

# Modelling Temporal Uncertainty in Archaeological Analysis

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**Abstract** This paper discusses the problem of temporal uncertainty in archaeological analysis and how it affects archaeological interpretation. A probabilistic method is proposed as a potential solution for modelling and quantifying time when high levels of uncertainty restricts temporal knowledge and scientific datings are unavailable, while Monte Carlo simulation is suggested as a means to formally integrate such knowledge into actual analysis. A case study focusing on counts of prehistoric hunter–gatherer pithouses in Mid-Holocene Japan provides an example of how uncertainty can be problematic and bias the results of the most straightforward archaeological analysis and how the coupling of a probabilistic and simulation-based approach nonetheless offers a useful solution. The discussion that follows also addresses the need for more robust and quantifiable ways to illustrate the chronological flow of our archaeological narratives.

**Keywords** Temporal uncertainty · Monte Carlo methods · Chronology · Jomon · Population dynamics

*‘The only relevant thing is uncertainty—the extent of our knowledge and ignorance.’ (de Finetti 1974:ix)*

## Introduction

In a seminal paper of 1973, Fred Plog pointed out that ‘archaeology’s strong point as a social science is a database that permits the observation of temporal variation in

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behaviour and cultural processes' (1973: 194). While this statement is widely accepted, and perhaps even regarded as a truism, there is a huge mismatch, in terms of disciplinary rigour, between two separate ways in which archaeologists consider time. On the one hand, the theoretical implications of time have been discussed from a wide range of perspectives (e.g. Ramenofsky 1998; Murray 1999; Karlsson 2001; Bailey 2007; Holdaway and Wandsnider 2008) along with the development of several methods for its measurement, ranging from the use of stylistic variation to build relative chronologies (see Lyman and O'Brein 2006 for an extensive review), to the use of scientific methods based on physics, chemistry and statistics (see Taylor and Aitken 1997). On the other hand, when we go beyond the strict domain of chronometry, we have often neglected the role of time in our quantitative methods, failing to integrate formally the temporal dimension as part of other analyses. When we infer something about the process of *change* in an archaeological phenomenon, our assessment of time is often restricted to introductory and concluding narratives, rarely reaching the core section of a paper in a formalised and quantitative manner. An exception to this trend can be found in several contexts where either absolute chronology is available from historical documents (e.g. studies on the end of Maya monument-building, see Premo 2004 for extensive bibliography) or from large number of radiocarbon dates (e.g. studies on the spread of agriculture in Europe; Bocquet-Appel *et al.* 2009; Collard *et al.* 2010). In both cases, time itself is treated as a dependent variable of spatial statistics, and both examples illustrate how proper quantitative integration of time is feasible. However, if we do consider these as exceptions, we must ask why in most other cases we neglect the role of time in quantitative methods.

Chronometry is somehow different and more complex than the measurement of other dimensions, as it requires the explicit definition of a model which links observable (and thus directly measureable) physical features to the flow of time (Spaulding 1960). When, for instance, an archaeologist dates an artefact, what she or he actually does is to measure properties associated with other non-temporal dimensions, such as the spatial location where the object was found (e.g. its stratigraphic context), its physical properties (e.g. residual contents of  $^{14}\text{C}$ ) or its stylistic features (e.g. presence absence of a specific decorative feature). Dates are then inferred from these indirect proxies based on some explicit or implicit model, which relates the variation of these variables to the actual flow of time. Therefore, we are dealing not with time itself but with measurable variables that act as the kernel of different *models* of time. There are three major consequences that we can expect from this: (1) imprecision and uncertainty in the measurements will be inherited with the estimate of time; (2) the model will be imperfect; and (hence) (3) it will be subjected to updates and revisions, altering our conclusions alongside the state of our knowledge. These factors will always lead to uncertainties in our evaluation of temporal data but whether the magnitude of this uncertainty is acceptable or not will depend on our primary research questions.

This paper tackles the thorny but surprisingly neglected problem of both the quantification of temporal uncertainties and their integration into archaeological analysis. 'Case Study: Jomon Pithouse Counts in South-West Kanto, Japan' presents a case study that provides an example of how temporal uncertainty limits our analysis and might lead to biased interpretations. 'Quantifying and Integrating

'Uncertainty' discusses the quantification of uncertainty through probabilistic weighting and its pitfalls. 'Monte Carlo Method-Based Solution' introduces the application of Monte Carlo methods for integrating temporal uncertainty in archaeological analysis. 'Rate of Change Analysis of South-West Kanto Pithouses' will illustrate its application for a case study and the last section will discuss the wider implications derived from its use in archaeological research.

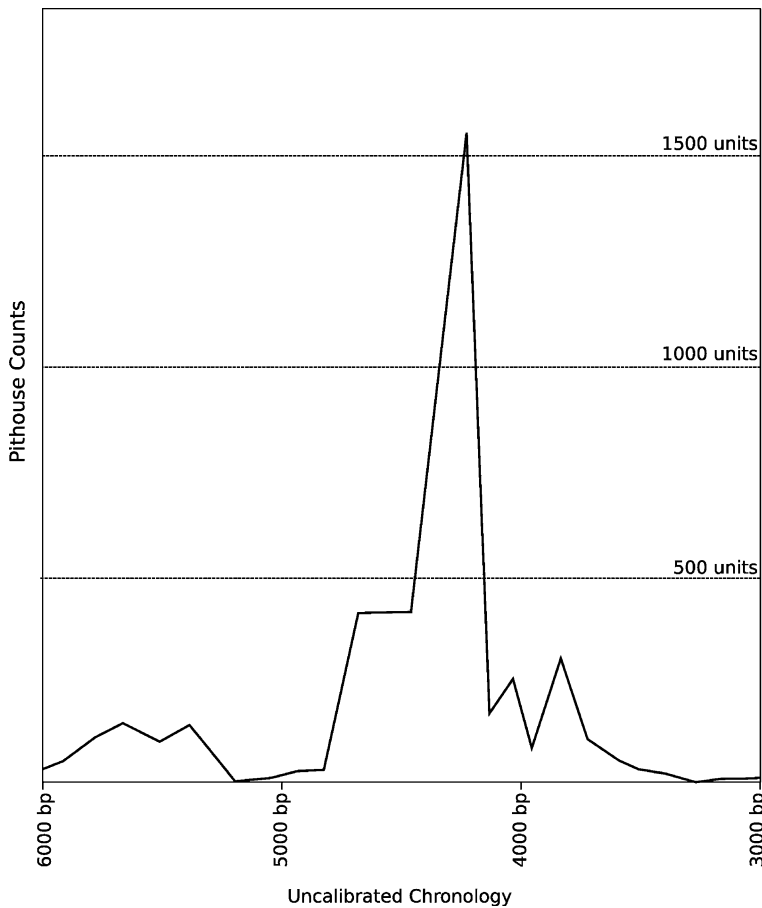
### Case Study: Jomon Pithouse Counts in South-West Kanto, Japan

The Jomon culture of Japan (ca 15700–2300 cal BP; Kobayashi 2008) provides unique opportunities for the study of the long-term dynamics of complex hunter–gatherer societies. The high number of emergency excavations (an average of ca. 8,500/year between 1990 and 2003; Okamura 2005), coupled with a detailed pottery-based chronology, supports the claim that Jomon culture is 'the best researched complex hunter–gatherer tradition known to archaeology' (Rowley-Conwy 2001:59).

A number of scholars (Imamura 1997; Uchiyama 2002, 2008; Habu 2001; Nishino 2005) have more or less explicitly fostered the hypothesis that a number of radical changes in population size, settlement systems and subsistence strategies occurred at multiple times over a time span of some 10,000 years, and in relation to episodes of climatic change. In the Kanto region of central Japan, for instance, at least three cycles of major population growth and crash have been suggested by studies of pithouse counts (Imamura 1996) and have been roughly correlated to episodes of changes in settlement configuration (nucleation *versus* dispersion), the observed degree of sedentism, transformations in subsistence practice and environment change (Nishino 2005).

In order to test the above hypothesis, there is an urgent need to firstly establish a precise and absolute chronological framework capable of correlating the archaeological record with palaeo-environmental data. However, in Japan, there has traditionally been a much higher reliance on pottery-based relative chronologies rather than absolute dating methods (Keally 2004), and this has severely limited opportunities to test formally any hypothesis about the cultural and economic response to environmental change. This trend has recently changed, thanks to an increased awareness of the importance of an absolute chronological frameworks and the establishment of a unique high-resolution archaeological record based on pottery styles and extensive excavations, which facilitates the re-assessment of previously collected data.

