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A reassessment of the impact of drought cycles on the Classic Maya

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ABSTRACT

The study reported here challenges the widely discussed hypothesis that cyclical droughts had a major impact on the Classic Maya. This hypothesis was developed by Hodell et al. (2001, 2005) on the basis of the results of time series analyses of cores from Lake Chichancanab in the Yucatán peninsula. Hodell et al.'s analyses indicated that the Maya region was affected by two drought cycles during the 1st millennium CE, one with a periodicity of 208 years and another with a periodicity of 50 years. The timing of the droughts was such, Hodell et al. argued, that they were likely responsible for several important sociopolitical events, including the collapse of Classic Maya society. In our study, we investigated two potentially important problems with Hodell et al.'s analyses: their use of interpolation to make their data regularly spaced, and their reliance on radiocarbon point estimates to generate age–depth models. We found that interpolation biased Hodell et al.'s results and that when it is avoided there is no evidence for a 208-year drought cycle in the Lake Chichancanab dataset. We also found that when the errors associated with the relevant radiocarbon dates are taken into account, there is no evidence for *any* drought cycles in the Lake Chichancanab dataset. Together, our analyses indicate that both the 208-year drought cycle and the 50-year drought cycle identified by Hodell et al. are methodological artifacts. The corollary of this is that the drought cycle hypothesis lacks an empirical basis and needs to be treated with skepticism.

1. Introduction

This paper reports a reassessment of an influential hypothesis concerning the impact of climate change on Classic Maya society. The traditional territory of the Maya-speaking people is located close to the middle of the isthmian portion of the North American continent (Fig. 1). Mayanists usually divide this area into three loosely defined regions (Sharer and Traxler, 2006). The *Highlands* is formed by the Chiapas highlands of Mexico and the elevated part of Guatemala. The *Southern Lowlands* consists of the southern portions of the Mexican states of Campeche, Quintana Roo, the Petén of northern Guatemala, and Belize. The *Northern Lowlands* comprises the rest of the Yucatán Peninsula. The Classic period of Maya history began around 250 CE and ended about 900 CE (Sharer and Traxler, 2006). Conventionally, the Classic period of Maya history is divided into the Early Classic (ca 250–600 CE), Late Classic (ca 600–800 CE), and Terminal Classic (ca 800–900 CE) (Sharer and Traxler, 2006).

The Classic Maya have attracted the interest of archaeologists, art historians, epigraphers, and linguists for several reasons. First, their socioeconomic system was among the most complex in prehispanic North America. They engaged in intensive agriculture, specialized craft production, and long-distance trade, and they lived in city-states ruled by divine kings (Coe, 2011). Classic Maya city-states normally comprised several civic-ceremonial centers and a large number of villages that were connected by a road network and, in some cases, causeways (Chase and Chase, 2001). Second, the material culture of the Classic Maya is unusually rich. They constructed large stone step-pyramids, built elaborate temples and palaces, and erected ornately carved stone stelae (Coe, 2011). They also created high-quality polychrome pottery, intricate jade funerary masks, and fine lithic artifacts, including a range of what seem to be primarily esthetic or ceremonial objects (Coe, 2011). Third, the Classic Maya had one of the few well-developed writing systems in the Americas (Houston et al., 2001). Their writing has been deciphered, and the texts and inscriptions that

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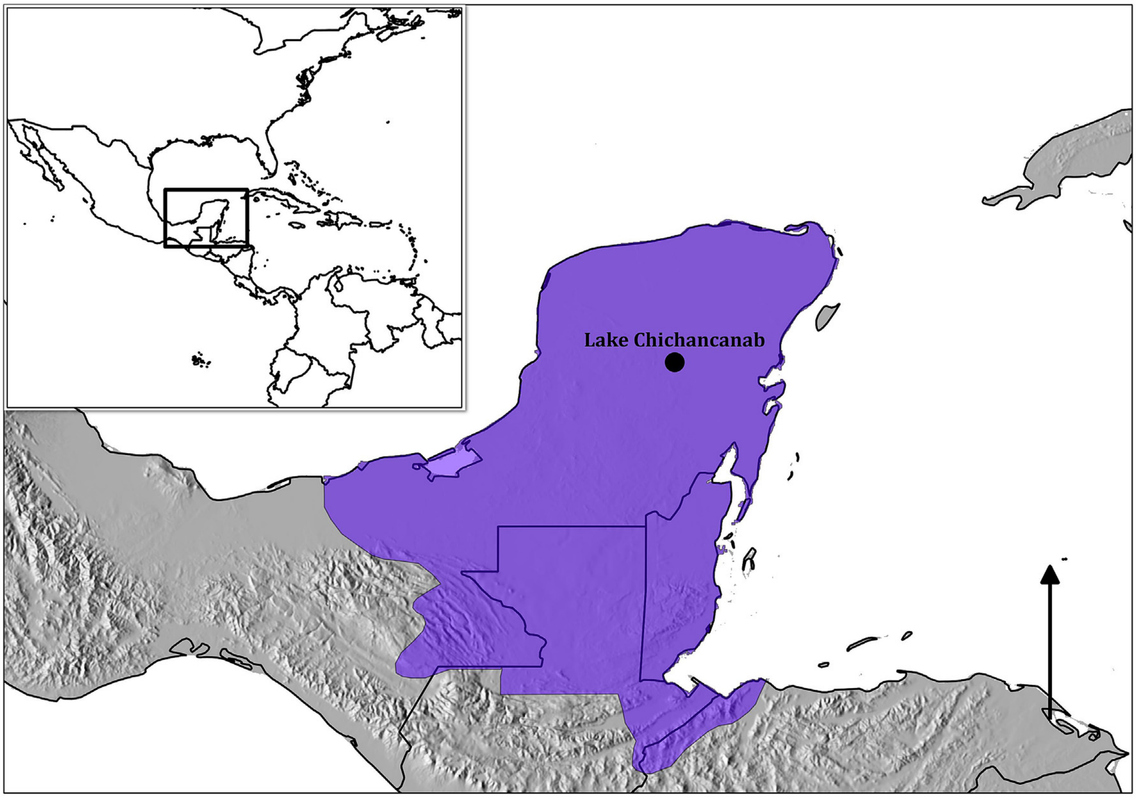

Fig. 1. Map of the Lowland Classic Maya region.

have been translated provide an often remarkably detailed history of political events, conflict, and mythology (Martin and Grube, 2008). Lastly, the Classic Maya developed a sophisticated system of calendars based on celestial movements (Rice, 2007).

