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Time-Averaging Slows Down Rates of Change in the Archaeological Record

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Abstract Measuring the pace of cultural change, and understanding its determinants is a fundamental goal of anthropological research. The archaeological record is the main source of information about the pace of cultural change, but it is an imperfect one, as taphonomic loss and mixing distort rate measurements. Here, I focus on the impact of time-averaging on rate measurements. Time-averaging arises when archaeological materials associated with activities and events that took place at different points in time are mixed into the same unit, whether because of depositional processes, disturbance factors, or because archaeologists lump together archaeological contexts when creating analytical units. I use analytical models to show how time-averaging can slow down the observed rates of change under two general modes of cultural change: random drift and directional change. I test this prediction using empirical rates of change from the archaeological record of North America. I show that empirical rates of change are indeed inversely correlated with the duration of time-averaging and provide a range estimate for this correlation.

Keywords Archeology · Taphonomy · Time-averaging · Analytical lumping · Rates · Cultural evolution · Random drift

Introduction

Measuring the pace of cultural change and understanding its determinants is a fundamental goal of anthropological research. How fast cultural traditions change governs

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how much cultural diversity can exist within and between societies (Currie and Mace 2014), how fast humans can colonize new environments (Perreault 2012), the level of mismatch between culture and environment due to cultural inertia (Mathew and Perreault 2015, 2016) and, by the same token, how far back in time we can trace the history of ethnolinguistic groups based on their current cultural repertoire (Greenhill et al. 2010). Rates of change have been used to infer the type of forces that have shaped the evolution of traditions (Rogers and Ehrlich 2008; Currie and Mace 2014). Likewise, archaeologists use rates to support or reject their hypotheses. For instance, abrupt change in a regional archaeological record demands a very different explanation (*e.g.*, societal collapses, migration) than gradual change that unfolds over millennia (*e.g.* stylistic drift).

The archaeological record is one of the main sources of information about the pace of change of cultural traits (Perreault 2012; Braun 1987). It is, however, an imperfect one, as taphonomic loss and mixing distort rate measurement. Indeed, archaeological rates of change are inversely correlated with the time interval over which they are measured (Perreault 2012). For example, rates calculated from assemblages separated by 500 years will be faster than rates calculated from ones that are 10,000 years apart, all other things being equal. Since the time gaps in the archaeological record are longer in older deposits than in younger deposits, rates of change in artifact morphology are also inversely correlated with their absolute age (Perreault 2012). Hence, time intervals need to be controlled for when measuring rates of change in the archaeological record.

Here, I focus on the impact of time-averaging on rate measurements. The phenomenon of time-averaging is important and has been recognized as such for decades not only in archaeology (*e.g.*, Ford 1962; Plog 1974; Brooks et al. 1982; Harding 2005; Ascher 1968; Bailey 2007, 1981; Holdaway and Wandsnider 2008; Lucas 2008; Malinksy-Buller et al. 2011; Fletcher 1992; Murray and Walker 1988; Stern 1994) but also in paleobiology (*e.g.*, Behrensmeyer and Schindel 1983; Kowalewski 1996, 1998; Olszewski 1999; Wilson 1988; Schindel 1980). Time-averaging arises when archaeological material associated with activities and events that took place at different points in time are mixed into the same analytical unit. Such mixing can arise through depositional and disturbance factors, as when successive activities take place at the same site and are superimposed and reworked, resulting in a "palimpsest" of human activity (Bailey 1981; Binford 1981; Foley 1981). Mixing can also arise analytically, as when archaeologists lump together archaeological contexts to create large units such as cultural time periods (Lyman 2003).

The research on time-averaging, much of which is conducted under the umbrella of "accumulations research," has focused on its impact on measures of richness and abundance of categorical traits (Gallivan 2002; Lyman 2003; Premo 2014; Mills 1989; Schiffer 1975, 1976, 1987; Shott 1989, 2004; Sullivan 2008; Varien and Mills 1997; Varien and Ortman 2005; Varien and Potter 1997; Surovell 2009; Vaquero 2008). In contrast, we know little about the effect of time-averaging on quantitative traits. Below, I use analytical models and simulations to develop theoretical expectations for the impact of time-averaging on rates of change in quantitative cultural traits. Then, I test these expectations with empirical data and show that time-averaging significantly slows down apparent rates of change and provide a range estimate for this effect.

