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# Culture process and the interpretation of radiocarbon data

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## Abstract

Over the last decade archaeologists have turned to large radiocarbon data sets to infer pre-historic population size and change. An outstanding question concerns just how direct of an estimate radiocarbon dates are for human populations. In this paper we propose that radiocarbon dates are a better estimate of energy consumption, rather than a direct one-to-one estimate of population size. We use a scaling model to describe the relationship between population size, economic complexity and energy consumption in human societies, and then parametrize the model using data from modern contexts. Our results suggest that energy consumption scales sub-linearly with population size, which means that the analysis of a large radiocarbon time-series has the potential to misestimate rates of population change and absolute population size. Energy consumption is also an exponential function of economic complexity. Thus, the radiocarbon record could change semi-independent of population as complexity grows or declines. Scaling models are an important tool for stimulating future research to tease apart the different effects of population and social complexity on energy consumption, and begin to explain variation in the forms of radiocarbon date time-series in different regions.

**Keywords: Prehistoric Demography, Summed Probability Distribution, Macroecology, Deep-time Economics**

## Introduction

The objective of this paper is to critically discuss how to learn about prehistoric social and demographic processes from large samples of radiocarbon dates. Archae-

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22 ologists increasingly use large samples of radiocarbon dates to estimate human  
23 population sizes, long-term population growth rates and other demographic pro-  
24 cesses (e.g., Contreras and Meadows 2014; Crema et al. 2016; Kelly et al. 2013;  
25 Peros et al. 2010; Pettitt et al. 2003; Shennan et al. 2013; Shennan 2008; Wang  
26 et al. 2014; Williams 2013, 2012; Zahid et al. 2016). Making inferences from  
27 these data sets about demography, however, is not without challenges (Attenbrow  
28 and Hiscock 2015; Brown 2015; Williams 2012). The issues stem from processes  
29 external and internal to prehistoric human populations. The majority of archaeo-  
30 logical studies focus on external processes that may bias inferences about popula-  
31 tion from radiocarbon date time-series, such as the effects of site sampling, sample  
32 size, radiocarbon date calibration and preservation bias (e.g., Brown 2015; Con-  
33 treras and Meadows 2014; Shennan 2013; Surovell et al. 2009; Williams 2012).  
34 These studies constitute invaluable frames of reference for making more informed  
35 inferences about demographic processes from the frequency of radiocarbon date  
36 time-series. However, little attention has been paid to the ways that cultural pro-  
37 cess, internal to prehistoric populations, may affect the creation of the radiocarbon  
38 record.

39       Simply put, fundamental changes in the basic contours of a society might  
40 prompt shifts in the relationship between population size and the datable mate-  
41 rials that people produce. As a first step in exploring this issue, we model the  
42 effects of population size and economic complexity on the production of waste  
43 products that archaeologists date, and explore how it might confound the ways we

44 currently make inferences about demographic and other cultural dynamics from  
45 the frequency distribution of large samples of radiocarbon dates. We use modern  
46 data to parametrize the model and, from our results, make two points relevant to  
47 the study of dates as data. (1) Radiocarbon date frequencies arrayed in a time-  
48 series, based on large samples of dates, probably misestimate rates of population  
49 growth. This is because radiocarbon dates, all else equal, are one measure of the  
50 energy consumed by prehistoric populations, and the scaling relationship between  
51 population and energy consumption is often sub-linear in human populations, but  
52 may also fluctuate from sub-linear-to-linear-to-super-linear over time. (2) Un-  
53 derstanding the previous point permits researchers to make predictions about how  
54 the radiocarbon record covaries with other classes of material culture and further  
55 evaluate the importance of changes in energy consumption in prehistoric social  
56 change.

## 57 **Dates as Data and Energy Consumption**

58 The premise behind using the frequency of radiocarbon dates in a time-series to  
59 infer population trends is that the number of person years a region is occupied is  
60 proportional to the production of cultural waste that archaeologists date. As Rick  
61 (1987:54) states,

62 “Despite intervening biases, I assume that the number of dates is related  
63 to the magnitude of occupation, or to the total number of person-years

64 of human existence in a given area. Using this premise, it is possible to  
65 assess and compare, in a relative fashion, the occupation histories within  
66 and between regions.”

67 This is a reasonable starting point, but there are two related critiques of this basic  
68 assumption.<sup>1</sup>

69 First, it lacks an explicit theoretical basis in basic principles of physics. Ther-  
70 modynamics provides such a theoretical basis. The organic materials that archae-  
71 ologists date are created, most often, through the process of transforming matter  
72 from a state of higher potential energy to a state of lower potential energy. For  
73 example, burning wood transforms the wood from a higher to lowered state of  
74 potential energy (ash). This transformation is energy consumption. Such energy  
75 consumption is a continuous process in human societies because human societies  
76 function as complex, open systems, and individuals within such societies must  
77 continuously process energy to live and reproduce (Georgescu-Roegen 1971). The  
78 constant flux of energy through an open, complex system, in turn, maintains order  
79 far from thermodynamic equilibrium (Georgescu-Roegen 1971). The consump-  
80 tion of energy by humans, thus, creates waste products that archaeologists can  
81 date, such as animal bone, mussel shell, charred seeds, wood charcoal, etc.

82 Given that human populations function as complex, open systems, we propose  
83 that the frequency of radiocarbon dates in a given region, at a given time, is more  
84 reasonably conceptualized as an estimate of the energy consumed in that region

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<sup>1</sup>See Attenbrow and Hiscock (2015) for different critiques.

