

1 **“Empirical pre-whitening” spectral analysis detects periodic but inconsistent signals in abyssal hill**
2 **morphology at the southern East Pacific Rise**

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11 Key Points:

- 12 1. A new algorithm is formulated to detect periodicities embedded in an aperiodic process using
13 “empirical pre-whitening” spectral analysis
- 14 2. Periodicities are detected at the southern East Pacific Rise, but are spatially and temporally
15 inconsistent
- 16 3. The dominant aperiodic signal is likely fault-constructed, while ephemeral periodic signals may
17 relate to internal melt supply variations

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Abstract. The existence, or not, of periodicities in abyssal hill morphology has been vigorously debated in recent publications, and some have hypothesized that such periodicities are evidence of the impact of Milankovitch cycle-caused sea level fluctuations on the volcanic construction process at mid-ocean ridges. Periodicities are detected by the presence of spectral peaks that rise significantly above the random variations of sample power spectra associated with an aperiodic, continuous spectrum process, typically modeled as a band-limited fractal (von Kármán model). Here I formulate and test a new algorithm to “empirically pre-whiten” the sample power spectrum which, without needing to model the continuous spectrum, flattens it to a zero-mean process. This greatly simplifies definition of the null hypothesis, and additional modeling approximates standard deviation levels that provide a conservative basis for detecting peaks that may be indicative of periodicity. The algorithm is applied to extensive bathymetric data flanking the southern East Pacific Rise. Significant periodicities are detected on many profiles analyzed, but the periods vary widely, and do not cluster at Milankovitch periods. The most substantial harmonic signals detected exhibit periods $\sim 0.082\text{-}0.216$ my, with root-mean square (RMS) heights approximately a quarter to a third of the RMS height for the aperiodic signal. It is hypothesized that the dominant aperiodic component of abyssal hills corresponds to morphology constructed by faults that follow a random distribution governed by scaling laws, whereas longer-scale periodic signals are associated with crustal thickness variations controlled internally by variations in melt supply.

Key Words: Mid-ocean ridge, faulting, melt supply, von Kármán model, stochastic processes, autocovariance

43 1. Introduction

44 A number of recent publications have endeavored to identify peaks in the sample power spectra
45 (periodograms) of abyssal hill bathymetry profiles, presumably indicative of periodicities that could be
46 interpreted as systemic temporal variations in mid-ocean ridge (MOR) processes (Crowley et al., 2015;
47 Tolstoy, 2015; Olive et al., 2016; Shinevar et al., 2019; Boulahanis et al., 2020). Discovery of topographic
48 periodicities would greatly impact our understanding of variability in MOR processes, whether externally
49 forced, such as proposed Milankovitch Cycle dependence (Crowley et al., 2015; Tolstoy, 2015;
50 Boulahanis et al., 2020), or internally forced, such as via modulations of mantle upwelling (Shinevar et
51 al., 2019; Parnell-Turner et al., 2020). There are, however, a number of potential pitfalls in these
52 analyses, and it is quite possible that the spectral peaks that have been discerned are instead typical
53 random fluctuations of a sample power spectrum estimated from an aperiodic time series, particularly if
54 detection thresholds are not sufficiently conservative.

55 As described in Priestley (1981), there are two end-member time series spectra: discrete and
56 continuous. Discrete spectra are those with one or more periodicities, detected by peaks on the sample
57 power spectrum at individual frequencies. Well-known methods are established for determining the
58 significance of those peaks as observed on a sample power spectrum in the presence of a background
59 white noise process. In contrast, continuous spectra processes are those that are characterized by a
60 smooth, continuous power spectral function $P(f)$ across a range of frequencies, f , and do not contain any
61 periodicities. However, sample power spectra derived from continuous-spectra time series are, in
62 Priestley's (1981) words, "erratic and wildly fluctuating", which is a result of two well-known properties:
63 (1) the variance of the sample power spectrum does not approach zero as the number of sample points
64 (N) approaches infinity, and (2) the correlation between two sample power spectrum points decreases
65 as N increases. Because of this erratic property, application of discrete-spectrum tests to continuous-
66 spectra processes "may indicate the existence of a large number of spurious periodic components",

67 according to Priestley (1981); the methods are not invalid, he states, but rather are misapplied when
68 used on time series with continuous spectra. Furthermore, since the variance of the sample power
69 spectrum scales with $P^2(f)$, such false detections are more likely where $P(f)$ is larger.

70 Between the discrete and continuous spectrum end members, Priestley (1981) describes a “mixed”
71 spectrum derived from the blending of time series of both periodic and aperiodic character, which is an
72 apt model for hypothesizing the existence of periodicities in abyssal hill morphology (Goff et al., 2018).
73 Abyssal hills are formed primarily by normal faults (McDonald et al., 1996; Durant et al., 1996;
74 Macdonald, 2015), whose throw and spacing can be modeled as random distributions that follow scaling
75 laws (Malinverno and Cowie, 1993; Bohnenstiehl and Carbotte, 2001). Abyssal hill morphology
76 statistical properties have been successfully characterized using a von Kármán functional form (von
77 Kármán, 1948), which is a continuous (aperiodic) spectrum that can also be described as a band-limited
78 fractal model (Goff and Jordan, 1988, Goff and Tucholke, 1997). Any periodic component of the seafloor
79 topography, such as might be caused by variations in crustal thickness, independent of the abyssal hill
80 faulting process, could be modeled as a superposition of periodic and aperiodic signals.

81 If we consider the aperiodic time series with continuous power spectrum, $P(f)$, to be a null
82 hypothesis, rejection of the null hypothesis would be established by observation of a spectral peak that
83 greatly exceeds the normal variation of the continuous sample power spectrum. However, to do this,
84 the null hypothesis must be defined, which requires either knowing $P(f)$ *a priori*, or modeling $P(f)$ by
85 fitting a functional form (e.g., Goff and Jordan, 1988). Vaughan (2005), for example, formulated a
86 methodology for detecting periodicities in the presence of a red (negative trend with frequency)
87 background noise, which can be fit with simple power-law, and where the null hypothesis variability
88 about this trend is characterized by a χ^2 distribution. Vaughan (2005) noted, however, that the
89 modeling fit itself adds additional uncertainty, leading him to strongly suggest that confidence levels 3-4
90 times the standard deviation (σ) should be applied when determining the significance of a spectral peak

91 in indicating a periodic component of a mixed spectrum, rather than the oft-assumed 2σ confidence
92 level (Crowley et al., 2015; Shinevar et al., 2019; Boulahanis et al., 2020).

93 Pre-whitening is another approach to assisting in the detection of periodicities in a mixed spectrum;
94 the general idea is to divide the sample power spectrum by $P(f)$ so that the overall trend is flat; i.e., it
95 emulates a discrete spectrum in the presence of white noise. In this construction, standard tests for the
96 significance of observed peaks can be applied (Priestley, 1981). The spectral analysis methodology
97 employed by Crowley et al. (2015) and emulated by others (Olive et al., 2016; Shinevar et al., 2019;
98 Boulahanis et al., 2020), does indeed attempt to apply pre-whitening to the spectrum. However, no
99 attempt was made in these analyses to estimate $P(f)$, applying instead simple f^2 multiplicative factor that
100 fails to flatten the spectrum. Rather, because abyssal hills are band-limited in their power-law (i.e.,
101 fractal) behavior, this attempt at pre-whitening causes the spectrum to arc, artificially enhancing
102 positive spectral fluctuations near the apex of the arc to appear more significant than they likely are.
103 Although modeling the spectrum using the von Kármán function would undoubtedly improve pre-
104 whitening, Priestley (1981) argues against pre-whitening in this way because, if there is indeed a
105 periodic component, it will distort the modeling of $P(f)$ in a way that adversely affects both that
106 estimation and the ultimate detection of periodic signals.

107 Harmonic components of a mixed spectrum profile can also be detected using multitaper techniques
108 (Thomson, 1990; Percival and Walden, 1993; Mann and Lees, 1996; Crowley et al., 2015). Multitaper
109 spectral estimation applies an orthogonal series of tapers to a time series, Fourier transforms each and
110 then adds the results together to form a sample power spectrum. This technique is widely used to
111 reduce the variability of the power spectrum estimate in comparison to the periodogram, and eliminate
112 spectral leakage (e.g., McCoy et al., 1998; Babadi and Brown, 2014). An embedded harmonic signal may
113 be detected by an F-test for phase-coherent variability at any one frequency across taper components
114 (Thomson, 1990; Mann and Lees, 1996). However, phase coherence does not necessarily imply

115 significance with respect to the variability associated with the aperiodic component of the process at
116 that frequency (Mann and Lees, 1996). Alternatively, or in addition to the F-test, the height of a spectral
117 peak can be compared against an assumed χ^2 distribution on local variability about the null hypothesis,
118 which is represented by the best estimate of $P(f)$ for the multitaper estimate of the power spectrum
119 (Percival and Walden, 1993; Mann and Lees, 1996; Crowley et al., 2015). This test is akin to the
120 procedure Vaughan (2005) utilized for the periodogram.

121 To obviate the need to model $P(f)$ for defining the null hypothesis and/or for pre-whitening,
122 Priestley (1981; Chapter 8) proposed an ingenious and simple solution that he termed the “ $P(\lambda)$ ” test.
123 The method utilizes the sample autocovariance function, which is the Fourier transform pair of the
124 sample power spectrum. The sample autocovariance consists of two components: (1) a central,
125 decaying portion that includes all information about the functional nature of the continuous, aperiodic
126 spectrum $P(f)$, and (2) a long tail that randomly fluctuates about 0 and, should they be present, also
127 includes harmonic fluctuations associated with periodic components of the time series because they do
128 not decay to zero with increasing lag. Priestley’s (1981) method consists of zeroing-out the central,
129 decaying portion of the sample autocovariance (which can be determined by simple inspection rather
130 than modeling), and then Fourier-transforming the remaining tails. The result will be a zero-mean (null
131 hypothesis), randomly fluctuating function, with positive spikes at frequencies if and where periodic
132 signals are present (deviation from null hypothesis). Despite the relative simplicity and elegance of the
133 $P(\lambda)$ test, a literature search found very few examples of its application (e.g., Bhansali, 1977; 1979;
134 Garrido and Garcia, 1992). For clarity in terminology, I propose the term “empirical pre-whitening” to
135 describe this simple technique.