The archaeological record used for the present case study is a good example of such trend. The data were first published as a time-series plot by Imamura in 1997 (Fig. 1), who used a dataset collected in the mid-1980s and recently republished by Suzuki (2006). The original data consist of a series of tables with the pottery-based chronological definition of 9,612 Jomon pithouses from six prefectures of central Japan (Tokyo, Saitama, Yamanashi, Kanagawa and Nagano). For the purpose of this paper, a subset of 6,757 pithouses dated between Early and Late Jomon (7000–3220 cal BP, Fig. 2) and located in South-West Kanto (Tokyo, Saitama and Kanagawa prefectures, Fig. 3) has been considered. Such a spatial and temporal extent



**Fig. 1** Early to Late Jomon pithouse counts in South-West Kanto region divided into 100-year temporal blocks (modified and expanded from Imamura 1997)

facilitates the adoption of the most recent and precise cross-referencing of established pottery sequences and absolute calibrated chronology suggested by Kobayashi (2008).

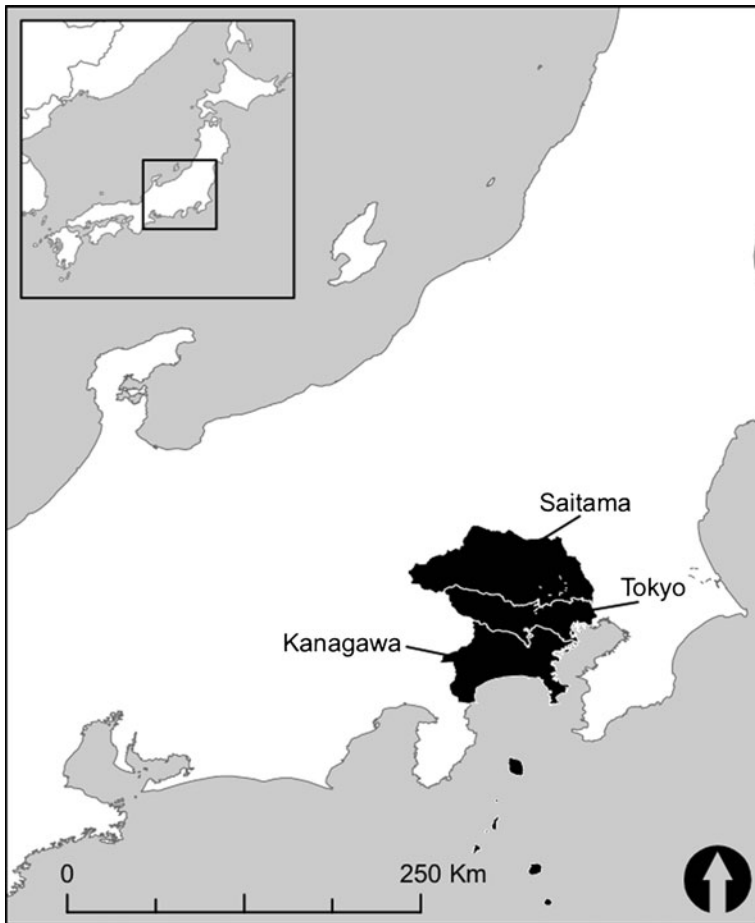
Imamura's chart has often been used as a proxy for the population dynamics of central Japan, showing that there are number of smaller fluctuations other than the main peak and crash of the Middle Jomon period. However, if we examine the actual raw data used by Imamura we see another picture. Figure 4 shows a subset of the same dataset published by Suzuki (2006) where the counts of pithouses have been distinguished based on their attributed dates and their degree of temporal uncertainty. Rows represent the pottery phases (compare with Fig. 2), while columns indicate the number of consecutive pottery phases within which pithouses might have existed, ranging from no uncertainty (leftmost column, listing pithouses attributed to a single pottery phase) to the highest level of uncertainty (rightmost column, with pithouses broadly attributed to the middle Jomon period). Thus, for instance, 49 pithouses are attributed to the time span between EJ3 and EJ5 (third to fifth row, third column).

Jomon Periods	Phase (this paper)	Pottery Phase (Suzuki 2006)	cal BP Interval (base on Kobayashi 2008)
Early Jomon	EJ1	Hanazumi Kasou/ Sekiyama	ca 7000 - 6450
	EJ2	Kurohama/Ario	6450-6050
	EJ3	Moroiso a	6050-5950
	EJ4	Moroiso b	5950-5750
	EJ5	Moroiso c	5750-5600
	EJ6	Jusanbodai	5600-5470
Middle Jomon	MJ1	Goryogadai 1	5470-5440
	MJ2	Goryogadai 2 / Otamadai 1a	5440-5380
	MJ3	Katsuzaka 1/ Otamadai 1b / Kakusawa	5380-5320
	MJ4	Katsuzaka 1/ Otamadai 1b / Aramichi	5320-5280
	MJ5	Katsuzaka 2/ Otamadai 2/ Fujiichi I	5280-5220
	MJ6	Katsuzaka 2/ Otamadai 3/ Fujiichi II	5220-5080
	MJ7	Katsuzaka 3/ Otamadai 4/ Idojiri I	5080-5000
	MJ8	Katsuzaka 3/ Otamadai 4/ Idojiri III	5000-4900
	MJ9	Daigi 8a/ Kasori E1 (I) / Sori I	4900-4840
	MJ10	Daigi 8b/ Kasori E2 (I) Sori II	4840-4750
	MJ11	Daigi 9/ Kasori E3 (II) Sori III	4750-4710
	MJ12	Daigi 9/ Kasori E3 (II) Sori IV	4710-4590
	MJ13	Daigi 10/ Kasori E4 (III) Sori V	4590-4520
	MJ14	Daigi 10/ Kasori E4 (IV) Sori V	4520-4420
Late Jomon	LJ1	Shomoyoji	4420-4245
	LJ2	Horinouchi 1	4245-3980
	LJ3	Horinouchi 2	3980-3820
	LJ4	Kasori B1	3820-3680
	LJ5	Kasori B2	3680-3530
	LJ6	Kasori B3	3530-3470
	LJ7	Soya	3470-3400
	LJ8	Angyo 1	3400-3300
	LJ9	Angyo 2	3300-3220

**Fig. 2** Comparison of the chronological sequences used in the present paper and the one used by Suzuki (2006) and Kobayashi (2008)

The series of numbers at the bottom are the relative percentage of pithouses divided by each level of uncertainty and shows how only 15.8% of the data can be attributed to the highest possible chronological resolution (a single pottery phase). The reasons of such wide variation in the temporal definition of these pithouses are various, but in most cases these are likely to be related to the quality, quantity and diversity of the recovered potsherds. Imamura acknowledged this problem and used a pragmatic solution centred on the redistribution of the uncertain data based on the knowledge provided by this 15.8%. Thus for instance, if the relative proportion of pithouses dated to subphase *A1* and *A2* were 0.3 and 0.7, 30 of the pithouse attributed to the broader phase *A* were ‘redistributed’ on *A1* and 70% to *A2*. This approach allowed the maintenance of the relative proportion suggested by the high-resolution sub-data. Imamura also acknowledged how his own definition of the absolute duration of the pottery phases might have been biased and stated that distinctions between the ‘real’ pattern and the pattern purely generated from his chronological definition remains untested.

The consequences of these limits are critical when we wish to estimate the correlation between environmental changes described with an absolute chronological framework and an archaeological record based on a pottery-based chronology where the degree of