The hypothesis we tested concerns the impact of drought on the Classic Maya. There is a long tradition of invoking drought as a cause of the disappearance of the distinctive traditions of the Classic Maya between 900 and 1100 CE—an event that is often referred to as the "Classic Maya collapse" (Gunn et al., 2002; Demarest et al., 2004). Today, most Mayanists accept that drought was involved in the collapse, but opinions differ about the number of droughts involved, and the causal relationship between drought and collapse (Aimers, 2007; Turner and Sabloff, 2012; Iannone, 2013). Some authors have argued that the Maya region was subject to a series of intense droughts that placed stress on resources, rapidly lowering the carrying capacity of the environment (Haug et al., 2003; Kennett et al., 2012). The reduction in carrying capacity caused a decrease in population from starvation and migration to less-affected areas, and this in turn led to the decline of the most affected lowland cities. Others have argued that a "mega-drought" was responsible for the collapse (e.g. Gill, 2000; Faust, 2001). First outlined by Gill (2000), this hypothesis posits that between 800 and 1000 CE the Maya lowlands were affected by a severe drought that peaked around 922 CE. The great length and severity of the mega-drought brought about thirst, famine, and disease, killing the majority of the lowland Maya. Still other authors have argued that drought's role in the collapse was mediated by ideological change (e.g. Lucero, 2002; Lucero et al., 2011; Moyes et al., 2009). One of the obligations of the divine kings was to ensure good harvests by correctly performing rituals and currying favor with supernatural forces. Another of their obligations was to maintain a certain level of peace and prosperity for their subjects. When the droughts occurred, crops failed and water stores were depleted leading to food stress and increased conflict between polities. Consequently, the system of divine kingship was perceived to have failed, leading people to abandon it along with other Classic Maya traditions. Lastly, some authors have placed more emphasis on environmental mismanagement by the Maya, which made Classic Maya society unsustainable and less resilient to the effects of drought (e.g., Culbert, 1973; Diamond, 2005; Dunning et al., 2012; Iannone et al., 2013). According to these models, the Classic Maya expanded into marginally productive areas to cope with population increase. The expansion involved clear-cutting and more intensive agricultural practices, which caused soil erosion and nutrient loss. Then, when drought occurred, the already fragile, unsustainable agricultural system could no longer support the population and consequently society collapsed.

The hypothesis we tested also posits that drought caused the collapse of Classic Maya society, but differs from the foregoing hypotheses in that it views the collapse as only one of a number of sociopolitical events that were caused by drought. Developed over the last 20 years by David A. Hodell and his collaborators (Hodell et al., 1995, 2001, 2005; Yaeger and Hodell, 2008) on the basis of results of analyses of sediment cores from lakes in the Yucatán peninsula, the hypothesis contends that the Maya region was subject to two drought cycles during the 1st millennium CE. The primary cycle was driven by solar activity, and had a periodicity of around 208 years. Droughts in this cycle caused the site abandonments that preceded the emergence of the Classic Maya at 250 CE, the temporary decline of the important centre of Tikal around 670 CE, and the collapse of Classic Maya society between 900 and 1100 CE. The second drought cycle had a periodicity of about 50 years. These higher-frequency droughts governed the tempo and pattern of the collapse. The collapse began in the Southern Lowlands with the onset of drought conditions around 900 CE, ebbed for roughly 50 years when a drought was skipped, and then continued in the Northern Lowlands as the 50-year drought cycle reengaged.

The drought cycle hypothesis has been influential. It has not only affected thinking about the Classic Maya (e.g., Dunning et al., 2002, 2012; Haug et al., 2003; Wahl et al., 2006; Lucero et al., 2011; Masson, 2012; Turner and Sabloff, 2012) but also influenced discussion about the impact of climate change on the sustainability of current human social, economic, and political systems (e.g. de Monocal, 2001; Jansen et al., 2007; Diaz and Trouet, 2014). However, it is possible that it has been accepted too readily. The reason for this is that the analyses that indicated that the Maya region was subject to cyclical droughts during the 1st millennium CE are potentially problematic.

The analyses in question involved applying a time series method to sediment density data from the bed of a large lake in the Yucátan peninsula named Lake Chichancanab (Hodell et al., 2001, 2005). Hodell et al. (2001, 2005) used variation in the sediment density as a proxy for variation in the ratio of evaporation to precipitation. The rationale for this was that sediment density reflects the ratio of evaporation to precipitation because calcium and sulfate ions precipitate out as the mineral gypsum when the water level drops, and gypsum is much denser than the organic matter that usually forms the bulk of lake-bed sediment. In order to assign calendar ages to their measurements of sediment density, Hodell et al. (2001, 2005) used age–depth models based on radiocarbon dates. In the 2001 analysis, they found evidence of several drought cycles in the sediment density time series. The most important of these had a periodicity of 208 years at the 95% confidence level. The other significant peaks identified in the analysis were at 50 years and 39 years. The results of the 2005 analysis differed somewhat from the results of the 2001 analysis. The 2005 analysis identified significant peaks at 213, 50, and 27 years rather than at 208, 50, and 39 years. But Hodell et al. (2005) argued that the differences were not meaningful.

There are two main potential problems with Hodell et al.'s (2001, 2005) analyses. One of these concerns a procedure that was necessitated by their choice of time series analysis technique. The method of time series analysis Hodell et al. (2001, 2005) used is usually referred to as the Blackman–Tukey (BT) method after its developers, Ralph Blackman and John Tukey (Blackman and Tukey, 1958a,b). The BT method is a parametric, frequency domain time series analysis technique that is designed to find periodic functions (Blackman and Tukey, 1958a,b). The BT method is effective with data that are regularly sampled (Kay, 1988). However, it cannot be applied to time series that contain irregular inter-observation times (Chatfield, 2009). Because the Lake Chichancanab time series, like most palaeoenvironmental time series, are irregularly sampled, Hodell et al. (2001, 2005) had to interpolate the data prior to analyzing them with the BT method. This is a problem because interpolation has been shown to artificially increase autocorrelation in time series (Horowitz, 1974; Levy and Dezhbakhsh, 1994; Rehfeld et al., 2011), and autocorrelation is what the BT method uses to identify periodic components in time series. Thus, it is possible that the signal of cyclical drought identified by Hodell et al. (2001, 2005) is an artifact of interpolation rather a real feature of the data.

Hodell et al.'s (2001, 2005) treatment of the radiocarbon dates obtained from the Lake Chichancanab cores is the other main reason to be skeptical of their claim to have found evidence of the occurrence of major droughts every 208 years and smaller but still damaging droughts every 50 years. The age-depth models they created were based on point-estimates of calibrated radiocarbon date distributions. Although this approach is common in palaeoclimate studies, it is flawed (Telford et al., 2004). Point estimates are inadequate descriptors of calibrated radiocarbon date distributions because the latter are typically multimodal and highly irregular (Parnell et al., 2011). Any single point estimate of such a distribution will fail to adequately describe the true calendar date represented by the radiocarbon assay. In fact, multiple calendar dates may be similarly probable because of the multimodal nature of the calibrated radiocarbon date distributions. As a result, multiple age–depth models are possible for any radiocarbon-dated time series. Any single age–depth model is, therefore, only one possible estimate of the true, unknown temporal structure of a given time series. In effect, the time series could be compressed or expanded in time by using different equally probable age-depth models to define its temporal structure. Neglecting this uncertainty has the potential to result in biased estimates of the true temporal structure of a radiocarbon-dated time series. Since it is the temporal structure of the series that time series methods are designed to study, the bias could greatly affect the results of a time series analysis. Thus, it is possible that the periodicity identified by Hodell et al. (2001, 2005) in their drought proxy time series is also an artifact of their treatment of radiocarbon dates.