85 over a given interval of time by prehistoric populations rather than a direct reflec-  
86 tion of the person years of occupation. This proposition assumes that the mate-  
87 rials we date (bone, charred wood and seeds, etc.) are the byproducts of energy  
88 consumption events that occur as populations live and reproduce, maintaining a  
89 social-economic system far from thermodynamic equilibrium. The more of such  
90 events that take place during a given time period, the more likely it is that organic  
91 waste products will preserve and accumulate. This assumption, we believe, is  
92 more informed by theory and closer to the data than the assumption that cultural  
93 waste products reflect, in some proportional way, person-years.

94 Second, following Rick's initial assumption, most studies assume that popula-  
95 tion size and the frequency of radiocarbon dates produced by prehistoric popula-  
96 tions are proportional (Peros et al. 2010:659). A proportional relationship means  
97 that a one unit increase in population will result in a one unit increase in the pro-  
98 duction of material that archaeologists can radiocarbon date, and, in a large sam-  
99 ple of dated cultural material, increases in date frequency reflect proportional in-  
100 creases in population. A subtle ancillary assumption of this relationship between  
101 population size and waste production is that individuals in a population are au-  
102 tonomous, and their production and consumption decisions that result in waste  
103 lack mutual interdependence.

104 This may be a poor assumption. Social networks and technological differences  
105 can create efficiencies of scale that lead to a sub-linear relationship between pop-  
106 ulation and the consumption of energy, materials and information in human soci-

107 eties (Freeman and Anderies 2015; Hamilton et al. 2007). And, as noted above, the  
108 consumption of energy, whether burning wood to stay warm or consuming bone  
109 marrow to maintain metabolic needs, drives the accrual of datable materials. We  
110 simply do not know whether the accumulation of cultural debris, due to the con-  
111 sumption of energy, and population size are related in a proportional manner, and  
112 this may bias our ability to make inferences about demographic processes from  
113 large samples of radiocarbon dates. Thus, to make inferences from such data, we  
114 need to build models for understanding how population and energy consumption  
115 are related, based on the fundamental principles of thermodynamics that underlay  
116 all contemporary and historically documented societies.

## 117 **Model and Methods**

118 To build a model that scales population and the production of datable materials we  
119 assume the following: All else equal, the frequency of radiocarbon dates collected  
120 via unbiased sampling is one estimate of the quantity of energy consumed by pre-  
121 historic populations, and the waste products that result are proportional to the total  
122 amount of energy consumed. These assumptions are simple, but, we argue, more  
123 reasonable than assuming radiocarbon date frequencies are an unmediated reflec-  
124 tion of population. Given the above assumptions, we propose a model of changes  
125 in energy consumption that shares the same structure as a widely used macroeco-  
126 nomic model of human impacts on ecosystems (York et al. 2003).

127 Formally,

$$E = F(A)P \quad (1)$$

128 where  $E$  is total energy consumed;  $F(A)$  is a function that describes the energy  
129 necessary for an average individual to live and reproduce; and  $P$  is population.

130 We assume that  $F(A)$  is defined by biological metabolism and economic com-  
131 plexity. By economic complexity we mean the number of specialties in an arbi-  
132 trarily bound economy. We assume that as the number of economic specialties  
133 increases, it takes more energy to integrate populations through exchange, visita-  
134 tion ceremonies, and the like. This, in turn, increases the per capita level of energy  
135 needed for an average individual to live and reproduce. We assume here that bio-  
136 logical metabolism is a constant across human populations (i.e., varies much less  
137 than complexity). Holding biological metabolism constant, the energy necessary  
138 per person is a function of complexity,  $C$ ; where  $C$  is a unitless index of the number  
139 of niches or capabilities in a system.

140 In mathematical notation, we write the effect of  $C$  on energy consumption as  
141 an increasing exponential function:

$$F(A) = m_1 e^{\beta_1 C} \quad (2)$$

142 where  $m$  is a constant metabolic rate (energy per person per unit time); and  $\beta_1$  is a  
143 coefficient that scales the rate of change in energy consumption per unit increase in  
144 complexity,  $C$ . This equation assumes that the consumption of energy compounds

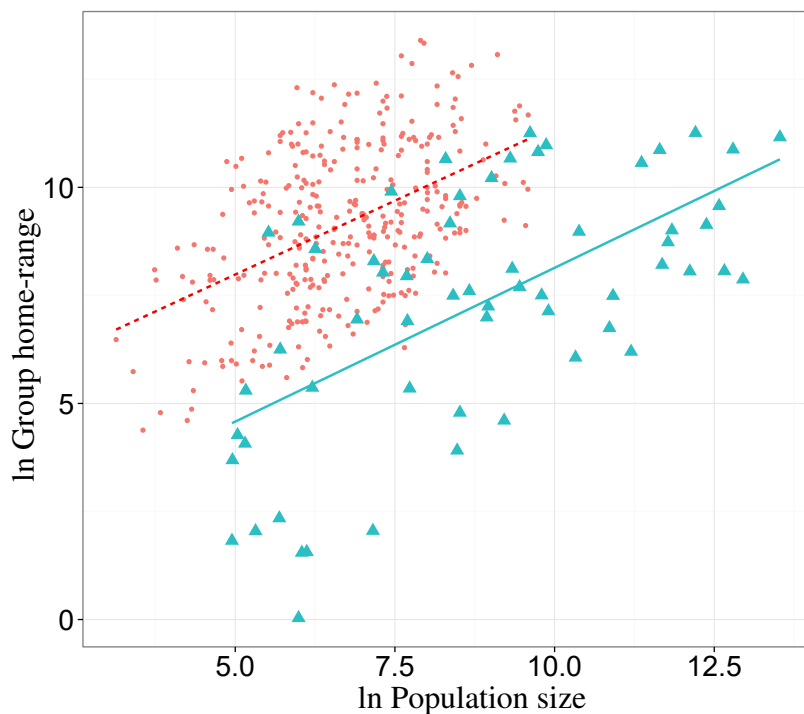


145 exponentially as the number of niches in a political–economy increases. Where  
146 the political–economy is very simple (has only one niche), then per capita energy  
147 consumption is very near an individual’s biological metabolic rate. As  $C$  increases,  
148 however, the consumption of energy necessary for a given population to live and  
149 reproduce compounds exponentially to account for all of the new specialties in an  
150 economy and the need to integrate those specialties.

