Resource selection of lithic raw materials in the Middle Palaeolithic in southern France

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Abstract

The work reported here uses several approaches to examine the costs and benefits associated with exploiting potential sources of lithic raw material in the Vaucluse, southern France, and then tests the results against the proportions of raw materials from various sources found in the lithic assemblage of a Middle Palaeolithic site, the Bau de l’Aubesier. A previously published equation designed to quantify the attractiveness of each source proves to be significantly correlated with source use, but the results show that it can be improved. We then individually test the components of the attractiveness equation (raw material quality, source extent, terrain difficulty, and the size and abundance of raw material pieces at the source) and additional variables (Calories expended to get from the source to the site using a straight-line route, Calories expended using a least-cost path, surface distance of the source from the site, and distance to the closest used source) using generalized linear models. Since very similar raw materials can be found at more than one source, we combine such similar sources into source areas, and test the area of the source area (AOSA) and the total area of sources within the source area (AOSISA), as two additional independent variables. The best model shows that raw material quality, source extent, abundance of large and very large rocks, and AOSISA, are positively correlated with use of sources, while terrain difficulty, abundance of small and medium rocks, Calories, and AOSA, are negatively correlated with source use. This shows that the hominins at the Bau de l’Aubesier optimized their raw material procurement to get the most good quality material that they could, while minimizing the time and energy spent getting and using it.

Keywords: Optimal foraging; Neandertal; Western Europe; Lithic procurement; Lithic source attractiveness

Introduction

Archaeology aims to reconstruct and explain the behaviour of past human groups through the study of the material remains they left behind. For modern humans, we can use ethnographic analogies and our own ‘common sense’ to guide our understanding of those material remains and the behavioural strategies that they reflect. This is arguably an appropriate strategy for understanding prehistoric modern humans, with whom we share so many behavioural and cognitive capabilities. With pre-modern humans, however, such as Neandertals, the whole point is to understand the capabilities of people who were not us, and who did not necessarily do things as we would have, nor for the reasons that make sense to us. Judging them according to our own common sense may therefore obscure, or perhaps over-emphasize, their differences with us. We need to find some suitable objective tool or approach to measure their behaviour, rather than subjectively interpreting what we find. A completely objective approach may be impossible to find, because any tool will only measure the things that we think should be measured. However, the worth of an objective approach can be determined based on its predictive ability. For instance, to what extent does this combination of factors account for the pattern that we actually find in a stone tool assemblage? This paper presents such an objective approach, used to evaluate the factors that influenced choices of lithic raw material sources used for the stone tools found at a Middle Palaeolithic site in southern France, the Bau de l’Aubesier.

One of us (LW) has worked for many years on determining which raw materials were chosen for the stone tools found at Lower and Middle Palaeolithic sites in southern France (Wilson, 1986, 1988, 1998, 2007a, 2011; Texier et al., 1996, 1998, 2003; Wilson et al., 2010). Determining which raw material sources were used, however, should only be a step along the way to determining why certain sources were used. What conditioned people’s choices amongst the potential resources offered by the landscape? A first attempt at this was an evaluation of the importance of terrain difficulty, and the energy expenditure that moving around in the

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landscape requires (Wilson, 2003, 2007b). This led to the source attractiveness equation published in Wilson (2007c), which aimed to encapsulate several of the factors that would have influenced resource choices (terrain difficulty, raw material quality, abundance, etc.), weight them appropriately, and create an equation that would reduce all of these factors to a single number for each potential source. It was hoped that this would explain, at least partly, why certain sources were used, and why some were used more than others. As Wilson (2007c) shows, applying this equation to a selected few sources did show promising results, but much remained to be done. In particular, if the equation were applied to all potential sources in the region, how well would its predictions match up with the actual uses of the sources, as shown by the stone tool assemblages in archaeological sites? Also, the equation used Wilson’s ‘best judgement’ of how to weight the various factors. Were those weightings ideal, or could they be improved? Were the factors included the best ones, or could some be excluded, or others added? The goal of the work reported here was therefore to test the attractiveness equation on all identified potential sources in the study area, to individually test the components of the attractiveness equation, and ultimately to build a better equation.

The study area

The Bau de l’Aubesier (hereinafter called the Bau) is a large rock shelter located in the Vaucluse region of southern France (Fig. 1). From north to south, the major topographic features of the region include the Mont Ventoux (1902 m), the hilly Monts de Vaucluse and the gorges of the Nesque river within which the site is located, the valley of the Calavon river, and the Luberon mountains. The region is bounded to the east and south by the Durance river, which comes down from the Alps and swings westward south of the Luberon mountains to join the Rhône at Avignon. The major structure of the region had been established by the mid-Miocene, apart from some minor ‘readjustments’ at the end of the Miocene and at the end of the Pliocene (Rouire, 1975). This region was never glaciated, and although the plains and major river valleys did receive meltwater flows and now contain Quaternary alluvial deposits, the most important of these are located outside of our area of study. There have certainly been periods of more or less erosion and infilling of various areas, but the overall topography of the region has remained broadly unchanged for several million years (mountains and rivers positioned basically where they are now). Given this, and because reconstructing the exact landscape at any given time in the past would be an enormous task, for the work reported here we believe that using the present day landscape as a proxy for the landscape(s) of the past 200,000 or so years is justifiable, as it will give valid (if never completely exact) results.

The Bau rock shelter contains sedimentary deposits approximately 13 m thick, within which several archaeological layers have been identified. These layers cover a time range from approximately 100,000 BP (before present) (or less) to more than 200,000 BP (Blackwell et al., 2001; Lebel et al., 2001; Fernandez, 2006). The site was first dug very early in the twentieth century (Moulin, 1903, 1904) and studied briefly in the mid-1960s (de Lumley, 1971), but serious scientific excavation was only undertaken starting in 1987 by a multidisciplinary international team led by Serge Lebel of the Université du Québec à Montréal, Canada (Lebel, 2000a; Wilson, 2007a). The site has produced very abundant lithic and faunal assemblages, as well as several Neandertal and pre-Neandertal teeth and a jaw fragment (Trinkaus et al., 2000; Lebel et al., 2001; Lebel and Trinkaus, 2002; Fernandez, 2006; Wilson, 2007a, 2011). A dozen excavation seasons, lasting two or three months each, were conducted from 1987 to 2000. In addition, LW conducted field work prospecting for lithic raw material sources in the region, every year from 1987 to 2007, inclusive (Wilson, 2007a, 2011).