Given how influential the drought cycle hypothesis has been, there is a need to determine whether or not the foregoing concerns are valid. With that in mind, we carried out a three-part study involving the dataset from Lake Chichancanab that is publicly available. In the first part of the study, we reanalyzed the dataset with Hodell et al.'s (2001, 2005) research protocol to ensure that the dataset was suitable for evaluating the impact of Hodell et al.'s (2001, 2005) methodological choices. In the second part of the study, we investigated the effect of interpolation on Hodell et al.'s (2001, 2005) results. In the final part of the study, we evaluated the impact of Hodell et al.'s (2001, 2005) failure to account for radiocarbon date errors on their results. Together, the analyses show conclusively that the findings underpinning the drought cycle hypothesis—that droughts occurred every 208 and 50 years in the Maya region during the 1st millennium CE—are methodological artifacts.

2. Replication of Hodell et al.'s (2001, 2005) analyses

As only one of the datasets analyzed by Hodell et al. (2001, 2005) has been made publicly available, it was necessary to begin by assessing its suitability for evaluating the impact of Hodell et al.'s (2001, 2005) methodological choices on their results. We accomplished this by reanalyzing the dataset in question with the research protocol that Hodell et al. (2001, 2005) employed, and comparing the significant peaks we obtained with the significant peaks they reported.

The dataset that Hodell and colleagues have released consists of a time series from a core from Lake Chichancanab that is designated CH17-III-04 (see Fig. 2). The time series consists of sediment density

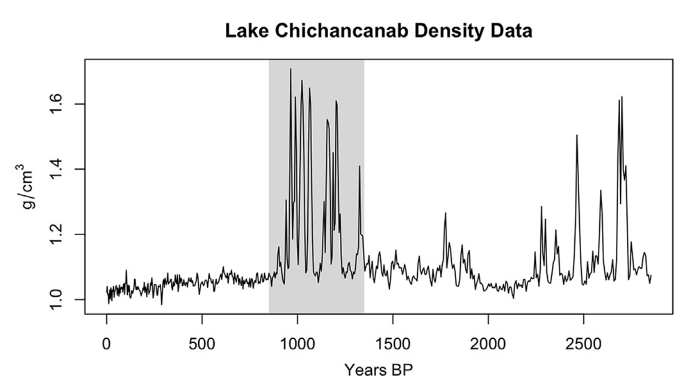

Fig. 2. Density time series from the Lake Chichancanab sediment core discussed in this paper (CH17-III-04). The gray area shows the section of the series that was analyzed.

measurements, which, as explained earlier, are thought to reflect changes in gypsum concentration and therefore changes in precipitation. The measurements were taken at 0.5 cm intervals along the core between 4.5 cm and 286.5 cm in depth, resulting in a total of 564 data points. However, following Hodell et al. (2005) methods, we only considered the 99 points between approximately 120 and 170 cm depth, which corresponds roughly to the time leading up to and including the Classic Maya collapse. Each point has a calendar date derived from Hodell et al.'s (2005) age–depth model, which was based on a regression of the median calibrated radiocarbon dates of 15 AMS assays on the depth of the carbon samples. The dataset was obtained from the website of the National Oceanic and Atmospheric Administration (www.ncdc.noaa.gov).

In line with Hodell et al.'s (2001, 2005) description of their methods, we used the BT method to derive a power spectrum and identify periodic functions in the sediment density data. A power spectrum is a function that describes the contribution of different periodic components to the total variance in a signal—peaks in the spectrum denote the frequencies of potentially significant periodic signal components. To begin, following Hodell et al. (2005), we removed a weak linear trend from the series by subtracting a straight-line function that was fit to the data by least squares. Linear de-trending is common in frequency-based time series analyses because it eliminates unimportant variation when searching for periodicity. Subsequently, a Bartlett window that incorporated a third of the series was used in the calculation of the autocorrelation function. Lastly, we tested the power spectrum for significant peaks by comparing it to the power spectrum of a random, white noise time series. Because palaeoenvironmental data usually contain some degree of background autocorrelation, comparison with a red noise spectrum rather than a white noise spectrum has been recommended (Mann and Lees, 1996). However, Hodell et al. (2001, 2005) compared their empirical power spectra with a white noise spectrum, so we used a white noise spectrum in our comparison. A significance level of 95% was used to identify significant peaks. We carried out this set of analyses in the kSpectra software package (www.spectraworks.com) because it has greater significance testing functionality than the software that Hodell et al. (2001, 2005) used, Analyseries (Paillard et al., 1996). We did, however, replicate the analyses with Analyseries to ensure that the spectra the programs produced were the same. The results of the two sets of analyses were identical.

The significant peaks in our BT power spectrum were similar to the peaks of the mean spectrum presented in Hodell et al. (2005). The peaks we obtained correspond to periods of approximately 232, 46, and 25 years. Specific differences between the peaks we identified and those Hodell et al. (2001, 2005) found at 213, 50, and 27 years are minor. They are likely accounted for by the fact that we had access to only one of the four time series Hodell et al. (2005) used to obtain an average spectrum. The close similarity between our results and those obtained by Hodell et al. (2005) indicates that the CH17-III-04 core data is suitable for evaluating Hodell et al.'s (2001, 2005) methodological choices.

3. Evaluation of the impact of interpolation on Hodell et al.'s (2001, 2005) results

In the second part of the study, we investigated the effect of the interpolation step in Hodell et al.'s (2001, 2005) research protocol. We did this in two ways. First, we applied the method Hodell et al. (2001, 2005) used to a simulated time series that was created in such a way that we could be sure it did not contain any periodic components. Subsequently, we reanalyzed the gypsum concentration time series data from the CH17-III-04 core with a method of time series analysis that does not require regularly spaced data, and therefore does not require irregularly-spaced data to be interpolated prior to analysis.

The simulated time series we created is based on white noise. By definition, such a time series contains no periodic components. The series contained 100 observations with a mean of zero and a standard deviation of one. The length of the simulated series approximately mirrors the length of the section of the Chichancanab series analyzed by Hodell et al. (2005). The observation times for the random series were also generated randomly. Beginning with an observation time of zero for the first observation in the time series, each observation time was then generated by incrementing the previous observation time by a random value drawn from a log-normal distribution with a mean of five and a standard deviation of one. This process created the effect of monotonically increasing irregular inter-observation times. Next, five experiments were conducted in which portions of the white noise series comprising from 10 to 50% of the total number of points were removed. Each subsample was interpolated and resampled at regular intervals. To search the interpolated series for periodicity, the power spectrum for each simulated series was estimated using the BT method implemented as per Hodell et al.'s (2001, 2005) description of their analyses. We then compared the results of these experiments to the power spectrum of an evenly spaced white noise signal of the same length, which is what would be expected if interpolation had no impact on the BT power spectrum.