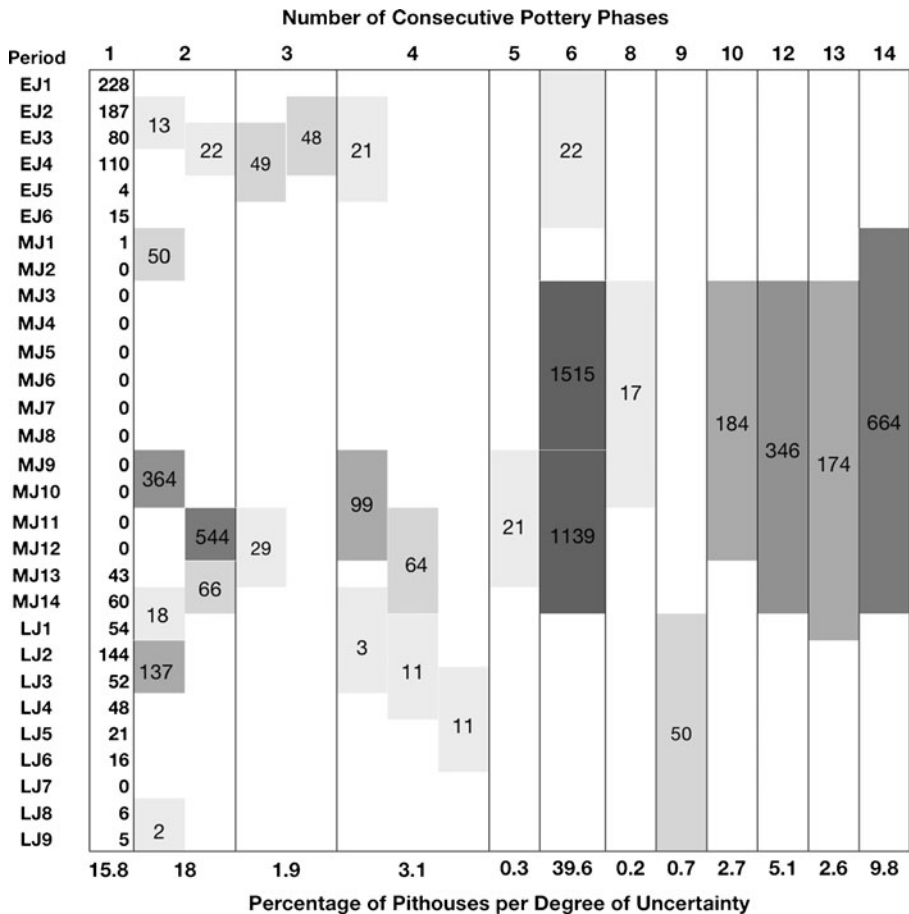
**Fig. 3** Location of the study area

temporal uncertainty is much higher and quantitatively undefined. In particular, while we can delineate broad dynamics, we are not able to formally assess whether, at any given window of time, the number of pithouses increased or decreased.

### Quantifying and Integrating Uncertainty

Imamura's approach is, as he notes, ultimately an opportunity for further testing as: (1) it does not integrate the absolute chronological duration of each pottery phase (which was in fact unavailable at the time of his publication) and (2) tackles the issue of temporal uncertainty by exploiting the knowledge of only a small portion of the available data. Undoubtedly, such an approach would be affected by how such knowledge is structured and distributed (Fig. 4).

A more formal approach can be derived from Laplace's 'principle of insufficient reason' (see Sinn 1980 for discussion). The principle states that in case of an absence



**Fig. 4** Subset of Suzuki's (2006) dataset showing the counts of pithouse distributed by temporal uncertainty. Rows represents pottery phases (here coded EJ1 to LJ6, compare with Fig. 2) while columns refers to the degree of temporal uncertainty expressed as number of possible pottery phases (the time span within which pithouses might have existed). The numbers on the bottom of each column shows the relative percentage of pithouses for each degree of uncertainty

of additional knowledge, a uniform probability distribution can be regarded as the best approximation of our knowledge of the system. In terms of our case study, this will translate into a probability distribution of the pithouses existence which will be uniformly distributed over time, meaning that the pithouses can be supposed to exist in any portion of our range of time  $\Omega$  (7000–3220 cal BP, Early to Late Jomon period) with the same probability. However, the recovery of diagnostic potsherds allow us to determine portions of  $\Omega$  where we know a pithouse might have existed and portions where we know it did not. We can define the former as the *time span* of existence of our pithouse and label this with  $\tau$ . From this, we can formally state that an 'event'  $e$  (a pithouse in our case) has a probability of existence  $p > 0$  for any portion of time within  $\tau$  and have  $p = 0$  for any portion outside  $\tau$ . The principle of insufficient reason allows us to assume that any equally long portion of time within  $\tau$  has the same probability of existence. Consequently,

for any given portion of time  $t_i$ , we can calculate the probability  $P[t_i]$  of the existence of the event  $e$  as follows:

$$P[t_i] = \Delta t_i / \Delta \tau \quad (1)$$

where  $\Delta t_i$  is the duration of  $t_i$  and  $\Delta \tau$  is the duration of the time span. When all the  $\Delta t$  have the same fixed value  $\varphi$ , we have the key concept of *aoristic analysis* (Ratcliffe 2000, introduced in archaeology by Johnson 2004) which is based on the creation of a series of artificial time-blocks with durations  $\varphi$  and the definition of their probability of existence through Eq. 1. Ratcliffe specifies that  $\Delta \tau$  should be rounded to the resolution specified by  $\varphi$ , with the boundaries of  $\tau$  coinciding with the boundaries of the first and last time-blocks. This limit could be easily overcome by defining a very small value  $\varphi_\alpha$  (usually equal to the best precision of our measurement) from which we retrieve the minimum probability  $P[\varphi_\alpha]$  through Eq. 1. Then, for each  $t_i$  we calculate the size of the portion of  $\tau$  within that time-block using a precision equal to  $\varphi_\alpha$  and then multiply this by  $P[\varphi_\alpha]$ . For instance if we have an event with its boundary of  $\tau$  at 342 BC and 288 BC, with  $\varphi=50$  and with the time-blocks  $t_1$  (350–300 BC) and  $t_2$  (300–250 BC). We will first define  $\varphi_\alpha=1$ , and then from Eq. 1 we will obtain  $\varphi_\alpha / \Delta \tau = 1/54 = P[\varphi_\alpha] \approx 0.018$ , which is the probability of existence in a single year. Then we can obtain the probabilities of existence for  $t_1$  and  $t_2$  as  $P[t_1] = P[\varphi_\alpha] \cdot 42 = 0.78$  (the cumulative probability of 42 years) and  $P[t_2] = P[\varphi_\alpha] \cdot 12 = 0.22$  (the cumulative probability of 12 years).

The main advantage of using a fixed temporal resolution instead of uneven blocks is to simplify the mathematics involved in the comparison of different time-blocks, making it much easier to carry out diachronic analysis and to integrate external knowledge such as palaeo-climate data. Other details on the application of aoristic analysis has been treated elsewhere (Ratcliffe 2000; Johnson 2004; Crema *et al.* 2010; Crema *in press*), but it is worth mentioning that multiple sources of knowledge (*e.g.* topological temporal relationships) from the same data can be integrated, and that Eq. 1 works as long as event  $e$  has a temporal duration which is insignificant in comparison to the time span of existence<sup>1</sup> ( $\Delta \tau$ ). The probability of existence can still be computed when the latter condition is not satisfied (see [Electronic Supplementary Material](#)), although the mathematics is slightly more complex.

For the purpose of this study, the chronological range of 3,780 years (rounded to 3,800) has been subdivided into 38 time-blocks with a resolution ( $\varphi$ ) of 100 years each, providing the same temporal scale adopted by Imamura. For all 6,757 pithouses, the probability for each of the 38 time-blocks has been computed following the procedure described above, converting Suzuki's pottery-based relative chronology to a calibrated absolute date chronological sequence proposed by Kobayashi (2008, see Fig. 2).

<sup>1</sup> In case a single pithouse is known to have been re-occupied multiple times, each episode of occupation should be treated as a single independent event. One potential problem of this approach is when the lack of data cannot distinguish episodes of multiple occupations from a simple case of large time span (higher temporal uncertainty). This suggests that, when available, multiple sources of evidence (other than the recovered pottery sherd) should be included in the analysis.

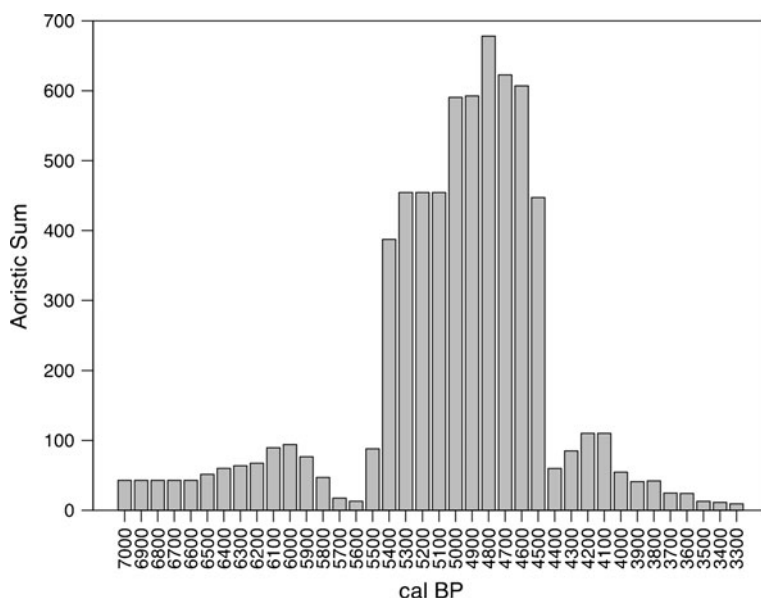


A common approach for describing these kinds of aoristic measures involves the sum of the probability (known as ‘aoristic sum’) for each time-block. This is the most common output of aoristic analysis (Ratcliffe 2000; Johnson 2004), and it is often used as a proxy for evaluating change in the total counts of events across time. Figure 5 illustrates the aoristic sum of Suzuki’s dataset which can be compared with Imamura’s plot on Fig. 1. While both plots show the presence of fluctuations with two minor and one major peak, the latter suggests a much longer persistence of high pithouse counts during part of the Middle Jomon period (5470–4420 cal BP, Kobayashi 2008). As previously noted by Crema *et al.* (2010), the main problem with this approach is that information related to uncertainty is embedded in the results and as such it provides a broad ‘likelihood’ of the intensity of the process for single time-blocks but is unable to provide formal probabilistic description when two or more time-blocks are directly compared.

