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A macroarchaeological view of mobility

P. Jeffrey Brantingham [a,*], Randall Haas [b], Steven L. Kuhn [c]

[a] *UCLA Anthropology, United States*
[b] *University of Wyoming Anthropology, United States*
[c] *University of Arizona Anthropology, United States*

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ABSTRACT

Archaeological evidence of mobility is often analyzed using ethnographic-scale models of individual foraging trips and residential moves as a point of reference. Due to site formation processes and the limitations of geochronology, the archaeological record rarely offers the kind of fine-grained resolution needed to identify mobility events at this scale. Here we explore an alternative, macroarchaeological approach that asks how site occupation patterns in a region balance the evolutionary tradeoff between exploration and exploitation. We use a statistical point process model that equates independent-in-time occupations with mobility-driven exploration and dependent-in-time occupations with mobility-driven exploitation. We evaluate the theoretical expectations against the archaeological record of North America using radiocarbon dates from multi-occupation sites. We find strong clustering at short waiting-time intervals of less than under 1000 years, consistent with a model of mobility-driven exploitation at those scales. At longer time scales, waiting times are consistent with a model of mobility-driven exploration. Implications for social learning and niche construction models are explored.

1. The Visibility of mobility

The quality of the archaeological record leaves much to be desired. The impact of site destructive processes means that much of what would have been there to observe does not survive (Surovell and Brantingham, 2007; Surovell, et al., 2009). The impact of pre- and post-depositional mixing processes means that what does survive is often inextricably jumbled (Brantingham, et al., 2007; Perreault, 2018). The impact of uncertainties in geochronological techniques means that much of what we do recover from the archaeological record cannot be assigned with great precision to a particular point in time. Given these challenges, we will start with a bold claim that the usual fine-grained differences between forager mobility regimes—obvious perhaps in ethnographic context—are mostly not easily differentiable in the archaeological record (Perreault, 2019; Premo, 2014; Stern, 1994).

This bold claim glosses over many efforts to use data on tool stone diversity, toolkit diversity, retouch intensity, faunal diversity, field processing of resources, site structure, and many other metrics, to identify residential and logistical mobility, within- and between patch movement patterns, and seasonal mobility rounds (Davies, et al., 2018; Féblot-Augustins, 1993; Kuhn, 2020; Marín, et al., 2019; Surovell, 2009). Nevertheless, we ask the reader to suspend disbelief and consider what we might say about mobility if we cannot look at fine-grained regime differences. Rather than focusing modeling and measuring the microscopic features of mobility, such as move-length and move direction (Brantingham, 2003; Haas and Kuhn, 2019), we could focus on macroscopic patterns in the archaeological record that emerge in part from ethnographic-scale mobility processes but are not easily reducible to them (McGill, 2019; Smith, et al., 2008). Here we suggest that the waiting time between discrete occupations is just such a macroarchaeological variable. A waiting time between archaeological occupations at a single location is the difference in time between the abandonment of an older occupation and the initiation of a younger occupation. These occupation events may be tied to a range of behavioral and ecological processes, but a proximate cause is mobility that carries people to and from activity locations. When aggregated over large spatial and temporal scales, and diverse cultural groupings, waiting times between occupations may reflect in part the broader adaptive function of mobility at higher scales. By way of analogy, the waiting time between occupations across a collection of locations is analogous to the time between the last appearance datum of an ancestral species and the first appearance datum of a daughter species across a collection of taxa. The distribution of waiting times between occupations thus may reveal the operation of macroarchaeological processes analogous to the

* Corresponding author.
E-mail addresses: branting@ucla.edu (P.J. Brantingham), whaas@uwyo.edu (R. Haas), skuhn@arizona.edu (S.L. Kuhn).

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macroevolutionary processes driving evolutionary sorting at higher taxonomic scales (Hautmann, 2020).

2. Adaptive exploration vs. Exploitation

Foragers are confronted with a fundamental tradeoff; whether to exploit a known environment, or to search for better conditions elsewhere. The tradeoff between exploration and exploitation is well-known to archaeologists through the marginal value theorem (e.g., Bettinger and Grote, 2016; Charnov, 1976), but it is a far more general distinction than that. The tradeoff features prominently, for example, in the design of machine learning algorithms (e.g., Auer, 2002) and is central to the idea of how natural selection traverses "adaptive landscapes" (Arnold, et al., 2001; Lenormand, et al., 2009). In all of these contexts, it is assumed that successful exploitation comes at the potential cost of being stuck on some local optimum rather than locating a global optimum. Conversely, continually searching for that global optimum comes at the cost of giving up on productively exploiting what is already known.

Mobility is a primary mechanism by which foragers navigate this fundamental tradeoff. Solutions to this tradeoff may be found in balancing movement (exploration) over sedentism (exploitation) (see also Bocinsky, et al., 2016; Kelly, 1992), or residential (exploration) over logistical (exploitation) mobility. However, as discussed above, the quality of the archaeological record may present a problem in distinguishing relative movement from relative sedentism, or unanchored (residential) from central place foraging across archaeological contexts. In spite of the ethnographic-scale differences inherent to these mobility regimes, they all generate archaeological deposits recognized as "occupations." A forager-centric approach urges us to look within such occupations for evidence of movement (Brantingham, 2003; Kuhn, 2020) or occupation intensity (Surovell, 2003) that might sort this out. A shift to a location-centric model may provide new ways of viewing mobility that are more suited to the quality of the archaeological record.

3. From a forager-centric to a location-centric model

Consider the following simplified model of an archaeological record. The record is contained in a spatially bounded (finite) region consisting of a large number of locations that could have been occupied by foragers. We are interested in all archaeological occupations dating between some starting and ending age (e.g., between say 10 ka and 15 ka). Therefore, the only observable measures considered here are the spatial locations and dates of discrete archaeological occupations. We use the term "discrete" to mean only that each occupation is well-bounded in space and time, not that they correspond to single ethnographic-scale behavioral event, nor to a specific culture-historic horizonation. The onset of an occupation is analogous to a first appearance datum of a taxon and abandonment to the last appearance datum in paleontology. We return to the potential impact of different sources of bias (e.g., site destruction) on the observability of archaeological occupations in the discussion. The primary question is how the spatio-temporal patterns of occupations might reflect the two proposed functions of mobility, exploration and exploitation, without relying on the common ethnographic-scale typologies of mobility regimes.

3.1. A model of adaptive exploration

We adopt a very specific definition of "adaptive exploration" from the literature on machine learning. The characteristic feature of adaptive exploration is the independence of the present course of action from past courses of action. In the case of forager mobility, this means that any location visited at time $t+1$ is independent of the location visited not only at time t, but also all previous times. In other words, occupations generated by adaptive exploration are "memoryless." Note here that adaptive exploration encompasses more than just the first encounter with a territory (i.e., initial landscape colonization). Adaptive exploration also includes repeated visits to a location where prior occupations have no detectible influence on the current occupation. That is, each repeated visit is made *as if* it has never been visited before. Intuitively, adaptive exploration would describe sequential occupations that were first encounters with the location by independent foraging groups who never shared information, or visits by the same foraging group (in some genetic or cultural sense) that had lost all information about the location between repeated occupations (Henrich, 2004), making them sequentially independent.

In a memoryless system, we are free to abandon a forager-centric approach, ignoring the microscale features of mobility, and adopt a macroscopic measure that is simply the rate of occupation of a location. The temporal pattern of occupation at a location is not exclusively generated by mobility, but mobility is a proximate mechanism that ends one occupation and initiates a new one. The temporal pattern of occupation at a given location can be characterized by a single macroscopic parameter λ, which is the stationary rate of site occupation. For example, $\lambda = 0.001$ reflects a mean rate of one independent occupation per 1,000 units of time (years, through the rest of the paper). Occupations at one location emerging at a stationary rate λ are recognized statistically as a Poisson point process. We would say that the macroscopic pattern across occupations is one of adaptive exploration because each of the occupations are statistically independent events. Note that at this scale of analysis we are not concerned with the ethnographic-scale exploration and exploitation of different resources in the vicinity of occupation, simply with whether people visited the place and left detectable evidence of that visit.