Theoretical Predictions

Time-averaging slows down observed rates when it lowers the amount of change observed over a given interval of time. Rates of change of quantitative traits such as length, thickness, or volume are calculated by dividing the amount of change, Δ_c, observed between two samples, x_1 and x_2 ($\Delta_c = \mid x_2 - x_1 \mid$), by the amount of time that separates the samples, Δ_t (Braun 1987). For instance, an increase of 3 cm (*i.e.*, $\Delta_c =$ 3 cm) in the average thickness of ceramic vessels between two cultural levels separated by five centuries (*i.e.*, $\Delta_t = 500$ year) corresponds to a rate of change of 3 cm/500 years or 0.006 cm/year. Time-averaging slows down rates by decreasing the observed Δ_c values.

Imagine a site that was occupied twice. During the first phase of occupation, dated to A.D. 500–750, the ceramic produced by the occupants of the site fluctuated stochastically in thickness between 2 and 4 cm. During the second occupation phase, A.D. 1000–1250, the average vessel thickness remained stable at 4 cm. Let us further assume that the two occupation phases have left two stratigraphically distinct cultural levels.

Now, let us look at two extreme scenarios. In the first scenario, the ceramic assemblage that corresponds to the first occupation phase of the first level has a high resolution and represents only 1 year of activity, the year A.D. 625. During that particular year, the average vessel thickness hovered around 2.2 cm. In the second scenario, the assemblage from the first occupation is time-averaged over the entire time period: it incorporates all the ceramic produced between A.D. 500 and A.D. 750. In the first scenario, the rate of change in vessel thickness calculated from the two cultural phases is (4 − 2.2 cm)/500 years or 0.0036 cm/year. In the second scenario, time-averaging causes the rate of change to appear smaller. Assuming that the average thickness in the time-averaged assemblage is 3 cm, the rate observed is (4–3 cm)/ 500 years or 0.002 cm/year. By incorporating temporal variation in the trait value, time-averaging has reduced the net amount of change observed between the two levels, resulting in a rate of change that is 55% smaller.

Many archaeological situations allow time-averaging to reduce observed Δ_c. Here, I focus on two cases: (1) traits that fluctuate randomly and (2) traits that evolve directionally.

Both cases are general, common, and represent the two ends of the spectrum of mode of technological change (Braun 1987). Random fluctuations in the value of a trait in a population characterize neutral traits that are shaped by stylistic drift and imitation errors (Neiman 1995; Lycett and von Cramon-Taubadel 2008; Hamilton and Buchanan 2009; Lipo and Madsen 2001; Eerkens and Lipo 2005). Directional change occurs when a trait is under selection and evolves towards an optimal value, such as projectile points decreasing in size after the advent of the bow-and-arrow. The form of directional change examined here is the one that takes the form of an s-shape curve (White 2008; Mariano et al. 1998; Braun 1987). The s-shape pattern arises from the interaction between the diffusion and the development of new technologies: the rate at which a technology evolves depends in part on the number of adopters in a population. Initially, new technologies have few adopters and change slowly. But as they rise in popularity, technologies evolve increasingly more rapidly as the number of people who have adopted them and that are tweaking them increases. Eventually, the pace of change decreases as most of the solution space of potential improvements for the technology has been explored (White 2008; Mariano et al. 1998; Braun 1987). Another form of directional change, by which a trait evolves at a constant rate and in the same direction (*e.g.*, towards large size) is not examined here, as in this situation, time-averaging could have not affected Δ_c and thus would not affect observed rates of change.

Traits that fluctuate randomly can be modeled as a random walk. Assume that each year, the mean trait value in a population shifts randomly by an increment α. Some years, α is negative (the mean trait value decreases) and other years, it is positive (the mean trait value increases). Thus, the random walk can be modeled as

$$y_t = y_{t-1} + \alpha + \varepsilon$$

where y_t is the mean value of the trait at time t, α is negative or positive with equal probability, and ε is some random error.

The case of a directionally evolving trait can be modeled using the logistic distribution function

$$y_t = \frac{1}{1 + e^{-\frac{t-\mu}{s}}}$$

where e is the base of the natural logarithm and μ and s are the location and scale parameters.