An abstract example better reveals the limits of aoristic sum when *change* is the core aim of the analysis. Suppose our system of interest has three pithouses  $\{a, b, c\}$  in three consecutive time steps  $\{t_1, t_2, t_3\}$  and we are dealing with a case where we have already obtained the probability of existence for each event as follows:

	$t_1$	$t_2$	$t_3$
$a$	1	0	0
$b$	0	0.5	0.5
$c$	0	0.8	0.2

Aoristic sum will suggest an increase between the first ( $1 + 0 + 0 = 1$ ) and the second time step ( $0 + 0.5 + 0.8 = 1.3$ ), but such approach will ignore the probabilistic nature of the problem.



**Fig. 5** Aoristic Sum of Jomon Pithouses in SW Kanto between Early and Late Jomon Period

We should in fact tackle the probability of transitions between the two consecutive time steps. This will involve firstly the assessment of each possible transition with the given probability distribution. Since  $a$  can exist only in  $t_1$ , we can focus only on what are the possible scenarios for  $b$  and  $c$  at  $t_2$ . The probability distribution indicates that we can have four possible permutations: (1) co-existence of  $b$  and  $c$ ; (2) existence of  $b$  and non-existence of  $c$ ; (3) existence of  $c$  and non-existence of  $b$ ; and (4) non-existence of both  $b$  and  $c$ . Each of these four possible permutations will yield a different total count of pithouses, namely 2, 1, 1 and 0. Since what we are interested are the total number of pithouses per time (and not the existence or the non-existence of a specific pithouse), we can safely combine the probability of the permutations (2) and (3). From this, we can obtain the exact probability of each possible total counts for  $t_2$  as follow:<sup>2</sup>

Total=2:

$$P[a] \cdot P[b] = 0.5 \cdot 0.8 = 0.4$$

Total=1:

$$(P[a] \cdot (1 - P[b])) + ((1 - P[a]) \cdot P[b]) = (0.5 \cdot 0.2) + (0.5 \cdot 0.8) = 0.5$$

Total=0:

$$(1 - P[a]) \cdot (1 - P[b]) = 0.5 \cdot 0.2 = 0.1$$

where  $P[x]$  indicates the probability of existence of an event  $x$  during a specific time-step. Since we have only one possible permutation for  $t_1$ , we can retrieve the transition probabilities as follows: increase=0.4; stability=0.5 and decrease=0.1. The results thus indicates how stability is the transition with the highest likelihood, with an increase in the number of pithouses between time-steps  $t_1$  and  $t_2$  having a slightly *lower* probability of 0.4 and even a 0.1 chance of decrease.

The abstract example shows an obvious but an often-neglected feature associated with the formal integration of uncertainty: when the input data are probabilistic, the output data should also be probabilistic. This implies that aoristic sum could be a misleading approach, as it will obscure possible alternative time series by showing one possible dynamic which is not necessarily the one with the highest chance of occurrence. In order to explicitly integrate temporal uncertainty, we should ideally calculate the probability of each permutation and then, for each consecutive time block, sum the probabilities satisfying a specific condition. In our case, such a condition might be an increase or decrease in the number of pithouses.

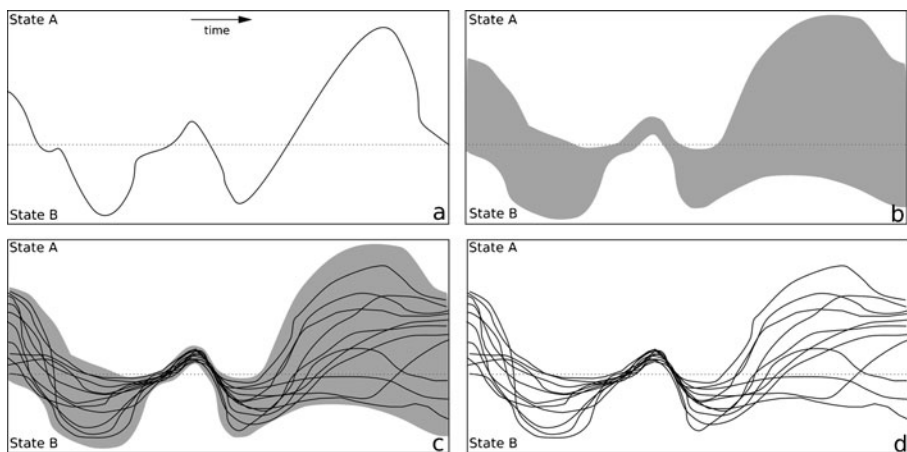
While from purely theoretical perspective this can be easily conducted with the same approach illustrated above, the total number of possible permutations is extremely large and will be practically impossible to calculate even for a relatively small number of events. For instance, a dataset of 50 pithouses having four time-blocks of possible existence will produce  $1.27 \cdot 10^{30}$  permutations!

This leads to a rather problematic question: if the aoristic sum provides a misleading temporal pattern without a full integration of our knowledge, and the computational effort for retrieving transition probabilities is prohibitive, how can we address a basic question such as the increase/decrease of pithouse counts between two consecutive time-blocks?

<sup>2</sup> Notice that this will also determine the probability of counts for  $t_2$ . Since mutual exclusiveness is given as a starting assumption, the non-existence of the event  $b$  at  $t_2$  will also indicate its existence at  $t_3$ .

## A Monte Carlo Method-Based Solution

Suppose we are assessing the dynamics of change of a variable  $v$  associated to the entity  $e$  at each of its time step  $t_1 \dots t_n$ . We can represent this as a time series of  $v(e, t_i)$  as shown in Fig. 6a. Furthermore, suppose that we are not interested in the exact value of  $v(e)$  but rather to some generic distinction between two qualitative states: A and B, which may for instance represent two forms of settlement pattern (*e.g.* clustered *vs.* dispersed) or two different population sizes above or below a critical threshold. While the phenomena we are analysing can be well represented, although in a very abstract way, by Fig. 6a, our state of knowledge is in most cases something similar to Fig. 6b, where we have an envelope of possible values of  $v(e)$  rather than a single line. For instance if  $v$  is the population size of a region  $e$  this will be bounded by a range of possible values for each moment in time. Clearly, the larger the envelope at any given time  $t$ , the greater will be our uncertainty in stating if  $v(e)$  is in state A or B. The formal mathematical definition of such envelope is essentially the process of probabilistic weighting described in ‘[Quantifying and Integrating Uncertainty](#)’. A critical point that must be stressed here is that the aim of any archaeological analysis is to make a sensible inference about the qualitative state of the line in Fig. 6a, but in practice what we are really dealing with is the shaded area of Fig. 6b that is both the object of our observation *and* the state of our knowledge. Such an envelope of existence can change its extent with advances in our state of knowledge, but will never become just a single line. The implication of this is that we must approach archaeological data as a domain of knowledge where uncertainty must be explicitly acknowledged. The aoristic sum of Fig. 5 ignores this issue entirely, and seeks to represent our data *as if* we could actually draw a line similar to Fig. 6a. Instead, the approach suggested by the computation of transition probabilities



**Fig. 6** Basic illustration of the Monte Carlo Methods. **a** The variation over time of some variable we seek to assess, with the *dotted line* subdividing the variable in two main categories: A and B. **b** Our domain of knowledge expressed as the ‘boundary of existence’ of the variable. Notice how different moments of time have different width of such boundary. **c, d** Images of how Monte Carlo methods consists on creating artificial ‘potential’ time series within the boundary of existence and how this can be used to assess the likelihood of the variable’s character state over time

explicitly acknowledges the uncertainty embedded in our data, by describing quantitatively the boundaries represented in Fig. 6b. At this point, we reach to the problem stated in the last paragraph of the previous section: how to quantitatively describe such envelope when its exact computation is computationally prohibitive.

