

The Importance of Spatial Data to Open-Access National Archaeological Databases and the Development of Paleodemography Research

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ABSTRACT

With generous support from the National Science Foundation, we have spent the past four years developing an archaeological radiocarbon database for the United States. Here, we highlight the importance of spatial data for open-access, national-scale archaeological databases and the development of paleodemography research. We propose a new method for analyzing radiocarbon time series in the context of paleoclimate models. This method forces us to confront one of the central challenges to realizing the full potential of national-scale databases: the quality of the spatial data accompanying radiocarbon dates. We seek to open a national discussion on the use of spatial data in open-source archaeological databases.

Keywords: Open Science, open access, Big Data, radiocarbon data, dates as data, paleodemography, paleoclimate modeling, GIS

Con el apoyo generoso de la National Science Foundation, hemos desarrollando en los últimos cuatro años una base de datos arqueológicos de radiocarbono para los Estados Unidos. Con esta base pretendemos destacar la importancia de los datos espaciales para las bases de datos arqueológicas a escala nacional de acceso abierto. Proponemos un nuevo método para analizar las series de tiempo de radiocarbono en el contexto de los modelos paleoclima. Este método nos ayuda a enfrentar uno de los retos principales y de esta manera aprovechar el potencial total de las bases de datos a escala nacional: la calidad de los datos espaciales que acompaña a las fechas de radiocarbono. Aquí buscamos abrir una discusión nacional sobre el uso de los datos espacial en bases de datos arqueológicas de acceso abierto.

Palabras clave: ciencia abierta, acceso abierto, macrodatos, datos radiocarbónicos, fechas como datos, paleodemografía, modelos paleoclimáticos, Sistema de Información Geográfica (SIG)

Archaeology currently sits at one of the most important crossroads in its disciplinary history, one created by the movement toward Open Science (Marwick et al. 2017) and the potential to develop Big Data. Open Science approaches make data and the methods used to analyze them openly available to professionals and public stakeholders to democratize science and enhance the reproducibility of research (OECD 2015). Big Data examines problems at various scales of research, up to a global scale (Chaput and Gajewski 2016; Chaput et al. 2015; Freeman et al. 2018; Zahid et al. 2016), and overcomes limitations in small datasets with the “power of numbers.” These approaches bring great promise for the future of archaeology and its role in the twenty-first century. Simultaneously, they open legal and ethical challenges for protecting and preserving cultural heritage resources.

These challenges are apparent in the recent development of large open-access archaeological radiocarbon databases. For example,

the Canadian Archaeological Radiocarbon Database (CARD; Gajewski et al. 2011; Martindale et al. 2016) houses tens of thousands of radiocarbon dates from various regions of the world. Since 2014, two of us (ER and RLK) have been funded by the National Science Foundation to collect radiocarbon dates from the lower 48 US states and deposit them into CARD. The majority of these dates come from cultural resource management (CRM) site reports, a literature traditionally accessed primarily by regional specialists with deep knowledge of a region’s archaeology and physical access to paper reports. At present, with just over \$900,000 in funding, we have collected approximately \$22.5 million worth of publicly funded radiocarbon dates (assuming an average of \$300/date). Consequently, this project puts the results of millions of dollars in public funding into the public domain. Once there, archaeologists can use them to investigate grand challenges (Kintigh et al. 2014), such as the growth of human populations on earth and the long-term history of

human-environment interactions at unprecedented spatial and temporal scales (e.g., Chaput and Gajewski 2016; Chaput et al. 2015; Freeman et al. 2018; Robinson et al. 2019; Zahid et al. 2016).

Spatial data present the greatest challenge in making archaeological radiocarbon datasets openly available (Bevan 2012; McCoy 2017). Ideally, each radiocarbon date that we submit to CARD would have metadata that include precise spatial coordinates. CARD ensures that such data do not fall into inappropriate hands by masking site location at 1:2,000,000 on the public side of the website and by vetting individuals requesting access to the data. However, due to Section 9 of the [Archeological Resources Protection Act of 1979](#) and following [SAA Ethical Principles 1 and 6](#), the only spatial data we submit to CARD is the county centroid for each date. This imposes serious limitations on the potential future use of these data.

This article seeks to open a dialogue about the importance of spatial data for national-scale archaeological databases. We do so by presenting a new method to model large radiocarbon databases within transient paleoclimate zones. This method provides a foundation for collaboration among archaeologists, paleoecologists, and paleoclimatologists. Archaeology can make unprecedented contributions to interdisciplinary problems facing contemporary societies. But this potential contribution is limited when the quality of the spatial data is poor.

RADIOCARBON “BIG DATA” AND “DATES AS DATA” APPROACHES

Archaeologists recognized the utility of radiocarbon dates as more than just a way to date sites and strata in the 1980s. Michael Berry and the late Claudia Berry (Berry 1982) set the stage for using aggregated radiocarbon dates as proxy evidence for the growth, decline, and migration of prehistoric human populations (see also Wright 1982). John Rick (1987) later gave the approach its name: “dates as data.” This approach was based on the assumption that, when summing all of the radiocarbon date frequencies from a particular region at some temporal interval, high frequencies of dates reflected larger populations, and low frequencies reflected smaller populations. Essentially, more dates equaled more people. This method provided an alternative to traditional demographic studies that relied on the preservation of skeletal material or the tabulation of a particular artifact type (e.g., pottery sherds). It therefore offered a more spatially and temporally representative proxy of prehistoric human demography on Earth.

Also in 1987, Richard Morlan of the Canadian Museum of Civilization and Roger McNeely of the Geological Survey of Canada Radiocarbon Laboratory participated in a meeting at Yale University organized by the late Renee Kra to develop an International Radiocarbon Database (Gajewski et al. 2011; Kra 1989). Although that round of efforts was shelved in the early 1990s (Elliott 2001), Morlan set about developing his own Canadian database, initially focusing on his particular regions of interest (Gajewski et al. 2011). The database blossomed into CARD, now housed at the University of British Columbia (Martindale et al. 2016).

As of January 2019, CARD houses or provides a portal to more than 100,000 dates from around the world. We have contributed approximately 40,000 dates to CARD from the 11 western US states. We also have another roughly 35,000 dates from the rest of the United States that we will eventually release to CARD. Most of the other data in CARD has been uploaded by various independent research projects. A good number of these projects were carried out in order to apply “dates as data” approaches to the reconstruction of paleodemography across millennia in various regions of the world. These projects have confronted the various biases (calibration, collection, taphonomic, and energetic) inherent in the data and helped make radiocarbon data the most spatially and temporally robust data available for reconstructing prehistoric human demography at regional and global scales.

Despite these advances, work remains to make “dates as data” approaches applicable to interdisciplinary research that integrates archaeological and paleoenvironmental data to understand long-term human-environment interactions. Providing a foundation for interdisciplinary research on human population ecology and long-term sustainability is possibly the area where “dates as data” approaches can make their most impactful contribution to archaeology’s grand challenges. To do so, however, we must overcome what we call “the spatial hurdle.”

Overcoming the spatial hurdle requires two interrelated advances. First, “dates as data” approaches by necessity are conducted within a region (often contemporary administrative space, such as a state). Developing radiocarbon time series to analyze human demography through time within a region does not consider the environmental variability within that region that established adaptive constraints on past populations. Moreover, analyses of human demography through time must track immigration and emigration, which are central considerations of population ecology (Berryman 1999). Failure to overcome the spatial hurdle limits the extent to which “dates as data” approaches can be integrated with paleoenvironmental data and therefore used in interdisciplinary research on human population ecology and long-term sustainability.

In this article, we propose a method that enables researchers to investigate the dynamics of human paleodemography between different paleoclimate and environmental contexts. Operationalizing this method, however, requires accurate spatial data. Without them, we are unable to conduct robust analyses of human demographic dynamics within the context of different paleoenvironments. We illustrate this below.

A CLIMATE MODEL APPROACH TO “DATES AS DATA”

Investigation of prehistoric human-environment interactions requires embedding prehistoric human populations in their environments. A considerable challenge in meeting this goal arises from the dynamism of paleoenvironments themselves, which was caused, in turn, by the dynamism of past climate changes. We must therefore contend with the transient nature of paleoclimate change if we wish to investigate prehistoric human population growth in different environmental contexts. Otherwise, static projections of paleoenvironments provide false baselines for

human-environment interaction through time. The method we present here embeds prehistoric human demography in transient paleoclimate and environmental space by developing different climate zones in which we reconstruct paleodemography. This enables us to reconstruct human population dynamics throughout the Holocene, compare population ecology in different paleoclimate zones, and evaluate migration processes between different zones.

GIS Analysis of Paleoclimate Zones

Statistical methods that digitally downscale and spatially grid large-scale earth system models (ESM) have made the analysis of high-resolution climate variables possible within GIS models. This study uses digitally downscaled and debiased Community Climate System Model 3 (CCSM3) data, developed by Lorenz and colleagues (2016), of average annual precipitation (PPT) and growing degree days (5°C base, GDD5) to model and recreate the geographic extent of paleoclimate zones in the American West from 10,000 to 500 cal BP. The spatially gridded CCSM3 climate data geoprocessed in a GIS model allow us to examine past climates at a relatively high temporal resolution. Although the CCSM3 data do not account for inter-annual, decadal, or century-scale changes in climate regimes, they do allow us to track large-scale temporal trends across the Holocene.