136 In this paper I present a new algorithm for utilizing Priestley’s (1981) $P(\lambda)$ /empirical pre-whitening
137 method to detect periodic signals in a mixed-spectra process. I first test the algorithm on synthetic
138 profiles generated by adding cosine functions of various amplitude and frequency to an aperiodic time

139 series corresponding to the von Kármán statistical model (Goff and Jordan, 1988). The algorithm is able
 140 to accurately detect the periodic components provided the amplitude is sufficient to rise significantly
 141 above the random fluctuations associated with the aperiodic component of the spectrum at that
 142 frequency. I then apply this algorithm to twelve bathymetric profiles of abyssal hill morphology along
 143 the southern East Pacific Rise (EPR) to test for the presence of periodicities. A portion of this region was
 144 also used by Tolstoy (2015) in a spectral analysis that discerned a ~100 ky periodicity, which is one of the
 145 Milankovitch periods. The profiles are converted from distance to crustal age versus depth using an
 146 existing, high-resolution age model for the region (Goff et al., 2018).

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148 2. Formulation

149 The following formulation is based on Priestley (1981; Section 8.4). Consider a discrete time or space
 150 series X_i , $1 \leq i \leq N$, evenly spaced by ΔX . Consider further that X_i represents the summation of two
 151 independent, zero-mean, stationary processes Y_i and Z_i , where Y_i is an aperiodic process with a
 152 continuous spectrum, and Z_i is represented by one or more sinusoidal forms. The autocovariance of X_i ,
 153 $R_X(s)$, is then represented by:

$$154 \quad E[X_i X_{i+s}] = R_X(s) = R_Y(s) + R_Z(s), \quad (1)$$

155 where $E[\cdot]$ is the expectation operator, s is the lag index, and $R_Y(s)$ and $R_Z(s)$ are the autocovariances of Y_i
 156 and Z_i , respectively. Because Y_i is aperiodic, $R_Y(s)$ will decay monotonically with increasing $|s|$. Because
 157 Z_i has periodic elements, $R_Z(s)$ will also vary sinusoidally for all s ; each sinusoidal element, defined by a
 158 frequency f and amplitude α , will contribute a term $\frac{1}{2} \alpha^2 \cos(2\pi s f)$ to $R_Z(s)$. The sample autocovariance,
 159 i.e., estimation of $R_X(s)$ based on samples X_i , is given by:

$$160 \quad \hat{R}_X(s) = \frac{1}{N-s} \sum_{i=1}^{N-s} X_i X_{i+s}, \quad 0 \leq s \leq N/2$$

$$161 \quad \hat{R}_X(-s) = \hat{R}_X(s). \quad (2)$$

162 The power spectrum of X_i , denoted by $P_X(f)$, is the Fourier transform conjugate of $R_X(s)$, and we can
 163 likewise define the power spectra of Y_i and Z_i in the same way such that

$$164 \quad P_X(f) = P_Y(f) + P_Z(f). \quad (3)$$

165 The sample power spectrum can be computed in two equivalent ways:

$$166 \quad \hat{P}_X(f) = DFT[\hat{R}_X(s)], \text{ or} \quad (4)$$

$$167 \quad \hat{P}_X(f) = |DFT[X_i]|^2, \quad (5)$$

168 where DFT indicates the discrete Fourier transformation. Equation (5) is far more commonly utilized since
 169 it does not require the extra step of computing the sample autocovariance as in Equation (2). However,
 170 Equation (4) is utilized here because it provides a mechanism for separating periodic from aperiodic
 171 components of the spectrum. Priestley (1981) proposes in his $P(\lambda)$ test to first inspect $\hat{R}_X(s)$ after
 172 computing it in order to identify a value m such

$$173 \quad R_Y(s) \sim 0, |s| \geq m. \quad (6)$$

174 In other words, we seek to identify that portion of the sample autocovariance which is monotonically
 175 decaying, and which contains all the structural information that constrains the continuous portion of the
 176 power spectrum $P_X(f)$. The remainder, or “tail,” is a zero-mean signal that, if there are no periodic
 177 elements in X_i , will fluctuate randomly (and which, after DFT, contributes to the erratic fluctuations of
 178 $\hat{P}_X(f)$). If, however, there are periodic elements, then those will be present in the tail, as noted above.

179 The next step in Priestley’s (1981) method is thus to remove the monotonically decaying portion of
 180 $\hat{R}_X(s)$ by zeroing it out for $|s| < m$:

$$181 \quad \hat{R}_X^m(s) = \begin{cases} 0, & |s| < m \\ \hat{R}_X(s), & |s| \geq m \end{cases}. \quad (7)$$

182 Finally, this altered sample autocovariance is transformed to create the “empirically pre-whitened”
 183 spectrum

$$184 \quad \hat{P}_X^m(f) = DFT[\hat{R}_X^m(s)]. \quad (8)$$

185 In practice, the “cut” edges at $|\pm s| = m$, as well as the ends of the function at $|\pm s| = N/2$, need to be
186 tapered prior to the DFT in order to minimize spectral leakage.

187 In the case of the null hypothesis, where no periodicity is present and $P_X(f) = P_Y(f)$, Priestly (1981)
188 demonstrates that

$$189 \quad E[\hat{P}_X^m(f)] = 0, \quad (9)$$

190 and

$$191 \quad VAR[\hat{P}_X^m(f)] \sim \frac{N-2m}{2} P_Y^2(f), \quad (10)$$

192 where VAR indicates the variance. Therefore, the standard deviation on the null hypothesis, σ , is
193 estimated by the square root of Equation (10). Deviation from the null hypothesis can be established by
194 observation of spectral peaks that significantly deviate from the typical erratic variability associated with
195 the continuous component of the spectrum. For this purpose, a conservative criterion must be applied.
196 Depending on N , the empirically pre-whitened spectrum could have hundreds or thousands of peaks
197 and valleys, so that numerous peaks are expected to surpass a 2σ (95%) threshold, and even several are
198 likely to surpass a 3σ (99%) threshold without the presence of a periodic signal. In the following
199 analyses, a value of 3.5σ will be used as a minimum detection threshold.

200 Equation (10) does require knowledge of the underlying continuous spectrum $P_Y(f)$. Where $P_Y(f)$ is
201 not known *a priori*, it must be modeled by fitting a smooth functional form to the sample
202 autocovariance or sample power spectrum. This will be demonstrated in Section 4. Addition of periodic
203 components will increase the overall variance of the profile compared to the null hypothesis, thus
204 increasing the modeled value of $P_Y(f)$ and subsequent estimation of σ . Fortunately, this has the effect of
205 increasing the confidence in detection of periodic contributions, since the level of significance of a
206 spectral peak should be considered a minimum value.

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208 **3. Synthetic Test**

209 To test the ability of an empirically pre-whitened spectrum to detect periodic elements of a mixed
 210 spectrum process, I constructed a series of synthetic profiles consisting of the addition of an aperiodic
 211 time series, generated from the von Kármán statistical model, and cosine functions of varying amplitude
 212 and frequency. The von Kármán statistical model can be expressed equivalently in either
 213 autocovariance or power spectral form (Goff and Jordan, 1988; Goff and Tucholke, 1997). For the
 214 autocovariance:

$$215 \quad R_{VK}(s) = H^2 G_\nu[k_0 s] / G_\nu(0) \quad (11)$$

216 where H is the RMS height, k_0 is a scaling parameter with dimensions time^{-1} (or distance^{-1}), and G_ν is
 217 defined by

$$218 \quad G_\nu(x) = x^\nu K_\nu(x). \quad 0 \leq x < \infty. \quad (12)$$

219 K_ν is the modified Bessel function of the second kind and order ν . The parameter ν largely controls the
 220 slope of $R_{VK}(s)$ at the origin. Where $\nu = 0$, $R_{VK}(s)$ intersects the origin at 0 slope, whereas at $\nu = 1$, $R_{VK}(s)$
 221 has infinite slope at $x = 0$. At $\nu = 1/2$, $R_{VK}(s)$ is an exponential function.

222 The functional form of the von Kármán power spectrum for a profile is given by:

$$223 \quad P_{VK}(f) = \frac{\Gamma\left(\nu + \frac{1}{2}\right)}{\Gamma(\nu)} \frac{2H^2 \sqrt{\pi} (k_0/2\pi)^{2\nu}}{((k_0/2\pi)^2 + f^2)^{\nu + \frac{1}{2}}}$$

224 (13)
225

226 where Γ is the gamma function. In the power spectral formulation, $k_0/2\pi$ serves as a corner frequency:
 227
 228 for $f \gg k_0/2\pi$, $P_{VK}(f)$ is a power-law form (i.e., red spectrum, or fractal), while for $f \ll k_0/2\pi$, $P_{VK}(f)$ is a
 229 constant (i.e., white spectrum). The order parameter ν determines the Hausdorff, or fractal dimension:

$$230 \quad D = E + 1 - \nu, \quad (14)$$

231 were E is the Euclidian dimension (i.e., $E = 1$ for a profile). D impacts the roughness at short scales
232 relative to long scales. For $D = 1$, the profile is quite smooth at short scales, whereas for $D = 2$, the
233 profile is so erratic at short scales that it fills 2-dimensional space.

234 A synthetic profile conforming to the von Kármán statistical model can be generated by: (1)
235 multiplying the amplitude spectrum (square root of Equation (13)) by a random phase $\exp(i\phi)$, where ϕ
236 is a uniform random value distributed on $(0, 2\pi]$, (2) enforcing Hermetian symmetry over negative
237 frequencies, and (3) transforming to the space domain by DFT (Goff and Jordan, 1988; Goff, 1995). The
238 uniform random phase results in a Gaussian distribution of profile values. In practice, a larger profile
239 than required should be generated, and then cropped to size in order to fully randomize the sample
240 power spectrum of the synthetic profile.

