including the panhandle, and eastern New Mexico, located within the "Plains" region of North America. The sampling unit contains 92 radiocarbon samples taken from the panhandle, 26 from the Trans-Pecos region, with the remaining 1,352 from southeast New Mexico. It does not contain the westernmost tip of

Table A2. The original 50-year time-scale results with 40 sampling units compared to results if 6 borderlands sampling units are removed.

Original 50-year time-scale results						
Subsistence	n	% boom	Median	Mean	SD	Skewness
Hunter-gatherer	2373	55.3	0.0004	0.0012	0.0023	3.948
Agriculturalist	2147	59.4	0.0002	0.0013	0.0035	5.936
Results without 6 borderlands sampling units at 50-year time-scale						
Subsistence	n	% boom	Median	Mean	SD	Skewness
Hunter-gatherer	2260	55.3	0.0004	0.0010	0.0017	3.976
Agriculturalist	1582	61.0	0.0002	0.0012	0.0034	5.760

Texas, which was occupied by the Southern Jornada Mogollon (Johnson and Hard 2014). The Panhandle does demonstrate widespread maize agriculture around 900 A.D, while the Trans-Pecos region south of the panhandle demonstrates large (1.5m+) burned rock middens indicating wild plant intensification (Johnson and Hard 2014). Finally, the region is at the very edge of the Mogollon cultural tradition, ~200 AD-~1400 AD (Thomas 1999). Given sampling unit's placement in between multiple agriculture traditions (including those in Mexico), I assigned it as containing agriculture.

Next, SU#25 is located in Delaware, Maryland, Virginia, Delaware, northeast North Carolina, eastern West Virginia, southwest New Jersey, and about 20 miles into southern Pennsylvania. This region is at the very edge of Woodland and Mississippian traditions. Notably, agriculturalist Adena cultural material from Ohio has been located in these areas, though the culture did not extend this far to the east (Snow 1989). The Iroquois peoples to the north (SU #36 mainly) practiced agriculture, while large moundbuilding groups occupied the southeast (Kopper 1986). Societies living in modern day Virginia practiced agriculture during the middle and late Woodland period ~900AD - 1607 (Egloff and Woodward 2006). Within North Carolina, agriculture was adopted later by coastal peoples than those on the inner coast or the Iroquoians on the coastal plain: ~A.D. 800 on the inner coast, but later than ~A.D. 1400 on the outer coast (Hutchinson 2002). I have chosen to label SU #25 as an agriculturalist box due to the whole-hearted adoption of late agriculture and the earlier surrounding of agriculture to the north, south, and west.

SU #29 is located in northern Utah, southern Idaho, and western Wyoming, while SU#30 is located in northeastern Utah (around the Uinta Basin), central Wyoming, and northern Colorado. The region is located at the northeastern extent of the Great Basin, the northwestern extent of the Colorado Plateau, and over the Snake River Plain in Idaho, and on the western extent of the central Plains area. The Fremont people occupied almost all of Utah, into southern Idaho and as far west as Ely, Nevada, planting maize, beans, and squash in the high desert around 200 B.C. at the earliest until about 1300 A.D. (Simms 2008). With this intense farming in mind, I wanted to assign either #29 or #30 as agriculturalists. One site, Steinaker Gap, located in the southwestern corner of #30, contains Fremont irrigation ditches dating to A.D. 250. Stable isotope analysis from this site suggests that a significant portion of the diet was maize, and the site contains bell shaped storage pits for maize (Madsen and Simms 1998). Meanwhile, many of the Fremont occupants in SU#29 maintained a strong foraging presence throughout most of the Fremont period. Therefore, I assigned SU#29 as not having agriculture and SU #30 as having agriculture.

SU #31 is in eastern Wyoming, northwest Nebraska, and southwest South Dakota. Wyoming, as mentioned previously, was predominately occupied by hunter-gatherers. Eastern Nebraska and South Dakota both contain an agriculture presence as the northwest edge of the Plains Village culture who began “rudimentary forms of agriculture” ~1000 B.C. (Thomas 1999), with a stronger presence at ~A.D. 1000 (Winham and Calbrese 1998). Nearby Kansas City Hopewell and Middle Woodland sites from northwest Iowa demonstrate clear signs of agriculture, including sunflower, squash, marshelder, and others (Bozell and Winfrey1994). Archaeologists have found Middle Missouri sites, whose occupants received the majority of their calories from both bison and cultivated plants, located as far west as the base of the Black Hills in South Dakota dating to ~A.D.

1000, though a majority have not been dated and many have conflicting dates (Winham and Calbrese 1998). The evidence for agriculture here is scanty but present, with multiple authors blaming recovery methods and poor chronology as why agriculture presence is uncertain within the area (Winham and Calbrese 1998; Bozell and Winfrey 1994), so I have assigned this unit as having agriculture.

Finally SU#37 is located on the eastern side of the Appalachians including eastern New York, much of New England, and portions of northern New Jersey and eastern Pennsylvania. To the western side of the Appalachians (mostly SU #36) the Iroquois people during the Woodland period practiced agriculture, including corn, beans, squash, and pumpkins. (Kopper 1986). New England has maize kernals are present and dated to 1050 ± 50 ^{14}C (Little 2002). Agriculture in eastern New York in the Hudson River Valley has been directly dated on maize kernals to 1050 ± 50 ^{14}C BP, and excavations of large sites within the Hudson River Valley demonstrate a distinct lack of horticulture practice ~1900 years ago (Brumbach and Bender 2002). Maize agriculture was practiced in the Saco River Valley in southwestern Maine at or earlier than 570 ^{14}C BP, and seeds and grasses affiliated with agriculture are found in this region 1000 years BP (Sidell 2002). I've assigned this sampling unit as containing agriculture despite the late arrival, as it was adopted wholeheartedly when it did arrive.

4. *Chance of a false positive difference in the mean stability of hunter-gatherer vs. agricultural sequences*

To test the significance of the relationship between subsistence strategy and radiocarbon stability, we built a model that randomly generated 1,000 presence/absence of agriculture values for the 40 sampling units. I then ran Wilcox tests on the 1,000 values with the stability measurements from all three time-scales. Where the Wilcox tests returned $p<0.05$, I ran a Yule's Q test to determine if the randomly generated agricultural values were similar to our assigned cultural values. Yule's Q tests range -1 through 1, with values closer to 0 representing no association between a significant randomly assigned subsistence identifier and our real assigned subsistence identifier. Table 4 documents the results of the 1,000 iterations. If I assign subsistence identification (agriculture present vs. absent) at random to our 40 sample boxes, only 3.5-4.2 % of the time is there a significant difference between the means of agricultural and hunter-gatherer sequences (see Table A3 for results). This indicates there is only a 3.5% and 4.2% chance that our results reflect a false positive. In fact, most of the random trials that replicated the results show a strong association with the real designations of hunter-

Table A3. Results for false positive test, which included random generation and assignation of presence or absence of agriculture to pre-existing mean population stability values for the 40 boxes.

Time Scale	Percent Significant Wilcox ($p\leq0.05$)	Mean Absolute Value of Yule's Q	Median Absolute Value of Yule's Q
50-year	4.2 (n=42)	0.28	0.20
100-year	4.2 (n=42)	0.38	0.39
200-year	3.5 (n=35)	0.39	0.38

gatherer vs. agricultural sequences. The mean Yule's Q column illustrates this result. If this were not the case, the average Yule's Q value would be virtually 0.

5. *Additional Plots and Tables*

Table A4. Statistical properties for positive first difference values (Booms) for each of the subsistence strategies at all three time scales.

Hunter-gatherer results						
Time-scale	n	% Total	Median	Mean	SD	Skewness
50-year bins	1313	55.3	0.0005	0.0010	0.0016	3.735
100-year bins	636	54.1	0.0019	0.0032	0.0039	2.597
200-year bins	335	59.1	0.0053	0.0087	0.0097	2.192

Agriculturalist results						
Time-scale	n	%Total	Median	Mean	SD	Skewness
50-year bins	1276	59.4	0.0003	0.0011	0.0024	6.178
100-year bins	634	59.6	0.0012	0.0037	0.0071	4.292
200-year bins	329	64.1	0.0034	0.0117	0.0211	3.542

Table A5. Statistical properties for negative first difference values (Busts) for each of the subsistence strategies at all three time scales.

Hunter-gatherer results						
Time-scale	n	% Total	Median	Mean	SD	Skewness
50-year bins	1060	44.7	0.0004	0.0011	0.0019	3.965
100-year bins	540	45.9	0.0014	0.0031	0.0047	3.583
200-year bins	232	40.9	0.0040	0.0072	0.0089	2.359

Agriculturalist results						
Time-scale	n	%Total	Median	Mean	SD	Skewness
50-year bins	871	40.6	0.0002	0.0015	0.0041	5.102
100-year bins	430	40.4	0.0010	0.0047	0.0112	4.244
200-year bins	184	35.9	0.0029	0.0122	0.0277	3.883

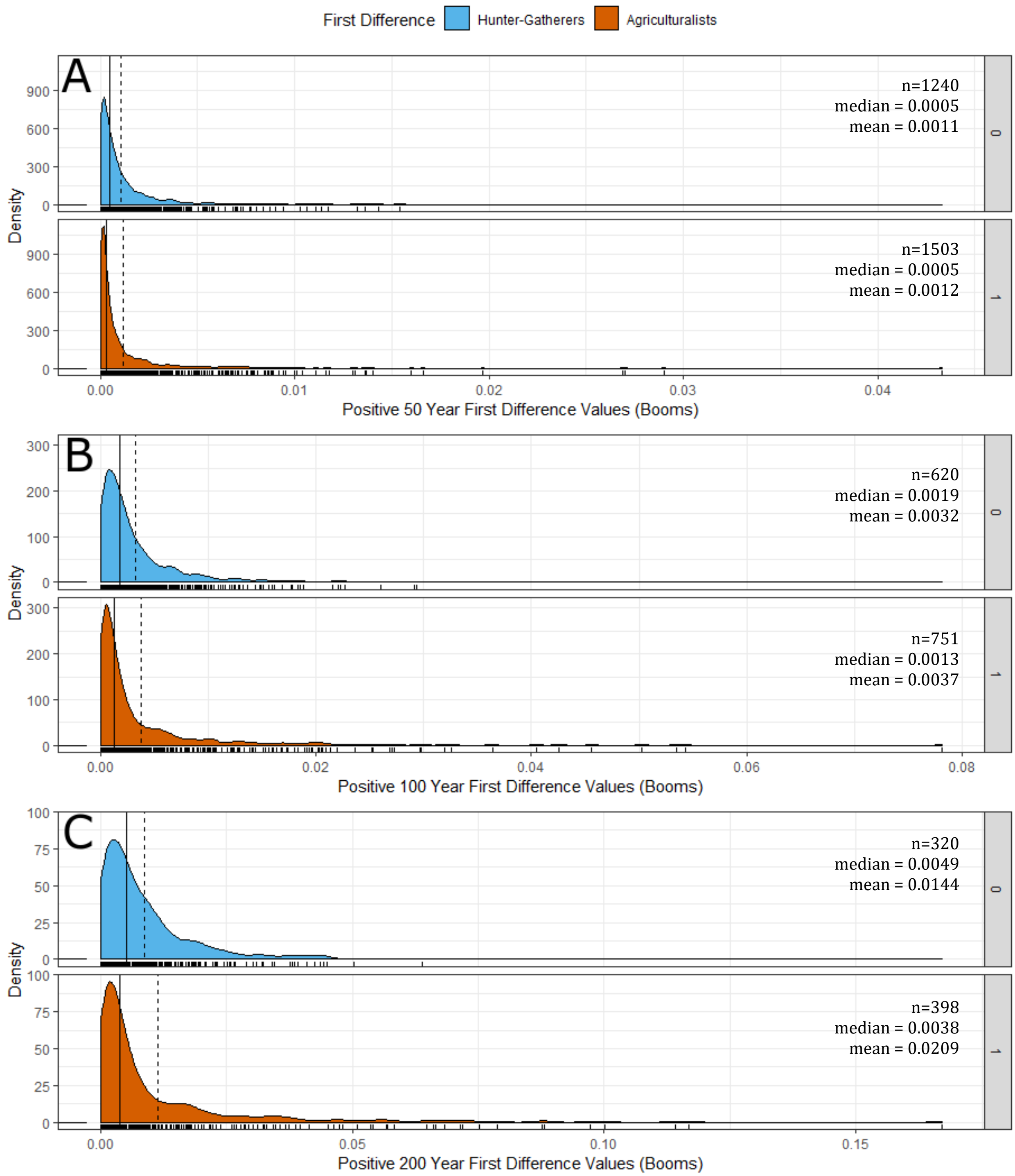


Figure A3: Density plots displaying population increase values at the (A) 50-year, (B) 100-year, and (C) 200-year time scales. Solid vertical lines mark the median value while the dashed lines mark the mean. At all three time scales, hunter-gatherers (blue) have the same or higher median and lower mean than agriculturalists (orange), demonstrating less skewing among hunter-gatherer sequences than among agricultural sequences.

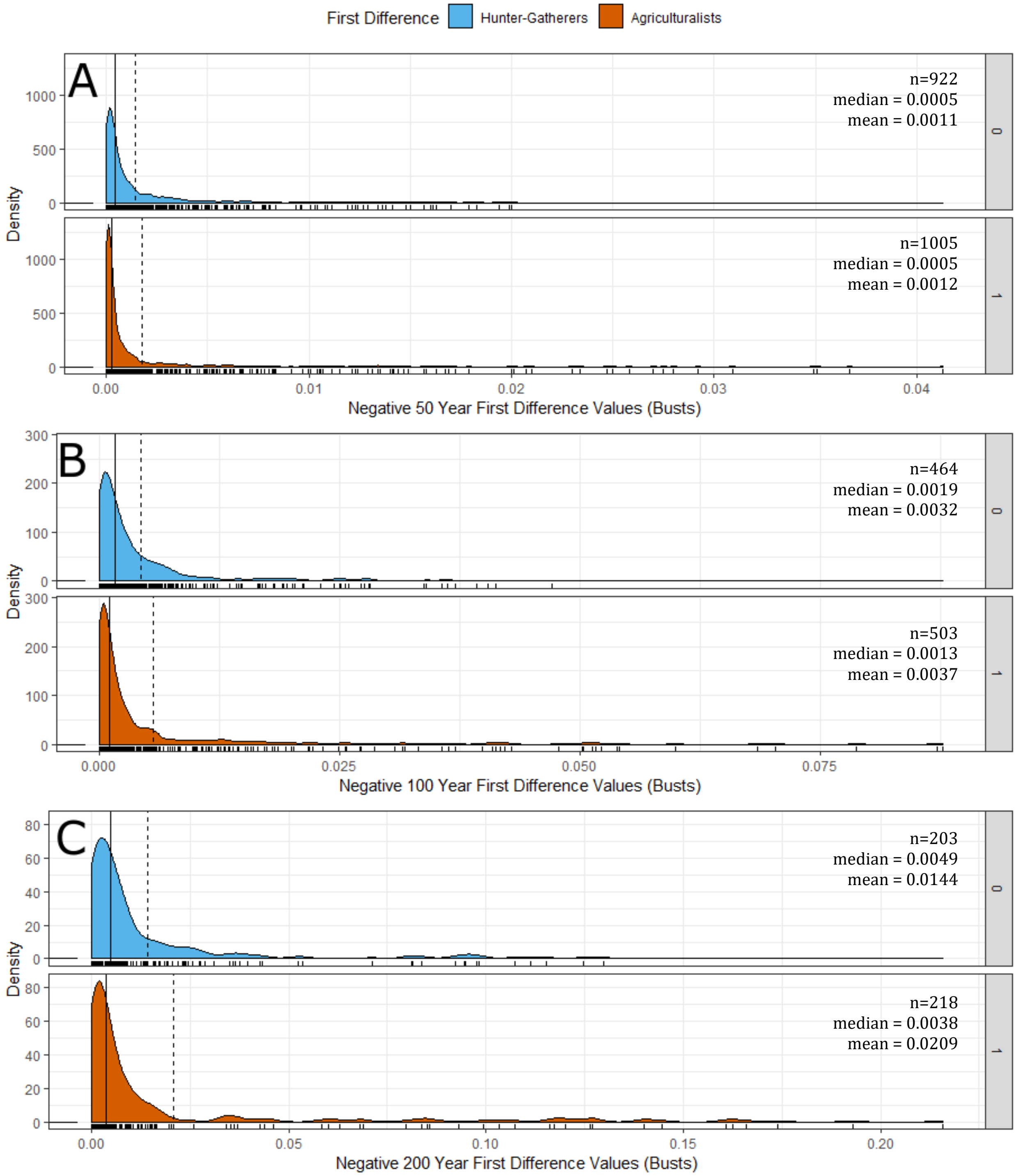


Figure A4: Density plots displaying population decrease values at the (A) 50-year, (B) 100-year, and (C) 200-year time scales. Solid vertical lines mark the median value while the dashed lines mark the mean. At all three time scales, hunter-gatherers (blue) have the same or higher median population decrease values and lower mean than agriculturalists (orange), demonstrating less skewing among hunter-gatherer sequences than among agricultural sequences.

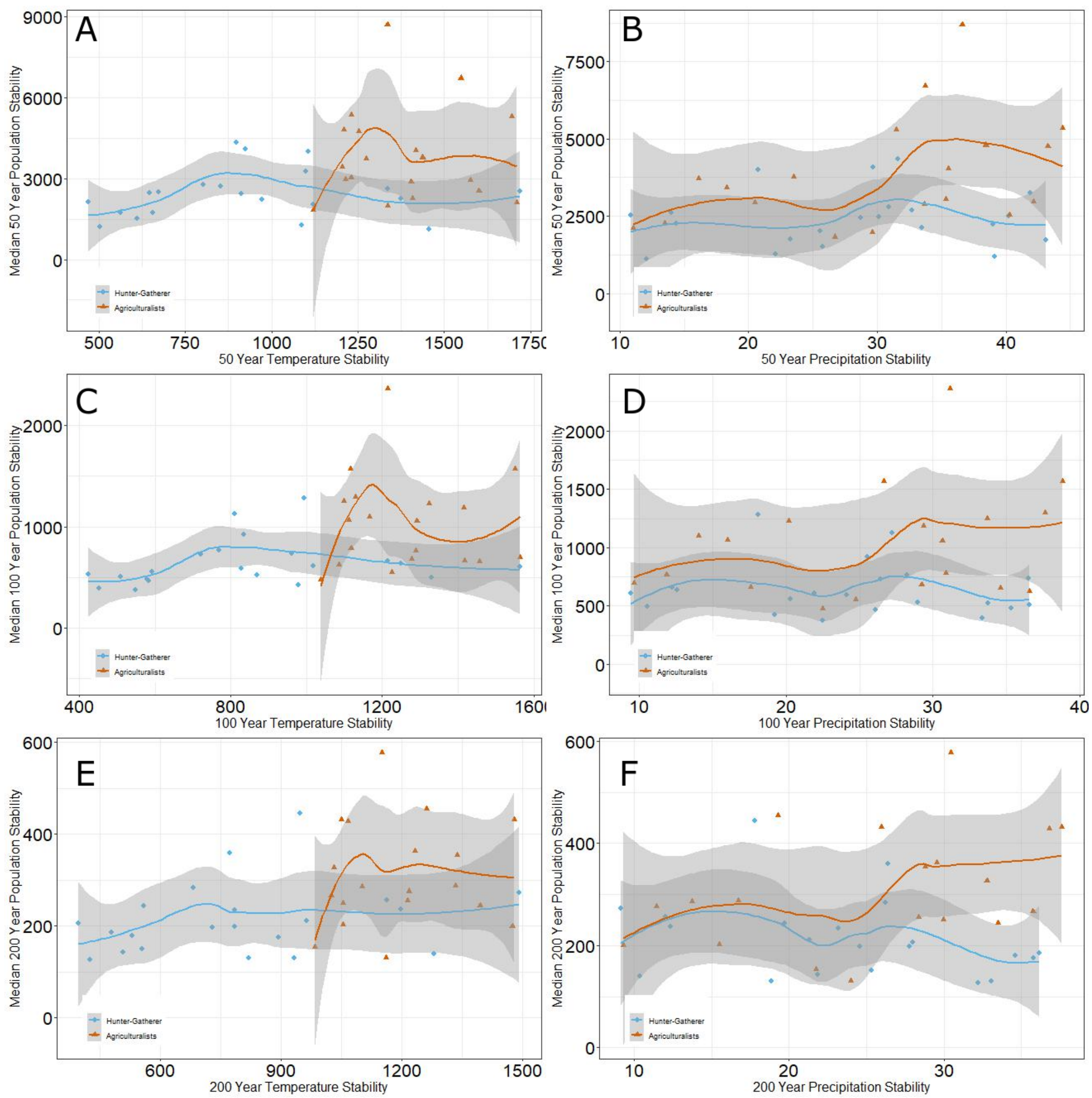


Figure A5: The left column (A, C, E) displays the relationship at all three time scales between precipitation stability and respective median population stability (i.e. 50-year population stability compared with 50-year precipitation stability) while the right column shows the relationship between mean temperature stability and median population stability.

R-Code

```
setwd("~/R/THESIS_2/")
RawData <- read.csv("thesis_radiocarbon_latlongremoved.csv")

library(plyr)
library(searchable)
library(reshape)
library(rcarbon)
library(ggplot2)
library(rcarbon)
library(ggpubr)
library(zoo)
library(robustbase)
library(moments)
#library(tidyverse)
#remove.packages(tidyverse)
#### 1. Extract climate data from Paleoview according to sampling
units ------


#### 2. Make Directory for all sample units with more than 200
lab numbers -------
Directory <- count(RawData, vars = "Sbox")
names(Directory) <- c("Sbox", "n")
Directory<-Directory[!(Directory$n<200),]
write.csv(Directory, "Directory_Sbox.csv", row.names = FALSE)

#### 3. Calibrate each sampling unit recursively --------

#Sometimes r treats values within a dataframe in a way you cannot
use. The lines ensure our calibration will work.
RawData$date <- as.numeric(RawData$date)
RawData$sd <- as.numeric(RawData$sd)
RawData$labnumber <- as.character(RawData$labnumber)

##Turn each sampling unit into a data.frame and make a list of
them.
SboxList <- list()
for(i in 1:length(unique(Directory$Sbox))){
  nam <- make.names(paste("Sbox", Directory[i,"Sbox"]))
  assign(nam, RawData[RawData$Sbox == Directory[i,"Sbox"],])
#This line makes a dataframe for each sampling unit
  SboxList[i] <-
lapply(make.names(paste("Sbox",Directory[i,"Sbox"])), get)  #this
makes a list of the sampling units.
}
remove(nam)
remove(i)

Sbox<-read.csv("TARL.csv")
```

```
cptcal <- calibrate(x = Sbox$date,  errors = Sbox$sd) #This
calibrates the dates using the default intcal13
Sboxbins <- binPrep(sites = Sbox$SiteID, ages = Sbox$date, h =
100) #This bins the values.
Sboxspd <- spd(x=cptcal, timeRange=c(6000,300), spdnormalised =
TRUE) #This produces normalized SPD values
write.csv(Sboxspd,file = paste("Sbox TX.csv")) #This writes the
SPD values to the working directory, allowing you to view them
outside of R and pull them back in later.



##Calibration function for each hemisphere according to the
different calibration curves
north <- function(Sbox){
  cptcal <- calibrate(x = Sbox$date,  errors = Sbox$sd) #This
calibrates the dates using the default intcal13
  Sboxbins <- binPrep(sites = Sbox$SiteID, ages = Sbox$date, h =
100) #This bins the values.
  Sboxspd <- spd(x=cptcal, timeRange=c(6000,300), spdnormalised =
TRUE) #This produces normalized SPD values
  write.csv(Sboxspd,file = paste("Sbox", Directory[i,"Sbox"],
".csv")) #This writes the SPD values to the working directory,
allowing you to view them outside of R and pull them back in
later.
}

south <- function(Sbox){
  cptcal <- calibrate(x = Sbox$date,  errors = Sbox$sd,calCurves
= 'shcal13') #This calibrates the dates using the default shcal13
  Sboxbins <- binPrep(sites = Sbox$SiteID, ages = Sbox$date, h =
100) #This bins the values.
  Sboxspd <- spd(x=cptcal, timeRange=c(6000,300), spdnormalised =
TRUE) #This produces normalized SPD values.
  write.csv(Norm,file = paste("Sbox", Directory[i,"Sbox"],
".csv")) #This writes the SPD values to the working directory,
allowing you to view them outside of R and pull them back in
later.
}

##Create a directory to store the SPD results
dir.create("~/R/THESIS_2/1_Sbox_SPD")
setwd("~/R/THESIS_2/1_Sbox_SPD")

#Run the code to calibrate recursively, This may take awhile.
for(i in 1:length(unique(Directory$Sbox))){
  if(nrow(data.frame(SboxList[i])) >= 200){
     if(RawData$Lat >= 0){
      north(data.frame(SboxList[i]))
    }
    else{
      (south(data.frame(SboxList[i])))
```

```
    }
  }
}

#Clean the environment.
rm(list=ls())


#### 4. Recursively bin all SPDs -----
setwd("~/R/THESIS_2/1_Sbox_SPD")

temp <- list.files(pattern="*.csv")
list2env(
  lapply(setNames(temp, make.names(gsub("*.csv$", "", temp))),
         read.csv), envir = .GlobalEnv)

files <- list.files(path="./")
dates <- read.table(files[1], sep=",", header=TRUE)[,11]     #
gene names
df    <- do.call(cbind,lapply(files,function(fn)read.table(fn,
header=TRUE, sep=",")[,12]))
df2 <- gsub('Sbox', '', files)
df2 <- sub(' ', '', df2)
df2 <- sub(' .csv', '', df2)
colnames(df) <- df2
df3 <- cbind(dates,df)

dir.create("~/R/THESIS_2/2_Sbox_Bins/")
setwd("~/R/THESIS_2/2_Sbox_Bins/")

###Sum the spd data at different bin widths
out10 <-
rollapply(df3,50,(sum),by=50,by.column=TRUE,align='right')
out10 <- as.data.frame(out10)
out10$dates <- ((out10$dates / 50) -25.5)
write.table(out10, file = "SboxSum50.csv", sep = ",", row.names =
FALSE)

out20 <-
rollapply(df3,100,(sum),by=100,by.column=TRUE,align='right')
out20 <-as.data.frame(out20)
out20$dates<-((out20$dates/100) - 50.5)
write.table(out20, file = "SboxSum100.csv", sep = ",", row.names
= FALSE)

out50 <-
rollapply(df3,200,(sum),by=200,by.column=TRUE,align='right')
out50<-as.data.frame(out50)
out50$dates<-((out50$dates/200)-100.5)
write.table(out50, file = "SboxSum200.csv", sep = ",", row.names
= FALSE)
```

```
rm(list=ls())


#### 5. Calculate First Difference Values ----
setwd("~/R/THESIS_2/2_Sbox_Bins/")
Sum50 <- read.csv("SboxSum50.csv")
Sum100 <- read.csv("SboxSum100.csv")
Sum200 <- read.csv("SboxSum200.csv")

setwd("~/R/THESIS_2/")
Directory <- read.csv("Directory_Sbox.csv")

dir.create("~/R/THESIS_2/3_FirstDiff/")
setwd("~/R/THESIS_2/3_FirstDiff/")

###Calculate First Difference Values for each time series. Let's
start with the 50 year time scale
dates<- Sum50$dates[-c(114)] ##extract the dates for the time
series
Sum50 <- Sum50[-c(1)] ###Remove the dates
Sum50_2 <- Sum50[-c(1),] ###Remove the first row (year 5950 BP)
rownames(Sum50_2) <- 1:113 ### Renumber row names so we can
properly subtract
Sum50 <- Sum50[-c(114),] ### Remove the last row (year 300BP)
SboxDif50 <- Sum50_2 - Sum50 ### younger SPD values (starting
with 5900BP) - older SPD values, so positive numbers will
demonstrate SPD increase, and negative will be decrease.
SboxDif50<- cbind(dates,SboxDif50) ###Recombine dates with the
SPD difference values
SboxDif50[SboxDif50 == 0] <- NA ### All first difference values
of "0" will be replaced with NA
remove(Sum50) #Clean up environment
remove(Sum50_2) #Clean up environment
remove(dates)
write.csv(SboxDif50, "SboxDif50.csv", row.names = FALSE) ##Write
to a csv.

###Let's move on to the 100 year time scale. The only change will
be how long the dataframe will be, which will affect the math.
dates<- Sum100$dates[-c(57)] ##extract the dates for the time
series
Sum100 <- Sum100[-c(1)] ###Remove the dates
Sum100_2 <- Sum100[-c(1),] ###Remove the first row (year 5900 BP)
rownames(Sum100_2) <- 1:56 ### Renumber row names so we can
properly subtract
Sum100 <- Sum100[-c(57),] ### Remove the last row (year 300BP)
SboxDif100 <- Sum100_2 - Sum100 ### younger SPD values (starting
with 5900BP) - older SPD values, so positive numbers will
demonstrate SPD increase, and negative will be decrease.
SboxDif100<- cbind(dates,SboxDif100) ###Recombine dates with the
SPD difference values
```

```
SboxDif100[SboxDif100 == 0] <- NA ### All first difference values
of "0" will be replaced with NA
remove(Sum100) #Clean up environment
remove(Sum100_2) #Clean up environment
remove(dates) #Clean up environment
write.csv(SboxDif100, "SboxDif100.csv", row.names = FALSE)
##Write to a csv.

###Finally, let's do the 200 year time scale.
dates<- Sum200$dates[-c(28)] ##extract the dates for the time
series
Sum200 <- Sum200[-c(1)] ###Remove the dates
Sum200_2 <- Sum200[-c(1),] ###Remove the first row (bin 6000-5800
BP)
rownames(Sum200_2) <- 1:27 ### Renumber row names so we can
properly subtract
Sum200 <- Sum200[-c(28),] ### Remove the last row (year bin 600-
400BP)
SboxDif200 <- Sum200_2 - Sum200 ### younger SPD values (starting
with 5600BP) - older SPD values, so positive numbers will
demonstrate SPD increase, and negative will be decrease.
SboxDif200<- cbind(dates,SboxDif200) ###Recombine dates with the
SPD difference values
SboxDif200[SboxDif200 == 0] <- NA ### All first difference values
of "0" will be replaced with NA
remove(Sum200) #Clean up environment
remove(Sum200_2) #Clean up environment
remove(dates) #Clean up environment
write.csv(SboxDif200, "SboxDif200.csv", row.names = FALSE)
##Write to a csv.

#### 6. Calculate mean and median first difference values, then
add to directory ----

##Let's start with 50 year time scale
NegDif50 <- as.data.frame(apply(SboxDif50,  MARGIN = c(1,2),
function(x) {ifelse(x < 0, NA, x)})) ###Create a dataframe of all
positive first difference values
PosDif50 <- as.data.frame(apply(SboxDif50,  MARGIN = c(1,2),
function(x) {ifelse(x > 0, NA, x)})) ###Create a dataframe of all
negative first difference values.

###This code calculates average mean amplitude, median amplitude,
mean positive first difference values, median positive first
difference values, mean negative first difference values, and
median negative first difference values.
amp50<- as.data.frame(cbind(colnames(SboxDif50),
                             colMeans(abs(SboxDif50), na.rm =
TRUE),

colMedians(as.matrix(abs(SboxDif50)), na.rm = TRUE),
                             colMeans(PosDif50, na.rm = TRUE),
```

```
                                colMedians(as.matrix(PosDif50),
na.rm = TRUE),
                                colMeans(NegDif50, na.rm = TRUE),
                                colMedians(as.matrix(NegDif50),
na.rm = TRUE)))
colnames(amp50) <- c("Sbox", "amp50", "mamp50", "posamp50",
"mposamp50", "negamp50", "mnegamp50") ###Rename column headings
to clarify

amp50$amp50 <- as.numeric(as.character(amp50$amp50)) ##Convert
the column from factors to non-integer numbers
amp50$mamp50 <- as.numeric(as.character(amp50$mamp50))
amp50$invamp50 <- sapply(amp50$amp50, FUN=function(x) 1/x) ##Take
the inverse of the mean amplitude values to represent mean
stability
amp50$minvamp50 <- sapply(amp50$mamp50, FUN=function(x) 1/x)
##Take the inverse of the median amplitude values
amp50 <- amp50[-c(1),] #Get rid of the dates row
amp50$Sbox <- sub('X', '', amp50$Sbox)

Directory <- merge(Directory, amp50, by.x = "Sbox", by.y =
"Sbox") ##Merge all of our stability measurements to the
directory.

###And then move to the 100 year time scale
NegDif100 <- as.data.frame(apply(SboxDif100,  MARGIN = c(1,2),
function(x) {ifelse(x < 0, NA, x)})) ###Create a dataframe of all
positive first difference values
PosDif100 <- as.data.frame(apply(SboxDif100,  MARGIN = c(1,2),
function(x) {ifelse(x > 0, NA, x)})) ###Create a dataframe of all
negative first difference values.

###This code calculates average mean amplitude, median amplitude,
mean positive first difference values, median positive first
difference values, mean negative first difference values, and
median negative first difference values.
amp100<- as.data.frame(cbind(colnames(SboxDif100),
                                colMeans(abs(SboxDif100), na.rm =
TRUE),

colMedians(as.matrix(abs(SboxDif100)), na.rm = TRUE),
                                colMeans(PosDif100, na.rm = TRUE),
                                colMedians(as.matrix(PosDif100),
na.rm = TRUE),
                                colMeans(NegDif100, na.rm = TRUE),
                                colMedians(as.matrix(NegDif100),
na.rm = TRUE)))
colnames(amp100) <- c("Sbox", "amp100", "mamp100", "posamp100",
"mposamp100", "negamp100", "mnegamp100") ###Rename column
headings to clarify

amp100$amp100 <- as.numeric(as.character(amp100$amp100))
```

```
##Convert the column from factors to non-integer numbers
amp100$mamp100 <- as.numeric(as.character(amp100$mamp100))
amp100$invamp100 <- sapply(amp100$amp100, FUN=function(x) 1/x)
##Take the inverse of the mean amplitude values to represent mean
stability
amp100$minvamp100 <- sapply(amp100$mamp100, FUN=function(x) 1/x)
##Take the inverse of the median amplitude values
amp100 <- amp100[-c(1),] #Get rid of the dates row
amp100$Sbox <- sub('X', '', amp100$Sbox)

Directory <- merge(Directory, amp100, by.x = "Sbox", by.y =
"Sbox") ##Merge all of our stability measurements to the
directory.


###Finally 200 year time scale
NegDif200 <- as.data.frame(apply(SboxDif200,  MARGIN = c(1,2),
function(x) {ifelse(x < 0, NA, x)})) ###Create a dataframe of all
positive first difference values
PosDif200 <- as.data.frame(apply(SboxDif200,  MARGIN = c(1,2),
function(x) {ifelse(x > 0, NA, x)})) ###Create a dataframe of all
negative first difference values.

###This code calculates average mean amplitude, median amplitude,
mean positive first difference values, median positive first
difference values, mean negative first difference values, and
median negative first difference values.
amp200<- as.data.frame(cbind(colnames(SboxDif200),
                             colMeans(abs(SboxDif200), na.rm =
TRUE),

colMedians(as.matrix(abs(SboxDif200)), na.rm = TRUE),
                             colMeans(PosDif200, na.rm = TRUE),
                             colMedians(as.matrix(PosDif200),
na.rm = TRUE),
                             colMeans(NegDif200, na.rm = TRUE),
                             colMedians(as.matrix(NegDif200),
na.rm = TRUE)))
colnames(amp200) <- c("Sbox", "amp200", "mamp200", "posamp200",
"mposamp200", "negamp200", "mnegamp200") ###Rename column
headings to clarify

amp200$amp200 <- as.numeric(as.character(amp200$amp200))
##Convert the column from factors to non-integer numbers
amp200$mamp200 <- as.numeric(as.character(amp200$mamp200))
amp200$invamp200 <- sapply(amp200$amp200, FUN=function(x) 1/x)
##Take the inverse of the mean amplitude values to represent mean
stability
amp200$minvamp200 <- sapply(amp200$mamp200, FUN=function(x) 1/x)
##Take the inverse of the median amplitude values
amp200 <- amp200[-c(1),] #Get rid of the dates row
amp200$Sbox <- sub('X', '', amp200$Sbox)
```

```
Directory <- merge(Directory, amp200, by.x = "Sbox", by.y =
"Sbox") ##Merge all of our stability measurements to the
directory.


####Finally, let's export that directory to reference is later.
setwd("~/R/THESIS_2/")
write.csv(Directory, "Directory_Sbox.csv", row.names = FALSE)

rm(list=ls())

#### 7. Let's begin the analysis.  ----
##First, you will need to open your Directory CSV and add
agriculture values (0,1). Then load it below.

setwd("~/R/THESIS_2/")
Directory <- read.csv("Directory_Sbox.csv")

cbbPalette <- c("#56B4E9", "#D55E00")
labels <- c("0" = "Hunter-Gatherers", "1" = "Agriculturalists")

###  7.1 Look at all SPDs at once. 50-year below, change 50 to
100 and 200 to see those instead. ----
setwd("~/R/THESIS_2/2_Sbox_Bins/")
Sum50 <- read.csv("SboxSum50.csv")
Sum100 <- read.csv("SboxSum100.csv")
Sum200 <- read.csv("SboxSum200.csv")

Sum50long <- melt.data.frame(Sum50, id=c("dates"))
Sum100long <- melt.data.frame(Sum100, id=c("dates"))
Sum200long <- melt.data.frame(Sum200, id=c("dates"))

Sum50long$variable <- gsub('X', 'Sbox ', Sum50long$variable)
Sum100long$variable <- gsub('X', 'Sbox ', Sum100long$variable)
Sum200long$variable <- gsub('X', 'Sbox ', Sum200long$variable)

dir.create("~/R/THESIS_2/4_SPDs/")
setwd("~/R/THESIS_2/4_SPDs/")

#50 year first

p.list = lapply(sort(unique(Sum50long$variable)), function(i) {
    ggplot(Sum50long[Sum50long$variable==i,], aes((dates),
(value))) +
    geom_line(show.legend=FALSE) +
    theme_bw() +
    theme(axis.text = element_text(angle=45, size=12, colour =
"black"), axis.title=element_text(size=18))+
    labs(x = "Cal years BP", y="Summed probability")+
    ggtitle(paste(i, "SPD"))+
    #geom_point(colour= ifelse(value < value, "red", "blue"))+
```

```
    #geom_hline(yintercept = mean(value))+
    scale_x_reverse(breaks = seq(500,6000,500))
    #geom_vline(aes(xintercept=650, colour= "red"),
linetype="solid", show.legend = FALSE)
})

p.list ##View your SPDs

pdf("Sum50_200.pdf", width = 6, height = 3) ##Export them as a
pdf.
p.list
dev.off()

#Now let's do 100 year time scale.
p.list = lapply(sort(unique(Sum100long$variable)), function(i) {
  ggplot(Sum100long[Sum100long$variable==i,], aes((dates),
(value))) +
    geom_line(show.legend=FALSE) +
    theme_bw() +
    theme(axis.text = element_text(angle=45, size=12, colour =
"black"), axis.title=element_text(size=18))+
    labs(x = "Cal years BP", y="Summed probability")+
    ggtitle(paste(i, "SPD"))+
    #geom_point(colour= ifelse(value < value, "red", "blue"))+
    #geom_hline(yintercept = mean(value))+
    scale_x_reverse(breaks = seq(500,6000,500))
})
p.list

pdf("SboxSum100.pdf", width = 6, height = 3) ##Export them as a
pdf.
p.list
dev.off()


#Finally, 200 year time scale.
p.list = lapply(sort(unique(Sum200long$variable)), function(i) {
  ggplot(Sum200long[Sum200long$variable==i,], aes((dates),
(value))) +
    geom_line(show.legend=FALSE) +
    theme_bw() +
    theme(axis.text = element_text(angle=45, size=12, colour =
"black"), axis.title=element_text(size=18))+
    labs(x = "Cal years BP", y="Summed probability")+
    ggtitle(paste(i, "SPD"))+
    #geom_point(colour= ifelse(value < value, "red", "blue"))+
    #geom_hline(yintercept = mean(value))+
    scale_x_reverse(breaks = seq(500,6000,500))
})
p.list

pdf("SboxSum200.pdf", width = 6, height = 3) ##Export them as a
```

```
pdf.
p.list
dev.off()


###  7.2 Make histograms ----
setwd("~/R/THESIS_2/3_FirstDiff/")
SboxDif50 <- read.csv ("SboxDif50.csv")
SboxDif100 <- read.csv ("SboxDif100.csv")
SboxDif200 <- read.csv ("SboxDif200.csv")

colnames(SboxDif50) <- gsub(x=colnames(SboxDif50), pattern= "X",
replacement = "")
colnames(SboxDif100) <- gsub(x=colnames(SboxDif100), pattern=
"X", replacement = "")
colnames(SboxDif200) <- gsub(x=colnames(SboxDif200), pattern=
"X", replacement = "")

Dif50long <- melt.data.frame(SboxDif50, id.vars = c("dates"))
Dif100long <- melt.data.frame(SboxDif100, id.vars = c("dates"))
Dif200long <- melt.data.frame(SboxDif200, id.vars = c("dates"))

Dif50long <- merge.data.frame(x=na.omit(Dif50long),
y=Directory[,c("Sbox", "ag")], by.x= "variable", by.y = "Sbox")
Dif100long <- merge.data.frame(x=na.omit(Dif100long),
y=Directory[,c("Sbox", "ag")], by.x= "variable", by.y = "Sbox")
Dif200long <- merge.data.frame(x=na.omit(Dif200long),
y=Directory[,c("Sbox", "ag")], by.x= "variable", by.y = "Sbox")

write.csv(Dif50long, "Dif50long.csv", row.names = FALSE)
write.csv(Dif100long, "Dif100long.csv", row.names = FALSE)
write.csv(Dif200long, "Dif200long.csv", row.names = FALSE)

Dif50long <- read.csv ("Dif50long.csv")
Dif100long <- read.csv ("Dif100long.csv")
Dif200long <- read.csv ("Dif200long.csv")

##Table Organization out of the way, let's view the histograms!
As always, 50 year scale first.

mu<-ddply(Dif50long, "ag", summarise, grp.mean=mean(abs(value)))
me<-ddply(Dif50long, "ag", summarise,
grp.median=median(abs(value)))
sd<-ddply(Dif50long, "ag", summarise, grp.sd=sd(abs(value)))

p<-ggplot(Dif50long, aes(x=(abs(value)), fill=factor(ag))) +
  geom_density(adjust=1, alpha=1,  position = "identity")+
  geom_rug(aes(x =(abs(value)) , y = 0), position =
position_jitter(height = 0))+
  geom_vline(data=mu, aes(xintercept=grp.mean),
             linetype="dashed", show.legend = FALSE)+
  geom_vline(data=me, aes(xintercept=grp.median),
```

```
              linetype="solid", show.legend = FALSE)+
  theme_bw() +
  scale_fill_manual(name="First Difference", labels = c("Hunter-
Gatherers", "Agriculturalists"), values = cbbPalette)+
  labs(x="Absolute Value of 50 Year First Difference Values", y =
"Density")+
  theme(legend.position="top")+
  facet_grid(factor(ag)~.)
p

jpeg("Sbox50_invamp.jpeg", width=912, height=390)
p
dev.off()

mu
me
sd

###100 year next
mu<-ddply(Dif100long, "ag", summarise, grp.mean=mean(abs(value)))
me<-ddply(Dif100long, "ag", summarise,
grp.median=median(abs(value)))
sd<-ddply(Dif100long, "ag", summarise, grp.sd=sd(abs(value)))

p<-ggplot(Dif100long, aes(x=(abs(value)), fill=factor(ag))) +
  geom_density(adjust=1, alpha=1,  position = "identity")+
  geom_rug(aes(x =(abs(value)) , y = 0), position =
position_jitter(height = 0))+
  geom_vline(data=mu, aes(xintercept=grp.mean),
              linetype="dashed", show.legend = FALSE)+
  geom_vline(data=me, aes(xintercept=grp.median),
              linetype="solid", show.legend = FALSE)+
  theme_bw() +
  scale_fill_manual(name="First Difference", labels = c("Hunter-
Gatherers", "Agriculturalists"), values = cbbPalette,
guide=FALSE)+
  labs(x="Absolute Value of 100 Year First Difference Values", y
= "Density")+
  theme(legend.position="top")+
  facet_grid(factor(ag)~.)
p

jpeg("Sbox100_invamp.jpeg", width=912, height=345)
p
dev.off()

mu
me
sd

###200 year last
```

```
mu<-ddply(Dif200long, "ag", summarise, grp.mean=mean(abs(value)))
me<-ddply(Dif200long, "ag", summarise,
grp.median=median(abs(value)))
sd<-ddply(Dif200long, "ag", summarise, grp.sd=sd(abs(value)))

p<-ggplot(Dif200long, aes(x=(abs(value)), fill=factor(ag))) +
  geom_density(adjust=1, alpha=1,  position = "identity")+
  geom_rug(aes(x =(abs(value)) , y = 0), position =
position_jitter(height = 0))+
  geom_vline(data=mu, aes(xintercept=grp.mean),
             linetype="dashed", show.legend = FALSE)+
  geom_vline(data=me, aes(xintercept=grp.median),
             linetype="solid", show.legend = FALSE)+
  theme_bw() +
  scale_fill_manual(name="First Difference", labels = c("Hunter-
Gatherers", "Agriculturalists"), values = cbbPalette,
guide=FALSE)+
  labs(x="Absolute Value of 200 Year First Difference Values", y
= "Density")+
  theme(legend.position="top")+
  facet_grid(factor(ag)~.)
p

jpeg("Sbox200_invamp.jpeg", width=912, height=345)
p
dev.off()

mu
me
sd


##### 7.21 Let's do positive population changes next
Dif50long_pos <- subset(Dif50long, value >0) ###Uncomment to view
only population increases. Change > to < to view only decreases.

mu<-ddply(Dif50long_pos, "ag", summarise,
grp.mean=mean(abs(value)))
me<-ddply(Dif50long_pos, "ag", summarise,
grp.median=median(abs(value)))
sd<-ddply(Dif50long_pos, "ag", summarise, grp.sd=sd(abs(value)))

p<-ggplot(Dif50long_pos, aes(x=(abs(value)), fill=factor(ag))) +
  geom_density(adjust=1, alpha=1,  position = "identity")+
  geom_rug(aes(x =(abs(value)) , y = 0), position =
position_jitter(height = 0))+
  geom_vline(data=mu, aes(xintercept=grp.mean),
             linetype="dashed", show.legend = FALSE)+
  geom_vline(data=me, aes(xintercept=grp.median),
             linetype="solid", show.legend = FALSE)+
  theme_bw() +
  scale_fill_manual(name="First Difference", labels = c("Hunter-
```

```
Gatherers", "Agriculturalists"), values = cbbPalette)+
  labs(x="Positive 50 Year First Difference Values (Booms)", y =
"Density")+
  theme(legend.position="top")+
  facet_grid(factor(ag)~.)
p

jpeg("Sbox50_posamp.jpeg", width=912, height=390)
p
dev.off()

mu
me
sd

###100 year next
Dif100long_pos <- subset(Dif100long, value >0) ###Uncomment to
view only population increases. Change > to < to view only
decreases.

mu<-ddply(Dif100long_pos, "ag", summarise,
grp.mean=mean(abs(value)))
me<-ddply(Dif100long_pos, "ag", summarise,
grp.median=median(abs(value)))
sd<-ddply(Dif100long_pos, "ag", summarise, grp.sd=sd(abs(value)))

p<-ggplot(Dif100long_pos, aes(x=(abs(value)), fill=factor(ag))) +
  geom_density(adjust=1, alpha=1,  position = "identity")+
  geom_rug(aes(x =(abs(value)) , y = 0), position =
position_jitter(height = 0))+
  geom_vline(data=mu, aes(xintercept=grp.mean),
             linetype="dashed", show.legend = FALSE)+
  geom_vline(data=me, aes(xintercept=grp.median),
             linetype="solid", show.legend = FALSE)+
  theme_bw() +
  scale_fill_manual(name="First Difference", labels = c("Hunter-
Gatherers", "Agriculturalists"), values = cbbPalette,
guide=FALSE)+
  labs(x="Positive 100 Year First Difference Values (Booms)", y =
"Density")+
  theme(legend.position="top")+
  facet_grid(factor(ag)~.)
p

jpeg("Sbox100_posamp.jpeg", width=912, height=345)
p
dev.off()

mu
me
sd
```

```
###200 year last
Dif200long_pos <- subset(Dif200long, value >0) ###Uncomment to
view only population increases. Change > to < to view only
decreases.

mu<-ddply(Dif200long_pos, "ag", summarise,
grp.mean=mean(abs(value)))
me<-ddply(Dif200long_pos, "ag", summarise,
grp.median=median(abs(value)))
sd<-ddply(Dif200long_pos, "ag", summarise, grp.sd=sd(abs(value)))

p<-ggplot(Dif200long_pos, aes(x=(abs(value)), fill=factor(ag))) +
  geom_density(adjust=1, alpha=1,  position = "identity")+
  geom_rug(aes(x =(abs(value)) , y = 0), position =
position_jitter(height = 0))+
  geom_vline(data=mu, aes(xintercept=grp.mean),
             linetype="dashed", show.legend = FALSE)+
  geom_vline(data=me, aes(xintercept=grp.median),
             linetype="solid", show.legend = FALSE)+
  theme_bw() +
  scale_fill_manual(name="First Difference", labels = c("Hunter-
Gatherers", "Agriculturalists"), values = cbbPalette,
guide=FALSE)+
  labs(x="Positive 200 Year First Difference Values (Booms)", y =
"Density")+
  theme(legend.position="top")+
  facet_grid(factor(ag)~.)
p

jpeg("Sbox200_posamp.jpeg", width=912, height=345)
p
dev.off()

mu
me
sd


##### 7.22 Negative now.
Dif50long_neg <- subset(Dif50long, value <0) ###Uncomment to view
only population increases. Change > to < to view only decreases.

mu<-ddply(Dif50long_neg, "ag", summarise,
grp.mean=mean(abs(value)))
me<-ddply(Dif50long_neg, "ag", summarise,
grp.median=median(abs(value)))
sd<-ddply(Dif50long_neg, "ag", summarise, grp.sd=sd(abs(value)))

p<-ggplot(Dif50long_neg, aes(x=(abs(value)), fill=factor(ag))) +
  geom_density(adjust=1, alpha=1,  position = "identity")+
  geom_rug(aes(x =(abs(value)) , y = 0), position =
position_jitter(height = 0))+
```

```
  geom_vline(data=mu, aes(xintercept=grp.mean),
             linetype="dashed", show.legend = FALSE)+
  geom_vline(data=me, aes(xintercept=grp.median),
             linetype="solid", show.legend = FALSE)+
  theme_bw() +
  scale_fill_manual(name="First Difference", labels = c("Hunter-
Gatherers", "Agriculturalists"), values = cbbPalette)+
  labs(x="Negative 50 Year First Difference Values (Busts)", y =
"Density")+
  theme(legend.position="top")+
  facet_grid(factor(ag)~.)
p

jpeg("Sbox50_negamp.jpeg", width=912, height=390)
p
dev.off()

mu
me
sd

###100 year next
Dif100long_neg <- subset(Dif100long, value <0) ###Uncomment to
view only population increases. Change > to < to view only
decreases.

mu<-ddply(Dif100long_neg, "ag", summarise,
grp.mean=mean(abs(value)))
me<-ddply(Dif100long_neg, "ag", summarise,
grp.median=median(abs(value)))
sd<-ddply(Dif100long_neg, "ag", summarise, grp.sd=sd(abs(value)))

p<-ggplot(Dif100long_neg, aes(x=(abs(value)), fill=factor(ag))) +
  geom_density(adjust=1, alpha=1,  position = "identity")+
  geom_rug(aes(x =(abs(value)) , y = 0), position =
position_jitter(height = 0))+
  geom_vline(data=mu, aes(xintercept=grp.mean),
             linetype="dashed", show.legend = FALSE)+
  geom_vline(data=me, aes(xintercept=grp.median),
             linetype="solid", show.legend = FALSE)+
  theme_bw() +
  scale_fill_manual(name="First Difference", labels = c("Hunter-
Gatherers", "Agriculturalists"), values = cbbPalette,
guide=FALSE)+
  labs(x="Negative 100 Year First Difference Values (Busts)", y =
"Density")+
  theme(legend.position="top")+
  facet_grid(factor(ag)~.)
p

jpeg("Sbox100_negamp.jpeg", width=912, height=345)
p
```