The CCSM3 data (Lorenz et al. 2016) used in this analysis are comprised of climate data layers (climate grids) for North America based on model simulations of a coupled atmosphere-ocean general circulation model (He et al. 2013; Liu et al. 2009; Lorenz et al. 2016). The downscaled and debiased CCSM3 model developed by Lorenz and colleagues (2016) was originally forced using trends in orbital parameters, ice sheet extent and height, sea level, greenhouse gases, and meltwater pulses to the North Atlantic. To achieve a temporal domain of 500 years, Lorenz and colleagues (2016) downscaled the CCSM3 model to 0.5 degrees using bilinear interpolation and then hindcast those results based on comparisons to modeled present climate into century-scale bins of 200 years, centered on 500-year intervals (Lorenz et al. 2016).

The paleoclimate zones presented here were created using the Maximum Likelihood Classification (MLC) function in ArcGIS 10.5 with Spatial Analyst (Nicholson 2017; Tercek et al. 2012), with the PPT and GDD5 from the CCSM3 datasets in 500-year intervals starting at 10,000 cal BP. MLC is a multivariate spatial tool designed to categorize analogous environmental and other geographic variables into a user-specified number of classes (ESRI 2011). MLC considers both the variances and covariances of class signatures when assigning raster cells to a particular class. These classes are characterized by the mean vector and a covariance matrix, with the assumption that the distribution of a class sample is normal. Given these characteristics for each raster cell, the statistical probability of an area being similar to another is computed to determine the membership of the cells to each class (ESRI 2011). We use PPT and GDD5 because these variables are common components of climate zone delineations (Kottek et al. 2006; Metzger et al. 2005; Nicholson 2017; Peel et al. 2007; Tercek et al. 2012).

The first step of the MLC analysis was to define our study area and then “clip” the CCSM3 raster datasets to our region of interest. We then created IsoCluster signature files to define the variance and covariance of PPT and GDD5 for each 500-year interval. The

signature files use a clustering algorithm to determine the characteristics of the natural groups of cells in multidimensional space. We created IsoCluster signature files of PPT and GDD5 for 15 climate zones for the western United States based on Metzger and colleagues’ (2013) delineation of climate zones for the entire modern global land surface. Prior to creating these climate zones for the entire globe, Metzger and colleagues (2005) developed a clustering algorithm to classify the number of environmental zones across the Earth based on statistical stopping tools (Bunce et al. 1996). As Metzger and colleagues (2013) had already established the number of climate zones (15) for the western United States, they used this number in the MLC as the number of classes. Note that although there are 15 climate zones, only 11 have radiocarbon dates in Wyoming and Utah.

We gave the modeled paleoclimate zones descriptive names based on Metzger and colleagues’ (2013) nomenclature, and we derived the precipitation and temperature classifications by extracting raster values with the Zonal Statistics Tool in ArcGIS 10.5 Spatial Analyst. We created six categories of temperature based on GDD5 to classify descriptive levels of temperature using the mean and standard deviation values. We also used the same method for classifying precipitation regimes to derive five categories of average annual precipitation. We concatenated final climate categories based on the combination of PPT and GDD5 values for each delineated climate zone for each time period. Figure 1 displays the climate zones and the locations of sites for each 500-year interval.

While others discuss the validity and reliability of the modeled global climate model inputs (Hargreaves 2010; Hargreaves et al. 2013; Kohfeld and Harrison 2000; Nikolova et al. 2013; van den Hurk et al. 2013), it is not possible to statistically verify the shape of the modeled paleoclimate zones presented here because many past ecological communities lack modern analogs to make equivalent climate comparisons (the so-called no-analog climates; Gonzales et al. 2009; Jackson and Overpeck 2000; Veloz et al. 2012; Williams and Jackson 2007; Williams and Shuman 2008). These no-analog climates make correlating fossil pollen data to the paleoclimate zones modeled here unfeasible because the climate envelopes for many of the plant taxa used to reconstruct past climates are elastic. This elasticity is evidenced specifically by intraspecies adaptation to local environments, atmospheric levels of CO₂, and the potential evolution/adaptation of a species to new environments based on continental- to local-scale climatic changes (Veloz et al. 2012; Williams and Jackson 2007). Thus, the 15 paleoclimate zones delineated and classified in this study are mathematical estimates of real-world, abiotic processes and should be viewed as our current best estimate of the climate landscape during the Holocene.

Developing Radiocarbon Time Series within Paleoclimate Zones

We develop summed probability distributions (SPDs) of radiocarbon date frequencies from each of the 11 climate zones with dates in Utah and Wyoming, two states where we have large radiocarbon datasets as well as specific site locational data. SPDs are developed from both the precise latitude-longitude or UTM data, and from centroids for each county, for each date. We compare the results obtained for each zone using three spatial resolutions

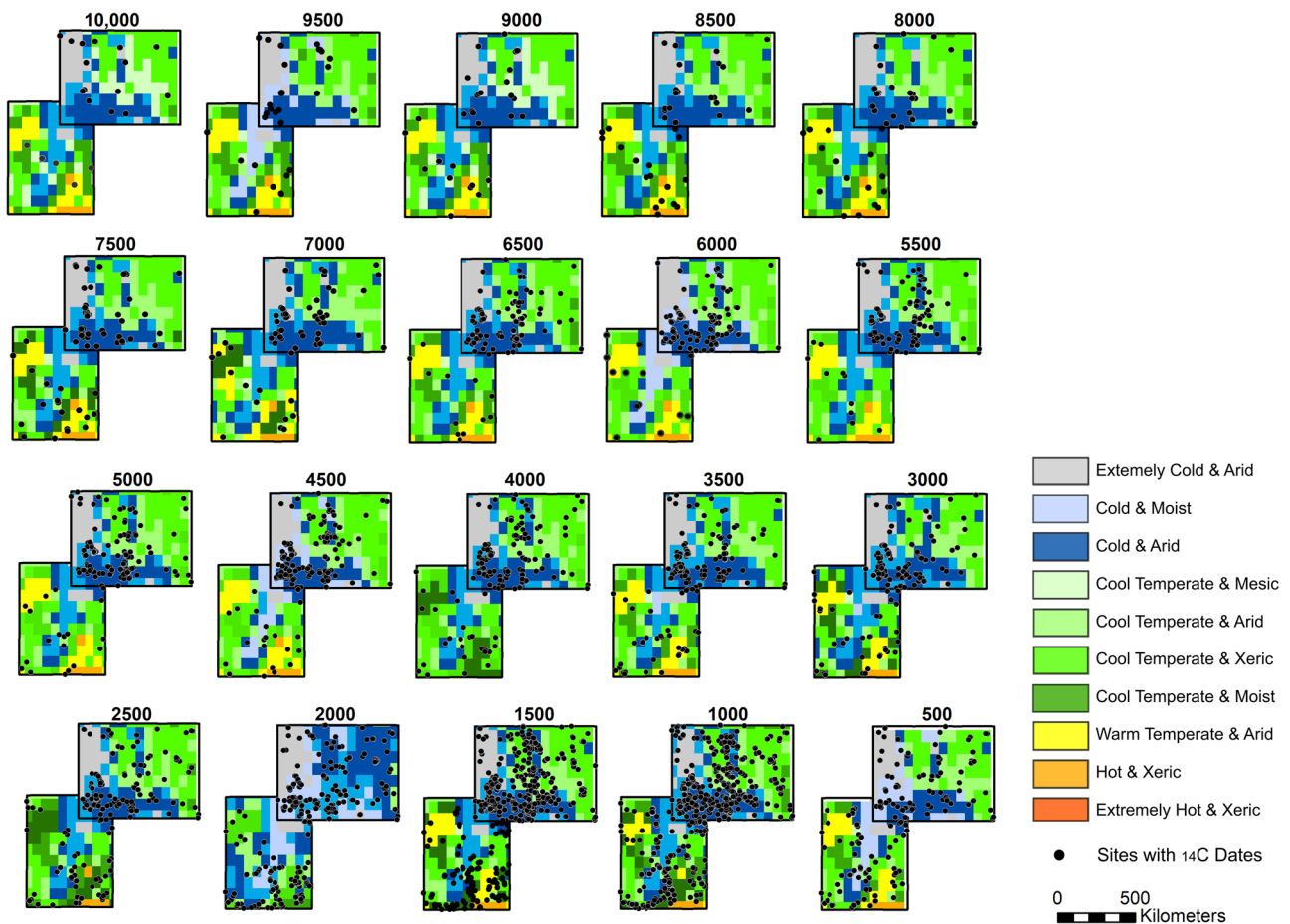


FIGURE 1. Map series of ¹⁴C site locations and paleoclimate zones in 500-year intervals, from 10,000 cal BP to 500 cal BP.

of the radiocarbon data, state, county, and specific levels. As mentioned above, we use county centroids because these are the level of spatial resolution for each date that we submit to CARD and that are effectively coded in sites' Smithsonian numbers.