Materials and methods

The data set

The archaeological lithic assemblage from the Bau de l’Aubesier consists of nearly 40,000 lithic pieces that have been catalogued into 46 types of raw materials, mainly varieties of flint, based on

![Figure 1. The study area.](image-url)
visual criteria such as colour, cortex, structure and fossils. The 46 types include seven categories to which pieces could be assigned when they were either so patinated (weathered) or so highly burned that their original raw material type could not be determined. These latter accounted for very few pieces, but unfortunately a very large number of pieces were patinated or burned and therefore had to be excluded from this study. However, the data set reported here is still very substantial, and includes 15,674 pieces. These pieces come from several different layers, but the lithic assemblages from all layers have been described as Typical Mousterian, rich in sidescrapers, by Lebel (2000b).

The lithic raw material types were defined as narrowly as possible, in the awareness that many would turn out to be variations of each other, rather than coming from distinct sources. At least one representative of each type was selected for a petrographic reference series. In a few cases of very rare types, the pieces were too small for thin sectioning, but most have been sectioned and analyzed under the polarizing microscope, so that they can be compared with samples from the surrounding environment.

Since 1987, a long-term prospecting campaign, the Vaucluse raw material project (Wilson, 2007a, 2011), has resulted in the localization of 352 potential sources of flint or other useful lithic raw materials. The region has now been thoroughly explored, and although it is always possible that a few more sources will be found, the basic pattern (shown in Fig. 2) is clear. There are areas where flint sources are abundant, and areas where they are scarce or absent. Sources include, in some cases, specific outcrops, and in some cases secondary (alluvial or colluvial) deposits. For each source, data including its precise location, geologic nature and age, extent of the source, size of the raw material pieces available, etc., have been recorded. We recognize that present resource availability is not necessarily the same as past availability, due to erosion, deposition of overburden, and use of the sources by hominins. As was described above for the broad topography of the region, however, we feel that reconstructing past availability at any given time would be extremely difficult, and that the present day lithic landscape can serve as a useful proxy for the prehistoric one(s), even if it will never give completely accurate results. For instance, it will be shown below that although raw material abundance at a source does not, by itself, predict whether or how much a source area was used, the most abundantly used raw material types do tend to be from sources where raw material is presently abundant. The most parsimonious assumption is therefore that such flint was also abundant in the past.

Samples collected from each source have been described, catalogued, and analyzed in a variety of ways. Details are available at http://pizza.unb.ca/~lwilson/. Descriptions include macroscopic criteria, such as the colour or colours of the raw materials available at the source, texture (grain size, homogeneity, inclusions), the characteristics of the cortex (if applicable), and any visible fossils. In most cases, samples from the source have been thin-sectioned and studied under the polarizing microscope, and the minerals, granulometry, microstructures (zoning, bands, etc.) and any microfossils recorded. In a smaller number of cases, samples have been analyzed using geochemical methods, the scanning electron microscope, or for their oxygen isotope ratios. Thus far, a combination of microfossils and macroscopic characteristics has proven to be the most useful for distinguishing the provenance of the samples (Wilson, 2007a; Wilson et al., 2010).

This provides us with a very substantial data set, both of archaeological material and of geologic knowledge of potential raw material sources in the region. However, we do need to acknowledge that some imprecision will always remain in this data set, for several reasons. First, identification of the rock type of each tool from the site can never be perfect because it will be influenced by patina and by the fact that small pieces look similar to each other even if they are of different flint varieties. Some imprecision may also be due to the fact that type identifications were made under field conditions, when time is always short and equipment is rudimentary. On the other hand, the fact that all identifications were made by the same person (LW), even if they were made over a period of many years, should lend some consistency to the results.

Identification of the source of the rock type for each piece is also based on some assumptions. It was impossible to make a thin section of every piece, so we have had to assume that every piece

![Figure 2. The source areas.](image)
called, for instance, type P because it looks like the example specimen for type P, actually came from the same source as that type specimen. Also, assigning some rock types to precise sources can be problematic, because in practice many of the rock types might come from one of several outcrops (of similar or essentially identical rock) in a small or large area.

The archaeological pieces come from several different archaeological layers, and thus were brought to the Bau by people who lived at very different times, thousands or tens of thousands of years apart. This may well have had an influence on resource procurement strategies. Combining layers no doubt obscures those variations in strategies, but should still allow us to find consistencies of behaviour. Using numbers of pieces (instead of, for instance, the weight of raw material that they represent, or some other measure) may also induce some bias, but those are the data we have. We therefore did not undertake this work expecting to find very precise details of past lithic raw material choice strategies, but rather were hoping to find a broad pattern of use and the main factors that influenced that pattern.

**Analytical methods**

The attractiveness equation Wilson (2007c) created the following equation to quantify the attractiveness of a raw material source:

\[
A(s) = \frac{\text{quality} \cdot \text{extent of source} \cdot (100)}{\text{difficulty of terrain} \cdot \text{cost of extraction}} \cdot \text{size} \cdot \text{scarcity}
\]

\(A(s)\) is thus a value describing the attractiveness of a raw material source, based on the relative benefits (quality, extent and size of pieces available) versus the costs (terrain difficulty, extraction cost, and scarcity of usable pieces at the source) that it offers. See Wilson (2007c) for details of how to use the equation. Its components are explained briefly below.

Quality is a subjective judgement of the suitability of the raw material for tool making using a scale from zero (very poor) to 16 (excellent). The quality value is based on criteria including homogeneity, the presence or absence of cracks, granulometry, and toughness or ease of breaking. Note that although flint is by definition extremely fine-grained, there are variations within that size category such that some flint is visibly coarser. Such coarse flints also tend to be tougher to knap. They require more force to break and give an inferior product.