We can use these two models to simulate archaeological data, lump it analytically into time periods of various durations, and measure how the lumping impacts rates. Imagine that a quantitative trait evolves over a period of 2000 years. For the random-walk model, let us assume that the mean value of the trait at the start of a simulation is 100 units (*i.e.*, $y_{t=1} = 100$). The units are arbitrary (they could be millimeters for instance). Then, every year, a coin is flipped, and with equal probability, the mean increases or decreases by $\alpha = 1$ unit plus some random noise ε drawn from a normal distribution with a mean of zero and a standard deviation of 1. In the case of the directional evolution model, $y_{t=1} \approx 0$ and then increases every year following the logistic distribution function (the output of the function multiplied by 2000 to scale it up to a more realistic range of value).

In order to isolate the effect of time-averaging, the effect of time intervals, Δ_t, on rates of change needs to be taken into account (Perreault 2012). The most straightforward way to do this is to compare rates calculated from time-averaged contexts to what they would be if the contexts had "Pompeii-like" temporal resolution but were separated by the same interval of time. Hereafter, I call this rate calculated from high-temporal resolution units the "true rate", *i.e.*, the rate that would be observed in the absence of time-averaging. In reality, there is no such thing as a true rate: rates are inescapably dependent on the scale of observation. The true rate used in the paper is nothing but a yardstick that allows me to compare rates from time-averaged contexts while maintaining everything else equal. As such, this true rate is no more or less true than any other rate calculated over a different scale.

The true rate used in the simulations is calculated using the trait values at year 500 and year 1500. For example, in the sample run shown in Fig. 1, the value of the trait at year 500 and 1500 is 95 and 117 units, respectively. Thus, in this case, the true rate is 22/1000, or 0.022 units/year. Of course, since the random walk is stochastic, the true rate between the year 500 and 1500 will be different in each run. In the case of the

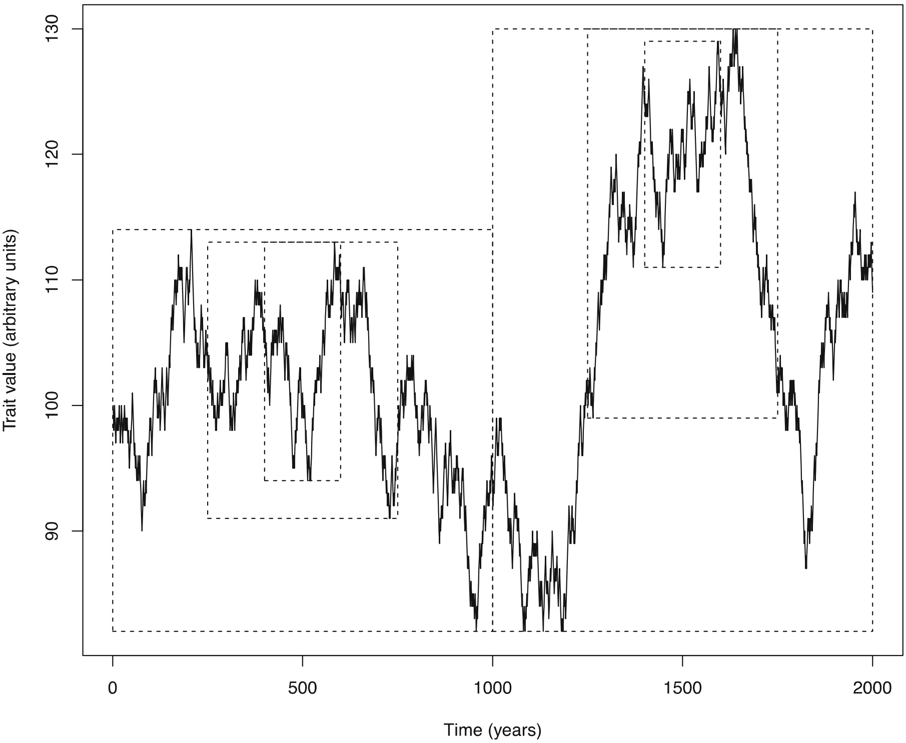

Fig. 1 An example of a simulation of the random-walk model (see text for details). The dotted boxes mark the temporal boundaries of the time-averaged assemblages. The innermost boxes correspond to 200-year long cultural time periods, the middlemost to 500-year long periods, and the outermost ones to 1000-year long ones

directional change model, which is deterministic and not random, the true rate is constant and equal to 1.7 units/year.