A central challenge in working with radiocarbon big data is the variable quality of the individual radiocarbon dates in each state dataset, and we caution researchers against simply downloading and immediately using all dates without implementing some sort of selection criteria. First, despite being called an "archaeological radiocarbon database," CARD also contains geological and paleontological dates. We must therefore select only archaeological dates. Second, because of the considerable role of variable legacy data in these datasets, some dates do not have associated lab numbers. In order to conduct work within an Open Science approach that provides the means for testing and replicating results, any analysis must have a lab number for each date used. Third, only normalized dates should be calibrated and summed, which requires us to omit all measured dates (or accept these as normalized dates with an assumed $\delta^{13}C$ value). Fourth, the older legacy dates have errors anywhere from 300 to 1,000 years. In this analysis, we only include dates with errors <200 years. Lastly, in order to correct for sampling biases caused by over-sampling at a particular site, we use only dates with associated site IDs. Using these criteria alongside the requirement that each date

have a georeference, Utah's dataset decreased from 3,363 to 1,126 dates, and Wyoming's decreased from 5,830 to 2,570 dates.

The first step in our method requires that we embed each georeferenced date into one of the 11 designated climate zones. Because these different zones are broken down in 500-year intervals, we start by calculating the median calibrated age for each individual radiocarbon date. We do this in OxCal version 4.2 (Bronk Ramsey 2009) using the IntCal13 calibration curve (Reimer et al. 2013). These median dates place each radiocarbon date into a specific climate zone for each 500-year interval. All dates for each climate zone are then exported from the GIS in order to create an SPD for each zone.

We develop two sets of SPDs using the *rcarbon* package (Bevan et al. 2017) in the R statistical computing language (R Core Team 2014), one using precise site locational data and the other using county centroid data. *Rcarbon* enables the calibration of dates, the binning of calibrated dates from the same site, the aggregation of dates and development of SPDs, Monte Carlo simulations providing tests for significant positive or negative deviations of the SPD from a selected null model, and permutation tests to compare different regions to each other. As our sample sizes for each climate zone vary, Monte Carlo simulations are important for determining spurious peaks or troughs in the SPDs versus truly

significant deviations from the null model. Despite these varying sample sizes, Timpson and colleagues (2014) have shown the robustness of the *rcarbon* method even with small sample sizes.

Our analysis calibrated dates using the IntCal13 calibration curve (Reimer et al. 2013). We used the binning function of *rcarbon* to aggregate multiple dates from the same site that are within 100 calibrated years of each other. SPDs were developed with a 100-year running mean. We carried out 500 Monte Carlo simulations comparing the empirical SPDs against a null model of exponential growth. We did not correct for taphonomic bias for two reasons. First, the exponential null model assumes the same increasing loss of radiocarbon samples through time (Crema et al. 2016). Second, taphonomic

correction (Bluhm and Surovell 2018; Surovell et al. 2009) does not alter the amount of significant positive or negative deviations from the null model compared to non-taphonomically corrected SPDs; it just increases the frequencies of radiocarbon dates for all SPDs in the middle Holocene relative to the late Holocene.

RESULTS: PALEODEMOGRAPHY AND PALEOCLIMATE

As noted above, this paper proposes a new method for reconstructing human paleodemography from radiocarbon SPDs. This

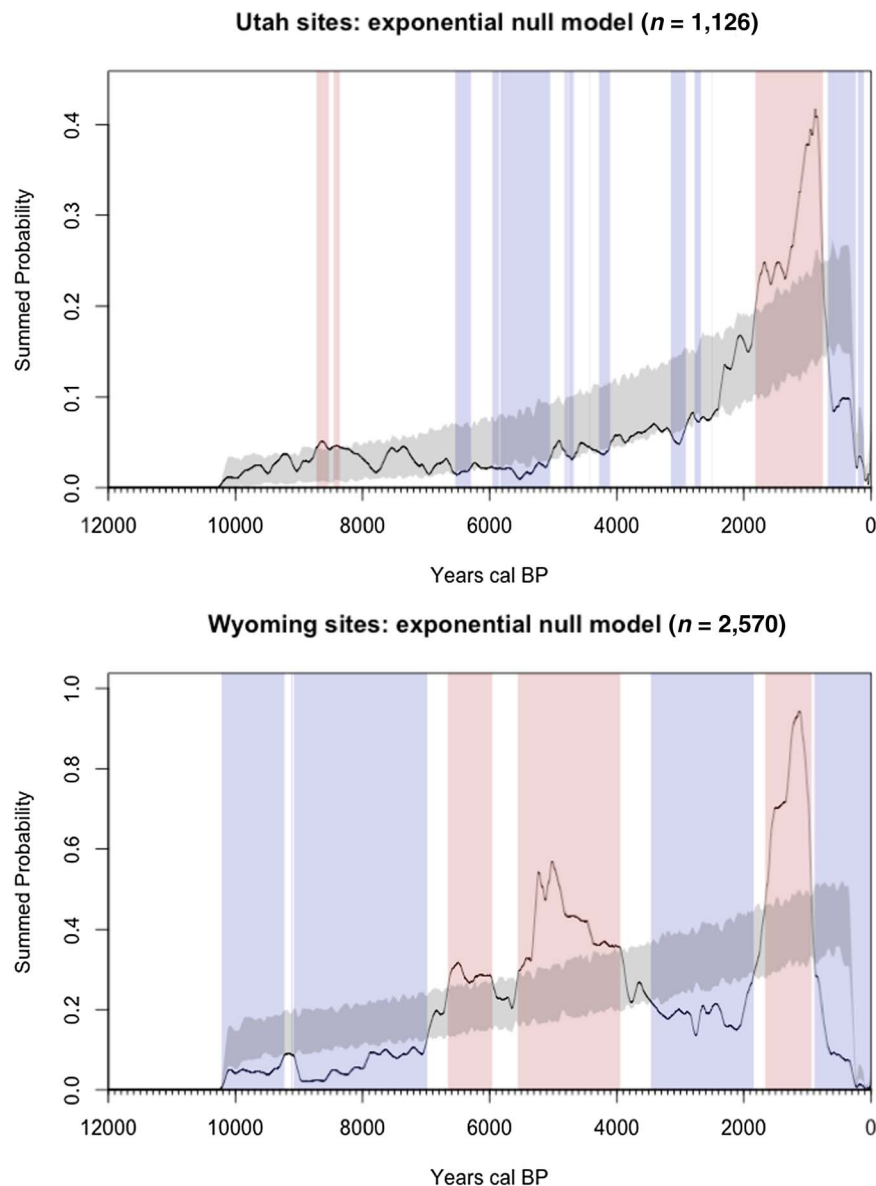


FIGURE 2. Radiocarbon Summed Probability Distributions (SPD) for Utah and Wyoming. Black line: empirical SPD with 100-year running mean. Gray band: exponential null model with 95% confidence limits. Blue: significant negative deviations from the null model (i.e., population “busts”). Red: significant positive deviations from the null model (i.e., population “booms”).