We use a subjective judgement of quality for ease of application, but acknowledge that a more objective measure would be desirable to facilitate comparisons between regions and between studies done by different researchers. As far as we are aware, however, there is as yet no generally agreed upon measure of quality, despite many years of work by many researchers (e.g., Goodman, 1944; Speth, 1972; Hounsell, 2005). This is probably because the necessary measurements (of crystallographic characteristics, purity, etc.) are cumbersome to make, and also because if the method is to be applied to different time periods, it would have to take into account the intended use of the tool, since different raw materials are suitable for different types of tools (e.g., grinding stones versus Mousterian points) (Hounsell, 2005).

The extent of source categorizes the size of the outcrop or deposit according to a numerical scale from one (<10 m diameter) to four (>100 m in diameter). The numbers are multiplied by 100 to eliminate needless decimal points.

The difficulty of terrain is a value in Calories per kilometre, determined by plotting routes from each raw material source to the Bau on a digital topographic base map at 1:25,000 scale (Wilson, 2007b). The routes were taken as straight lines as much as possible but were allowed to detour around overly steep (>60%) slopes. Each route was divided into slope segments and the gradient and length of each segment were calculated. Using values for Calories expended per kilometre walked over various gradients (Wilson, 2007b), a caloric expenditure for each segment was calculated. For each route, the total Calories and total length were used to give a value in Calories per kilometre, which corresponds to the difficulty of the terrain crossed. (Note that ‘Calories’ is capitalized because it is the measurement equal to ‘kiloCalories’, one thousand Calories.) This method was published in Wilson (2007b), and used in Wilson (2007c). It is a time consuming and essentially manual technique, and we were tempted to replace it with a least-cost path method that could be performed by the Geographic Information System (GIS) software. However, as will be shown below, the values from the Wilson (2007b) method actually produced a better multivariate model than did the least-cost path values, and because our first goal was to fully test the attractiveness equation published in Wilson (2007c), we decided to use the values previously calculated according to that method. That means that although we now know of 352 potential raw material sources in the region, this paper uses only the 306 sources that were included in the analyses reported earlier. In future work, we intend to add in the additional sources, and also examine other ways of calculating energy costs, such as by varying speed of travel, and/or by comparing our values in Cal/km to the similar pattern of energy/slope values reported in J/(kg m) by Minetti et al. (2002).

The cost of extraction is given as one in this paper because it is assumed that the rocks were collected as loose surface material. We are nonetheless aware that some cases of quarrying in Middle and even Lower Palaeolithic sites have been reported (see for instance Padday et al., 2006; Sampson, 2006). Extraction cost was given a place within the equation in order to make it easier to apply it to such situations.

Size is the maximum dimension in centimetres of the nodules or pieces at the source. In situations where a smaller size is much more abundant, the equation allows two or more sizes to be used (see Wilson, 2007c). The sizes are divided by their corresponding scarcity values. Scarcity is the inverse of abundance and uses a categorical scale ranging from one (very abundant, >50% of the surface area of the source consists of potential raw material) to four (scarce, <5% of surface area of the source). The sum of the values is used in the equation.

Testing the attractiveness equation. Our first goal was to calculate the attractiveness value of every potential source in the region, and determine if there is a significant relationship between source attractiveness and the number of stone tool pieces found at the Bau from each source. Unfortunately, since many sources contain raw material that closely resembles that from other sources, the exact source of each stone tool piece found at the Bau could not always be determined. We therefore grouped the 306 sources into 110 source areas containing one or more sources with similar lithic raw materials (see Fig. 2). The areas are of various sizes, and because some rocks of different ages can occur close together, many of the source areas overlap with others. In addition, since some of the raw material types identified at the Bau did indeed turn out to be variations of each other, there are cases where several types came from the same source area. Therefore, among that total of 110 source areas, 17 were identified as having been used to provide the raw materials found in the assemblage at the Bau (Fig. 3). Three of these source areas consist of a single, precise, outcrop or deposit, while the others contain a range from three to 15 outcrops or deposits providing similar materials.

Our next problem was to assign an attractiveness value to each of the 110 source areas, rather than to the individual sources for which the attractiveness equation was designed. We therefore tried four different methods, and compared their results. The first
method aimed to incorporate all sources in a source area to get a value representing the entire area. For this we calculated the mean attractiveness value of all sources within each source area. The other three methods attempted to choose one source to represent each source area, and for this we tried using (1) the source with the maximum attractiveness value within each source area, (2) the attractiveness value for the source with the lowest difficulty value (Cal/km), and (3) the attractiveness value for the source that is the closest (Euclidean, i.e., straight-line distance) to the Bau within each source area.

We used Spearman’s rank correlation (data were not normally distributed) to quickly examine correlations between source area attractiveness (using each of the four versions) and the number of stone tool pieces found at the Bau for each source area. We used a = 0.05 to determine statistical significance for all tests unless stated otherwise. We then used generalized linear models (GLMs) with a negative binomial distribution and log link function to more fully examine the relationship between source area attractiveness and the number of stone tool pieces. The maximum number of step-halvings was increased from the default setting of five to 30 (for all GLM models throughout this paper) to avoid separation in the data set. The GLM results provide a measure of the statistical significance of each independent variable (p value), and a relative measure of the importance of each independent variable (Wald Chi-Square value). The Beta values indicate whether each independent variable is positively or negatively related to the dependent variable. Finally, we used Akaike Information Criteria (AIC) to identify the most parsimonious model (Burnham and Anderson, 2002). All statistics were conducted using PASW Statistics 18, Release Version 18.0.2 (SPSS Inc., 2010). Breaking down the attractiveness equation We used GLMs with a negative binomial distribution and log link function to examine the relationship between the number of stone tool pieces found at the Bau and each of the core variables that were used to calculate the attractiveness equation. Quality, extent of source, and difficulty of terrain were entered directly into the GLMs as independent variables. Rock size and scarcity, however, could not be entered directly, because for each source, scarcity values corresponded with specific rock sizes. We therefore re-categorized this variable set into four independent variables that measured the abundance (inverse of scarcity) of (1) small rocks, 0–5 cm; (2) medium rocks, 6–15 cm; (3) large rocks, 16–35 cm; and (4) very large rocks, >35 cm in size. Each source thus had an abundance value for each of the four size categories. We calculated values for each source area using the four different methods outlined above (mean value, highest quality, easiest terrain, shortest distance from the Bau). In the second method, in cases where quality was equal for two or more sources within a source area, we broke ties by using the source characteristics that we believed were most closely related to source quality: the greatest abundance of large rocks, followed by the abundance of very large rocks, the abundance of medium rocks, the abundance of small rocks, the largest extent, and then the shortest surface distance, if necessary. Independent variables were examined for correlations with each other, and variables were not analyzed within the same model if Pearson correlations were greater than 0.6. This holds true for all GLM models throughout this paper.

