Archaeology in Dominica

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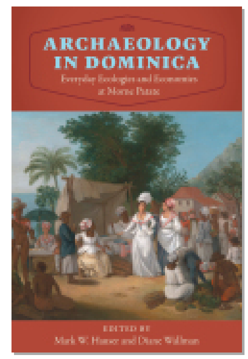

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Building an Archaeological Chronology for Morne Patate

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This chapter establishes an archaeological chronology for the Morne Patate Estate using a suite of statistical methods that Digital Archaeological Archive of Comparative Slavery (DAACS) researchers have used successfully to infer and evaluate similar chronologies on scores of archaeological sites from early-modern slave societies in North America and the Caribbean. While initially technical in its approach, this chapter is critical to understanding the evolution of the domestic core of Morne Patate. It provides a temporal framework for understanding how enslaved laborers, their descendants, and French and English owners and overseers created, reshaped, and used the landscape of Morne Patate between the mid-eighteenth and late nineteenth centuries.

Our exposition begins with an outline of DAACS's collaboration in the Morne Patate project. We offer a brief overview of the methods we employ, the models behind them, and the relationships among them: frequency seriation, mean ceramic dates, correspondence analysis, and *termini post quem*. We describe the resulting plantation-wide chronology for the estate (Locus 1) and village (Locus 2). We use the chronology to assign assemblages to temporal phases whose larger sample sizes facilitate the use of artifact abundance measures to highlight material trends across the plantation and through time.

The Digital Archaeological Archive of Comparative Slavery and Morne Patate

In 2015 the Digital Archaeological Archive of Comparative Slavery (DAACS; www.daacs.org) was asked to conduct the artifact identification and cataloging, context analysis and digitization, and map compilation and digitization for the Morne Patate project. Dr. Lynsey Bates visited excavations at Morne Patate in 2015 to help prepare artifacts for export and to advise on field recording methods. By 2016 all artifacts from the Morne Patate excavation seasons (2013–2016) had been exported to the DAACS Lab at Monticello, where each artifact was identified and cataloged into the DAACS database by DAACS staff using publicly and exhaustively documented DAACS protocols and standards.[1] DAACS staff parsed and entered all Morne Patate field records into the DAACS database. Unit and feature plans were compiled and digitized by Bates. Complete archaeological data from Morne Patate, including artifactual, contextual, spatial, and image data, are now available to scholars and the public through www.daacs.org. Jillian Galle and colleagues (2019) provide details on the development and history of DAACS.

Methods

Building reliable chronologies is an essential first step in archaeological data analysis. In the case of the Morne Patate project, documentary and archaeological evidence pointed to occupations that span the British seizing control of Dominica from the French in 1763, the economic dislocations associated with the American Revolution, and ensuing decades of European wars (O'Shaughnessy 2000), the legal end of the transatlantic slave trade in 1807, and emancipation in 1834 (Ward 1988). These events, and the larger social and economic processes that underlay them, surely affected and were affected by the lives of Morne Patate's residents, enslaved and free, and left traces in the archaeological record. Understanding this history requires placing Morne Patate's archaeological assemblages in a chronological sequence and assigning calendar dates to segments of that sequence.

The importance of a reliable chronology places a heavy epistemological burden on the methods and data we use for chronological inference. Over the long term, we can increase our own, our colleagues', and our successors' chances of success in establishing accurate chronological timelines by pursuing two complementary strategies. First, we want to harness analytical methods that expose flaws in potential interpretive claims that are based on them. To test chronological hypotheses, as one would other scientific hypotheses, we must account for flaws or errors, allowing us to evaluate if they are wrong (Mayo 2018). More on this below. Second, we need to ensure that the methods, their implementation, the data, and the protocols used to capture the data on which our hypotheses are based are publicly shared and accountable (Marwick 2017; Marwick et al. 2017). To accomplish this, the data and protocols used below are available on the DAACS website (www.daacs.org). We have developed a reproducible workflow, described below. It is implemented in the R, a free, open-source statistical programming language. The code and data as well as an online supplement containing supplementary figures are available in an archival repository at the Open Science Foundation (see https://osf.io/52jfn/). We encourage readers to download the code, check our results, and adapt the code for their own research and data.

How do methods facilitate the process of exposing flaws in claims based on them? We highlight two avenues. First, we need to be explicit about the models on which the methods are based. This makes it possible to check results for "goodness of fit" with a model's assumptions and, critically, offers the opportunity to learn from a lack of fit. Second, we use two methods backed by different models so we can assess between-model agreement. Below we briefly review the models behind our methods and the relationships among them.

Frequency Seriation

Frequency seriation is the foundation for our approach to Morne Patate and other sites whose data are shared via DAACS. Frequency seriation is based on a simple model of how the relative frequency of types, usually of ceramics, varies across archaeological assemblages (Dunnell 1970; Lyman et al. 1997). The seriation model says that (1) there is temporal overlap among types—subsets of types do not appear and then disappear synchronously—and that (2) the type frequencies follow unimodal or battleship-shaped curves over time. The model implies that, given a data matrix with undated assemblages on the rows, types as columns, and entries the proportion of each type in a given assemblage, the row order in which the type proportions best fit the model is inferred to be a chronology. Culture historians realized that types needed to be defined so they are "historical"—that is, they had unimodal response curves against time. And the assemblages need to be large, similarly time averaged, more or less evenly sampled across a single temporal continuum, and derived from a single, spatially homogeneous "cultural tradition"(Dunnell 1970).

Because the method is based on a model, it offers opportunities to expose flaws in hypotheses based on its application by assessing goodness of fit. The application can fail outright: it may be impossible to produce an ordering of rows in which the unimodal curves appear, suggesting the assemblages are effectively contemporary. Or it may be possible to achieve an order that more or less fits the model. In that case, identifying exactly where the data do not fit and investigating why offer learning opportunities. For example, amount of change in type proportions between adjacent rows may vary, revealing temporal gaps in the sequence or punctuated change linked to appearance in the sequence of assemblages generated by distinct cultural groups. Assessment of goodness of fit should advance our understanding of Morne Patate. If British control disrupted exchange networks and led to an influx of new social groups, we could expect to see a synchronous shift across all or most type frequencies in a seriated sequence.