Importantly, this model of adaptive exploration also applies when our bounded region contains several different patch types. For simplicity, we assume that these patch types are spatially stationary and stable over time. We consider the consequences of this assumption in the discussion. While we might not be able to directly observe any of the biotic and abiotic conditions that characterize these patches, we can imagine that patch conditions influence occupation rates. Thus, a poor-quality patch (Type 0) might be expected to host an independent occupation once every 20,000 years, or $\lambda_0 = 0.00005$. Two slightly better patches (Type 1 and Type 2) might host independent occupations once every 2,500 years, or $\lambda_1 = 0.0004$, or once every 1,000 years, or $\lambda_2 = 0.001$, respectively. The best patch (Type 3) might host an occupation once every 250 years, or $\lambda_3 = 0.004$. If occupations *within* patches are independent of one another, then occupations in adjacent patches are also independent of one another (Short, et al., 2009). At this macroscopic scale we ignore the impact of things such as the distance between patches because the role of ethnographic-scale mobility in navigated these challenges is largely unobservable. Similarly, we ignore such things as seasonal variation since this variation is necessarily built into the mean occupation rate. Hypothetically, patches of Type 0 might represent a proportion $w_0 = 0.5$ of the region, those of Type 1 a proportion $w_1 = 0.3$ of the regions, Type 2 $w_2 = 0.15$ of the region, and Type 3 $w_3 = 0.05$ of the region. Thus, poor-quality patches are common and high-quality patches are rare. This setup is represented as a type of compartmental model in Fig. 1**A**.

Remarkably, under the conditions outlined above, the expected spatial distribution of archaeological occupations at the regional scale may be highly clustered (and therefore spatially non-random), or entirely randomly (Fig. 2). It all depends on the spatial distribution of patch qualities. At the same time, there can be extreme variation in the concentration of archaeological occupations between patches, regardless of the regional pattern. The degree of concentration of archaeological occupations is controlled by between-patch differences in the occupation rate. The key observation is that adaptive exploration is capable of generating both high levels of clustering and highly unequal levels of occupation concentration, even though occupations are modeled as completely memoryless.

The pattern of archaeological occupations through time tells a somewhat different story. A natural way to look at the temporal record

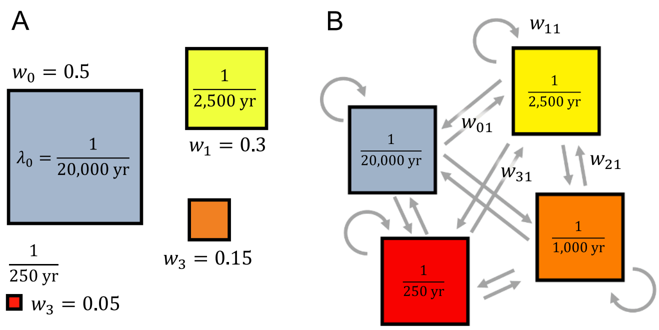

Fig. 1. Compartmental models for occupation dynamics of a region. (A) Adaptive exploration is modeled as a series of *independent* compartments with occupation rates λ_k. Each patch can only be of one type (color coded) that remains constant over time. Patches occur at different frequencies in the environment w_k, which is also reflected by compartment size. (B) Adaptive exploitation is modeled as a series of coupled (non-independent) compartments. Each compartment is associated with an occupation rate λ_k and each time a discrete occupation occurs it triggers a probabilistic "transition" to a different occupation rate (or probabilistically remains the same). Only transition paths to occupation rates of Type 1 (yellow) are labeled. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

for our model region is to examine how occupations are distributed over time. Assume that we are able to date each and every discrete occupation. We take all of those dates and produce a histogram of the number of dates falling into 250 year bins across our temporal window of observation (e.g., 10 to 15 ka). It is possible to show via both theory (Short, et al., 2009) and via simulation that the expected frequency distribution of occupations under mobility-driven exploration is uniform over time (Fig. 3**A**). This is because exploratory occupations are defined theoretically as a random arrival process—hidden ethnographic-scale mobility being responsible for the arrivals—that happens independently in each patch. That this distribution is uniform, in spite of the variation in patch qualities, may be surprising. However, as long as patch qualities remain stationary over time (i.e., this is a homogeneous Poisson Process), the spatial variation in patches is of no consequence to the expected frequency occupations in any given year. Technically, the sum of k independent Poisson processes is also a Poisson process with rate $\lambda = \sum_k \lambda_k$.

A different observation pertains to the distribution of waiting time *between occupations* under mobility-driven exploration. Recall that we are studying a bounded region over a fixed period of time, hypothetically between 10 ka and 15 ka. Imagine that we take each patch under observation and count the number of discrete occupations that fall within the observational time window. For example, imagine one patch with dated occupations at 8500 BP, 10,200 BP, 13,700 BP and 15,975 BP. The oldest and youngest occupations are outside of our time window of interest between 10 ka and 15 ka and therefore are not counted. The two intermediate occupations, at 10,200 BP and 13,700 BP, are within the observational window. This is an example of a repeat occupation, but we can imagine other patches that generate zero, one, three, four or more occupations over a fixed observational time window. Define a k-occupation patch as a location that sees exactly k discrete occupations over the observational time window. So, in the hypothetical example above, this is a two-occupation site (or "2-occupation" to underscore the numerical quantity).

The next step is to take all two-occupation sites in the region that fall within the fixed observational time window and compute the "waiting time" between those occupations on a site-by-site basis. This is simply the date of the older occupation minus the date of the younger occupation at each two-occupation site; in our example, 13,700 BP – 10, 200 BP = 3,500 years. Whereas theory leads us to expect that each year over the observational window is equally likely to contain an occupation, we do not expect all waiting times between occupations to be equally likely. The reason is straightforward. Assume a bin size of 250 years, and a temporal window of observation lasting 5000 years. In this case, there

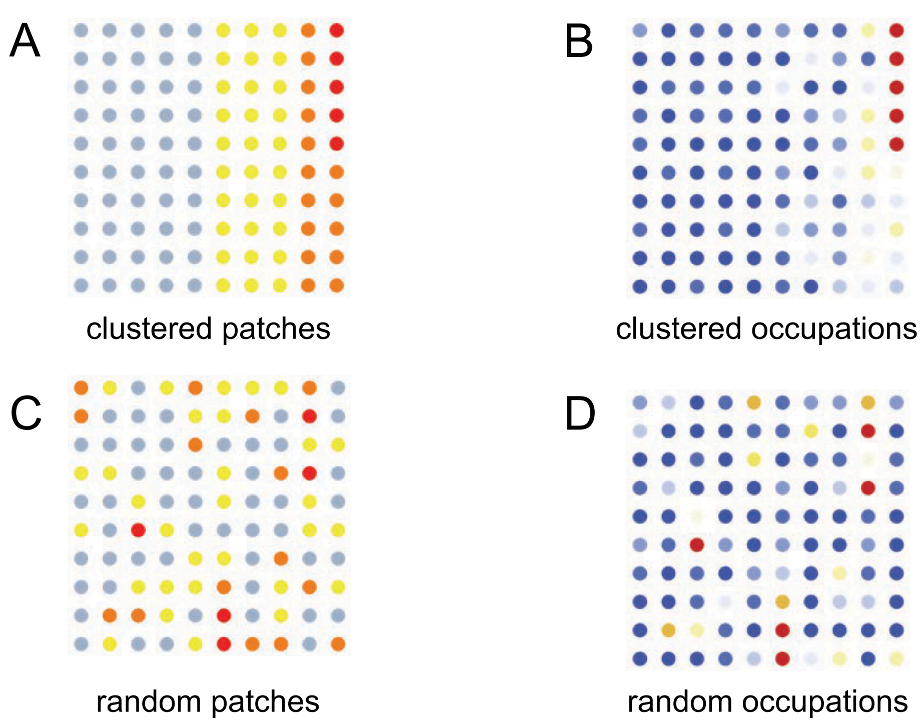

Fig. 2. Relationship between the spatial distribution of patches (A and C) and spatial distribution of archaeological occupations (B and D) under exploratory adaptations. Colors of patches indicate increasing occupation rate from 1 occupation per 20 ka (gray) to 1 occupation per 250 years (red) (see Fig. 1). Occupations are simulated using a within-patch Poisson processes with rate λ_k for each patch type k. Note how the areas of highest occupation concentrations (red locations in B and D), correspond to the highest quality patches (red patches in A and C) and the lowest occupation intensities (blue locations) correspond to lowest quality patches (gray). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