Examining additional variables We examined six additional variables, not included in the original equation, to determine if they would improve our models. These variables were: Calories, Calories using least-cost route, surface distance, area of the source area (AOSA), area of the sources in the source area (AOSISA), and distance to the closest used source area.

Calories: the amount of energy required to travel from the source to the Bau using a straight-line path except for deviations around areas that have slopes greater than 60%. Calories were calculated in the process of calculating difficulty (Cal/km; see above).

Calories using least-cost route: the amount of energy required to travel from the source to the Bau using the least-cost route calculated by the GIS. This route requires the least amount of energy despite its length or difficulty, with allowance made for deviations around slopes greater than 60%. The Path Distance tool in ArcMap 9.3 (ESRI 1999–2008) was used to calculate the least-cost routes.
This tool calculated the cost (measured in Calories for our analysis) to travel from each pixel in a designated area to a specified point (the Bau). The cost to travel from each source to the Bau was then extracted from the data layer created by the Path Distance tool.

A digital elevation model (DEM) was used to enable the Path Distance tool to calculate the slope and the surface distance of each pixel that was crossed on the least-cost route from each source to the Bau. The DEM was created by the United States of America’s National Aeronautics and Space Administration (NASA) and National Geospatial-Intelligence Agency (NGA) from data collected from the Shuttle Radar Topography Mission (SRTM). The SRTM collected DEM data globally for all land between 60° north latitude and 56° south latitude (Farr et al., 2007). We used a SRTM3 DEM (three arc-seconds resolution) in raster format with a pixel size of 81 × 81 m. The SRTM DEM is available to the public and can be downloaded free of charge from the United States Geological Survey (USGS, 2010).

We compiled a table containing 121 values for slope ranging from −60% (downhill) to +60% (uphill) and the associated value of Cal/km for each slope based on values published in Wilson (2007b). This table was used in the Path Distance tool to calculate the costs of each route.

**Surface distance:** the straight-line distance between two points measured via a ground route, which is slightly longer than an air route because the slope of the terrain is considered. Surface distance was calculated in ArcMap 9.3 using the Path Distance tool and the SRTM DEM.

**AOSA:** the surface area covered by a source area. We created minimum convex polygons using the locations of sources within each source area and calculated area using Hawth’s tools (Beyer, 2004) in ArcMap 9.3. Areas were packed with raw materials.

**AOSISA:** the total surface area covered by the sources within a source area. The size of each source was recorded categorically for the variable ‘Extent’ in the original attractiveness equation (see above). We assigned a source size to the categorical data in the variable ‘Extent’ as follows: 1 = 5 m diameter, 2 = 30 m diameter, 3 = 75 m diameter, and 4 = 150 m diameter. We then calculated an area for each source and added together the area values for all sources within each source area to calculate AOSISA. Note that this does not represent the proportion of overall area that consists of sources. That value can, however, be indirectly obtained by the GLM by contrasting AOSA and AOSISA because preferring a smaller AOSA and a larger AOSISA indicates a preference for areas more densely packed with raw materials.

**Distance to the closest used source area:** the straight-line distance from a source area to the nearest source area that has been confirmed to have been used for the lithic assemblage at the Bau. Values for source areas that were themselves used were calculated by using the distance to the next closest used source area (i.e., not the source’s distance to itself).

We repeated the GLM analyses with these six additional variables. We then used the best resulting model as the basis for formulating a new attractiveness equation, using the following log-linear equation, which is assumed to characterize the influence of covariates on relative use, w(x):

\[ w(x) = \exp(\beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots + \beta_p x_p) \]

where \(\beta_i\) are selection coefficients estimated for each of p covariates (Johnson et al., 2006).

Testing the predictive ability of the new attractiveness model We used five-fold cross-validation to determine the internal consistency of the new attractiveness model (with the best combination of variables as identified in the previous step). This technique randomly divides the data into five groups, each consisting of 20% of the data. For each ‘fold’, four groups (80% of the data) are used as training data, to create a model explaining the data. The other group (20% of the data) is used to test that model to see how good it is at predicting results for data that were not used to create it. A Spearman’s rank correlation between predicted and observed frequencies (Boyce et al., 2002) was used to determine correlations (\(r_s\) value) and statistical significance (p value). This is then repeated four more times, using each group only once as the test data. The average of the five correlation and significance values is used to judge the overall predictive ability and consistency of the model. Thus in this case, the source areas were divided randomly into five groups. We ran five GLM analyses using the five sets of training data for the new attractiveness model. We then computed a \(w(x)\) equation for each fold using the Beta coefficients from each GLM model. This equation was used to calculate an attractiveness value for each sample in the training data for each respective fold. The attractiveness values from the training data for each fold were arranged in order of lowest to highest and then divided into five bins with equal frequency of data. The bin with the lowest range of attractiveness values was ranked as bin 1, and so on with bin 5 having the highest attractiveness values. The lowest and highest values for each bin group set the ranges for placing the test data results into the bins. An attractiveness value for each source area that was represented in the Bau’s lithic assemblage was then calculated from the test data and assigned to a bin. The number of used source areas from the test data was tallied for each bin and the distribution was compared to bin rank (1 = lowest, 5 = highest) using a Spearman’s rank correlation. A higher number of samples in the higher ranked bins indicate an internally consistent model, and therefore, a model with good predictive ability.