Fig. 3 shows the relationship between low-frequency autocorrelation and the percentage of the simulated series that is derived from linear interpolation after some portion of it was randomly removed. Increasing the percentage of a randomly generated series that is derived from interpolation increases low-frequency autocorrelation. The autocorrelation functions also become more sinusoidal as greater percentages of the white noise series are interpolated (see the bottom panel of Fig. 3). Fig. 4 shows the effect of this increasing autocorrelation on the BT power spectrum. Using the BT method for transforming an artificially inflated autocorrelation function into a power spectrum resulted in spurious peaks, primarily in the low-frequency end of the spectrum where the power becomes concentrated (Fig. 4). These spectra decline exponentially toward the high-frequency end of the spectrum. In contrast, the spectrum of the evenly spaced white noise series is relatively flat, which indicates that power is evenly distributed between frequencies. If a white noise spectrum were used as the benchmark for identifying statistically significant peaks, the spurious peaks in the spectra of the interpolated simulation series would be considered significant. This demonstrates that interpolation effectively inflates the BT method's Type I error rate, i.e. the rate of obtaining false positive results. Thus, our simulation demonstrates that interpolation of the kind employed by Hodell et al. (2001, 2005) does indeed increase autocorrelation and the Type I error rate, and supports the idea that the periodicity identified by Hodell et al. (2001, 2005) may have been artificially imposed by interpolation.

The alternative method of time series analysis we used to reanalyze the sediment density time series data from the CH17-III-04 core is called Least Squares Spectral Analysis (LSSA) (Vaníček, 1971). LSSA differs from other frequency-based methods of time series analysis in that it does not rely on autocorrelation functions or Fourier transforms. Instead, it uses the least squares principle to sequentially fit sinusoidal functions of incremental frequencies to a time series. This means that LSSA does not require regularly spaced data and, therefore, can handle irregularly spaced time series without interpolation.

The LSSA analysis involved two steps. First, we iterated through a set of evenly spaced frequencies fitting a sinusoid by least-squares

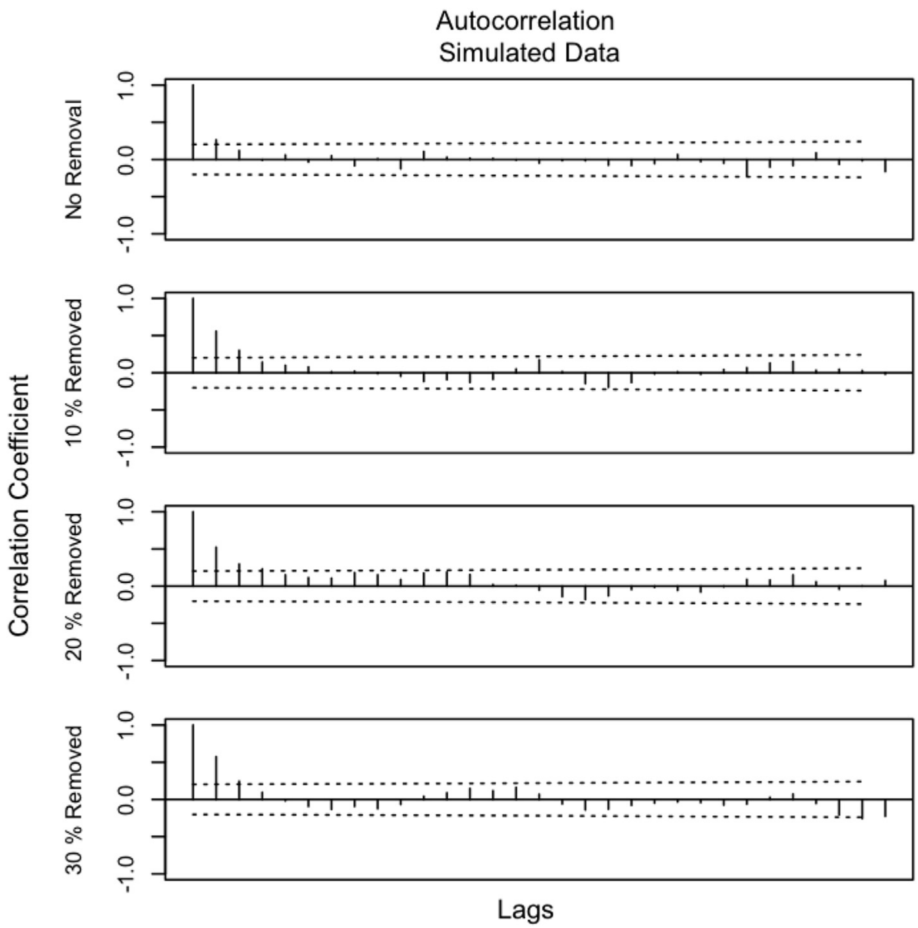

Fig. 3. Sample of the results of the white noise simulation demonstrating the effect of incrementally increasing the percentage of the series derived from interpolation on the autocorrelation function. The autocorrelation function describes the correlation between a series and itself at different lags. The top panel shows the autocorrelation function of an evenly spaced white noise process for comparison and the dashed lines indicate theoretical 95% confidence levels. Any vertical lines that are above the dashed lines indicate statistically significant correlations when the series is compared to itself after being shifted by a given lag distance. Since the underlying process used to generate these white noise time series is random, there should be no significant correlations between a series and itself at any lag beyond the first (a series will correlate perfectly with itself if it has not been shifted by a lag). What this sample of results shows is that the autocorrelation function increases for low lag distances as the simulated series is subjected to greater amounts of interpolation.

to the time series. Each sinusoid was subtracted from the time series before the next fit was performed. This procedure removed the variation caused by components at each frequency, thereby partially mitigating what is often called "spectral leakage". Spectral leakage occurs when a periodic component of the underlying signal generating process lies between frequencies that were assessed by least-squares, resulting in partial fits by sinusoids of nearby frequencies.

In the second step of the analysis, we searched for significant peaks in the LS-spectrum. To do this, we compared it to both a white noise LS-spectrum and a red noise LS-spectrum. We used two null hypothesis spectra because, as explained earlier, there is a difference between the procedure for identifying significant peaks employed by Hodell et al. (2001, 2005) and the currently recommended best practice. To reiterate, Hodell et al. (2001, 2005) identified significant peaks in their empirical spectra by comparing them to white noise spectra, whereas the currently recommended best practice is to use red noise spectra to identify significant peaks in the spectra of palaeoenvironmental data. Red noise spectra are preferable for significance testing because they reduce the potential for the background autocorrelation often contained in palaeoenvironmental datasets to give rise to false-positive results in the low-frequency range (Mann and Lees, 1996). To run the two tests, we simulated ensembles of white and red noise time series that contained no other periodic functions and calculated their LS-spectra. Each ensemble contained 5000 simulated time series. The white noise time series were calculated by drawing from a normal distribution with mean and variance equal to those of the section of the Chichancanab time series. The red noise time series were generated following the methods outlined in Schulz and Mudelsee (2002). Again, each simulated time series had the same observation times as the original Chichancanab series. We then compared the Chichancanab LS-spectrum to the 95th percentile of the distributions of simulated white and red noise LS-spectra. Peaks in the Chichancanab spectrum that were higher than the 95% levels of the simulated LS-spectra were considered statistically significant.

Fig. 5 shows the results of comparing the LS-spectrum of the Chichancanab series to the LS- spectrum of a white noise process at the 95% confidence level. Using the white noise null spectrum, we identified 5 significant peaks centered at 492, 250, 167, 63, and 46 years. Only the 46-year cycle in the LS-spectrum corresponds roughly with a peak from Hodell et al.'s (2001) analyses, namely their putative 50-year cycle. However, the 46-year cycle appears significant compared to white noise at the 95% confidence level whereas it only appeared significant at the 80% level in Hodell et al.