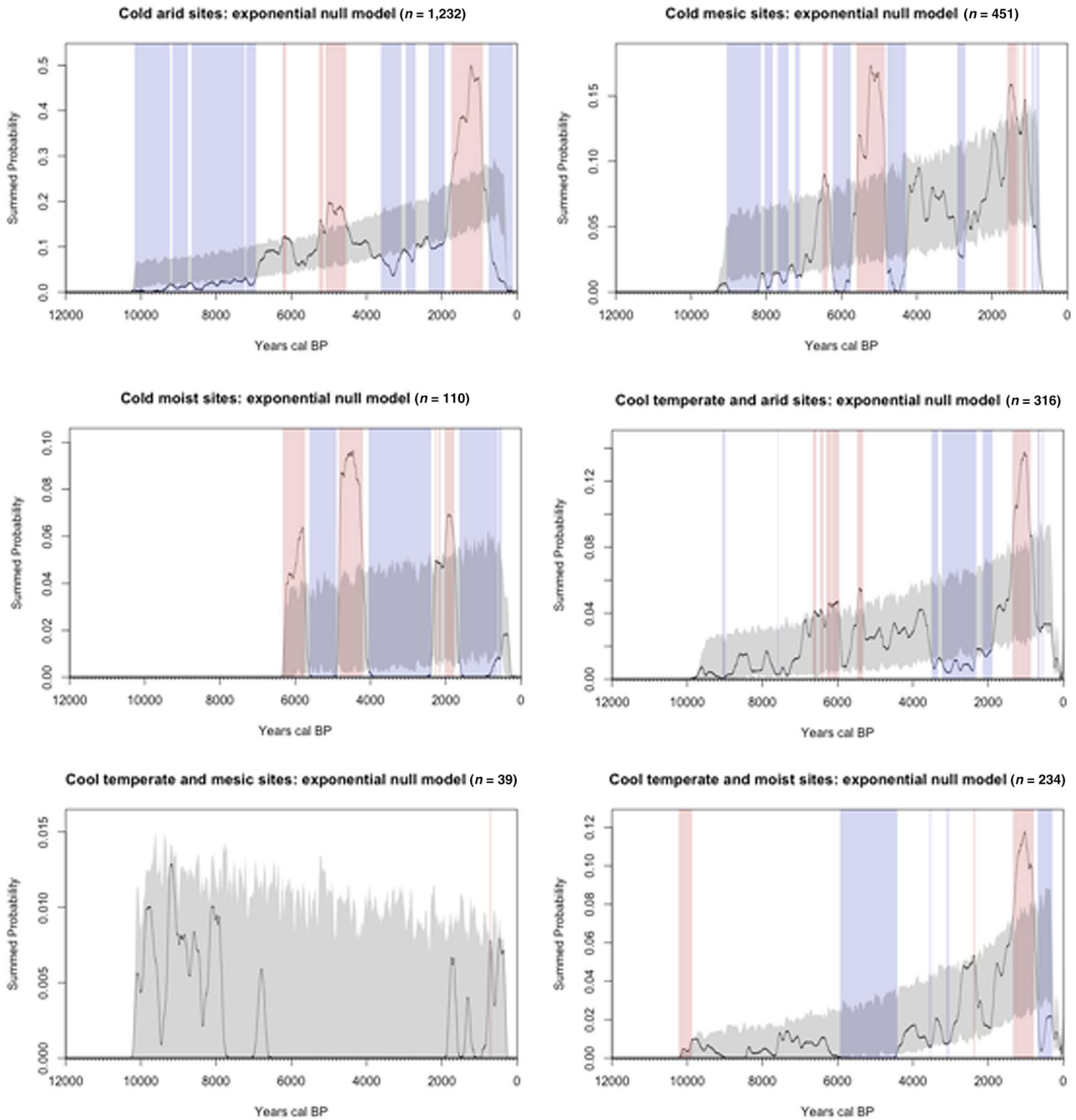


FIGURE 3. Radiocarbon Summed Probability Distributions (SPD) for climate zones with precise site locational data. Black line: empirical SPD with 100-year running mean. Gray band: exponential null model with 95% confidence limits. Blue: significant negative deviations from the null model (i.e., population “busts”). Red: significant positive deviations from the null model (i.e., population “booms”).

method moves beyond traditional approaches that develop SPDs for arbitrarily defined geographic regions. We propose developing SPDs from transient climate models that can provide more realistic assessments of the geographic and environmental spaces inhabited by prehistoric human populations. This method requires high-quality spatial data, which we will critically assess here.

State-Wide SPDs Versus Climate Zone SPDs

Figure 2 shows the Holocene SPDs for the entire states of Utah and Wyoming. Figure 3 shows the SPDs for the different climate zones using precise site locational data for each radiocarbon date. Figure 4 compares the significant population “booms” and

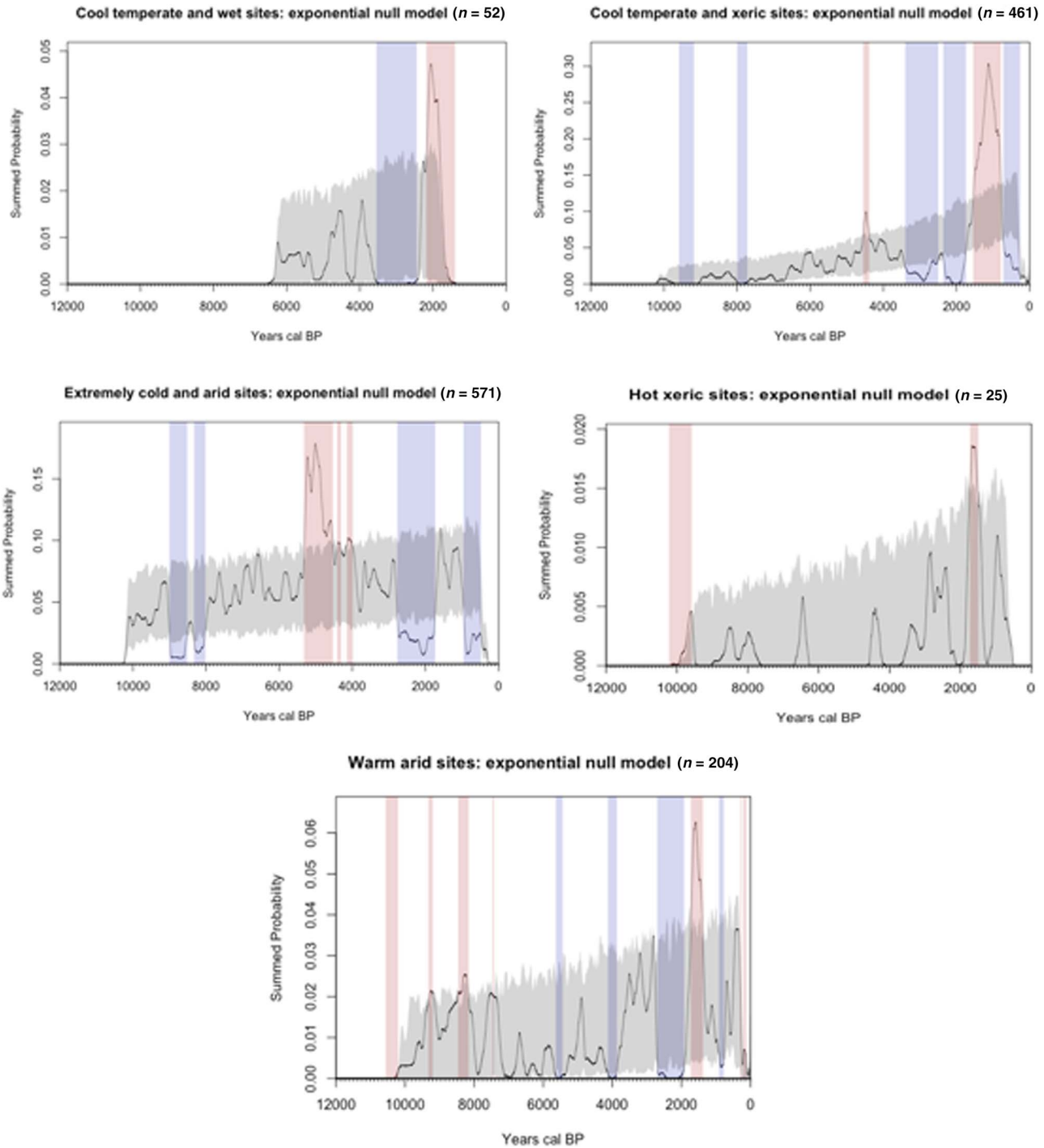


FIGURE 3. Continued.

“busts” from SPDs at the state-wide level to the different climate zones.

Figure 4 displays the unique power of the “dates as data” approach to provide coarse-grained reconstructions of human paleodemography. At the state-wide level, some interesting

patterns are immediately apparent. First, we see that during the early Holocene, Wyoming exhibits significant population busts, while Utah shows a slight boom within a broader period that fits within the expected trends of the exponential null model. The opposite occurred during the middle Holocene, when we see a population boom in Wyoming at the same time that a

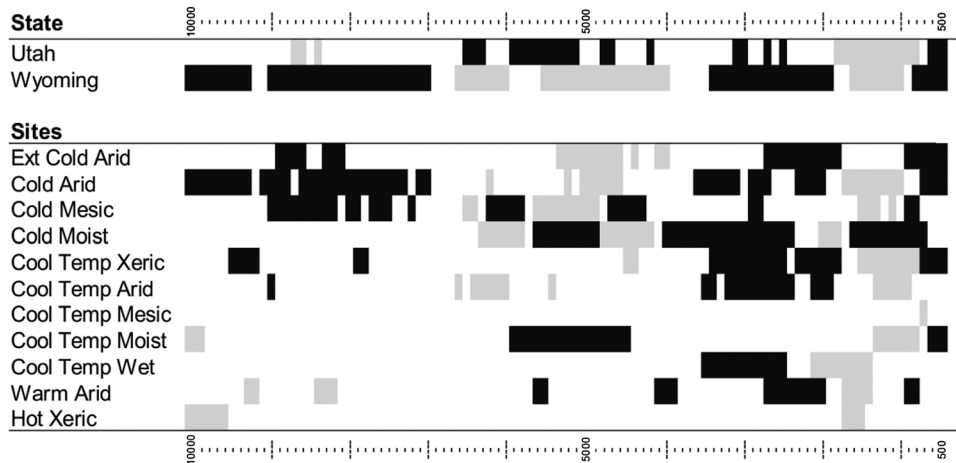


FIGURE 4. Comparison of significant population “booms” and “busts” between states and among climate zones with precise site locational data. Black: population “busts.” Gray: population “booms.” White: no significant deviation from the exponential null model.

population bust appears in Utah. At this coarse-grained scale, these patterns suggest possible population migration. We reiterate that the coarse-grained nature of SPDs provides first approximations, enabling the development of testable hypotheses (Williams 2012). These state-wide comparisons suggest that future research explore and test hypotheses for the migration of populations out of the eastern Great Basin during the middle Holocene.