These true rates are compared to rates calculated from time-averaged units that represent cultural time periods of 200, 500, and 1000 years. In order to keep time intervals constant, these cultural time periods are all centered around the year 500 or the year 1500 (the dotted boxes in Figs. 1 and 2). For instance, the two 200-year time periods span from the year 400 to 600 and from year 1400 to 1600. Similarly, the two 500-year periods encompass the years 250–750 and 1250–1750, whereas the two 1000-year periods range from year 1 to 1000 and from 1001 to 2000. Thus, the time interval between the midpoints of each cultural time periods is always the same, 1000 years.

Time-averaged rates are based on the average trait value across the time periods. For instance, a rate calculated from the 200-year time periods is based on the difference between the average trait value from the year 400 to the year 600 and the average value between years 1400 and 1600. In the example shown in Fig. 1, the average trait value during the time periods 400–600 and 1400–1600 is 92 and 108 units, respectively, resulting in a rate of 16 units/1000 years or 0.016 unit/year. This corresponds to a ratio between the time-averaged rate and true rate of 0.72: the time-averaged rate is 28%

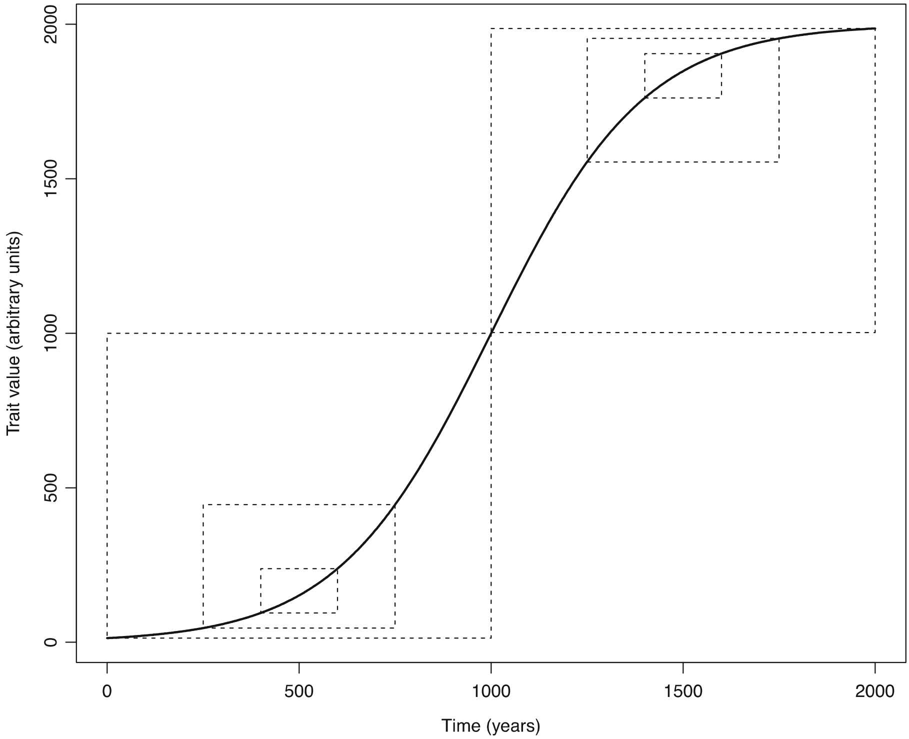

Fig. 2 A trait evolving following an s-shaped trajectory. The dotted boxes mark the boundaries of the time-averaged assemblages. The dotted boxes mark the temporal boundaries of the time-averaged assemblages. The innermost boxes correspond to 200-year long cultural time periods, the middlemost to 500-year long periods, and the outermost ones to 1000-year long ones

slower than the true rate. Similarly, when using the 500- and 1000-year time periods, the ratios time-averaged rate: true rate are 0.64 and 0.27, respectively.

I tallied the time-averaged rate: true rate ratios for 10,000 independent runs of the random-walk model. The results show that time-averaged rates are slower, on average, than true rate (Fig. 3). With the 200-year periods, the median time-averaged rate: true rate ratio is 0.96, and 57% of the time-averaged rates observed were slower than the true rate. When lumping archaeological data into 500-year time periods, the median ratio is 0.91, and 60% of the rates are slower than the true rate. When using 1000-year time periods, the median ratio is 0.81 and 66% of the rate are slower than the true rate.