241 For the synthetic experiment, parameters chosen were: $H = 1 u_h$, $k_0 = 1 u_d^{-1}$, and $\nu = 0.8$, where u_h
242 and u_d are arbitrary units of height and distance (or time), respectively. The profile length is 10,000
243 points with a node spacing of $\Delta X = 0.05 u_d$. The top profile of Figure 1 displays the profile generated
244 with these parameters. To generate a mixed-spectrum profile, $X_M(i\Delta X)$, I superpose cosine functions on
245 the von Kármán profile using:

$$246 \quad X_M(i\Delta X) = X_{VK}(i\Delta X) + \alpha[\cos(i\Delta X 2\pi f_1) + \cos(i\Delta X 2\pi f_2) + \cos(i\Delta X 2\pi f_3)], \quad (15)$$

247 where $X_{VK}(i\Delta X)$ is the profile generated with the von Kármán statistical model, and f_1 , f_2 and f_3 are
248 frequencies chosen to be 0.02, 0.1, and 0.5 cycles/ u_d , respectively. Figure 1 displays the results of
249 Equation (15) for values of α ranging from 0 to 0.5. A surprising observation regarding these profiles is
250 that they look very similar; i.e., that the harmonic components are not visually self-evident, even at the
251 largest value of α . This observation can be understood by considering the contribution of each
252 sinusoidal component to the overall RMS height. For example, at $\alpha = 0.3 u_h$, the variance is of the
253 sinusoidal component is $\frac{1}{2}\alpha^2$, or $0.045 u_h^2$. Added to the aperiodic variance of $1 u_h^2$, the combined

254 variance is $1.045 u_h^2$, and taking the square root yields an overall RMS of $1.022 u_h$. Thus, the addition of
255 one sinusoidal component of amplitude $0.3 u_h$ increases the RMS by only 2.2%.

256 In contrast to the profiles, the sample autocovariances of these profiles (Figure 2) display clear visual
257 evidence of the harmonic components, which come to dominate the tails as α increases because they do
258 not decorrelate as lag increases, as the aperiodic signal does. This is a clear visual confirmation of the
259 utility of the sample autocovariance to isolate the harmonic components of a mixed spectrum process
260 from the aperiodic components. Using these sample autocovariances, I have conducted a spectral
261 analysis where I compare (1) the sample power spectrum computed by DFT of the full sample
262 autocovariance, and (2) the empirically pre-whitened spectrum computed by DFT of the sample
263 autocovariance after zeroing-out the shaded regions shown in Figure 2, which self-evidently includes the
264 full span of the monotonically-decaying portion of the function. In addition, a \cos^2 taper is applied over
265 10% of the profile at each edge to suppress spectral leakage. The full suite of results is presented in the
266 Supplementary Material, and cases $\alpha = 0 u_h$ and $\alpha = 0.3 u_h$ are presented in Figures 3 and 4, respectively,
267 to illustrate key findings.

268 The null ($\alpha = 0 u_h$) case is presented in Figure 3. As noted earlier, the von Kármán statistical model is
269 a band-limited fractal, following a power-law form (negative linear trend on a log-log plot) at high
270 frequencies, and flat at low frequencies, with the transition governed by the corner frequency. The
271 sample power spectrum from the synthetic profile (Figure 3a) closely follows this functional form, as
272 expected, but with the highly erratic variability that is characteristic of continuous-spectrum, aperiodic
273 profile. The empirically pre-whitened spectrum for the null case (Figure 3b), is also highly erratic, but
274 with a mean of zero which indicates success in removing the structural form of the continuous power
275 spectrum. Comparison between Figures 3a and 3b demonstrates that the variations of the sample
276 power spectrum about the model function are retained in the variation of the empirically pre-whitened
277 spectrum about zero. The 2σ upper bound does well in characterizing the envelope of variability, which

278 increases as f decreases, but is not a hard limit; at least two peaks are observed to exceed 2σ , which is
279 expected statistically.

280 The $\alpha = 0.3 u_h$ case is presented in Figure 4. Frequency f_3 (0.5 cycles/ u_d) is detectable at $\alpha = 0.1 u_h$
281 (Supplementary Material) owing to the fact that the variations of the aperiodic component of the profile
282 are very small at this frequency. Frequencies f_1 (0.02 cycles/ u_d) and f_2 (0.1 cycles/ u_d), however, are only
283 detectable at $>3.5\sigma$ for $\alpha = 0.3 u_h$ (Figure 4b) and larger (Supplementary Material). Because they all
284 have the same amplitude, the peaks at all three frequencies are expected to be of the same height on
285 the empirically pre-whitened spectrum. However, the peak at f_2 is observed to be less than the peaks at
286 f_1 and f_3 by about 25% (Figure 4b). This emphasizes an important point: the height of the discrete
287 spectral peaks are modulated by the random highs and lows of the continuous spectrum upon which it is
288 superposed, leading to uncertainty in detection and measurement of amplitude (which will be
289 considered in the next section).

290 This synthetic experiment demonstrates the efficacy of the empirically pre-whitened spectrum in
291 detecting periodic components of a mixed spectrum profile. Even with a conservative detection
292 criterion of 3.5σ , positive identification was made of harmonic signals that add only 2.2% each to the
293 overall RMS variability. The certainty of detection increases as the amplitude of the sinusoidal
294 component increases (Supplementary Material), providing confidence that any substantial harmonic
295 component to the profile will be detected. The empirical pre-whitening algorithm has the potential for a
296 wide variety of applications. Examples cited earlier include tide data (Bhansali, 1977), lynx population
297 data (Bhansali, 1979) and precipitation data (Garrido and Garcia, 1992).

298

299 **4. Application to the Southern East Pacific Rise**

300 The southern East Pacific Rise (Figure 5) is the site of some of the most extensive publically-available
301 multibeam bathymetric coverage in the world of a mid-ocean ridge (MOR) and its flanks (Scheirer et al.

302 1996). The region also exhibits some of the fastest MOR spreading rates (~7.7-7.8 cm/yr half rates
303 DeMets et al., 1990). Tolstoy (2015) applied a spectral analysis in a limited area of this region and found
304 a spectral peak at a period of ~100 ky, inferring that Milankovitch cycles may be influencing volcanic
305 construction at the MOR. Goff et al (2018) further fine-tuned the Müller et al. (2016) age model for this
306 region, and applied a stacking analysis to identify any temporal variations in bathymetry that were
307 coherent across the region, which would be expected if the rise and fall of sea-level associated with
308 Milankovitch cycles, and external forcing, were controlling abyssal hill construction. They found,
309 however, that there was no evidence for spatially coherent temporal signals, periodic or otherwise.
310 Nevertheless, lack of synchronicity does not imply lack of periodicity. Rather than an external forcing
311 that affects the MOR uniformly either globally or regionally, variations in volcanic output might be
312 internally forced within the mantle (Shinevar et al., 2019; Parnell-Turner et al., 2020), which could be
313 periodic (or at least episodic) and which may vary in period, phase and amplitude from one segment to
314 the next. If so, then the stacking analysis of Goff et al. (2018) would not detect such signals.

315 To search for possible temporal periodicities, I have selected 12 profiles of residual height (Figure 5)
316 and converted to age versus residual height using the crustal age model presented in Goff et al. (2018).
317 Each profile is ~2.5-3 my long, resampled at a uniform interval of 0.0025 my, and linearly interpolated
318 over any gaps in coverage. Such gaps were few as profiles were carefully selected to correspond to
319 swaths of nearly complete coverage and no seamounts. Profiles were also restricted to ages > 0.5 my to
320 avoid the MOR axial high and associated negative sidelobes that form with the high-pass filter of the
321 original bathymetry.

322 For example purposes, I present here the full analysis of Profile 7a (Figures 6 and 7), which is one of
323 the more convincing detections of a periodic component. The full suite of profiles analyses are
324 presented in the Supplementary Material, with results listed in Table 1. The age-versus-residual height
325 values for Profile 7a are shown in Figure 6a, and its sample autocovariance function is shown in Figure

326 6b. A von Kármán model is fit to the sample autocovariance (Figure 6b) via weighted, least-squares
327 inversion as formulated in Goff and Jordan (1988). The estimated value for RMS height, H , is 61.1 ± 4.7
328 m, and the scale parameter, k_0 , is $68.3 \pm 13.8 \text{ my}^{-1}$. Estimation of the parameter ν tends to become
329 unstable as it approaches its upper limit of 1 (Goff, 1991); that was the case here and in most of the
330 estimations in this analysis, and was assumed to be 0.9. A characteristic time, λ_0 , can be defined by the
331 width, or second moment of the autocovariance model (Goff and Jordan, 1988):

$$332 \quad \lambda_0 = \frac{\sqrt[2]{2(\nu+1/2)}}{k_0}. \quad (16)$$

333 The characteristic time roughly corresponds to the visually dominant (on average) peak-to-peak distance
334 (Goff, 1991), and thus is an important point of comparison for any potential identification of a harmonic
335 component. For Profile 7a, $\lambda_0 = 0.049 \pm 0.010 \text{ my}$ (which equates to $\sim 3.8 \text{ km}$). The tail of the sample
336 autocovariance (Figure 6b) exhibits a number of evidently regularly-spaced peaks and troughs that
337 strongly suggest the presence of a harmonic component to the profile.

338 The spectral analysis of Profile 7a is shown in Figure 7. The sample power spectrum (Figure 7a)
339 follows the modeled von Kármán power spectrum well at lower frequencies, but deviates at the higher
340 frequencies. This deviation from the power law trend is a phenomenon noted by Goff and Jordan
341 (1988), who attributed it to the “response”, or beam width of the multibeam echosounder being larger
342 than the sample interval. This effect may also be caused by the averaging associated with the gridding
343 process. In any case, it is not a concern in this analysis because any periodic elements at that scale
344 would exhibit very small amplitudes. In addition to the overall von Kármán-like trend, a noticeable peak
345 is observed corresponding to a period of 0.145 my, approximately three times the characteristic time of
346 the best-fitting von Kármán model. That same peak is shown on the empirically pre-whitened spectrum
347 (Figure 7b) to be significant at a very high level of confidence of 5.1σ . Therefore, it can be stated that a
348 periodic signal, with period of 0.145 my, is present in Profile 7a with a very high degree of certainty.