Monte Carlo methods (see Robert and Casella 2004 for a detailed overview) offer a simple but effective approach to these problems and have been previously applied by different authors within archaeology (e.g. Buck *et al.* 1996; Lake and Woodman 2003; Crema *et al.* 2010). If we wish to continue the example illustrated in Fig. 6, the first step will involve the creation of  $n$  possible ‘trajectories’ of  $v(e)$  within the boundary of existence (Fig. 6c). If we assume potentially some form of dependence of  $v(e)$  at  $t_n$  to the value of  $t_{n-1}$  we will have a Markov Chain Monte Carlo, in which the future trajectory of  $v(e)$  will have form of restriction within the boundary of existence, based on its value at present. In both Monte Carlo and Markov Chain Monte Carlo, the simulation will create  $n$  time series, each with a complete knowledge of  $v(e)$  for any moment  $t$ . Such absence of uncertainty allows us to assess each of the  $n$  simulated pattern using standard procedures. In this case for instance, we might simply count for a given moment in time  $t_i$  the number of scenarios where the  $v(e)$  is in state A or in state B (see Fig. 6c and d). This will determine the frequency  $f$  of the simulated value of  $v(e)$  where a specific condition is satisfied. Such frequency can be regarded as the maximum likelihood estimator of the exact probability of the occurrence of a specific scenario (Izquierdo *et al.* 2009).

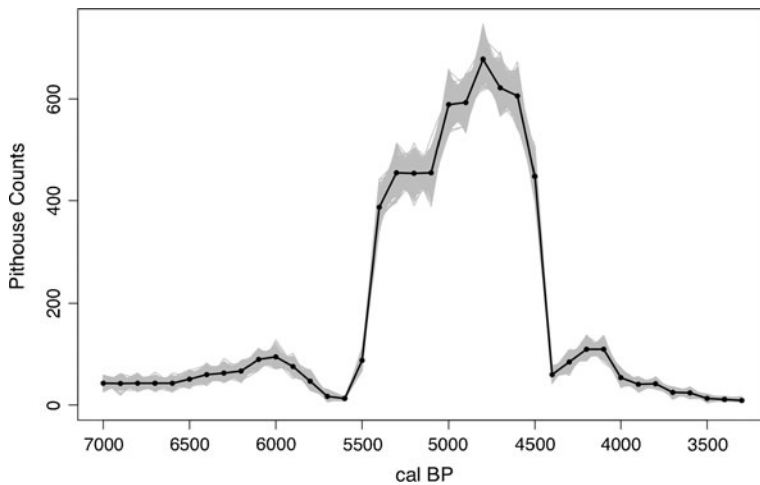
However, a key question is: how many runs of the simulation do we need? In practical terms, the most straightforward solution is to compare the outcome of different set of runs with increasing values of  $n$  and stop the analysis when we start to observe a relatively good degree of convergence (*i.e.* when the change in the variance of the outcome becomes minimal with the increase of  $n$  in our results; e.g. Fig. 8 in Crema *et al.* 2010) or when the standard error of our results becomes minimal.

## Rate of Change Analysis of South-West Kanto Pithouses

Following the procedure described in ‘Monte Carlo Method-Based Solution’, 1,000 Monte Carlo simulation runs<sup>3</sup> were made from a subset of Suzuki’s data. In each of these, each pithouse has been allocated to one of the 38 time-blocks, following the probability distribution obtained by the aoristic analysis. This created 1,000 possible time series of pithouses counts, with a temporal resolution of 100 years. Figure 7 shows the envelope created by overlapping all the simulated time series of pithouse counts in light grey, with the superimposition of the average counts per each time-block depicted as black marked line. The plot nicely illustrates how different degrees of temporal uncertainty are present, with the thickness of envelope changing through time (compare with Fig. 6b).

However our initial aim was to assess *whether there was an increase or decrease in the number of pithouses in specific windows of time*. While Fig. 7 allows us to

<sup>3</sup> Incremental runs of 500, 750 and 1,000 has shown no substantial difference in the outputs, indicating how 1,000 runs are sufficient for the present dataset.



**Fig. 7** Cumulative plot of 1,000 time series created by Monte Carlo simulation of Jomon pithouse counts in SW Kanto region. The *grey shaded lines* are the simulated time series; the *solid marked line* is the average number of pithouse counts through all simulations

determine an overall trend (much like the aoristic sum of Fig. 5), it appears to be much more difficult to assess specific transitions between consecutive time-blocks.

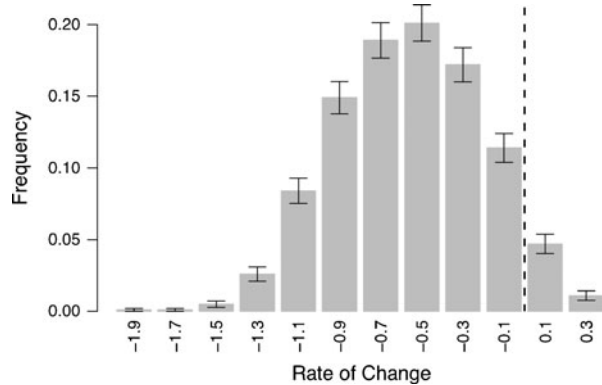
One solution is to examine for each run of the simulation the *rate of change*<sup>4</sup> between two consecutive time-blocks, and then combine the result as a distribution of rates. Figure 8 illustrates an example of such approach for the transition between the time block 4800–4700 cal BP and 4700–4600 cal BP. The histogram shows the frequency of runs with specific interval of rate of change along with an estimate of the standard error. The results in this case shows how for this sequence of time-blocks it is very likely that the number of pithouses decreased, with the gradient being most likely around  $-0.9$  and  $-0.1$ . However, the figure also shows that there are chances than there were very small decrease, and even some chance ( $f=0.058$ ) of an actual increase in the number of pithouses.

We can apply this analysis for all the 37 pairs of consecutive time steps and plot all the distributions of rates of change on a single box and whisker plot (Fig. 9).<sup>5</sup> A quick look of the plot shows several transitions having their median around 0 (*i.e.* no change) while other have a relatively large inter-quartile range (IQR). Examples of the first can be found in the first few centuries (7000–6500 cal BP) where the degree of temporal uncertainty is such that we cannot define whether there was an increase

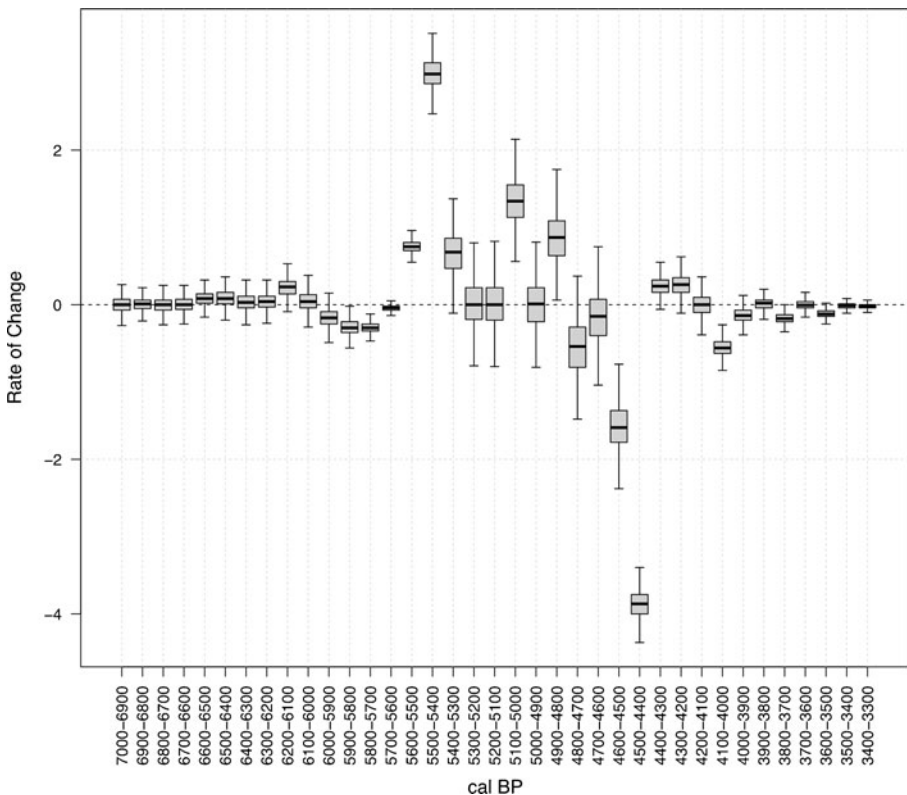
<sup>4</sup> The rate of change is given as the number of pithouses at  $t_{i+1}$  minus the number of pithouses  $t_i$ , divided by the temporal resolution  $\varphi$ . An alternative approach is to divide the difference with the number of pithouses at  $t_i$ , this will be a slightly different measure corresponding to the per capita rate of growth. Discussions on the differences between the two methods are out of the scope of the paper, but it could be stated that the former approach provides a more generic method, while the latter is more suited for evaluating population dynamics. In the present case study, the pithouse count does not necessarily correlates to the population dynamics in an equal manner through different time-blocks, as variability in the residential mobility could be expected. Hence, the latter method has been regarded as less suitable in this case.