Since only 17 source areas were used for the Bau lithic assemblage, the sample sizes were low, with only three or four used source areas per fold. We therefore chose, a priori, a limit of \(\alpha = 0.2\) to determine statistical significance, in order to reduce the chance of committing a type II error (not finding a significant difference that really exists). A power analysis for this test showed that \(\alpha = 0.2\) is an appropriately conservative value since the corresponding \(\beta\) value (~0.335) is much higher. This means that the chance of not detecting a significant difference that really exists is larger than the chance of identifying a significance difference that does not exist.

**Results**

**Testing the attractiveness equation**

The attractiveness equation was tested on four different models, as explained above. Two of these models showed significant correlation between attractiveness and the number of stone tool pieces found at the Bau (Table 1). Those using the least-difficult and the closest sources had p-values of 0.002 and 0.022, respectively. However, the correlation coefficients were fairly low for both \(r_s = 0.295\) and 0.218, respectively.

The GLMs produced significant results in three of the four cases tested for a positive relationship between the numbers of stone tool

<table>
<thead>
<tr>
<th>Attractiveness model</th>
<th>Correlation coefficient</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>-0.090</td>
<td>0.350</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.048</td>
<td>0.622</td>
</tr>
<tr>
<td>Least-difficulty</td>
<td>0.295</td>
<td>0.002</td>
</tr>
<tr>
<td>Closest</td>
<td>0.218</td>
<td>0.022</td>
</tr>
</tbody>
</table>

Significant values in bold print.

Table 1: Spearman’s rank correlation coefficients between the number of stone tool pieces found at the Bau and the attractiveness value for each source area.
Significant values in bold print. Maximum Quality model.

Table 2
Generalized linear model results examining the relationship between the number of stone tool pieces found at the Bau and the attractiveness value for each source area.

<table>
<thead>
<tr>
<th>Attractiveness model</th>
<th>Beta</th>
<th>S.E.</th>
<th>Wald Chi-Square</th>
<th>p-value</th>
<th>AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>-0.003</td>
<td>0.0071</td>
<td>0.180</td>
<td>0.671</td>
<td>1315.634</td>
</tr>
<tr>
<td>(Intercept)</td>
<td>5.227</td>
<td>0.6384</td>
<td>67.019</td>
<td>&lt;0.001</td>
<td></td>
</tr>
<tr>
<td>Maximum</td>
<td>0.038</td>
<td>0.0063</td>
<td>36.406</td>
<td>&lt;0.001</td>
<td>1272.876</td>
</tr>
<tr>
<td>(Intercept)</td>
<td>1.257</td>
<td>0.5801</td>
<td>4.549</td>
<td>0.033</td>
<td></td>
</tr>
<tr>
<td>Least-difficulty</td>
<td>0.049</td>
<td>0.0054</td>
<td>80.849</td>
<td>&lt;0.001</td>
<td>1204.325</td>
</tr>
<tr>
<td>(Intercept)</td>
<td>2.637</td>
<td>0.2240</td>
<td>138.611</td>
<td>&lt;0.001</td>
<td></td>
</tr>
<tr>
<td>Closest</td>
<td>0.012</td>
<td>0.0022</td>
<td>28.867</td>
<td>&lt;0.001</td>
<td>1281.886</td>
</tr>
<tr>
<td>(Intercept)</td>
<td>4.314</td>
<td>0.1325</td>
<td>1059.663</td>
<td>&lt;0.001</td>
<td></td>
</tr>
</tbody>
</table>

Each of the new variables showed significant relationships to the number of pieces found at the Bau in at least two of the four model versions. AIC values were lower (i.e., better) in three of the four model versions that contained the variable Calories as opposed to those with the variable Calories using least-cost route. The models that contained either the variable Calories or Calories using least-cost route all had lower AIC values than the models with surface distance, and AIC values were highest (worst) in the models with distance to the closest used source area.

Average AIC values were lowest in the models that used the source with the highest raw material quality value to represent each source area (mean AIC = 387.744), followed by the models that used the sources with the lowest difficulty values (mean AIC = 380.881), the shortest distances (mean AIC = 381.846), and the mean value for each variable (mean AIC = 425.011).

Overall, the best model, with the lowest AIC value, used the values for the source with the highest quality value within each source area, and the variable set including Calories (Table 4). The number of stone tool pieces found at the Bau was positively related to quality, extent, large rocks, very large rocks, and AOSA, and negatively related to difficulty, small rocks, medium rocks, Calories, and AOSA. The Beta values from this model were then used to create a new equation to calculate source area attractiveness: source area attractiveness = exp(2.099 × quality) + (1.184 × extent) + (−0.046 × difficulty) + (−11.272 × small rocks) + (−5.891 × medium rocks) + (0.859 × large rocks) + (1.802 × very large rocks) + (−0.002 × Calories) + (−1.5e−7 × AOSA) + (5.6e−5 × AOSISA).

Table 3
Generalized linear model results examining the relationship between the number of stone tool pieces found at the Bau and core independent variables from the attractiveness equation using the maximum quality approach (the best model).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Beta</th>
<th>S.E.</th>
<th>Wald Chi-Square</th>
<th>p-value</th>
<th>AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quality</td>
<td>2.116</td>
<td>0.1783</td>
<td>140.894</td>
<td>&lt;0.001</td>
<td>456.709</td>
</tr>
<tr>
<td>Extent</td>
<td>1.640</td>
<td>0.1952</td>
<td>70.564</td>
<td>&lt;0.001</td>
<td></td>
</tr>
<tr>
<td>Difficulty</td>
<td>−0.007</td>
<td>0.0095</td>
<td>0.511</td>
<td>0.475</td>
<td></td>
</tr>
<tr>
<td>Small rocks</td>
<td>−0.891</td>
<td>1.5116</td>
<td>35.380</td>
<td>&lt;0.001</td>
<td></td>
</tr>
<tr>
<td>Medium rocks</td>
<td>−5.027</td>
<td>0.6189</td>
<td>65.982</td>
<td>&lt;0.001</td>
<td></td>
</tr>
<tr>
<td>Large rocks</td>
<td>2.222</td>
<td>0.2851</td>
<td>60.764</td>
<td>&lt;0.001</td>
<td></td>
</tr>
<tr>
<td>Very large rocks</td>
<td>1.808</td>
<td>0.4716</td>
<td>14.099</td>
<td>&lt;0.001</td>
<td></td>
</tr>
<tr>
<td>(Intercept)</td>
<td>2.000</td>
<td>1.7713</td>
<td>1.275</td>
<td>0.259</td>
<td></td>
</tr>
</tbody>
</table>

Significant values in bold print. Maximum Quality model.