But checking the goodness of fit to the model is only one way to rule out flaws. A second essential avenue requires independent evidence that the seriation-derived order is in fact chronological. Types can demonstrate unimodal responses along nontemporal gradients, including geographical and social space (Kruskal 1971). So comparing an initial chronological hypothesis against one derived using different methods or data (e.g., stratigraphy, radiometric dating, a second seriation) is the key to detecting failures and to objective evaluation (on objectivity, see Kosso 2001). How can we realize the analytical potential of the seriation method at sites like Morne Patate, where we are confronted with tens of thousands of artifacts and scores of contexts? We need statistical methods backed by models that can then be related to the seriation chronology. We use two: mean ceramic dating and correspondence analysis.

Mean Ceramic Dating

When Stanley South proposed mean ceramic dating (MCD) nearly a half century ago, he recognized there was a connection to the unimodal response curves of the seriation model (South 1971). But the statistical details were only worked out by ecologists two decades later (ter Braak and Prentice 1988). MCDs are simply weighted averages of the historically documented manufacturing midpoints for each type found in an assemblage, where the weights are the type frequencies. An MCD offers a maximum-likelihood estimate of the mean date of an assemblage (the value that maximizes the chance of getting the type frequencies in the assemblage) under a model in which type responses follow Gaussian functions, with means equal to manufacturing midpoints and identical variances. An obvious improvement to Stanley South's MCD is to dispense with the equal variance assumption. To do that, we assume that type-manufacturing spans are 6 standard deviations long, so the standard deviation for each type is

$$\sigma = span/6$$

We then compute a BLUE (best linear unbiased estimate) MCD, weighting each midpoint (μ_i) not only by its counts but also inversely by its variance, so types with shorter spans get greater weight.[2]

$$BLUE\ MCD = \frac{\sum_{i=1}^{n} x_i \frac{1}{\sigma_i^2} \mu_i}{\sum_{i=1}^{n} x_i \frac{1}{\sigma_i^2}}$$

The connection between the model behind MCDs and the seriation model is important because it immediately suggests a way to expose flaws in using MCDs to order assemblages into a proposed chronology. We check for goodness of fit to the model by sorting the assemblages on their MCD scores and plotting them in a seriation diagram. If the actual type proportions do not show unimodal response curves or an approximation to them, then time is not the primary factor in determining type frequencies. This simple check remedies a major defect in the MCD method: a data matrix of random numbers will return an MCD. Without checking goodness of fit to the underlying model, this flaw will go undetected.

Other flaws in an MCD-based chronological hypothesis may be more subtle. As MCD-using archaeologists recognized almost immediately, the MCDs could be influenced by social or economic gradients as well as temporal ones (Turnbaugh and Turnbaugh 1977). For example, poor households might have fewer up-to-date ceramics than contemporary wealthy ones. This is one manifestation of a more general issue: the MCD model assumes that the Gaussian response functions of the types along calendar dates are the same in all times and places. Correspondence analysis can be seen as an attempt to address this issue by extracting estimates of the means of the types (analogous to the fixed manufacturing midpoints in MCD) from the data themselves so that they honor the actual trajectories of type responses in a set of assemblages from a particular time and place.

Correspondence Analysis

There are two complementary statistical motivations for correspondence analysis (CA).[3] On the one hand, it is an ordination technique that offers archaeologists a way to visualize the pattern of similarity among a set of assemblages, based on the proportions of a large number of types that occur in them, by scoring them on a small number of underlying dimensions. Assemblages with similar type proportions will have similar scores and fall close together in a scatter plot of the dimension scores. The second motivation highlights its connection to the Gaussian response model behind MCDs and the battleship curves of seriation (Hill 1973; ter Braak 1985; ter Braak and Prentice 1988). Here the CA solution is derived from "reciprocal averaging." We start by substituting random numbers between 0 and 1 for the type-manufacturing midpoints in the MCD equation. We then compute assemblage scores. Using the assemblage scores, we compute new type scores, as weighted averages of the scores of the assemblages in which the types occur. Then we compute new assemblage scores, and so on, until the scores stabilize. The result is a set of scores for the assemblages that place them on the gradient that we assume underlies their Gaussian responses as well as a "corresponding" set of type scores that, when scaled, estimate the positions of the types' maximum popularity along the gradient.

It is possible to compute additional underlying dimensions, up to one less than the number of types, using the same algorithm while constraining each set of scores to be uncorrelated with all the previous ones. Each successive dimension accounts for less variation, dubbed "inertia" in CA lingo, in the original data. A "scree plot" of the amount of inertia accounted for by each dimension against the dimension number often displays a steep decline on the first few dimensions, followed by a shallower one on the rest. The leading dimensions, to the left of the elbow, usually portray the substantively important variation among the assemblages.

The price we pay for being able to use CA to accurately estimate assemblage locations on a single gradient is additional assumptions. The assemblage and type scores, which comprise the first dimension of CA, approximate maximum-likelihood estimates under a model in which the locations of the assemblages and the type maxima are uniformly distributed along the gradient and have Gaussian responses with equal variances (ter Braak 1985). A simple way to detect flaws in those assumptions is to assess goodness of fit to the model: sort the assemblages on their dimension-1 scores and plot them on a seriation diagram. We should see unimodal responses if there is a single dominant gradient and if sampling error has not overwhelmed the unimodal type responses. In that case, and if the gradient is long enough relative to the variance of the responses, we also expect to see the "arch effect" in a scatter plot of the dimension-2 scores against the dimension-1 scores, where the former are a quadratic function of the latter.

Unlike frequency seriation and MCDs, CA can help archaeologists identify cases in which a second gradient determines type responses independently of the first. For example, dimension-1 scores may register time while dimension-2 scores can simultaneously measure functional variation, say, food preparation versus consumption. Plotting CA scores against MCDs offers a way to identify which CA dimension captures a temporal gradient. It is usually the first, but we have encountered examples in which synchronic spatial gradients overwhelm a temporal signal that emerges on CA dimension 2. The CA dimension that is best correlated with MCDs is more likely to measure time for those assemblages than the MCDs themselves since the scores arise from the unique history of type trajectories in the analyzed assemblages. We check flaws in this expectation by comparing seriation diagrams with rows sorted using CA scores against those with rows sorted by MCDs.

CA scatter plots allow us to see clustering among assemblages and gaps between them. These indicate discontinuities in type frequencies that may register depositional hiatus or sudden shifts in the identity of site's occupants, their economic networks, or their activities. These patterns can offer useful clues to the historical processes that generated the assemblages. They also point to violations of the assumptions in the model behind CA. A critical assumption is that assemblages are uniformly distributed across the dominant (temporal) gradient. When they are not, variation in the gradient may actually be distributed across both CA dimensions 1 and 2. We will encounter an example at Morne Patate where dimension 1 separates early assemblages from later ones, while dimension 2 captures time within the later assemblages (for another example, see Smith and Neiman 2007).