When traits change stochastically, as they do in the random-walk model, time-averaging can sometimes lead to faster rates. By chance alone, the trait can take more steps in one direction than in the other (*e.g.*, more increases than decreases), leading to larger net Δ_c values. In Fig. 3, these faster rates are the ones that appear on the right side of the dotted vertical line. Thus, in the case of traits that drift stochastically, the slowing down of rates is the *expected* effect of time-averaging: it is its *average* effect, and it is due to the autocorrelative nature of random walk. In a random walk, the value of a trait at time t depends on its value at the previous step, t_{-1}. Because of this, two time-averaged samples will, on average, be closer to each other than they would be by chance alone.

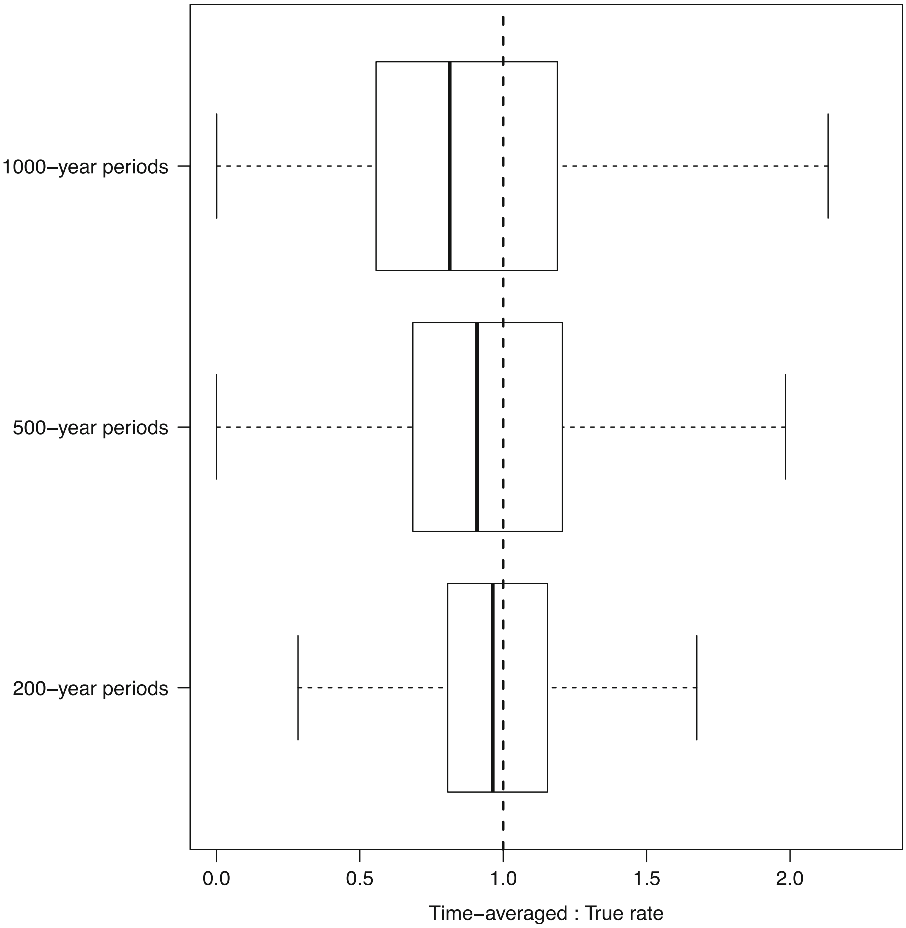

Fig. 3 Boxplot distribution of the ratio between time-averaged rates and true rates, under random-walk conditions (see text for details). The dotted vertical line marks the point where the time-averaged rates are equal to the true rates. Boxes show the median, 25th, and 75th percentiles; error bars show 1.5 interquartile distance. The distribution of rates calculated from 200-year time periods is significantly different than that calculated from 500-year periods (two-sample Kolmogorov–Smirnoff (KS) test, two-sided, $D = 0.13$, $p < 0.0005$) and from those calculated from 1000-year periods (two-sample KS test, two-sided, $D = 0.24$, $p < 0.0005$). Similarly, the 500-year period distribution is different than the 1000-year period distribution (two-sample KS test, two-sided, $D = 0.12$, $p < 0.0005$)

In the case of the directional model of change, the ratio between the time-averaged rate and the true rate with time periods of 200, 500, and 1000 years are 0.99, 0.96, and 0.85, respectively.