Testing the predictive ability of the new attractiveness model

We were unable to test the exact equation given above, because only one source area had a value other than 1 for the variable ‘small rocks’. This parameter therefore caused a problem called a Hessian matrix singularity when the data were divided into five groups. However, we ran the model for that set of variables, but excluding ‘small rocks’, and again got a good AIC result and significant results for each variable (Table 5). Five-fold cross-validation showed that this model had very good predictive ability (average ρs = 0.762, average p = 0.147).

Table 4
Generalized linear model results examining the relationship between the number of stone tool pieces found at the Bau and independent variables including Calories, calculated using the maximum quality approach.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Beta</th>
<th>S.E.</th>
<th>Wald Chi-Square</th>
<th>p-value</th>
<th>AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quality</td>
<td>2.099</td>
<td>0.2571</td>
<td>66.654</td>
<td>&lt;0.001</td>
<td>368.724</td>
</tr>
<tr>
<td>Extent</td>
<td>1.184</td>
<td>0.2518</td>
<td>22.118</td>
<td>&lt;0.001</td>
<td></td>
</tr>
<tr>
<td>Difficulty (Cal/km)</td>
<td>−0.046</td>
<td>0.0142</td>
<td>10.658</td>
<td>0.001</td>
<td></td>
</tr>
<tr>
<td>Small rocks</td>
<td>−11.272</td>
<td>1.8451</td>
<td>37.319</td>
<td>&lt;0.001</td>
<td></td>
</tr>
<tr>
<td>Medium rocks</td>
<td>−5.891</td>
<td>0.8595</td>
<td>43.266</td>
<td>&lt;0.001</td>
<td></td>
</tr>
<tr>
<td>Large rocks</td>
<td>0.859</td>
<td>0.3225</td>
<td>7.086</td>
<td>0.008</td>
<td></td>
</tr>
<tr>
<td>Very large rocks</td>
<td>1.802</td>
<td>0.5858</td>
<td>9.459</td>
<td>0.002</td>
<td></td>
</tr>
<tr>
<td>Calories</td>
<td>−0.002</td>
<td>0.0003</td>
<td>29.165</td>
<td>&lt;0.001</td>
<td></td>
</tr>
<tr>
<td>AOSA</td>
<td>−1.5e−7</td>
<td>5.1e−8</td>
<td>8.336</td>
<td>0.004</td>
<td></td>
</tr>
<tr>
<td>AOSAISA</td>
<td>5.6e−5</td>
<td>1.1e−5</td>
<td>28.138</td>
<td>&lt;0.001</td>
<td></td>
</tr>
<tr>
<td>(Intercept)</td>
<td>11.688</td>
<td>2.3940</td>
<td>23.835</td>
<td>&lt;0.001</td>
<td></td>
</tr>
</tbody>
</table>

Significant values in bold print. All variables are significant. Maximum Quality model.
Discussion

The original attractiveness equation and all of this subsequent work stem from an optimal foraging theory perspective (Pyke et al., 1984): the idea that it is evolutionarily desirable, even inescapable, for foragers to maximize their ‘return on investment’ either by minimizing their expenses (for instance of energy expended, or of time), or by maximizing their returns (usually considered to be food energy obtained). Although the original development of optimal foraging theory concerned food resources, in archaeology it was soon expanded to include other aspects of life, especially raw material procurement and stone tool technology (see for instance Torrence, 1983, 1989; Jeske, 1992). Lithics fit into this viewpoint because getting raw material and making tools require time and energy, while using the tool helps the forager to obtain more food energy or the same food energy with less energy cost. For instance, good tools may promote better hunting success, or better efficiency in processing the carcass.

When determining the food resources that would have been available to past human groups, our best evidence is the bones and pollen found at archaeological sites, because the present day faunal and floral landscape is only remotely related to that of 100,000 or 200,000 years ago. Faunal availability, for instance, varies through time because of climatic variation, vegetation changes, and even the fact that animals move around over the course of a day or a season. When dealing with lithics, on the other hand, we are dealing with a lithic landscape that is much closer to that which was available to prehistoric hominins. As was discussed above, the present day landscape can serve as a reasonable proxy for prehistoric one(s), because the same mountains, rivers and rocks are present in much the same places (with the exception of variations in alluvial deposits), and therefore factors such as terrain difficulty, raw material quality, and so on can be fairly accurately reconstructed. Thus, although the information from lithics may be seen as only an indirect measure of foraging constraints, it has the advantage that it can be directly placed within the lithic landscape that the prehistoric group actually experienced.

It is generally agreed (Geneste, 1989; Kuhn, 1995) that for any group of foragers, subsistence activities are crucial, and other activities, such as making tools, are likely to be organized around the demands of subsistence. In areas where lithic resources are widely available, therefore, tool materials will be acquired ‘along the way’. This is generally called embedded procurement (Binford, 1980, 1989; Binford and Stone, 1985). In other cases, raw materials may be obtained as the result of deliberate, strategic, trips to the sources (Gould and Saggers, 1985). Obtaining raw material through chance encounters (expedient procurement) must also have happened, but in most cases procurement probably involved some degree of planning, and curation of the materials and the tools, so that they were available when the need arose (Binford, 1977; Bamforth, 1986; Roebroeks et al., 1988). The degree of planning or anticipation will have influenced the strategy adopted, as will a large number of other factors that various authors have examined, including the effort required to extract the raw material (Ataman et al., 1992; Elston, 1992), the distance of transport (Renfrew, 1977; Newman, 1994), the topography and the mode of transport (Eriksen, 1977; Findlow and Bognolene, 1982; Reid, 1986; Wilson, 2007b), the time available (Torrence, 1983, 1989; Elston, 1992), the weight of material to carry (Elston, 1992; Metcalfe and Barlow, 1992; Beck et al., 2002), and the distribution and ubiquity or otherwise of raw material sources (Geneste, 1988; Kuhn, 1995; Wilson, 2007a).