349 Having identified a likely periodic signal, the next step is to estimate its amplitude, α . That value can
350 be estimated from the amplitude of the peak observed on the empirically pre-whitened spectrum,
351 which is proportional to α^2 (Priestley, 1981). However, the coefficient is a complex function of N , m and
352 the tapers used prior to DFT of $\hat{P}_X^m(f)$. Priestly (1981) calculated closed-form approximations for linear
353 or no tapers, neither of which I found appropriate to the application at hand. Rather than attempt the
354 same calculation for the \cos^2 tapers used here, a far simpler method is to generate a simple cosine
355 function and pass it through the same spectral analysis applied to the data profile. Then, α is adjusted
356 until the height of the resulting spectral peak matches what is observed on the empirically pre-whitened
357 spectrum. With this procedure I estimated α to be ~ 30 m for the 0.145 my period peak detected for
358 Profile 7b. The variance of this sinusoidal contribution is $\alpha^2/2 = 450 \text{ m}^2$, which equates to an RMS of 21.2
359 m. The overall variance of Profile 7a is $H^2 = 3730 \text{ m}^2$. Therefore, $3730 \text{ m}^2 - 450 \text{ m}^2$, or 3280 m^2 of the
360 total variance of Profile 7a, is attributed to the aperiodic component of the profile. This equates to an
361 RMS of 57.3 m, and which is 2.7 times the RMS of the sinusoidal component. Thus, while significant in
362 its measurability, the sinusoidal contribution at 0.145 my period represents a relatively minor
363 component of Profile 7a compared to the aperiodic signal.

364 I next test the ability of the mixed spectrum statistical model, of the form presented in Equation
365 (15), to match these observations. To do so I formulated a synthetic profile composed of: (1) a von
366 Kármán aperiodic component using the parameters $H = 57.3$ m (the estimated RMS height of the
367 aperiodic component, rather than the overall RMS), and k_0 and ν as derived from the best-fit model, and
368 (2) an added cosine function corresponding to amplitude 30 m and period 0.145 my. Initially this
369 created a spectral peak that was too large, so the amplitude was reduced to 24 m to match the height
370 exactly. This reiterates the point that the estimation of harmonic amplitude has significant uncertainties
371 owing to modulation by the random, aperiodic component of the spectrum. The level of uncertainty will
372 depend on the variation of the empirically pre-whitened continuous spectrum in proportion to the

373 height of the discrete spectral peak at the frequency of interest. The synthetic profile and sample
374 autocovariance are shown in Figure 8, and the resulting spectral analysis is shown in Figure 9. The
375 similarity of these plots to Figures 6 and 7, respectively, is very strong, particularly in the self-evident
376 harmonic component in the tail of the sample autocovariance (Figure 8b), and in the size of spectral
377 peaks noted both on the sample power spectrum (Figure 9a) and the empirically pre-whitened spectrum
378 (Figure 9b). The only notable difference between real and synthetic spectra is in the power at the
379 highest frequencies (Figures 7a versus 9a), which causes the real profile (Figure 6a) to have a smoother
380 appearance than the synthetic profile (Figure 8a) at the smallest scales.

381 Spectral analysis plots for all twelve profiles are presented in the Supplementary Material. Estimated
382 von Kármán and cosine function parameters from each analysis are listed in Table 1, and the detected
383 periods with the largest amplitude on each line are shown on Figure 5. Periodicities were detected in all
384 but three of the profiles, and in several there were multiple periodicities detected. The periods
385 detected were highly variable, however, ranging at least an order of magnitude from 0.02 my (the
386 minimum considered for inclusion in Table 1) to 0.216 my. There is no evident clustering of values at
387 the Milankovitch periods of 0.100 my, 0.041 my or 0.026 my, although there are several detected
388 periods that are equal or close to those values. More importantly, there is no evidence of spatial or
389 temporal consistency (Figure 5). For example, Profiles 3, 6 and 8 are quite proximal, but exhibit no
390 consistency in the periods of their harmonic components (Figure 5, Table 1). The same inconsistency is
391 also true of Profiles 1a and 1b, and Profiles 7a and 7b (Table 1), although each pair is sited along the
392 same flow line (Figure 5) and so were generated at the same ridge crest segment but at different times.

393 To gauge the significance of each detected periodicity to variability of each profile, I calculate a
394 value R as the ratio of RMS heights of the periodic to aperiodic components, respectively. By this
395 measure (Table 1), there is a clear separation of significance between those harmonic detections with
396 periods greater than or less than the characteristic time of the best-fitting von Kármán model. Those

397 periods greater than the characteristic time, seven in all, exhibit R values ranging from 0.19 to 0.38, with
398 all but the smallest of those >0.27 . In contrast, periods less than the characteristic time exhibit R values
399 ranging from 0.03 to 0.11, with only the largest > 0.08 . In all cases, however, the aperiodic component
400 of the profiles is the dominant source of variability.

401

402 **5. Conclusions and Discussion**

403 Application of an “empirical pre-whitening” spectral analysis, based on the “ $P(\lambda)$ test”
404 formulated by Priestly (1981), has enabled detection of temporal periodicities at high confidence in a
405 number of profiles sampled from multibeam bathymetric data along the southern EPR. However, these
406 harmonic signals are relatively minor components of the overall variability of the profiles, which are
407 instead dominated by an aperiodic signal conforming to a continuous, rather than discrete spectrum.
408 Furthermore, the periods expressed by the harmonic signals are widely variable, and do not exhibit any
409 spatial or temporal consistency. These observations are not inconsistent with that of Tolstoy (2015),
410 who found a 0.1 my periodicity near the axis at $\sim 17^{\circ}30'S$, but does suggest that compatibility with a
411 Milankovitch period may be serendipitous rather than systematic. On the other hand, Tolstoy’s (2015)
412 analysis was limited to ages < 0.8 my, where the 0.1 my forcing during glacial/interglacial cycles is
413 expected to be most pronounced. Because the analysis presented here is limited to ages > 0.5 my, such
414 cycles might have been missed. However, if consistent periodicity was present at younger ages, it
415 should have been detected by the stacking analysis of Goff et al. (2018), but was not.

416 The inconsistent behavior of the harmonic signals in abyssal hills makes their origin enigmatic, but
417 does rule out external forcing such as may be applied by Milankovich cycle-based variability in sea level.
418 Rather, the forcing must be internal, highly localized, and subject to changing conditions over time.
419 Abyssal hills generated at fast spreading rates are predominantly fault-bounded, horst-and-graben
420 structures (e.g., Macdonald et al., 1996; Macdonald, 2015). Furthermore, fault scaling parameters

421 (spacing, length, throw) are successfully modeled as random distributions constrained by scaling laws
422 (Malinverno and Cowie, 1993; Bohnenstiehl, and Carbotte, 2001). The dominant aperiodic component
423 of abyssal hills can thus reasonably be assumed to be associated with this fault-generated morphology,
424 characterized statistically by a von Kármán model defined by parameters RMS height, characteristic
425 time, and fractal dimension. The most significant harmonic contributions to abyssal hills, typically with
426 RMS heights around a quarter to a third of the aperiodic RMS, exhibit periods that are larger than the
427 characteristic time. Such variations in bathymetry could plausible be associated with variations in crustal
428 thickness associated with temporal variations in magma supply (Canales et al., 2000; Shinevar et al.,
429 2019; Parnell-Turner et al, 2020). Parnell-Turner et al. (2020), in a spectral analysis of abyssal hill
430 morphology on the flanks of the medium-spreading-rate Southeast Indian Ridge, also discerned a scale
431 of morphology (although no clear indication of periodicity) that was larger than the characteristic
432 time/width of abyssal hills. They hypothesize that variations in melt supply at <0.2 my time scales could
433 be associated either with time-varying, melt rich “porosity waves” in the mantle, or by small-scale
434 mantle heterogeneities. Investigating whether these or other mechanisms could apply to the super-fast
435 spreading southern EPR would be an important avenue of investigation for a modeling effort (though
436 beyond the scope of this paper). These results provide key observations that need to be accounted for
437 in any such effort, including the range of periods observed, their spatio-temporal variability, and their
438 topographic amplitudes.

439

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518 Table 1. Modeled aperiodic and detected periodic components of southern EPR profiles

519

520	Profile	H, m	λ_0 , my	Period, my (min 0.02)	Z_σ (> 3.5)	α , m	R
521							
522							
523	1a	65.5	0.065	0.112	4.6	25	0.28
524				0.021	3.9	3	0.03
525	1b	83.8	0.089	0.037	3.9	7	0.06
526	2	74.1	0.050	0.143	5.3	35	0.35
527				0.042	4.0	11	0.11
528	3	51.3	0.038	0.111	3.9	19	0.27
529				0.082	6.2	20	0.29
530	4	50.4	0.049	-	-	-	-
531	5	50.3	0.043	0.032	3.7	6	0.08
532				0.027	6.2	6	0.08
533	6	48.2	0.056	0.216	4.2	24	0.38
534				0.022	4.8	3	0.05
535	7a	68.3	0.049	0.145	5.1	30	0.33
536	7b	80.3	0.068	-	-	-	-
537	8	41.3	0.034	0.047	4.1	11	0.19
538	9	58.4	0.065	0.040	3.7	7	0.08
539				0.030	4.0	5	0.06
540				0.025	7.4	5	0.06
541				0.020	6.0	4	0.05
542	10	55.5	0.034	-	-	-	-

543

544 H: RMS height of best-fit von Kármán model

545 λ_0 : Characteristic time of best-fit von Kármán model

546 Z_σ : Height of spectral peak expressed as multiple of standard deviation σ .

547 α : Estimated amplitude of harmonic component.

548 R: Ratio of periodic to aperiodic RMS

549 -: No detection of harmonic component

550

551 **Figure Captions**

552 **Figure 1.** Synthetic profiles constructed using Equation (15) and parameters listed in the text. The
553 vertical scale corresponds to the $\alpha = 0$ profile; all others are offset a constant distance for visualization.
554 The first 100 u_d of each synthetic profile, out of a total distance of 500 u_d , are plotted.