<sup>5</sup> Notice how the labelling of the transition refers to the initial dates of each time-block. Thus a transition between 3000 and 2900 cal BP actually refers to the rate of change between 3000–2900 and 2900–2800 cal BP.

**Fig. 8** Frequency of Monte Carlo simulations with specific rate of change between time-block 4800–4700 and 4700–4600 cal BP. The error bar was created following the procedure described in Izquierdo *et al.* (2009)



or decrease of pithouses. Instances where the IQR is large are likely the results of the higher number of pithouses potentially attributed to the temporal interval and can be observed in the transitions between 5500 and 4500 cal BP. During this interval several transitions have a median rate of change which is smaller or larger than 0, providing support to claims of increase or decrease in the pithouse number, although with smaller confidence in the definition of the exact gradient of change.



**Fig. 9** Box and whisker plots of the distribution of rates of change for each of the 37 transitions

The outcome of this kind of rate of change analysis is essentially a combination of the observed temporal knowledge and the assumption suggested by the principle of insufficient reason. Thus, with a complete absence of knowledge (with all pithouses having the duration of their time span equal to the entire temporal extension of the case study) we will still have some pattern determined entirely by our initial assumption and the randomness derived by the Monte Carlo simulation. How can we state that an observed increase is not determined by such stochastic component, derived entirely from the underlying uniform probability distribution? One solution is to compare the outcome of the observed rate of change of Fig. 9, to the outcome a dummy set having the same sample size but with each event having largest possible time span of existence. This means that in the dummy set, each pithouse has the same probability of existence for any of the 37 time steps (except for time step 38 which have a slightly smaller probability derived by a duration of 80 instead of 100 years). The proportion of the rate of changes of the observed set which are below the envelope defined such dummy set allow us to define the likelihood  $pLo$  that there were indeed a decrease in the number of pithouses. Conversely, we can define  $pHi$  as the likelihood of increase in two consecutive time-blocks. It is important to notice how this method is conservative in its results, as small actual changes in the pithouse counts will be virtually indistinguishable from episodes of low temporal uncertainty. Nonetheless, the evaluation of  $pLo$  and  $pHi$  will answer the crude and basic question of whether there is likely to have been a real increase or decrease in the pithouse counts, and should always be associated with the actual gradient depicted in Fig. 9.

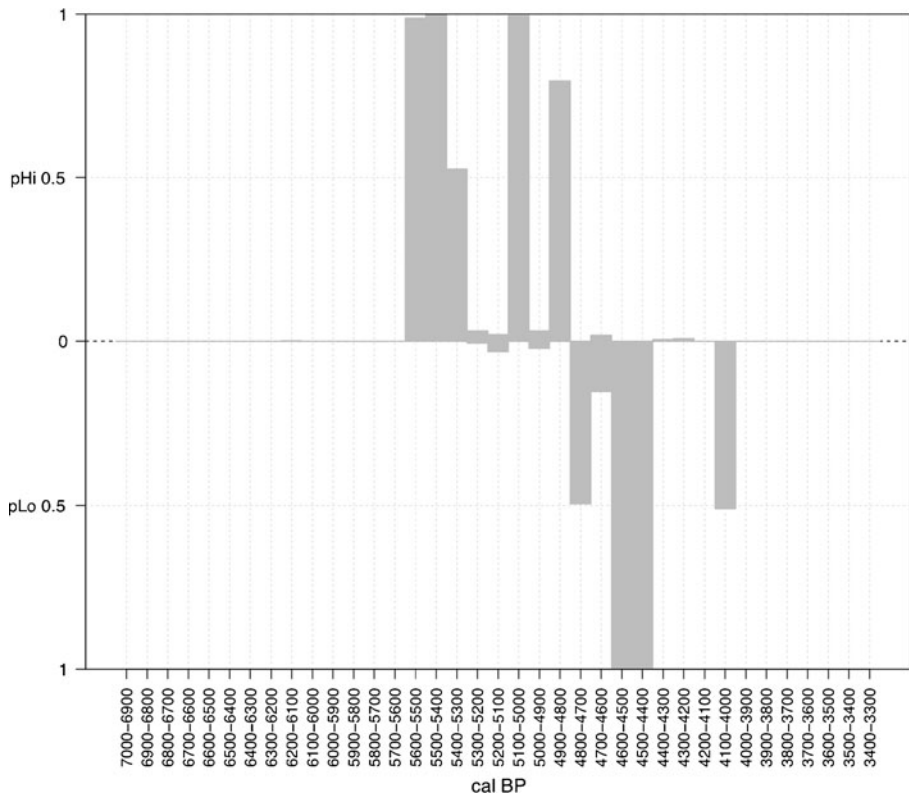
Figure 10 shows for each time-step the values of  $pLo$  and  $pHi$  for a dummy set based on 100 runs. Thus for instance in the transition from 5500 to 5400 cal BP, all the simulated rate of changes of the observed temporal distribution has shown a value higher than one expected by the rate of changes derived from the dummy set.

A review of Figs. 7 and 10 shows that although the former shows numerous fluctuations, we actually know very little about when exactly a significant increase or decrease occurred with a resolution of 100 year. The increasing trends in the beginning of the second half of the Middle Jomon period (5600–5500 cal BP with  $pHi=.935$ ; 5500–5400 cal BP with  $pHi=1$ ; and 5100–5000 cal BP with  $pHi=.987$ ) and a series of decreasing transitions towards the end of the Middle Jomon Period (4600–4500 cal BP with  $pLo=.996$  and 4500–4400 cal BP with  $pLo=1$ ) can be regarded as exceptions where high degree of temporal knowledge are associated to a marked transition in pithouse counts.

The analysis of the pithouse count dynamics has so far been based on a temporal resolution of 100 year, following the original analysis conducted by Imamura. Clearly, real fluctuations in the past will have occurred over different timescales, and thus different temporal resolutions should be examined. However, choices of finer resolution will also mean smaller probabilities of existence for each time-block since the numerator of Eq. 1 will be smaller.

Figure 11c, d illustrates the barplots of  $pHi$  and  $pLo$  for three different temporal resolutions (50, 100 and 200 years), along with different proxies of environment change (Fig. 11a, b) such as episodes of weak monsoon (Wang *et al.* 2005), sea regression (Fukusawa *et al.* 1999), and rapid climate change events (Mayewski *et al.* 2004), Adhikari *et al.*'s (2002) Holocene temperature reconstruction and Kudo's subdivision of major climatic phases (Kudo 2007).