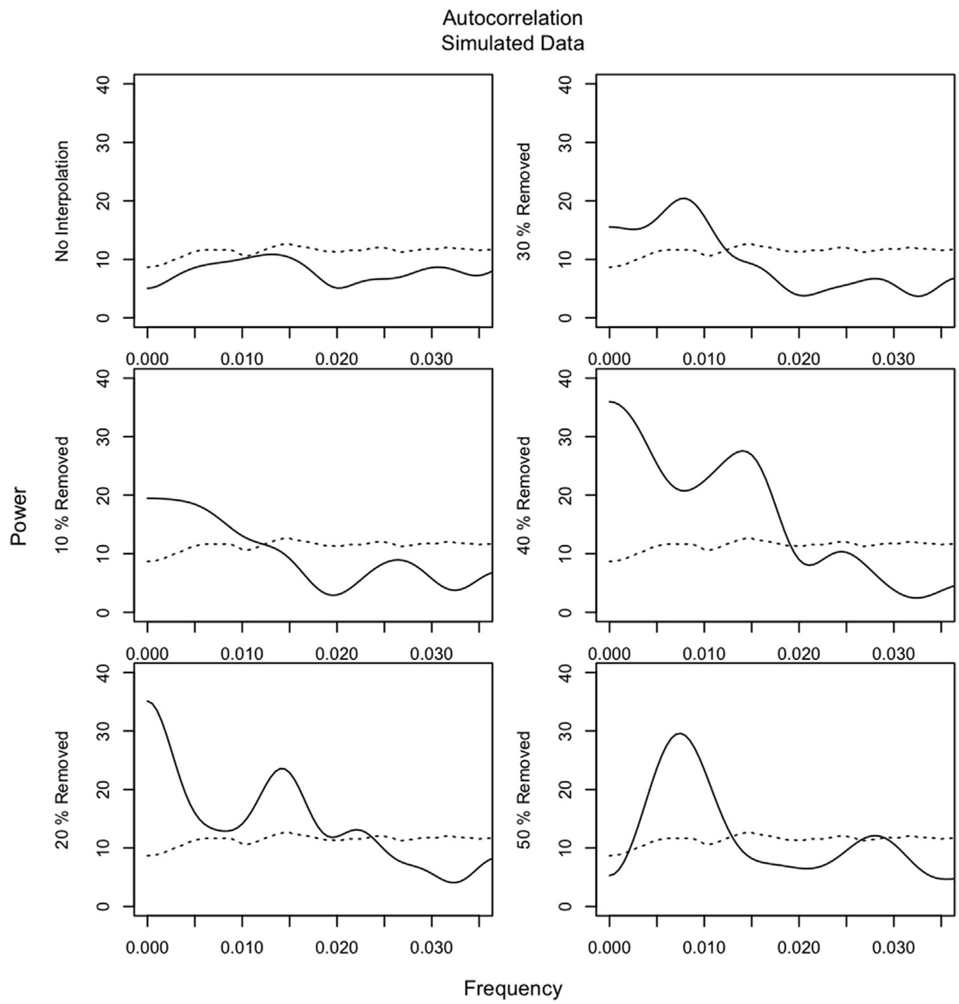

Fig. 4. Sample of the results of the white noise simulation demonstrating the effect of incrementally increasing the percentage of the series derived from interpolation on the BT estimate of the power spectrum. The top left panel shows the power spectrum of an evenly spaced white noise process for comparison. The dashed lines indicate the 95% confidence level of the BT spectrum for an evenly spaced white noise process, estimated from 100 bootstrap iterations. As with the autocorrelation functions in Fig. 3, no obvious or statistically significant features should be visible in the spectrum of a white noise process. What this sample of results shows is that increasing the percentage of a series that is subject to interpolation increases the size and distinctiveness of features in the BT spectral estimates.

(2001). More notably, the 208-year drought cycle is absent in the LS-spectra. These results suggest that the 208-year drought cycle identified by Hodell et al. (2001, 2005) was a spurious peak caused by their interpolation procedure.

Fig. 6 shows the results of comparing the LS-spectrum of the Chichancanab series to the LS- spectrum of a red noise process at the 95% confidence level. Using the red noise null spectrum, the LSSA indicated that the only statistically significant peaks in the Chichancanab spectrum were at approximately 46- and 24-years. The peaks at 492, 250, and 167 years identified in the white noise comparison were not significant when the red noise null spectrum was employed. Thus, the red noise comparison also suggests that the 208-year drought cycle identified by Hodell et al. (2001, 2005) was a spurious peak caused by their interpolation procedure.

Taken together, our simulation and LSSA analyses show that Hodell et al.'s (2001, 2005) findings were indeed greatly affected by interpolation. Hodell et al.'s 50-year drought cycle does not seem to be a product of interpolation, but their 208-year drought cycle, which they viewed as considerably more important than the 50-year drought cycle, is clearly an artifact of interpolation.

4. Evaluation of impact of radiocarbon date errors on Hodell et al.'s (2001, 2005) results

In the last part of the study, we evaluated the impact of Hodell et al.'s (2001, 2005) failure to account for radiocarbon date errors. We accomplished this by reanalyzing the gypsum concentration time series data from Hodell et al.'s CH17-III-04 core with LSSA in combination with a bootstrap simulation to account for error in the calibrated radiocarbon dates. The simulation was necessary because the calibration process used to convert radiocarbon dates into calendar dates produces multimodal posterior probability distributions, so their errors cannot be modeled analytically (see Supplementary Materials).

We began by calibrating the AMS dates reported by Hodell et al. (2005) in OxCal (Ramsey and Lee, 2013) with the INTCAL09 (Reimer et al., 2009) curve. Next, the calibrated date distributions (i.e., multimodal posterior probability density functions) were resampled within one standard deviation of their means—the sampling occurred non-uniformly with replacement in accordance with the relative probabilities of each calendar date specified by the calibrated radiocarbon date distributions. If a sample of dates violated