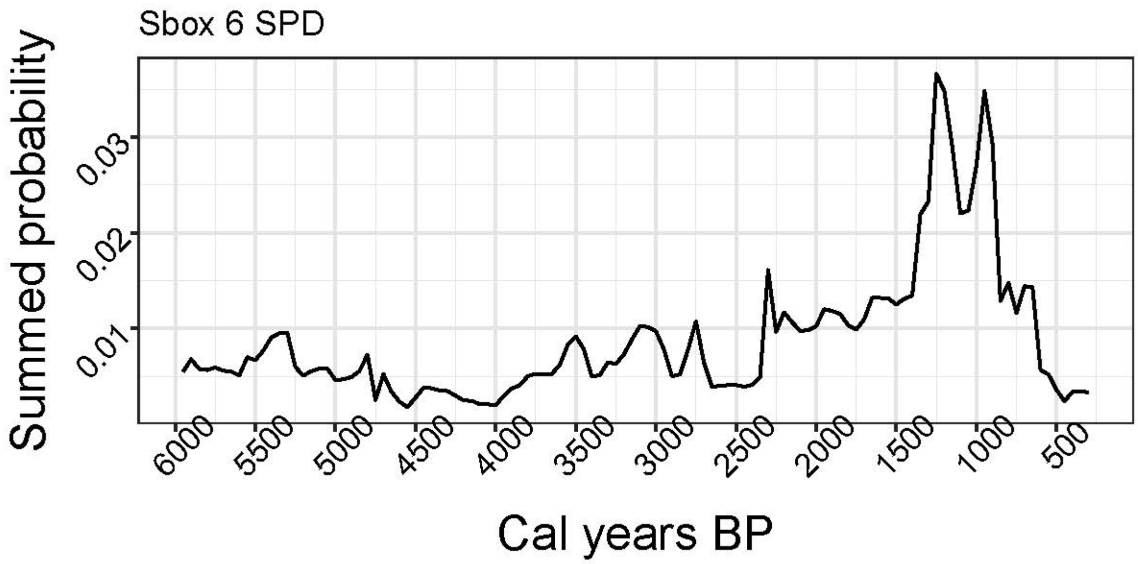
```
dev.off()

mu
me
sd

###200 year last
Dif200long_neg <- subset(Dif200long, value <0) ###Uncomment to
view only population increases. Change > to < to view only
decreases.

mu<-ddply(Dif200long_neg, "ag", summarise,
grp.mean=mean(abs(value)))
me<-ddply(Dif200long_neg, "ag", summarise,
grp.median=median(abs(value)))
sd<-ddply(Dif200long_neg, "ag", summarise, grp.sd=sd(abs(value)))

p<-ggplot(Dif200long_neg, aes(x=(abs(value)), fill=factor(ag))) +
  geom_density(adjust=1, alpha=1,  position = "identity")+
  geom_rug(aes(x =(abs(value)) , y = 0), position =
position_jitter(height = 0))+
  geom_vline(data=mu, aes(xintercept=grp.mean),
             linetype="dashed", show.legend = FALSE)+
  geom_vline(data=me, aes(xintercept=grp.median),
             linetype="solid", show.legend = FALSE)+
  theme_bw() +
  scale_fill_manual(name="First Difference", labels = c("Hunter-
Gatherers", "Agriculturalists"), values = cbbPalette,
guide=FALSE)+
  labs(x="Negative 200 Year First Difference Values (Busts)", y =
"Density")+
  theme(legend.position="top")+
  facet_grid(factor(ag)~.)
p

jpeg("Sbox200_negamp.jpeg", width=912, height=345)
p
dev.off()

mu
me
sd

##### Scatter Log N vs. invamp -----
dir.create("~/R/THESIS_2/7_lognCheck/")
setwd("~/R/THESIS_2/7_lognCheck/")

q <- ggplot(data=Directory, aes(x=(invamp200), y=log(n)))+
  theme_bw() +
  #aes(shape=factor(ag), colour=factor(ag))+
  #scale_colour_manual("", labels=c("Hunter-
Gatherer","Agriculturalists" ), values= cbbPalette)+
```

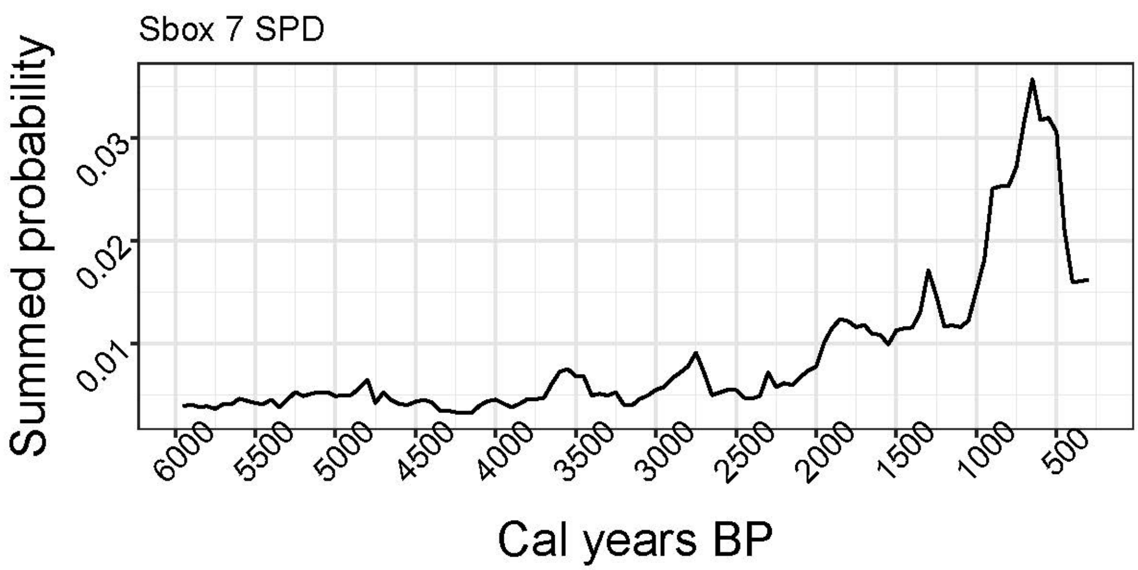
```
  #scale_shape_manual("", labels=c( "Hunter-Gatherer",
"Agriculturalists"), values= c(16,17))+
  geom_point(size=2.5) +
  theme(axis.text = element_text(size = rel(1.9), colour =
"black"), axis.title=element_text(size=16))+
  labs(x = "200 Year Mean Population Stability", y="Logged Number
of 14C dates")+
  geom_smooth(method="lm")+
  theme(legend.position = c(0.14, 8))
#facet_wrap(~(ew))
q

stab<-lm((minvamp200)~log(n), data=Directory)
summary(stab)

jpeg("200invamp_n.jpeg", width=656, height=440)
q
dev.off()


##### Model ------
dir.create("~/R/THESIS_2/6_SI/")
setwd("~/R/THESIS_2/6_model/")

library(psych)
library(gmodels)

df <- read.csv("model_base.csv")

df2<- replicate(1000, sample((0:1),40,replace=T))

df<- cbind(df, df2)

results50 <- lapply(df[6:1005],function(x)
wilcox.test(invamp50~x, data=df, alternative = "two.sided"))
results50_1 <-
do.call(cbind,lapply(results50,function(v){v$p.value}))
results50_2 <- as.data.frame(rbind(results50_1,df2))
results50_1 <-
as.list(do.call(cbind,lapply(results50,function(v){v$p.value})))

results100 <- lapply(df[6:1005],function(x)
wilcox.test(invamp100~x, data=df, alternative = "two.sided"))
results100_1 <-
do.call(cbind,lapply(results100,function(v){v$p.value}))
results100_2 <- as.data.frame(rbind(results100_1,df2))
results100_1<-
as.list(do.call(cbind,lapply(results100,function(v){v$p.value})))

results200 <- lapply(df[6:1005],function(x)
wilcox.test(invamp200~x, data=df, alternative = "two.sided"))
results200_1 <-
```

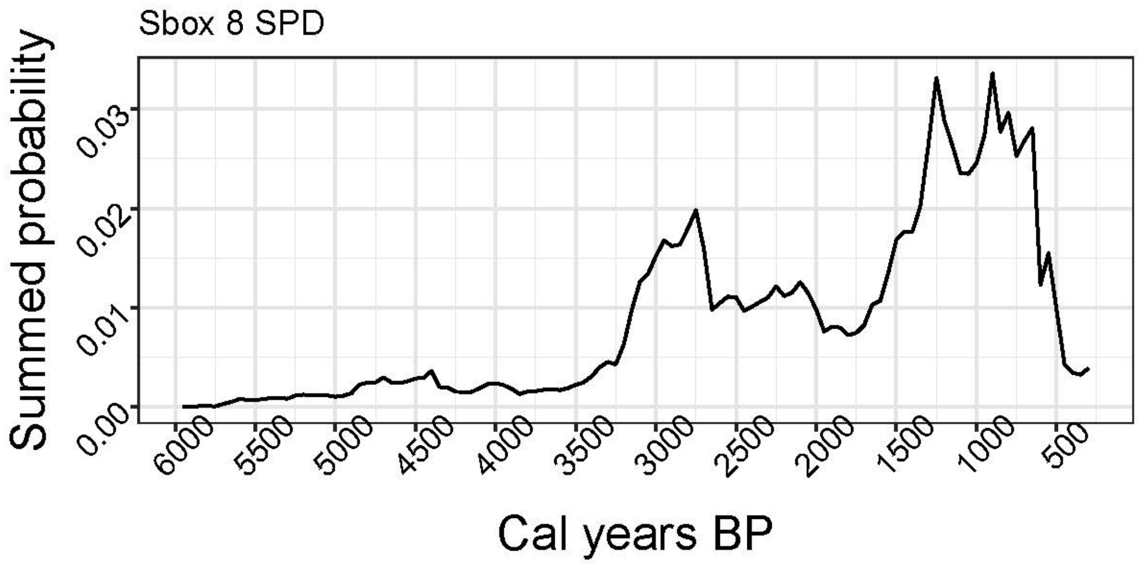
```
do.call(cbind,lapply(results200,function(v){v$p.value}))
results200_2 <- as.data.frame(rbind(results200_1,df2))
results200_1 <-
as.list(do.call(cbind,lapply(results200,function(v){v$p.value})))

result_50 <- data.frame(matrix(nrow = 3, ncol = 2))
result_100 <- data.frame(matrix(nrow = 3, ncol = 2))
result_200 <- data.frame(matrix(nrow = 3, ncol = 2))

for (i in 1:1000){
  if(results200_1[i] <= 0.05){
    staty <- Yule(table(df2[,i],df[,2]))
    result_200[i, 1] <- i
    result_200[i, 2] <- staty
  }
}

result_200 <- na.omit(result_200)


for (i in 1:1000){
  if(results100_1[i] <= 0.05){
    staty <- Yule(table(df2[,i],df[,2]))
    result_100[i, 1] <- i
    result_100[i, 2] <- staty
  }
}

result_100 <- na.omit(result_100)


for (i in 1:1000){
  if(results50_1[i] <= 0.05){
    staty <- Yule(table(df2[,i],df[,2]))
    result_50[i, 1] <- i
    result_50[i, 2] <- staty
  }
}

result_50 <- na.omit(result_50)

write.csv(result_50, "result50.csv", row.names = FALSE)
write.csv(result_100, "result100.csv",  row.names = FALSE)
write.csv(result_200, "result200.csv",  row.names = FALSE)
```

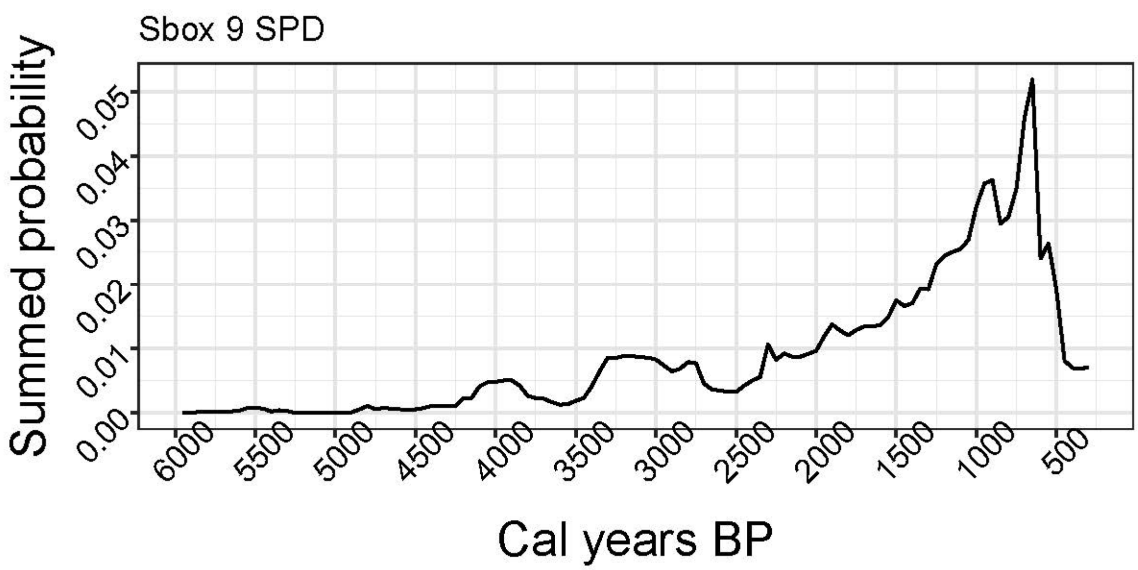
Appendix II: Summed Probability Distributions (SPDs)

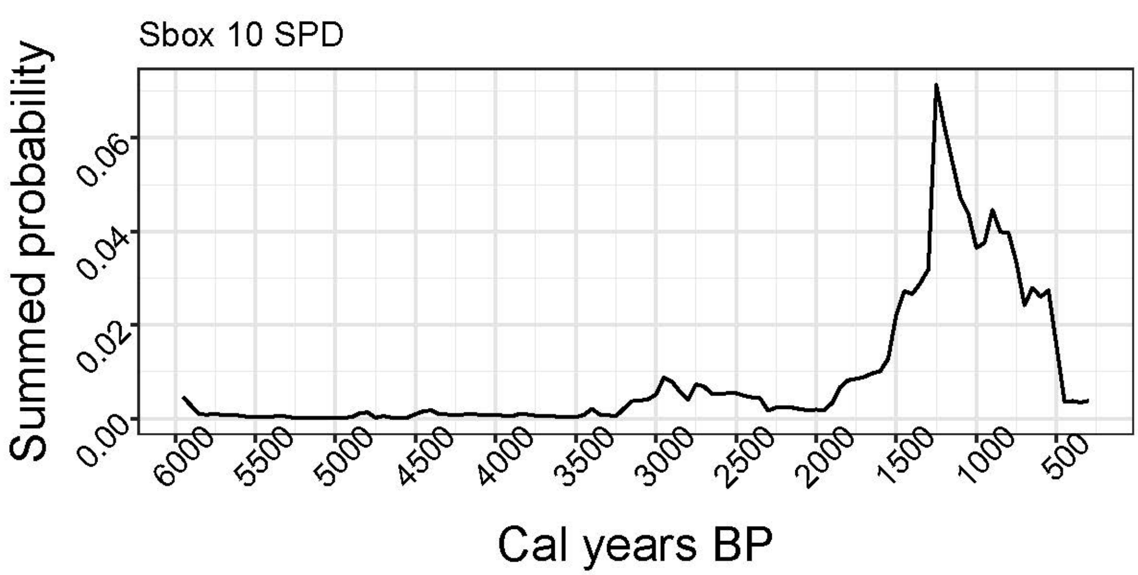
At the 50-year time scale:

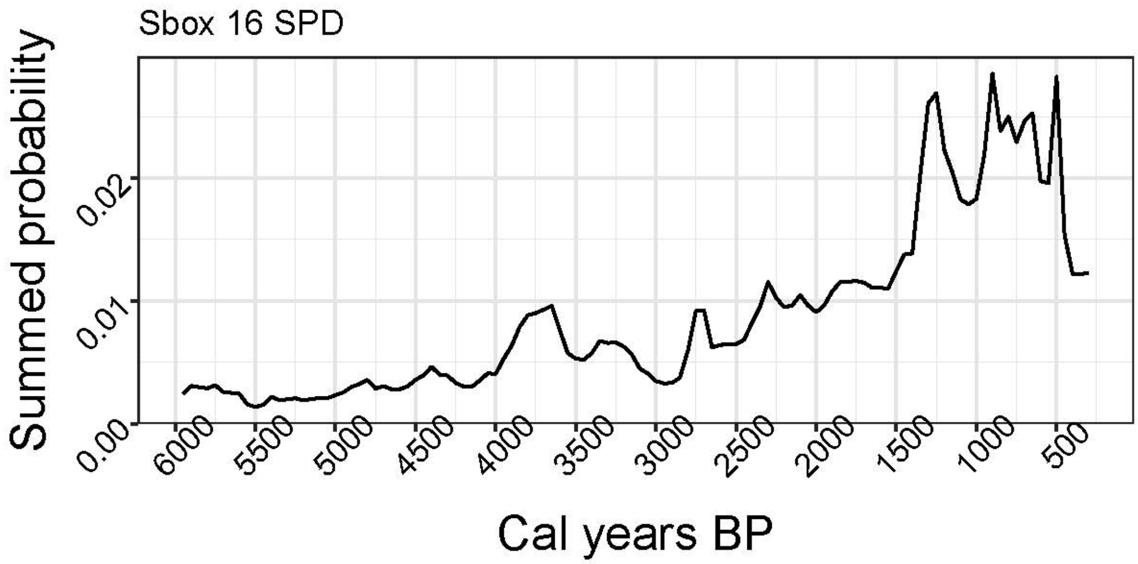


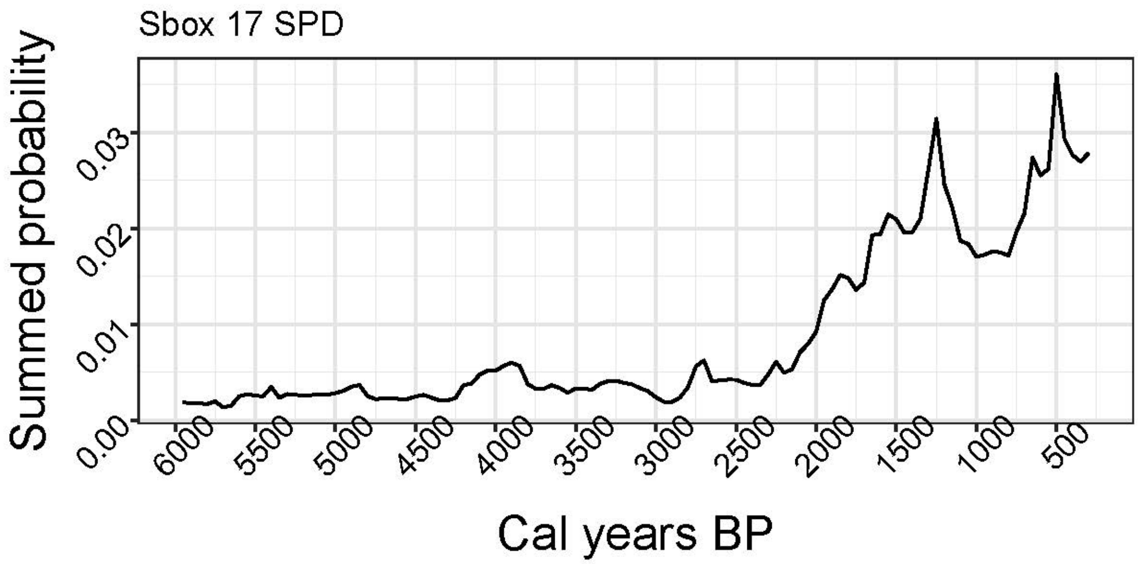


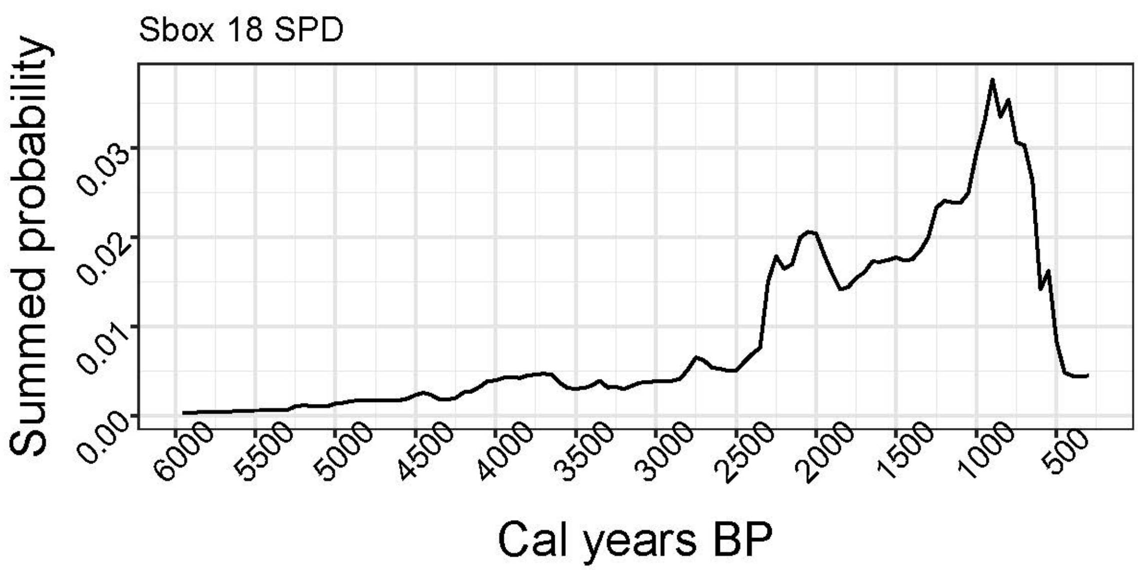

Sbox 8 SPD
Summed probability
0.00
0.01
0.02
0.03
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP

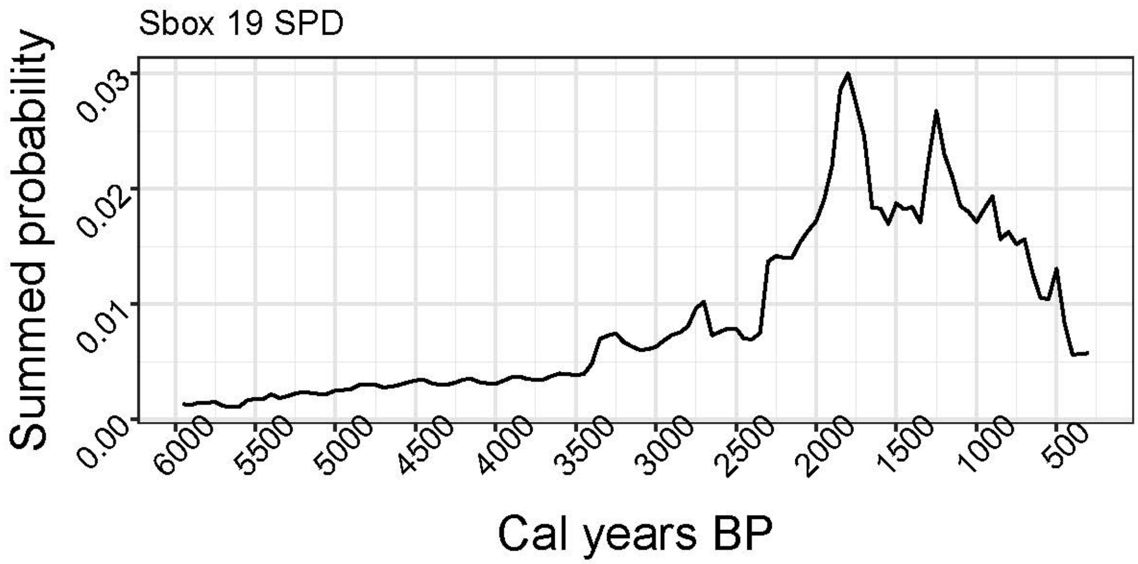

Sbox 9 SPD
Summed probability
0.00
0.01
0.02
0.03
0.04
0.05
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP

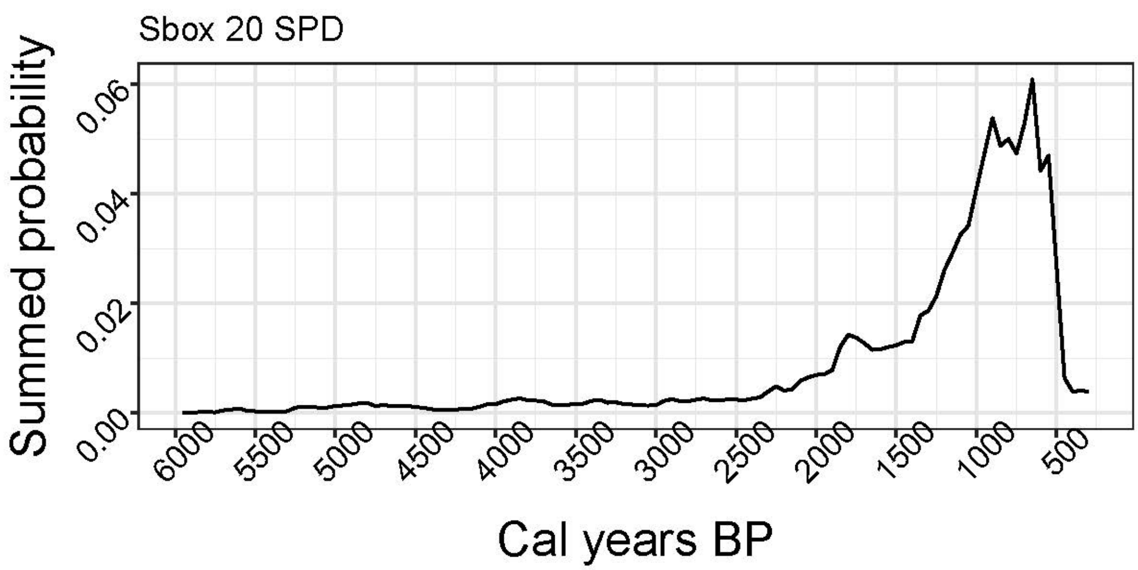

Sbox 10 SPD
Summed probability
0.00
0.02
0.04
0.06
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP

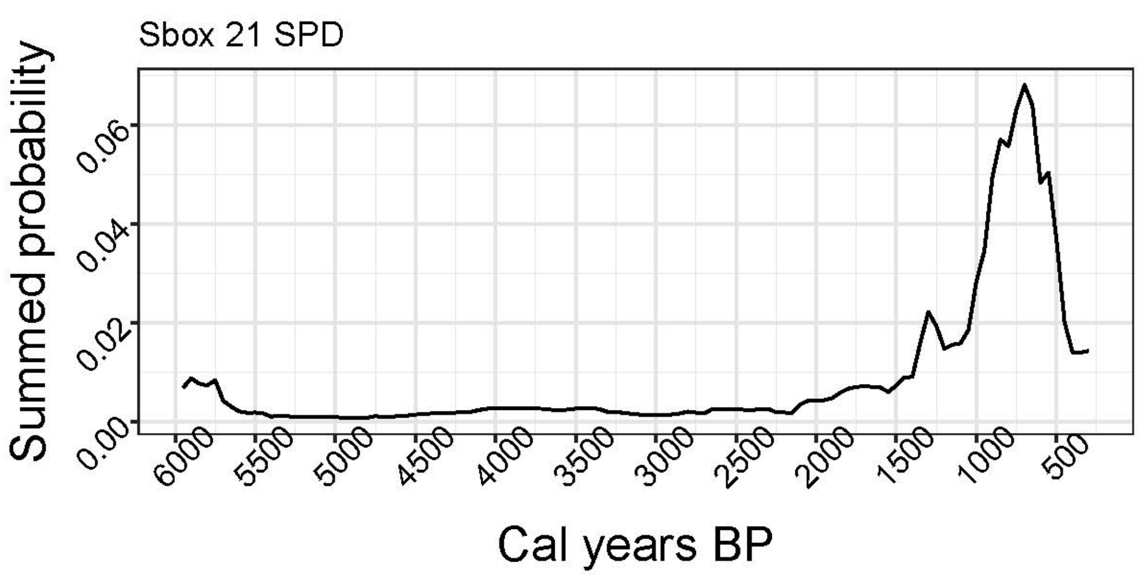

Sbox 16 SPD
Summed probability
0.00
0.01
0.02
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP

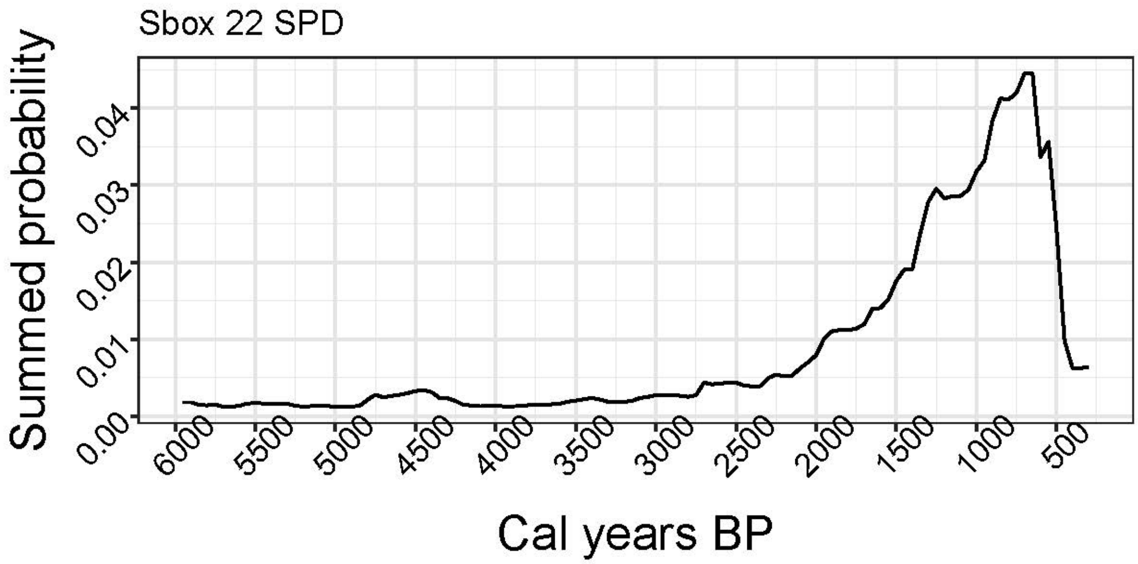

Sbox 17 SPD
Summed probability
0.00
0.01
0.02
0.03
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP

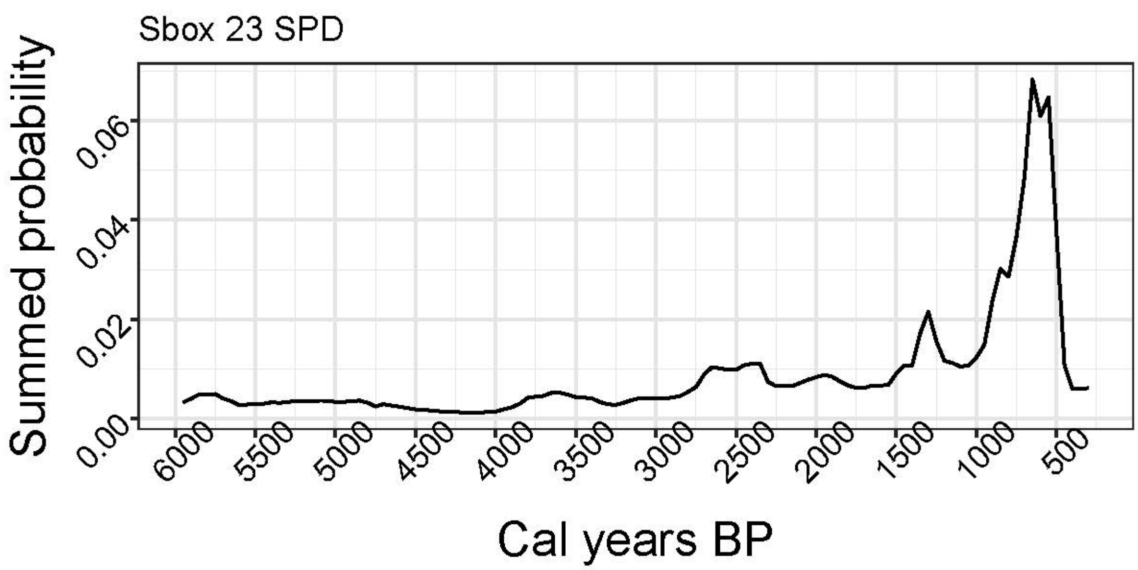

Sbox 18 SPD
Summed probability
0.00
0.01
0.02
0.03
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP

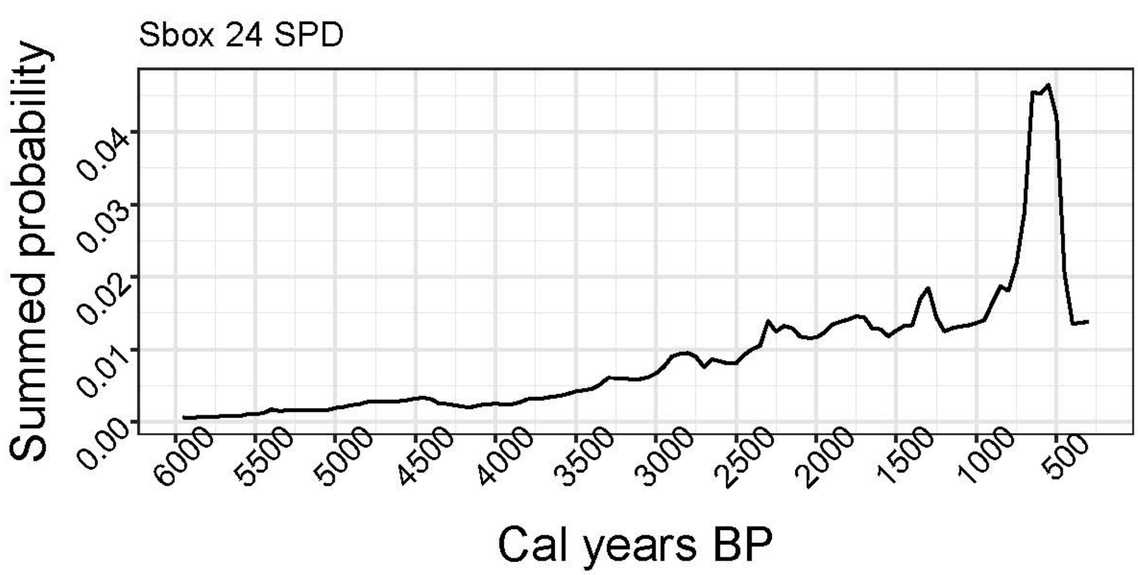

Sbox 19 SPD
Summed probability
0.00
0.01
0.02
0.03
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP

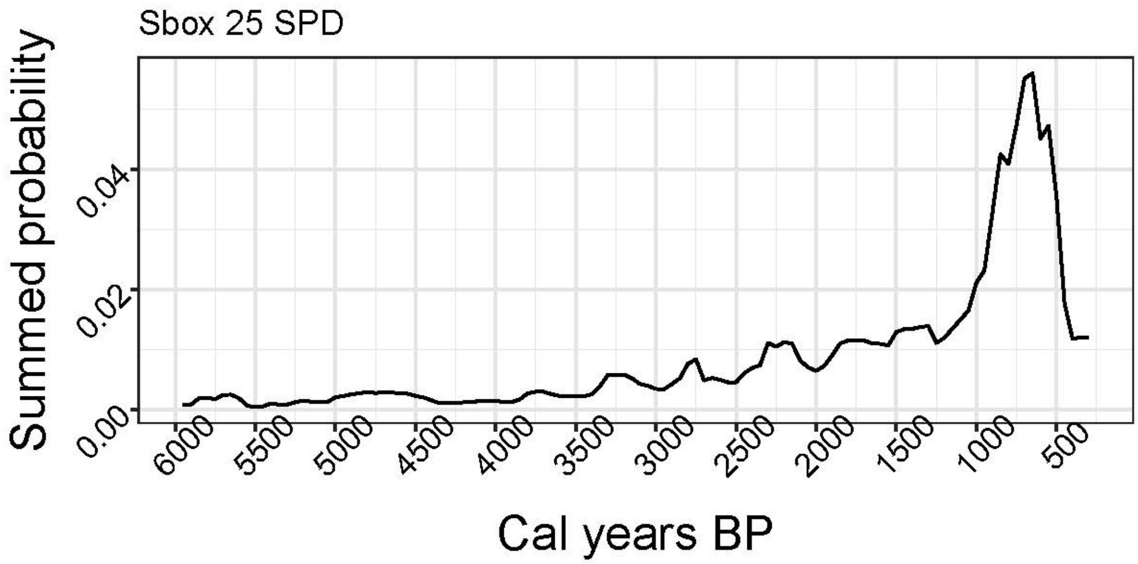

Sbox 20 SPD
Summed probability
0.00
0.02
0.04
0.06
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP

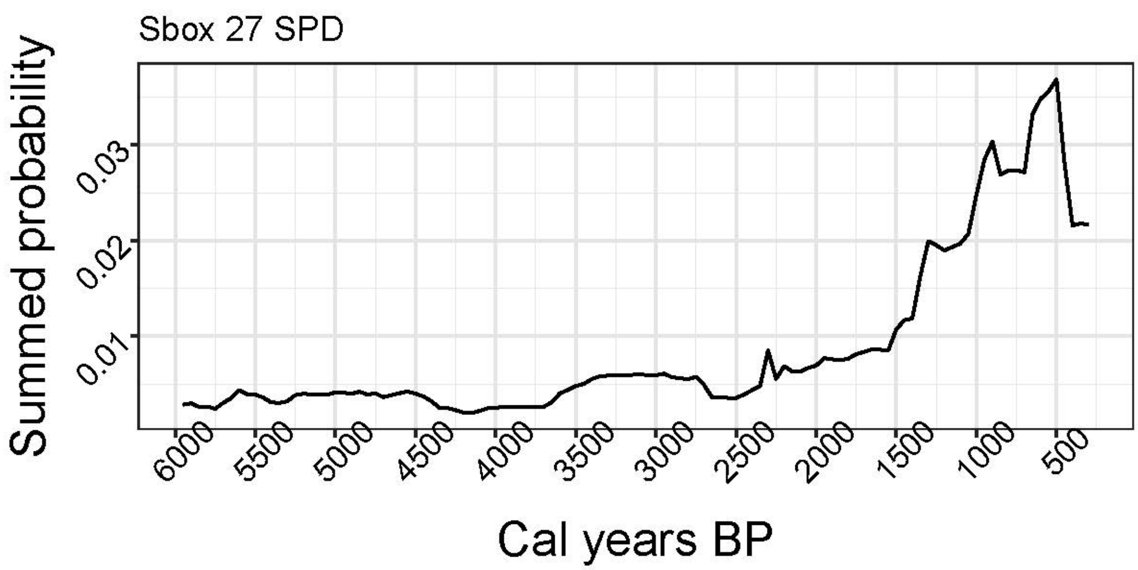

Sbox 21 SPD
Summed probability
0.00
0.02
0.04
0.06
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP

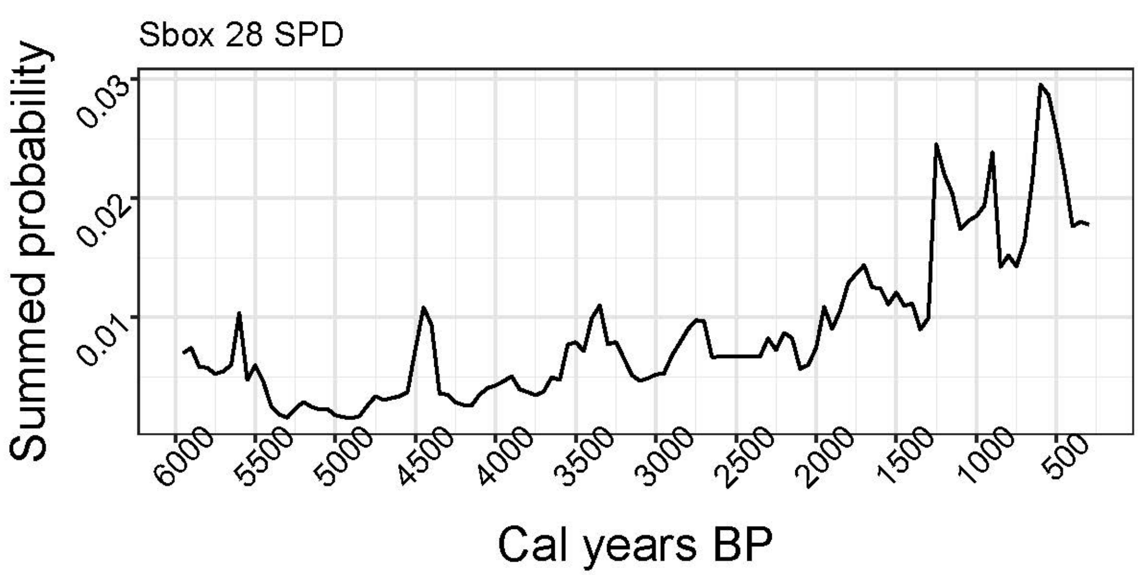

Sbox 22 SPD
Summed probability
0.00
0.01
0.02
0.03
0.04
6000 5500 5000 4500 4000 3500 3000 2500 2000 1500 1000 500
Cal years BP

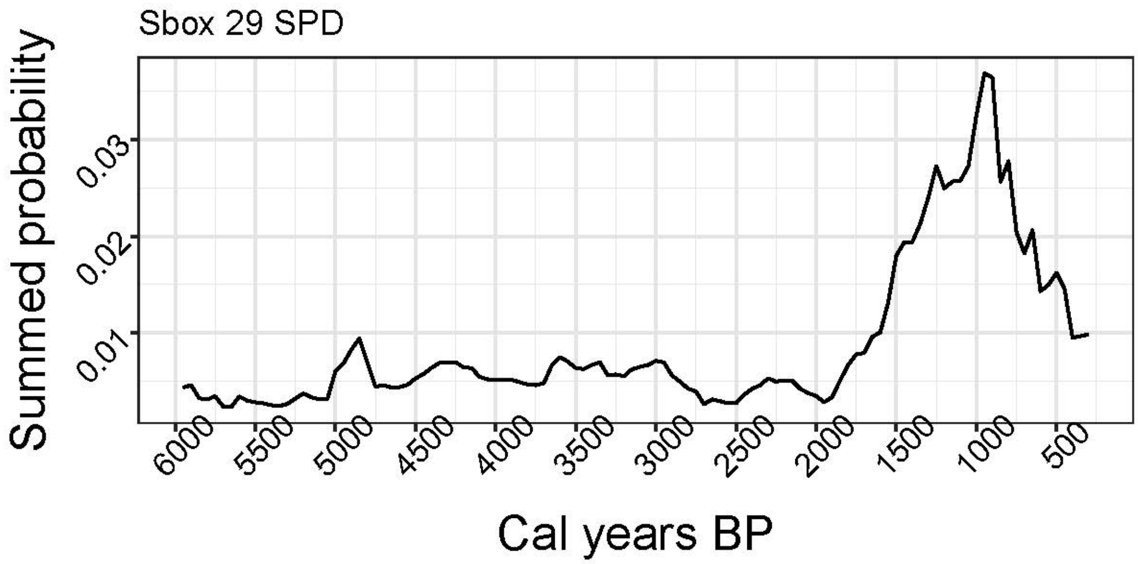

Sbox 23 SPD
Summed probability
0.00
0.02
0.04
0.06
6000 5500 5000 4500 4000 3500 3000 2500 2000 1500 1000 500
Cal years BP

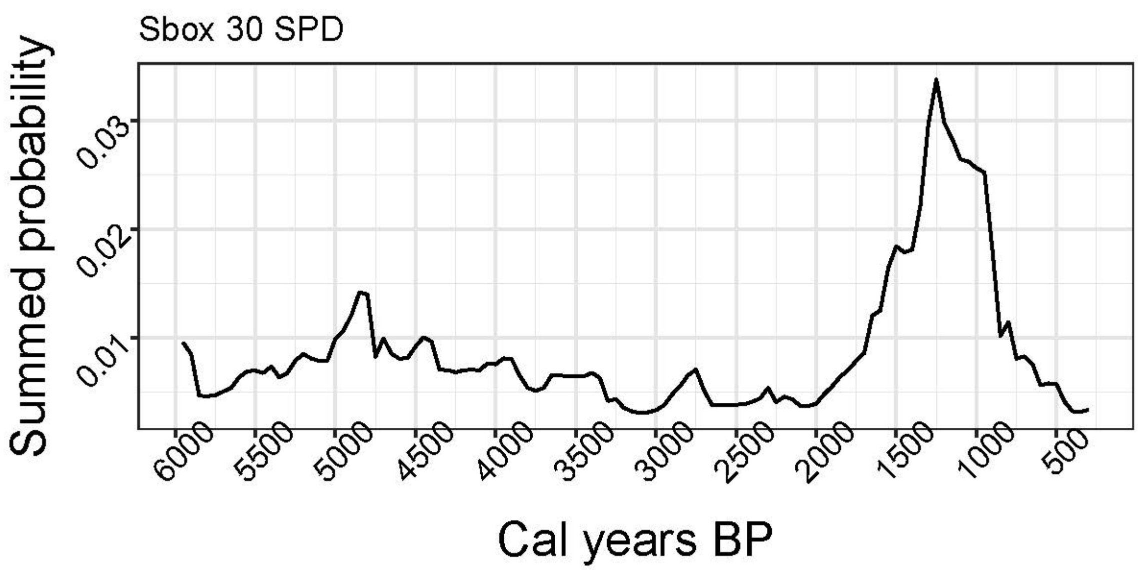

Sbox 24 SPD
Summed probability
0.00
0.01
0.02
0.03
0.04
6000 5500 5000 4500 4000 3500 3000 2500 2000 1500 1000 500
Cal years BP

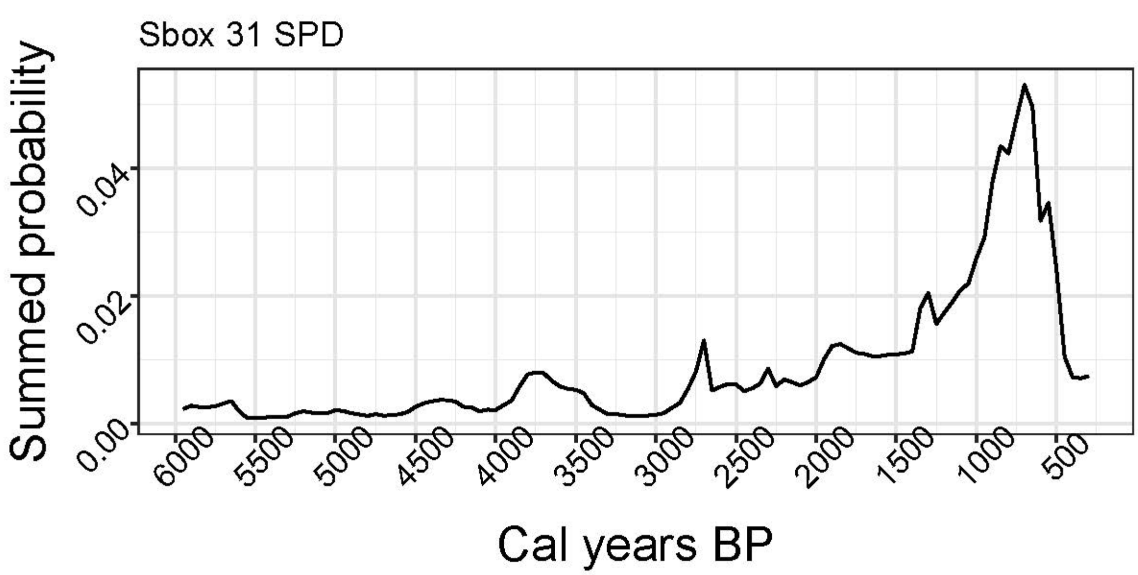

Sbox 25 SPD
Summed probability
0.00
0.02
0.04
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP

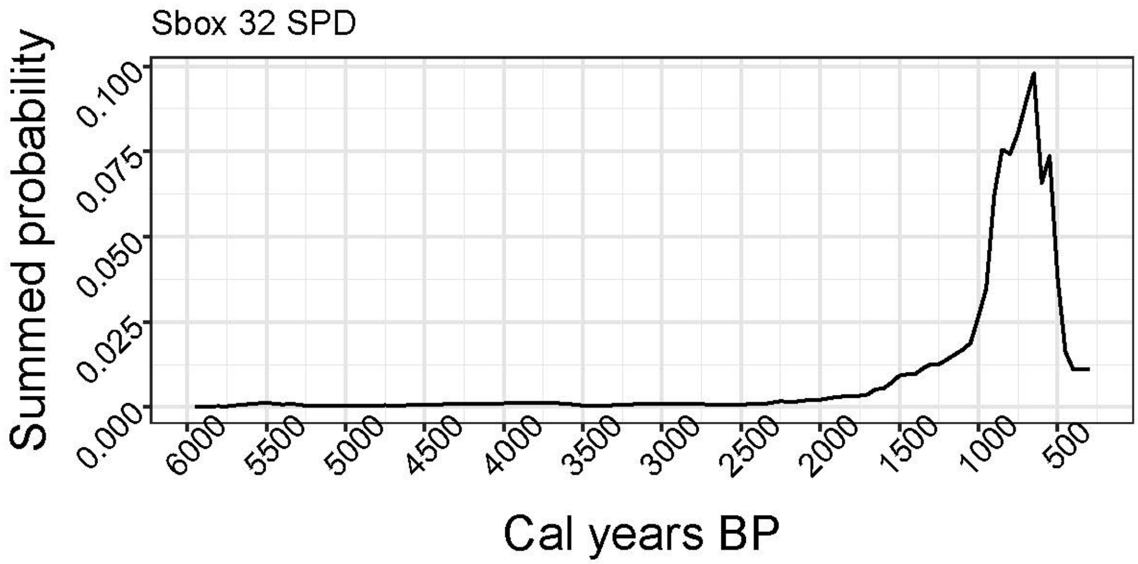

Sbox 27 SPD
Summed probability
0.01
0.02
0.03
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP

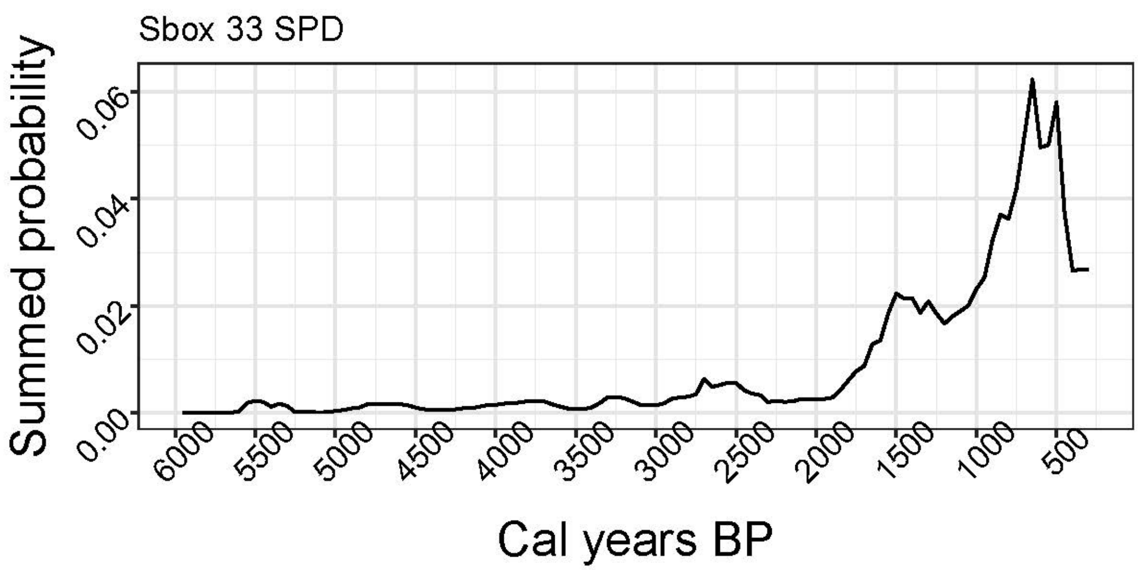

Sbox 28 SPD
Summed probability
0.01
0.02
0.03
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP

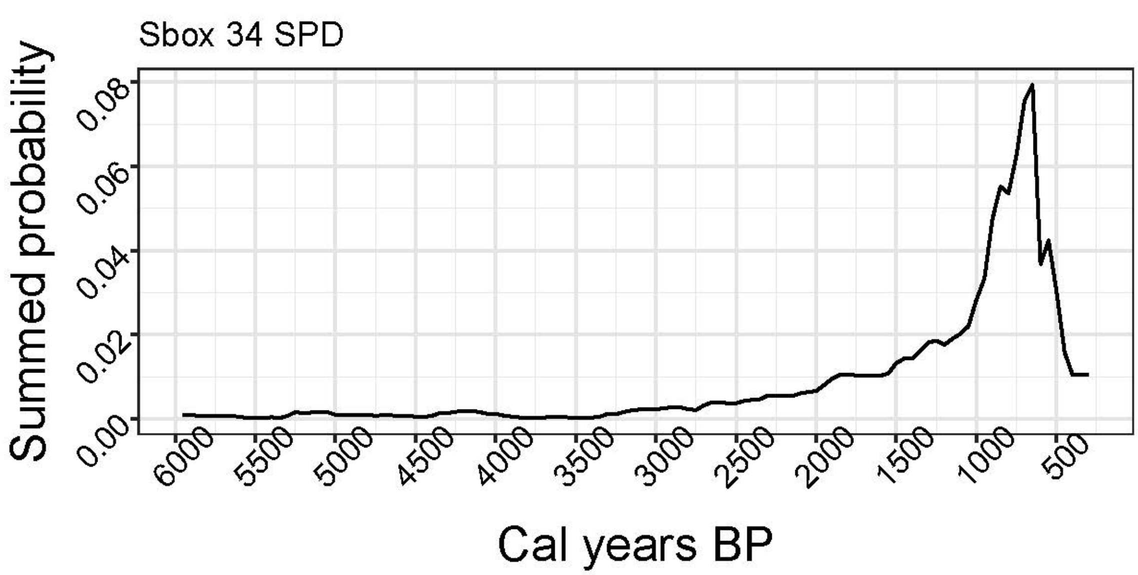

Sbox 29 SPD
Summed probability
0.01
0.02
0.03
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP

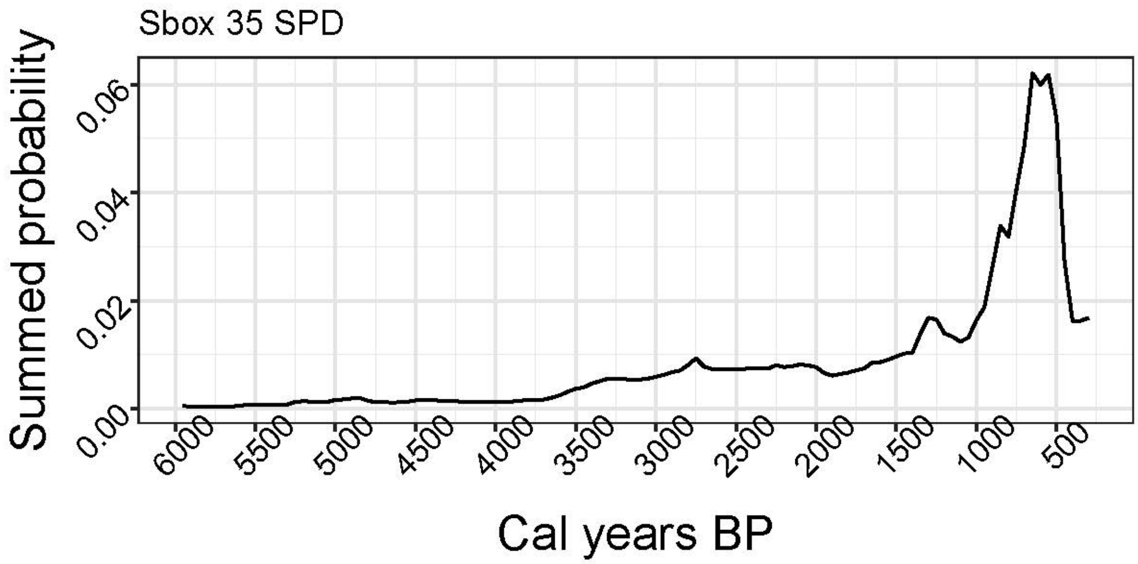

Sbox 30 SPD
Summed probability
0.01
0.02
0.03
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP

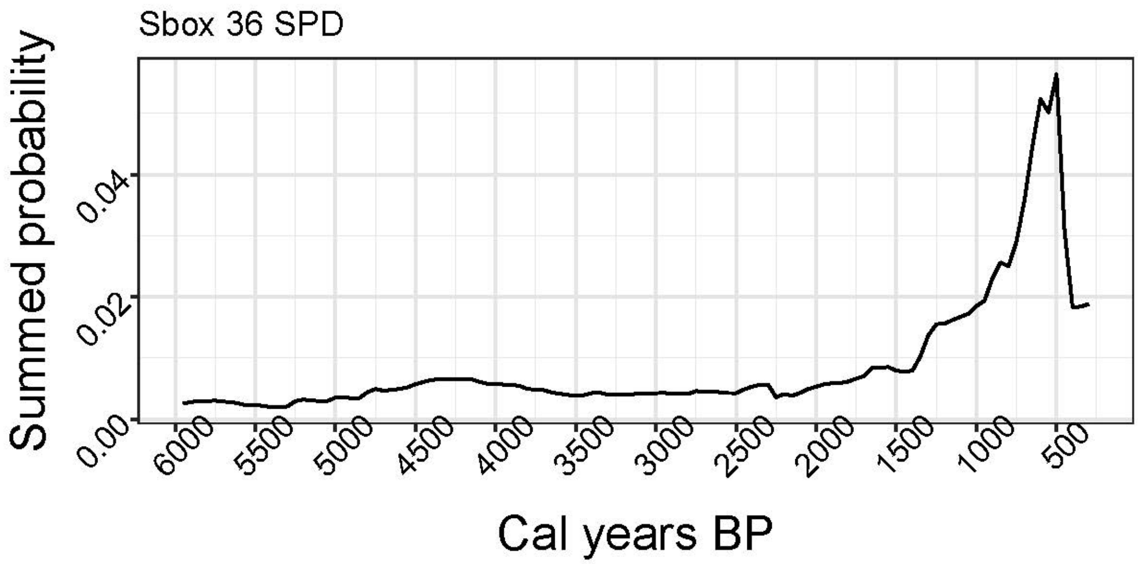

Sbox 31 SPD
Summed probability
0.00
0.02
0.04
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP

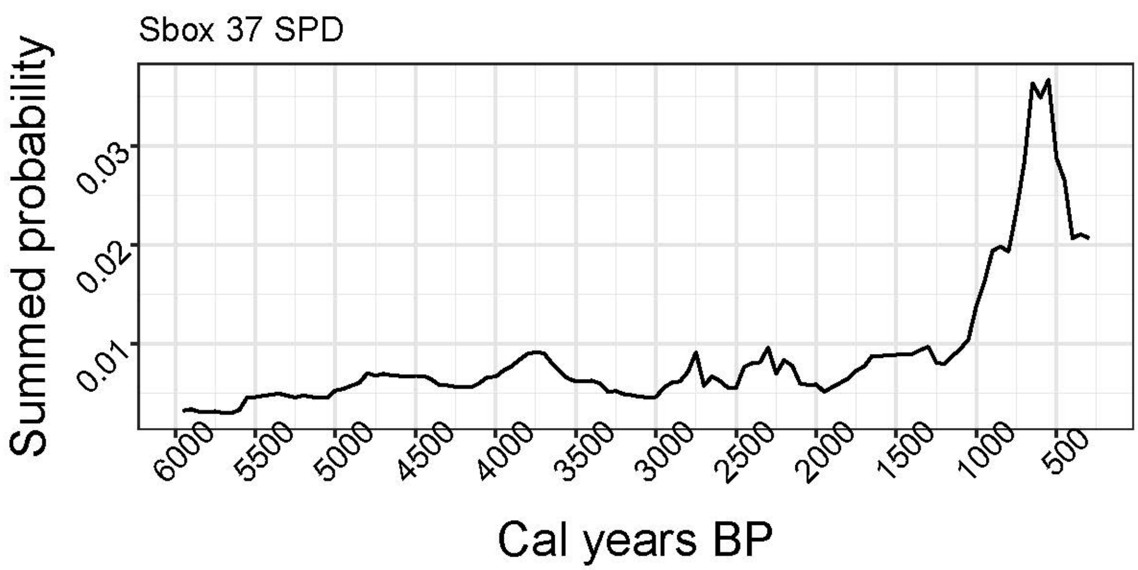

Sbox 32 SPD
Summed probability
0.000
0.025
0.050
0.075
0.100
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP

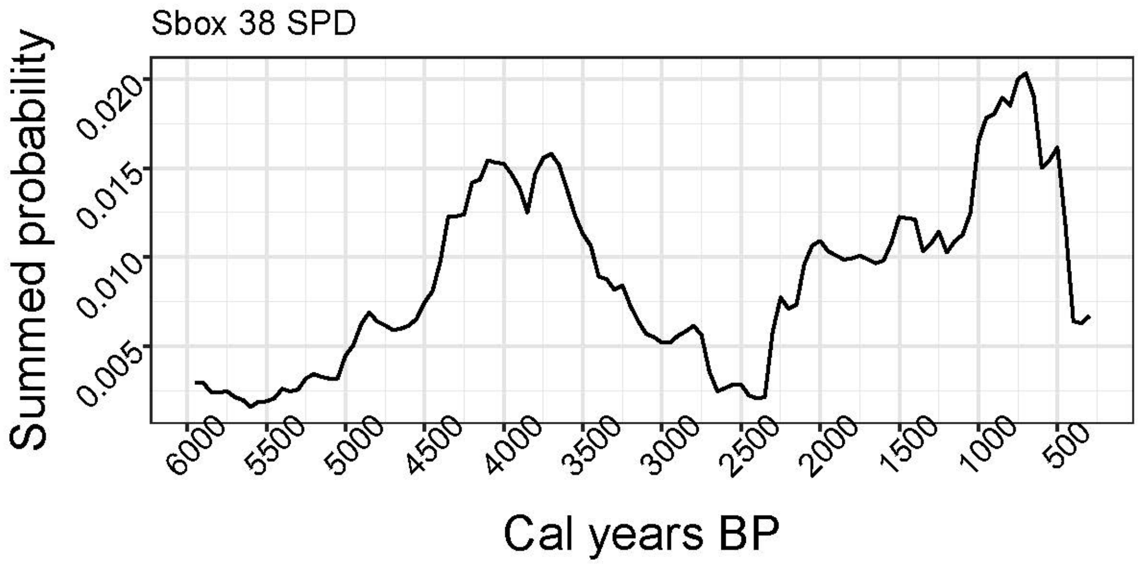

Sbox 33 SPD
Summed probability
0.00
0.02
0.04
0.06
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP

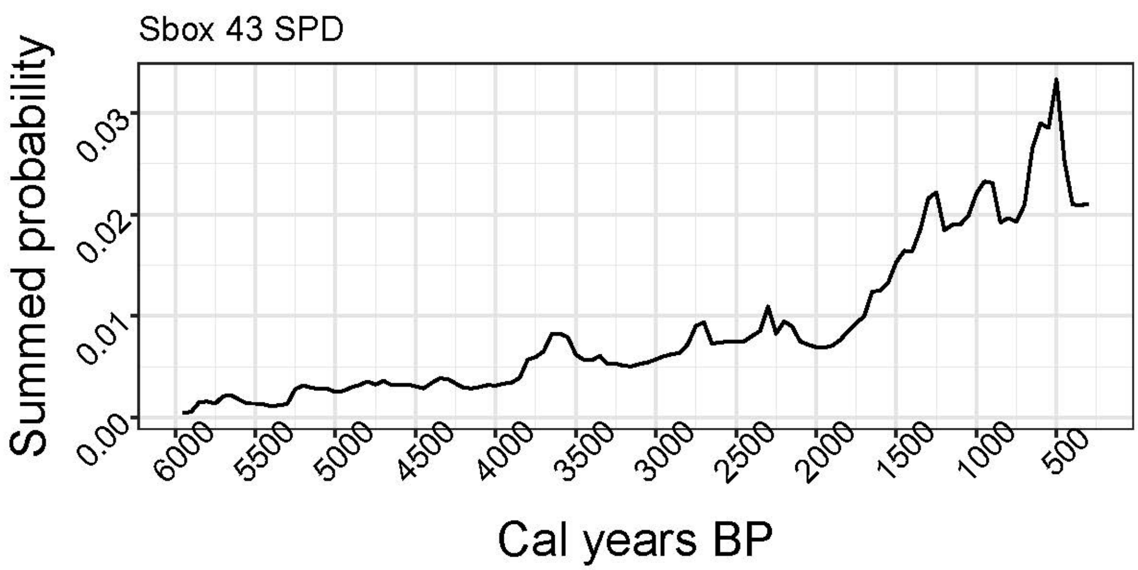

Sbox 34 SPD
Summed probability
0.00
0.02
0.04
0.06
0.08
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP

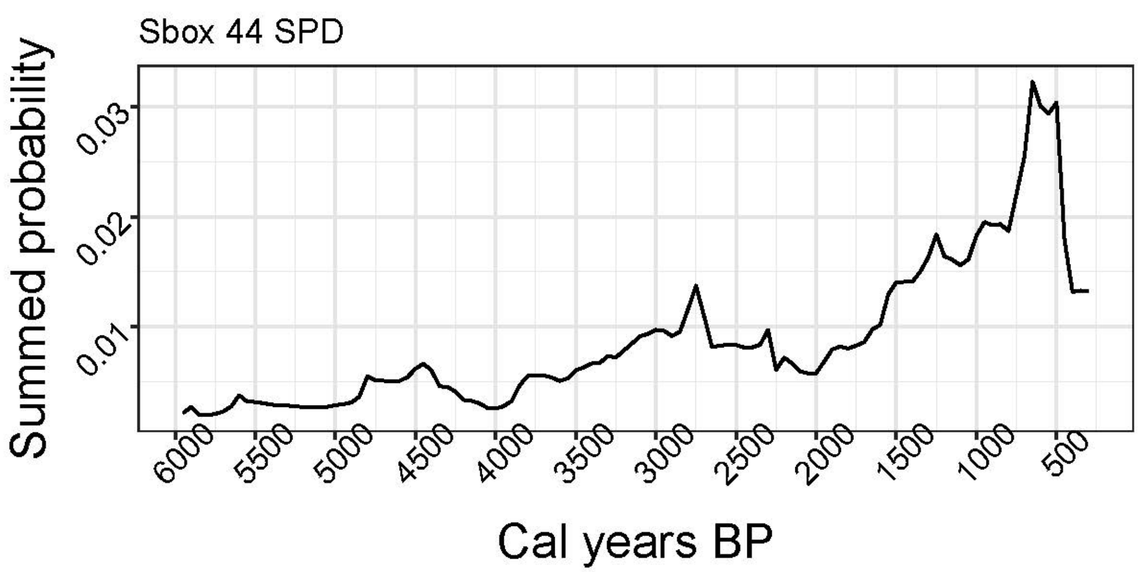

Sbox 35 SPD
Summed probability
0.00
0.02
0.04
0.06
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP

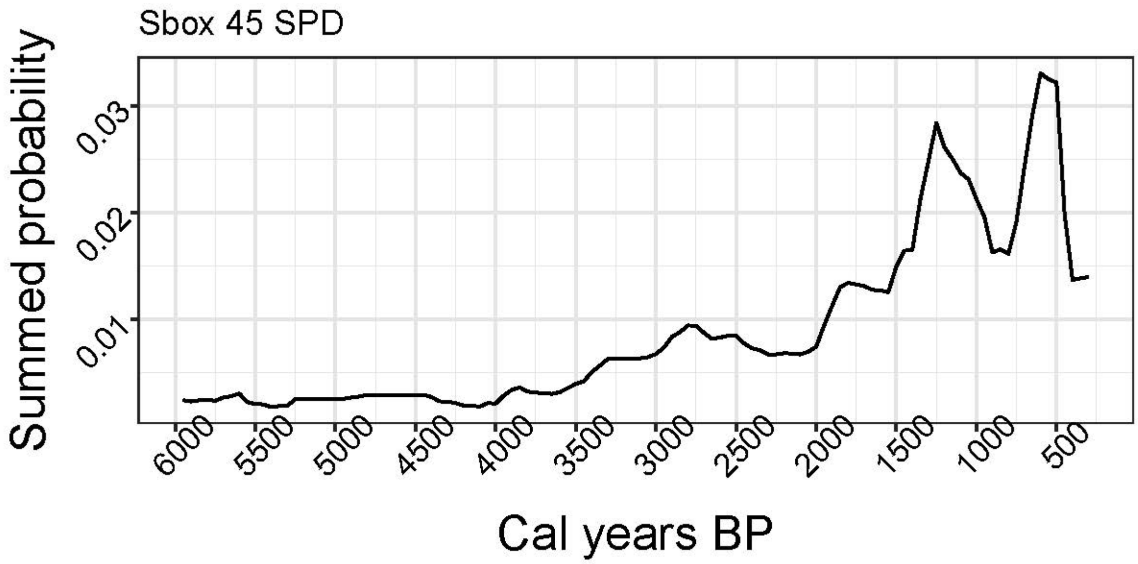

Sbox 36 SPD
Summed probability
0.00
0.02
0.04
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP


Sbox 37 SPD
Summed probability
0.01
0.02
0.03
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP


Sbox 38 SPD
Summed probability
0.005
0.010
0.015
0.020
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP


Sbox 43 SPD
Summed probability
0.00
0.01
0.02
0.03
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP


Sbox 44 SPD
Summed probability
0.01
0.02
0.03
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP


Sbox 45 SPD
Summed probability
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0.02
0.01
6000
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5000
4500
4000
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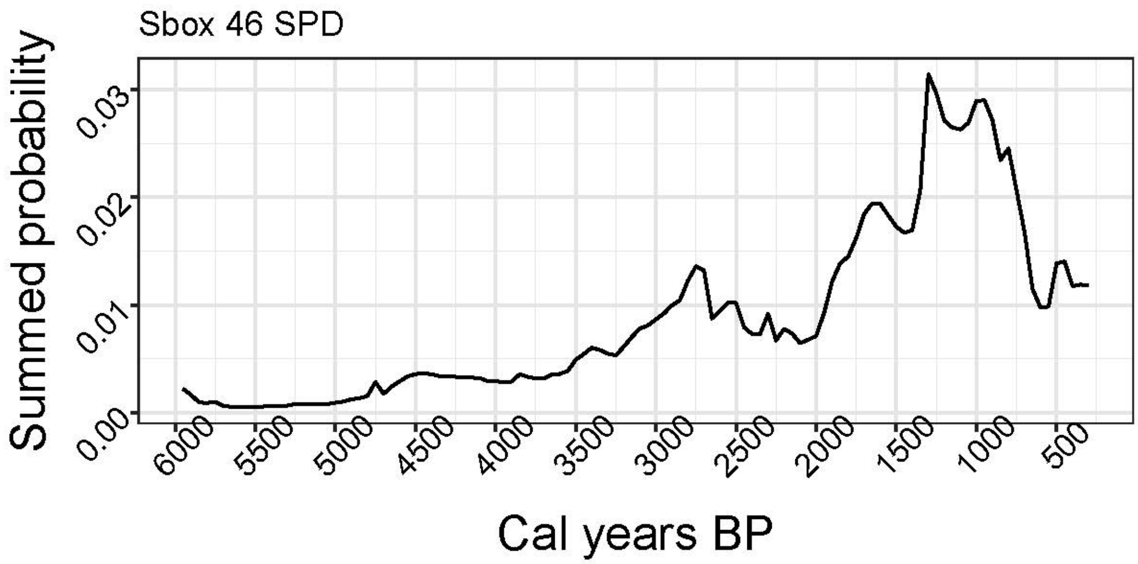
3000
2500
2000
1500
1000
500
Cal years BP


Sbox 46 SPD
Summed probability
0.03
0.02
0.01
0.00
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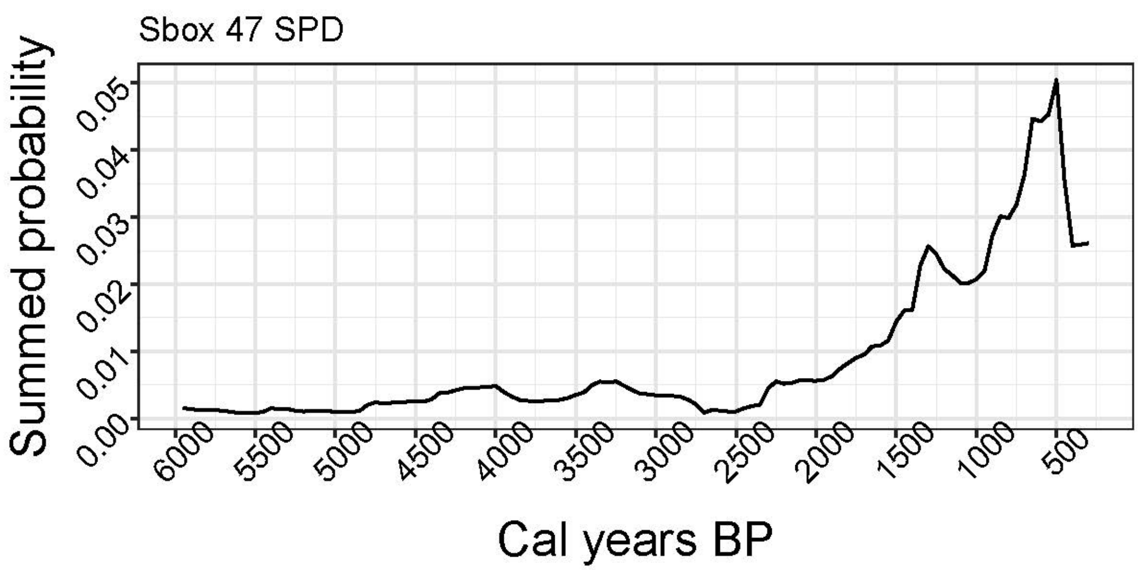
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP


Sbox 47 SPD
Summed probability
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0.04
0.03
0.02
0.01
0.00
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5000
4500
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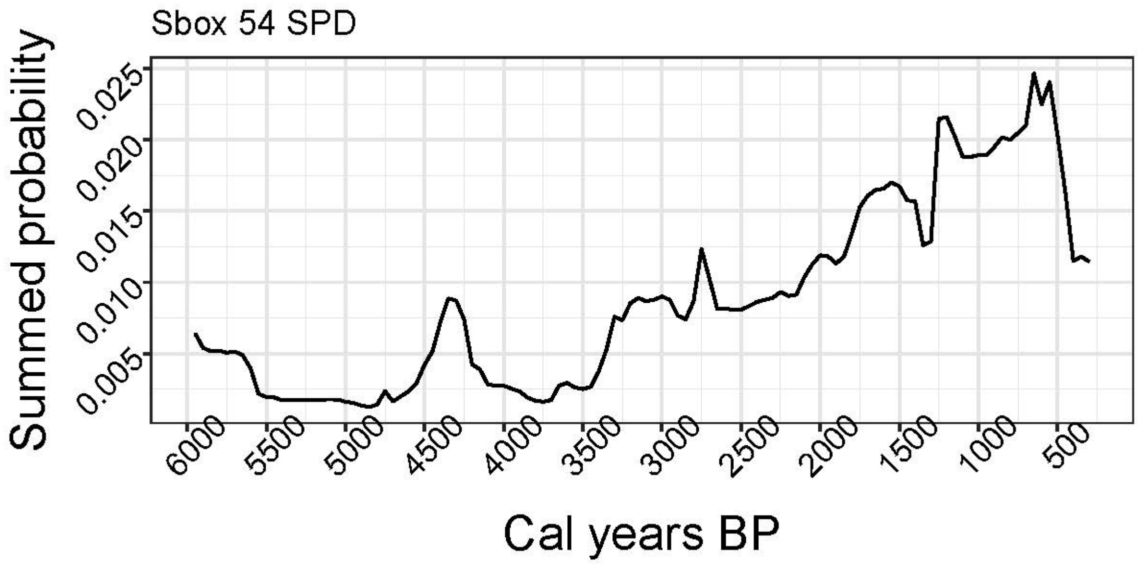
3000
2500
2000
1500
1000
500
Cal years BP


Sbox 54 SPD
Summed probability
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0.020
0.015
0.010
0.005
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3000
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2000
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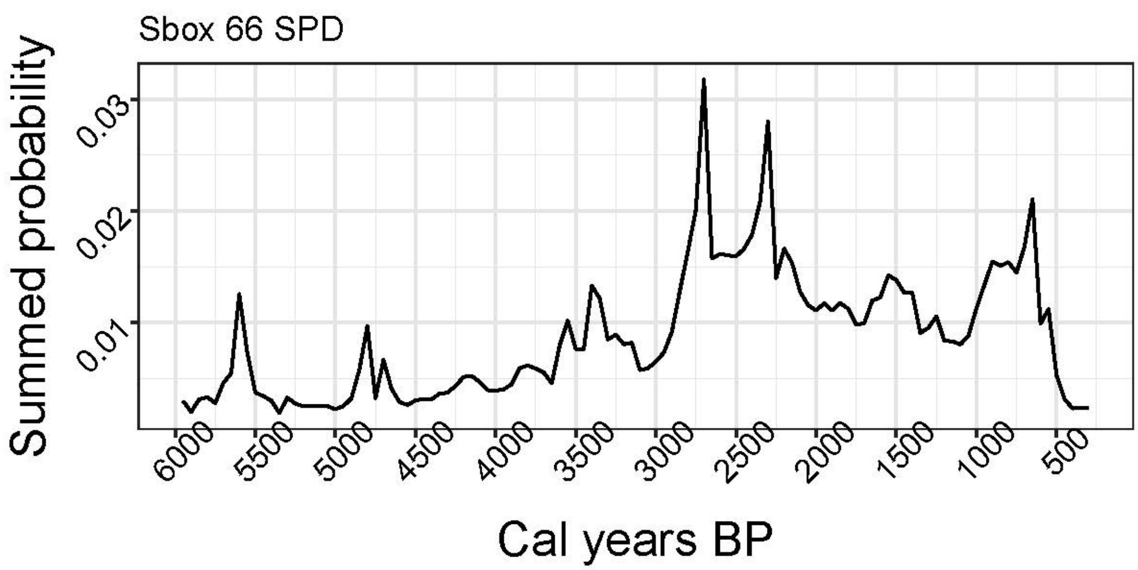
Cal years BP


Sbox 66 SPD
Summed probability
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1000
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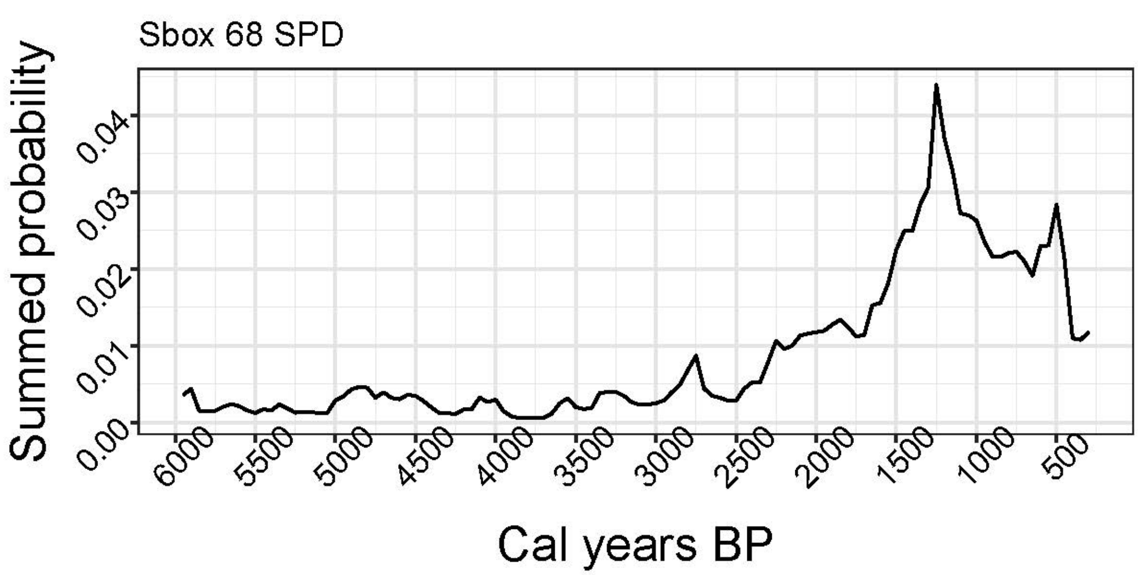
Cal years BP


Sbox 68 SPD
Summed probability
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0.03
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0.01
0.00
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3000
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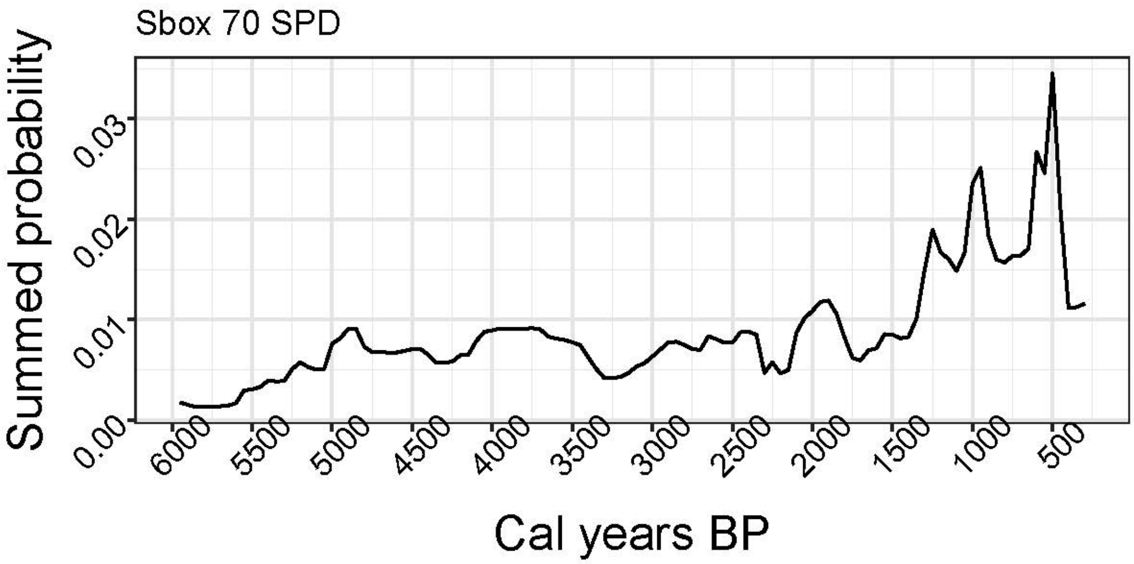
1000
500
Cal years BP


Sbox 70 SPD
Summed probability
0.00
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0.02
0.03
6000
5500
5000
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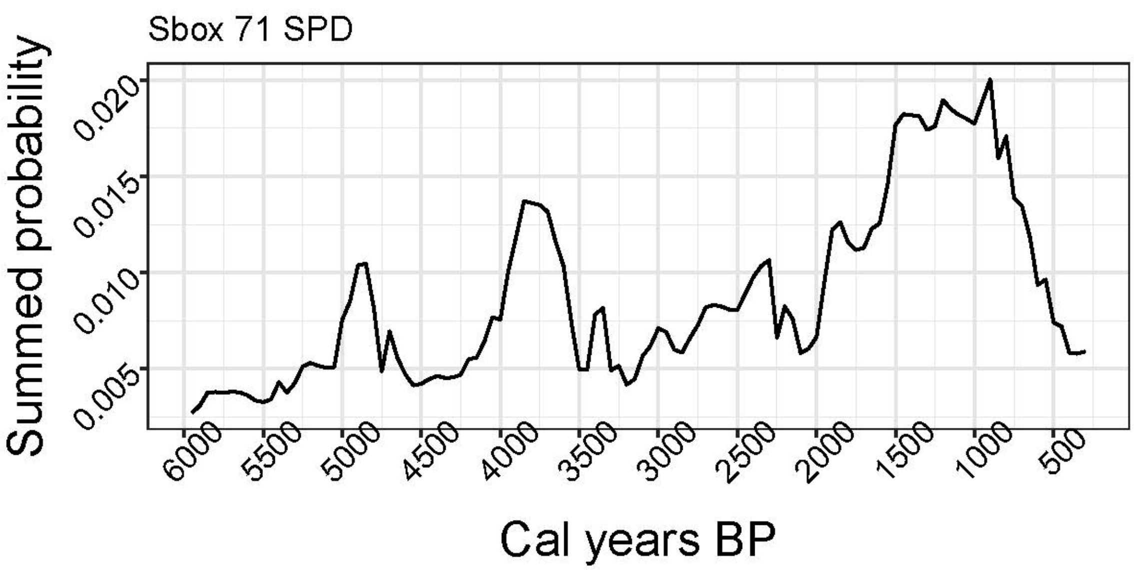
Cal years BP


Sbox 71 SPD
Summed probability
0.005
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0.020
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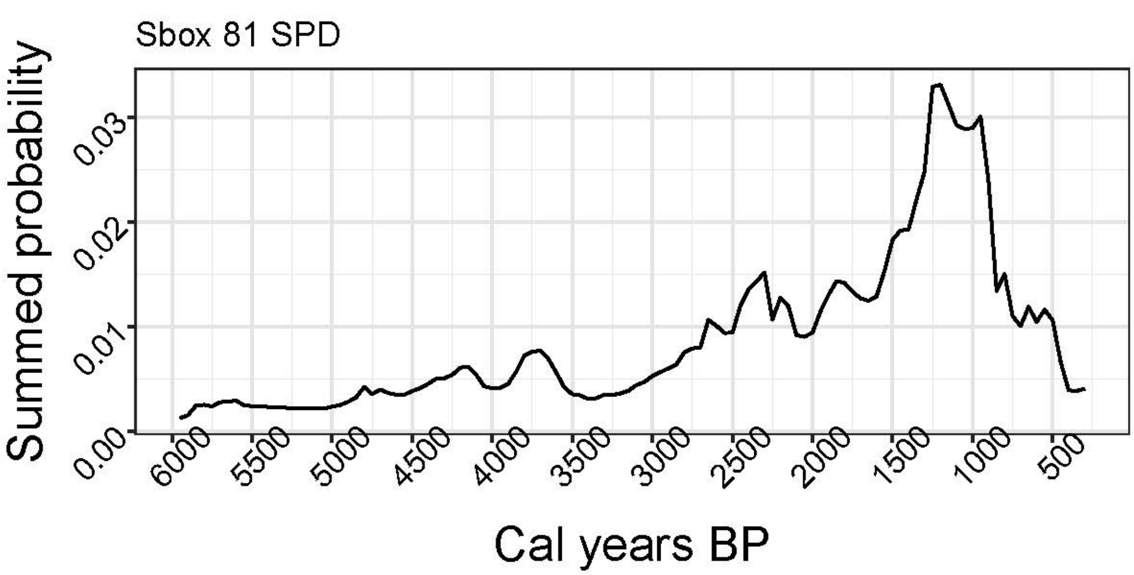
1000
500
Cal years BP


Sbox 81 SPD
Summed probability
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0.03
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2000
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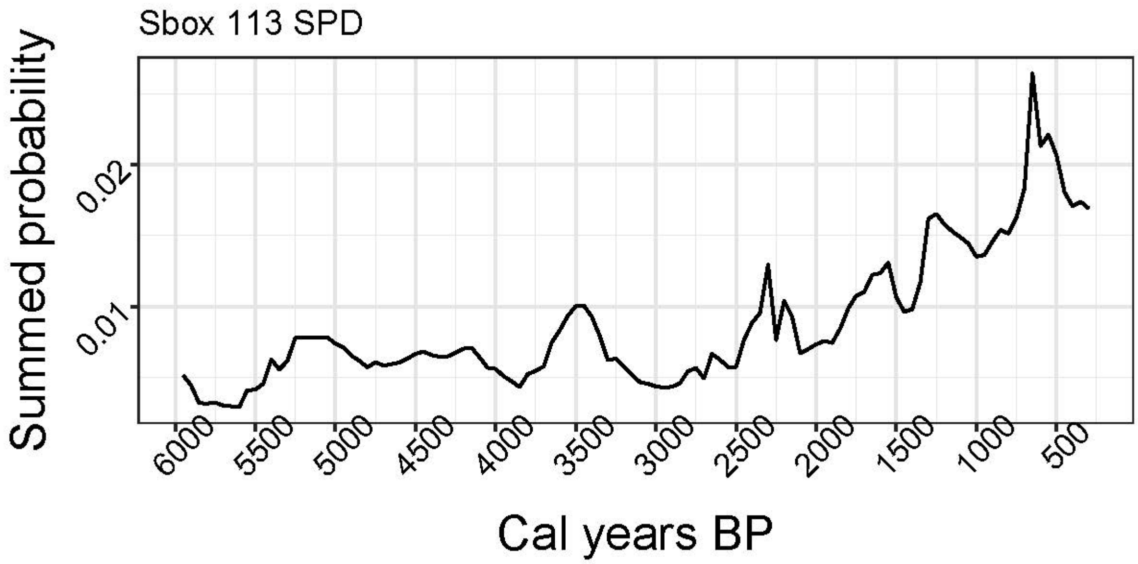
1000
500
Cal years BP


Sbox 113 SPD
Summed probability
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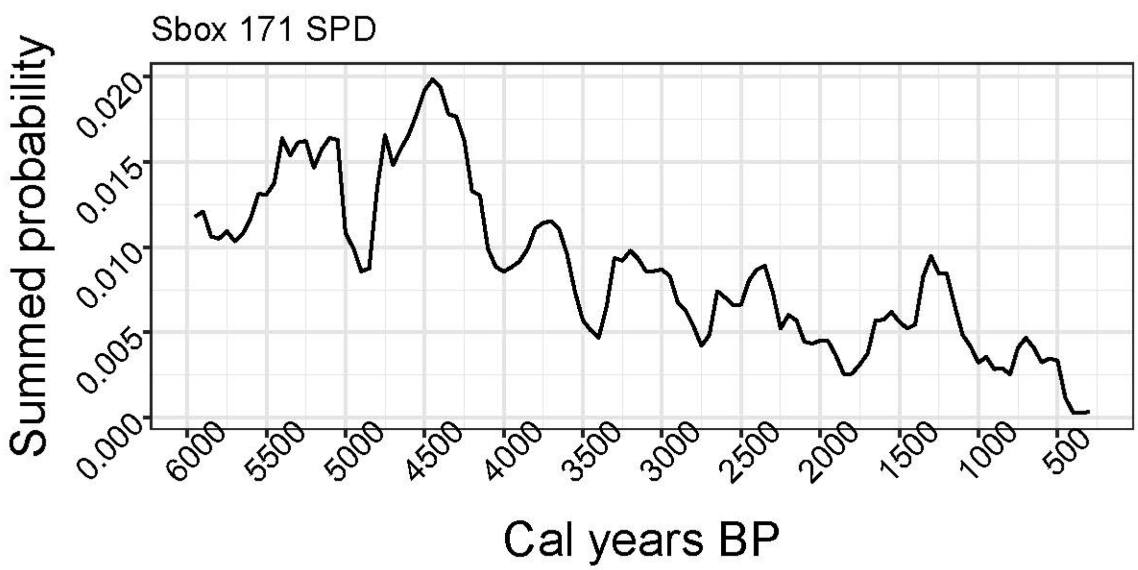
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP


Sbox 171 SPD
Summed probability
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0.015
0.010
0.005
0.000
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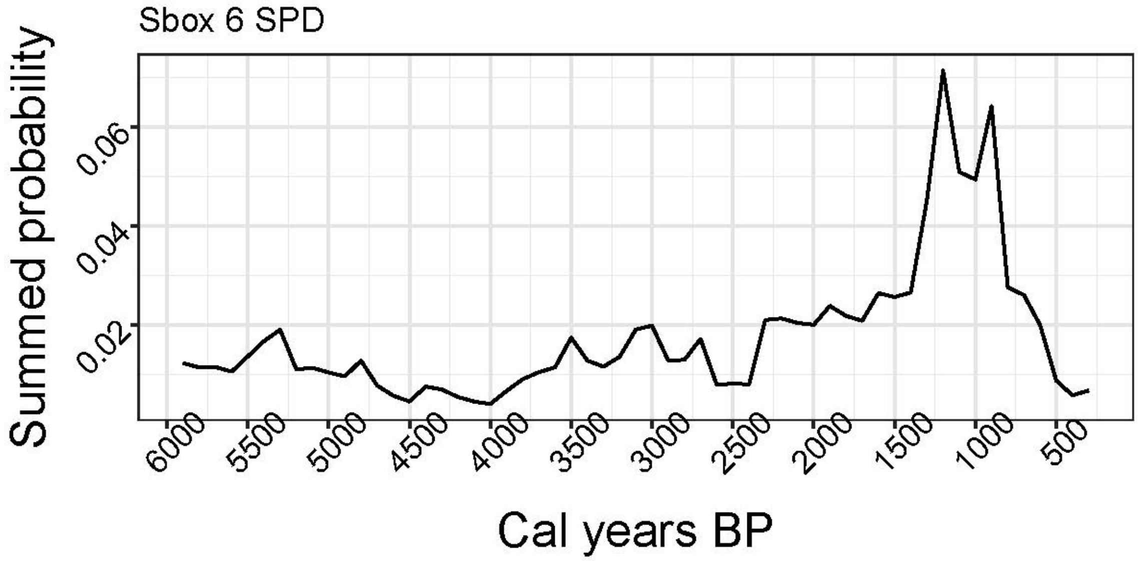
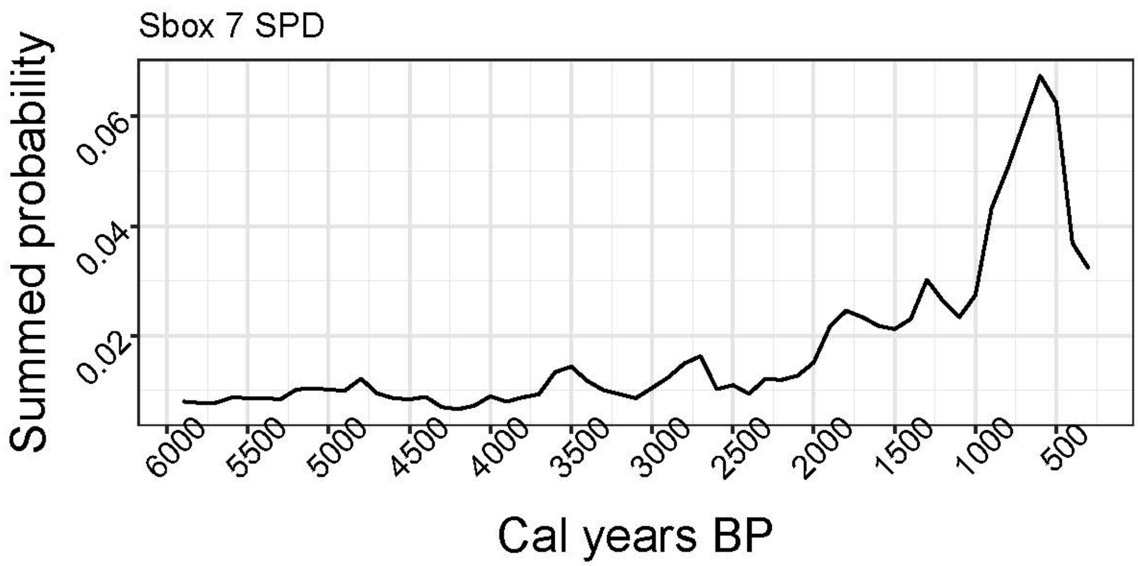
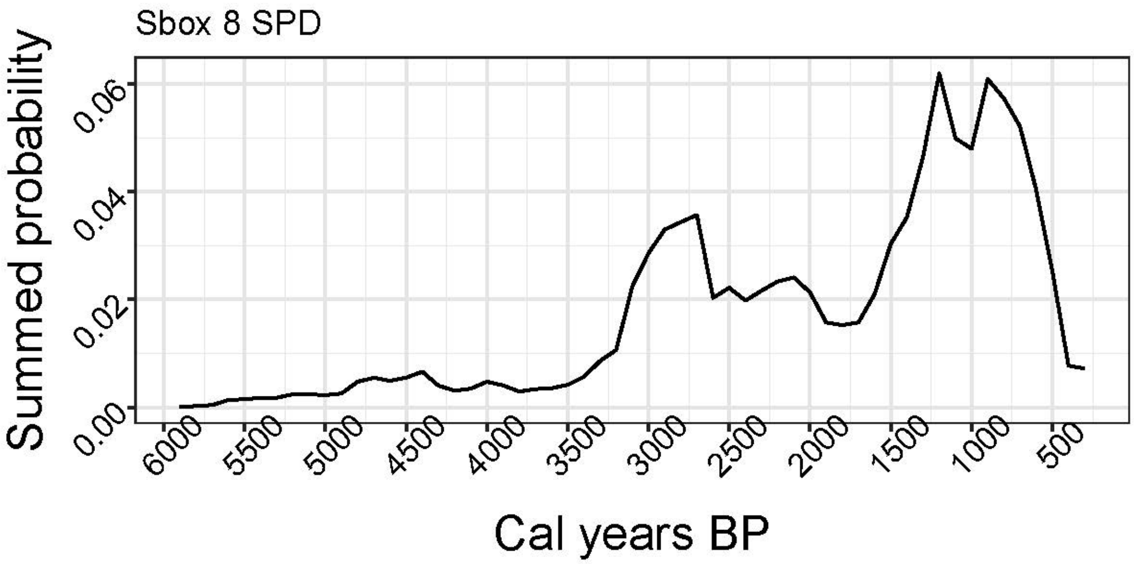
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP

At the 100-year time scale:






Sbox 8 SPD
Summed probability
0.00
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0.04
0.06
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5500
5000
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4000
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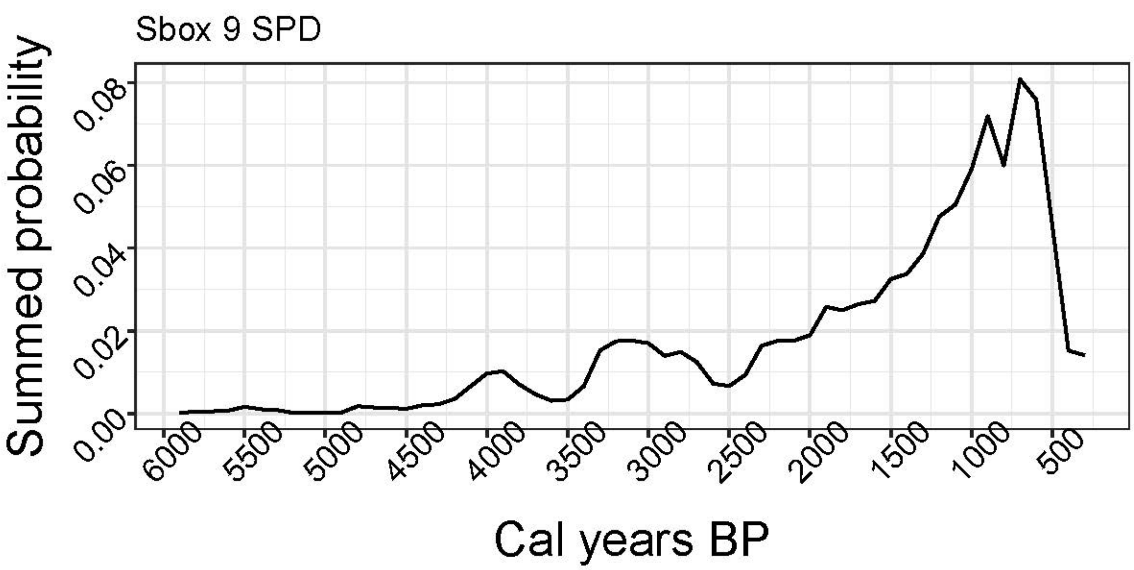
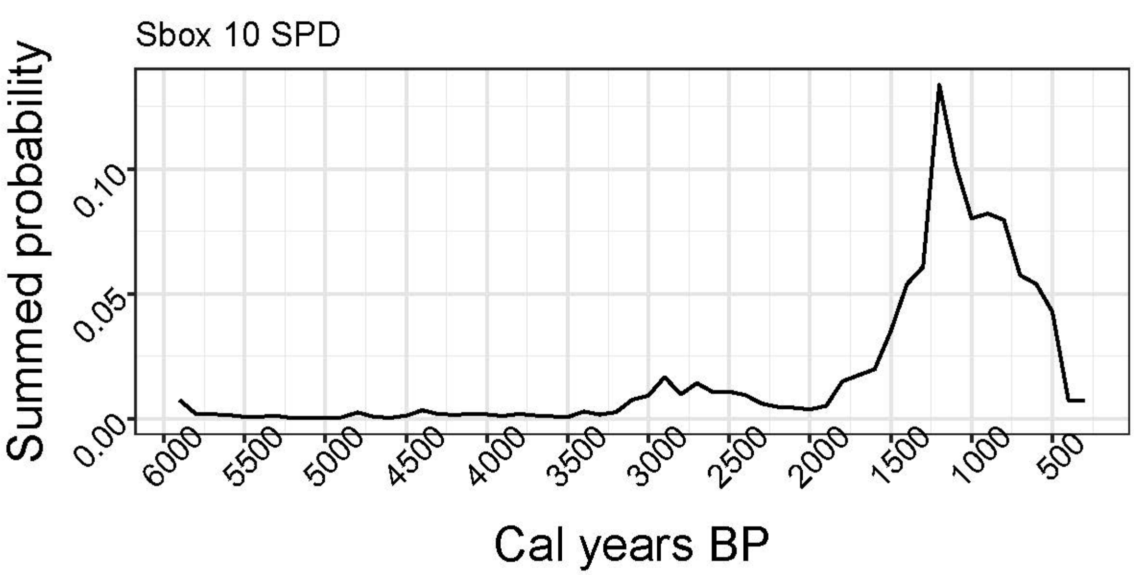
3000
2500
2000
1500
1000
500
Cal years BP


Sbox 9 SPD
Summed probability
0.00
0.02
0.04
0.06
0.08
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP


Sbox 10 SPD
Summed probability
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0.10
6000
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5000
4500
4000
3500
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2500
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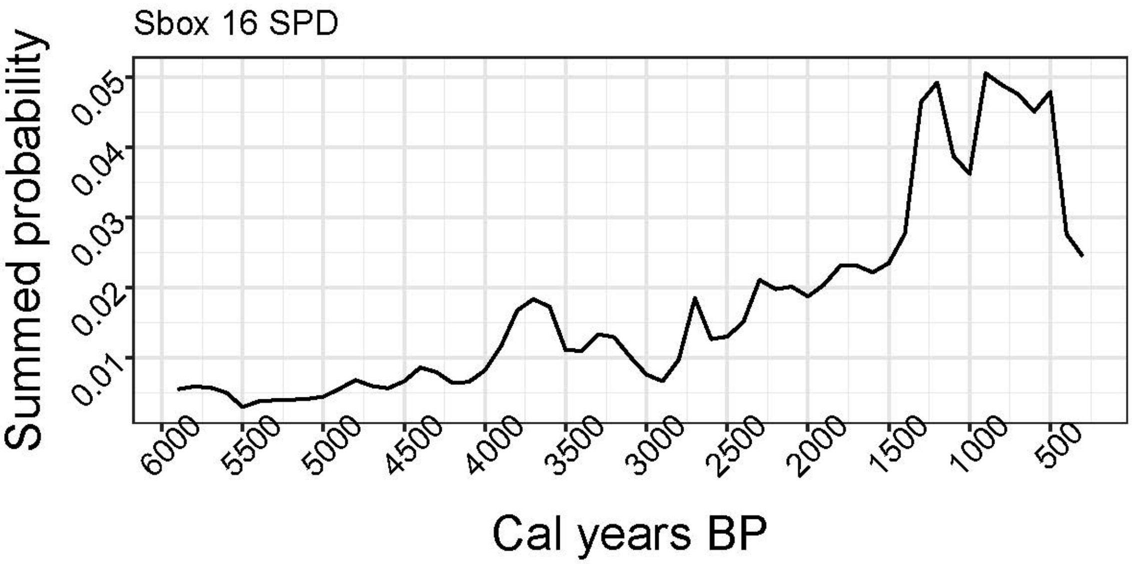
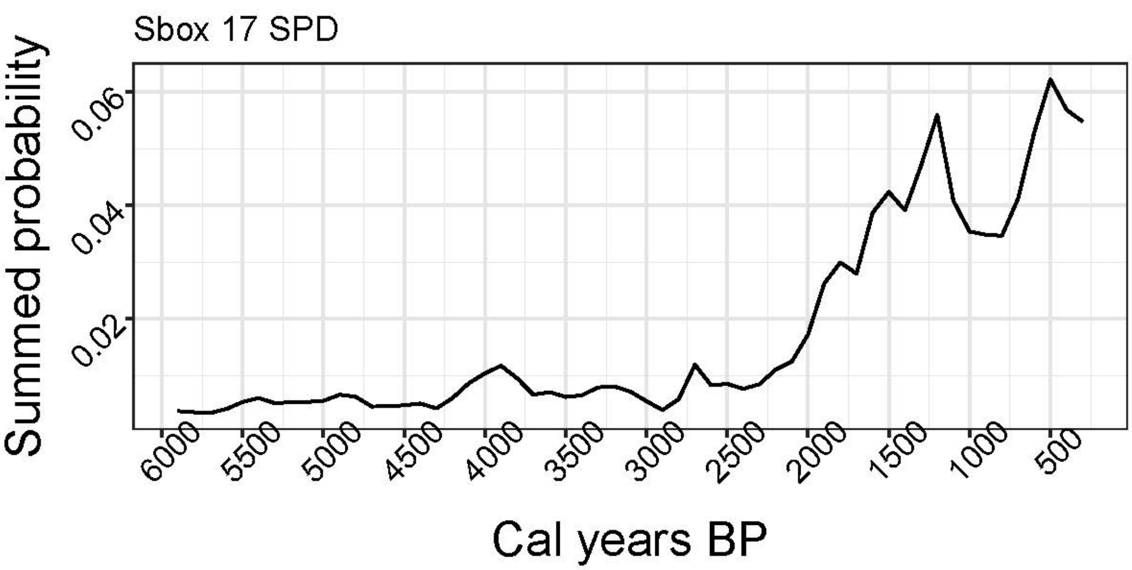
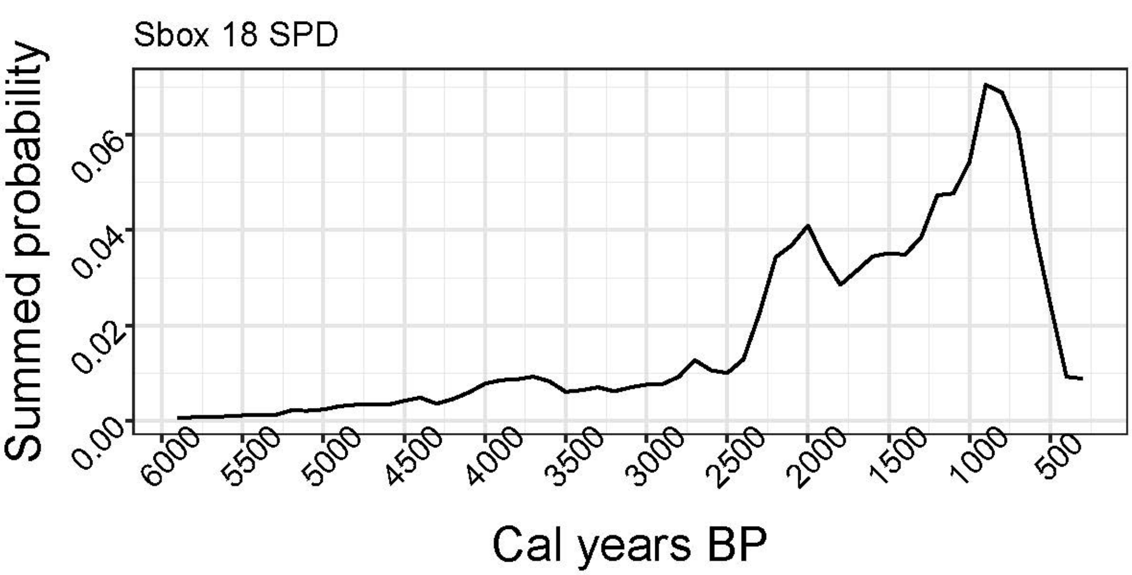
1500
1000
500
Cal years BP