However, when we compare state-wide trends to the different climate zones, the hypothesis for human migration becomes more complex. Significant population booms or busts are not recorded for each climate zone during the early and middle Holocene. This suggests more complex and nuanced vulnerabilities to booms or busts for different environmental contexts.

The different climate zone SPDs suggest that certain zones might have been more susceptible to demographic fluctuations than others. This enables us to ask questions that align with central questions in population ecology, such as the processes by which species inhabit and fill in different landscapes (Allee et al. 1949; Berryman 1999; Fretwell and Lucas 1969). The ability to ask questions that align with population ecology is a key benefit of climate zone approaches to SPDs. The climate zones in Figure 4 enable us to have a coarse-grained perspective on how prehistoric human populations filled in different ecosystems throughout Utah and Wyoming during the Holocene. The patterns of different booms, busts, and expected populations between the different climate zones highlight how, during the early and middle Holocene, human populations were able to adapt to environmental or social perturbations by simply moving from one environmental context to another. This ability to migrate is apparent by the mix of booms, busts, and expected population levels for the different time slices during the early and middle Holocene. The late Holocene highlights a very different situation, in which we see a greater number of contemporaneous booms or busts across all climate zones. The large number of population busts across most climate zones ~3000 cal BP suggests something like the beginning of a broad-scale population turnover, with populations starting to grow ~2000 cal BP, populations booming from ~2000–

1000 cal BP, and populations busting after ~1000 cal BP. At this coarse-grained scale, it appears that the relatively contemporaneous boom and bust pattern across different environmental contexts shows that human populations were saturating landscapes throughout Utah and Wyoming during the late Holocene. Whereas early and middle Holocene populations were able to move freely among different environmental contexts because they were sparsely populated, late Holocene populations had to contend with landscapes that were fully populated—which, we propose, initiated new population ecology processes guided more by endogenous social-ecological, and perhaps epidemiological (e.g., Phillips et al. 2018), processes. This might be attributed to both the impact of the spread of domesticated plants into certain zones (Simms 2008) and large-scale migration into the region (e.g., Madsen and Simms 1998; Thomas 2019). This widespread population boom-bust ~1000–700 cal BP is the subject of ongoing research, as it appears to have occurred across many regions throughout North America and even the world (Chaput and Gajewski 2016; Freeman et al. 2018; Peros et al. 2010).

Although it is not our aim in this article to further elaborate on these initial interpretations, our comparison of state-wide and climate zone SPDs indicate that climate-zone SPDs provide an exciting foundation for asking fundamental questions about human population ecology. The coarse-grained scales offered by climate-zone SPDs also enable new perspectives on some of the most dominant research themes in the archaeology of the western United States, such as the Numic Spread hypothesis, the spread of maize agriculture beyond the Southwest, and the widespread late prehistoric collapse of populations across different social-ecological contexts throughout the West.

Precise Site Location SPDs versus County Centroid SPDs

As we are currently releasing data that we have collected from our NSF project to CARD in the form of county centroids, we seek to compare results of climate-zone SPDs using county centroid

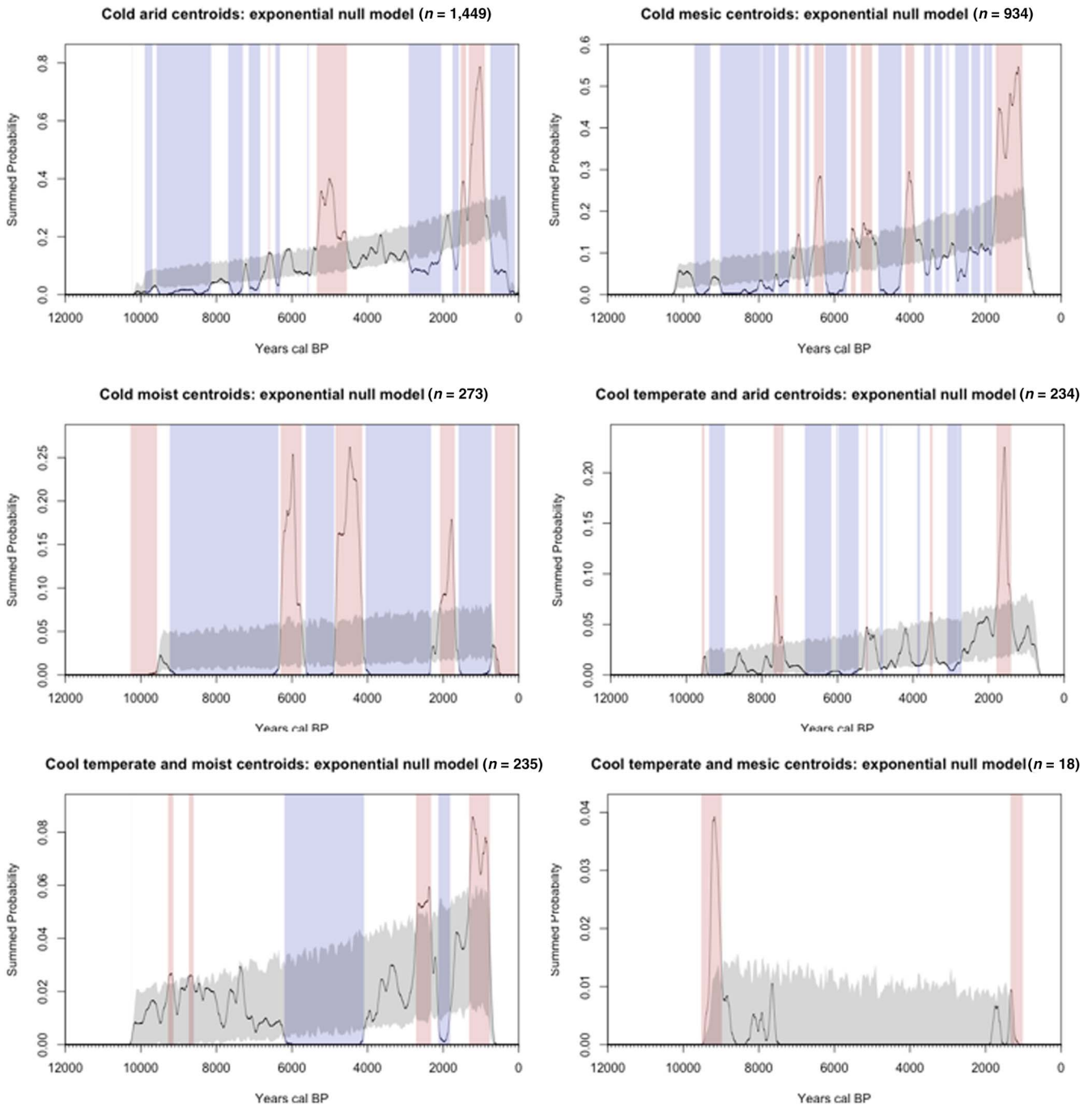


FIGURE 5. Radiocarbon Summed Probability Distributions (SPD) for climate zones with county centroid data. Black line: empirical SPD with 100-year running mean. Gray band: exponential null model. Blue: significant negative deviations from the null model (i.e., population “busts”). Red: significant positive deviations from the null model (i.e., population “booms”).

versus those using precise site locational data. We developed SPDs for county centroid climate zones using the same parameters we used for the SPDs with site locational data. Figure 5 shows these different SPDs. Figure 6 compares the booms and busts for the different climate zones using centroid versus site location data.