151 Holding complexity equal, Equation 1 captures the basic assumption that pop-  
152 ulation scales linearly with total energy consumption, and that individuals in a  
153 population do not interact in ways that create increasing or decreasing efficiencies  
154 in the consumption of energy. Our working hypothesis here is that the relationship  
155 between population and energy consumption is sub-linear rather than in proportion  
156 as equation 1 assumes. This means that adding one more individual to a foraging  
157 camp does not require one more cubic meter of wood to keep that individual warm.  
158 We suspect that the relationship is sub-linear because of previous work on territory  
159 size in human societies.

160 Not unlike our assumption that the frequency of radiocarbon dates estimates  
161 energy consumption, ecologists have long assumed that the size of an animal’s  
162 range (territory) is an estimate of the energy that an average individual needs to  
163 consume (Brown et al. 2004; Jetz et al. 2004; Lindstedt et al. 1986; Milton and  
164 May 1976; McNab 1963). For instance, the larger an animal’s body size, the larger  
165 its range because big animals consume more energy than small animals (McNab  
166 1963). Models of animal territory size applied to hunter-gatherers and subsistence

167 agricultural societies also assume that the size of a group's territory is an emergent  
168 outcome of the area needed to consume energy by a population (Freeman 2016;  
169 Freeman and Anderies 2015; Hamilton et al. 2009, 2007). These studies indicate  
170 that, among both hunter-gatherers and agriculturalists, territory size is often a sub-  
171 linear function of population size (Figure 1). Why this is the case remains an open  
172 question, but current hypotheses concur that as population size increases, individ-  
173 uals become more efficient consumers of energy and information and, thus, have  
174 more overlapping individual home-ranges (Freeman and Anderies 2015; Hamilton  
175 et al. 2009).



**Figure 1:** Population–territory size scaling Dots=hunter-gatherer societies; triangles=agricultural societies. The dashed line is an OLS regression line for hunter-gatherers; the solid line is the same for agriculturalists. Reproduced from Freeman (2016).

176 A common way to capture the possibility that the relationship between popula-

177 tion and energy consumption might be sub-linear is with a power function,  $\beta$ :

$$E = m_2 P^{\beta_2}. \quad (3)$$

178 Where  $E$  is the total energy consumed by a population;  $m_2$  is a scaling constant;  
179 and  $\beta_2$  is the scaling exponent. Where  $\beta_2$  is equal to one, population scales linearly  
180 with energy consumption;  $0 > \beta < 1$  the scaling is sub-linear; and  $\beta > 1$  the  
181 scaling is super-linear.

182 Given equations 2 and 3, we can combine the constants of  $m_1$  and  $m_2$  and set  
183  $m_1 * m_2 = M$  to re-write equation 1 as,

$$E = F(A)P = M e^{\beta_1 C} P^{\beta_2}. \quad (4)$$

184 In sum, equation 4 states that the total energy consumed by a population is biolog-  
185 ical metabolism times economic complexity, which defines a cultural metabolism  
186 per person to live and reproduce, times the total number of people in a population.

## 187 **methods**

188 Equation 4 allows us to investigate the scaling relationship between population  
189 size and energy consumption, holding economic complexity constant. We can  
190 evaluate whether the scaling of population and energy consumption is linear, sub-  
191 linear or super-linear in contemporary contexts using robust linear regression. By  
192 taking the log of the right and left hand sides of equation 4, we obtain a linear

193 model:

$$\ln E = \ln M + \beta_1 C + \beta_2 \ln P + \varepsilon \quad (5)$$

194 where  $\varepsilon$  is the variance in the log of energy consumption not explained by popula-  
195 tion. We use the log transformations to make equation 4 linear, because this allows  
196 us to use robust techniques for estimating  $\beta_2$  using a linear regression model.

197 To evaluate the relationship between population and energy consumption, we  
198 use four data sets that document the relationship in contemporary societies. In the  
199 first, we use International Energy Agency estimates of total energy consumption  
200 (IEA 2016) in 146 countries in 2013 and population estimates for each country  
201 from the World Bank in 2013 (TWB 2016). The energy consumption data are self  
202 reported by each of the countries in the data set. The data, thus, come from coun-  
203 tries with mainly subsistence economies to countries with post-industrial knowl-  
204 edge economies (e.g., Tanzania vs. Japan), and the data vary in accuracy, which  
205 is a source of measurement error. We have made an attempt to control for vari-  
206 ance in energy consumption driven by big differences in economic complexity by  
207 collecting data from Hausmann et al. (2014) on economic complexity. The data  
208 are available for 117 countries that also have population and energy consumption  
209 data. Hausmann et al. (2014) measure economic complexity as the diversity and  
210 ubiquity of products in an economy, which reflect the amount of information and  
211 the scale of networks in the economy. The larger the scale of information and  
212 networks, the more organizationally complex the economy. Using these data, we

213 can examine the scaling relationship between population and energy consumption  
214 holding economic complexity constant.