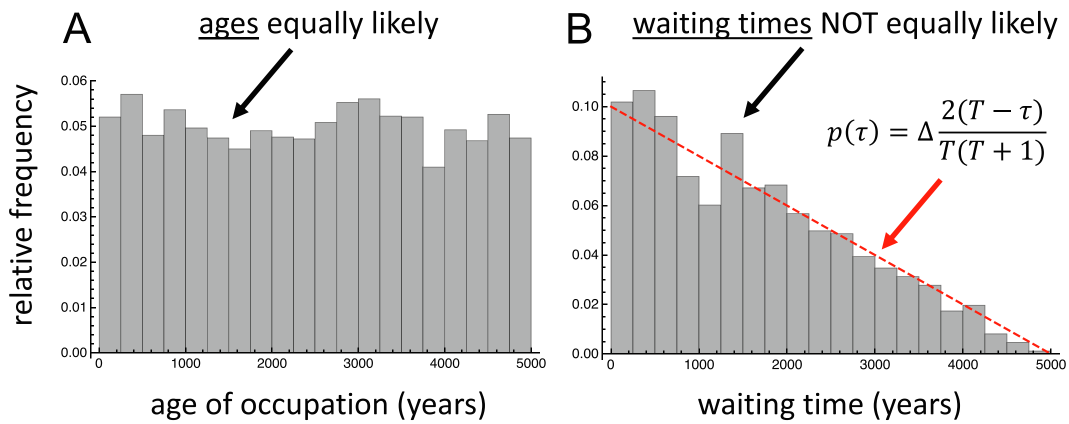

Fig. 3. Temporal occupation patterns arising from mobility-driven exploration. (A) The frequency distribution of all occupations in the region grouped into 250 year bins. (B) The frequency distribution of waiting times between occupations for patches (locations) that preserve *exactly two occupations* in a fixed time window.

are 20 bins overall and exactly 20 −1 ways in which two occupations can differ in age by 250 years. For example, the occupations might date to the 10,000–10,250 BP bin and 10,250–10,500 BP bin, the 10,250–10,500 BP bin and 10,500–10,750 BP bin, …, or the 14,500–14,750 BP bin and the 14,750–15,000 BP bin. There are 20 −2 ways in which two occupations can differ in age by 500 years. That is, the occupations might date to 10,000–10,250 BP bin and the 10,750–11,000 BP bin, the 10,500–10,750 BP bin and 11,250–11,500 BP bin, …, or the 14,000–14,250 BP bin and 14,750–15,000 BP bin. Extending the logic of this counting process shows that there is only one way (20 −19) in which two occupations at the same site can differ by 4,500 years. That is, the occupations *must* date to the 10,000–10,250 BP bin and the 14,750–15,000 BP bin. Viewed as a combinatorial problem, it is possible to write out an explicit equation describing the expected distribution of waiting times between the occupations at two-occupation sites arising from mobility-driven exploration (Short, et al., 2009):

$$p_{k=2}(\tau) = \Delta \frac{2(T-\tau)}{T(T+1)} \quad (1)$$

where T is the total duration of the fixed window of observation (e.g., $T = 5000$ years), τ is the waiting time between occupations, and Δ is the bin size at which we decide to count (e.g., $\Delta = 250$ years). Simulations of archaeological occupations arising from adaptive exploration follow very closely the theoretical predictions of Equation (1) (Fig. 3**B**). Indeed, we propose that Equation (1) provides the basis for a robust test of whether occupations in a region correspond to adaptive exploration. We will address sample size questions in the empirical case study presented below.

3.2. Adaptive exploitation

The assumptions that underlie the proposed model of adaptive exploration are quite strict. In particular, the assumption that occupations of all patches are "memoryless" seems likely to be violated, though we should not discount out of hand the evolutionary value of "memoryless" adaptations (Lenormand, et al., 2009). The history of occupations in a patch may indeed influence the future occupations and we need a model to describe how this happens.

Consider, as we did above, a region that contains patches of different qualities, which are marked by different occupation rates λ_k. Imagine now a process whereby foragers learn something about or modify the patches they encounter in a way that leads them to increase the rate of occupation of that patch. The most obvious case in which this might occur is where foragers engage in *niche construction* (Haas and Kuhn, 2019; Odling-Smee, et al., 1996), modifying the environment in ways that make the patch more amenable (than the baseline state of nature) to future occupation. As long as what is learned about the patch or the niche construction persists over supra-ethnographic time scales, then the process is macroarchaeological. We can represent this process mathematically as a connected compartmental model (Fig. 1**B**). No matter what state a patch starts in, the occurrence of a discrete occupation triggers a probabilistic transition that may land that patch in a different occupation rate group. For example, imagine one of the rare occupations in a low-quality patch with an average rate of occupation once every 20,000 years. Foragers present during this occupation engage in some level of niche construction that "improves" patch quality above the baseline. The rate of occupation then becomes one occupation every 2,500 years. The transition process is described by a term w_{01}, which is the probability that a patch in state $k = 0$ transitions to a patch in state $k = 1$. Another occupation in that same patch at some later time (on average within the next 2500 years after the first) might lead to a probabilistic transition back to that same state (i.e., w_{11}) or a transition to some other state (i.e., w_{1k}). This dynamic process happens for all patches in continuous time and constantly generates occupations across the region.

The impact of this dynamical process on the spatial patterning of discrete occupations across the region is surprising for its lack of distinctiveness (Fig. 4). As with adaptive exploration, adaptive exploitation is also capable of producing clusters of occupations (note the spatial cluster of locations highlighted in the upper left corner) and substantial concentration of occupations in particular patches (red and orange locations). An obvious conclusion is that spatial clustering (and concentration) of occupations alone is not sufficient on its own to determine if mobility systems follow adaptive exploration or adaptive exploitation.

By contrast, the temporal pattern of occupation associated with adaptive exploitation can be very distinctive. Using the same "fixed window" counting procedures presented above, we can plot the histogram of waiting times for 2-repeat occupations in patches in our region. Recall that k-repeats are patches that display exactly k discrete occupations in a fixed time window of observation. We draw again on the example of a 5,000 year observational window, but this time we simulate patch change using transition probabilities to new states $w_{k0} = 0.5$, $w_{k1} = 0.3$, $w_{k2} = 0.15$, and $w_{k3} = 0.05$. Probabilistic transition to the same state is the complement of the transition out of that state; for example, $w_{33} = 1 - w_{k3} = 0.95$. Except for poor quality patches, a probabilistic transition into a higher quality patch is likely to remain so for a while (the higher the quality the longer it will stay there). Behaviorally, this may be interpreted as a principle that more extensive niche construction persists longer. Importantly, the observed patterns are not particularly sensitive to these modeling choices. Fig. 5 shows that the frequency distribution of waiting times between occupations (for 2-repeats) clusters much more strongly around short waiting time

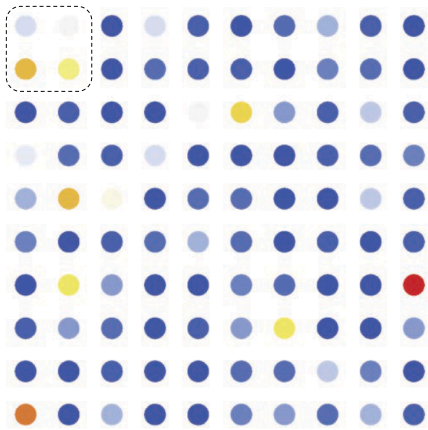

Fig. 4. Distribution and concentration of occupations in a region experiencing adaptive exploitation. The normalized number of occupations is represented by color (dark blue = few; red = many). A spatial cluster of four adjacent location with a higher density of occupations is circled. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

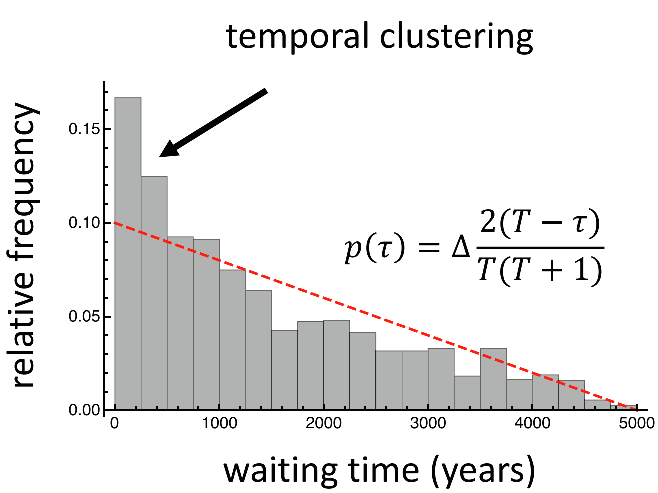

Fig. 5. Frequency distribution of waiting time between discrete occupations for patches with exactly two occupations (k-repeat, $k = 2$) observed over a fixed time window of 5,000 years. Shown is the simulated distribution compared with the expectation for adaptive exploration, which is computed mathematically. There is much more clustering of short waiting times between occupations where there is adaptive exploitation of patches.

intervals compared with adaptive exploration (red line) (compare with Fig. 3**B**).