555
556 **Figure 2.** Sample autocovariance functions (solid) computed from profiles shown in Figure 1, plotted to a
557 lag of 100 u_d . The von Kármán (VK) statistical model autocovariance, from which the synthetic profiles
558 were generated, is overlain (dashed). The vertical scale corresponds to the $\alpha = 0$ function; all others are
559 offset a constant distance for visualization. For Figures 3 and 4, the discrete Fourier transformation of
560 the sample autocovariance (with Hermetian symmetry) is used to compute the sample spectral density,
561 while the empirically pre-whitened spectrum is computed in the same way after values in the shaded
562 region are zeroed out. The region starts at 0 lag, where the autocovariance is equal to the variance, and
563 stretches to a lag value of $m \Delta X$, ($=15 u_d$ in this instance) which is chosen by inspection to encompass the
564 monotonically decaying portion of the autocovariance; at larger lags, it is a zero-mean function. A value
565 of $\alpha = 0$ is the null condition of no periodic component to the sample profile. Periodic components come
566 to dominate the tail of the autocovariance with increasing α , compared to the far more subtle visual
567 impact evidenced in the synthetic profiles of Figure 1.

568
569 **Figure 3.** (a) Sample power spectrum and (b) empirically pre-whitened spectrum calculated from the $\alpha =$
570 0 sample autocovariance shown in Figure 2. The von Kármán model is overlain on the power spectral
571 density, and the 2σ , 3σ , and 4σ upper bounds on the null hypothesis are overlain on the empirically pre-
572 whitened spectrum. Examples of “false positive” detection of periodic components are observed in the
573 if the 2σ bound is used as a threshold.

574

575 **Figure 4.** (a) Sample power spectrum and (b) empirically pre-whitened spectrum calculated from the $\alpha =$
576 0.3 sample autocovariance shown in Figure 2. The von Kármán model is overlain on the power spectral
577 density, and the 2σ , 3σ , and 4σ upper bounds on the null hypothesis are overlain on the empirically
578 pre-whitened spectrum. All three harmonic components are resolved at $> 3.5\sigma$ in this example.

579

580 **Figure 5.** Multibeam bathymetry along the flanks of the southern East Pacific Rise, high-pass filtered
581 with a 40 km box filter and masked to removed seamounts (modified from Goff et al., 2018). Crustal
582 ages are contoured at 1 my increments (Muller et al., 2016; Goff et al., 2018). Profiles used for analysis
583 are indicated by thick black lines and numbered identifiers. Associated values in parentheses are the
584 most significant periodicities (my) detected on each profile (Table 1).

585

586 **Figure 6.** (a) Bathymetric profile 7a converted from distance to age on the x-axis using the age model of
587 Goff et al. (2018); location shown in Figure 5. (b) Sample autocovariance (solid) computed from (a), with
588 best-fit von Kármán model (dashed). The power spectral density in Figure 7a is computed by discrete
589 Fourier transform of the full sample autocovariance (with Hermetian symmetry), whereas the
590 empirically pre-whitened spectrum in Figure 7b is computed in the same way after zeroing out the
591 shaded region that fully encompasses the structural (non-zero mean) portion of the autocovariance and
592 tapering the edges.

593

594 **Figure 7.** (a) Sample power spectrum and (b) empirically pre-whitened spectrum calculated from the
595 sample autocovariance of Profile 7a shown in Figure 6b. The best-fit von Kármán model is overlain on
596 the power spectral density, and the 2σ , 3σ , and 4σ upper bounds on the null hypothesis are overlain on
597 the empirically pre-whitened spectrum. One harmonic component at a period of 0.145 my is detected
598 at 5.1σ confidence.

599

600 **Figure 8.** (a) Synthetic profile formed from the summation of (1) an aperiodic von Kármán profile, with
601 parameters as noted in the text, and (2) a cosine function of amplitude 24 m and period 0.145 my. (b)
602 Sample autocovariance (solid) computed from (a), with best-fit von Kármán model for Profile 7a
603 (dashed). The power spectral density in Figure 9a is computed by discrete Fourier transform of the full
604 sample autocovariance (with Hermitian symmetry), whereas the empirically pre-whitened spectrum in
605 Figure 9b is computed in the same way after zeroing out the shaded region that fully encompasses the
606 structural (non-zero mean) portion of the autocovariance and tapering the edges.

607

608 **Figure 9.** (a) Sample power spectrum and (b) empirically pre-whitened spectrum calculated from the
609 sample autocovariance of the synthetic profile shown in Figure 8. The best-fit von Kármán model is
610 overlain on the power spectral density, and the 2σ , 3σ , and 4σ upper bounds on the null hypothesis are
611 overlain on the empirically pre-whitened spectrum. The height of the spectral peak at 0.145 my period,
612 observed in spectral analysis of Profile 7a (Figure 7), is successfully reproduced by the synthetic profile.