215 In the second data set, we use estimates of total energy consumption in US  
216 states in 2014 obtained from the United States Energy Information Administra-  
217 tion (EIA) (EIA 2016) and estimates of population in 2014 obtained from the US  
218 Census. These data are standardized estimates of energy consumption collected  
219 by energy professionals in the EIA. We treat economic complexity among US  
220 states as a constant because the variation in complexity is less than the global  
221 sample. This means that all US states are similar in economic complexity to say  
222 France, but no state approaches the lower 1/2 of the economic complexity distri-  
223 bution observed at a global scale. In the global and US data sets we combine all  
224 forms of energy consumption (e.g., wind, solar, nuclear, coal) and sectors (e.g.,  
225 transportation, industrial, residential). We are not concerned that many of these  
226 energy sources would not result the production of datable materials, but, rather,  
227 with describing the general scaling relationship between population and energy  
228 consumption.

229 In the third data set, we look at the relationship between the number of fami-  
230 lies in villages and wood-fuel consumption in Bangladesh (Miah et al. 2009:Table  
231 2). This last data set is not sufficient for a formal regression analysis because the  
232 sample size is well below 30 and, thus, standard errors are inflated. Yet, the data  
233 set is instructive because we can observe energy consumption at a much smaller  
234 scale and level of analysis than in the first two data sets. These data were collected

235 among subsistence farmers as part of an ethnographic study on fuel consump-  
236 tion and deforestation. Again, economic complexity varies little from village-to-  
237 village in this data set, so we treat complexity as a constant.

238 Finally, in the fourth data set we observe the relationship between the popu-  
239 lation size of Kalahari Bushman camps and the number of hearths in each camp.  
240 We assume that the number of hearths is a proxy for the amount of fuel-wood  
241 and other organics consumed by the population of each camp to cook, stay warm,  
242 etc. Thus, we treat the number of hearths in a camp as an estimate of energy con-  
243 sumption among these hunter-gatherers. All data come from Yellen's (1977) eth-  
244 noarchaeological study of Kalahari Bushman. We tabulated the data from Yellen's  
245 camp descriptions. We estimated the total number of hearths in a camp by adding  
246 the formal hearths described for each camp with informal hearths. We estimated  
247 the number of informal hearths using Yellen's feature list for each camp site and  
248 tabulating the number of small one-time or special-purpose roasting pits, scatters  
249 or mounds of charcoal and ash that might be fire hearths. We avoided any that he  
250 specifically listed as hearth clean-outs, but it is possible that some informal hearths  
251 are clean-outs. This gave us a data set of 15 camps. As above, the caveat about  
252 small sample size applies, and economic complexity varies little from camp-to-  
253 camp, so we treat complexity as a constant.

254 We would like to emphasize that we are using data from three different scales  
255 (global, national, local), and these data come from a wide variety of economies.  
256 One might worry that differences in economic complexity might change the population-

257 energy consumption relationship; this is why we have taken the time and care to  
258 build data sets at very different scales and range of economic contexts. Convergent  
259 results would suggest that population has a wide spread effect on energy consump-  
260 tion that transcends types of economies.

## 261 **Results**

262 In sum, our results indicate that, at a global scale of analysis, population size  
263 and economic complexity both have effects on the total energy consumed by a  
264 population. Further, at a global scale, the scaling relationship between popula-  
265 tion and energy consumption, holding economic complexity equal, is sub-linear.  
266 The sub-linear scaling of population and energy consumption is replicated at finer  
267 scales of analysis where economic complexity varies much less than at a global  
268 scale. The scaling of population and energy consumption is sub-linear among US  
269 states, Bangladesh villages and Kalahari Bushman camps. Remarkably, the scal-  
270 ing coefficients identified in our analysis are similar to the population–fuel-wood  
271 consumption (energy consumption) coefficient of 0.79 (s.e.=0.04), controlling for  
272 forest cover and GDP, found by Knight and Rosa (2012:Table 2) in their study  
273 of wood consumption in 87 developing economies. This means that a sub-linear  
274 scaling of population and energy consumption, holding other factors equal, occurs  
275 across five different data sets collected at different scales of analysis and with vary  
276 different levels of technological variation.

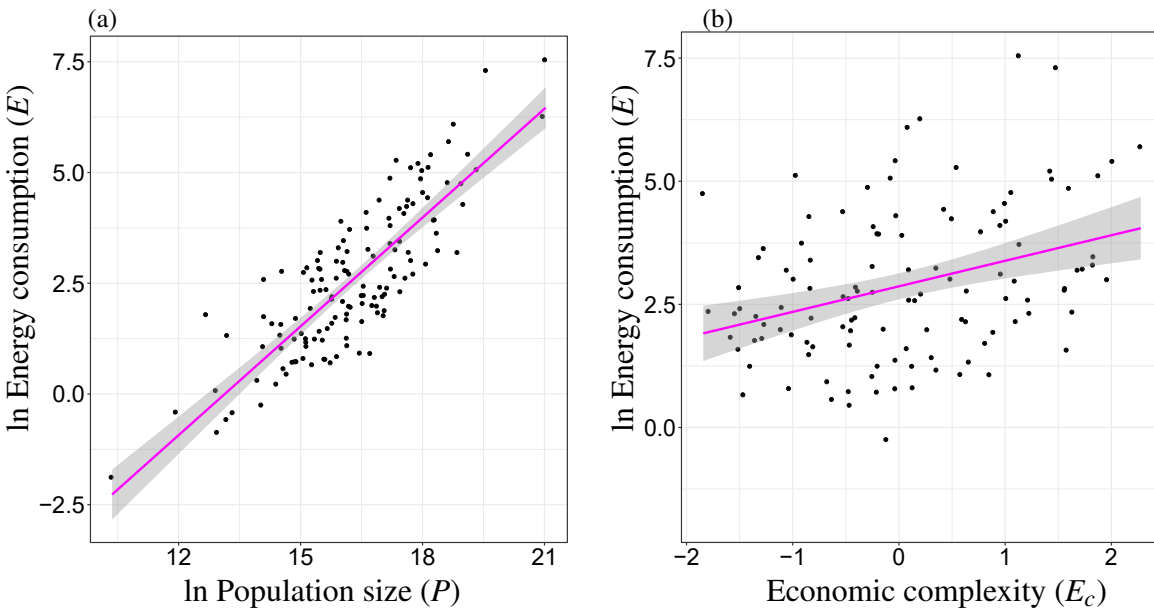
**Table 1:** Coefficients, standard errors and t-values of population and economic complexity regressed on ln energy consumption.  $R^2=0.78$ .  $P$ =population size;  $E_c$ =economic complexity;  $M$ =energy/person (y-intercept).