The assignment of the spatial location of each radiocarbon date to a specific climate zone for a 500-year interval shows significant

mismatches between the county centroid data and site locational data for each state (Wyoming $\chi^2 = 963$, $df = 19$ $p < 0.000$; Utah $\chi^2 = 176$, $df = 19$ $p < 0.000$). Table 1 shows the number of total mismatching dates assigned to climate zones for each 500-year interval for Utah. In total, there is a significant mismatch for Utah, where 53% of the radiocarbon dates using centroid data were assigned to the wrong climate zones than with precise site locational data. Table 1 also shows the number of total mismatching

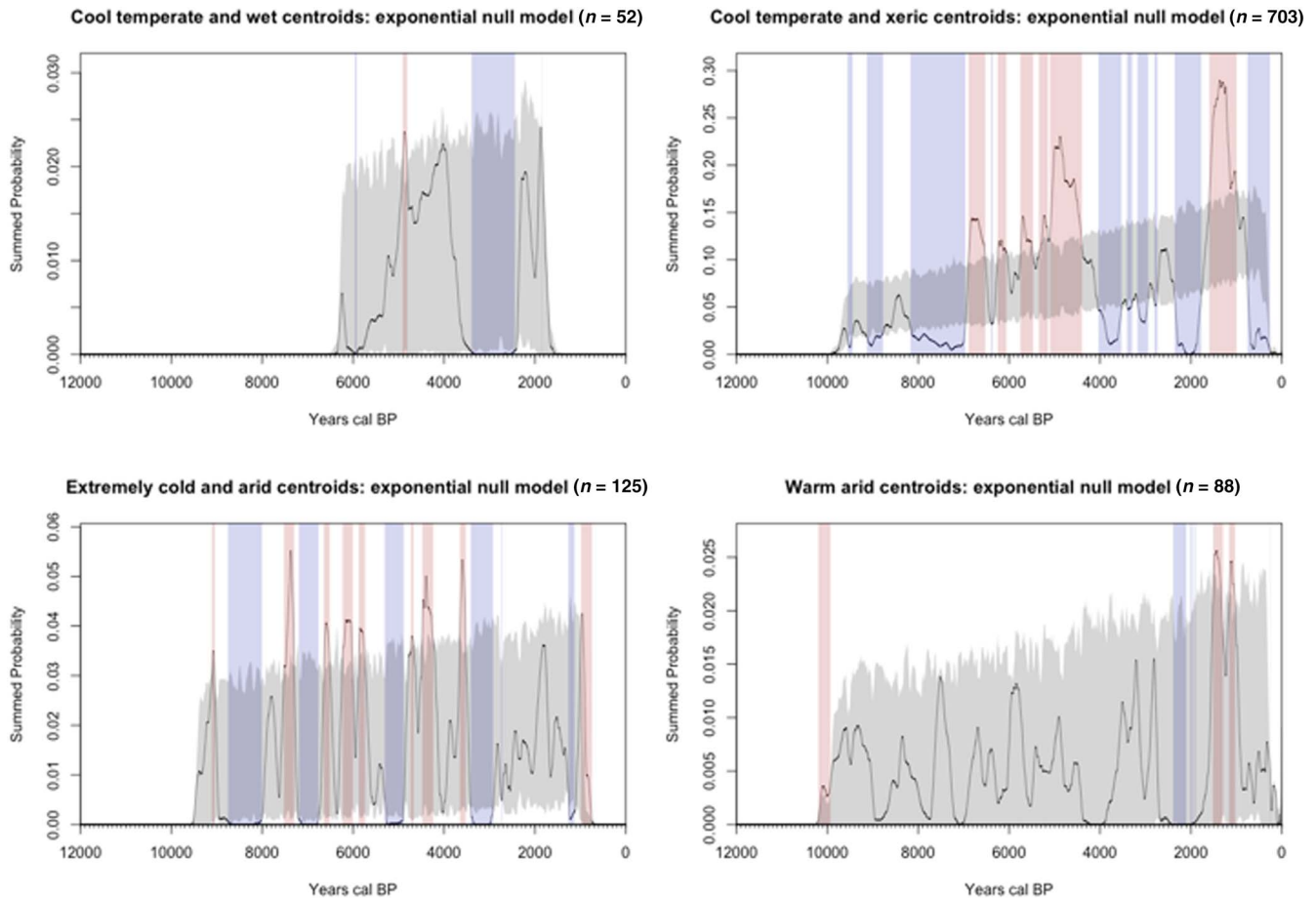


FIGURE 5. Continued.

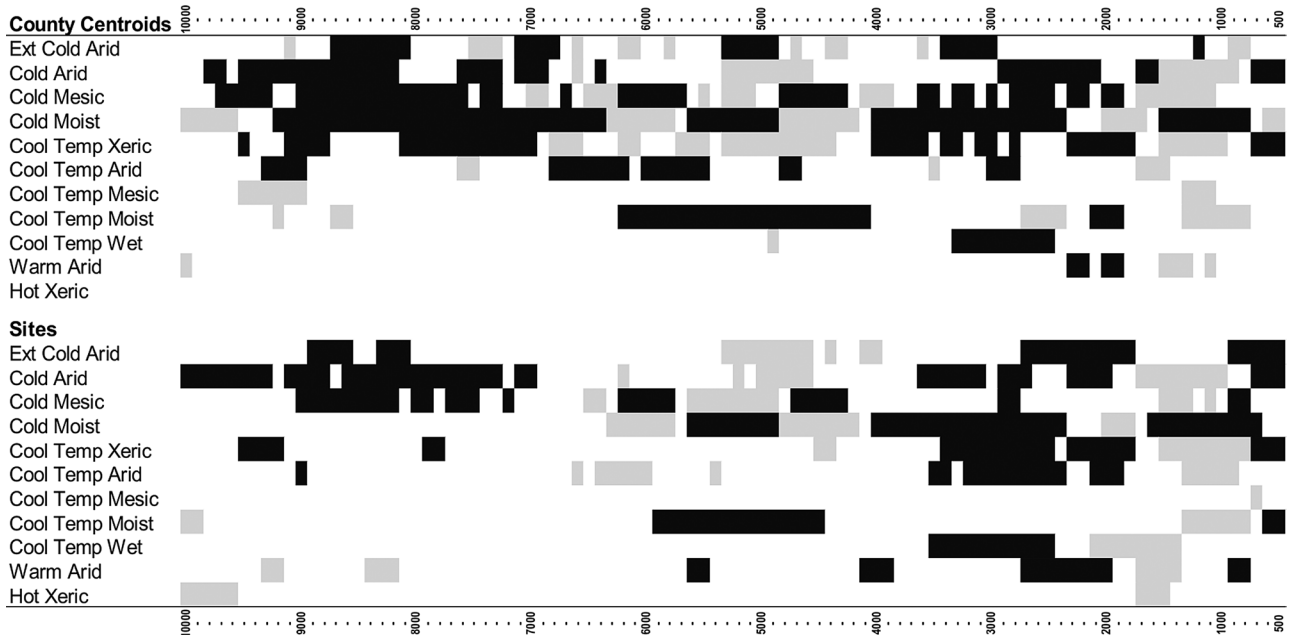


FIGURE 6. Comparison of significant population “booms” and “busts” between different climate zones for county centroid and site locational data. Black: population “busts.” Gray: population “booms.” White: no significant deviations from the exponential null model.

TABLE 1. Comparing Mismatching Climate Zones between Precise Site Location Data and County Centroid Data for Utah and Wyoming.

Utah				
cal BP	Match	Mismatch	%Mismatch	Grand Total
500	54	84	61	138
1000	141	115	45	256
1500	67	101	60	168
2000	117	60	34	177
2500	21	20	49	41
3000	27	18	40	45
3500	15	21	58	36
4000	4	20	83	24
4500	18	11	38	29
5000	8	13	62	21
5500	3	7	70	10
6000	7	4	36	11
6500	5	6	55	11
7000	5	6	55	11
7500	6	38	86	44
8000	4	18	82	22
8500	7	29	81	36
9000	7	11	61	18
9500	11	6	35	17
10,000	1	5	83	6
Wyoming				
cal BP	Match	Mismatch	%Mismatch	Grand Total
500	14	51	78	65
1000	103	333	76	436
1500	112	279	71	391
2000	17	95	85	112
2500	20	43	68	63
3000	27	55	67	82
3500	24	85	78	109
4000	28	112	80	140
4500	50	158	76	208
5000	56	169	75	225
5500	28	97	78	125
6000	37	137	79	174
6500	40	130	76	170
7000	12	57	83	69
7500	11	51	82	62
8000	6	42	88	48
8500	4	17	81	21
9000	5	20	80	25
9500	3	20	87	23
10,000	0	10	100	10

climate zones for Wyoming. In total, there is a significant mismatch for Wyoming, where 77% of the radiocarbon dates using centroid data were assigned to the wrong climate zones than when using precise site locational data.

CONCLUSION

Given the size of most counties in western states, it is no surprise that low-resolution county centroid data causes the misassignment of dates to particular climate zones. The point is that such data cause major problems for using open-access radiocarbon dates for research on human paleodemography and human-environment interaction throughout prehistory. As [Figure 6](#) illustrates, the county centroid data show more booms and busts than the precise site locational data. This could lead to overinterpretations of prehistoric human population dynamics, with the different climate zones seeming more vulnerable to boom-bust dynamics. As SPDs are coarse-grained, first approximations of prehistoric demography, we must minimize overinterpretations such as these. Furthermore, for certain periods of time in certain climate zones, county centroid data show busts when the site locational data show booms. The precise site locational data provide not only more realistic and accurate reconstructions of human demography in paleoclimate space but also more conservative assessments of the data, which can minimize the potential for misinterpretation or overinterpretation of these coarse-grained population trajectories.

We have made the case here for the use of locational data that is as precise as possible. And this is as important to research as it is to CRM, which needs access to spatial data to plan for development and land management. Obviously, there is really no argument that precise data are more useful than imprecise data. The problem comes in accessing those data. A researcher has the option to seek site locations from the relevant state authorities. But if one's research question requires multiple states, or the entire country, that researcher will encounter a considerable amount of additional work and may be denied access, leaving a gap in data and forcing a less precise analysis.