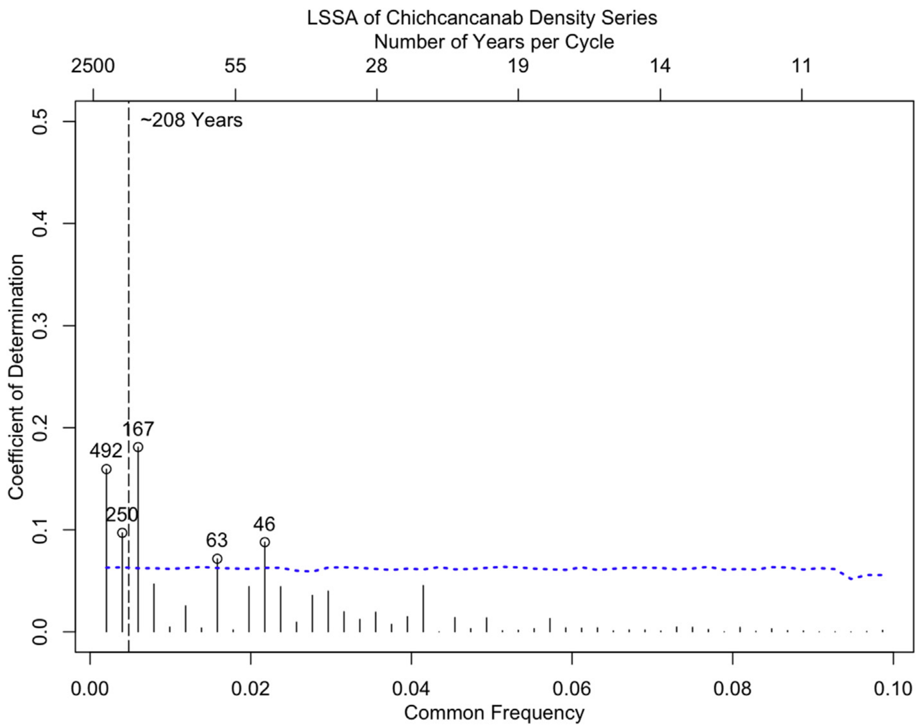

Fig. 5. LSSA spectrum of the Lake Chichcancanab density time series compared to the LSSA spectrum of a white noise process. Vertical lines in the LS spectrum denote the frequencies of the sinusoids that were fit to the series and their heights indicate the coefficient of determination of the regression. Higher vertical lines indicate frequencies for which the fits between the relevant sinusoids and the series are better. These higher vertical lines, or 'peaks', in the LS spectrum indicate potential cyclical components in the series. The short-dash line shows the 95% level of the null hypothesis spectrum. Peaks that are higher than the short-dash line are statistically significant—these peaks have been circled and labeled with the length of the relevant period (in years). The vertical long-dash line shows where a 208-year peak would be, if it were a feature of the time series.

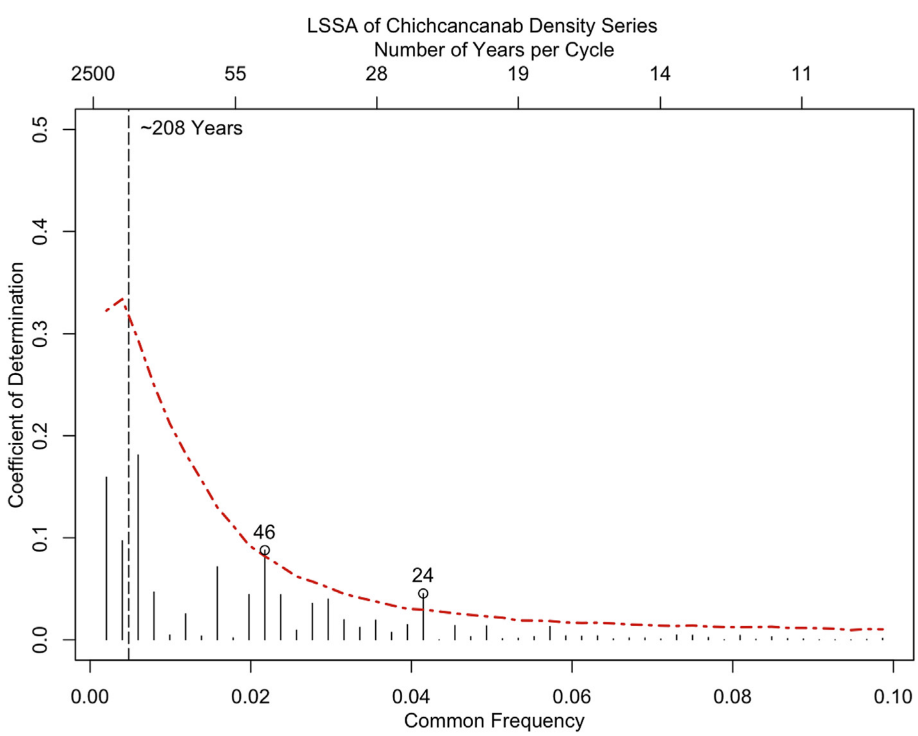

Fig. 6. LSSA spectrum of the Lake Chichcancanab density time series compared to the LSSA spectrum of a red noise process. Vertical lines in the LS spectrum denote the frequencies of the sinusoids that were fit to the series and their heights indicate the coefficient of determination of the regression. Higher vertical lines indicate frequencies for which the fits between the relevant sinusoids and the series are better. These higher vertical lines, or 'peaks', in the LS spectrum indicate potential cyclical components in the series. The short-dash line shows the 95% level of the null hypothesis spectrum. Peaks in the LS-spectrum that are higher than the short-dash line are statistically significant—these peaks have been circled and labeled with the length of the relevant period (in years). The vertical long-dash line shows where a 208-year peak would be, if it were a feature of the time series.

the stratigraphic relationships of the carbon samples, it was discarded and a new sample was drawn. Then, a new age-depth model was created for each sample of dates by using a monotonic polynomial function in R (R Core Team, 2013). The new age-depth models were used to create an ensemble of 5000 simulated time series. Following Hodell et al. (2005), only the sections of the simulated time series dating to between 600 and 1200 CE were used in further analysis so that the results would be comparable. Each of the 5000 simulated series was then analyzed using LSSA, allowing us to explore the effect of the true chronological error of the age-depth model on a frequency-based analysis. As in the previous analysis, statistical significance was assessed using both white and red noise LS spectra derived from a bootstrap simulation—an additional 5000 iterations were used to find the 95th percentile of the white and red noise LS-spectra for each simulated series. Adjusting the confidence levels for multiple comparisons would not have been straightforward because of spectral leakage between frequencies. Consequently, they were not adjusted and the values should be viewed as point-wise estimates that constitute a best-case scenario for supporting Hodell et al.'s (2005) findings. The analyses were performed in R (see Supplementary Materials for code) and run on Westgrid's Bugaboo High Performance Computing Cluster (www.westgrid.ca).

The LSSA–bootstrap simulations found no significant periodicity in the gypsum concentration time series data. Figs. 7 and 8 show the proportion of the simulation over which a signal component with a given frequency was significant compared to white and red noise null spectra respectively at the 95th percentile of confidence. Neither the red nor white noise tests identified signal components with frequencies that correspond to a 208-year period. Both simulations identified statistically significant peaks corresponding to periods of roughly 50 years, but in less than 20% of the simulated LS-spectra when compared to white noise, and less than 10% when compared to red noise. Other peaks were identified as statistically significant in the simulations (see Figs. 7 and 8), but they occurred even less frequently. Thus, once calibrated radiocarbon date error is taken into account, there is no strong evidence for Hodell et al.'s 208-year drought cycle or for their 50-year drought cycle. Indeed, there is no strong evidence for *any* periodicity in the sediment density time series at all.

5. Discussion

Our study casts doubt on Hodell et al.'s (2001, 2005) claims regarding the impact of cyclical droughts on the Classic Maya. Our first set of analyses confirms that the sediment density data derived from Hodell et al.'s (2001, 2005) CH17-III-04 core are suitable for assessing the impact of their choice of time series analysis method and their failure to take into account the errors associated with the radiocarbon assays they used to generate their time–depth models. Our second set of analyses suggest that the interpolation step in Hodell et al.'s (2001, 2005) research protocol inflated low-frequency periodicity in the sediment density data power spectra and caused the method of time series Hodell et al. (2001, 2005) employed to identify false peaks at 208 years. Our third set of analyses suggests that Hodell et al.'s (2001, 2005) core sediment density data do not contain any peaks when the data are not interpolated and the errors associated with the radiocarbon assays are dealt with appropriately. Thus, our analyses do not support the existence of a 208-year drought cycle or a 50-year drought cycle in the Maya region during the 1st millennium CE. Consequently, they also do not support the hypothesis that periodic droughts repeatedly caused important sociopolitical events among the Classic Maya.