Variable	$\beta_i$	Std. Error	t-statistic	p-value
$M$	-11.983	0.781	-17.176	< 0.001
$\ln P$	0.891	0.042	21.237	< 0.001
$E_c$	0.533	0.059	8.966	< 0.001

277 Table 1 illustrates that the scaling relationship between population and en-  
 278 ergy consumption is sub-linear, even after controlling for economic complexity,  
 279 at the global scale (Table 1). As expected, population has a positive effect on  
 280 energy consumption, with a sub-linear coefficient of  $\beta_2 = 0.89$  (se=0.042, 95 %  
 281 C.I. 0.97-0.81). Also, as expected, economic complexity has a positive effect on  
 282 energy consumption. The more complex a country's economy, the more energy  
 283 the population of a country consumes. Finally, although both population size and  
 284 economic complexity have effects on energy consumption consistent with theory;  
 285 population size explains more of the variance in energy consumption than eco-  
 286 nomic complexity. This is intuitively illustrated by Figure 2. Note that the points  
 287 are a much tighter fit around the best fit line in Figure 2a vs. 2b.

288 Figure 3 illustrates that the scaling of population size and energy consumption  
 289 is sub-linear at finer scales of analysis where economic complexity is much less  
 290 variable among US states and Bangladesh villages. Among US states, a one unit  
 291 increase in population results in a  $\beta_2 = 0.86$  (se=0.04, 95 % C.I. 0.93-0.78) unit  
 292 increase in energy consumption (Figure 3a). Among Bangladesh villages the scal-  
 293 ing of population and fuel-wood consumption is again sub-linear, at  $\beta_2 = 0.89$   
 294 (se=0.19). However, due to the very small sample size, the standard error of  $\beta_2$  in



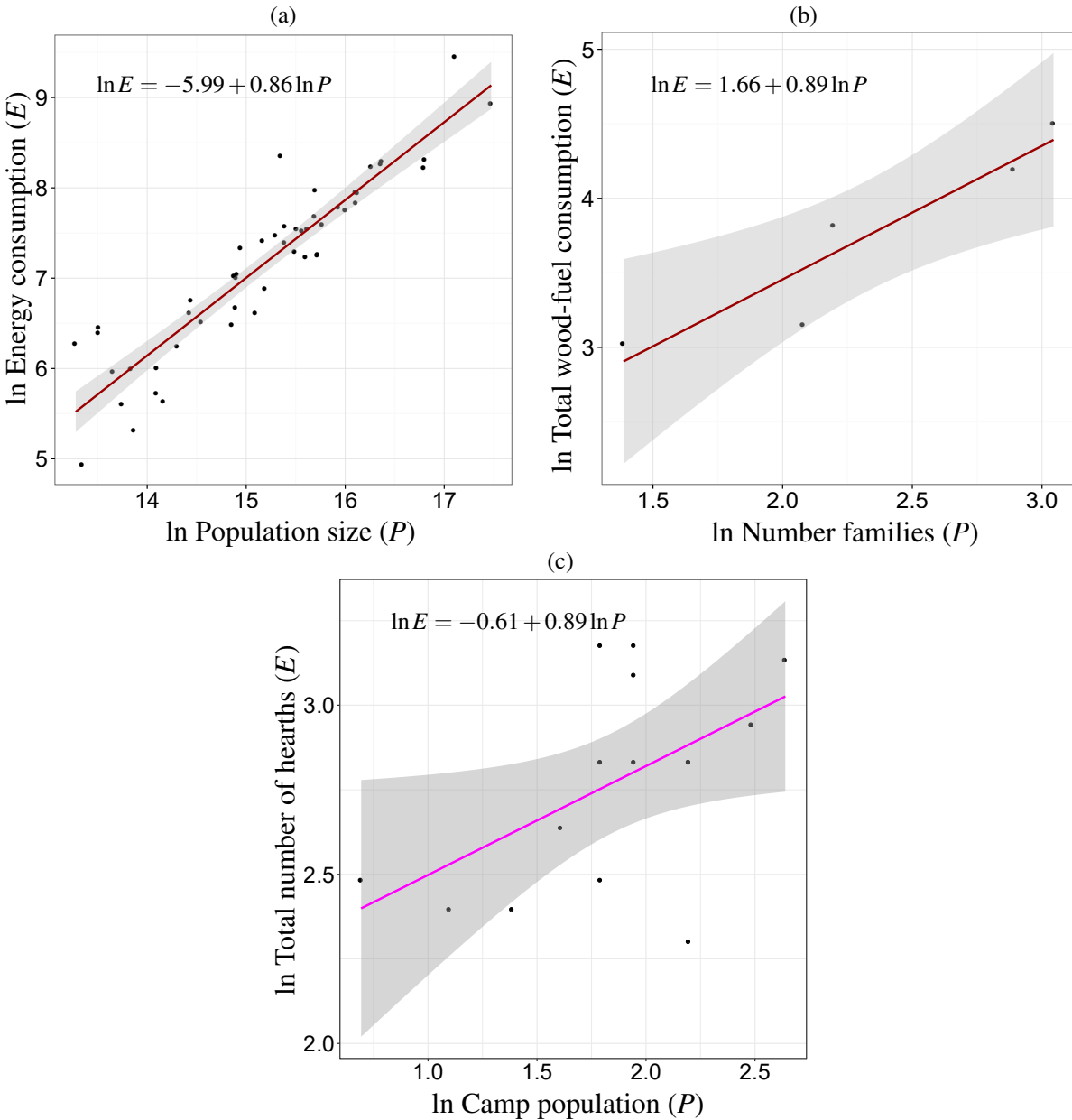


**Figure 2:** The relationship between population and total energy consumption among world countries (a); & the relationship between economic complexity and total energy consumption among world countries (b).