So, what to do? How do we protect sites and yet make spatial data available to researchers with minimal effort? We note that the SAA has recently created a Task Force of Sharing Public Outcomes of CRM, chaired by Joshua Wells (Indiana University, South Bend), whose mandate includes drafting guidelines for the sharing of site location for research purposes. We look forward to the task force's report and offer three suggestions.

First, this issue requires a conversation with relevant federal agencies, beginning with the lead agency on archaeological matters: the National Park Service. All parties, including federal and state entities, must recognize that we no longer operate in the research environment that existed when protective legislation was enacted in the 1960s and 1970s. A regional study in the 1970s was probably contained within a state, but one today might encompass the continent (or even the world; see [Freeman et al. 2018](#)). The idea of Big Data didn't exist in the 1960s and 1970s, nor did the technology to store and analyze large datasets that crosscut state boundaries. This has now changed. By controlling access to data, state authorities, as well as the federal authorities that provide legislative guidance, must recognize their ethical responsibility to assist in this new research paradigm. This includes the recognition that tribal sovereignty and consultation are central to developing new guidelines for data sharing in the twenty-first century.

Second, state authorities could require that database gatekeepers (such as CARD) explicitly accept responsibility for the misuse of information contained in their databases. This might take the form

of language in, for example, memoranda of understanding (MOUs) that absolve state authorities from responsibility should data given to databases be misused. Additionally, and accordingly, gatekeepers should create rigorous vetting procedures and publish them. These could include notification of the relevant state authorities when a state's data are downloaded.

Third, locational data in databases could be made intentionally imprecise at a scale that protects site location and yet allows researchers to proceed with most spatial analyses. For example, site location could be masked by taking a site's actual location, choosing a random direction (0 to 359 degrees), and then choosing a random distance (e.g., between 2 and 5 km). That might be enough to ensure that unauthorized personal could not find the actual site (the published location would always be, in this example, at least 2 km away in an unknown direction) but not so far off that it would impede spatial analyses. Such an approach would also alert analysts to the maximum level of error in spatial data and allow them to decide whether it is acceptable for their research.

The era of Big Data is upon us. It requires that we rethink how we approach the control and dissemination of information, and that means an open dialogue concerning the quality of open-source spatial data. If not, our discipline will miss a unique opportunity to make important contributions to the public that funds our work. And if we cannot learn from prehistory, then that hands ammunition to those who would seek to recall protective legislation. The future preservation of the archaeological record goes hand-in-hand with its ability to be used by researchers and accessed by all stakeholders (Clarke 2015; Faniel et al. 2015; Huggett 2015; Kansa 2012).

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Data Availability Statement

No original data were presented in this article.

REFERENCES CITED

- Allee, Warder Clyde, Orlando Park, Alfred Edwards Emerson, Thomas Park, and Karl Patterson Schmidt
1949 *Principles of Animal Ecology*. WB Saunders, Philadelphia.
- Berry, Michael S.
1982 *Time, Space, and Transition in Anasazi Prehistory*. University of Utah Press, Salt Lake City.
- Berryman, Alan A.
1999 *Principles of Population Dynamics and Their Application*. Stanley Thornes, Cheltenham, United Kingdom.
- Bevan, Andrew
2012 Spatial Methods for Analyzing Large-Scale Artefact Inventories. *Antiquity* 86:492–506.
- Bevan, Andrew, Enrico R. Crema, and Fabio Silva
2017 Package “rcarbon”: Calibration and Analysis of Radiocarbon Dates. Electronic document, <https://cran.r-project.org/web/packages/rcarbon/index.html>.
- Bluhm, Lara E., and Todd A. Surovell
2018 Validation of a Global Model of Taphonomic Bias Using Geologic Radiocarbon Ages. *Quaternary Research* 2018:1–4.
- Bronk Ramsey, Christopher
2009 Bayesian Analysis of Radiocarbon Dates. *Radiocarbon* 51:337–360.
- Bunce, Robert G. H., Colin J. Barr, Ralph T. Clarke, David C. Howard, and Andy M. J. Lane
1996 Land Classification for Strategic Ecological Survey. *Journal of Environmental Management* 47:37–60.
- Chaput, Michelle A., and Konrad Gajewski
2016 Radiocarbon Dates as Estimates of Ancient Human Population Size. *Anthropocene* 15:3–12.
- Chaput, Michelle A., Björn Kriesche, Matthew Betts, Andrew Martindale, Rafal Kulik, Volker Schmidt, and Konrad Gajewski
2015 Spatiotemporal Distribution of Holocene Populations in North America. *Proceedings of the National Academy of Sciences* 112:12127–12132.
- Clarke, Mary
2015 The Digital Dilemma: Preservation and the Digital Archaeological Record. *Advances in Archaeological Practice* 3:313–330.
- Crema, Enrico R., Junko Habu, Kenichi Kobayashi, and Marco Madella
2016 Summed Probability Distribution of ¹⁴C Dates Suggests Regional Divergences in the Population Dynamics of the Jomon Period in Eastern Japan. *PLoS ONE* 11(4):e0154809.
- Elliott, Kim
2001 Renee Kra (1936–2001). *Radiocarbon* 43:vii–viii.
- ESRI
2011 ArcGIS Desktop 9.3 Help.
- Faniel, Ixchel M., Anne Austin, Eric Kansa, Sarah Whitcher Kansa, Phoebe France, Jennifer Jacobs, Ran Boytner, and Elizabeth Yakel
2015 Beyond the Archive: Bridging Data Creation and Reuse in Archaeology. *Advances in Archaeological Practice* 6:105–116.
- Freeman, Jacob, Jacopo A. Baggio, Erick Robinson, David A. Byers, Eugenia Gayo, Judson Byrd Finley, Jack A. Meyer, Robert L. Kelly, and John M. Anderies
2018 Synchronization of Energy Consumption by Human Societies throughout the Holocene. *Proceedings of the National Academy of Sciences* 115:9962–9957.
- Fretwell, Stephen Dewitt, and Henry L. Lucas
1969 On Territorial Behavior and Other Factors Influencing Habitat Distribution in Birds. *Acta Biotheoretica* 19:16–36.
- Gajewski, Konrad, Samuel Munoz, Matthew Peros, André Viau, Richard Morlan, and Matthew Betts
2011 The Canadian Archaeological Radiocarbon Database (CARD): Archaeological ¹⁴C Dates in North America and Their Paleo-Environmental Context. *Radiocarbon* 53:371–394.
- Gonzales, Leila M., John W. Williams, and Eric C. Grimm
2009 Expanded Response-Surfaces: A New Method to Reconstruct Paleoclimates from Fossil Pollen Assemblages That Lack Modern Analogues. *Quaternary Science Reviews* 28:3315–3332.
- Hargreaves, Julia C.
2010 Skill and Uncertainty in Climate Models. *Wiley Interdisciplinary Reviews: Climate Change* 1:556–564.
- Hargreaves, Julia C., James D. Annan, R. Ohgaito, André Paul, and Ayako Abe-Ouchi
2013 Skill and Reliability of Climate Model Ensembles at the Last Glacial Maximum and Mid-Holocene. *Climate of the Past* 9:811–823.
- He, Feng, Jeremy D. Shakun, Peter U. Clark, Anders E. Carlson, Zhengyu Liu, Bette Otto-Bliesner, and John E. Kutzbach
2013 Northern Hemisphere Forcing of Southern Hemisphere Climate Change during the Last Deglaciation. *Nature* 494:81.
- Huggett, Jeremy
2015 Challenging Digital Archaeology. *Open Archaeology* 1:79–85.
- Jackson, Stephen T., and Jonathan T. Overpeck
2000 Responses of Plant Populations and Communities to Environmental Changes in the Late Quaternary. *Paleobiology* 26:194–220.
- Kansa, Eric
2012 Openness and Archaeology's Information Ecosystem. *World Archaeology* 44:498–520.
- Kintigh, Keith W., Jeffrey H. Altschul, Mary C. Beaudry, Robert D. Drennan, Ann P. Kinzig, Timothy A. Kohler, W. Fredrick Limp, Herbert D. G.