Empirical Test

The inverse correlation between time-averaging and rates predicted by the theoretical models can be detected in the archaeological record of North America. Figure 4 shows

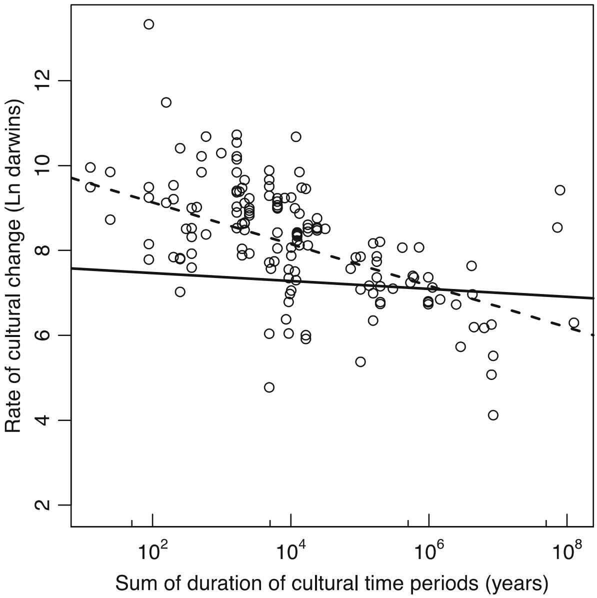

Fig. 4 Archaeological rates of change ($n = 150$) plotted against the sum of the duration of the two cultural time periods over which they are calculated, on a natural log-log scale. The solid line is a linear regression model fitted to the data that controls for the effect of time interval (model 2, Table 1), and the dashed line is a linear regression model that includes only the summed duration of the cultural time periods as a predictor (model 3, Table 1)

the subset of rates of archaeological change analyzed in a previous paper (Perreault 2012) that are calculated from units representing cultural time periods ($n = 150$). The rates are calculated from the published literature and come from a variety of technological traditions found in the Holocene North American archaeological record, such as Anasazi pit structure depth, Chesapeake pipe stem diameters, and Missouri ceramic vessel wall thickness. The rates are measured in units called darwins (see Perreault 2012 for details). Darwins are a standardized unit of change developed in paleobiology that measures changes in factors of e, the base of the natural logarithm, per millions of years (Haldane 1949):

$$d = (\ln x_2 - \ln x_1)/\Delta_t$$

where x_1 and x_2 are the mean trait value at time 1 and 2, respectively, and Δ_t is the time interval between x_1 and x_2, in millions of years (darwins were developed when biological evolution was assumed to occur over long time intervals).

In Fig. 4, the rates are plotted against the sum of the duration of the two cultural time periods from which they are calculated. The effect of time intervals complicates the analysis of the effect of time-averaging on rates, as both the summed duration of cultural time periods and the interval of time over which rates are calculated covary. In the theoretical model discussed earlier, the effect of time intervals was removed by keeping the midpoints of the time periods constant. But real-world cultural chronologies are not as convenient. As a result, longer time periods often mean, *ipso facto*, longer time intervals. In order to factor out the confounding effect of time interval, I fitted three different linear regression models (Table 1).

The first model incorporates only time interval as a predictor and can be used as a yardstick to evaluate the other two models. The second model includes both time interval and time-averaging as predictors and is plotted as a solid line in Fig. 4. The third model includes time-averaging (*i.e.*, the summed duration of the cultural time periods) and exclude time interval. It shows a stronger negative effect size of time-averaging than the second model and is plotted as a dashed line in Fig. 4. The Akaike information criterion (AIC) score of the models indicate that time-averaging does have an effect on rates, above and beyond that of time interval, as the AIC of the model that incorporates both predictors (Model 2) is lower than that of either model 1 or 3.

The true effect size of time-averaging on rates probably lies somewhere between the effect size of model 2 and 3, *i.e.*, from −0.093 to −0.493. This is because when controlling for the effect of time interval (model 2), some of the effect of time-averaging is absorbed by the beta coefficient of time interval. Conversely, when time interval is not controlled for (model 3), the effect of time-averaging also captures the effect of time intervals and is inflated.