Terminus post quem

The *terminus post quem* (TPQ) method is ubiquitous in historical archaeology. We use it as an additional check by plotting CA dimension scores for each assemblage against their TPQs. The two orders will be correlated if both measure time. However, we do not expect the correlation to be perfect. In theory, CA places assemblages on a continuous temporal gradient while TPQs can take only a few discrete values established by documented beginning type-manufacturing dates. Used alone, the TPQ method invites archaeologists to slip from the warranted inference that a deposit could date any time between the TPQ and the present to the unwarranted inference that it probably dates soon after the TPQ. The latter interpretation assumes that the absence of evidence for later types in an assemblage is evidence of their absence on the site when the deposit was sealed. This inference is only legitimate if we can show that the assemblage in question fits into a chronological sequence of assemblages in which the absent later types eventually do appear. This demonstration is the missing ingredient that the temporal sequence of assemblages from frequency seriation and related methods provides. Since TPQs are highly sensitive to stratigraphic excavation errors that may introduce one or two intrusive later sherds, we include robust estimates, TPQp95 and TPQp90, which are the 95th and 90th percentiles of the beginning manufacturing dates of all the sherds in an assemblage.

Phases

The individual assemblages that comprise the units for chronology building at Morne Patate have sample sizes that are too small to allow us to measure reliably temporal and spatial variation in the abundance of many artifact classes, particularly "small finds." We need to use our chronology to construct counting units with larger samples. To do that, we use CA dimension-1 scores that our analysis indicates measure time reliably. To help identify clusters of assemblages with similar dates, we use weighted histogram of dimension-1 scores, where the weights are the sample sizes of the assemblages supplemented by kernel density estimates (Baxter et al. 1997). We assess the likely calendar dates of the phases using MCDs and TPQs.

Analytical Workflow

We have provided a brief outline of the methods we use to build archaeological chronologies along with the models on which they are based. Clarity on the models and their relationships enables us to use the methods to find flaws in the hypotheses we derive from them. We have assembled the methods into a flexible, flaw-finding workflow composed of the following steps:

1. Compute the CA. Use a scatter plot of assemblage and type scores on the leading CA dimensions to identify outliers that may distort the results, eliminate them, and try again until results stabilize.
2. Once a stable CA solution is achieved, use the scree plot of inertia (variation) accounted for by each dimension to identify the dimensionality of the data. Focus on these dimensions.
3. Compute the MCDs, BLUE MCDs, and TPQs for the assemblages.
4. Use scatterplots of CA dimension-1 and -2 scores for ware types and for assemblages versus MCDs to identify which dimension(s) capture time.
5. Check fit of the CA solution to the frequency-seriation model by sorting the assemblages on the temporally sensitive dimension and producing a frequency-seriation diagram.
6. If both CA dimensions register time, identify the earliest cluster of assemblages on dimension-1 and assign this cluster to DAACS Phase 1. Compute weighted histograms and kernel density estimates to help identify the Phase 1 cluster.
7. Compute the CA without the Phase 1 cluster and circle back to steps 2–5.
8. Use weighted histograms and kernel density estimates of dimension-1 scores to help identify clusters of assemblages with similar positions along the temporal gradient. Assign the clusters to DAACS phases.
9. Compute MCDs, BLUE MCDs, and TPQs for the phases.

Developing a Plantation-Wide Chronology

We employed the foregoing workflow to develop a plantation-wide chronology for Morne Patate ceramic assemblages. The assemblages are derived from two areas. “Locus 1” is the presumed domestic complex that housed the estate’s owners and managers. It includes three excavation blocks: the Estate Block, the Stable Block, and Block E. “Locus 2” is the presumed site of the slave village and includes six excavation blocks: Blocks A, B, C, D, F, and G. The excavation blocks are composed of one or more two-meter quadrats. A third area, “Locus 3,” is thought to be the site of a provision ground. It was investigated using shovel test pits, which did not yield ceramic samples large enough to be included in this analysis.

Implementing the methods described above requires counts of ceramic types in assemblages. We used the DAACS Ware Type field. DAACS Ware Types and their manufacturing date ranges are defined in the *DAACS Ceramics Manual* (https://www.daacs.org/about-the-database/daacs-cataloging-manual/). We know from decades of work that the DAACS Ware Types are likely to be "historical types" and therefore might be expected to yield respectable fits to the seriation model. We created assemblages using the archaeological contexts identified by the excavators in the field. Where we felt confident that several contexts in the same excavation quadrat or in adjacent quadrats belonged to a single lithological unit or layer, we assigned them to a DAACS stratigraphic group (SG) and used the SG to aggregate ceramic sherds into assemblages.

To reduce the noise introduced by sampling error, only ceramic assemblages with more than five sherds and more than two ceramic types were included in our initial analysis. We excluded assemblages from topsoil, unit cleanup, and surface collections. Chronology building using CA is an iterative process. After running a first analysis, it was clear that several types were poor fits to the seriation model in these data: they occurred at low frequencies and in an unpredictable fashion across assemblages. These types could be identified because their dimension-1 and -2 scores made them outliers relative to the other types. And they made the assemblages in which they occurred outliers as well. We removed them from this analysis (American Stoneware; Astbury Type; Black Basalt; Delftware, Dutch/British; British Brown/Fulham Type; Nottingham; Refined Earthenware, modern; Refined Stoneware, unidentifiable; Saintonge). Three coarse earthenware types, Morne Patate Type 1, Morne Patate Type 1a, and Morne Patate Type 1b (see Bloch and Bollwerk, this volume), share similar attributes and were in close proximity along dimension-1 in this initial CA. We combined them into a single type that we called Morne Patate Type 1 Combined.