613

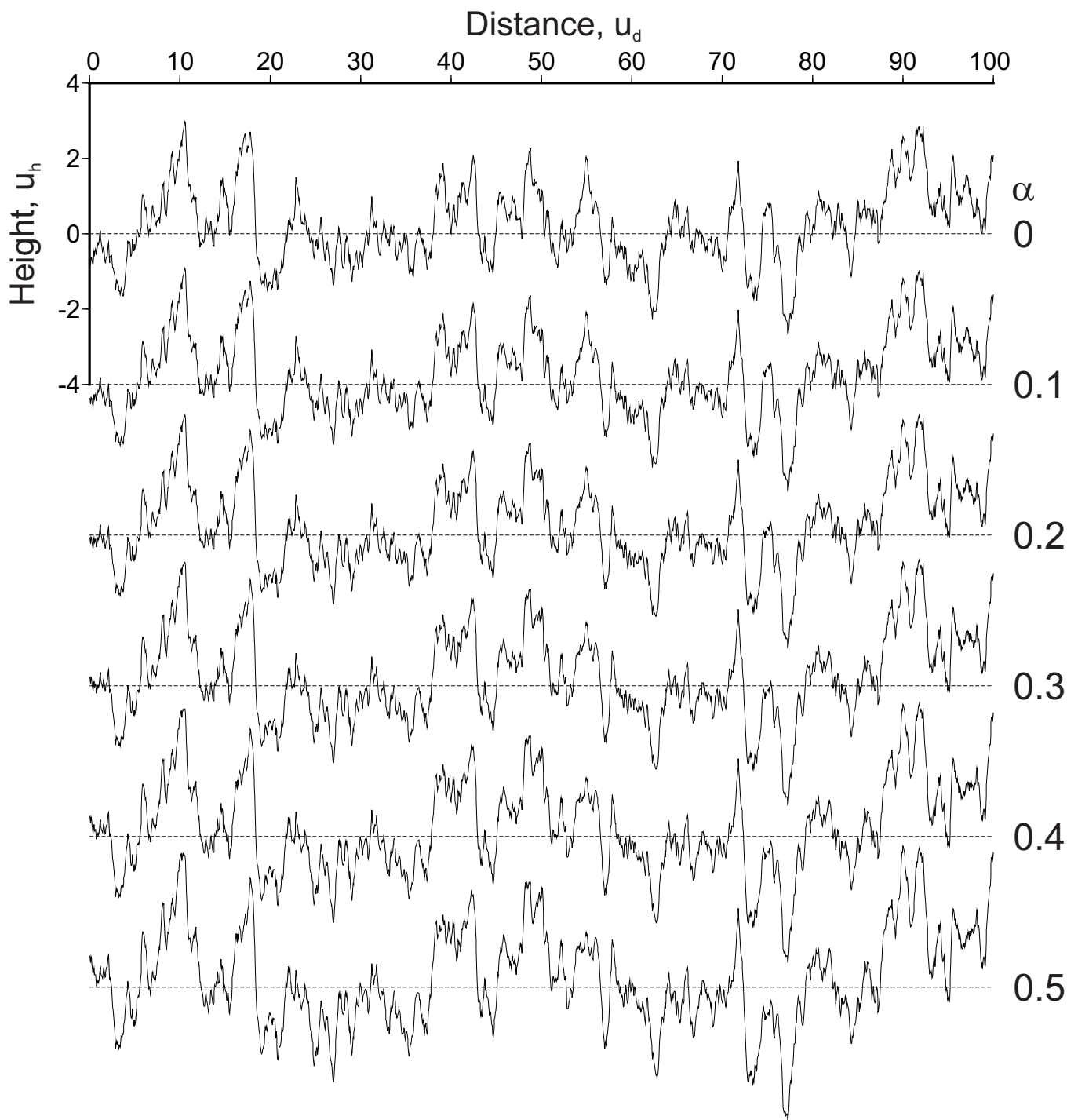


Figure 1

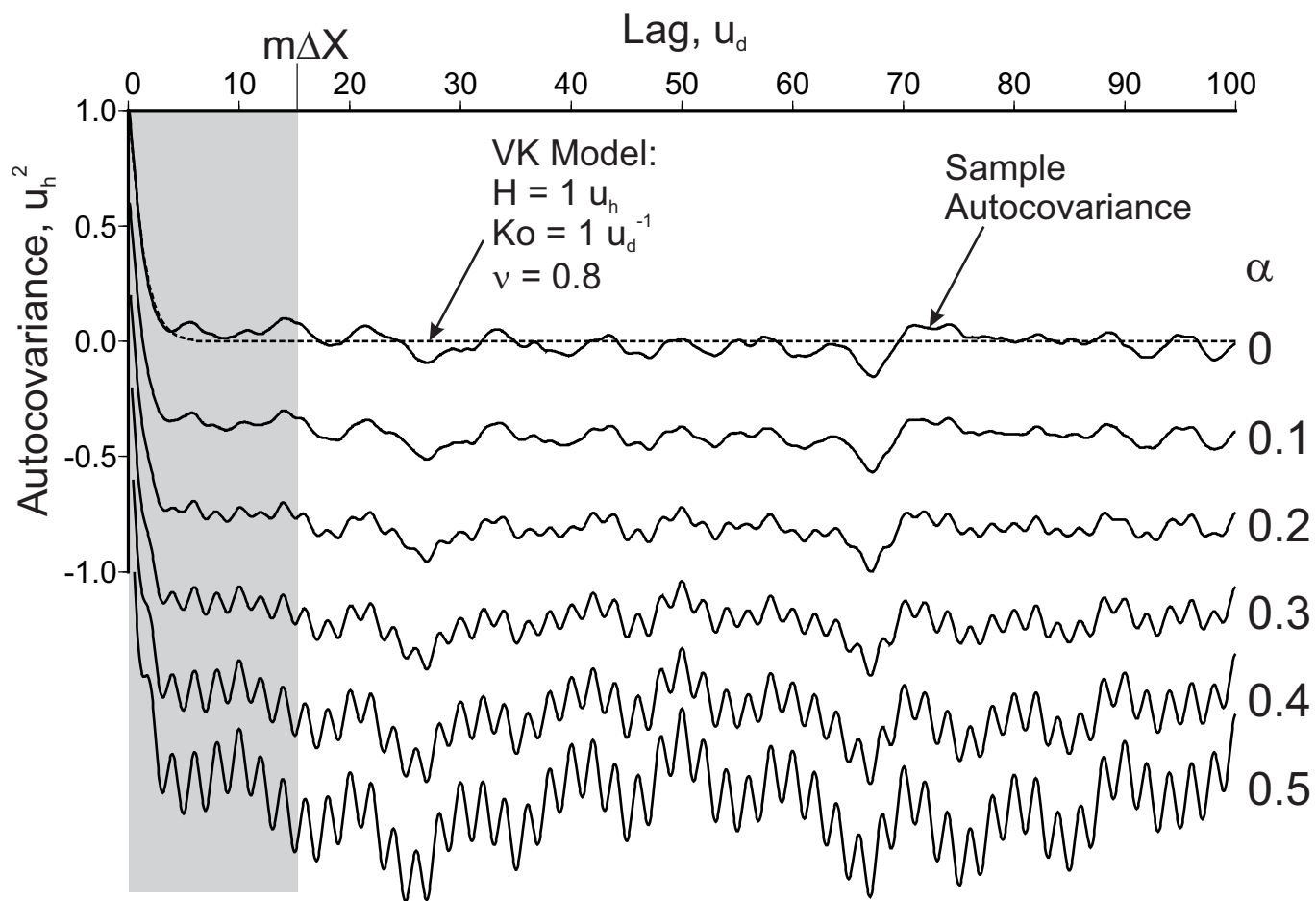


Figure 2

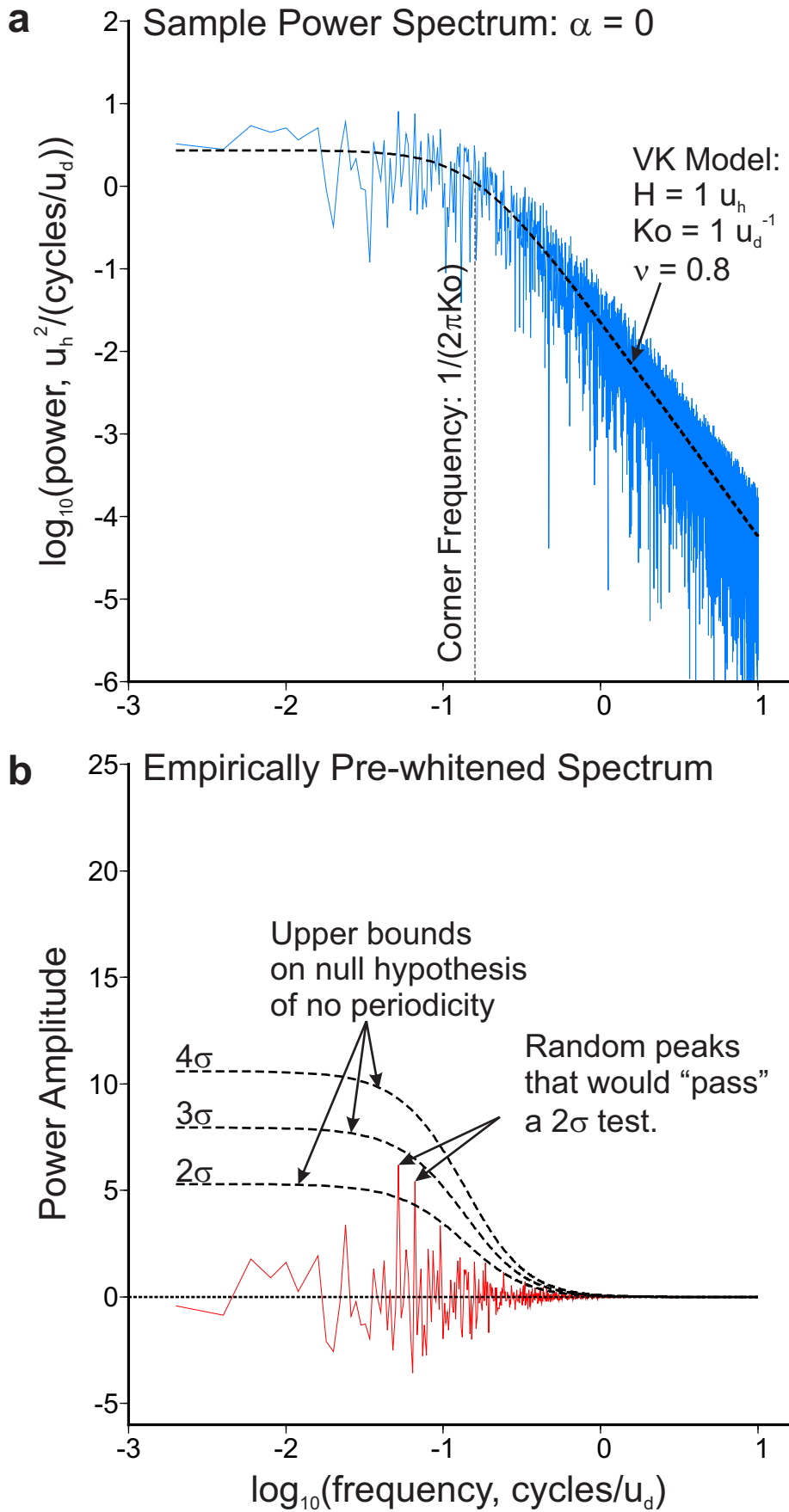


Figure 3

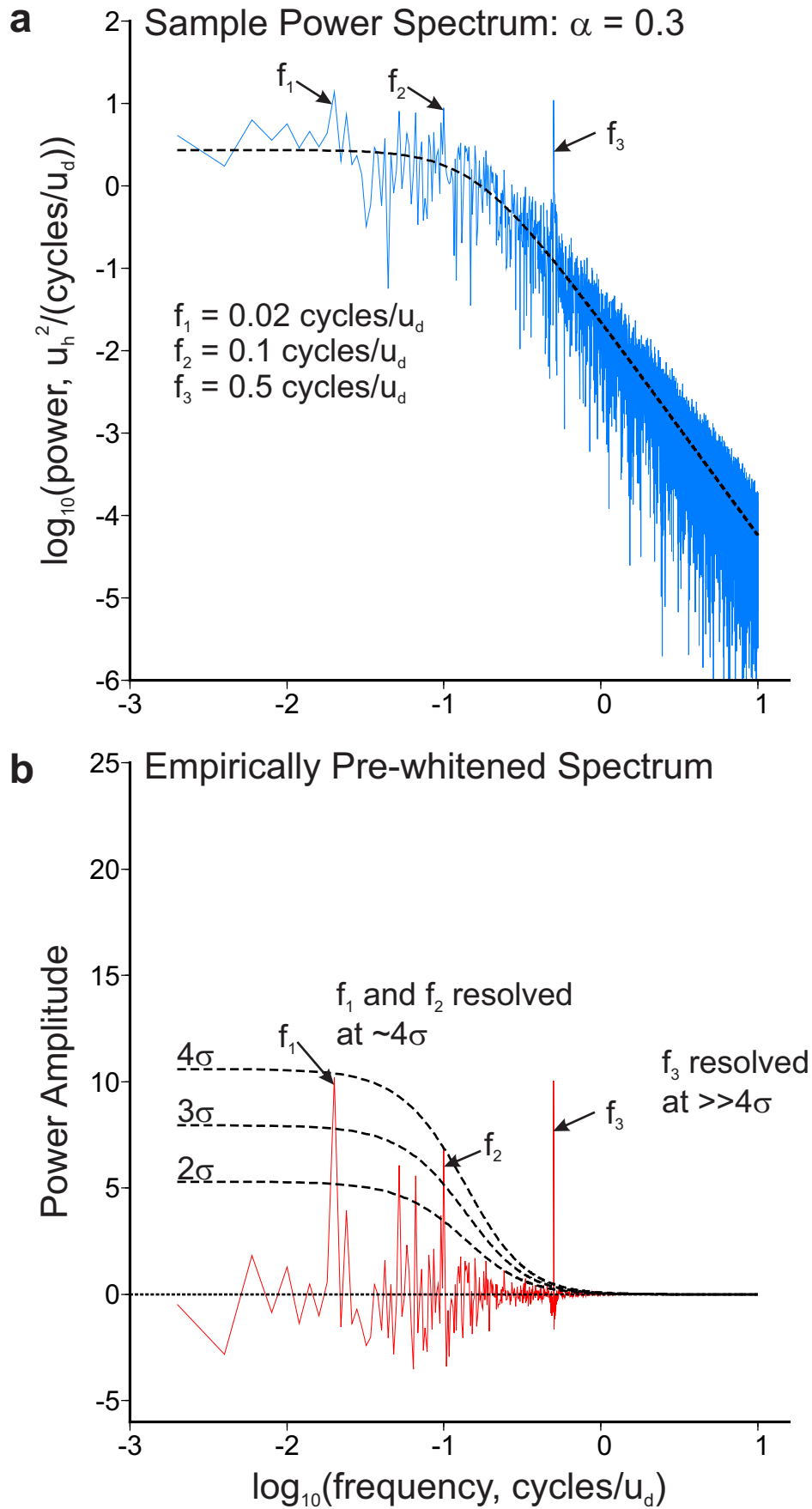