Hodell et al. (2001, 2005) are not alone in suggesting that drought cycles were an important influence on prehispanic Maya

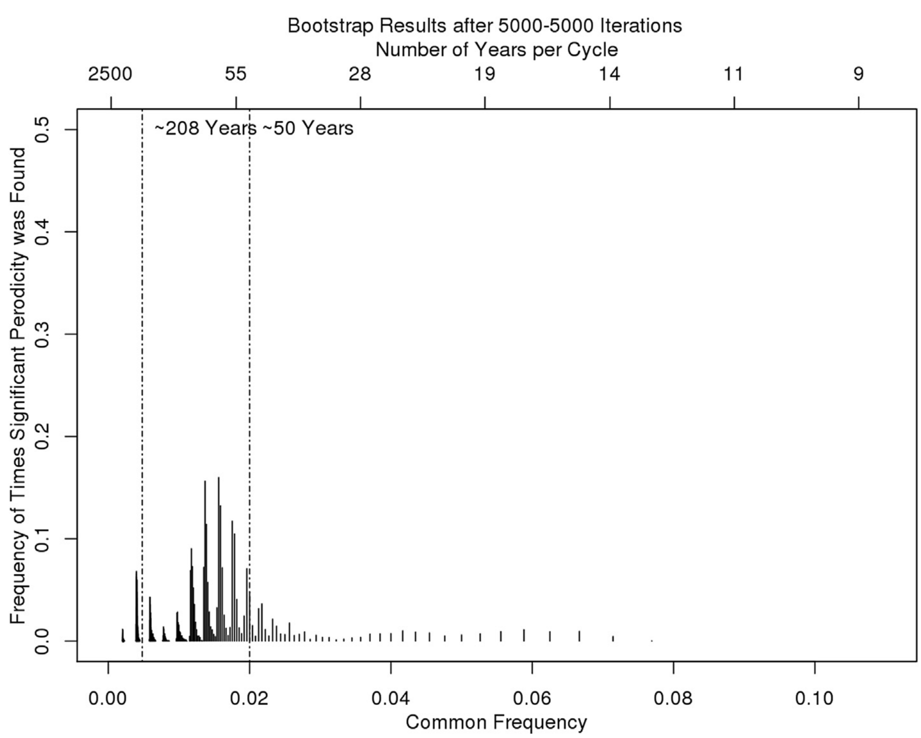

Fig. 7. Results of the bootstrap simulation when the Chichancnab density series LS-spectrum was compared to a white noise null spectrum. The vertical long-dash lines show where a 208-year peak and a 50-year peak would be, if they were features of the time series. Unlike the LS-spectrum results in Fig. 5 and 6, the peaks in this plot show only the percentage of the simulation runs that identified a particular frequency (shown on the *x*-axis) as statistically significant. It does not show the strength of the correlation between the relevant sinusoid and the series, only the relative likelihood that a given frequency is significant despite chronological error.

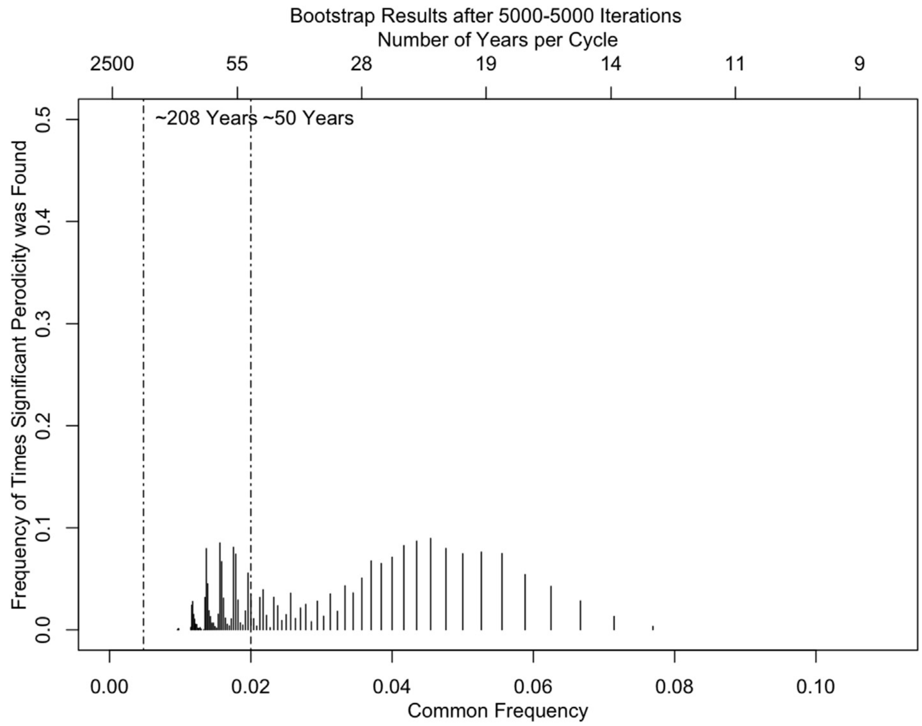

Fig. 8. Results of the bootstrap simulation when the Chichancnab density series LS-spectrum was compared to a red noise null spectrum. The vertical long-dash lines show where a 208-year peak and a 50-year peak would be, if they were features of the time series. Unlike the LS-spectrum results in Fig. 5 and 6, the peaks in this plot show only the percentage of the simulation runs that identified a particular frequency (shown on the *x*-axis) as statistically significant. It does not show the strength of the correlation between the relevant sinusoid and the series, only the relative likelihood that a given frequency is significant despite chronological error.

history. A number of authors have argued that Maya society went through repeated cycles of growth, regional integration, decline, and disintegration during the 1st millennium CE, and suggested that periodic severe droughts were a major factor in these cycles (Gill et al., 2007; Dunning et al., 2012; Masson, 2012; Turner and Sabloff, 2012). Our study does not speak to the existence or otherwise of recurring sociopolitical cycles in Maya history. However, it casts doubt on the idea that such cycles were driven by drought cycles. Major droughts that affected the whole Maya lowlands may have occurred during the 1st millennium CE, as Hodell et al. (1995, 2001, 2005) and other researchers have suggested (e.g. Curtis et al., 1996; Haug et al., 2003; Kennett et al., 2012). But our analyses indicate that, if such droughts did occur, they did not do so with a regular periodicity. A corollary of this is that, if there were sociopolitical cycles in prehispanic Maya history, the primary driver must have been something other than drought cycles.