4. A Tentative empirical case study

We focus on the temporal patterns of occupation to evaluate our working model, leaving spatial patterns for future consideration. Specifically, we examine the frequency distribution of the waiting times between archaeological occupations defined by statistical clustering of radiocarbon dates. We focus on 59 archaeological sites in North America dated between 11,500- and 0.5 cal. ka. The sample includes sites that are identified as having *exactly two* discrete occupations in this 11,000 year window of observation. Sites with a single occupation, or more than two occupations are not considered (see the discussion).

If the adaptive exploration model holds true, we expect to observe a linear distribution waiting times between occupations. If the adaptive exploitation model is closer to the actual situation, resulting in preferential attachment to certain sites on the landscape, we expect a curvilinear departure from the linear distribution such that short-duration hiatuses are over-represented and long-duration hiatuses under-represented. Here we describe the procedures for data preparation, cluster analysis, and hypothesis evaluation, as well as a few leading cautionary notes.

4.1. Data preparation

To generate a database of two-occupation archaeological sites, we use the Canadian Archaeological Radiocarbon Database (CARD) (Kelly, et al., 2022) as downloaded on October 26, 2021. CARD is a compilation of radiocarbon dates and standard error terms from archaeological sites throughout North America. The raw dataset includes 104,641 entries. However, many of these are irrelevant to the current analysis, thus requiring a data culling and cleaning procedure including the following five steps: (1) All date types that are identified as non-archaeological are removed. This tends to include geologic or paleoecological dates; (2) Normalized dates and standard errors, which account for material-specific isotopic fractionation, are used where possible. Measured dates and standard errors are used in other cases. Any dates without error estimates are removed; (3) Individual archaeological sites are identified as the composite of the site ID and site name fields. This step avoids spurious associations of unrelated sites that share the same name and sites that do not have a site ID or site name. Sites with neither a site ID nor site name are removed; (4) Dates that are younger than 95 14C BP or older than 50,193 are removed due to unreliability and incompatibility with radiocarbon calibration curves; and (5) Sites with fewer than 30 dates are removed to reduce small-sample effects. The resultant database after cleaning includes 10,769 radiocarbon dates from 227 archaeological sites.

Dates are then calibrated using the Intcal20 calibration curve (Reimer, et al., 2020) using the Bchron radiocarbon calibration package (Haslett and Parnell, 2008) as implemented in R statistical computing language. For each date, the highest probability integer date is selected from the calibrated probability curve. If several integer dates share the highest probability value, they are averaged. These calibrated maximum likelihood radiocarbon dates serve as the basis for identifying two-occupation sites and the time spans between occupations.

4.2. Cluster analysis

To identify temporally discrete occupations in the radiocarbon records of each site in the North American database, we use univariate Gaussian mixture models with unequal variance. The assumption of Gaussian models for the temporal densities of archaeological site occupations logically follows from the statistical support of temporal data, which are theoretically unbounded and continuous. Furthermore, seriation studies empirically establish that temporal phenomena in human cultures commonly approximate normal curves (Peeples and Schachner, 2012).

We implement the mixture model approach using the mclust package in R statistical computing environment (Scrucca, et al., 2023). This approach uses the expectation–maximization (EM) algorithm to confront the data with 1–9 mixture components (clusters), allowing for unequal variance, and select the model that generates the greatest Bayesian Information Criterion (BIC) value. BIC identifies the model that simultaneously explains the most data and minimizes parameters–in this case, Gaussian clusters. Having solved for the optimal solution for each site, we then isolate two-occupation solutions for hypothesis testing. R code sufficient to reproduce the dataset is included as **supplemental material**.

To determine the gap between occupation pairs for each site, the earliest date of the later occupation is subtracted from the latest date of the earlier occupation. This occasionally produces negative gaps, reflecting the rare case when one cluster is identified interior to a larger cluster. Such negative-gap two-occupation sites are removed from the dataset. The resultant dataset of two-occupation sites includes 2,610 radiocarbon dates from 64 archaeological sites. We further limit the sample to the 59 two-occupation sites with 2,392 total dates ranging in age between 500 years BP and 11,500 years BP (Table 1). The spatial and temporal distribution of sites is shown in Fig. 6.

Table 1
Two-occupation sites and their associated calibrated radiocarbon ages extracted from the CARD database (Kelly et al. 2022).

ID	Site	State	Lat	Long	N Dates	Min Age	Max Age	Occupation 1 End Age	Occupation 2 Start Age	Waiting Time
6661	36MR5 Smithfield Beach	Pennsylvania	41.056916	−75.336173	35	194	4152	2726	1978	748
15245	7 K-F-11/169 Gray Farm	Delaware	39.097086	−75.503073	30	125	4640	2130	1066	1064
2002	18AN50 Pig Point	Maryland	38.992333	−76.569358	30	4	9129	5308	2340	2968
6740	36TI28 Losey 3	Pennsylvania	41.773775	−77.253772	30	110	5591	3365	914	2451
6508	36CN164 Memorial Park	Pennsylvania	41.24145	−77.63672	30	496	7671	1709	1110	599
6780	36WH297 Meadowcroft Rockshelter	Pennsylvania	40.188779	−80.247841	42	215	15953	5584	4905	679
11259	46WD83-A West Blennerhassett	West Virginia	39.212523	−81.514126	34	1295	9551	7842	4858	2984
15602	8LL2 Mound Key	Florida	26.577579	−81.921462	32	336	1997	1228	956	272
15612	8LL54 Wightman	Florida	26.577579	−81.921462	40	1142	3675	2626	2361	265
1416	15BL35 Main Site	Kentucky	36.735535	−83.672646	30	2344	10250	4412	3169	1243
2546	1JA305 Widows Creek	Alabama	34.776174	−86.002129	55	834	4847	2108	1347	761
973	12VG1 Angel Mounds	Indiana	38.023	−87.583527	63	381	2319	966	834	132
2566	1LU496 Dust Cave	Alabama	34.903733	−87.647581	44	5729	12546	11186	9939	1247
2491	1BA21 Bayou St. John	Alabama	30.654881	−87.754736	30	917	1534	1411	1240	171
699	11PP2/11MX2 Kincaid	Illinois	37.411349	−88.573214	33	561	5749	1744	1034	710
7578	40SY1 Chucalissa	Tennessee	35.1843	−89.892262	40	336	1445	871	679	192
11392	47LC95 Tremaine	Wisconsin	43.907641	−91.110152	41	306	1530	1292	678	614
3288	23CY64 Arnold Research Cave	Missouri	38.836209	−91.924532	56	733	10246	3455	1995	1460
3222	23BE125 Rodger's Shelter	Missouri	38.2991	−93.288478	38	168	12610	5899	4825	1074
2943	21ML12 Wilford	Minnesota	45.929539	−93.632525	31	221	1546	1354	652	702
3247	23CE426 Big Eddy	Missouri	37.722485	−93.864759	51	3000	15827	8128	4997	3131
5609	34LF40 Spiro/Craig Mound	Oklahoma	34.903005	−94.701145	39	4	2336	2336	1408	928
5700	34PU116 Bug Hill	Oklahoma	34.415152	−95.364329	33	502	3696	1528	1214	314
1093	13ML12 House III	Iowa	41.033605	−95.618292	31	568	751	636	572	64
8981	41WB557 Boiler	Texas	27.770428	−99.327204	50	66	5410	1602	1296	306
8549	41KR621 Gatlin	Texas	30.062193	−99.348662	47	66	7466	3669	2108	1561
8907	41VV162 Conejo Shelter	Texas	29.894131	−101.1515	39	1303	7515	3524	2856	668
8970	41VV99 Arenosa Shelter	Texas	29.894131	−101.1515	30	1296	10939	10939	6300	4639
8586	41LU1 Lubbock Lake	Texas	33.6117	−101.81989	31	202	15090	1377	526	851
3939	25SX115 Hudson-Meng	Nebraska	42.480782	−103.77126	39	7524	11540	9400	8544	856
8705	41PS800 Arroyo de la Presa	Texas	29.998304	−104.22926	38	4	7423	2892	1261	1631
14382	5JF321 Swallow site	Colorado	39.587467	−105.24681	39	946	9337	1997	1785	212
14036	48WE917 NA	Wyoming	43.90722	−107.68429	37	396	3961	2979	1846	1133
14687	5MF1915 Red Rose site	Colorado	40.608316	−108.20244	31	293	6744	6744	3756	2988
14862	5MN4253 Schmidt site	Colorado	38.405803	−108.26908	34	37	2987	1653	1347	306
19849	LA? Wind Mountain	New Mexico	32.729422	−108.37932	31	615	2236	2236	1528	708
20712	LA4935 Bat Cave	New Mexico	33.92386	−108.41655	32	731	6744	6396	4140	2256
13342	48SW101 Pine Springs	Wyoming	41.657588	−108.89409	47	110	13743	1942	1266	676
12699	48PA201 Mummy Cave	Wyoming	44.493416	−109.56323	37	469	10479	8946	8410	536
14037	48YE1 NA	Wyoming	44.603293	−110.47819	31	66	10172	7631	4826	2805
12541	48LN373 Plant	Wyoming	42.260038	−110.70266	41	681	10188	1996	1740	256
16352	AA:2:2 (ASM) Grewe	Arizona	32.5	−111.5	101	684	1408	1226	1195	31
9889	42SV662 Backhoe Village	Utah	38.746559	−111.79705	31	675	2108	2108	1520	588
9484	42JB394 Dust Devil site	Utah	39.711399	−112.79595	32	662	9006	6787	1353	5434
9075	42BO36 Hogup Cave	Utah	41.514922	−113.09714	40	515	9336	5006	4261	745
4152	26EK13006 CrNV-11–16509	Nevada	37.785829	−117.63207	30	88	5199	2980	2387	593
4170	26EK3032 Tosawihi Quarry sites	Nevada	37.785829	−117.63207	43	4	4538	3983	1306	2677
6309	35ML65 Dirty Shame Rock Shelter	Oregon	43.205538	−117.63358	37	403	12503	6650	2806	3844
17538	CA-ORA-378 Christ College site	California	33.674967	−117.7774	89	941	9411	3187	2979	208
16999	CA-LAN-43 SjÔøΩtkanga, Encino Village	California	34.184667	−118.26199	38	112	5729	5308	1846	3462
18284	CA-SCLI-43 Eel Point	California	32.898728	−118.49285	72	551	11249	6295	5591	704
9322	42FR? NA	Washington	46.536896	−118.90477	33	299	10575	2686	2183	503
18352	CA-SCRI-333 El Monton	California	34.012989	−119.72877	85	1303	6671	6214	5931	283
4344	26OR3 NA	Nevada	39.1669	−119.7678	33	299	1664	1401	1066	335
19037	CA-SMI-261 Daisey Cave	California	34.038218	−120.36063	30	1301	12627	6846	4414	2432
17,243	CA-MNT-229NA	California	36.23931	−121.31062	36	731	8452	6945	4640	2305
10739	45KI429 West Point Site Complex	Washington	47.474506	−121.84428	39	202	4056	2391	1228	1163
16502	CA-ALA-704/H Rummey Ta KuccuwiÔøΩ Tiprectak	California	37.653853	−121.91395	31	144	2398	1844	1461	383
10728	45JE6 Bugge Spit	Washington	47.844076	−123.57579	40	1110	2769	2025	2000	25