After these adjustments, we achieved a CA solution that reveals fit and lack of fit to the seriation and CA models. Both are informative. A scree plot of the amount of variation (inertia) accounted for by the successive CA dimensions suggests that these data can be usefully summarized in a three-dimensional space (Figure 4.1a). Patterns in the scores of types and assemblages across these three dimensions are revealing. The first dimension registers time: types that we know are early (White Salt Glaze, Tin-Enameled)

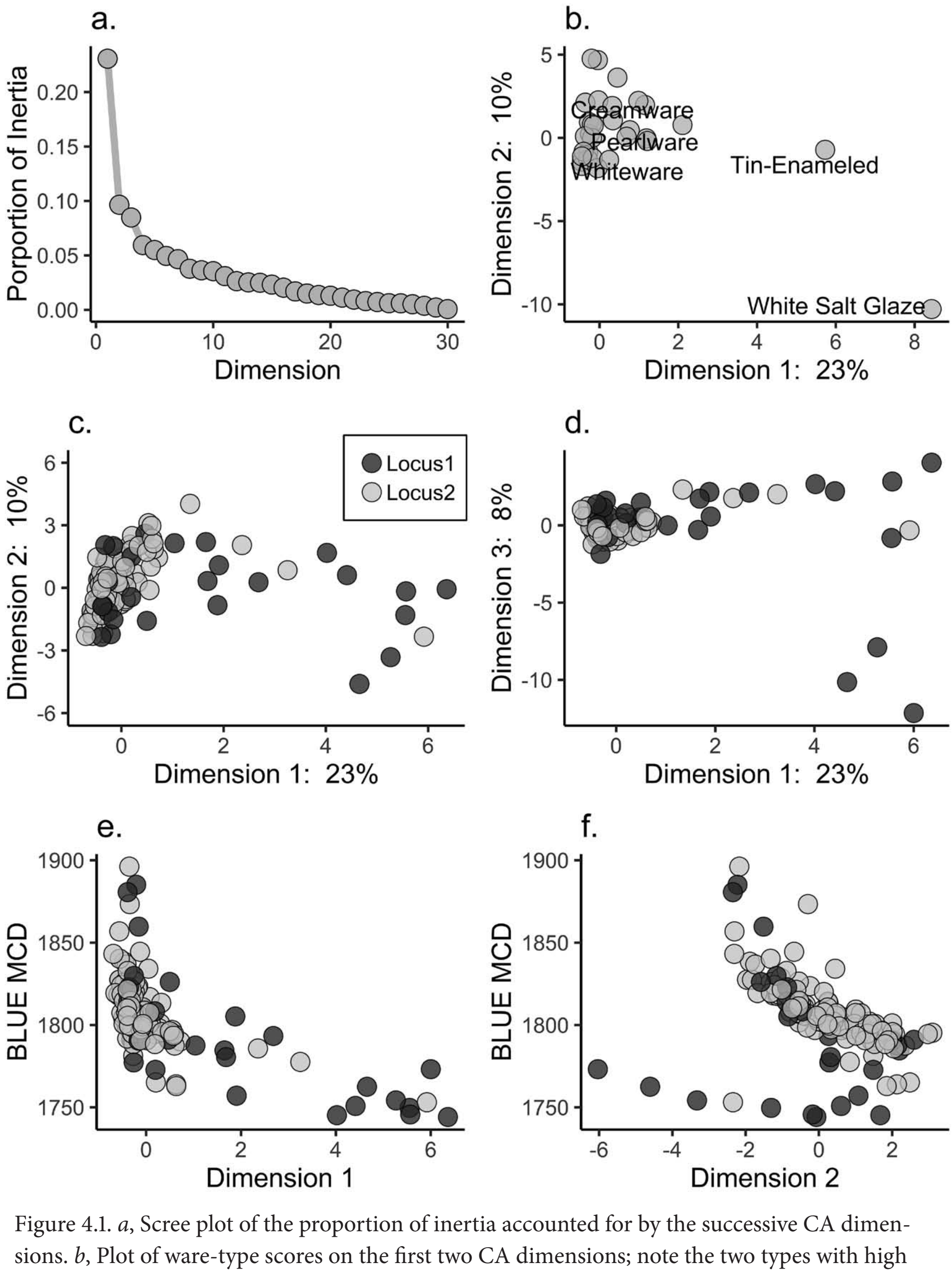

Figure 4.1. *a*, Scree plot of the proportion of inertia accounted for by the successive CA dimensions. *b*, Plot of ware-type scores on the first two CA dimensions; note the two types with high dimension-1 scores: "White Salt Glaze" and "Tin-Enameled, unidentified." *c*, Plot of the assemblage scores on CA-dimensions 1 and 2; dark gray points denote Locus1 assemblages; light gray points denote Locus -1 assemblages. *d*, Plot of the assemblage scores on CA-dimensions 1 and 3. *e*, Plot of BLUE MCDs on dimension-1 assemblages scores; note the correlation in the early part of the sequence, but not in the late part. *f*, Plot of BLUE MCDs on dimension-1 assemblages scores; note the correlation in the late part of the sequence, not on the early part.

have high scores while types we know are late have low scores (Whiteware) (Figure 4.1b). But dimension-2 also has a temporal component. The dimension-2 scores of Creamware, Pearlware, and Whiteware are negatively correlated with their known manufacturing midpoints.

Plotting the assemblage scores reveals a U-shaped pattern—an arch—that is typical of CA solution for data arising from long temporal gradients along which type frequencies wax and wane in popularity (Figure 4.1c). Assemblages on the right side of the arch are early. The plot makes it clear that the Locus 1 assemblages from the estate are distributed across the arch. But the Locus 2 assemblages from the village area are concentrated on the left and later side.

There are two assemblage clusters: a diffuse one composed of the early assemblages and a dense one composed of the later assemblages. The gap between them indicates the assemblages are not uniformly distributed along a single underlying gradient. The gap may register a temporal hiatus or, more likely, a shift in what cultural historians would have called the "cultural tradition" of the people generating the assemblages. The discontinuity in type-frequency trajectories is also registered in a seriation diagram of type frequencies in assemblages sorted by CA dimension-1 scores. It shows the early assemblages at the top of the diagram are distinctively dominated by White Salt Glaze and Tin-Enameled ceramics. The shift may register the British takeover of the island.

What about dimension-3? Dimension-3 separates the early Locus 1 assemblages into two groups (Figure 4.1d). One (contexts 6182, 6224, 6225) is dominated by White Salt Glaze; the other, by Tin-Enameled (contexts 6210, 6208, 6155, Block E SG01, 6209) (online supplement, Figure 2). Both clusters contain contexts from the Estate Block and Block E. One Locus 2 context (Block A SG04) occurs in the latter cluster, raising the possibility that its contexts may be more closely related to the village-area occupation. On the other hand, there is no indication that there is anything but random variation between the Locus 1 and Locus 2 assemblages that fall into the later assemblages. The CA scores of the later assemblages from the two loci are indistinguishable, revealing that, when measured in terms of ware-type variation, they are part of the same evolving tradition.

Our conclusion about the chronological significance of both dimensions-1 and -2 can be evaluated by plotting their scores against BLUE MCDs (Figure 4.1e and 4.1f). In the former case, we see a strong, negative, and nonlinear relationship. In the latter, we see an equally strong, negative correlation for later assemblages, confirming our suspicion that dimension-2 captures time for them.