The results of our study also have some important implications for future work in archaeology and palaeoenvironmental studies involving the analysis of time series. One concerns interpolation. Many types of archaeological or palaeoenvironmental proxy time series are sedimentary in nature (Gornitz, 2009), like Hodell et al.'s (2005) lakebed cores, and they will almost always be irregularly sampled because of natural variation and taphonomic processes. Our study shows that interpolating such time series can create methodological artifacts, and that these can lead to misinterpretation of the time series. Therefore, our study suggests that, when analyzing archaeological or palaeoenvironmental time series data, methods designed to handle irregular inter-observation times directly should be used (e.g., Bretthorst, 2003; Lomb, 1976; Schulz and Stattegger, 1997; Vanícek, 1971; Zechmeister and Kürster, 2009).

Equally importantly, our study demonstrates that dating error must be taken into account when analyzing archaeological and palaeoenvironmental time series that are dated with radiocarbon assays. Many archaeological and palaeoenvironmental studies rely on calibrated radiocarbon assays to date time series. As discussed earlier, the calibration procedure produces date distributions that are often highly irregular and multimodal, which means that the probability distributions cannot be adequately described by point estimates. Our study demonstrates that frequency-based analyses are greatly affected by irregular temporal errors. This is because periodic functions of different frequency will fit the time series data better or worse depending on which point estimates are used. The effect would also be important for studies that attempt to correlate palaeoenvironmental and archaeological data. In such cases, the problem with chronological uncertainty may be compounded when two or more time series are involved. Chronological uncertainty is often cited as a problem for such work (e.g., Bryson, 1994; Hodell et al., 2007; Caseldine and Turney, 2010; Aimers and Hodell, 2011; Iannone et al., 2013), but its effects have never been explored empirically before. Our results show that ignoring temporal uncertainty can introduce significant statistical bias into time series analyses and result in specious conclusions about palaeoclimate systems and their effects on human societies. Until an analytical solution to this problem is developed, irregular temporal errors can be accounted for by a simulation-based approach, like the one we used.

A third, somewhat less obvious issue that our study raises is the importance of using the correct null-spectra when searching power spectra for significant peaks. In our second and third sets of analyses we compared the data from Lake Chichancanab to both white noise and red noise spectra in order to identify significant peaks. As we explained earlier, we used two null spectra because the current recommended best practice differs from the way Hodell et al. (2001, 2005) tested for significant peaks. To reiterate, the current recommended best practice is to compare palaeoenvironmental spectra to a red noise spectrum (Mann and Lees, 1996) whereas Hodell et al. (2001, 2005) compared the Lake Chichancanab data to a white noise spectrum. It is clear from our analyses that the choice of null spectrum can greatly affect the results of time series analyses carried out to identify periodic functions. The peaks identified by the white noise test were concentrated toward the low-frequency end of the spectrum, whereas the peaks identified by the red noise test were in the high-end. Thus, the selection of null spectrum can influence which set of significant peaks that are identified and where in the spectrum they are more likely to occur. If the wrong one is selected, peaks may be incorrectly identified as significant—specifically, incorrectly specifying a white noise null spectrum will cause low-frequency peaks to be spuriously identified as significant, and it will likely cause potentially significant high-frequency peaks to be missed altogether. As others have pointed out, climate time series will naturally contain low-frequency autocorrelation (Mann and Lees, 1996). This background autocorrelation is a result of the similarity between observations in a time series that is due entirely to temporal proximity—the amount of rainfall today is expected to be similar to the amount of rainfall tomorrow, for example. When transformed into a power spectrum, this autocorrelation creates a distribution that declines exponentially with increasing frequency so that there is always more power—i.e., higher peaks—in the low-frequency end of the spectrum. As a result, low-frequency peaks are to be expected and should not be considered significant unless the power of the peak is sufficiently high that it stands out against the background autocorrelation. Thus, assuming that peaks which are higher than those expected from a completely random, uncorrelated series—i.e., a white noise null hypothesis—ignores the nature of the climate processes that created the observations. In such cases, where autocorrelation is expected because of the nature of the underlying processes, an appropriate null hypothesis should account for those expectations—i.e., a red noise null hypothesis. Without setting such a benchmark for identifying significant peaks, any relatively high peaks in the spectrum could be arbitrarily selected leading to spurious causal inferences, as was the case with Hodell et al.'s (2001, 2005) analyses. Many archaeological time series can also be expected to contain low-frequency autocorrelation, and should also be compared to a red noise null hypothesis.

6. Conclusions

In the study reported here, we re-evaluated the empirical basis of the widely discussed hypothesis that cyclical droughts played a major role in Classic Maya history, causing several important events, including the disappearance of the Classic Maya's distinctive traditions between 900 and 1100 CE. Hodell et al. (2001, 2005) developed this hypothesis on the basis of time series analyses of lake-cores. These analyses suggested that the Maya region was affected by two drought cycles during the 1st millennium CE, one with a periodicity of 208 years and another with a periodicity of 50 years.

Our study was motivated by two concerns about Hodell et al.'s (2001, 2005) analyses. One was that, because the method of time series analysis they employed requires regularly-spaced data, they interpolated their data prior to analysis. This is potentially problematic because interpolation is known to introduce low-frequency periodicity in time series data by artificially increasing autocorrelation. The other cause for concern is that Hodell et al. relied on radiocarbon date means to generate time-depth models, and radiocarbon date means are not necessarily the best estimates of dated events due to the multimodal nature of most radiocarbon date errors.

Our study had three parts. In the first, we replicated Hodell et al.'s (2001, 2005) results using data from their 2005 study. In the second part of the study, we examined the effects of interpolation through a simulation-based analysis and a reanalysis of Hodell et al.'s Chichancanab data using a method of time series analysis that does not require regularly-spaced data. In the third part of the study, we used a bootstrap-based resampling procedure to investigate the effects of ignoring the dating error.

Our exploration of the effects of interpolation clearly shows that the 208-year drought cycle Hodell et al. identified is an artifact of interpolation. The results of our assessment of the effects of ignoring the dating error are equally decisive. They return no evidence of drought cycles in the Maya region during the 1st millennium CE, which indicates that the 50-year drought cycle identified by Hodell et al. is an artifact of their reliance on point estimates of calibrated radiocarbon date distributions.

Given that both of the putative drought cycles appear to be methodological artifacts, and the Chichancanab data contains no other significant periodicities, our results have obvious implications for current thinking about the role played by cyclical drought in Classic Maya history. Clearly, it cannot be argued that drought periodicity was the cause of anything in the vicinity of Lake Chichancanab during the 1st millennium CE, since there is no evidence for such periodicity. The corollary of this is that discussions of Classic Maya history that invoke drought cycles to explain socio-political events should be viewed with skepticism (e.g., Gill et al., 2007; Dunning et al., 2012; Masson, 2012; Turner and Sabloff, 2012).

Our results also have important implications for future archaeological and palaeoenvironmental work involving time series data. They indicate that we need to be more conscious of the idiosyncrasies of our data and the analytical decisions we make to cope with them. Most time series of archaeological or palaeoenvironmental data can be expected to contain natural autocorrelation, irregular inter-observation times, and chronological uncertainty. All of these characteristics pose challenges for time series analysis because they introduce biases and have the potential to generate spurious results. Future research needs to evaluate their effect on time series analyses, particularly the impact they have on uncertainty. We need to better understand the uncertainties involved in analyzing past human–environment interactions so that we can evaluate the level of confidence that should be given to our interpretations, especially if they could affect contemporary debate and policy about climate change.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.quascirev.2014.09.032.

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