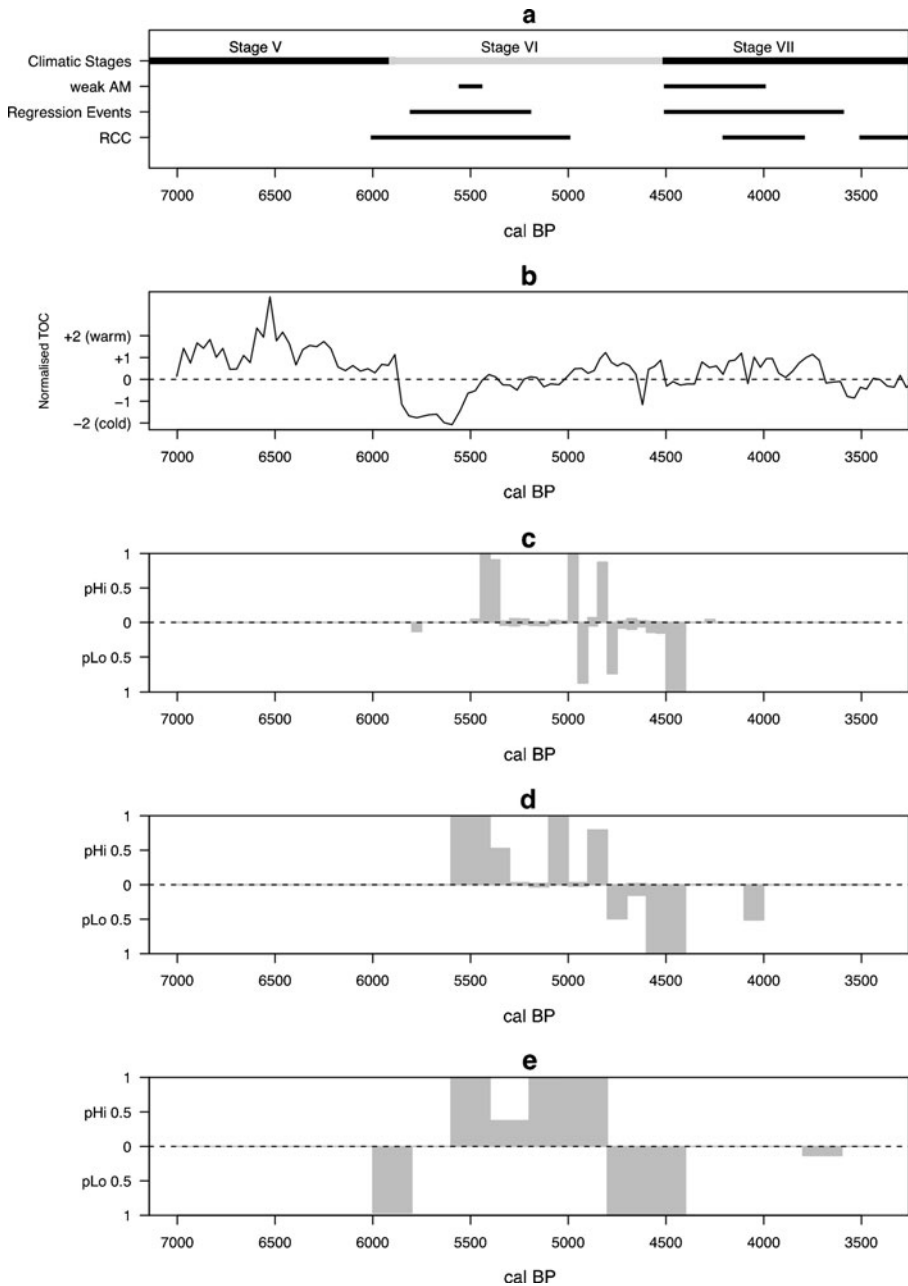


**Fig. 10** Bar plots showing the likelihood of increase (*pHi*) and decrease (*pLo*) for each time-block transition

The results depicted in Fig. 11 show a number of interesting features. Broadly speaking, the increase at 5500 cal BP the decrease at 4500 cal BP are visible at all temporal resolutions, depicting a similar trend to the one observed by Imamura's analysis, although the absolute dates are shifted by ca. 500 years. With a coarse resolution of 200 years, the Late Early Jomon 'collapse' at the beginning of the 6th millennium cal BP becomes evident, while a fine-grained resolution of 50 years shows a fluctuating pattern in the early 5th millennium cal BP. Both trends are not visible when the resolution is set to 100 years and indicates how the adoption of multiple scales of analysis is necessary in order to handle different degrees of temporal uncertainty and to capture patterns visible only at certain scales.

The multi-scale approach becomes important especially when correlations with environmental changes are sought. The broad dynamics shown in Fig. 11e initially appears to support the hypothesis of an increase in population around 5500 cal BP, when several proxies indicate a period of environmental change. The results however are misleading in this case, as the increasing trend starts at ca. 5600 cal BP. The rate of change analysis with the finest resolution shows how, in fact, the major increase in pithouse counts occurred at ca. 5400 cal BP, when the temperature was already increasing (Fig. 11b) and an adaptive response to environment changes was likely occurring.





**Fig. 11** Rate of change analysis: summary of results (c–e; with resolutions 50, 100 and 200 year) and comparison with palaeo-environmental data (a, b)

The second major trend visible at all the temporal scales assessed here is a strong decrease in pithouse counts around the middle of the 5th millennium cal BP. Again, the outcome of the analysis with the finest resolution indicates that the strongest decrease occurred around ca. 4500–4450 cal BP, which correlates to the weak monsoon events

and the marine regression occurring at the same time and supports hypothesis suggested by some authors (*e.g.* Imamura 1997; Habu 2008 for northern Japan).

The 50-year resolution analysis is also capable of depicting a previously unseen pattern of a ‘fluctuation’ in the pithouse counts during the early 5th millennium cal BP. This period is characterised by relative stasis from an environment perspective, and thus the cyclic pattern may well indicate of the role of endogenic processes.

Fine-grained resolutions are however weak in determining gradual changes. The most relevant example is the decrease in pithouse counts during the end of the Early Jomon period (early 6th millennium cal BP). This is a known trend, which has been extensively studied by Imamura (1992) and Habu (2002). The rate of change analysis shows how such ‘collapse’ was either more gradual than the one which occurred during the late Middle Jomon period (mid-5th millennium cal BP), or the temporal knowledge was insufficient to establish a narrow ‘moment’ of collapse with a resolution of 50 and 100 years. The coarse resolution makes the comparison with the environment data difficult, and in fact establishing the relation between the Early Jomon collapse (6000–5800 cal BP), the early Middle Jomon increase (*ca.* 5500–5400 cal BP) in relation to the climatic events of the 6th millennium cal BP (Fig. 11a) is not straightforward, and requires further investigations.

A purely visual inspection of Figs. 5, 7 and 9 suggests a possible small peak in pithouse counts, followed by a decrease by the end of the 5th millennium cal BP. None the rate of change analysis has however detected this, with the exception of a weak likelihood of decrease at 4000 cal BP with the 100-year resolution analysis (Figs. 10 and 11d). The failure to depict such a trend does indicate the importance of visualising the raw distribution of the rates of change as shown in Fig. 9, and highlights how defining the significance using the random dummy dataset might lead to something very close to a type-II error, where significant trends are erroneously rejected. This is particularly the case when the variance of the distribution of the rate of changes is small (*i.e.* the pattern is ‘strong’), but its mean is also small (*i.e.* the actual rate of change is low).

It is worth to mention also that the actual temporal frequency of pithouse counts does not necessarily mirror demographic trajectories nor does a simplistic explanation of the observed trends as a consequence of environment change be supported as a conclusive argument. Diversity in residential strategy and length of occupation, amongst other things, might affect the relationship between the number of dwellings and the number of individuals in a non-linear fashion, while the effects of ‘taphonomic biases’ (Surovell and Brantingham 2007) might alter the overall shape of the temporal frequency distribution. Further analysis which integrates the spatial dimension in order to establish a more robust association between the frequency of pithouses and the population dynamics are necessary, as well as models which can incorporate in their hypothesis the effects of both taphonomic and recovery biases. The evaluation of the environment proxy should also be carefully applied. The present paper proposes only few data while a thorough analysis will necessitate the comparison of a higher number of proxies, possibly integrating the uncertainty of those data as well. At this stage, assessing the correlation between specific anthropic and natural events is still problematic but remains a priority, in order to explore the actual role of exogenic (*e.g.* environment change) forces to the system rather than reducing the whole issue to a simple deterministic correlation based ‘explanation’.

Finally, although the chronological definition provided by Kobayashi (2008) is the most accurate and up-to-date dataset currently available, uncertainty derived from its adoption should also be considered. Pottery-based chronometry is not restricted to the temporal dimension but also to the spatial one (the spatial limit of their application), and are subject to continuous updates. One approach that could be easily integrated to the method proposed here is to depart from multiple hypotheses of chronological sequences, from which several aoristic analyses are computed. This will in turn determine multiple outcomes for the rate of change analysis and their combination can determine how robust is an observed pattern. Trends which are jointly observed in the outcome of the analysis of different starting assumptions (differently proposed chronological sequences) can be regarded as robust, while patterns which emerge only within a specific chronological sequence should be treated cautiously due to their strict dependence to the proposed chronological models.

The combination of Aoristic analysis and Monte Carlo simulation thus appears to offer a method which can enhance our ability to determine how much we can actually tell and with what degree of confidence. The outcome of the analysis did not point out radically new trends in the Jomon demography but instead provided additional insight into the robustness of each observed phenomenon, distinguishing what is a strong claim from what is not, and enhancing the temporal precision of these statements. However, it is important to point out that substantial limits to its application can be recognised when the nature of the input data does not allow the quantification of temporal uncertainty. For instance, the analysis proposed here cannot be applied in some regions of the Japanese archipelago where Kobayshi's sequence is not applicable and only few  $^{14}\text{C}$  dates are available. The limited applicability of the proposed method should however be regarded as an incentive to strengthen our efforts to provide precise chronometric data suitable for techniques which can incorporate different sources of uncertainty.

## Conclusions

Uncertainty is habitually regarded as a negative aspect of our research. We avoid it wherever and whenever possible, often ignoring it in our narratives even when we explicitly admit its presence lurking in the background. Statistical analysis might provide us with a quantitative characterisation of reality in probabilistic terms, but our conclusions are usually much crisper than this and the fuzziness of our knowledge is lost in translation and/or treated with only passing interest.