Since variation on both dimensions-1 and -2 is chronologically significant, we cannot simply use dimension-1 scores to assign assemblages to chronological phases. A simple way forward is to identify those assemblages that are most important in determining the dimension-1 scores that separate the early from late assemblages. We can then remove them from the dataset and perform a second CA for the remaining assemblages, hoping that a single set of new dimension-1 scores will capture the chronological variation in the later part of the sequence. If it does, we can assign those assemblages to later phases based on their new dimension-1 scores.

We created a histogram and a complementary kernel density estimate of dimension-1 scores, where the vertical axis measures ceramic assemblage size (online supplement, Figure 3). It shows that a majority of the assemblages and the ceramics they contain fall in a single cluster on the far left of the histogram. They have dimenion-1 scores less than 0.8.

The highly skewed shape of the histogram is itself informative. There are at least two hypotheses that might explain it. First, the later phases of the occupation at Morne Patate witnessed a dramatic increase in either the number of (enslaved?) people living at the site, or in their per capita discard rate of ceramics, or both. The second possibility is that excavated quadrats happened not to intersect areas occupied by the bulk of Morne Patate's residents in the early phase of the occupation. In other words, most of the site's residents moved into the sampled areas in the later period. We explore change in occupation intensity in the next section of this chapter.

To isolate and explore further the structure of the later assemblages, we assigned assemblages with scores greater than 0.8 to plantation-wide Phase 1 and computed a second CA solution without them. The scree plot of the new CA solution shows a dip in inertia values between dimensions-2 and -3, suggesting that, in this case, two dimensions summarize patterning in the data (online supplement, Figure 4). There is no indication of a significant third dimension. The plot of dimension-1 and -2 scores for types shows that dimension-1 captures time: earlier types have high scores (Creamware); later types have low ones (Whiteware) (online supplement, Figure 5). Dimension 2 may capture synchronic variation in assemblages whose significance remains opaque. Earlier assemblages vary more on dimension 2 than later ones (online supplement, Figure 6), with high dimension-2 scoring assemblages having more unidentified Caribbean Coarse Earthenware,

Table 4.1. Chronological indicators for Morne Patate plantation-wide phases

Phase	MCD	BLUE MCD	TPQ	TPQp95	TPQp90	Count
Unassigned	1823	1801	1840	1820	1820	180
P01	1768	1766	1830	1762	1762	320
P02	1797	1792	1840	1820	1775	1129
P03	1818	1800	1840	1820	1820	1858
P04	1843	1810	1840	1820	1820	3513
P05	1866	1824	1840	1820	1820	813

Morne Patate Type 1, Faience, and Redware, and low-scoring assemblages having more Albisola, Red Agate, and Frechen Brown. The overall similarity of the scores for Locus 1 and Locus 2 assemblages again suggests they are part of a single, evolving "tradition," when variation is measured using ceramic ware types.

We evaluated the inference that new dimension-1 scores represent time by plotting them against their BLUE MCDs (online supplement, Figure 7). As expected, the relationship is strong and negative. On the other hand, there is no relationship between dimension-2 scores and BLUE MCDs (online supplement, Figure 8), indicating that dimension-1 completely captures chronological variation in these later assemblages. We assigned each of the later assemblages to one of four plantation-wide phases, Phase 2 through Phase 5, based on the location of dips in the weighted histogram and kernel density estimation of dimension-1 scores (online supplement, Figure 9). We combined these four plantation-wide phases with the single early plantation phase (Phase 1) identified in the earlier CA, producing a total of five plantation-wide phases. These phases are groups of assemblages that have similar CA scores and similar MCDs and are therefore inferred to be broadly contemporary.

We computed MCDs, BLUE MCDs, and the three TPQ measures for each plantation phase (Table 4.1). They suggest that Morne Patate was occupied from the third quarter of the eighteenth century into the third quarter of the nineteenth century. The significant amounts of time averaging displayed by both the phases and their assemblages make chronological precision difficult. However, plantation Phase 1 likely samples the period of French control while Phase 2 probably registers the arrival of the British and is followed by a massive increase in the number of people living in the sampled areas of the site or in per capita discard rates or both. We suspect the plantation Phase 4 to 5 transition coincides with emancipation. The dispersal from Locus 2 of most of the plantation's formerly enslaved people would explain the decline in the abundance of ceramics in Phase 5.

Changes in Occupational Intensity across the Site

With the plantation chronology in hand, we can now chart change over time in the number of ceramic sherds deposited within Locus 1 (Estate) and Locus 2 (Village) and among the different excavation zones or blocks that comprise them. The goal is to infer the pattern of increase and decrease in the size of the population using, breaking, and discarding ceramics in each of the blocks. A simple way to do this is to count and then plot the number of ceramic sherds found in the assemblages assigned to each phase for each excavation block. A key assumption here is that the different phases are characterized by similar amounts of time averaging. Figure 4.2 portrays the total number of ceramic sherds assigned to each phase within each block as a series of bar charts. Note that the *y* axis, which measures the number of sherds, is different for each of the graphs so that the patterns within each block are not obscured by variation in sample size among blocks driven by variation in excavation area.

We have seen in earlier chapters that Locus 1 is composed of three excavation blocks, the Stable Block, the Estate Block, and Block E. All three have architectural evidence for multiple episodes of architectural construction. An early nineteenth-century foundation remains visible at the Estate Block, while excavators encountered postholes below overlying layers, which hint at earlier, eighteenth-century construction at the site. The phased bar chart for the Estate Block offers evidence for late eighteenth-century (Phases 1 and 2) occupation, an occupational or depositional hiatus in Phase 3, and then a resumption of deposition in Phases 4 and 5.

The extant stable is thought to date to the early nineteenth century. Oral history suggests that the stable was turned into an overseer's residence in the mid-nineteenth century. The phased bar chart (Figure 4.2) reveals that the stable was built on top of an earlier eighteenth-century occupation. The lack of assemblages from Phases 2–4 is striking. Occupation—by people—resumed in Phase 5, confirming the oral history about the arrival of an overseer in the postemancipation period.