It is important to note that this approach will always identify a singular best-fit model, even if multiple models offer plausible fits to the data, and thus comes with a risk of false-positive model selection. Nonetheless, the model-based approach offers a principled, objective procedure for occupation classification, that minimizes potential for systematically biasing data structure.

4.3. Hypothesis testing

A visual comparison of the observed distribution of waiting times relative to the expected distribution given by Equation (1) gives an initial impression of whether we might reject the null hypothesis that mobility is strictly about exploration. However, the sparsity of the archaeological record means that small sample sizes may lead to spurious rejection. To counter this possibility, we develop a Monte Carlo method that allows us to construct confidence intervals for the expected distribution of waiting times when occupations are purely exploratory. Specifically, we simulate a Poisson occupation process generating a location with 10 dated occupations. We then apply a fixed time window from 500 yr BP to 11,500 yr BP (11,000 years in total) to the simulated site and discard dated occupations that fall outside the fixed window. We then retain the simulated locality if it has *exactly two* dated occupations in the fixed window of observation. We repeat this process until the number of simulated two-occupation sites is the same as the empirical sample size in question. We then compute the waiting times between the two occupations for each of the retained locations and count the proportion of sites with waiting times that fall into each 250 year bin in the fixed window of observation. This constitutes one *replicate* of the simulation.

To produce statistical expectations, we generate 1,000 replicates, each at the observed sample size, using the above process. We then compute the mean and variance in the proportion of sites in each waiting time bin over all the replicates. The question of interest is whether the observed proportion in each bin falls outside the confidence interval for the simulated proportion. If an observed proportion does *not* fall outside the confidence interval, then we cannot reject the null hypothesis that the observation at that time scale was generated by memoryless mobility-driven exploration. If an observed proportion falls outside the confidence interval, then we can reject the null hypothesis and suggest that the observation at that time scale was generated by mobility-driven exploitation. We note that the *per bin* comparison is similar to evaluating m hypotheses, where m is the number of bins. We therefore apply a Bonferroni correction to the confidence intervals to guard against spurious rejections of the null hypothesis (Bland and Altman, 1995). A Mathematica notebook sufficient to reproduce the results is included in the **supplementary online material**.

4.4. Cautionary notes

It is important to identify some of the important challenges with these data before presenting results. First, the data scrubbing process yielded a sample of dates representing just 2.3 % of the total CARD database. The resulting sample thus is certainly unrepresentative of the broader radiocarbon record, leaving aside general coverage concerns in CARD overall. Younger sites are almost certainly over-represented as a result of both sampling and taphonomic biases. Sites in the West may be over-represented due to abundance of Federal land relative to the East. These limitations are not easily rectified at present and therefore the observations we make based on the CARD data should be treated with caution.

Second, our approach to clustering of dates into occupations is justified on strictly on statistical grounds. A "dirt archaeologist" could certainly look skeptically at the approach and would likely arrive at different occupation clusters based on stratigraphy and other site-based criteria. However, the context-heavy approach is problematic at scale given the complex inferences involved in stratigraphic analysis and the variability in published evidence from hundreds of sites in CARD. While rigorous field observation of stratigraphy is still an irreplaceable part of archaeological research, three decades of micromorphological and refitting studies have taught us that some important elements of site occupational histories may simply be undetectable to the naked eye. The data-driven clustering approach used here has the advantage that it is consistent across sites and replicable. Nevertheless, the date clusters we identify are perhaps best thought of as "*meta*-occupations." But the reader should be aware that statistically-defined occupations may combine materials from more than one occupation defined based on macroscopic field observation, or they may split materials into separate occupations that would otherwise be combined. Thus, our use of the term "occupation" should not be conflated with activity-cultural-stratigraphic occupations as understood using other classification methods. Future work might fruitfully compare the different approaches.