Sbox 16 SPD
Summed probability
0.05
0.04
0.03
0.02
0.01
6000 5500 5000 4500 4000 3500 3000 2500 2000 1500 1000 500
Cal years BP


Sbox 17 SPD
Summed probability
0.06
0.04
0.02
6000 5500 5000 4500 4000 3500 3000 2500 2000 1500 1000 500
Cal years BP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Summed probability
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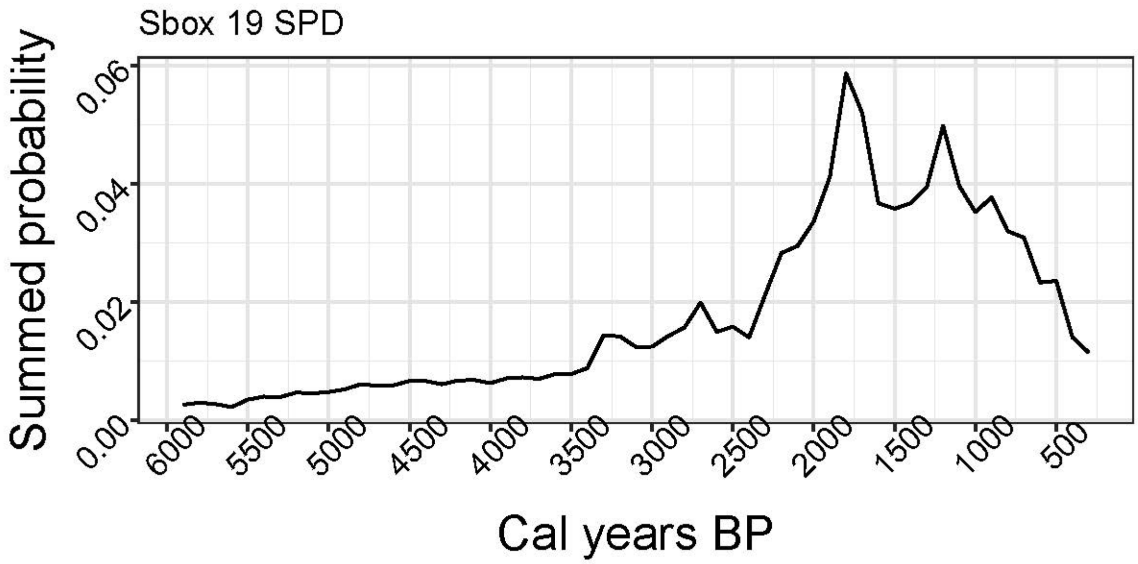
0.04
0.02
0.00
6000 5500 5000 4500 4000 3500 3000 2500 2000 1500 1000 500
Cal years BP


Sbox 19 SPD
Summed probability
0.00
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0.06
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1000
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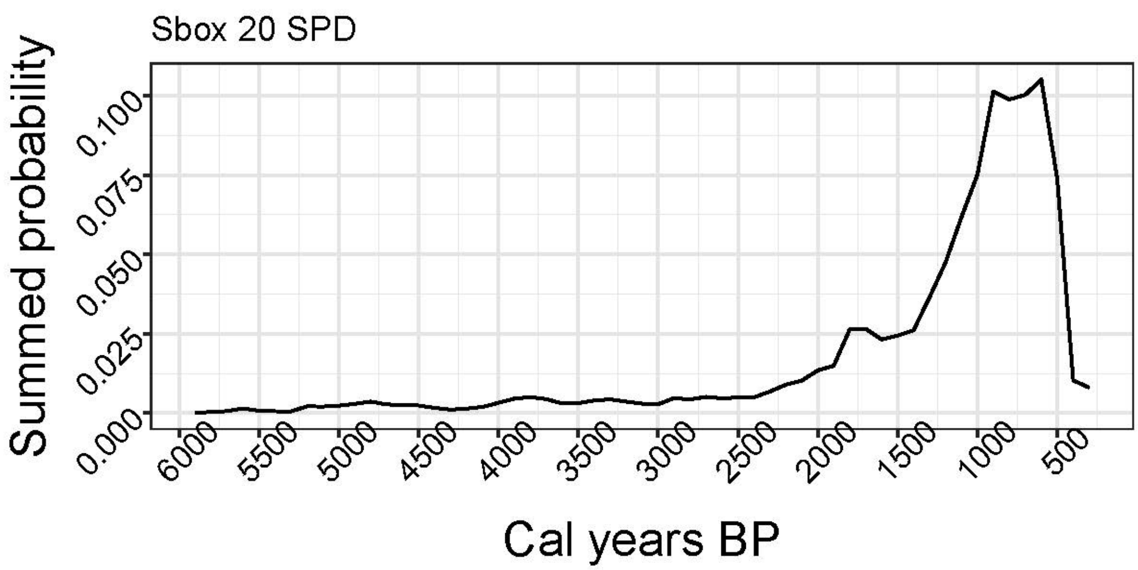
Cal years BP


Sbox 20 SPD
Summed probability
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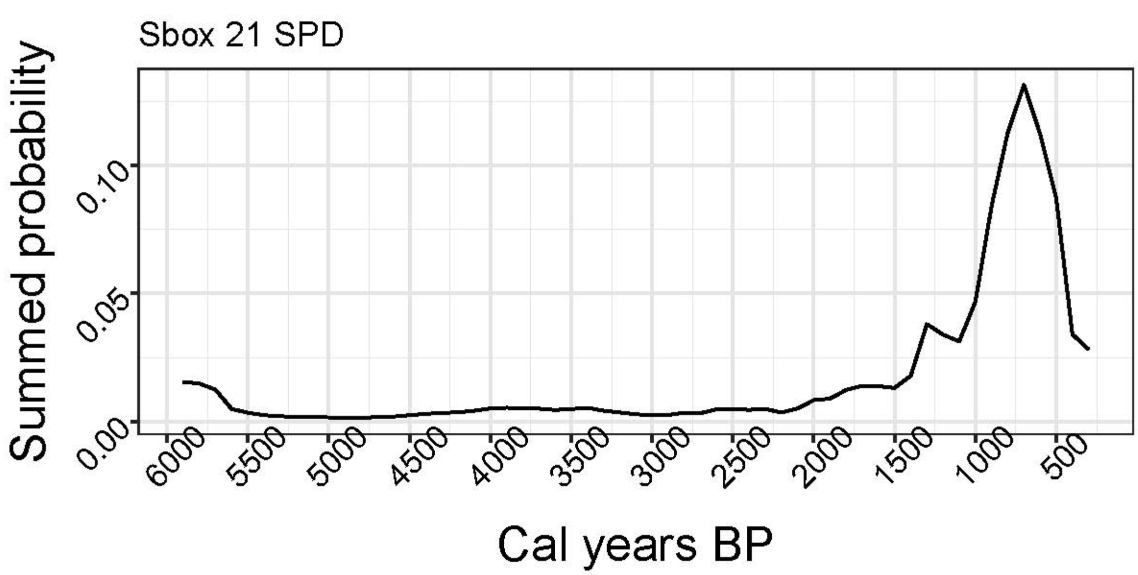
1500
1000
500
Cal years BP


Sbox 21 SPD
Summed probability
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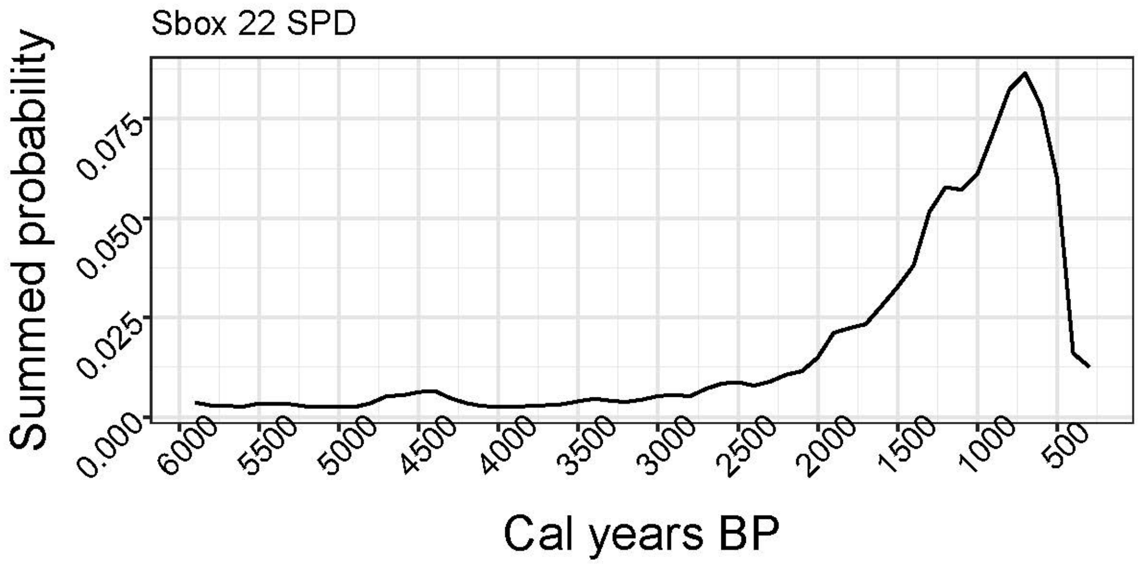
Cal years BP


Sbox 22 SPD
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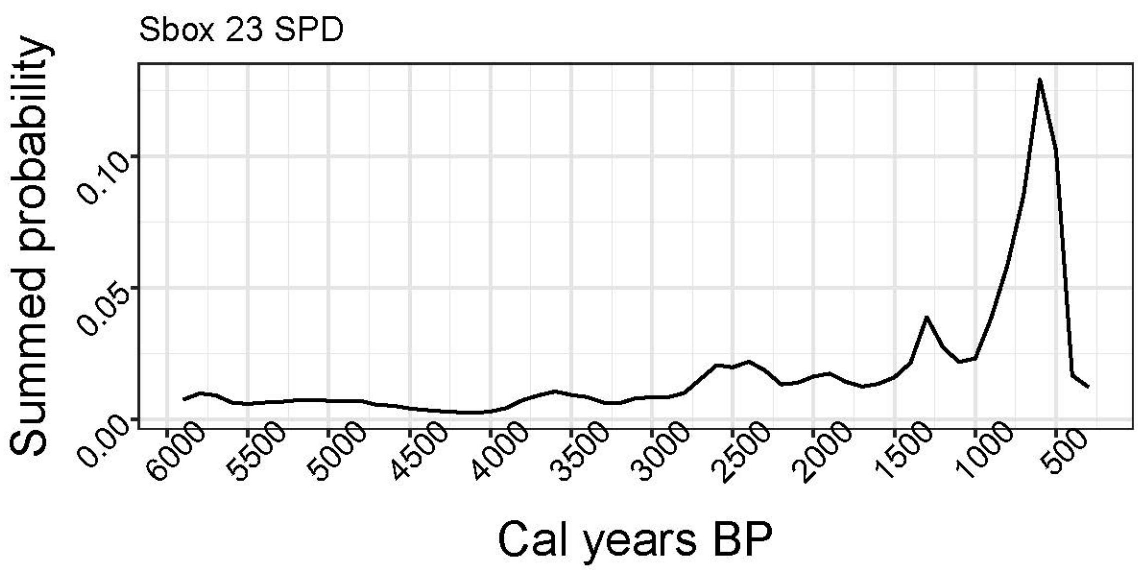
Cal years BP


Sbox 23 SPD
Summed probability
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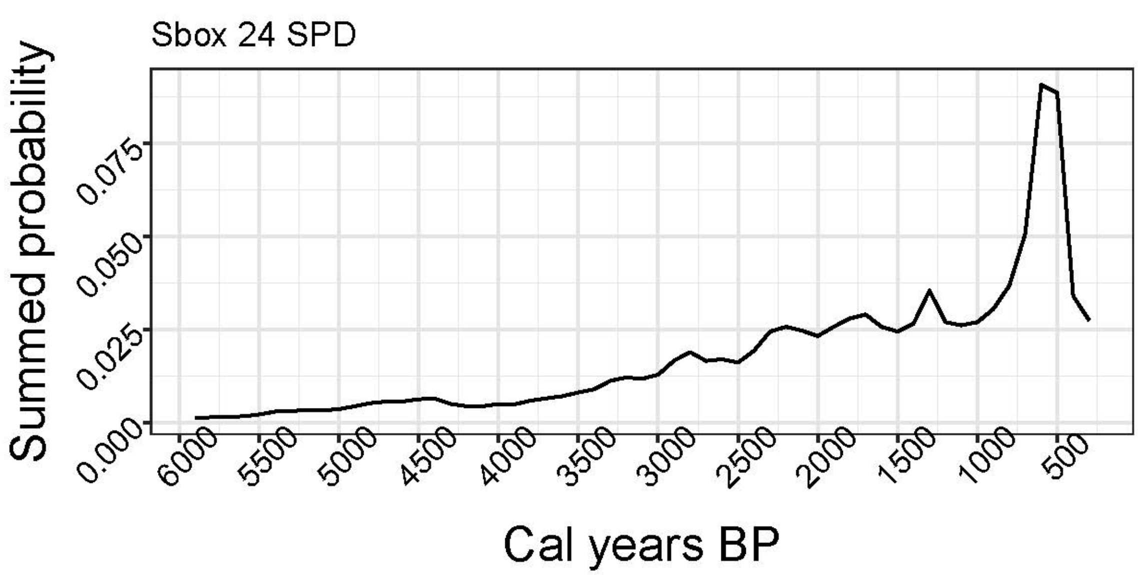
500
Cal years BP


Sbox 24 SPD
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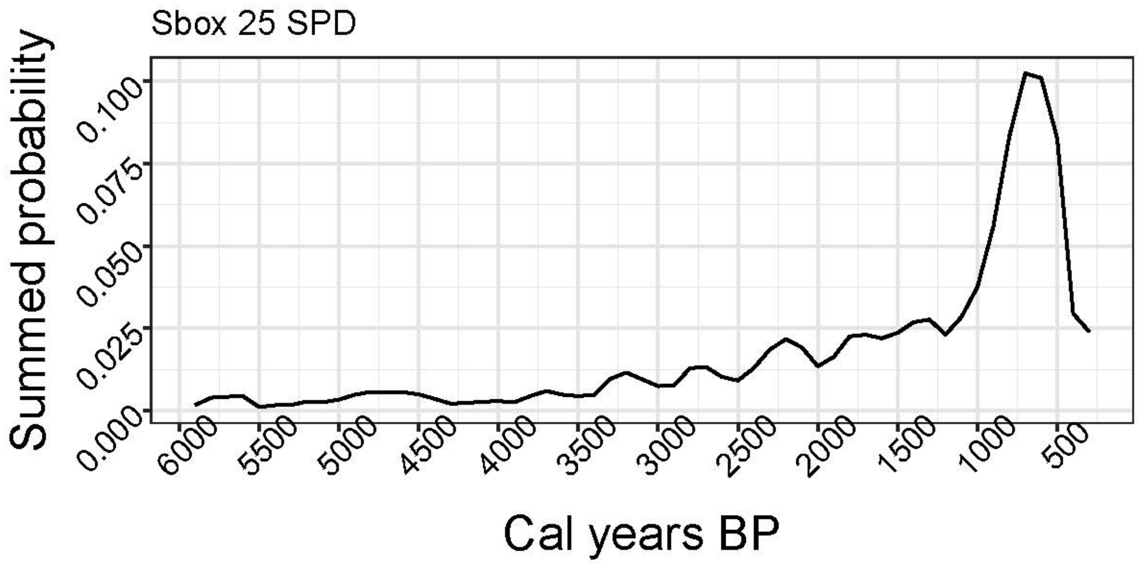
Cal years BP


Sbox 25 SPD
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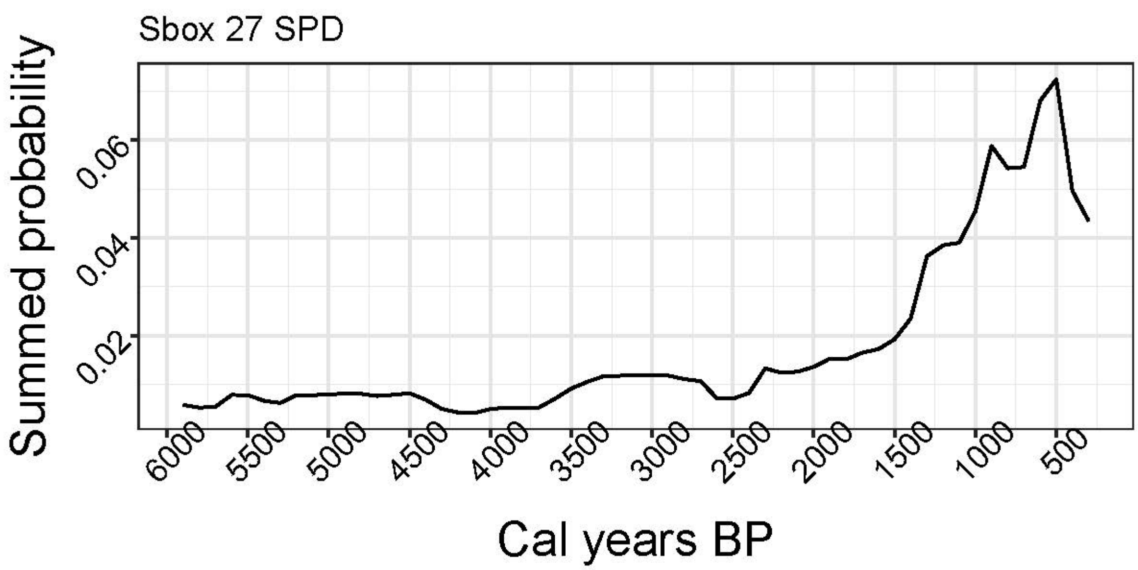
Cal years BP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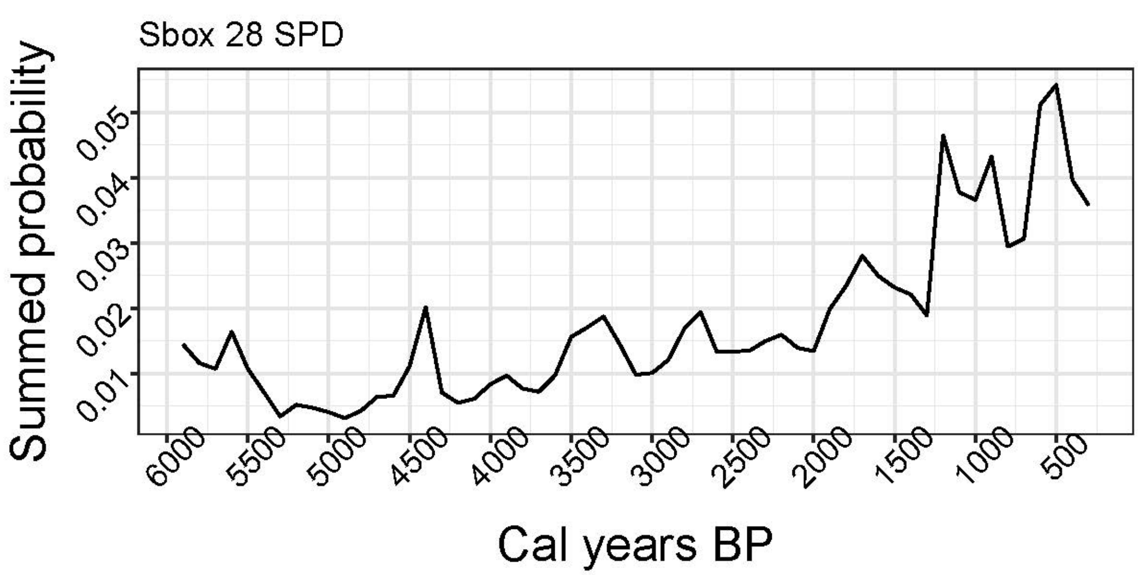
Cal years BP


Sbox 28 SPD
Summed probability
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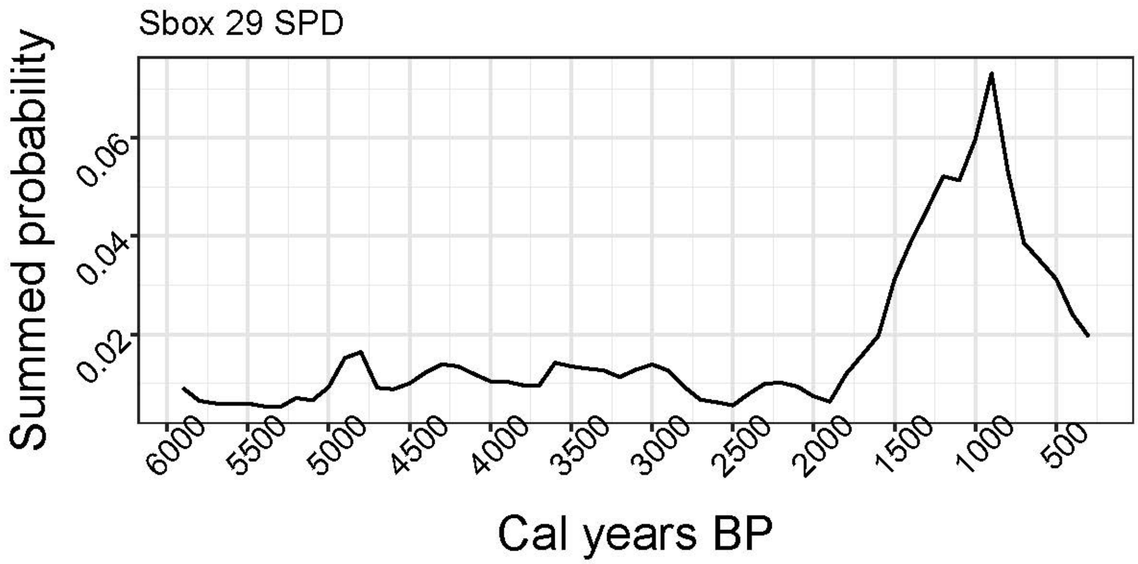
Cal years BP


Sbox 29 SPD
Summed probability
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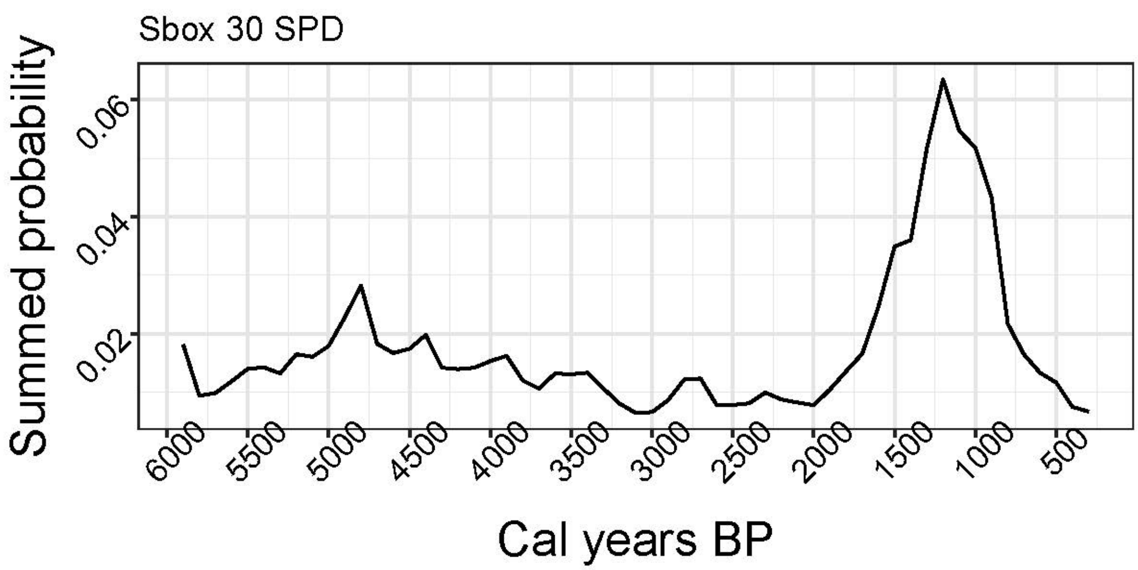
Cal years BP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Summed probability
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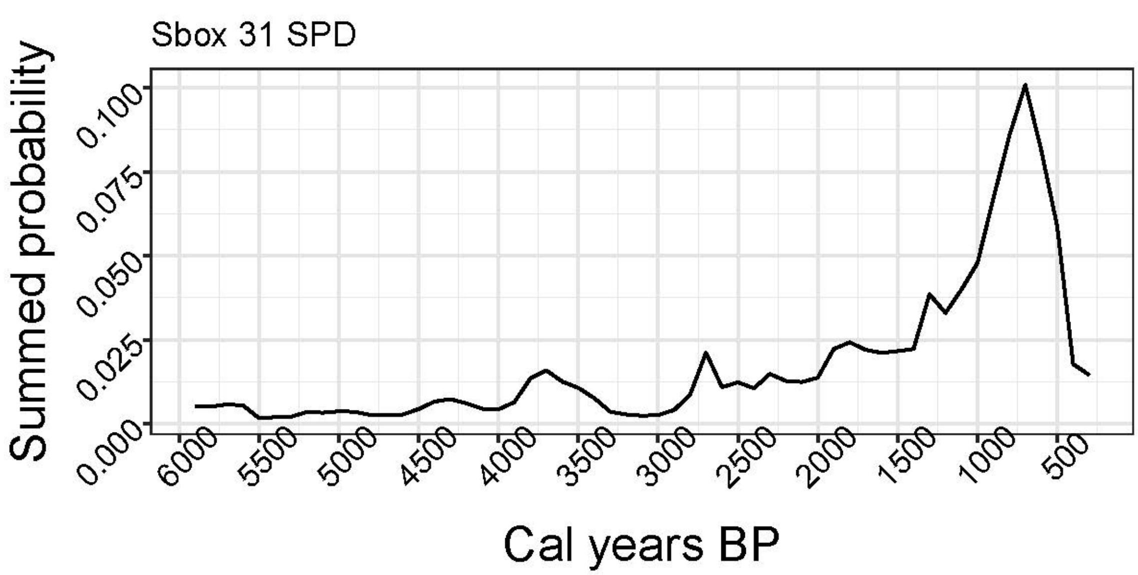
Cal years BP


Sbox 31 SPD
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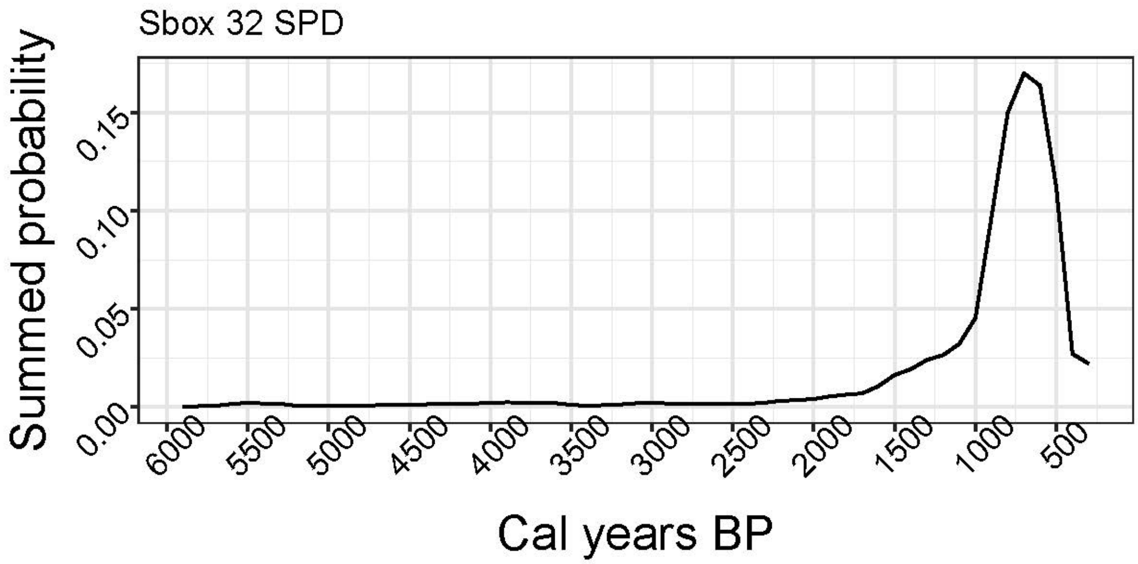
Cal years BP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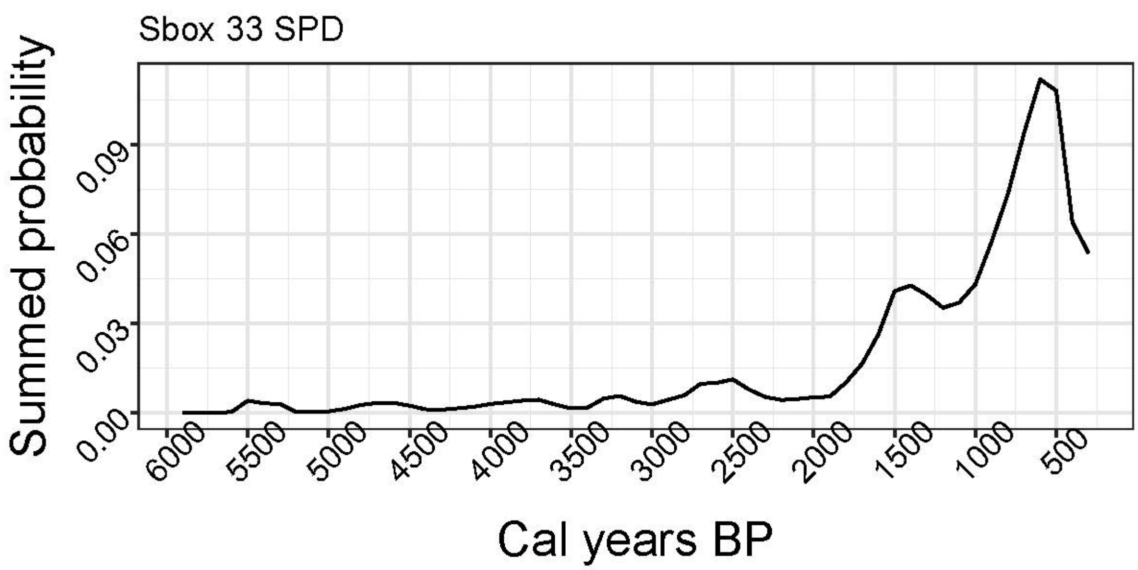
Cal years BP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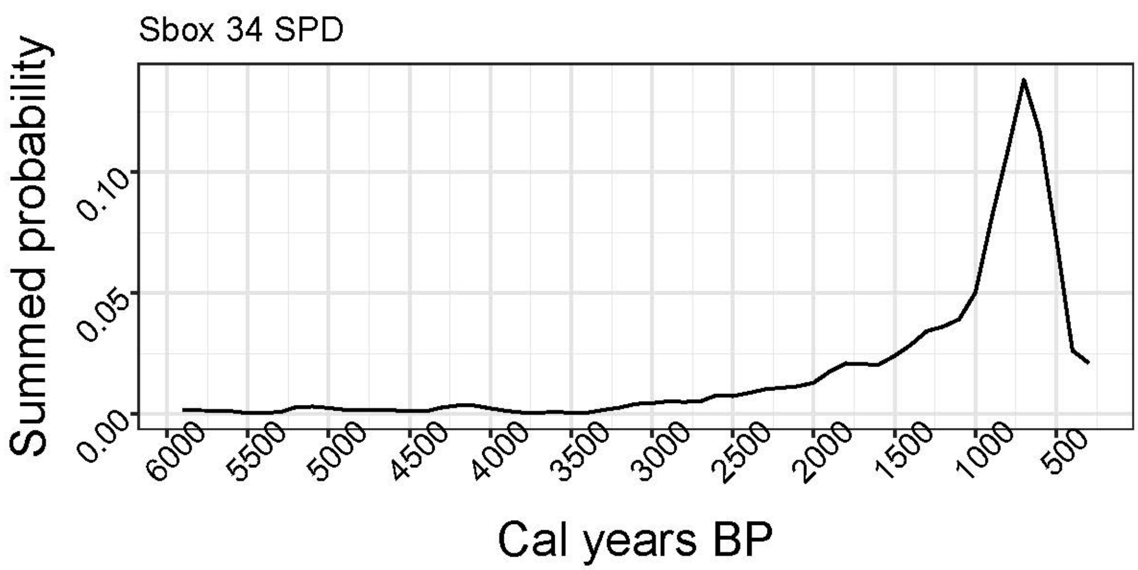
Cal years BP


Sbox 34 SPD
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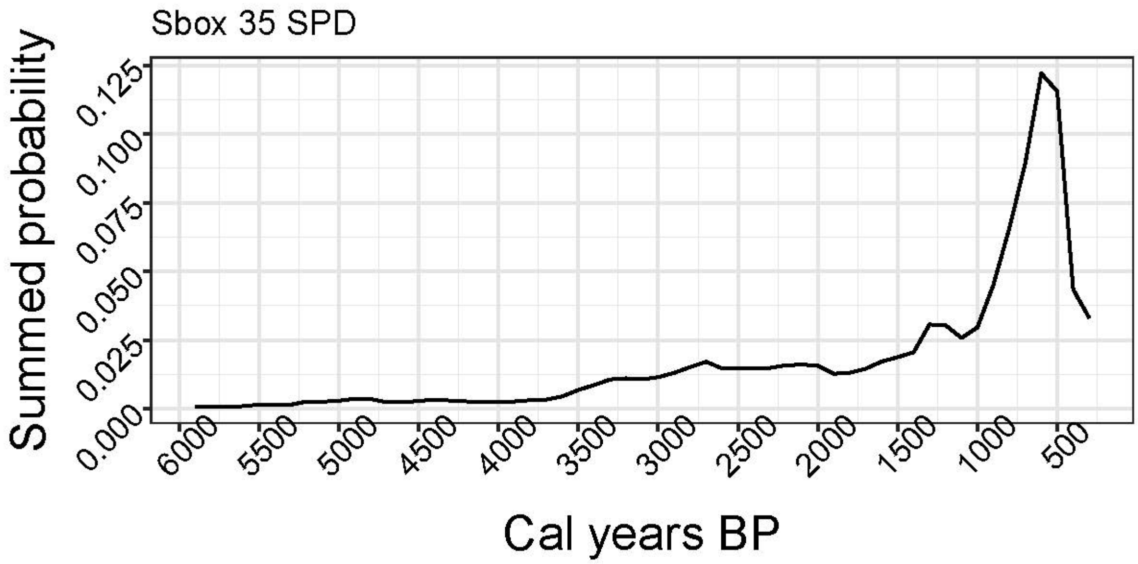
Cal years BP


Sbox 35 SPD
Summed probability
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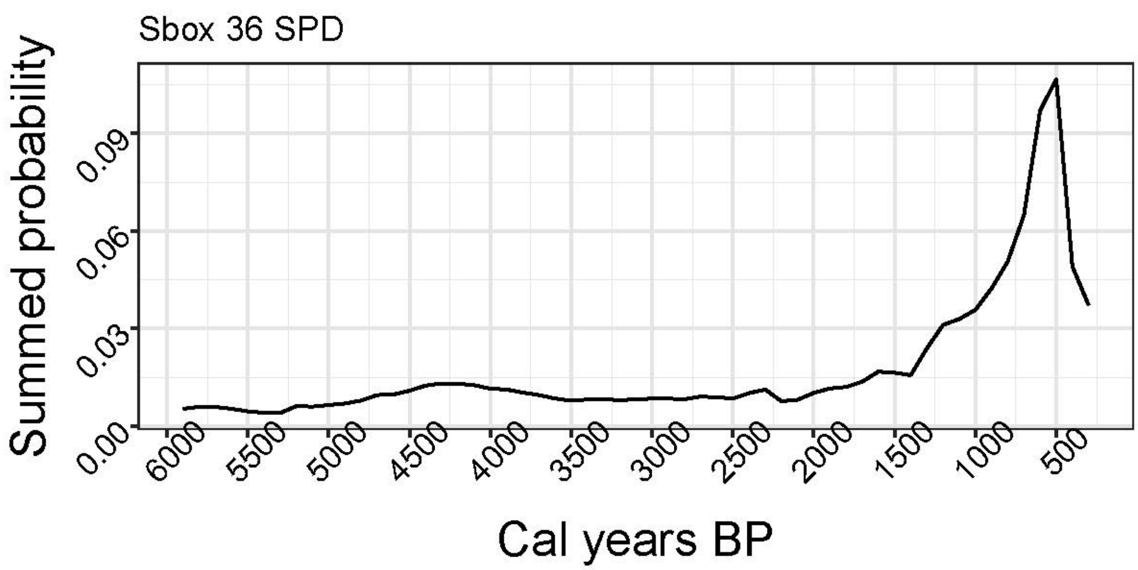
Cal years BP