Figure 4

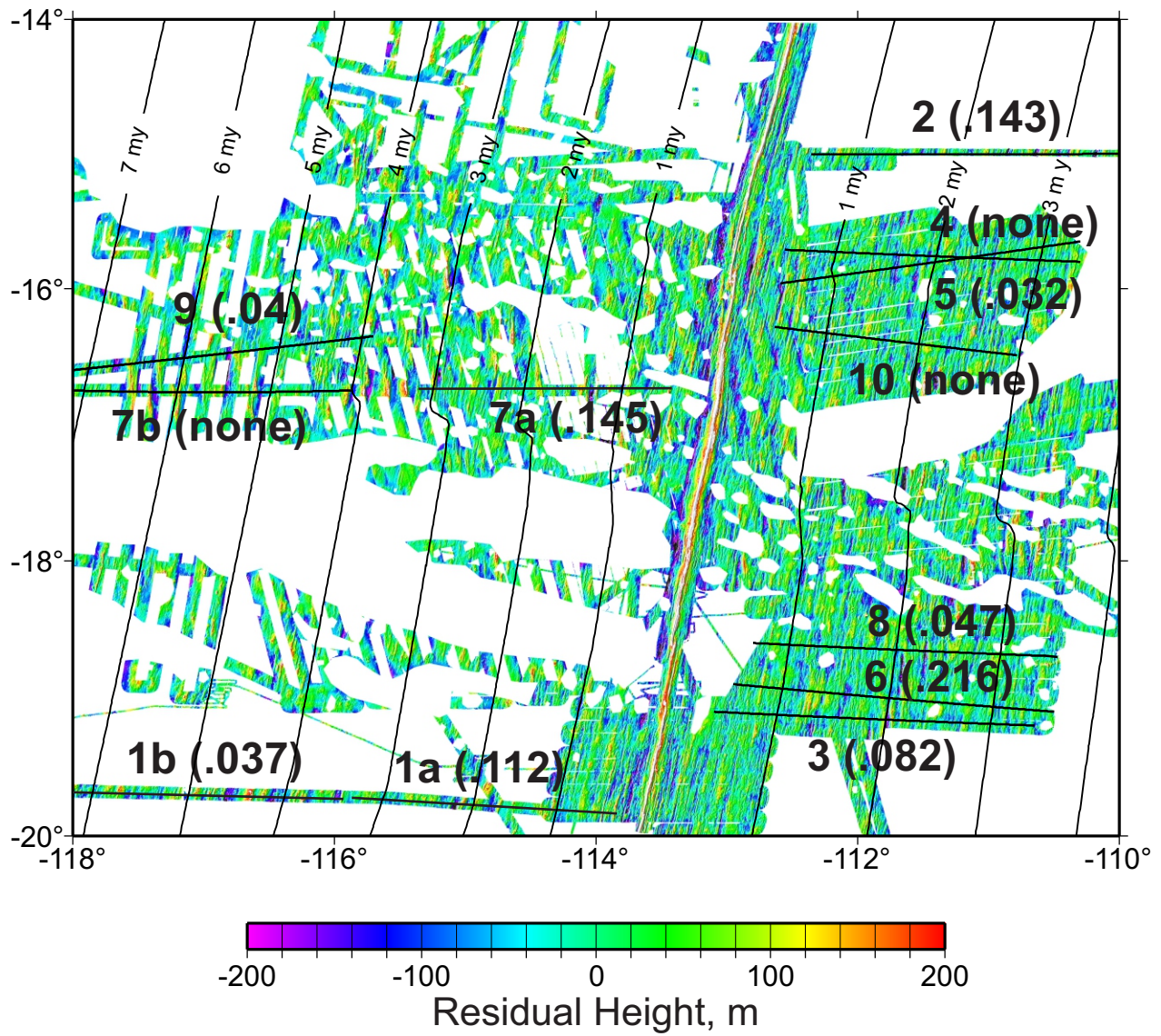


Figure 5

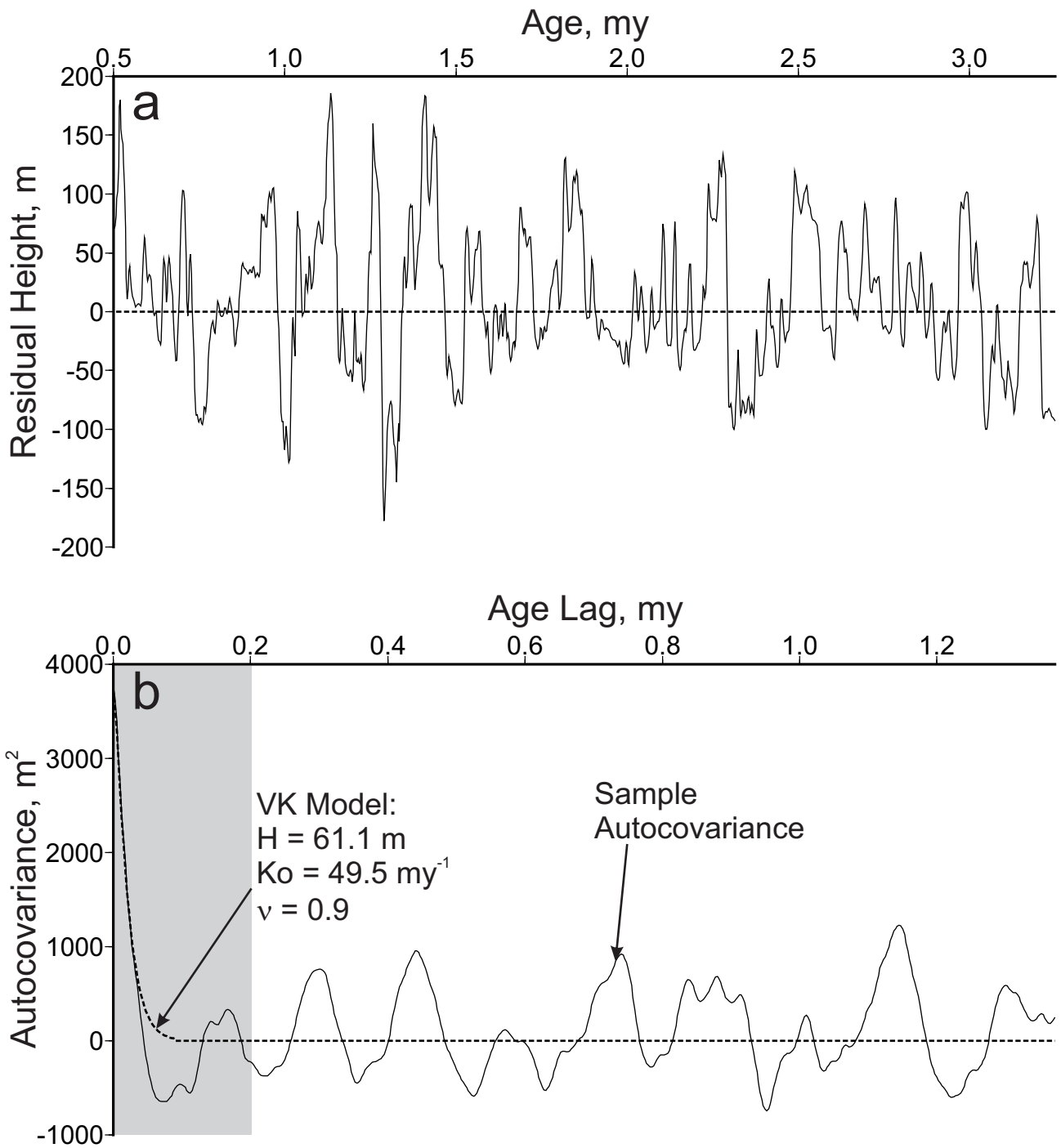


Figure 6

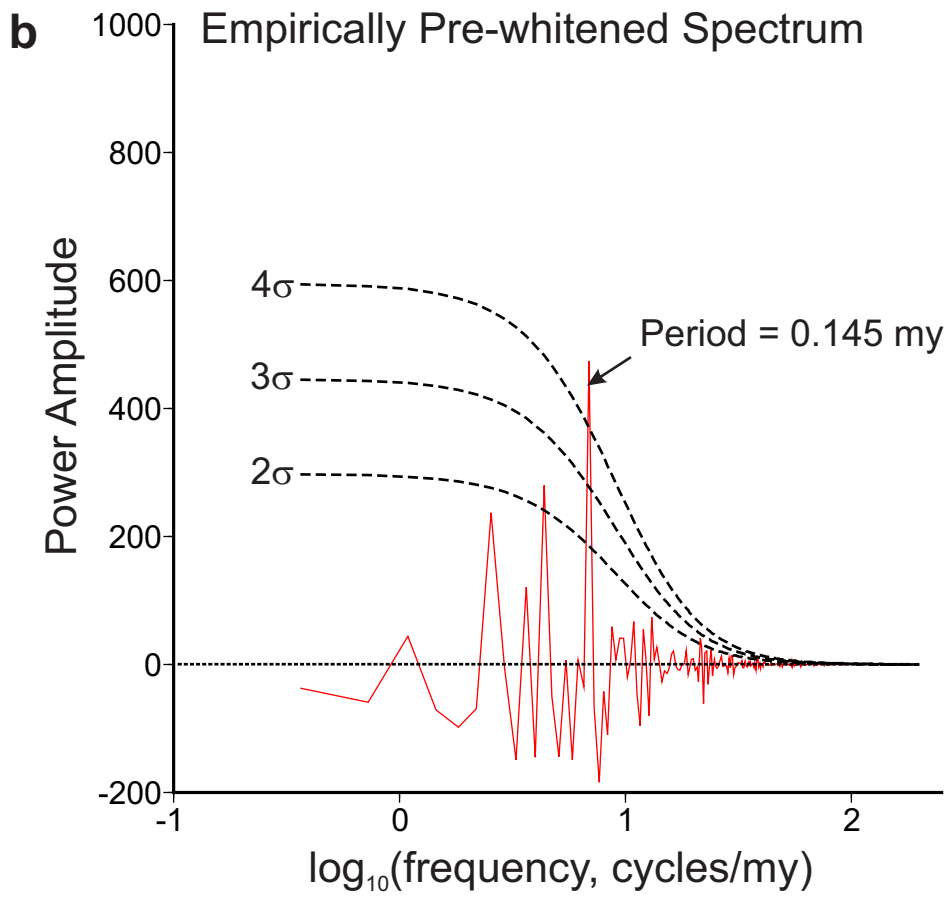
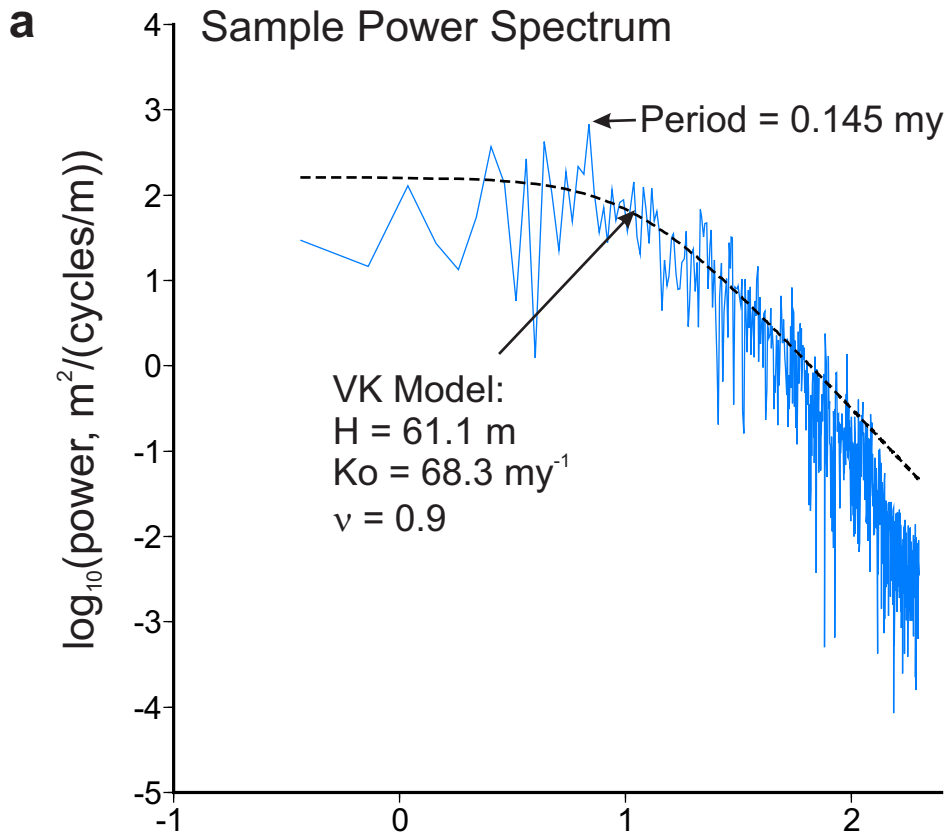