Finally, we note that the resulting collection of dates combine archaeological materials from a range of cultural contexts that include both dedicated foragers as well as horticulturalists. While this might strike some readers as odd, it is entirely consistent with a macro-archaeological (as well as macroecological/evolutionary) approach that aggregates across spatial, temporal and cultural (taxonomic) scales to reveal emergent patterns (McGill, 2019; Perreault, 2019; Smith, et al., 2008). We do not consider mobility to be a typological feature that only applies to foragers. Thus, the distinction between adaptive exploration and exploitation is not limited to the study of foragers. It is equally applicable to what would traditionally be considered more sedentary lifeways at the time scales we are interested in (e.g., Bocinsky, et al.,

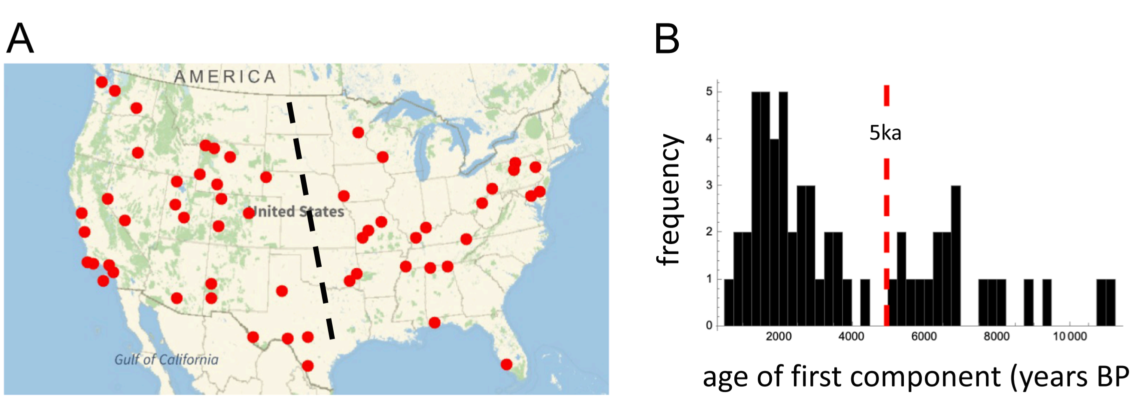

Fig. 6. Spatial and temporal distribution of the 59 two-occupation sites examined. (A) An arbitrary partition of the sites into Eastern and Western groups is shown. (B) The temporal distribution plots ages for the oldest occupation in each two-occupation site and the chronological partition used for assessing change through time in reoccupation dynamics.

2016). Nevertheless, the observations offered below are meant to be broadly relevant to the macroarchaeological understanding of mobility-driven land use separate from specific geographic, temporal and cultural processes that might also be at play.

4.5. Results

Fig. 7 presents the frequency distribution of waiting times between occupations for North American archaeological sites with exactly two occupations. The total sample includes 59 unique sites. Waiting times are binned into 250 year intervals over the 11,000 year fixed window of observation. There are $m = 44$ such bins in total, which features in a Bonferroni correction of $1 - \alpha/m$ and corresponds to a confidence interval of approximately 99.8 %.

The observed distribution is strongly clustered at short waiting time intervals. The longest observed waiting time was 5,434 years from Dust Devil Cave, Utah. The shortest observed waiting time, while still constituting two discrete occupations, was 25 years from the Bugge Spit site, Washington. The clustering at short intervals, and the absence of waiting times at very long intervals, in general is quite different from the expected trend for "exploratory" mobility. However, considering the relatively small sample size, we can only reject the null hypothesis for the shortest waiting times of 250, 500 and 750 years between occupations. These are the only bins that fall outside the confidence intervals for the memoryless process. All other observed waiting times fall within the confidence interval envelope suggesting that these reflect exploratory mobility.

We now consider whether there are any emergent geographic differences in the temporal data. The distribution of the 59 two-occupation sites across the continental USA is consistent with a spatially random Poisson point process (ChiSquare = 11.579, p = 0.314219). Thus, there are no natural clusters to compare. Nevertheless, we impose an arbitrary divide between Eastern and Western sites and examine the waiting time distributions within each grouping (Fig. 8). The results from the two regions are broadly similar to the aggregate sample. To the extent that there are reoccupation waiting times that deviate from the null expectations, these are for shorter time scales. Among the 24 Eastern sites we see reoccupation waiting times of 750 and 1,250 years that fall outside the confidence interval for mobility-driven exploration. Among the 35 Western sites we see reoccupation waiting times of 500 and 750 years

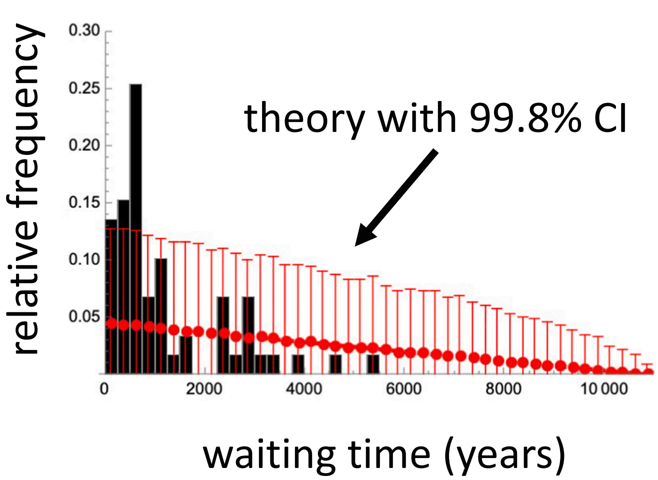

Fig. 7. Observed and expected waiting times between occupations for 59 two-occupation North American archaeological sites dated between 500 yr BP and 11,500 yr. BP. Only sites with at least 30 dates are considered. Observed waiting times between occupations of 250, 500, and 750 years greatly exceed the expected frequency for "exploratory" mobility. The conclusion is that reoccupation on these time scales represent "exploitation." Waiting times longer than 750 years are consistent with repeated occupations driven by memoryless "exploratory" mobility.

that fall outside of the confidence interval. In both cases, for all other times scales we cannot reject the null hypothesis that reoccupation reflects mobility-driven exploration.

We are similarly interested in whether there is variation over time in the prevalence of mobility-driven exploration and mobility-driven exploitation. It is entirely plausible that the balance of these two mobility strategies would change over the course of 11,000 years, particularly given that the mix of horticultural adaptations increased over this time relative to dedicated foraging adaptations. We use K-Means clustering to partition the dated occupations shown in Fig. 6 (above) into two groups dating before and after 5,000 years BP. Importantly, this partition is based solely on the statistical properties of the date distribution and is not meant to coincide with any culture-historical or environmental event.

Fig. 9 shows the fixed window counts for two-occupation sites dated before 5,000 years BP (a 6000 year fixed window), the sites younger than 5,000 years BP (using a 4,500 year fixed window). The oldest cluster of sites displays temporal reoccupation patterns that are largely consistent with mobility-driven exploration. However, there are four sites (20 % of the sample) that show reoccupation on a time scale of 2,750 years, which falls outside of the expected frequency for mobility-driven exploration. Though statistically significant, the deviation is hard to align with any theoretical reason why repeated exploitation of these environments would occur at time-scales of around 2,700 years and not shorter time scales. Since four sites involved have earliest occupations that date between approximately 7,800 and 5,300 years BP, the reoccupation pattern would not appear to be an artifact of imprecision in the radiocarbon calibration curve such as the 2450 ^{14}C BP Hallstatt Plateau (Jacobsen et al. 2017).

For sites dating after 5,000 BP there is more apparent clustering of short waiting times between reoccupations at the same site. Specifically, there is a peak in reoccupation waiting times of 750 years consistent with mobility-driven exploitation. Waiting times of 250 and 500 years are also above the expected mean for mobility-driven exploration, but we cannot reject the null hypothesis due to the small sample size.

5. Discussion & Conclusions

We began this paper with the controversial suggestion that most micro-scale differences in mobility regimes, though obvious perhaps in ethnographic contexts, are largely invisible in archaeological context. The limits of geochronological methods and the pernicious effects of site formation processes mean that mostly we are dealing with time-averaged deposits that mask most of the variation that would be useful for closely dissecting mobility. Thus, we suspect it is very hard if not impossible to make clear distinctions between archaeological materials that reflect mobility dedicated to search within patches versus mobility dedicated to travel between them as required, for example, by the Marginal Value Theorem (Charnov, 1976). We argued that a shift to location-based analyses is therefore appropriate to the quality of the archaeological record (Perreault, 2019). However, this focus on locations also necessitates a shift in the questions we ask about forager mobility. The suggestion here was that we can seek to detect differences between mobility oriented around exploration and that oriented around exploitation in a macroarchaeological measure of the waiting time between site occupations. These ideas are well-defined in approaches to machine learning as well as evolutionary theory. Thus, adaptive exploration was suggested to entail "memoryless" mobility, where occupations at any one time and place were independent of the time and place of all prior occupations and exerted no influence on the time and place of future occupations. To see why this arguably extreme strategy facilitates exploration consider that, in the absence of any memory or history, there can be no bias to steer foragers towards (or away from) any one patch. If *all* patches are of equal quality, then eventually *all* patches (in a finite environment) will be visited and, given enough time, all patches will be visited an equal (infinite) number of times. The entirety of space is