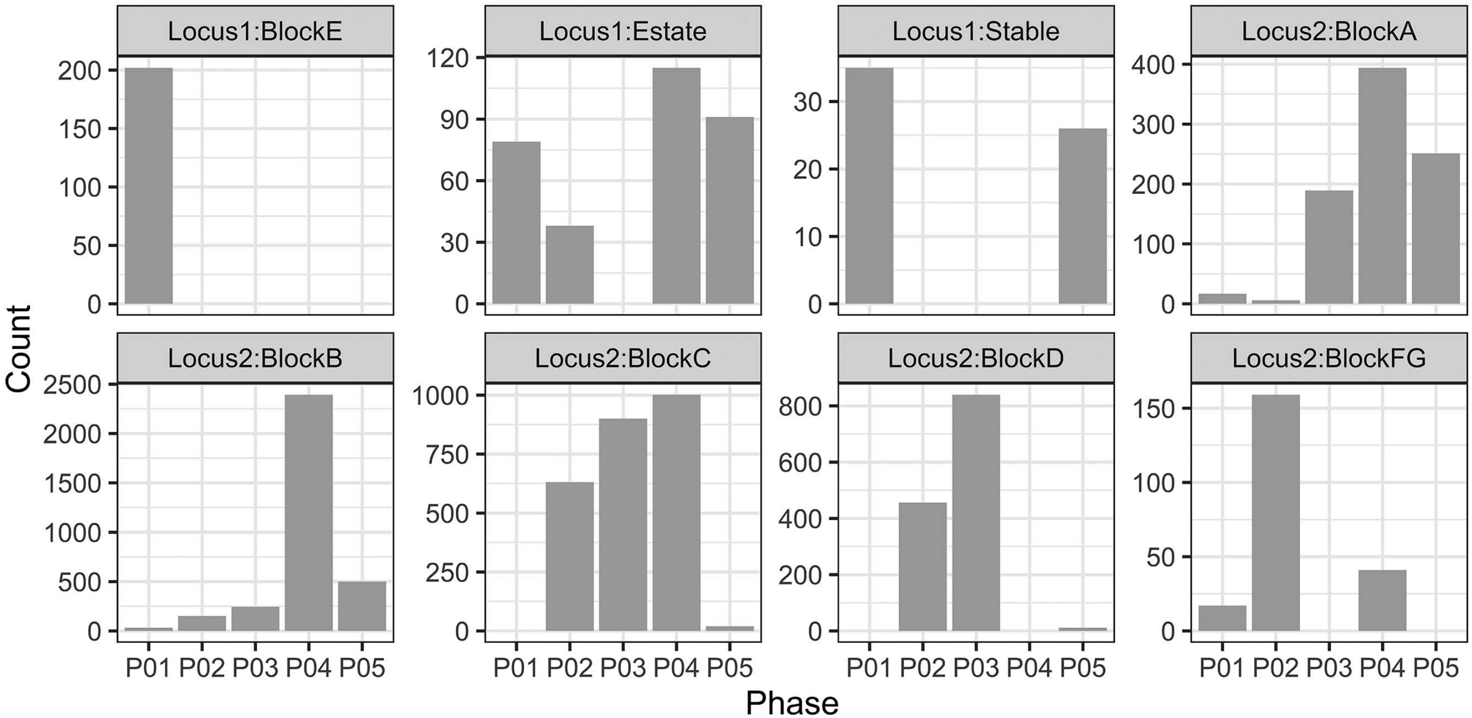

Figure 4.2. Total number of ceramic sherds assigned to each phase within each block.

Block E is adjacent to a *glacée* for coffee drying. Excavators encountered numerous postholes and small features, which Hauser has identified as architectural. The bar chart reveals that these almost certainly date to Phase 1.

Locus 2 includes excavation Blocks A, B, C, D, F, and G. For this analysis, we combined the phased assemblages from Blocks F and G, which are near each other and have small samples, into a single Block FG. The phased bar charts reveal an order-of-magnitude increase in deposition in Blocks C, D, and FG during Phase 2. A similarly large increase occurs in Block A during Phase 3 and in Block B during Phase 4. During these same two phases, deposition at Blocks FG and D (respectively) drops off. All five blocks show precipitous drops in deposition in Phase 5. Only Blocks A and B remained occupied during the final phase.

The foregoing patterns of change in the different excavation blocks support the hypothesis of two punctuations in settlement location, one during the early decades of British control and one at emancipation. Phase 2 witnessed a decline in the intensity of occupation and perhaps eventual abandonment of the estate area. This may have been ultimately linked to the economic and political uncertainty that plagued the Caribbean in the wake of the American Revolution. Simultaneously, there was a massive increase in deposition (and number of enslaved people responsible for it) into the village-area blocks, followed by continued increases in Blocks A, B, and C. This corresponds with the increase in enslaved laborers indicated by historical documents discussed by Hauser in the first chapter of this volume. This is followed by a precipitous decline at the Phase 4–5 transition, which we suspect is coincident with emancipation. However, some newly freed workers remained in Blocks A and B areas. Meanwhile, the estate area was reoccupied in Phase 4 and the occupation continued into the postemancipation period.

Changing Domestic Economies through Time

Our chronology also allows us to trace change over time in assemblage content within Locus 1 and Locus 2 while also measuring synchronic variation between them. We use an abundance index (AI), a flexible measure of variation in the frequency of one artifact class relative to another: $AI = x/(x+y)$. In the equation, x is the assemblage count of the artifact class—the numerator class—whose abundance we hope to measure, while y is the count of a second artifact class—the denominator class—whose abundance we are using as a baseline.

The analytical goal is to use AI estimates as proxies for discard rates of the numerator artifact class (*x*). Discard rates are in turn linked to breakage, use, and acquisition rates of the artifacts in question, all of which are linked to the strategies people employ to navigate their worlds and to the costs and benefits those strategies confer. We want to pick a denominator class whose discard rate (i.e., the number of sherds deposited per person per year) is more or less constant across the assemblages being analyzed. Or, if it is not constant, its discard varies much less than the discard rate of the numerator class. If the denominator class meets these assumptions, then variation in the AI will reflect variation in the discard rate of the numerator class.

Galle has suggested that, for many eighteenth- and early nineteenth-century sites in North America and the Caribbean, green glass from "wine bottles" is a promising candidate (Galle 2006, 2010, 2011, 2017). A second possibility is coarse earthenware. We use AI results for these two classes to determine if they do meet the assumptions required for a valid proxy. This offers an opportunity to catch and rule out flaws. To take advantage of it, we compute AI values for coarse earthenwares, with wine bottle glass as the denominator class. The result validates the use of the method with the Morne Patate assemblages and offers clues to changing domestic economies at the core of Morne Patate.