In their manual on Bayesian approaches in archaeology, Buck *et al.* (1996) have cited the definition of uncertainty proposed by de Finetti (1974) quoted at the very beginning of this paper. Uncertainty is indeed our degree of knowledge, and as such we need to explicitly define its scope in order to provide a secure basis for our analyses and our narratives. Implicitly, we already recognise this, as no archaeologist will ever claim that his/her own hypothesis is what actually happened. We do know that everything we write is just the state of our knowledge and as such, its fate as a description is to be eventually discarded as obsolete. Our knowledge of time is heavily dependent on such continuous and perhaps never-ending updates. Nevertheless, since archaeology can be regarded as the social science of time, this means

that our entire knowledge evolves following such continuous updates. However, the re-use of archaeological data is in many cases confined to a marginal role in the archaeological endeavour, which concentrates instead on the insights brought by new data. Consequently, re-assessment of established narratives is often an extremely slow process. What is claimed once, with a certain degree of certainty, often becomes the uncritical basis for subsequent research. This can certainly be avoided by a more critical approach to established knowledge, but more fundamentally, this issue can be tackled if our methods for incorporating uncertainty become explicit and quantitative. This will allow us to construct much more formal narratives, where the robustness of each statement can be measured accordingly.

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**SUPPLEMENTARY MATERIAL FOR:  
Modelling Temporal Uncertainty in Archaeological Analysis  
E. R. Crema**

**Appendix A: Computing probabilities for events with duration.**

When an event has a known continuous and consecutive duration in time, the computation of the probability of existence for each time block will be slightly different from the method described in the paper. For the sake of simplicity, we will consider values that are rounded to the resolution  $\varphi$ , but the general approach can be applied here as well. We define  $b$  as a numerical index indicating the temporal blocks within the time span of existence  $\tau$ , so that  $b$  ranges from 1 to  $\Delta\tau/\varphi$  (e.g. if  $\varphi=50$  and  $\tau$  is between 3000 BP to 2450 BP, then  $b$  will range between 1 and 11)

The first thing to notice here is that:

$$\sum_{b=1}^{\Delta\tau/\varphi} P_b = d/\varphi \quad [1]$$

where  $P_b$  is the probability of existence at each block  $b$  and  $d$  is the duration of the event (rounded to the value of  $\varphi$ ). Notice also that the smallest value of  $d$  will be  $\varphi$  in this case, and in such case, the total sum of probabilities will be equal to 1. This is the same outcome of aoristic analysis, although there are some conceptual differences here. For instance a probability of 1 for a given time-block in aoristic analysis will indicate that the event have occurred sometime within the time-block, while when duration is introduced this indicates that the event persisted through the same time-block. If we subdivide such time-block in two equally sized sub-blocks, aoristic analysis will provide two probabilities of 0.5, while in case duration is introduced both sub-blocks will still have a probability equal to 1. In other words, decreasing the value of  $\varphi$  will increase the outcome of equation [1], while for aoristic analysis this will have no effects in the total sum of probabilities.

The second critical difference is that  $P_b$  (the probability of existence for each time-block) is not constant but will vary as a function of  $b$  and will be bounded by two possible extremes, a minimum of  $1/\pi$  and a maximum of 1, where  $\pi$  is the number of all possible permutations, equal to  $(\Delta\tau-d)/\varphi+1$ . The exact probability of existence for each time-block  $b$  will be the ratio between the number of permutations where the event exists in  $b$  and the total number of possible permutations  $\pi$ . This can be formally described with the following equation:

$$P_b = \frac{\sum_{i=0}^{\pi-1} \sum_{j=1}^{d/\varphi} \theta(i+j, b)}{\pi} \quad [2]$$

where  $\theta(i+j, b)$  is

$$\theta(i+j, b) = \begin{cases} 1, & \text{if } i+j = b \\ 0, & \text{if } i+j \neq b \end{cases} \quad [3]$$

Equation [2] and [3] states that broadly speaking time-blocks at the edges of the time-span ( $b=1$  or  $b= \Delta\tau/\phi$ ) have generally lower probabilities than those in the middle.

Equation [2] indicates the probability of existence of each time block independently and does not tell us any information on the adjacent time-blocks. This becomes a problem when we wish to compare probabilities between different time-block as in the rate of change analysis described in the paper.

One solution to this problem is to shift the kernel of analysis from a probabilities-per-time-block basis to a probabilities-per-permutations basis. For instance, suppose we have two events  $e_1$  and  $e_2$  having the same  $\tau$  with  $\Delta\tau = 5$  and durations of  $d(e_1) = 2$  and  $d(e_2) = 4$ . The number of each permutations will be  $\pi(e_1) = 4$  and  $\pi(e_2) = 2$ , which will provide the total number of permutations 8 ( $4*2$ ), as seen in figure A1.

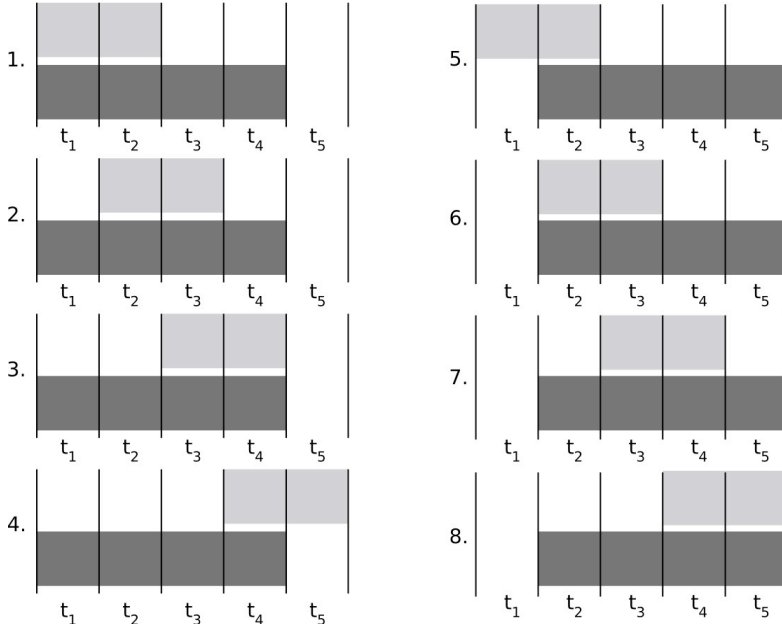


Figure A1: All possible permutations for two events with length 2 and 4 in a common timespan with length 5.

Based on the principle of insufficient reason we can assume that each of these permutations will have the same probability of existence. Thus, we will have all the permutations of the first event with  $p = 0.25$  ( $1/\pi(e_1)$ ) and all the permutations of the second with  $p = 0.5$  ( $1/\pi(e_2)$ ). From this we can also evaluate the probability of each combined permutations between the two events as the product between these two values (0.125). In other words, there are 8 possible scenarios for the existence of the two events, each with an equal probability of occurrence. If we wish to look at the likelihood of the occurrence of any particular combination, we simply need to count the number of permutations where the conditions satisfying such combination are met. For instance, in this specific case, an increase of the number of events from time-block 1 to time-block 2 occurs in 5 scenarios (scenario 2,5-8 in figure A1), and thus have a probability of 5/8 (0.625).



This approach can be extended also for events with unknown duration. We can safely define the possible values of  $d$  as ranging between  $\varphi$  (in probabilistic terms with discrete time-blocks, there is no difference between  $d = \varphi$  and  $d < \varphi$ ) and  $\Delta\tau$ . Thus we can derive from this that the number of possible time-blocks where the event might have existed is between 1 and  $\Delta\tau/\varphi$ . If we then consider the principle of insufficient reason, and assume that all these possible values of  $d$  have an equal chance of occurrence, we can derive the total number of possible scenarios as follow:

$$\pi = \sum_{k=1}^{\Delta\tau/\varphi} (\Delta\tau/\varphi) - k + 1 = \frac{(\Delta\tau/\varphi) \cdot (\Delta\tau/\varphi + 1)}{2} \quad [4]$$

where  $k$  is an index which loops through all the possible number of blocks where the event might have occurred. The value of  $\pi$  is clearly much larger when duration is unknown and its sequential growth in relation to the length of the time-span corresponds to the sequence of triangular numbers. For instance an event with a  $\Delta\tau=500$  and with  $\varphi=100$ , will have potentially 15 different scenarios each having a probability of occurrence equal to 0.067 (1/15).

The permutation based approach can be easily incorporated in the Monte Carlo method described in the paper, where each simulation run will simply create one of the possible combination of temporal allocation and event duration.