Figure 7

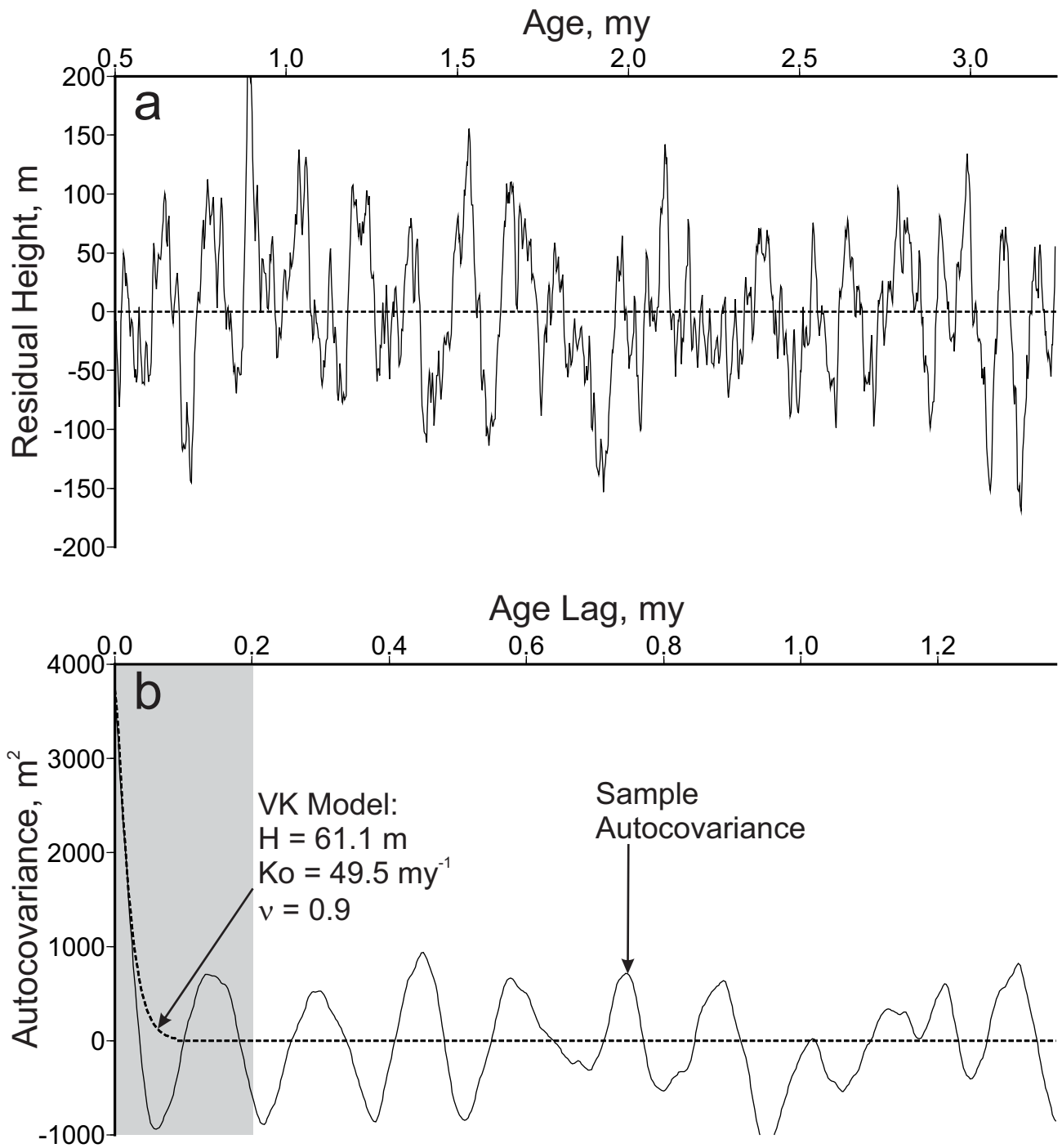


Figure 8

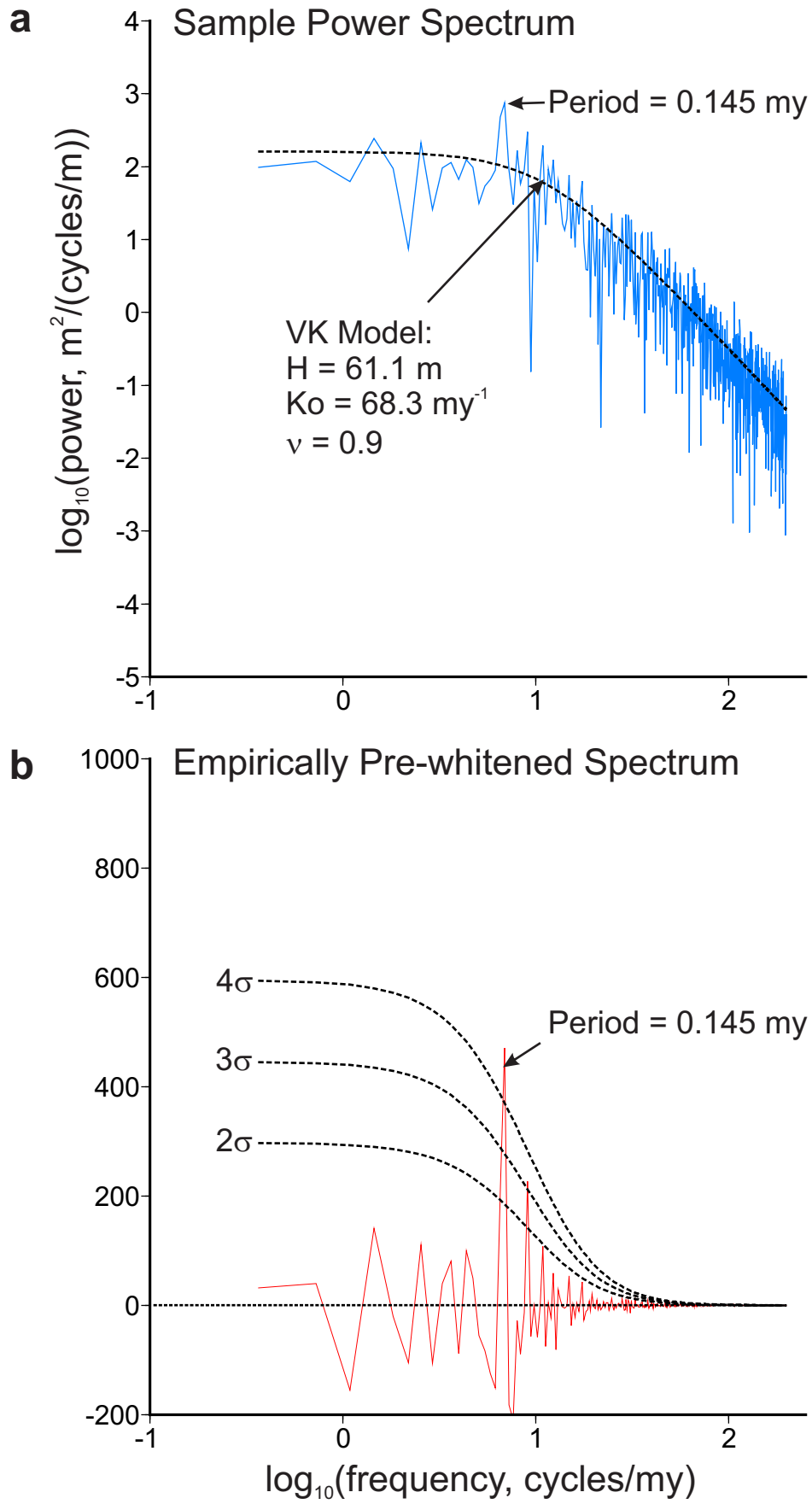


Figure 9