Sbox 36 SPD
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0.09
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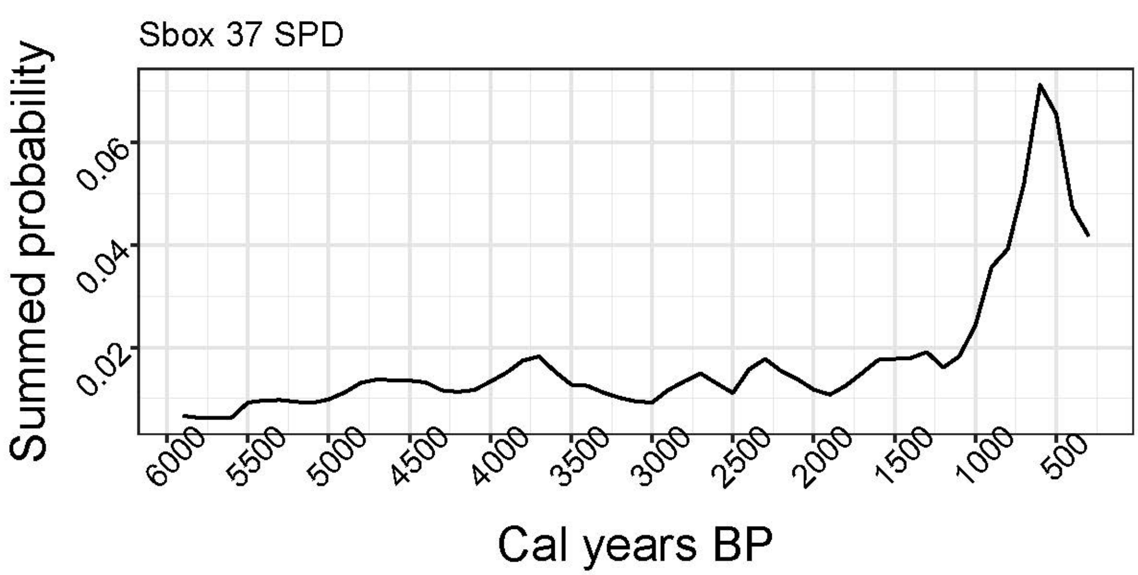
Cal years BP


Sbox 37 SPD
Summed probability
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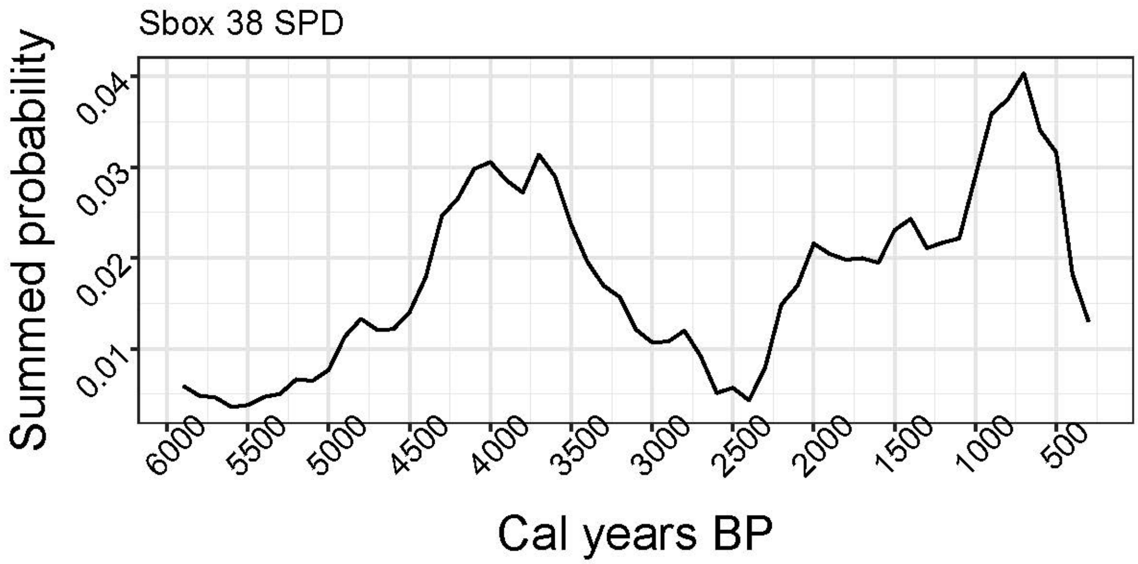
Cal years BP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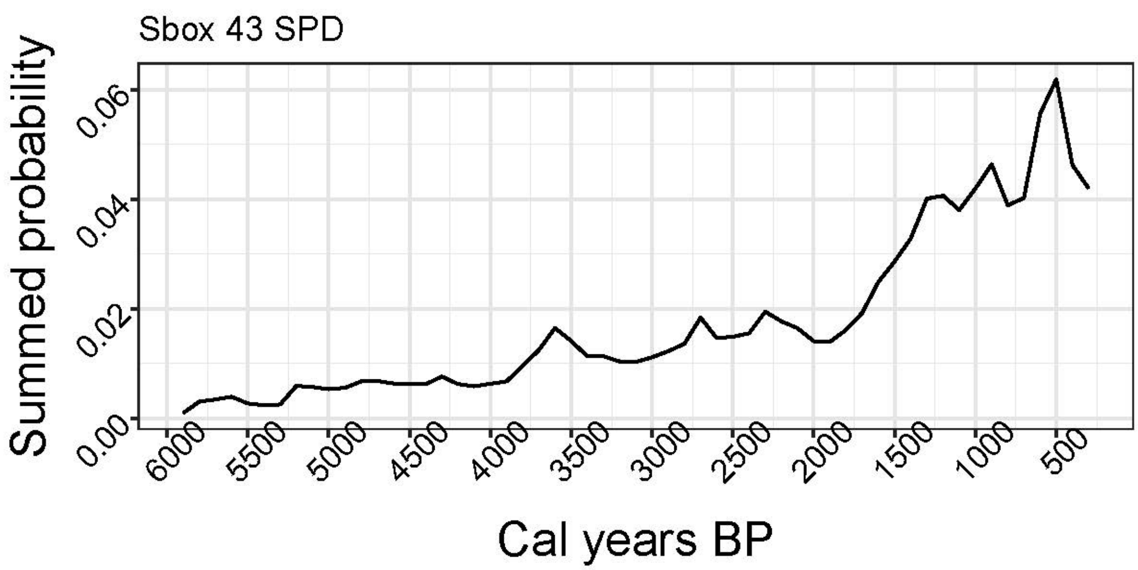
Cal years BP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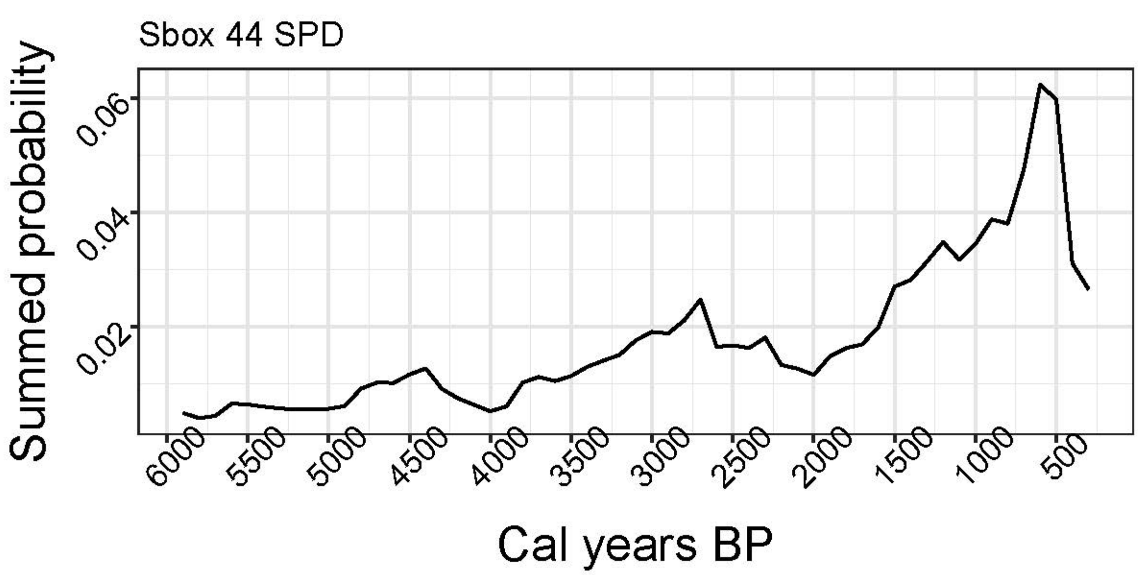
Cal years BP


Sbox 44 SPD
Summed probability
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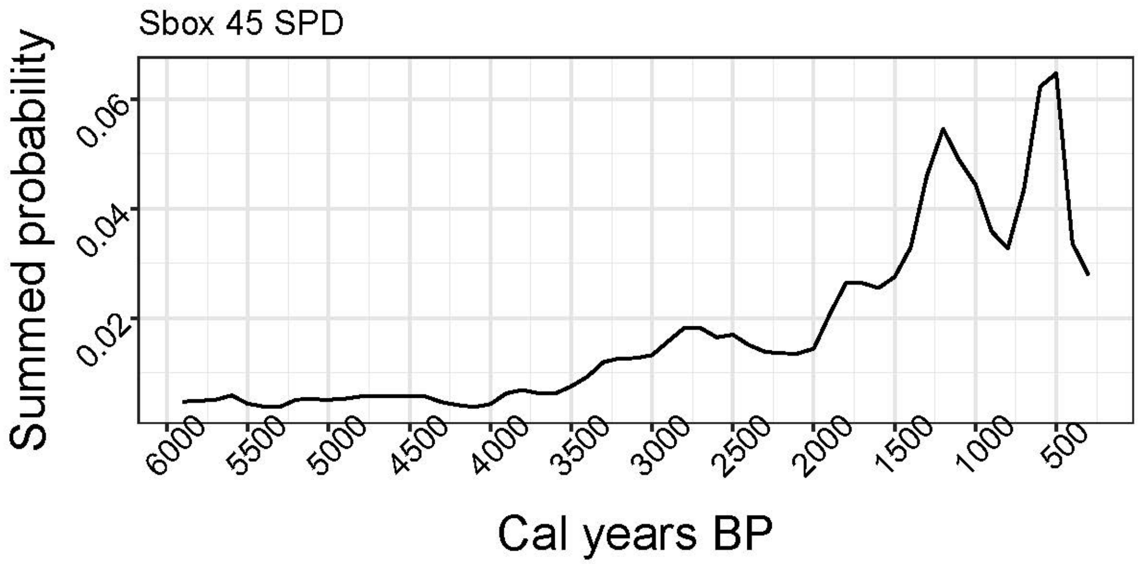
Cal years BP


Sbox 45 SPD
Summed probability
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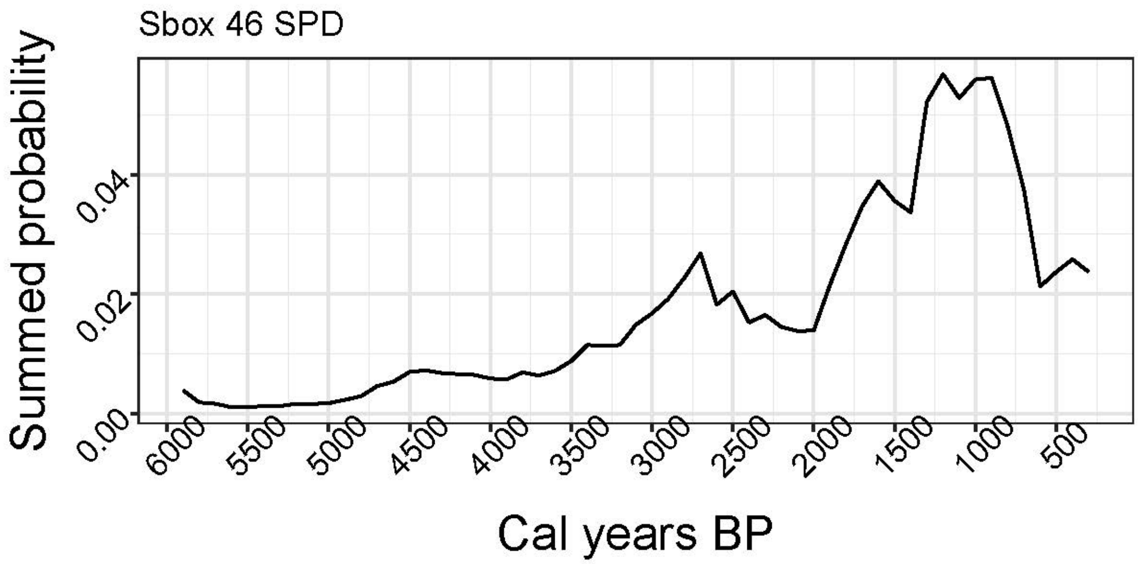
Cal years BP


Sbox 46 SPD
Summed probability
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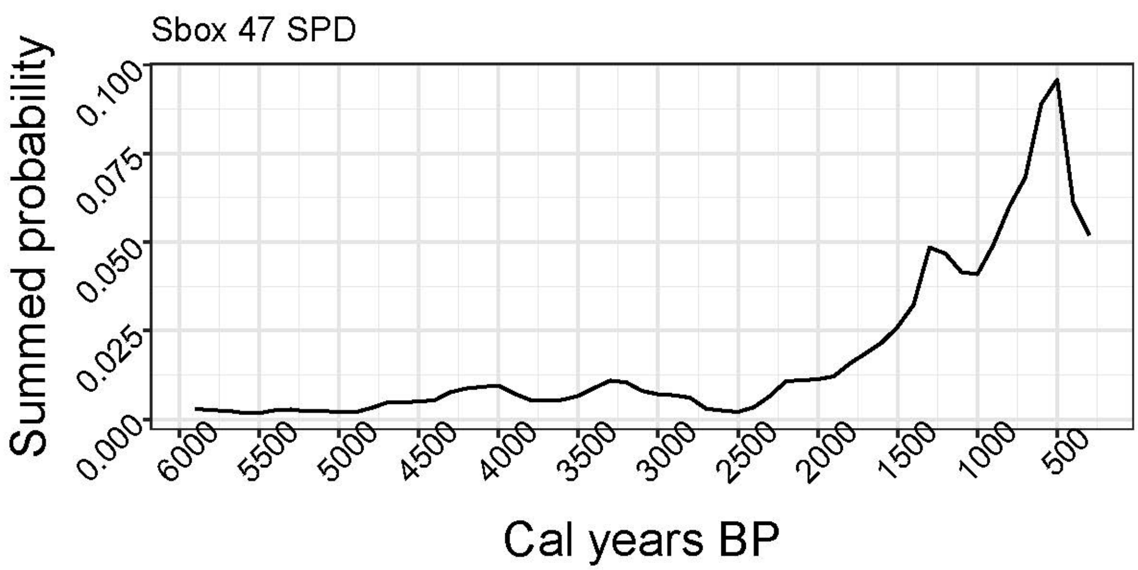
Cal years BP


Sbox 47 SPD
Summed probability
0.000
0.025
0.050
0.075
0.100
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4500
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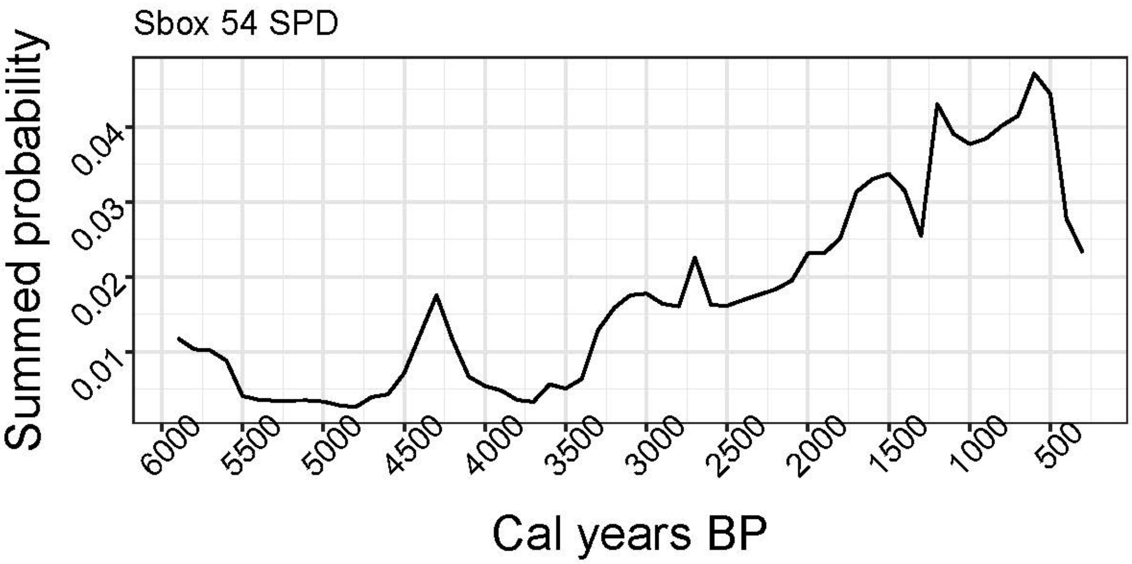
1000
500
Cal years BP


Sbox 54 SPD
Summed probability
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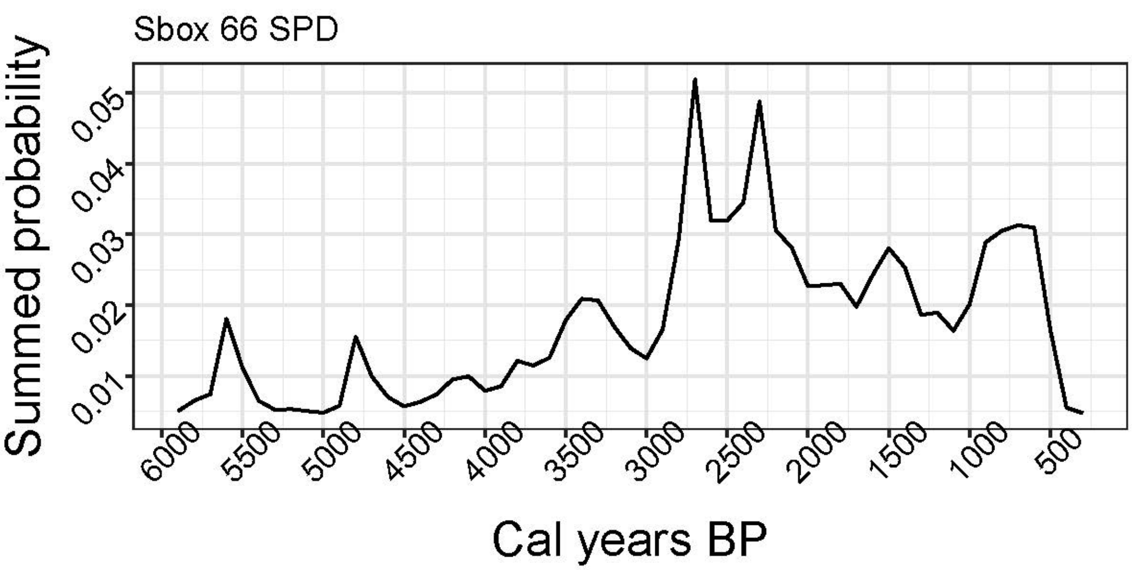
Cal years BP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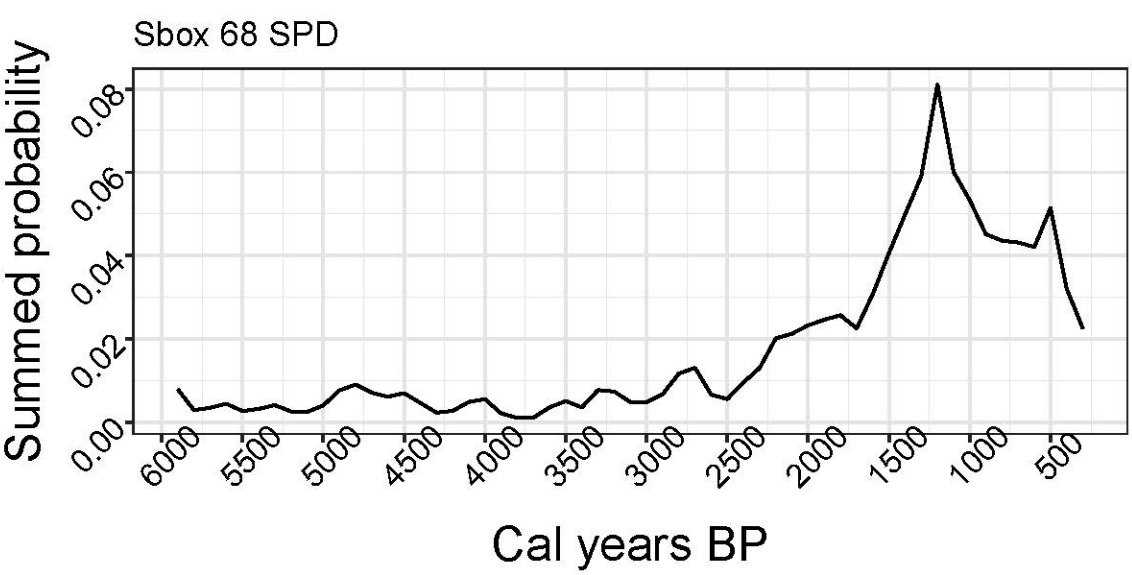
Cal years BP


Sbox 68 SPD
Summed probability
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0.08
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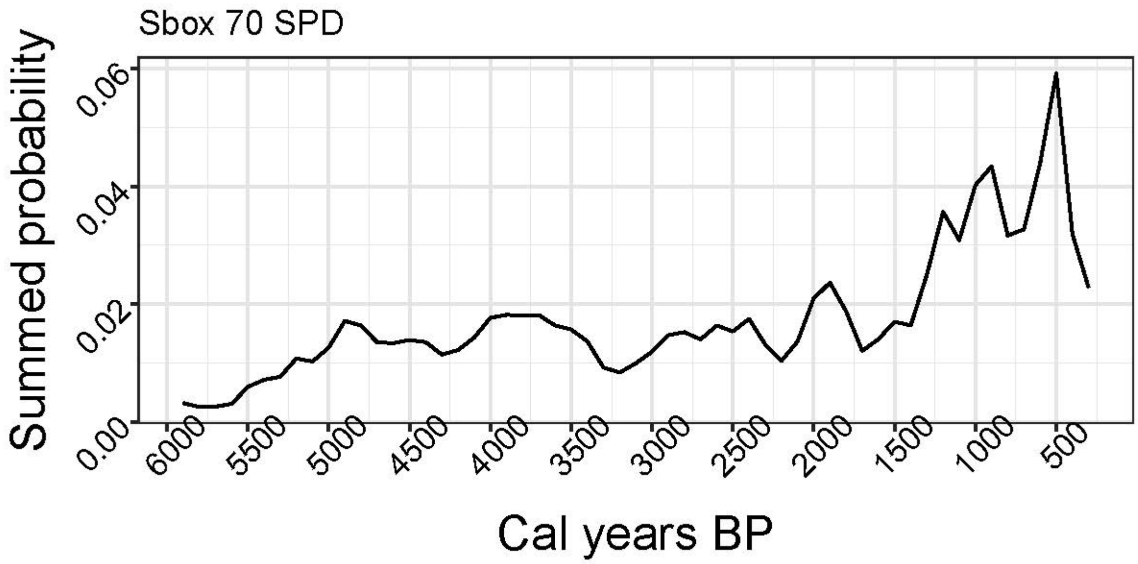
Cal years BP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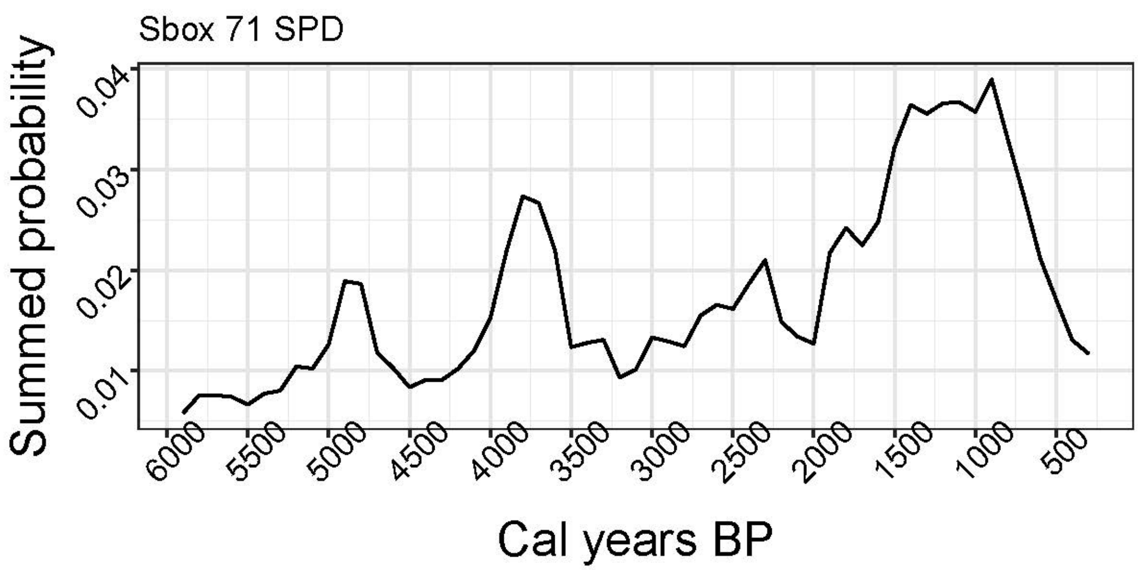
2000
1500
1000
500
Cal years BP


Sbox 71 SPD
Summed probability
0.01
0.02
0.03
0.04
6000
5500
5000
4500
4000
3500
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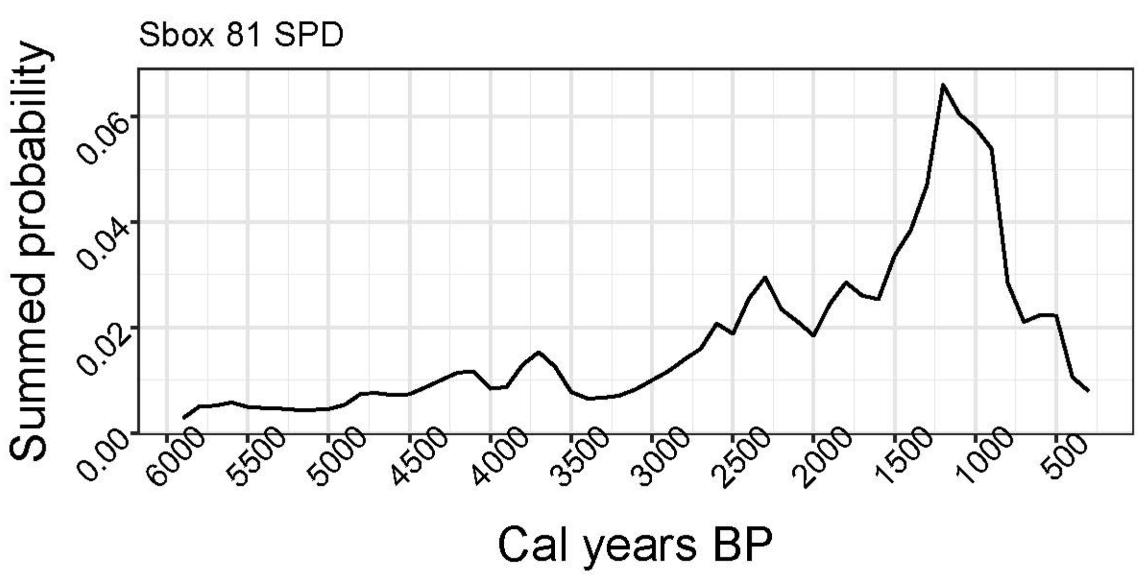
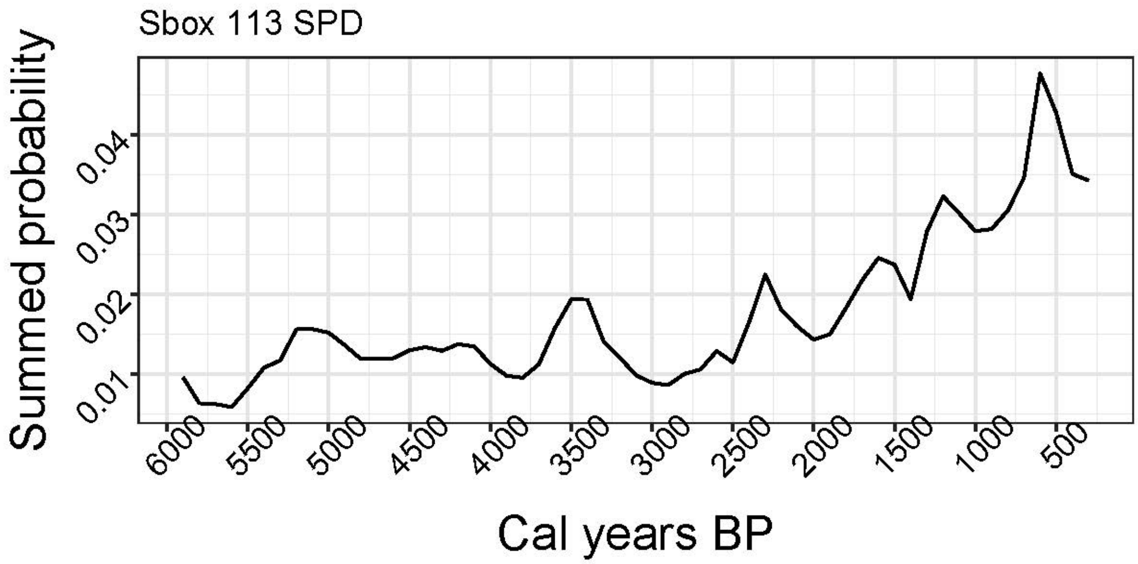
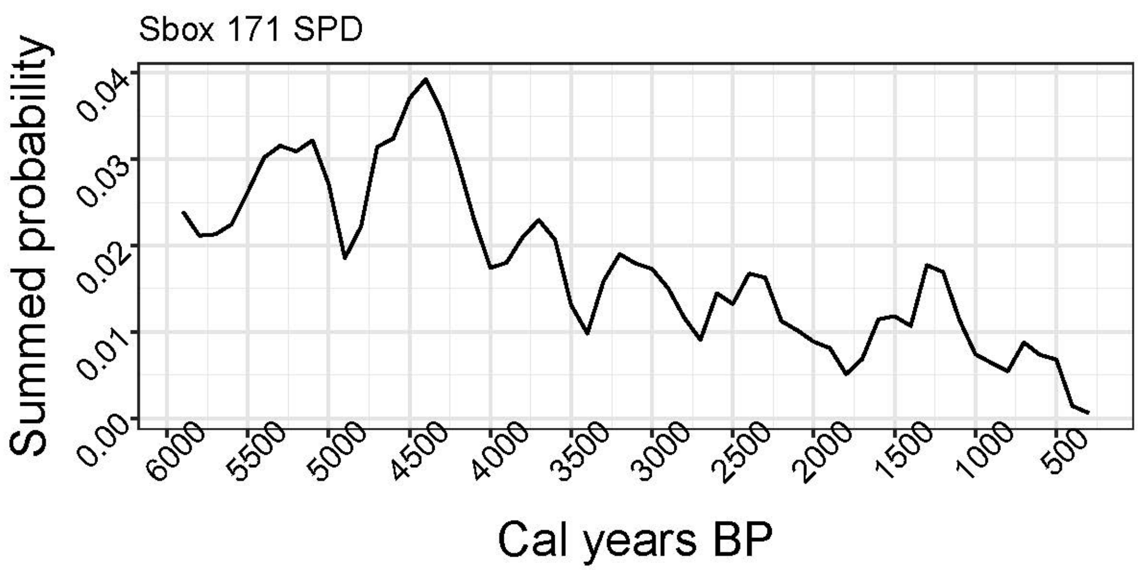
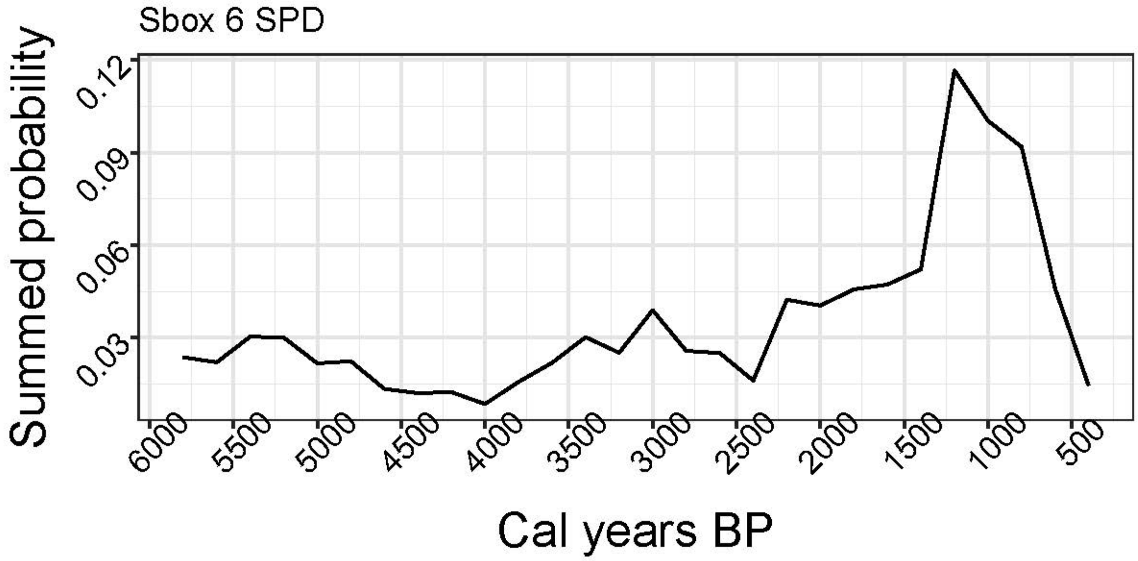
2500
2000
1500
1000
500
Cal years BP

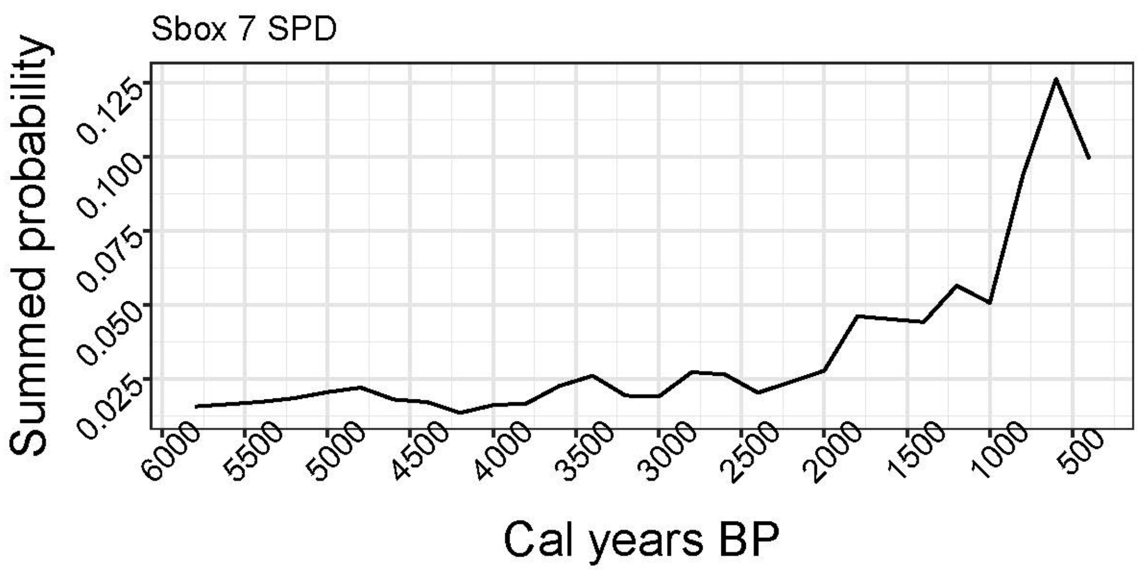

Sbox 81 SPD
Summed probability
0.00
0.02
0.04
0.06
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP

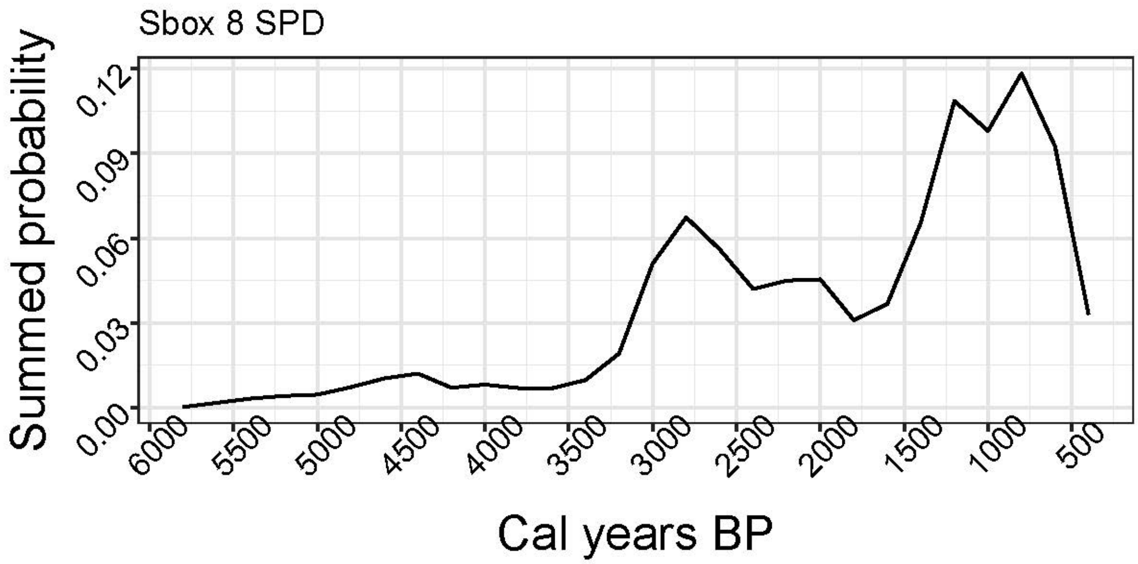

Sbox 113 SPD
Summed probability
0.01
0.02
0.03
0.04
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP

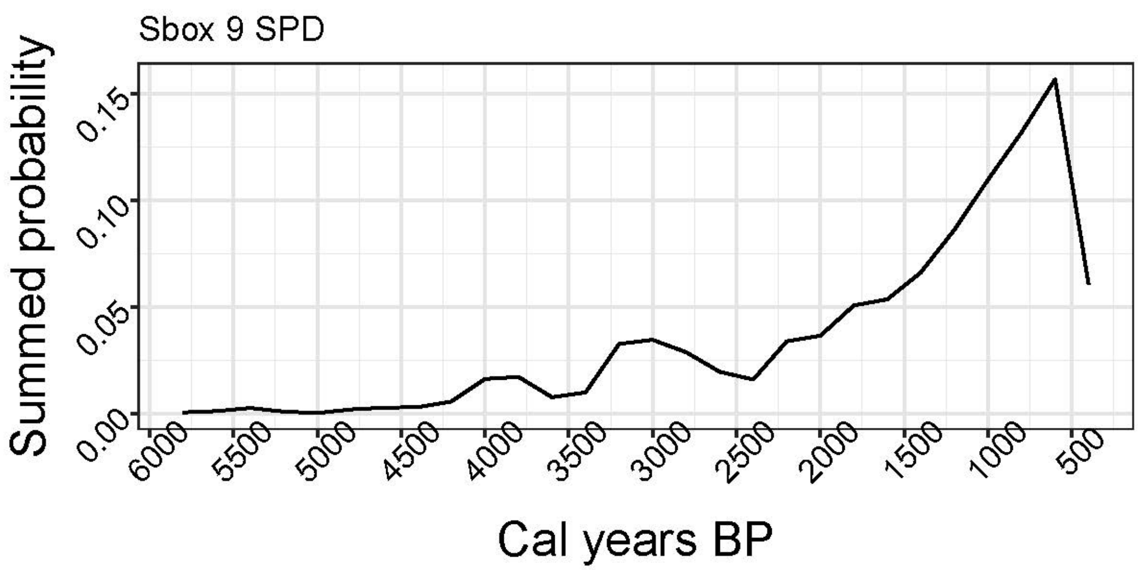

Sbox 171 SPD
Summed probability
0.00
0.01
0.02
0.03
0.04
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP

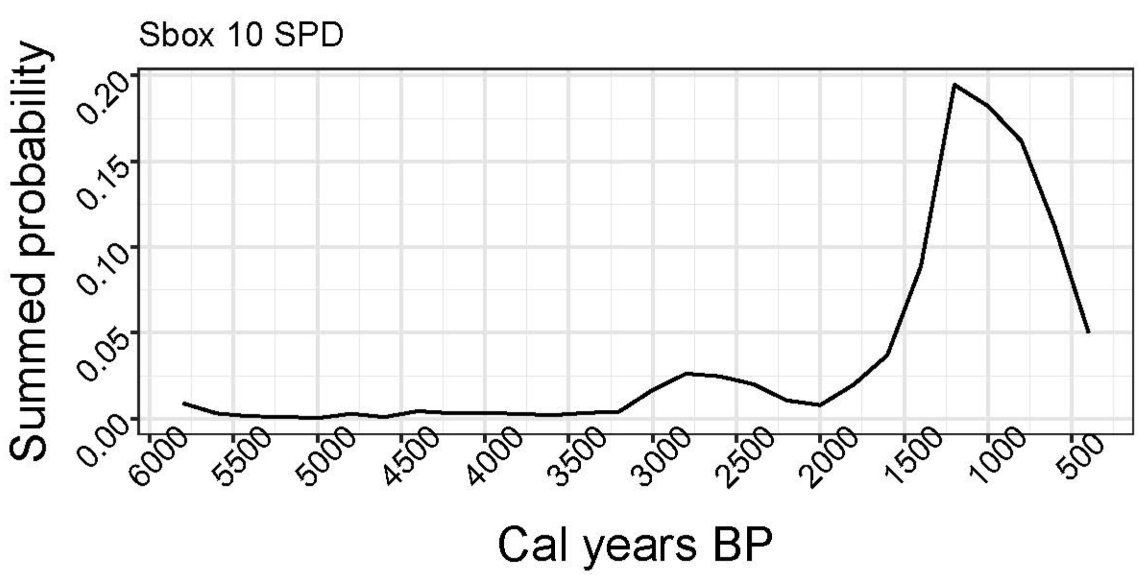
At the 200-year time scale:

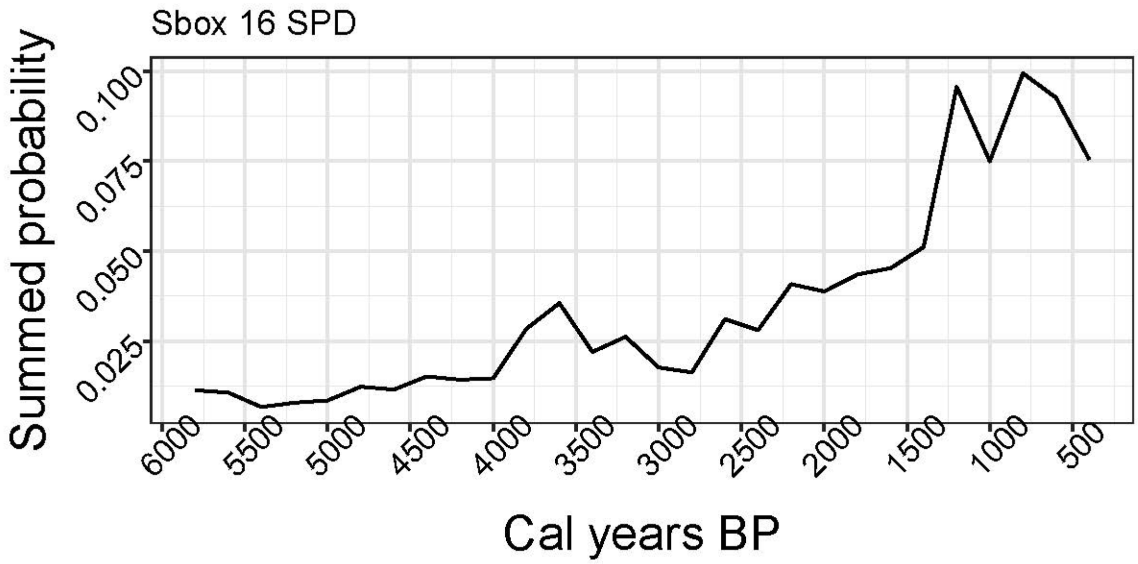


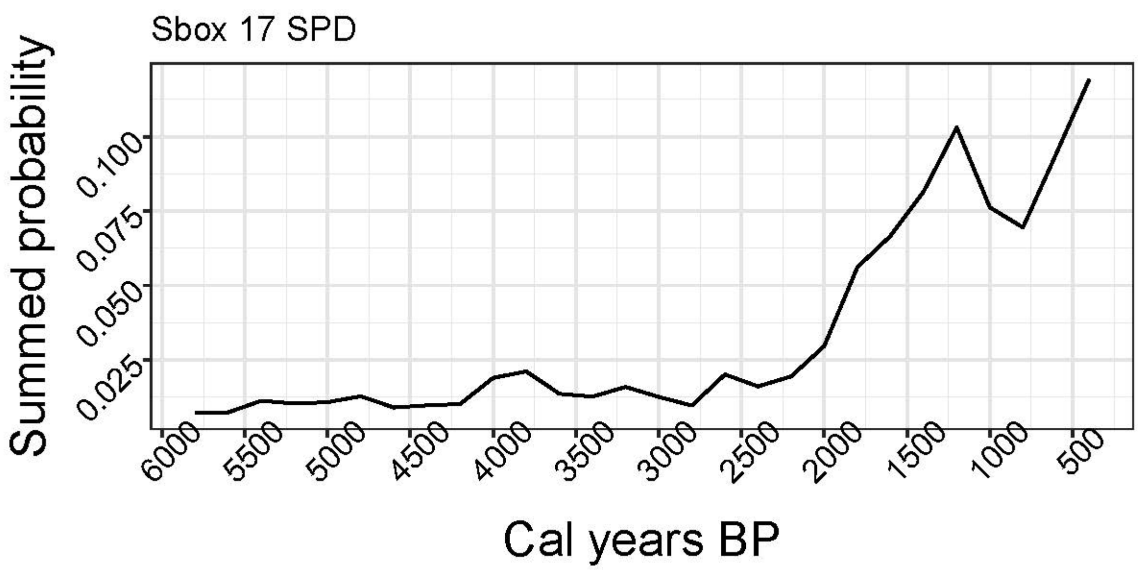


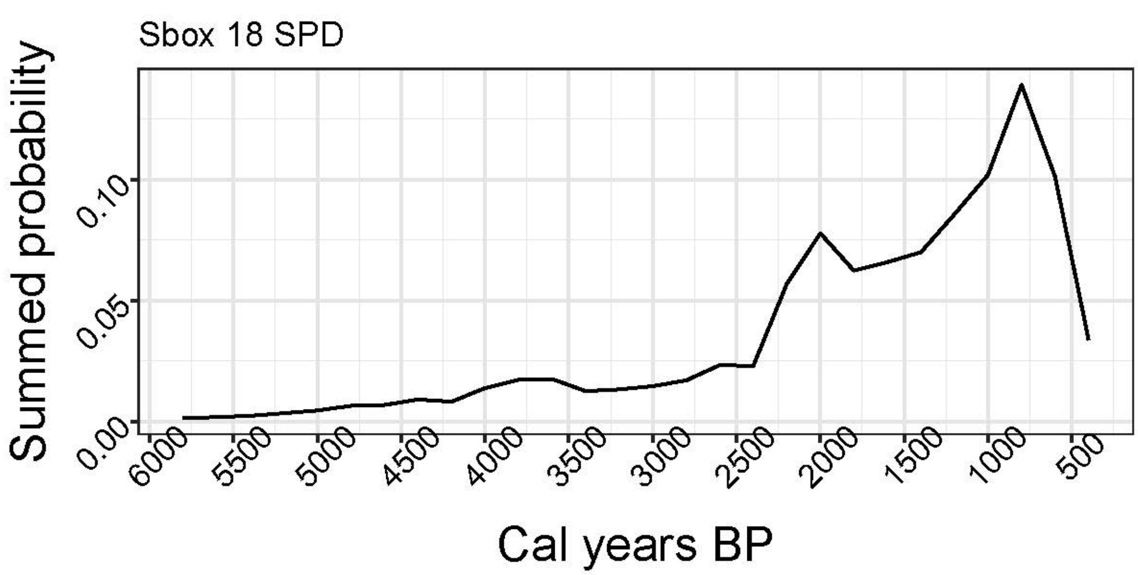

Sbox 8 SPD
Summed probability
0.00
0.03
0.06
0.09
0.12
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP

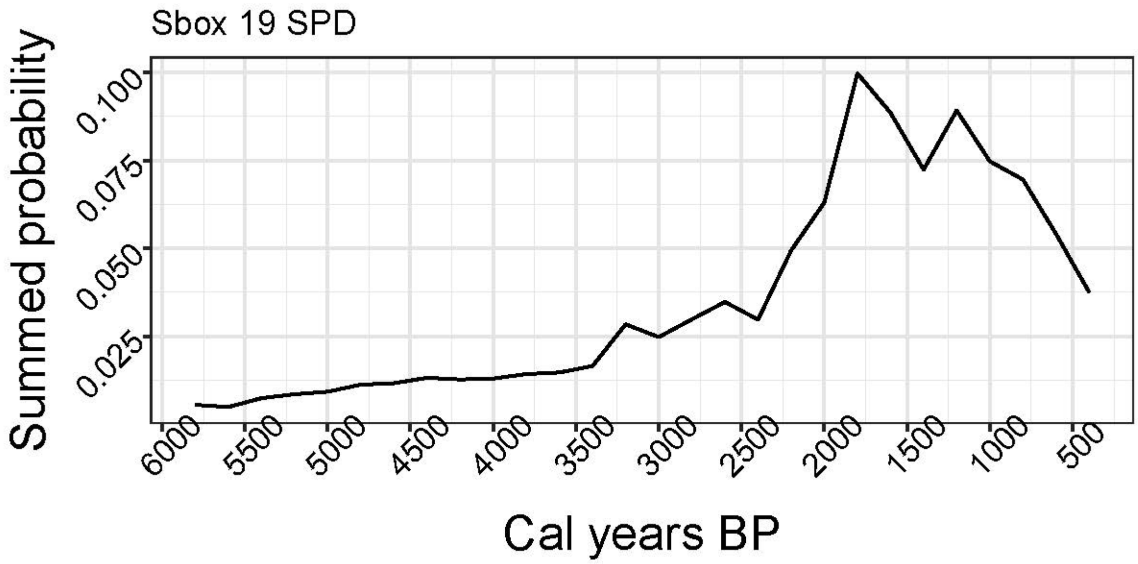

Sbox 9 SPD
Summed probability
0.00
0.05
0.10
0.15
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP

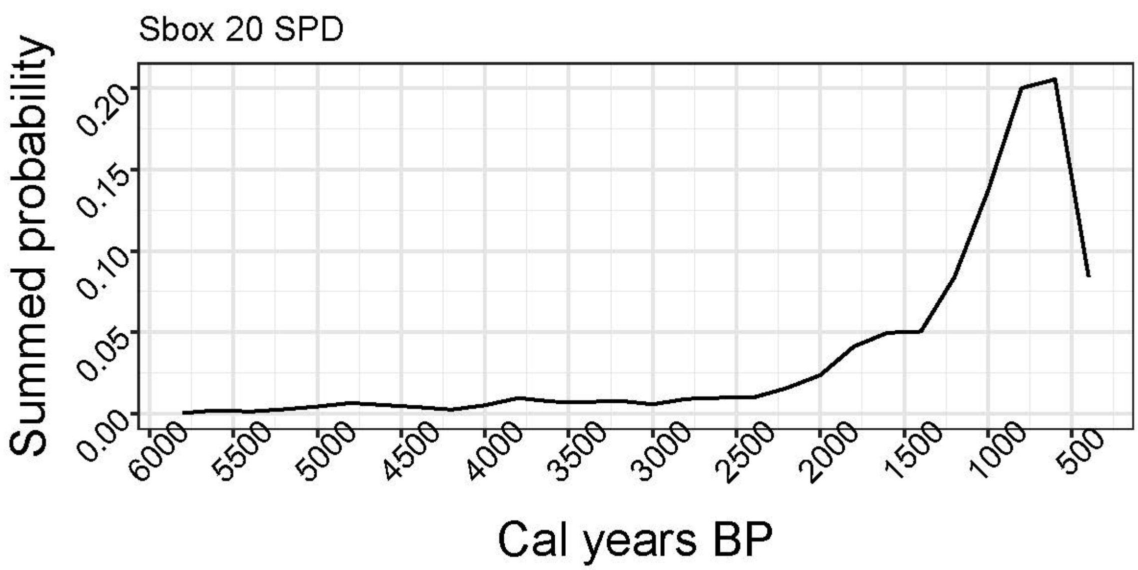

Sbox 10 SPD
Summed probability
0.00
0.05
0.10
0.15
0.20
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP

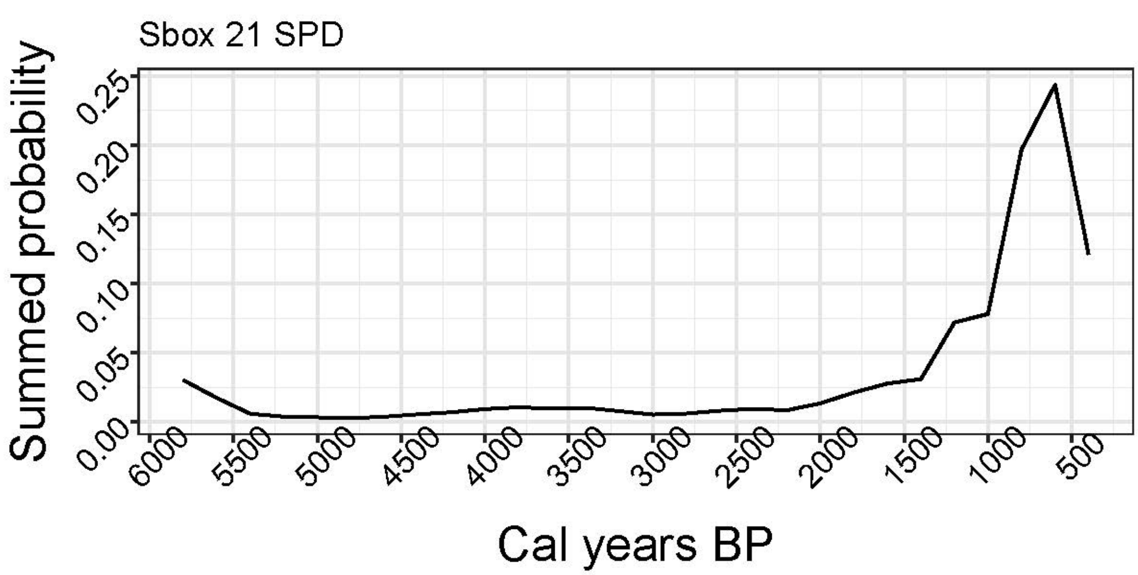

Sbox 16 SPD
Summed probability
0.100
0.075
0.050
0.025
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP

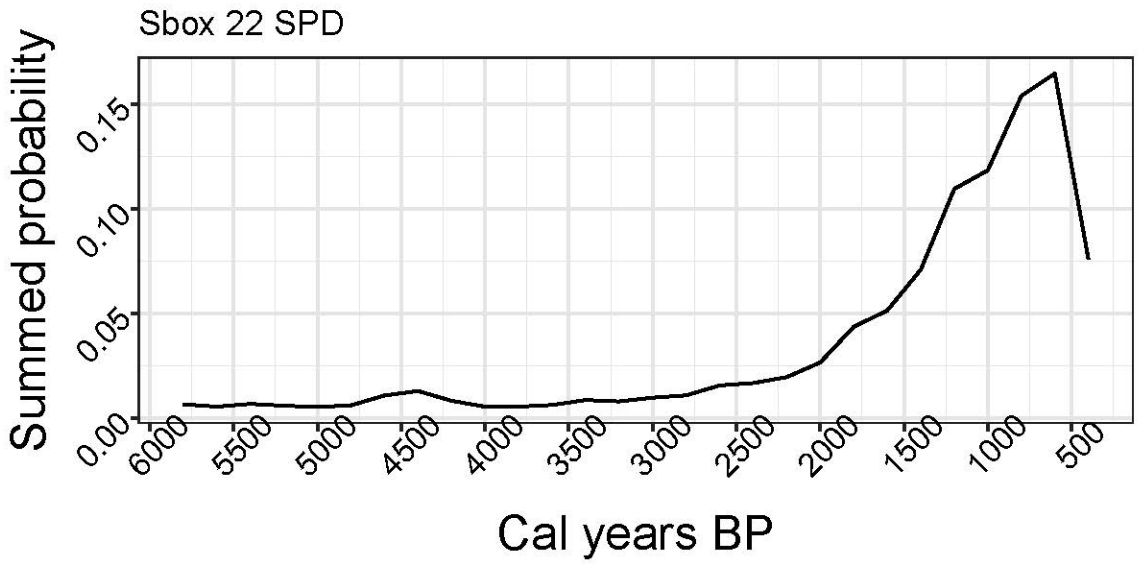

Sbox 17 SPD
Summed probability
0.100
0.075
0.050
0.025
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP

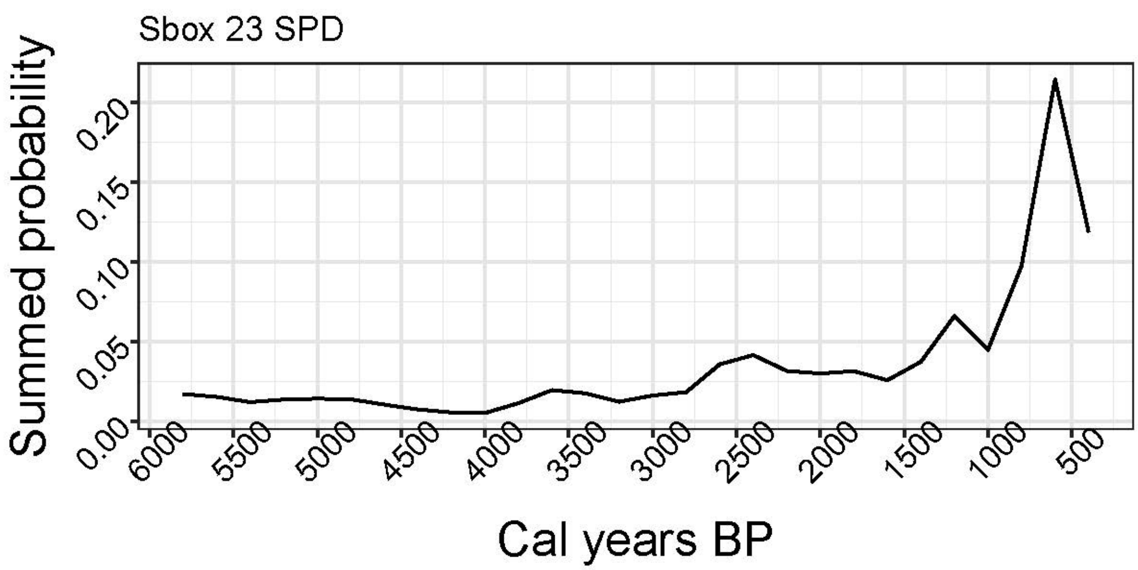

Sbox 18 SPD
Summed probability
0.10
0.05
0.00
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP

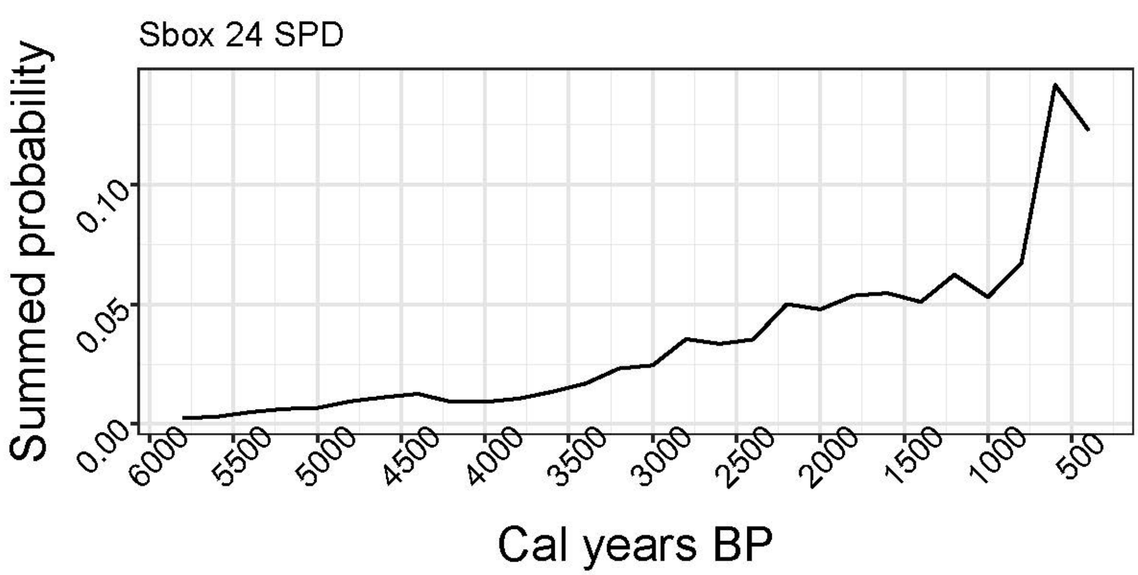

Sbox 19 SPD
Summed probability
0.100
0.075
0.050
0.025
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP


Sbox 20 SPD
Summed probability
0.20
0.15
0.10
0.05
0.00
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP


Sbox 21 SPD
Summed probability
0.25
0.20
0.15
0.10
0.05
0.00
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP


Sbox 22 SPD
Summed probability
0.00
0.05
0.10
0.15
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP


Sbox 23 SPD
Summed probability
0.00
0.05
0.10
0.15
0.20
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP


Sbox 24 SPD
Summed probability
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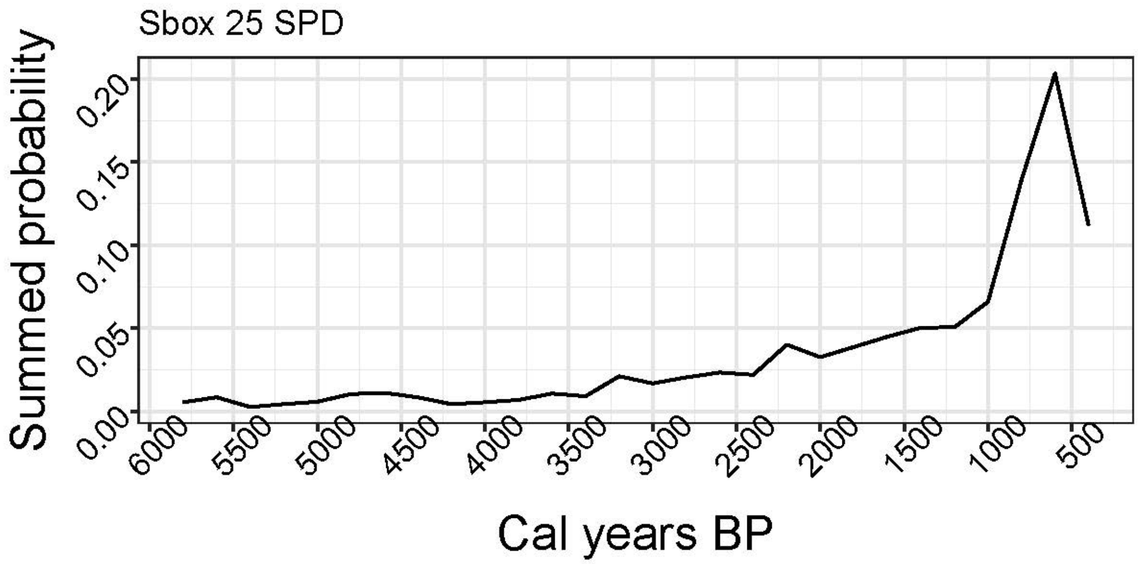
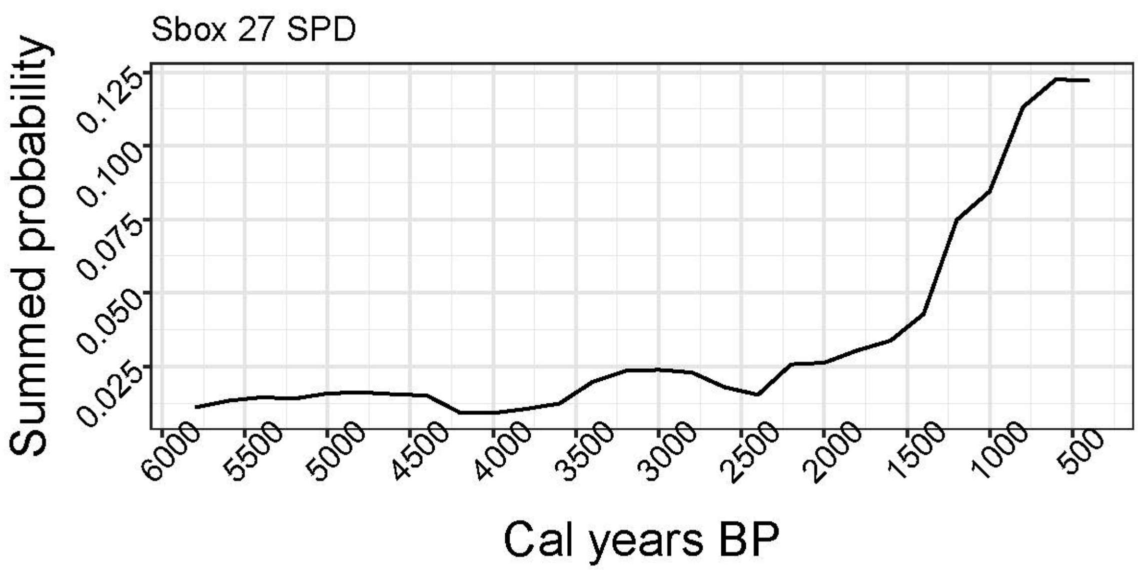
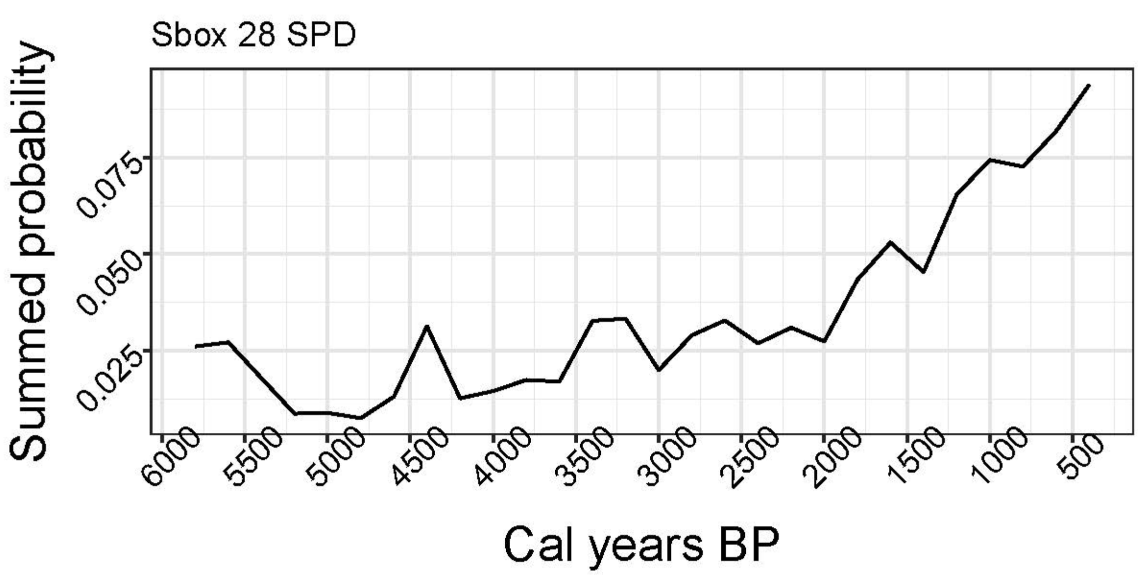
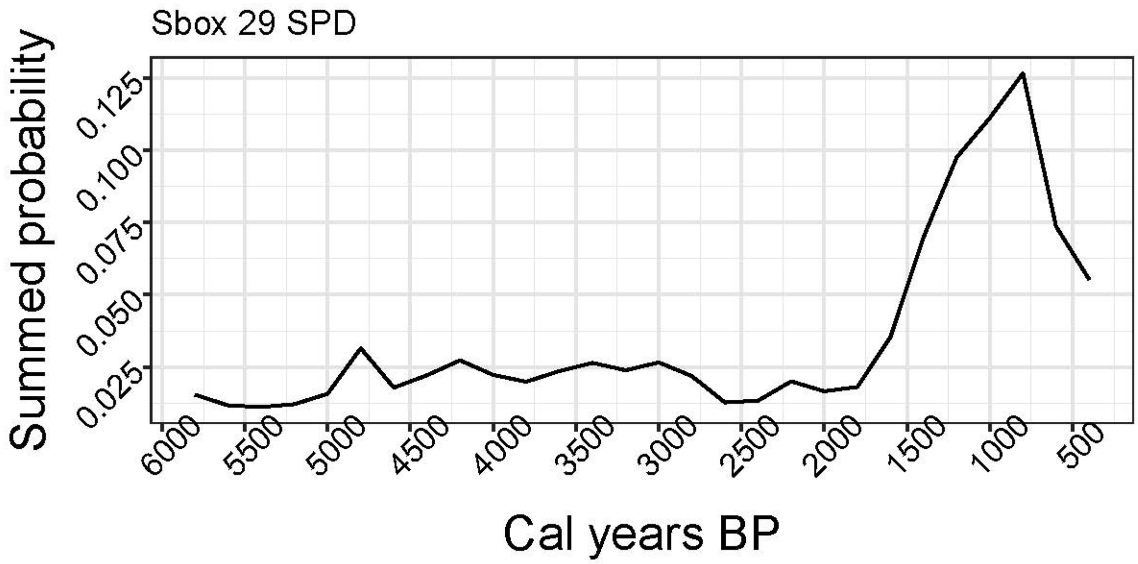
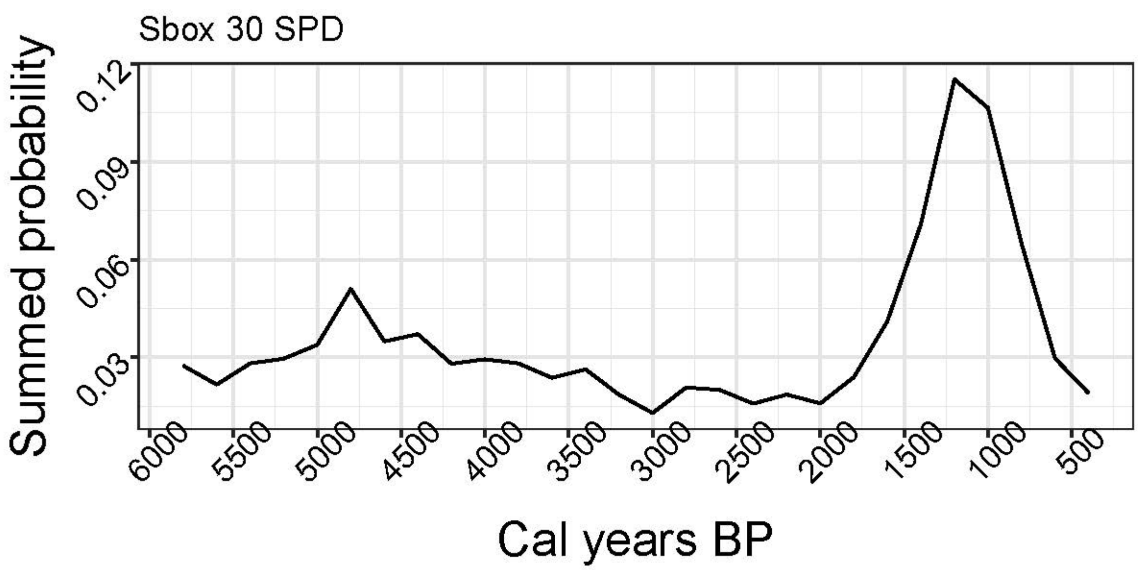
0.05
0.10
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP

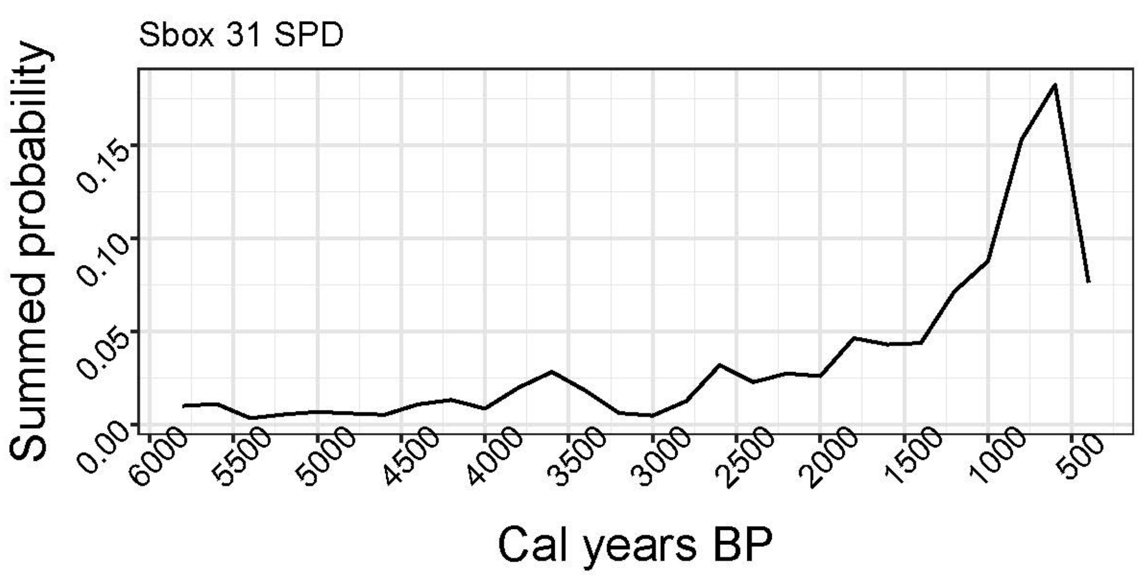

Sbox 25 SPD
Summed probability
0.00
0.05
0.10
0.15
0.20
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP

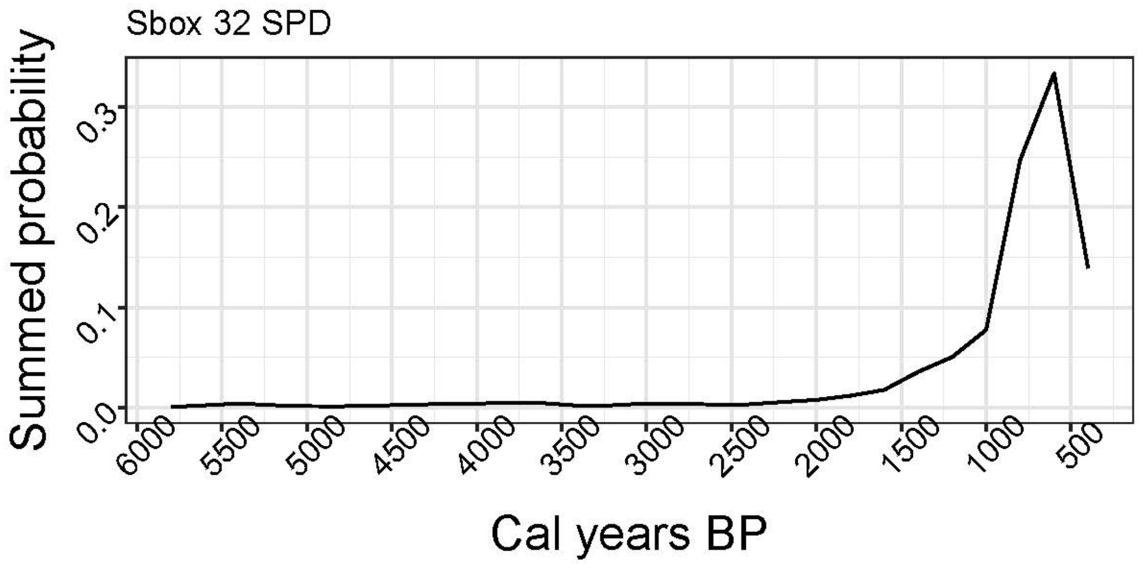

Sbox 27 SPD
Summed probability
0.025
0.050
0.075
0.100
0.125
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP

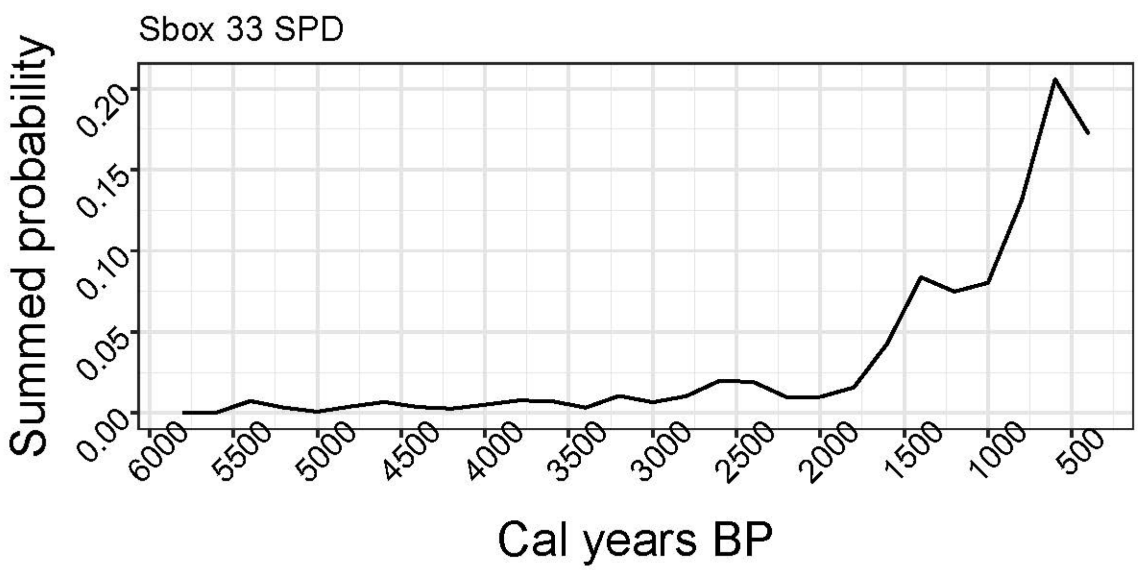

Sbox 28 SPD
Summed probability
0.025
0.050
0.075
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP

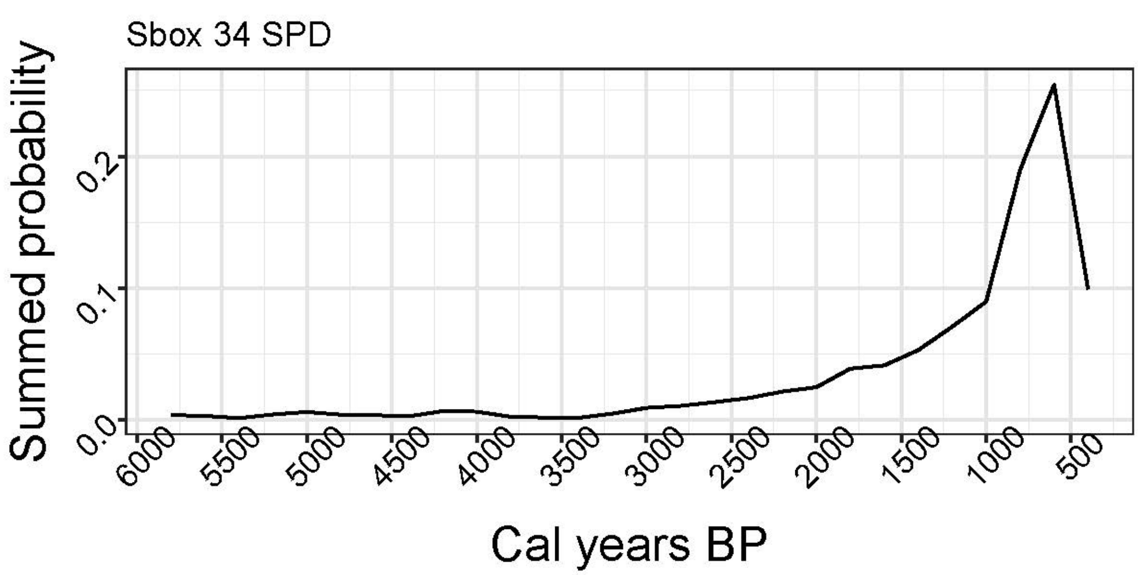

Sbox 29 SPD
Summed probability
0.025
0.050
0.075
0.100
0.125
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP


Sbox 30 SPD
Summed probability
0.03
0.06
0.09
0.12
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP


Sbox 31 SPD
Summed probability
0.00
0.05
0.10
0.15
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP


Sbox 32 SPD
Summed probability
0.0
0.1
0.2
0.3
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP


Sbox 33 SPD
Summed probability
0.00
0.05
0.10
0.15
0.20
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP


Sbox 34 SPD
Summed probability
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0.1
0.2
6000
5500
5000
4500
4000
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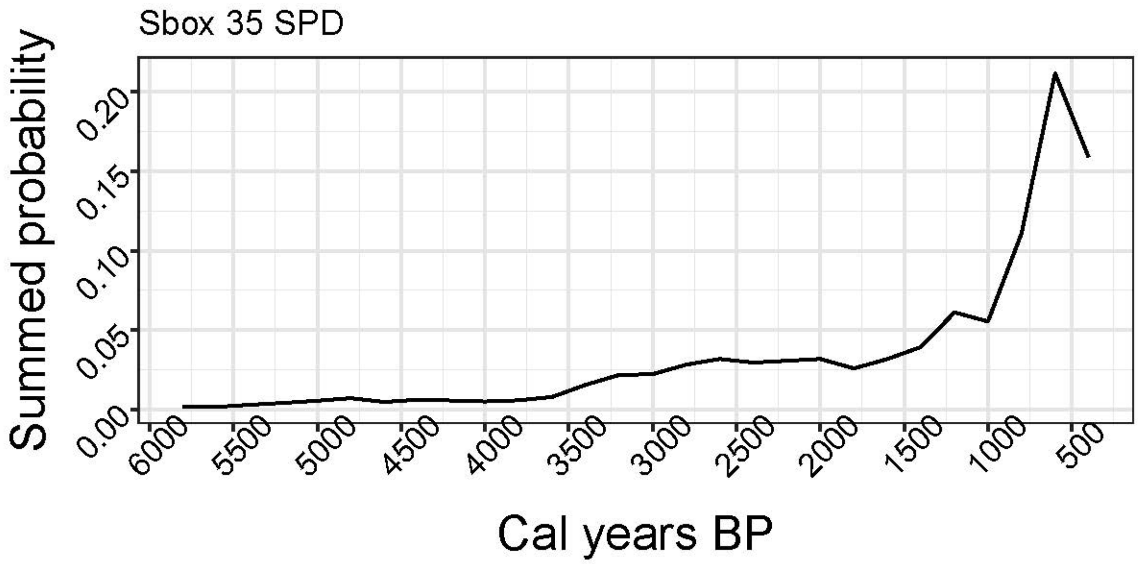
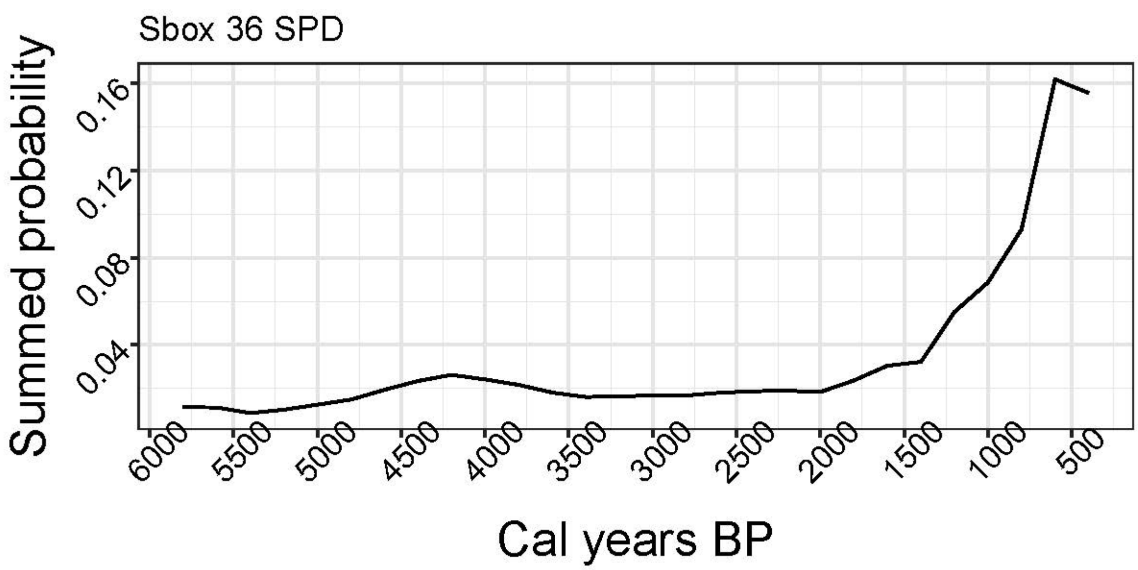
3000
2500
2000
1500
1000
500
Cal years BP


Sbox 35 SPD
Summed probability
0.00
0.05
0.10
0.15
0.20
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP


Sbox 36 SPD
Summed probability
0.04
0.08
0.12
0.16
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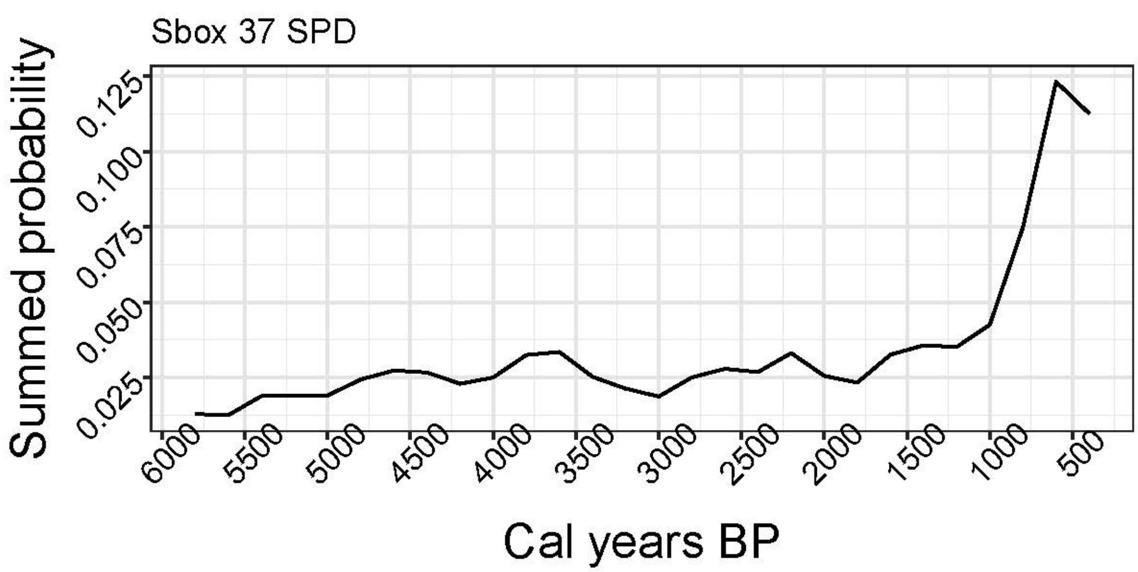
2500
2000
1500
1000
500
Cal years BP


Sbox 37 SPD
Summed probability
0.025
0.050
0.075
0.100
0.125
6000
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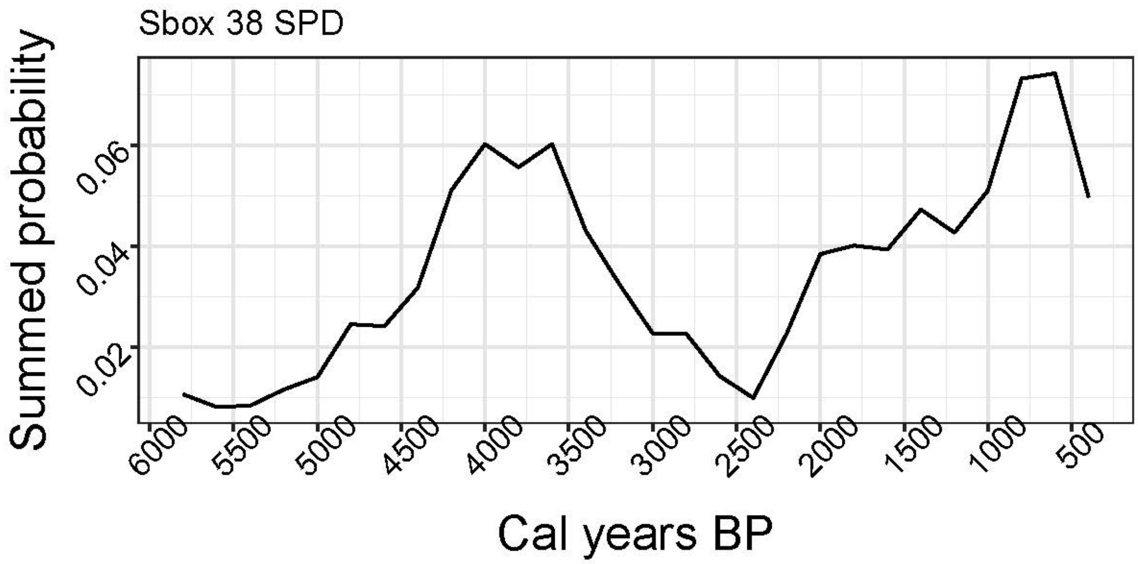
3000
2500
2000
1500
1000
500
Cal years BP


Sbox 38 SPD
Summed probability
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0.06
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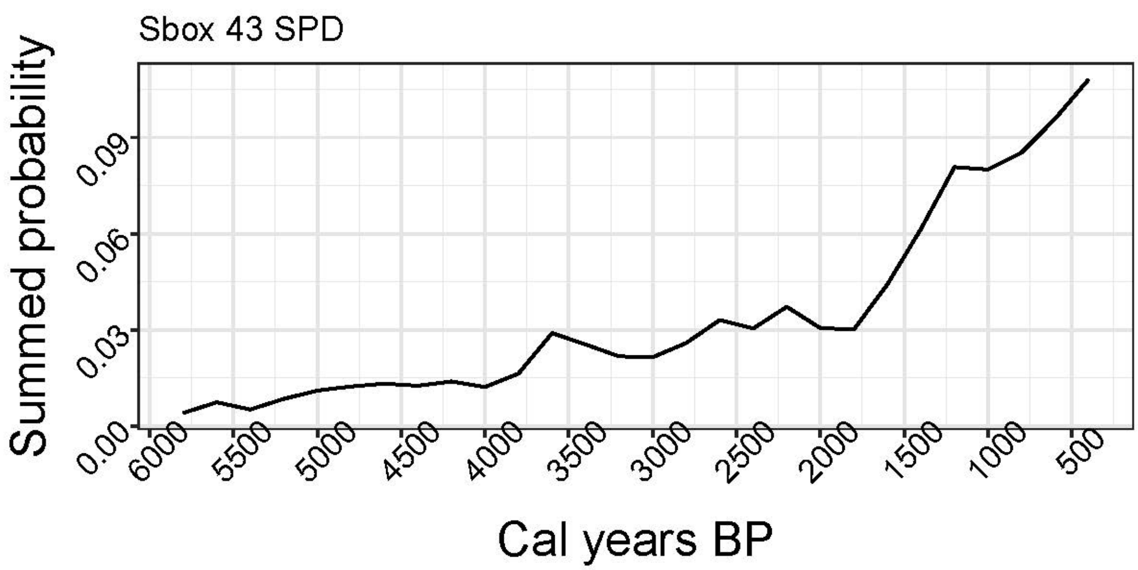
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP


Sbox 43 SPD
Summed probability
0.00
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0.06
0.09
6000
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5000
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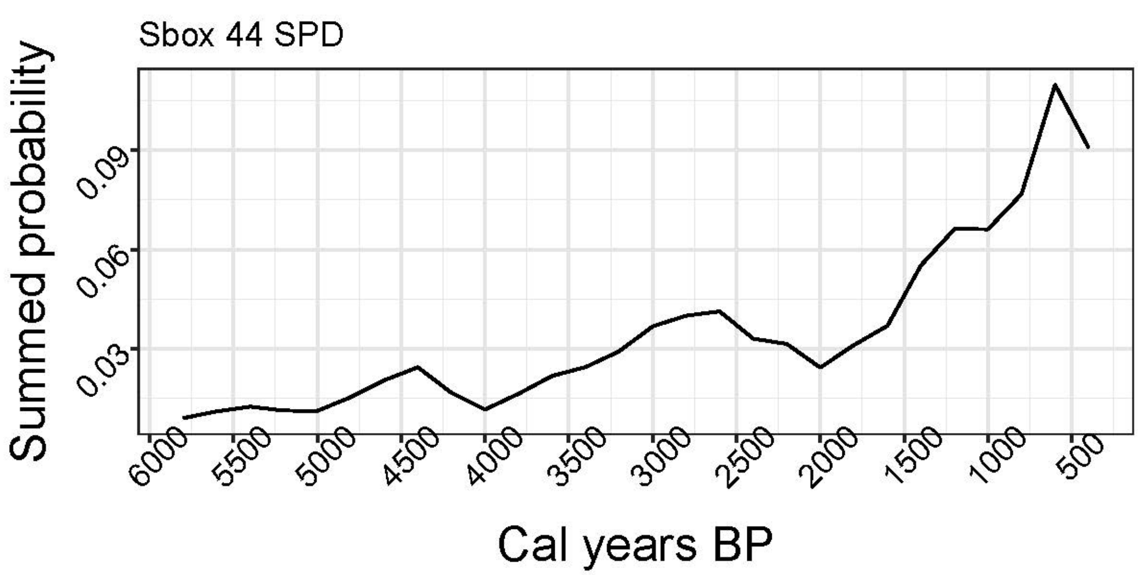
3000
2500
2000
1500
1000
500
Cal years BP


Sbox 44 SPD
Summed probability
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0.09
6000
5500
5000
4500
4000
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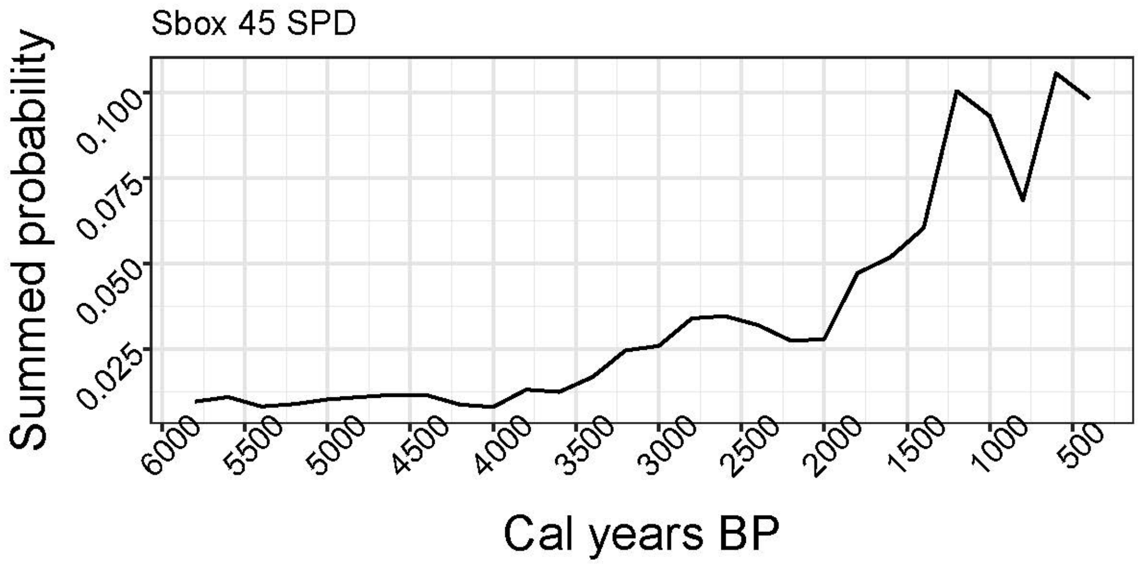
3000
2500
2000
1500
1000
500
Cal years BP


Sbox 45 SPD
Summed probability
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0.025
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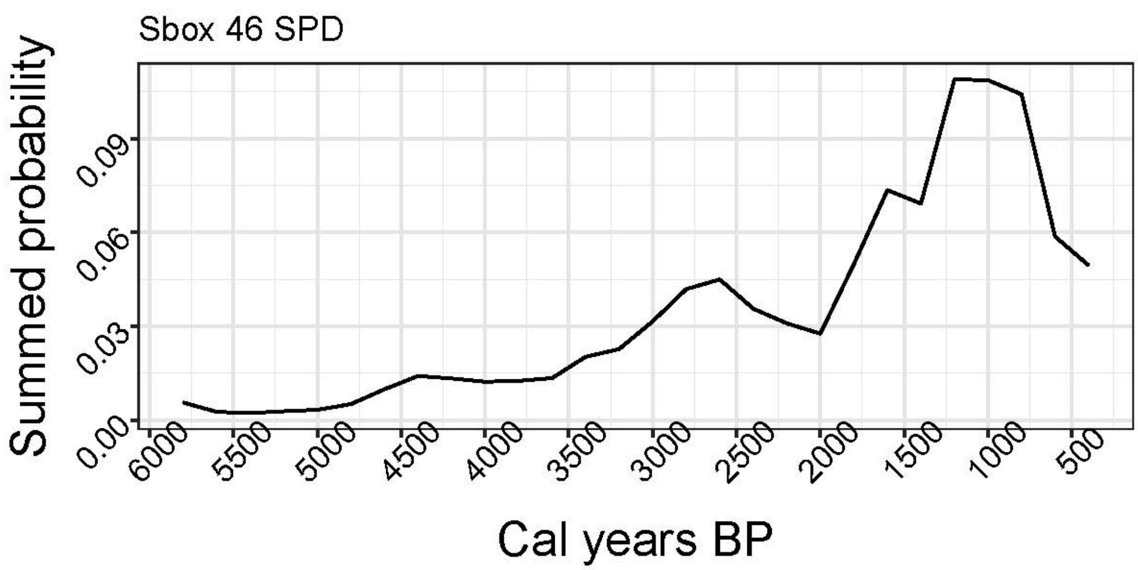
2500
2000
1500
1000
500
Cal years BP


Sbox 46 SPD
Summed probability
0.09
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0.00
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4000
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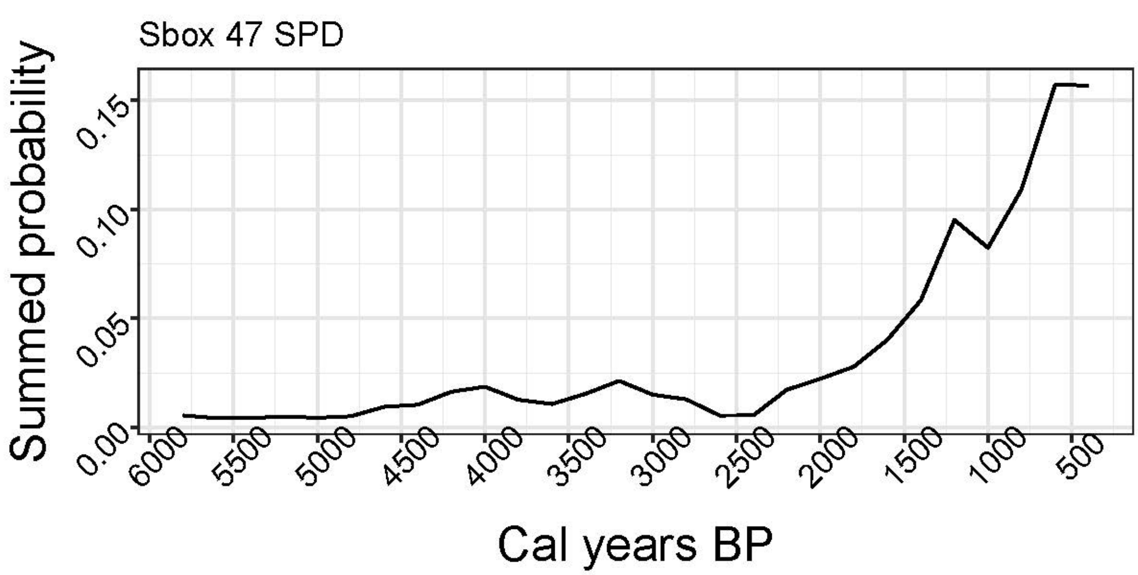
3000
2500
2000
1500
1000
500
Cal years BP


Sbox 47 SPD
Summed probability
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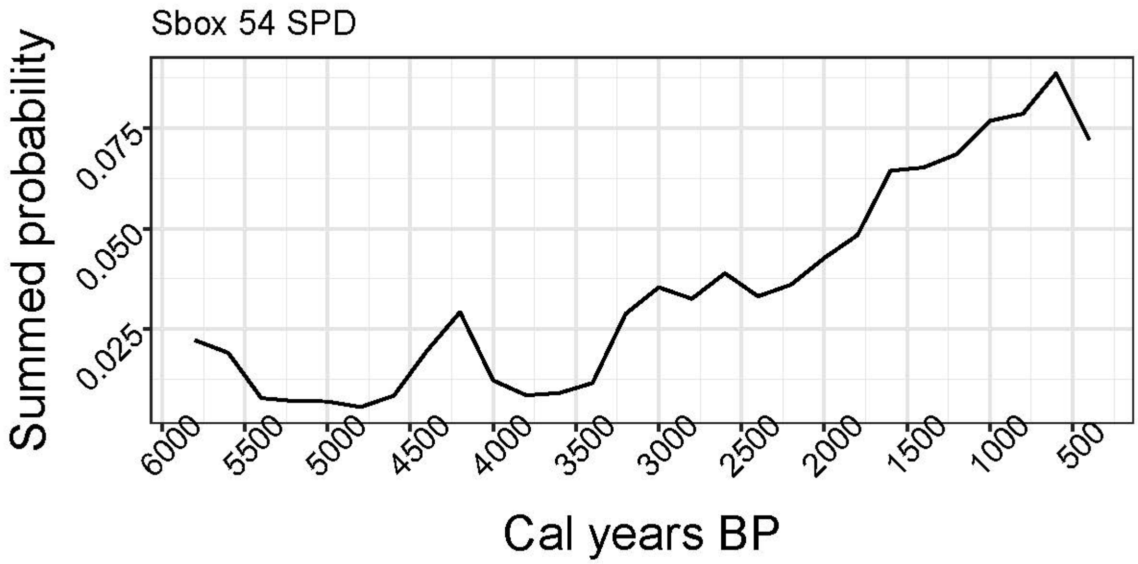
2000
1500
1000
500
Cal years BP


Sbox 54 SPD
Summed probability
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0.075
6000
5500
5000
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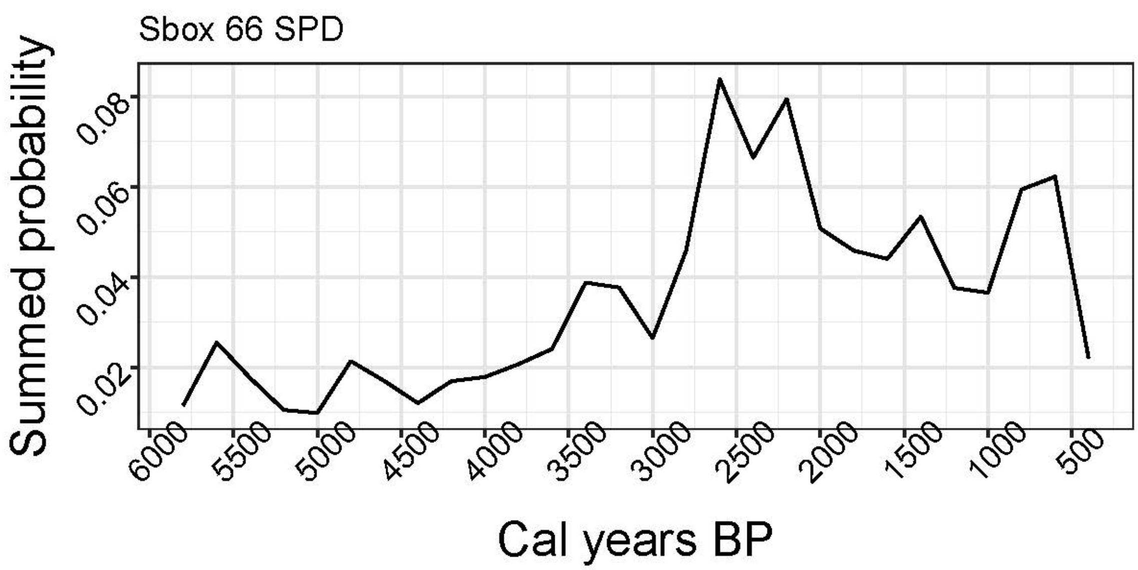
2000
1500
1000
500
Cal years BP


Sbox 66 SPD
Summed probability
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0.08
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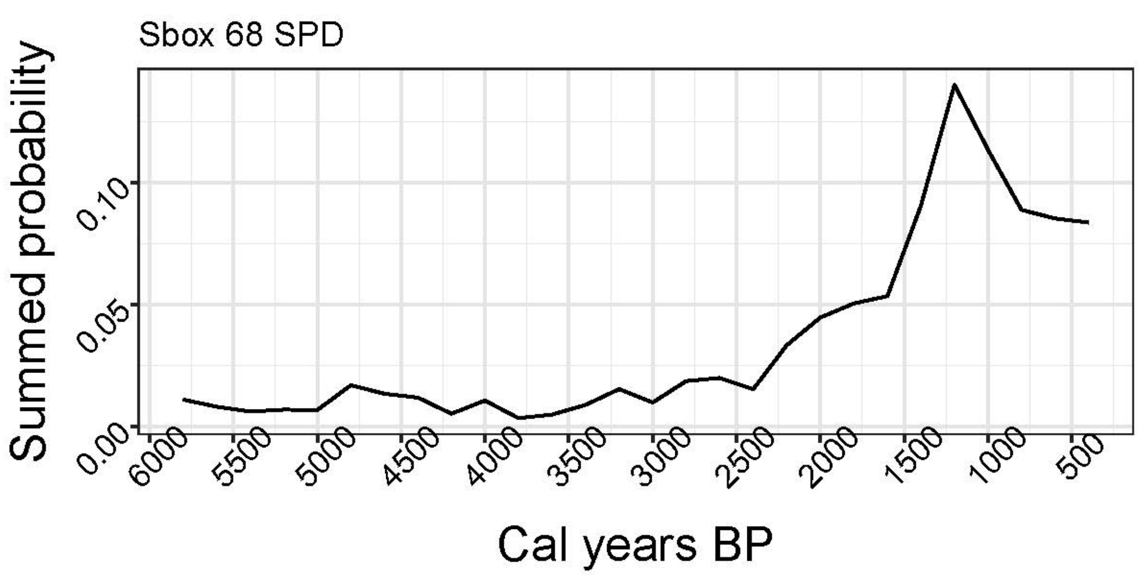
1500
1000
500
Cal years BP


Sbox 68 SPD
Summed probability
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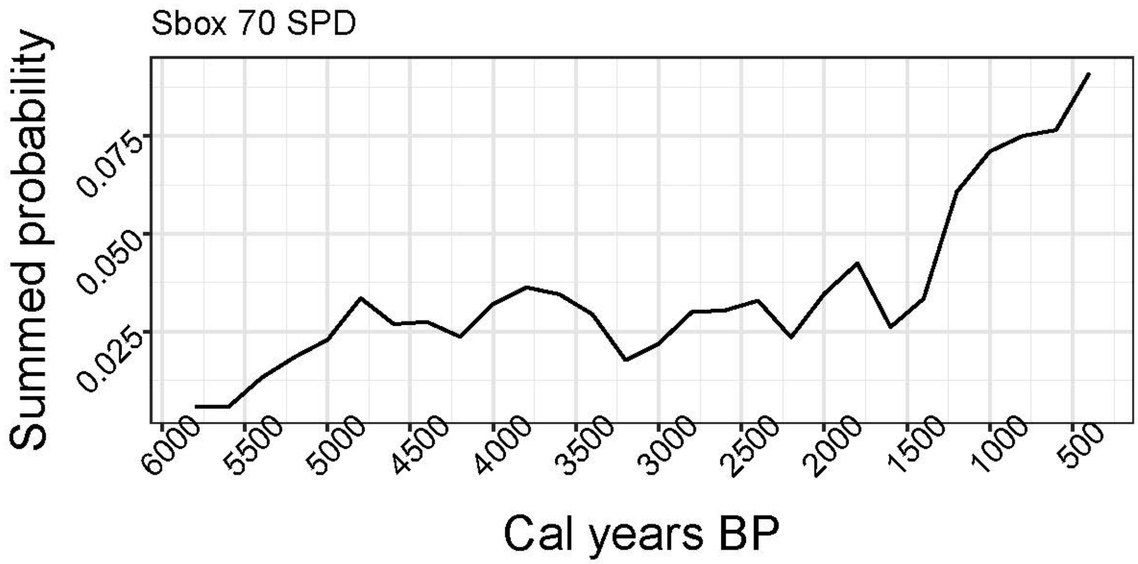
1000
500
Cal years BP


Sbox 70 SPD
Summed probability
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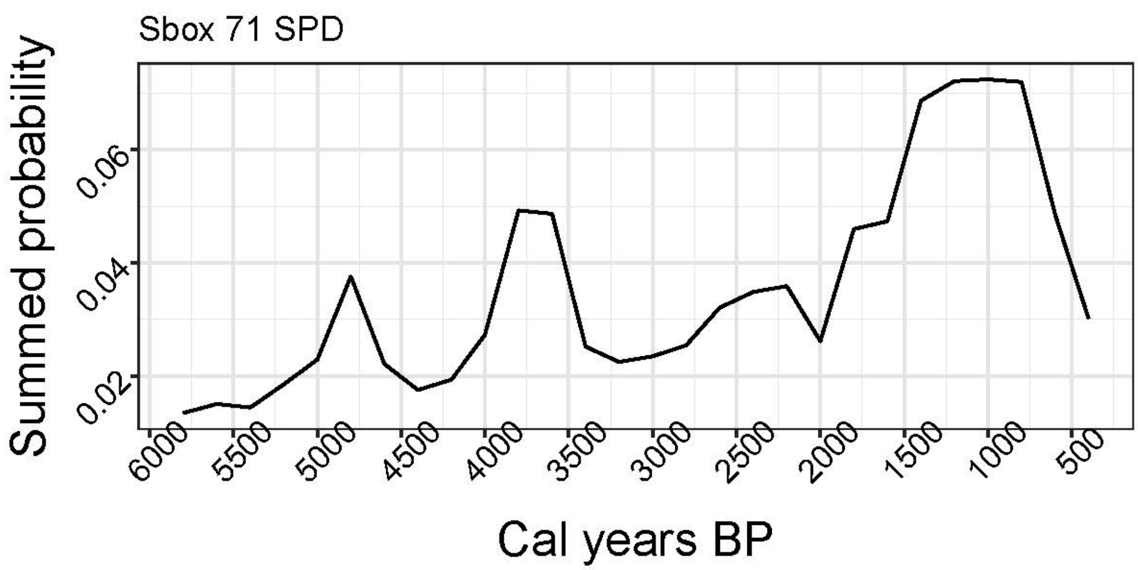
1500
1000
500
Cal years BP


Sbox 71 SPD
Summed probability
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0.06
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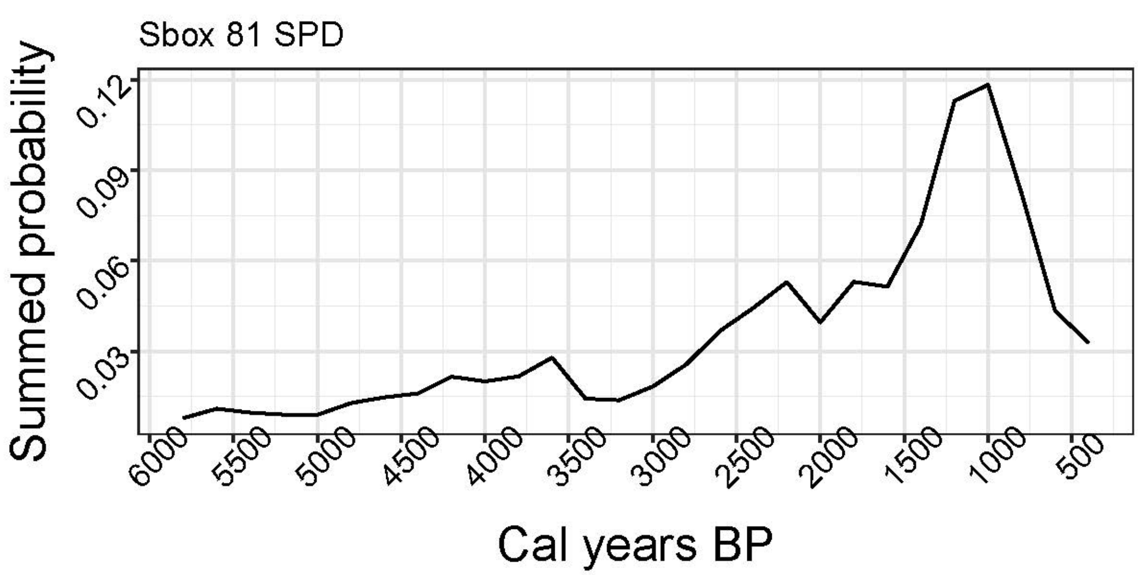
3000
2500
2000
1500
1000
500
Cal years BP


Sbox 81 SPD
Summed probability
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0.09
0.12
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4000
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3000
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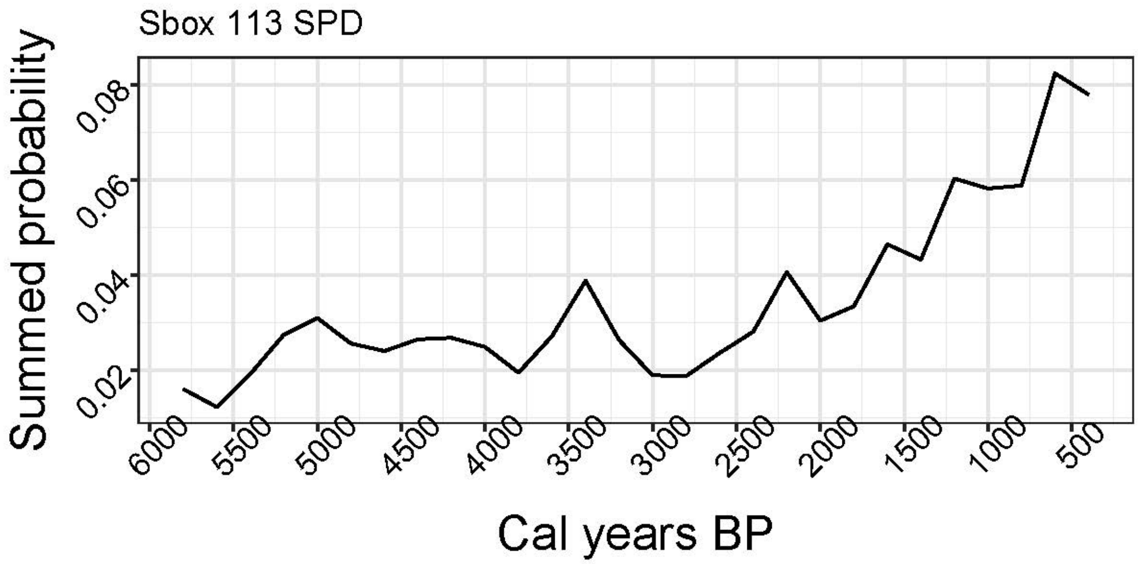
2000
1500
1000
500
Cal years BP


Sbox 113 SPD
Summed probability
0.02
0.04
0.06
0.08
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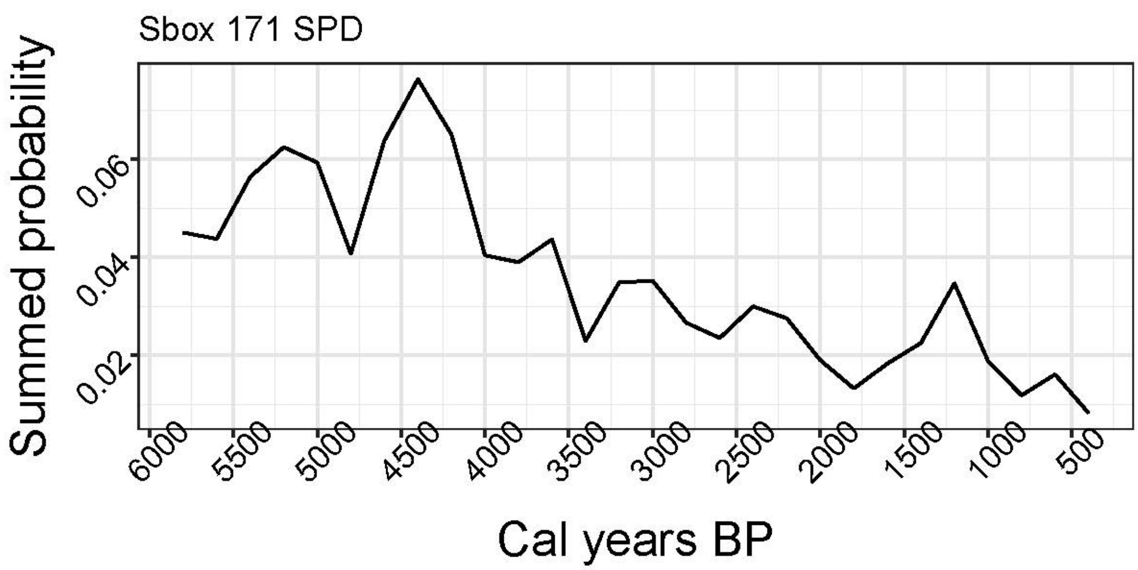
1500
1000
500
Cal years BP


Sbox 171 SPD
Summed probability
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0.06
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4500
4000
3500
3000
2500
2000
1500
1000
500
Cal years BP