Rates of change, on average, decrease proportionally with the summed duration of the time periods. For instance, doubling the duration of the two cultural time periods from 50 to 100 years will lead to rates that are, on average 6–29% lower. Similarly, increasing the duration of the cultural time periods tenfold (*e.g.*, going from two cultural time periods of 50 years to two cultural time periods of 500 years) results in rates that are between 19 and 68% slower.

The empirical data is thus consistent with the theory presented in the first part of this paper. But the correlation between rates and the duration of the cultural time period may be due, in part, to something else besides time-averaging. It is possible that rates of change were intrinsically slower in the deeper past than in more recent times. If this were true, and since the older cultural time periods in the sample tend to be longer than the more recent ones (Pearson correlation coefficient between duration of duration of cultural time periods and age = 0.67), the pattern shown in Fig. 4 could be due to time-averaging as much as to a general acceleration in the pace of change of material cultural over time. While this hypothesis cannot be distinguished from the effect of time-

Table 1 Three linear regression mixed models fitted to the data ($n = 150$)

Model	Effect size of time-averaging	AIC
1. Intercept + time interval	–	1671.42
2. Intercept + time interval + time-averaging	−0.093	386.18
3. Intercept + time-averaging	−0.493	455.9

All models are fitted on the natural logarithmic values of time intervals (“time interval”) and the sum of duration of the cultural time periods (“time-averaging”), with the study from which the rates are drawn ($n = 13$) treated as a random effect. AIC scores are Akaike Information criterion and are used to compare the relative quality of the models (lower scores are better) averaging with the data at hand, there are no theoretical reasons for why rates of technological change in North America should have accelerated during the Holocene period.

Discussion

Observed rates of change are inversely correlated with time-averaging: the longer the duration of time-averaging, the slower the rate. This inverse correlation will happen when time-averaging causes the two analytical units from which a rate is calculated to converge towards the same mean trait value, like they can do when traits drift randomly or are under selection.

The empirical data analyzed in this paper likely underestimates the effect size of time-averaging on rates of change. The duration of a cultural time period is only a proxy for the amount of time that is represented in a sample. For instance, a secondary refuse assigned to a cultural time period that is 1200 years long may represent any amount of time that is 1200 years or less. In all likelihood, the duration of cultural time periods overestimate the amount of time represented in a sample, and thus underestimate how fast rates decrease in proportion to the duration of cultural time periods.

The net effect of time-averaging on rates of change may be significant. One of the dominant features of the global archaeological record is that the pace of change in the archaeological record appears to decrease as we go back in time. The results presented here suggest that time-averaging may be contributing to this pattern, along with the effect of time intervals (Perreault 2012), as archaeologists lump archaeological material into increasingly longer cultural time periods as they analyze older deposits.

And time-averaging is here to stay. First, the discard in secondary refuse and site reoccupation means that most archaeological assemblages are time-averaged to a certain extent (Schiffer 1972, 1987). What is more, the lumping of material by cultural time period is a pervasive research strategy in archaeology. Archaeologists have long divided human history into chronological units such as "periods," "phases," "stages," "horizons," or "culture" and treat these as their units of analysis (Wiley and Sabloff 1993). Such analytical lumping is useful. Some research questions demand, in and of themselves, analytical lumping at a large scale, for instance, assessing the diet of a population demands that we lump and average together contexts that represents single meals (Lyman 2003). Analytical lumping also gives us statistical power. Pooling assemblages into groups allows archaeologists to create samples that are sufficiently large to conduct statistical analyses. Finally, cultural time periods are useful chronological tools. While it may be possible to directly date single artifacts in a dataset and plot individual trait value against individual ages (*e.g.*, Eerkens and Lipo 2005), in many cases, assigning an archaeological context to a cultural time period based on the period-specific artifacts it contains is the only way to date it.

Before patterns in rates of cultural change can be treated as meaningful anthropological signals, the effect of time-averaging needs to be factored in. Practically, archaeologists can take time-averaging into account, in the field, by deploying geochronological techniques to estimate, however roughly, the amount of time represented in assemblages. These estimates, in turn, can be incorporated into statistical regression models. How fast did traditions change *above and beyond* the effect of time intervals and time-averaging? This is the question that should guide the study of rate of change in the archaeological record.

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