295 this case is quite large, and  $\beta_2 = 1$  is within the 95 % confidence interval for the  
 296 scaling exponent. Among Bushman camps the scaling of population and number  
 297 of hearths is sub-linear, at  $\beta_2 = 0.89$  (se=0.38). As with the Bangladesh villages,  
 298 the sample size and standard error caveats apply.

## 299 Discussion

300 So far, we have proposed a model that scales population against the production  
 301 of datable materials in social-ecological systems, and we have parametrized the  
 302 model using modern data on population size and energy consumption. We assume  
 303 that a one unit increase in the energy consumed by a prehistoric society results in  
 304 a proportionate increase in the accrual of materials that archaeologists ultimately  
 305 date. Contemporary data sets demonstrate a sub-linear scaling relationship be-



**Figure 3:** The relationship between population and total energy consumption among US states (a); number of families and total fuel-wood consumption in Bangladesh villages (b); & camp population and total number of hearths in Kalahari Bushman camps (c).

306 tween population size and total energy consumption, and do so at three different  
 307 levels of analysis and in five different data sets (Figures 2 & 3). Further, at a global  
 308 scale where variation in economic complexity is widest, economic complexity has  
 309 a positive effect on the consumption of energy (Table 1 & Figure 2).

310 The model proposed by equation 4 and the results of our analysis, which are  
311 consistent with equation 4, suggest two points relevant to the study of dates as  
312 data. (1) Radiocarbon date frequencies arrayed in a time-series, based on large  
313 samples of dates, as currently constructed, probably misestimate rates of popula-  
314 tion growth. This is because radiocarbon dates, all else equal, are one estimate  
315 of the energy consumed in prehistoric social-ecological systems, and the scaling  
316 relationship between population and energy consumption is often sub-linear in  
317 human populations. (2) Equation (4) provides a framework to make predictions  
318 about how the radiocarbon record should covary with other classes of archaeo-  
319 logical material culture and further evaluate the importance of changes in energy  
320 consumption in prehistoric social change.

### 321 **Estimating population size and growth**

322 The sub-linear scaling of population size with energy consumption documented  
323 above suggests that current approaches to interpreting radiocarbon date frequen-  
324 cies systematically misestimate population size over a given interval of time and  
325 growth rates. This is not a concern if we don't care about absolute population  
326 sizes and growth rates. For example, some researchers pool together dates that  
327 are associated with the same context/site (e.g. Shennan et al. 2013; Timpson et al.  
328 2014). This is done to control for sampling bias by archaeologists, and shifts the  
329 frequency of radiocarbon dates from an estimate of the number of individuals to an  
330 estimate of the number of sites. Counting sites is the classic method that archaeol-

331 ogists use to estimate changes in population. This method is probably pretty good  
332 for understanding relative changes in population over time. However, this method  
333 degrades the information contained within the radiocarbon record. We may want  
334 to know about absolute values of population size and change. In this case, we  
335 need to think about how to adjust frequencies of radiocarbon dates to account for  
336 the non-linear relationship between population and energy consumption, without  
337 simply using them to count sites, which has the benefit of controlling for sampling  
338 intensity but also has the cost of lost information.

339 Given our model and results, we propose, as a thought experiment, a method for  
340 rescaling radiocarbon datasets to estimate relative population sizes that accounts  
341 for a sub-linear relationship between population size and the evidence for energy  
342 consumption. To conduct this thought experiment we hold economic complexity  
343 constant because this factor appears to determine less variation in energy con-  
344 sumption than population size. It is the evidence of energy consumption events,  
345 not population size, that archaeologists analyze, and the available data suggest a  
346 sub-linear relationship between population size and the consumption of energy.  
347 Starting with equation 4, since  $M$  is a constant, we can let  $M = 1$ , hold  $C = 1$ , and  
348 solve for  $P$  at a given time  $t$  by raising each side of the equation to a power of  $1/\beta$ :

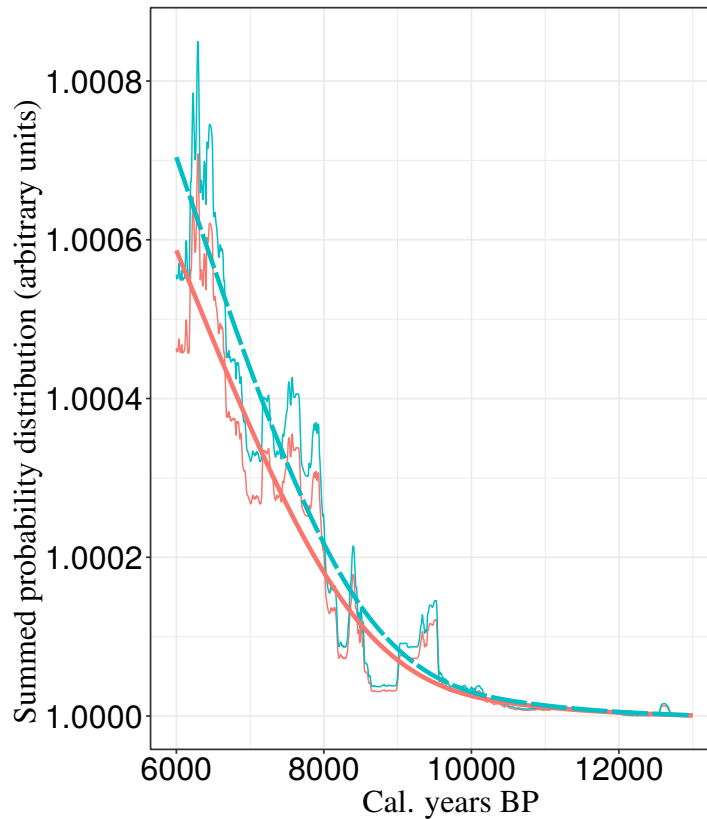
$$P_t = E_t^{\frac{1}{\beta}}. \quad (6)$$