- Maschner, William K. Michener, Timothy R. Pauketat, Peter Peregrine, Jeremy A. Sabloff, Tony J. Wilkinson, Henry T. Wright, and Melinda A. Zeder
2014 Grand Challenges for Archaeology. *American Antiquity* 79:5–24.
- Kohfield, Karen E., and Sandy P. Harrison
2000 How Well Can We Simulate Past Climates? Evaluating the Models Using Global Palaeoenvironmental Datasets. *Quaternary Science Reviews* 19:321–346.
- Kottek, Markus, Jürgen Grieser, Christoph Beck, Bruno Rudolf, and Franz Rubel
2006 World Map of the Köppen-Geiger Climate Classification Updated. *Meteorologische Zeitschrift* 15:259–263.
- Kra, Renee
1989 The International Radiocarbon Data Base: A Progress Report. *Radiocarbon* 31:1067–1075.
- Liu, Z., B. L. Otto-Bliesner, F. He, E. C. Brady, R. Tomas, P. U. Clark, A. E. Carlson, J. Lynch-Stieglitz, W. Curry, E. Brook, D. Erickson, R. Jacob, J. Kutzbach, and J. Cheng
2009 Transient Simulation of Last Deglaciation with a New Mechanism for Bølling-Allerød Warming. *Science* 325(5938):310–314.
- Lorenz, David J., Diego Nieto-Lugilde, Jessica L. Blois, Matthew C. Fitzpatrick, and John W. Williams
2016 Downscaled and Debaised Climate Simulations for North America from 21,000 Years Ago to 2100 AD. *Scientific Data* 3:160048. DOI:10.1038/sdata.2016.48.
- McCoy, Mark D.
2017 Geospatial Big Data and Archaeology: Prospects and Problems Too Great to Ignore. *Journal of Archaeological Science* 84:74–94.
- Madsen, David B., and Steven R. Simms
1998 The Fremont Complex: A Behavioral Perspective. *Journal of World Prehistory* 12:255–336.
- Martindale, Andrew, Richard Morlan, Matthew Betts, Michael Blake, Konrad Gajewski, Michelle Chaput, A. Mason, and Pierre Vermeersch
2016 Canadian Archaeological Radiocarbon Database (CARD 2.1). Electronic document, <https://www.canadianarchaeology.ca>.
- Marwick, Ben, Jade d'Alpoim Guedes, C. Michael Barton, Lynsey A. Bates, Michael Baxter, Andrew Bevan, Elizabeth A. Bollwerk, R. Kyle Bocinsky, Tom Brughmans, Alison K. Carter, Cyler Conrad, Daniel A. Contreras, Stefano Costa, Enrico R. Crema, Adrienne Daggett, Benjamin Davies, B. Lee Drake, Thomas S. Dye, Phoebe France, Richard Fullagar, Domenico Giusti, Shawn Graham, Matthew D. Harris, John Hawks, Sebastian Heath, Damien Huffer, Eric C. Kansa, Sarah Whitche Kansa, Mark E. Madsen, Jennifer Melcher, Joan Negre, Fraser D. Neiman, Rachel Opitz, David C. Orton, Paulina Przystupa, Maria Ravielo, Julien Riel-Salvatore, Philip Riris, Iza Romanowska, Jolene Smith, Néhémie Strupler, Isaac I. Ullah, Hannah G. Van Vlack, Nathaniel VanValkenburgh, Ethan C. Watrall, Chris Webster, Joshua Wells, Judith Winters, and Colin D. Wren
2017 Open Science in Archaeology. *SAA Archaeological Record* 17(4):8–14.
- Metzger, Marc J., Robert G. H. Bunce, Rob H. G. Jongman, C. A. Múcher, and J. W. Watkins
2005 A Climatic Stratification of the Environment of Europe. *Global Ecology and Biogeography* 14:549–563.
- Metzger, Marc J., Robert G. H. Bunce, Rob H. G. Jongman, Roger G. Sayre, Antonio Trabucco, and Robert Zomer
2013 A High-Resolution Bioclimate Map of the World: A Unifying Framework for Global Diversity Research and Monitoring. *Global Ecology and Biogeography* 22:630–638.
- Nicholson, Christopher M.
2017 Eemian Paleoclimate Zones and Neanderthal Landscape-Use: A GIS Model of Settlement Patterning during the Last Interglacial. *Quaternary International* 438:144–157.
- Nikolova, Irina, Qiuzhen Yin, Andre Berger, Umesh K. Singh, and Mehdi P. Karami
2013 The Last Interglacial (Eemian) Climate Simulated by LOVECLIM and CCSM3. *Climate of the Past* 9:1789–1806.
- OECD (Organization for Economic Cooperation and Development)
2015 *Making Open Science a Reality*. OECD Science, Technology, and Industry Policy Papers No. 25. OECD Publishing, Paris.
- Peel, Murray C., Brian L. Finlayson, and Thomas A. McMahon
2007 Updated World Map of the Köppen-Geiger Climate Classification. *Hydrology and Earth System Science* 11:1633–1644.
- Peros, Matthew C., Samuel E. Munoz, Konrad Gajewski, and André E. Viau
2010 Prehistoric Demography of North America Inferred from Radiocarbon Dates. *Journal of Archaeological Science* 37:656–664.
- Phillips, David A., Jr., Helen J. Wearing, and Jeffrey J. Clark
2018 Village Growth, Emerging Infectious Disease, and the End of the Neolithic Demographic Transition in the Southwest United States and Northwest Mexico. *American Antiquity* 83:263–280.
- R Core Team
2014 R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. <http://www.R-project.org/>.
- Reimer, Paula J., Edouard Bard, Alex Bayliss, J. Warren Beck, Paul G. Blackwell, Christopher Bronk Ramsey, Caitlin E. Buck, Hai Cheng, R. Lawrence Edwards, Michael Friedrich, Pieter M. Grootes, Thomas P. Guilderson, Hafliði Hafliðason, Irka Hajdas, Christine Hatté, Timothy J. Heaton, Dirk L. Hoffmann, Alan G. Hogg, Konrad A. Hughen, K. Felix Kaiser, Bernd Kromer, Sturt W. Manning, Mu Niu, Ron W. Reimer, David A. Richards, E. Marian Scott, John R. Southon, Richard A. Staff, Christian S. M. Turney, and Johannes van der Plicht
2013 IntCal13 and Marine13 Radiocarbon Age Calibration Curves 0–50,000 Years cal BP. *Radiocarbon* 55:1869–1887.
- Rick, John W.
1987 Dates as Data: An Examination of the Peruvian Preceramic Radiocarbon Record. *American Antiquity* 52:55–73.
- Robinson, Erick, H. Jabran Zahid, Brian F. Coddling, Randall Haas, and Robert L. Kelly
2019 Spatiotemporal Dynamics of Prehistoric Human Population Growth: Radiocarbon “Dates as Data” and Population Ecology Models. *Journal of Archaeological Science* 101:63–71.
- Simms, Steven R.
2008 *Ancient Peoples of the Great Basin and Colorado Plateau*. Left Coast Press, Walnut Creek, California.
- Surovell, Todd A., Judson Byrd Finley, Geoffrey M. Smith, P. Jeffrey Brantingham, and Robert L. Kelly
2009 Correcting Temporal Frequency Distributions for Taphonomic Bias. *Journal of Archaeological Science* 36:1715–1724.
- Tercek, Michael T., Stephen T. Gray, and Christopher M. Nicholson
2012 Climate Zone Delineation: Evaluating Approaches for Use in Natural Resource Management. *Environmental Management* 49:1076–1091.
- Thomas, David Hurst
2019 A Shoshonean Prayerstone Hypothesis: Ritual Cartographies of Great Basin Incised Stones. *American Antiquity* 84:1–25.
- Timpson, Adrian, Sue Colledge, Enrico Crema, Kevan Edinborough, Tim Kerig, Katie Manning, Mark G. Thomas, and Stephen Shennan
2014 Reconstructing Regional Population Fluctuations in the European Neolithic Using Radiocarbon Dates: A New Case-Study Using an Improved Method. *Journal of Archaeological Science* 52:549–557.
- van den Hurk, Bart, Pascale Braconnot, Veronika Eyring, Pierre Friedlingstein, Peter Glecker, Reto Knutti, and Joao Teixeira
2013 Assessing the Reliability of Climate Models, CMIP5. In *Climate Science for Serving Society: Research, Modeling, and Prediction Priorities*, edited by Ghassem R. Asrar and James W. Hurrell, pp. 237–248. Springer, Dordrecht, The Netherlands.
- Veloz, Samuel D., John W. Williams, Jessica L. Blois, Feng He, Bette Otto-Bliesner, and Zhengyu Liu
2012 No-Analog Climates and Shifting Realized Niches during the Late Quaternary: Implications for 21st Century Predictions by Species Distribution Models. *Global Change Biology* 18:1698–1713.
- Williams, Alan N.
2012 The Use of Summed Radiocarbon Probability Distributions in Archaeology: A Review of Methods. *Journal of Archaeological Science* 39:578–589.
- Williams, John W., and Bryan Shuman
2008 Obtaining Accurate and Precise Environmental Reconstructions from the

- Modern Analog Technique and North American Surface Pollen Dataset. *Quaternary Science Reviews* 27:669–687.
- Williams, John W., and Stephen T. Jackson
2007 Novel Climates, No-Analog Communities, and Ecological Surprises. *Frontiers in Ecology and the Environment* 5:475–482.
- Wright, Gary A.
1982 Notes on Chronological Problems on the Northwestern Plains and Adjacent High Country. *Plains Anthropologist* 27:145–160.
- Zahid, H. Jabran, Erick Robinson, and Robert L. Kelly
2016 Agriculture, Population Growth, and Statistical Analysis of the Radiocarbon Record. *Proceedings of the National Academy of Sciences* 113(4):931–935.

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