Although each of these factors has been shown to be individually important, prehistoric people will no doubt have been influenced by a combination of factors, some more important than others in any given situation. Our work has thus aimed to evaluate the importance of a variety of factors, some newly proposed by us. The new model, the new equation, and the original attractiveness equation, are all cost-benefit analyses. The variables have been evaluated separately and in combination with each other to get an overall result showing what mattered to hominins at the Bau over the course of the Middle Palaeolithic: why some sources were used and not others, and why some were used more than others.

This work does simplify matters, however, by combining pieces from all layers and implicitly treating the Bau as a home base in what may be considered a central-place foraging perspective (Hodder and Orton, 1976; Pyke, 1984). Previous work (Wilson, 1998) has shown that for some layers, the Bau was most likely not a home base, and in future work we plan to apply the methods presented here to each individual layer (samples sizes permitting). That will allow us to also incorporate relevant information on, for instance, procurement strategies, residence and mobility strategies, and technological choices (Geneste, 1985; Féblot-Augustins, 1993; Brantingham, 2003, 2006).

Testing the attractiveness equation

The GLMs showed that a significant positive relationship exists between source area attractiveness and the number of stone tools found at the Bau, which provides support that Wilson’s (2007c) attractiveness equation can be used to indicate the likelihood that a source would be used by hominins, and therefore does incorporate some of the factors that influenced their choices. The correlations between source area attractiveness and the number of stone tool pieces are relatively weak, however, so this equation can clearly be improved.

The equation was tested on four models (see above). The most parsimonious model used the least-difficult source within each source area, which suggests that hominins selected sources that were located in less difficult terrain (rather than closer or more attractive overall). However, the results of our subsequent analyses led us to modify this interpretation.

Breaking down the attractiveness equation

Examining the core variables of the equation using multivariate statistics produced much better models, which confirms that the attractiveness equation as published in Wilson (2007c) does not have the best possible weighting of the variables. The multivariate model results suggest that quality, extent, and size/abundance of rocks are significant variables in source selection by hominins, but difficulty of terrain is not (Table 3). The multivariate model using the values for the source with the highest quality raw material

<table>
<thead>
<tr>
<th>Variable</th>
<th>Beta</th>
<th>S.E.</th>
<th>Wald</th>
<th>p-value</th>
<th>AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quality</td>
<td>1.710</td>
<td>0.2215</td>
<td>59.577</td>
<td>&lt;0.001</td>
<td>398.825</td>
</tr>
<tr>
<td>Extent</td>
<td>1.039</td>
<td>0.2439</td>
<td>18.156</td>
<td>&lt;0.001</td>
<td></td>
</tr>
<tr>
<td>Difficulty (Cal/km)</td>
<td>-0.042</td>
<td>0.0139</td>
<td>9.122</td>
<td>0.003</td>
<td></td>
</tr>
<tr>
<td>Medium rocks</td>
<td>-4.544</td>
<td>0.7516</td>
<td>36.544</td>
<td>&lt;0.001</td>
<td></td>
</tr>
<tr>
<td>Large rocks</td>
<td>0.891</td>
<td>0.3081</td>
<td>8.364</td>
<td>0.004</td>
<td></td>
</tr>
<tr>
<td>Very large rocks</td>
<td>1.615</td>
<td>0.5640</td>
<td>8.195</td>
<td>0.004</td>
<td></td>
</tr>
<tr>
<td>Calories</td>
<td>-0.002</td>
<td>0.0003</td>
<td>28.149</td>
<td>&lt;0.001</td>
<td></td>
</tr>
<tr>
<td>AOSA</td>
<td>-1.3e-7</td>
<td>4.9e-8</td>
<td>7.117</td>
<td>0.008</td>
<td></td>
</tr>
<tr>
<td>AOSISA</td>
<td>5.4e-5</td>
<td>1.1e-5</td>
<td>25.842</td>
<td>&lt;0.001</td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>0.390</td>
<td>1.4994</td>
<td>0.068</td>
<td>0.795</td>
<td></td>
</tr>
</tbody>
</table>

All variables are significant.
within each source area produced the most parsimonious model, suggesting that hominins preferentially selected sources that have good quality material (versus the other three options).

Examining additional variables

Each of the six variables that we examined contributed significantly to explaining the variation in abundance of stone tool pieces found at the Bau. The one possible exception is ‘distance to the nearest used source’, which gave unclear results. That variable was included to test whether sources were preferentially used when they were in the neighbourhood of other used sources: a source is more easily accessible when you are already near it for some other reason. However, it was only significant in the highest quality model, and because its Beta value in this model was zero, it does not appear to have played an important role in explaining patterns of lithic resource use.

‘Calories’ and ‘Calories using least-cost route’ were tested because of Wilson’s (2007b) contention that it is not just the distance travelled that matters to someone walking across the landscape, it is the energy expended to cover that distance. Both variables were significant in a negative direction, meaning that sources requiring more caloric expenditure to reach were less likely to be used. The variable ‘Calories’ explained more of the variation than did ‘Calories for the least-cost route’, suggesting that hominins travelled in relatively straight lines (but avoiding very steep slopes, >60%) rather than choosing easier but longer routes. This may suggest that travel time was more important to them than energy expenditure, so in the future we plan to examine the effect of travel time (taking into account the fact that travel time varies depending on terrain steepness). Energy expenditure clearly did matter to them, however, since both of those variables explained more variation than did the simple surface distance that is usually considered in lithic sourcing studies (Geneste, 1985, 1988, 1989; Newman, 1994; Kuhn, 1995; but see also Ericson, 1977, for an alternate view of path use rather than straight-line distance). The added complexity of calculating Calories was necessary to obtain a superior model.