349 Taking our contemporary data as a starting point, we could rescale the fre-  
350 quency of dates in any given time period by a scaling factor between 1.12–1.26,

351 (i.e.,  $1/\beta$ ) for the range of values derived above from the modern data sets (Knight  
352 and Rosa 2012:Table 2; this study). It is important to note that by doing this we  
353 assume that the sub-linear scaling of population and energy consumption (and,  
354 inversely, the super-linear scaling of energy consumption and population) is an in-  
355 variant law of human social-ecological dynamics. This is a strong assumption, and  
356 one we make with caution. For now, however, a hypothetical scaling exponent of  
357 1.15 recognizes the sub-linear relationship between population and the production  
358 of datable material. Doing this does two things: It raises estimates of population  
359 size in any given time interval, and it increases estimates of population growth.

360 In this case, the rate of change in the scaled summed probability distribution  
361 (SPD) is 15 % faster, and, thus, the estimated growth rate 15 % faster than an un-  
362 scaled SPD of radiocarbon dates (the dashed curve increases faster than the solid  
363 curve in Figure 4). In terms of real numbers, Zahid et al. (2016: 934) estimate  
364 the annual population growth rate of SW Wyoming and Colorado, using an SPD  
365 uncorrected for taphonomic loss, as 0.053 %. Our results suggest that this under-  
366 estimates population growth from between 12 % to 26 %, which yields growth  
367 rates from 0.05936 % to 0.0667 %. Simply put, an unscaled SPD underestimates  
368 population size, and, because the relationship between energy consumption and  
369 population may be sub-linear, an unscaled SPD will also underestimate rates of  
370 population growth.

371 For context, Zahid et al. (2016:932) correct their raw growth rate of 0.053 %  
372 for taphonomic loss to obtain a growth rate of 0.041 % during the period from



**Figure 4:** Raw and transformed SPDs. Dashed blue curve is the best fit for the transformed SPD; the solid red curve is the best fit for the raw SPD.

373 13000 to 6000 Cal. BP. Thus, in absolute terms, the energy scaling adjustment is  
 374 comparable to the taphonomic adjustment. In fact, deep in time both adjustments  
 375 cancel each other out. However, as one moves closer to the present taphonomic  
 376 loss is less important and an adjustment for population–energy scaling would have  
 377 more of an effect. In relative terms, at low population sizes, neither adjustment  
 378 probably matters all that much.

379 However, the energy scaling adjustment applies through a whole time-series at  
 380 a constant rate; and a change of 15 % in growth rate may be more meaningful  
 381 for larger populations, and over time periods in which populations were growing  
 382 at faster rates. For example, if a population of 1000 experienced a period of ex-

383 ponential growth at 1 % vs. 1.15 % over 200 years, the population growing at  
384 1 % would have a population of approximately 7,316 people and the population  
385 growing at 1.15 % a population of approximately 9,844 people (about a 35% dif-  
386 ference). Keep in mind also that the energy scaling adjustment factor also changes  
387 absolute population sizes and, holding space constant, population density. Theory  
388 suggests that critical population density thresholds fundamentally change the se-  
389 lective pressures put on individuals (Binford 1999; Freeman et al. 2015; Freeman  
390 and Anderies 2012; Winterhalder et al. 1988). If we are systemically underes-  
391 timating population densities, we may be missing evidence that such thresholds  
392 were approached and crossed.

393 In sum, if the goal of a project is to reconstruct absolute population densities or  
394 growth rates, then an informed researcher might transform their radiocarbon date  
395 curve to account for the non-linear scaling of energy consumption and population  
396 size, as documented here. To be clear, we are not suggesting that all SPDs need  
397 to be adjusted to account for the sub-linear scaling of population and energy con-  
398 sumption. Rather, if absolute growth rates are important, then we need to build  
399 frames of reference useful for estimating absolute growth rates from SPD data.  
400 Conceptualizing radiocarbon date time-series as estimates of energy consump-  
401 tion, thus, does not preclude using SPDs to estimate demographic parameters, but  
402 rather, gives us a more informed way to do so. This is just one advantage of devel-  
403 oping a model framework, from the factors that should drive energy consumption  
404 in human societies, for predicting variation radiocarbon date frequencies.

## 405 **Predicting covariates in the archaeological record**

406 We know from previous research that archaeologists must control for the effects  
407 of calibration, over sampling of single features or sites (sampling intensity) and,  
408 under certain circumstances, taphonomic processes before inferring population  
409 parameters from large radiocarbon time-series (Brown 2015; Contreras and Mead-  
410 ows 2014; Surovell et al. 2009; Williams 2012). Proper radiocarbon hygiene limits  
411 over-sampling induced bias, and recent research has shown that large sample sizes  
412 (1000+ assays) are more robust to the effects of preservation bias (Williams 2012).  
413 Much work has gone into these issues. Intuition probably tells most archaeologists  
414 that these issues are more important than the social dynamics of prehistoric pop-  
415 ulations that created the radiocarbon record through energy consumption events.  
416 This, however, is an empirical question, and our approach does not reject the im-  
417 portance of sampling bias and taphonomic processes. Our approach simply puts  
418 processes external and internal to prehistoric systems on a more equal footing so  
419 that we can begin to tease apart the most important factors.