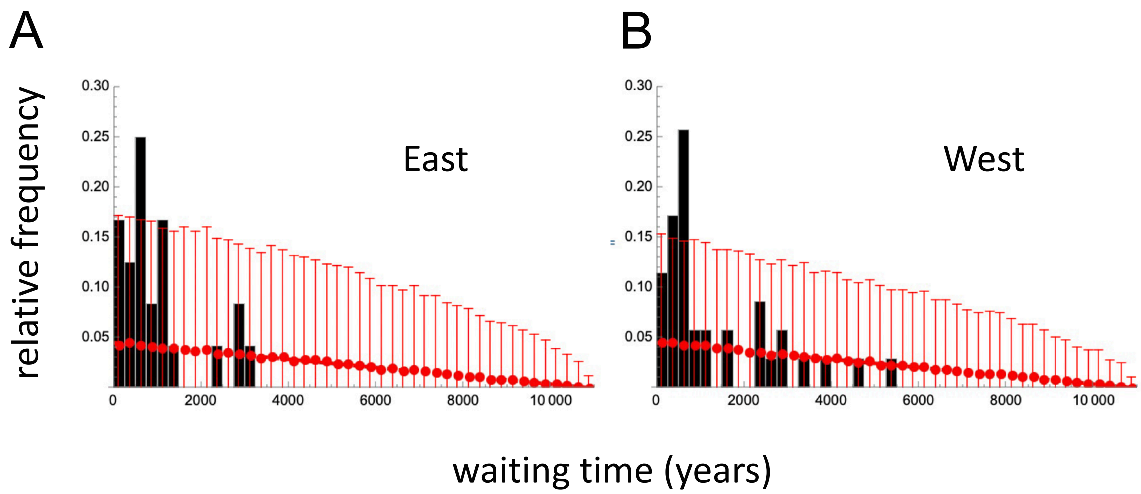

Fig. 8. Comparison of geographic patterns across (A) Eastern and (B) Western groups of sites (see Fig. 6). For Eastern sites mobility-driven exploitation is suggested at time scales of 750 years and (marginally) 1,250 years. For Western sites, mobility-driven exploitation is suggested at time scales of 500 and 750 years. All other reoccupation time scales are consistent with mobility-driven exploration.

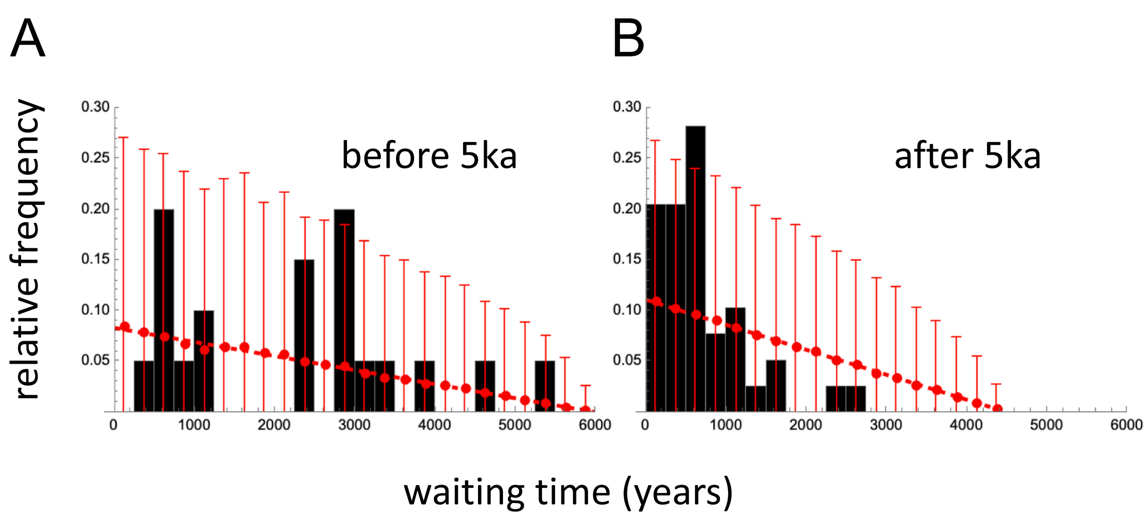

Fig. 9. Analyses for chronological groupings of the 59 two-occupation sites. Groupings were determined by K-Means clustering which (A) A total of 20 sites with exactly two occupations date older than 4,500 years BP. (B) A total of 39 sites with exactly two occupations date younger 4,500 years BP. For sites older than 4,500 years BP the counting window is 6,000 years. For sites younger than 4,500 years BP the counting window is 4,500 years.

guaranteed to be explored under these circumstances. If patches differ in quality, then all patches that can support humans will be occupied at some point, and the frequency of occupations will be proportional to patch quality in the long run.

By contrast, when foragers engage in adaptive exploitation, occupations at one point in time trigger changes (or transitions) in occupation rates for future points in time. For example, if foragers engage in niche construction that improves patch quality, then this improvement would show up as an increase in the occupation rate and repeated occupations that occurs sooner than would be expected under the conditions that existed prior to the instance of niche construction. Occupations that produce lasting degradation or depletion of a patch would show up as a decrease in the occupation rate and times between reoccupations that are longer than would be expected under the prior conditions.

As interesting as these models may be, do they generate patterns that might be the subject of empirical archaeological investigation? On the face of it, spatial clustering of sites in some locations suggests that archaeological populations revisited known locations that were valued in some way (due to access to natural resources for example, or because materials left behind could be re-used). However, the simulations presented here suggest that we need to interpret spatial clustering of sites with caution. Both adaptive exploration and adaptive exploitation can generate spatial clustering of archaeological occupations. Spatial patterns alone are not sufficient to tell us if foragers routinely “remembered” a network of favored locations and utilized those preferentially (Freeman, et al., 2019). Temporal patterns of occupation seem more promising for making such distinctions. Adaptive exploration, as defined here, produces waiting time distributions for occupations (specifically for 2-repeats) that can be predicted exactly by theory (see Short, et al., 2009). The expected frequency of 2-repeat waiting times decreases linearly with the length of the waiting time. Adaptive exploitation is identified primarily by how it deviates from the expected pattern for adaptive exploration. Specifically, when occupations drive transitions to higher occupation rates—as we might expect in cases of niche construction—this appears empirically as a greater frequency of shorter waiting times between occupations than would be the case with adaptive exploration.

How should we interpret findings adaptive exploration or adaptive exploitation? An empirical case consistent with an emphasis on adaptive exploration might lead us to conclude that human mobility strategies—though possibly optimally planned at an ethnographic-scale—end up being random or unplanned at a macroarchaeological scale. A substantial degree of randomness at aggregate scales may be why formal diffusion models—in the sense of gas or particle systems—often do a reasonably good job of describing animal dispersal (Turchin, 1998). Though this interpretation seems antithetical to the traditional study of forager mobility, recall that successful adaptations require variation to avoid getting stuck. Exploration—in the sense of mobility that undertaken independent of the history of past occupations—might be a source of such variation. At a macroscopic scale, a strategy dominated by random occupation of random patches at random times might produce more adaptive benefits over the long-run than strict exploitation strategies. By contrast, if an empirical case is consistent with only adaptive exploitation, then one interpretation is that mobility strategies incorporate multigenerational learned behavior (i.e., culture) or substantial environmental modification (i.e., niche construction) both operating at a macroscopic scale. Occupations of a patch at one time may produce cultural knowledge that biases the timing of reoccupation of that patch, perhaps centuries later. The temptation is to imagine the relevant learned behavior concerns things like instantaneous patch quality information (Bettinger and Grote, 2016), though this is an ethnographic-scale framing that we resist. Alternatively, cultural knowledge in the form of relatively simple heuristics or rules (Ross, et al., 2018) might feasibly operate over many generations to influence patch occupation decisions in ways that appear as adaptive exploitation.

At evolutionary time scales, we might expect macroscopic mobility to shift generally from exploration- to exploitation-dominant. Such might follow the long-term evolution of cognitive and social learning systems that favor greater reliance on cumulative culture (Paige and Perreault, 2024). The culmination in exploitation-dominant strategies is perhaps inherent to the global shift towards greater population sedentism during the Holocene (Bocinsky, et al., 2016). It is less clear that there should be any particular directionality in the reliance on exploration versus exploitation over the course of the Middle and Late Pleistocene. Rather, one might expect a trend towards greater flexibility involving reliance on exploration when environmental conditions are volatile and exploitation when conditions are stable (Rendell, et al., 2010). Spatially, we might encounter regions that are more suitable for exploration-dominant strategies and others exploitation-dominant. In other words, exploration may yield greater adaptive benefits in some environments and exploitation in others. However, more work will be needed to try and tease the possibilities apart.