Consider first the methodological implications. If discard rates for both wine bottle glass and coarse earthenwares are constant through time, then we expect a plot of AI estimates for coarse earthenwares, computed with wine bottle glass as the denominator class, to show no trend and no significant variation among assemblages. Figure 4.3a plots these AI estimates for the five phases at both Locus 1 and Locus 2, along with their 95% binomial confidence limits. The confidence limits offer an approximate and probably optimistic (in the sense that it is too low) measure of uncertainty in each estimate that is the inevitable consequence of sampling error. For Locus 2, the trend is flat and there is very little among-assemblage variation. This validates our reliance on wine bottle glass as the denominator class in what follows. The flat trend in the discard of utilitarian vessels suggests that Locus-2 residents—enslaved individuals living in household units, whether with kin or not—had relatively stable food processing, storage, and preparation routines through the occupation.

The anomalous results for Locus 1 are a learning opportunity. AIs for

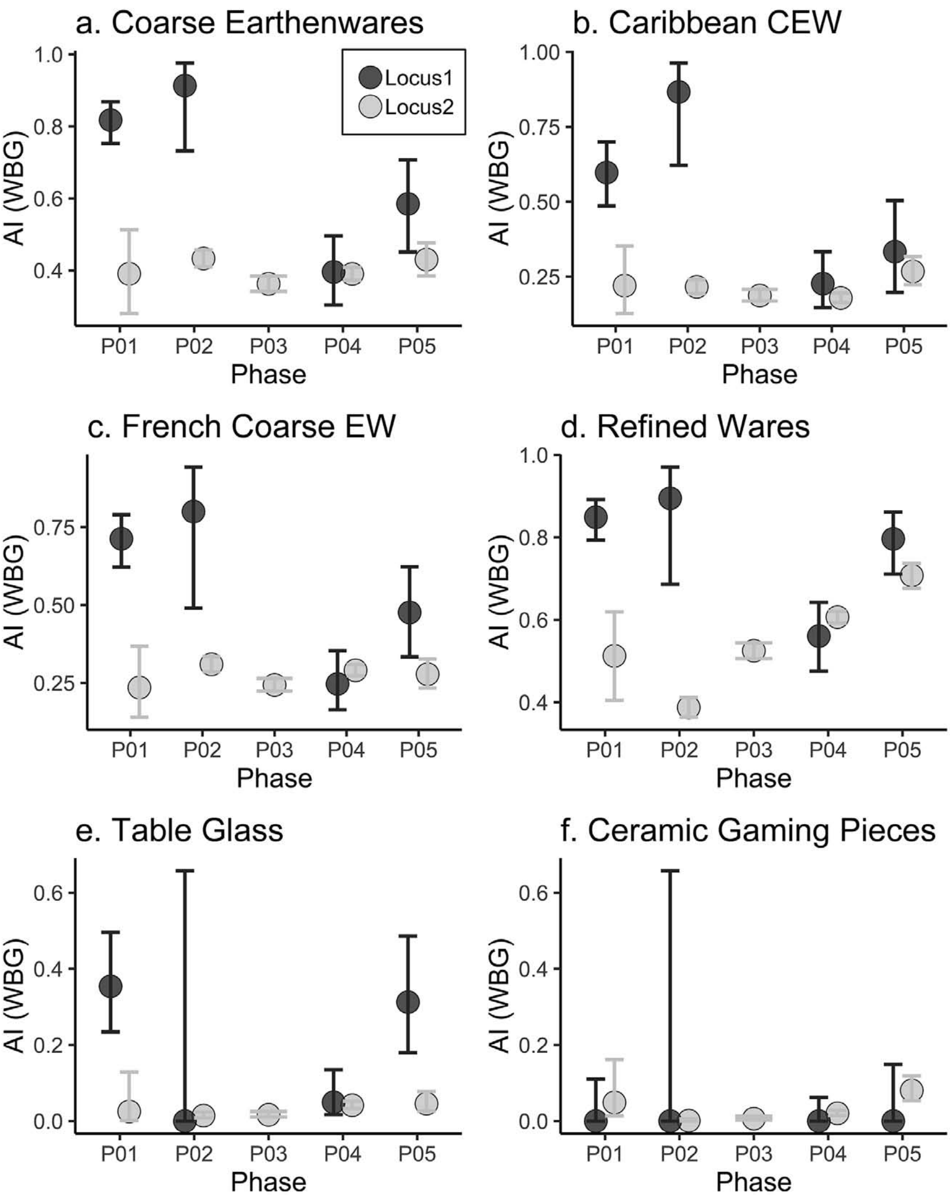

Figure 4.3. Abundance Index (AI) estimates for six artifact classes, all computed with wine bottle glass as the denominator class. Approximate 95% binomial confidence intervals computed using the Wilson score method (Agresti and Coull 1998).

Locus 1 in Phases 1 and 2 are far higher than those for Locus 2. We suggest these higher rates of coarse earthenware discard indicate wealthier households with complex domestic economies that required more involved ceramic-mediated food processing, preparation, and storage routines than food processing routines within contemporary enslaved households at Locus 2. If this is right, it implies that the domestic-economic complexity of Locus 1's new residents during Phase 4 declined to the level found in Locus 2, although it increased slightly in Phase 5. This pattern suggests that Locus 1 deposits in Phases 1 and 2 represent a resident-owner household, while their successors in Phases 4 and 5 were significantly less wealthy, perhaps hired overseers.

The contrasting trajectories of change in AI values and discard rates at Locus 1 and Locus 2 in all coarse earthenwares persist when we break this large artifact class down into its two most abundant components: Caribbean coarse earthenwares and imported French coarse earthenwares (Figure 4.3b and 4.3c). However, the finer-grained classification reveals subtle differences late in the sequence. For Locus 2, we now see a significant uptick in the AI for Caribbean coarse earthenwares but not French ones in Phase 5. For Locus 1, the pattern is the opposite. This raises the possibility of a marginal increase in domestic-economic complexity at both loci, coupled with increased inequality between them, with Locus 1's residents discarding slightly more costly imported coarse earthenware ceramics at higher rates.

Subtle differences earlier in the sequence are also noteworthy. For Caribbean coarse earthenwares, an increase in the AI in Phase 2 at Locus 1 may point to import-substitution (Figure 4.3b). Perhaps discard of locally produced utility ceramics increased because they replaced imported ones, which were harder to get in the war-torn late eighteenth century. We would expect a complementary decrease in the French coarse earthenware AI in Phase 2. But the large confidence interval prevents evaluation of this idea.

On the other hand, despite the statistical uncertainty, it is clear that French imports continued to be discarded at a relatively high rate in Phase 2 at Locus 1. This may point to the impact of the 1766 Free Port Act that enabled Dominican and Jamaican ports to trade freely with any ship that docked in their ports. Rampant smuggling, the lack of enforcement of British Navigation Acts, and the loosening of French trade laws in the late eighteenth century all contributed to the flow of goods throughout the Caribbean, especially in the Lesser Antilles, where trade between adjacent islands was easily accomplished. Dominica is sandwiched between Guadeloupe and

Martinique, French colonies that are still part of France's overseas regions today. So it seems likely that French coarse earthenwares were both abundant and inexpensive on the island throughout the eighteenth and nineteenth centuries (Hauser and Kelly 2011; Kelly et al. 2008).