420 As a final discussion point, the theoretical framework developed above provides  
421 a starting point to observe the relationships between radiocarbon date frequencies  
422 and other classes of phenomena related to energy consumption in the archaeolog-  
423 ical record. We do not argue that radiocarbon date frequencies are a sufficient  
424 measure of energy consumption. Rather, the radiocarbon record is one estimate of  
425 energy consumption. We can correlate the radiocarbon record with other estimates  
426 of energy consumption using other classes of material culture to evaluate this idea



427 further. For example, if the radiocarbon curve is an estimate of total energy con-  
428 sumption, we would expect to see spikes in the radiocarbon curve correlate with  
429 the use of more energy dense biomass, like grass seeds and nuts, as opposed to less  
430 energy dense resources on the landscape. So macrobotanical evidence of seed use  
431 should spike or evidence of agricultural intensification should spike as the radio-  
432 carbon record spikes, depending on the region and economic context. The model  
433 we have proposed is not an end product, but is a beginning theory, justified by  
434 basic relationships between population and energy consumption in modern con-  
435 texts, and these modern relationships suggest that the model may prove useful in  
436 archaeological contexts as well.

## 437 **Conclusion**

438 The purpose of this paper has been to critically discuss how to observe prehistoric  
439 social and demographic processes from large samples of radiocarbon dates. While  
440 much thought has been given to non-cultural biasing agents, much less attention  
441 has been paid to how prehistoric culture process may affect the accumulation of  
442 datable materials in prehistoric social-ecological systems and, thus, the amount  
443 of material available for archaeologists to come along date. Consequently, we  
444 suggest that understanding the energy consumption dynamics of human societies  
445 represents both a critical and logical next step to make predictions that explain  
446 variation in radiocarbon date time-series.

447 We propose that large, regional-scale samples of radiocarbon dates estimate  
448 changes in the consumption of energy in prehistoric populations rather than popu-  
449 lation *per se*. It is important to note that this is just one estimate. If this approach  
450 has validity, then future research will show clear positive covariation between fre-  
451 quencies of radiocarbon dates and other material estimates of energy consumption,  
452 like the frequency of ground stone or the size of middens. Our results suggest that  
453 energy consumption is a sub-linear function of population size and is positively  
454 related to economic complexity, at a global scale. Given these relationships, if  
455 one is interested in using radiocarbon data to estimate population growth rates, it  
456 may be productive to adjust a resultant time-series to estimate relative population  
457 sizes and changes in population over time. This adjustment should not be viewed  
458 as a “correction” of a radiocarbon curve. Correction implies that a given curve  
459 is wrong. Rather, the adjustment represents an informed judgment that should be  
460 made if one’s research goal is to estimate absolute population growth rates, and  
461 if future research supports the hypothesis that the scaling of population size and  
462 energy consumption is sub-linear. We have presented this correction example as a  
463 thought experiment; as a challenge to make us think about what kind of correction  
464 we might need and when.

465 Large samples of radiocarbon dates are a potentially informative way to mea-  
466 sure prehistoric culture process. More work is needed, however. We suggest three  
467 lines of research that may complement the already vigorous research into how best  
468 to make inferences from radiocarbon time-series.

- 469 ● Collect more data on contemporary or ethnographically recorded economies  
470 to empirically investigate the scaling relationship between population and  
471 energy consumption. If the scaling of population and energy consumption  
472 is an invariant law driven by basic metabolic processes (Brown et al. 2004;  
473 Hamilton et al. 2007), this would be incredibly convenient for archaeologists  
474 interested in making inferences from large radiocarbon data sets. However,  
475 the scaling may vary with technology or social institutions over time and  
476 space (DeLong and Burger 2015; Freeman and Anderies 2015), which would  
477 mean that different parts of the radiocarbon date time-series would need to  
478 be rescaled, from the perspective of estimating population size and growth  
479 rates, by different scaling factors over different segments of time.
  
- 480 ● Evaluate the scaling of population and energy consumption in archaeological  
481 contexts. We would simply need an area in which researchers have invested  
482 in collecting many radiocarbon dates and there are preserved structures that  
483 are partly independent of the radiocarbon record due to recording on sur-  
484 vey that would allow for traditional population estimates based on structure  
485 counts in the same region.
  
- 486 ● Study further the effects of economic and political complexity on energy  
487 consumption. Fluctuations in radiocarbon date time-series curves, holding  
488 all else equal, also result from changes in social and economic organization  
489 (Crombé and Robinson 2014). Holding population constant, changes in eco-

490        nomic organization, as well as complexity, should affect how much energy  
491        an average individual consumes.

492        To end, we would like to emphasize again that our contribution is theoretical.  
493        We have proposed a quantitative model to describe the relationship between the  
494        production of radiocarbon dates and human population. The practical relevance is  
495        twofold. First, the model we have specified allows us to predict how radiocarbon  
496        dates should covary with other classes of archaeological material culture. Second,  
497        and the nominal focus of our paper, the model allows us to make better judgments  
498        about how to infer prehistoric population parameters from large samples of radio-  
499        carbon dates. Our approach is not a finished product, but it is an initial step toward  
500        a more mature, deductive approach to learning about social and demographic pro-  
501        cesses from large samples of radiocarbon dates.

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