The empirical case study introduced here is just a first attempt at using dated multi-occupation archaeological sites to disentangle macroscopic mobility strategies. We used the CARD radiocarbon database to create a sample of 59 sites with at least 30 radiocarbon dates and exactly two occupations observed over a time window fixed between 500 years BP and 11,500 years BP. Though this is a small, imperfect sample, it was enough to suggest that waiting times between occupations were distributed unlike a pure "exploration" strategy. Specifically, waiting times of 250, 500 and 750 years between occupations occur at much higher frequencies than would be expected in a memoryless mobility strategy. The suggestion is that these data reflect a bias towards adaptive exploitation over exploration. However, this is not true for longer waiting times which are consistent with exploration being the primary driver of reoccupation of these sites. We tentatively conclude that mobility-driven "exploitation" is indicated over periods of < 1000 years. This may suggest something about the "half-life" of processes that preferentially draw foragers back into attractive locations, above and beyond what would be expected from pure exploration. Such features may be durable improvements that are independent of the groups exploiting the environment. For example, in aggrading environments, necessary for formation of stratigraphically differentiated occupations, features or materials left by previous occupants of a locality do not stay on the surface forever. In the absence of physical niche construction, it could be that some kinds of socially transmitted knowledge about attractive patches has a "half-life" measurable in centuries. Finally, the mechanism might be dependent upon external environmental change such that discrete patches remain attractive for about 1000 years before further exploration becomes necessary. However, this last possibility requires more modeling to address in any detail (see below).

Examination of the data in geographic and chronological groups does not substantially change our observations. Eastern and Western groups of sites display very similar patterns suggestive of mobility-driven exploitation on time scales $< 1{,}000$ years. Sites grouped chronologically based on the age of the oldest occupation present a somewhat different pattern. Older sites are mostly consistent with mobility-driven exploration, though a surprising peak in reoccupation at time scales of 2,700 years is difficult to explain. Younger sites may suggest stronger clustering around shorter waiting times for reoccupation. This appears to be the case when looking at all of the sites younger than 4500 years BP, but not so when looking at those sites younger than 2500 BP. We suspect that taphonomic biases may play a significant role in the observed pattern (see below).

Though we suggest some interesting possibilities about the nature of macroscopic mobility strategies, a number of limitations inherent to the present study must be considered. The first concerns the theoretical basis for using waiting times between occupations as a macroarchaeological measure of mobility. Clearly a range of ecological and environmental factors play a role in occupation initiation and abandonment. However, mobility is a proximate mechanism driving the activity at particular places that ultimately accumulates as an archaeological record. We suggest that this general fact is true across the full spectrum of ethnographic-scale mobility regimes such that we can simply point to occupation patterns across time as being a product of mobility, at least in part. It is possible that many other causal processes, including post-depositional taphonomic processes, may obscure or "cancel out" any effects of mobility in driving occupation patterns. Positively, perhaps, the counting methods presented here are conservative in that causal processes pulling in different directions would tend to result in patterns consistent only with adaptive exploration. Thus, one could interpret findings consistent with "adaptive exploration" as a neutral or null result where there is no evidence for adaptive exploitation of a landscape *or*, equivalently, the biases in the record are such that we cannot reject the hypothesis that the record simply preserves occupations at random times (Brantingham, 2003).

The second limitation concerns modeling assumptions about stationary environmental conditions, specifically that environments are composed of different patches that do not change in spatial location or quality over time. This assumption is useful for demonstrating that clustering of occupations in space does not necessarily represent adaptive exploitation, and that spatial clustering of occupations can also be generated entirely by memoryless adaptive exploration (see also Short, et al., 2009). We expect, however, that change through time in patch qualities could mimic an exploitation mobility strategy. For example, memoryless occupations that occur on either side of an environmental change, where improving patch qualities drive an increase in independent occupation rates from $\lambda_2 = 0.001.$ to $\lambda_3 = 0.004$, will appear to have shorter than expected waiting times that look like adaptive exploitation if constant environments are assumed. The opposite holds if patches deteriorate, producing independent occupation rates that fall from $\lambda_3 = 0.004$ to $\lambda_3 = 0.001$. Here occupations will appear to have longer waiting times compared with a stationary environment. In both cases, the environmental change driving occupation rates is exogenous to the mobility regime and therefore suggests nothing about learned patterns of adaptive exploitation. In practice, fixed window counts of waiting times between occupations can be conditioned on environmental (or other) covariates (Park, et al., 2021), but more work is needed to develop this approach. Given the current limitations, however, it is likely that the North American radiocarbon record examined here likely overestimates the prevalence of an exploitation strategy.

Correcting for environmental change would likely remove some of the apparent deviations from Poisson expectations.

A third set of limitations stems from uncertainties in geochronology (including irregularities in radiocarbon calibration) and the effects of site formation processes. We invoked these challenges as motivation to shift to a location-based macroscopic scale of analysis, but they are still likely to have had an impact in the empirical testing at this scale as well. For example, the shape of the calibration curve over certain age ranges may make reoccupation times appear shorter or longer than was the case on the ground. Thus, radiocarbon calibration alone might drive patterns that appear like exploration or exploitation using our methodology. Similarly, we treated the dating of archaeological occupations as generating neat minimum and maximum ages of occupation, which obviously is far from realistic. Incorporating dating uncertainty into the counting models is possible but will require more work. We also need to account for taphonomic destruction of archaeological occupations and mixing of deposits. The last and first appearance dates of archaeological occupations, akin to the "last appearance datum" [LAD] and "first appearance datum" [FAD] in paleontology, are subject to taphonomic and sampling biases that generally cause the former (LAD) to appear older than the true age of last appearance and the latter (FAD) to appear younger than the true age of first appearance (Marshall, 2019; Perreault, 2011). However, it is unclear whether this would simply tend to dampen the signal of adaptive exploitation—making the aggregate pattern look more like adaptive exploration—or would produce occupation patterns that are lagged longer than would be expected by chance alone. Our approach to the North American archaeological record was to include only sites that have at least 30 radiocarbon dates, which hopefully reduces (though certainly does not eliminate) the error in waiting time estimates (Perreault, 2011). More generally, it is well known that there is a strong "pull-of-the present" inherent to the archaeological record (Surovell and Brantingham, 2007; Surovell, et al., 2009). In the present context, this means that older two-occupation sites are likely to be underrepresented and younger two-occupation sites overrepresented in any given sample due to taphonomic destruction alone. Younger two-occupation sites are constrained to having relatively short reoccupation times, while older sites may have short or long reoccupation times. Thus, a sample dominated by younger sites counted with a wide fixed window may appear to favor mobility-driven exploitation when in fact mobility-driven exploration was dominant. Untangling how taphonomic processes impact the counting methods introduced here will require more modeling work.

More challenging is the effect of researcher choices, which may substantially impact what we know about archaeological occupations. Consider a simple scenario of an archaeological site with three discrete occupations dated as $t_1 > t_2 > t_3$. Assume that the researcher produces only two dates from the site. The dating will make the site look like a 2-repeat and, to add the problem, there are three possible 2-repeats that might be presented (i.e., $\tau = t_2 - t_1$ *or* $t_3 - t_2$ *or* $t_3 - t_1$). Under ideal circumstances, such researcher choices would be random and independent across sites and projects. But, to the extent that they are not, it may bias waiting time distributions in unexpected ways. One could seek to model such biases, though it will probably be necessary to scrutinize the empirical record to identify and control for the actual effects of researcher bias. In the present case, we have sought to minimize this problem by focusing on sites with large numbers of radiocarbon dates, giving the greatest possibility of identifying all discrete occupations. However, the combined effect of research choice as well as methodological variability means that aggregate databases such as CARD involve compounded errors, which raises questions about dates-as-data approaches to archaeological modeling (Becerra-Valdivia, et al., 2020). However, macroarchaeological approaches are dependent upon aggregate datasets that cover the spatial, temporal and cultural scales at which macroscopic ecological and evolutionary processes are likely to operate. We conclude that it is still better to attempt to test a model with imperfect data than to just simulate a world as we would like it to be and call it a day.

CRediT authorship contribution statement

P. Jeffrey Brantingham: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Randall Haas:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Steven L. Kuhn:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jasrep.2024.104895.

Data availability

All data used in the study are presented in the manuscript.

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