Next we turn to AI estimates for more costly, imported refined wares (Figure 4.3d). Included here are fashionable porcelains, refined stonewares, tin-enameled wares, and refined earthenwares, all of which were key to strategies of conspicuous consumption related to food and drink (Galle 2010). The link to wealth offers an opportunity to use refined ware AIs to independently evaluate the ideas we offered to explain variation in the coarse earthenware AIs. The hypothesis of a drop in the wealth level of the residents of Locus 1 after Phase 2 is supported by a precipitous drop in the AI values for refined wares. In Phase 4, the new Locus 1 residents invested far less in status-driven displays than the earlier resident-owner occupiers. However, investment apparently increased in Phase 5, paralleling evidence for a modest increase in wealth based on coarse earthenware AIs.

We also discovered significant, although more subtle, changes in refined earthenware AIs in Locus 2. A significant decrease in Phase 2 may point to a decline in consumption driven by war-related economic stress. The sustained increase across Phases 3 and 4 may point to marginal improvements in the motive and means to participate in consumption rituals related to food and drink, which in turn may be related to marginal improvements in living conditions made by slave owners anxious about the end of the transatlantic slave trade. The continued increase in the refined ceramics AI estimate in Phase 5 for Locus 2 may register expansion of economic opportunities for newly freed individuals within and outside of Morne Patate Estate.

AI estimates for sherds from table-glass vessels (e.g., stemmed vessels, tumblers) serve as an independent check on the conclusions based on refined ceramics. Table-glass vessels were linked to conspicuous rituals of drink consumption. The pattern of change for table-glass discard in Locus-1 assemblages largely mirrors our findings for refined ceramics. We again see evidence for the decrease in discard rates after Phase 3, relative to Phase 1, although this is tempered by massive uncertainty about the AI value for Phase 2. There is also general agreement in the pattern of change for Locus 2. Discard rates for table glass drop from Phase 1 to 2. This is again followed by a modest increase after Phase 3. This contrasts with the much larger increase for Locus 1 in Phase 5, suggesting that social rituals diverged, with Locus 1 residents investing much more heavily in drinking.

A unique feature of the Morne Patate ceramic assemblages is the abundance of gaming pieces for which there is evidence of on-site manufacture from ceramics, mostly refined, transfer-printed pearlware and whiteware ceramic plates. Discard rates for gaming pieces may be constrained by discard rates of the vessels from which they were manufactured. But the constraint is a loose one—there were plenty of discarded ceramics across the occupation—and additional factors must have been at work. Among the most important was variation in the amount of time individuals invested in social interactions involved in gaming, including the time they devoted to game-piece manufacture. This may in turn be linked to economic stress. For Locus 2, the pattern of change in AI values is a familiar one. We see a significant decline from Phase 1 to 2, followed by modest increases across Phases 3 and 4, and a much larger increase in Phase 5. On the other hand, small samples and the general rarity of gaming pieces generate so much uncertainty that we cannot make credible inferences about gaming-piece discard rates at Locus 1.

Conclusion

Establishing a robust chronology is critical to tracking changes in occupation intensity, and household complexity through time and space at Morne Patate. At Locus 1, the presumed location of the household of the estate's owners or overseers, we have uncovered evidence for a steep decline in occupational intensity or perhaps a hiatus in the last decade of the eighteenth century (Phase 3), corresponding to the shift to sugar production on the island and associated transition on Morne Patate after British annexation. In Phases 1 and 2, the Locus 1 household has much higher wealth levels than the Locus 2 households. After Phase 3, Locus 1 wealth drops precipitously, leading to our inference that hired overseers replaced owners in the early nineteenth century (after Phase 3). In Locus 2, the presumed site of the slave village, we have detected a sharp increase in occupational intensity in Phase 2, followed by further increases in Phases 3 and 4, and then a sharp decline with emancipation in Phase 5. These trends likely reflect an increase in the size of the enslaved population from the start of British control in 1763 until emancipation. Emancipation was followed by dispersal of many enslaved households. But significant numbers remained. There are subtle hints that enslaved people managed to achieve marginal increases in economic opportunities starting in the late eighteenth century and extending through the early nineteenth century (Phases 2, 3, and 4). This trend continued after emancipation. Finally, we have discovered evidence for deteriorating living conditions during Phase 2, with declining discard rates for material culture recovered from this period.

These initial conclusions warrant further fine-grained exploration using a host of additional artifact classes, including a focus on coarse and refined ware vessel forms. We look forward to a spatially more fine-grained analysis of variation in trajectories of change among excavation blocks within both Locus 1 and Locus 2. However, smaller sample sizes for phases within excavation blocks will require more sophisticated statistical methods than we have employed here. Our goal has been to lay out a few major trends in each locus and thereby construct a foundation on which future analysis may build. The data are freely available to all scholars at www.daacs.org. Jump in!

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Notes

1. DAACS Cataloging Manuals, accessed January 13, 2020, https://www.daacs.org/about-the-database/daacs-cataloging-manual/.

2. Where m_i is the manufacturing midpoint for the *i'th* ceramic type, p_i is its relative frequency, and s_i is its manufacturing span. The idea here is to weight the manufacturing midpoint not only by the frequency of each type but also inversely by the variance of the response function that describes the trajectory of change over time in the popularity or relative frequency of the type. We assume that, over time, the relative frequency of each type roughly follows a Gaussian response function, with the manufacturing start date three standard deviations below the manufacturing midpoint and the manufacturing end date three standard deviations above it. This implies that $s[_i]/6$ is a reasonable estimate of the response function's standard deviation, and its square is a reasonable estimate of the variance.

3. Textbook introductions for archaeologists include Shennan (1997) and Baxter (1994). Greenacre (2017) is the canonical statistical introduction. Useful archaeological case studies include Duff (1996) and Peeples and Schachner (2012), while de Leeuw (2007) offers an insightful overview of archaeological applications from a statistical point of view. Further details on and applications of the perspective we sketch below can be found in Neiman and Alcock (1995); Ramenofsky, Neiman, and Pierce (2009); and Smith and Neiman (2007). Baxter and Cool (2010) and Carlson (2017) provide basic guidance on using R for correspondence analysis.