AOSA (area of the source area) and AOSISA (area of sources in source area) were also both significant, but AOSA negatively so, while AOSISA showed a positive relationship with source use. This means that larger source areas were not selected, or that smaller ones were, and in particular, that smaller source areas with a greater proportion of the area consisting of actual sources were preferred. In such areas, raw material density must be greater, which increases the ease of finding something usable, and/or decreases the time spent searching. This has analogies to the ‘patch size’ and ‘patch richness’ sometimes considered in optimal foraging studies (Pyke et al., 1977; Pyke, 1984).

The AIC values were lowest, and therefore best, in the models where each source area was represented by the source within it that has the highest quality raw material value. This suggests that hominins selected lithic material from sources that have high quality material rather than sources that are easy to get to, close to the Bau, or other factors (which would have shown up in the mean models).

The best model of all (Table 4) suggests that the hominins at the Bau selected sources that have high quality material, large extents, less difficult terrain, fewer small and medium sized rocks, abundance of large and very large sized rocks, require less energy to travel to, and are in source areas that are smaller but more densely populated with potential raw materials.

The variables in this model can be described as costs or benefits, and within each of those two categories, assigned to either time or energy, or in some cases both. For instance, selecting better quality raw materials can be seen as a way of reducing the energetic cost of making and using the tool, making increased quality an energy benefit (and to some degree probably a time benefit, too). Source extent would presumably be a time benefit, because a bigger source should be easier to find. It would also be an energy benefit, because less time spent searching means less energy expended.

Difficulty (Cal/km) is obviously an energy cost, as is Calories. We should emphasize that although these two values must be related because the Calories value is used to calculate difficulty, a Pearson’s correlation test showed them not to be significantly correlated with each other ($r = 0.115, p = 0.232$). This means that they do measure different things and can be included in the same model. Interestingly, difficulty of terrain was not a significant variable when only the core variables from the attractiveness equation were examined, but it became significant once ‘Calories’ was added to the model.

Difficulty was therefore not by itself a strong driver for lithic raw material selection, but if the routes from two sources to the Bau required similar amounts of energy, then it appears that the hominins preferred the source in the least-difficult terrain.

Rock size matters because for any given stone tool technology, there is probably an optimal size range for the initial pieces of raw material. Indeed, Neandertals are known to have been capable of changing their techniques to deal with differently-sized raw material packages if they had to. Kuhn’s (1991) work on the Pontinian in Italy, where only small pebbles were available, is a good example of this. In cases such as the Vaucluse, however, where raw material of a variety of sizes was abundant, Neandertals were free to select the sizes that they wanted, disdaining pieces that were too small (too much of a struggle to work with, and anyway the resultant tool would be too small to use well), or too large (too much work breaking them down to a usable size). The rock size values given are actually a measure of the abundance of pieces of that size at the source, and were defined based on the distribution of sizes commonly found at all of the sources, rather than on any preconceived notion of how big a ‘useful’ rock should be. Greater abundance of small rocks (or lack of larger ones) at a source would be an energy cost, or perhaps a time cost. Our ‘small’ size category ($0–5$ cm) seems to have been undesirable, as does our ‘medium’ category ($6–15$ cm), while ‘large’ ($16–35$ cm) and ‘very large’ ($>35$ cm) were desirable, based on our best model results.

AOSA, the size of the source area, equals AOSISA when there is only one source in the source area, but often represents an area containing two or more sources and a lot of space where no raw materials are available. Larger source areas would therefore generally include much more such ‘empty’ space, and represent a time and energy cost, because of the time spent searching for the sources within this area. Greater AOSISA would be a time (and energy) benefit, because it would mean less time spent searching for sources.

Table 6 shows that the variables that we can consider costs all have a negative relationship with the number of stone tool pieces at the Bau from the various sources, and those that we consider benefits have positive relationships, which reinforces the consistency and explanatory value of the model. The results also suggest that although time and energy were both considerations, energy minimization may have been more important to the hominins (although we may eventually want to revise that opinion based on the work we plan to do on travel time as opposed to travel effort).

Testing the predictive ability of the new attractiveness model

The AIC values produced by the analysis of each model indicate the parsimony of the model, so that the lowest AIC value indicates the model which explains the most variation with the fewest variables. They do not, however, represent an estimate of how
Table 6

Variables as certain or (in brackets) likely costs (−) or benefits (+), and negative (−) or positive (+) relationships with numbers of stone tool pieces from sources, based on the model in Table 4.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Time</th>
<th>Energy</th>
<th>Positive or negative relationship</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quality</td>
<td>(+)</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Extent</td>
<td>+</td>
<td>(+)</td>
<td>+</td>
</tr>
<tr>
<td>Difficulty (Cal/km)</td>
<td>−</td>
<td>−</td>
<td>−</td>
</tr>
<tr>
<td>Small rocks</td>
<td>−</td>
<td></td>
<td>−</td>
</tr>
<tr>
<td>Medium rocks</td>
<td>(−)</td>
<td>(−)</td>
<td>−</td>
</tr>
<tr>
<td>Large rocks</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Very large rocks</td>
<td>(+)</td>
<td>(+)</td>
<td>+</td>
</tr>
<tr>
<td>Calories</td>
<td>+</td>
<td></td>
<td>+</td>
</tr>
<tr>
<td>AOSA</td>
<td>−</td>
<td>(−)</td>
<td>−</td>
</tr>
<tr>
<td>AOSISA</td>
<td>+</td>
<td>(+)</td>
<td>+</td>
</tr>
</tbody>
</table>

Maximum Quality model.

much the variables explain. The five-fold cross-validation technique, on the other hand, does provide a Spearman's rank correlation value which can be taken as a rough estimate of the proportion of predictive ability of the model, where a value of one would indicate a perfect match.

The predictive ability of the combination of variables in the best new model, excluding 'small rocks' (see above), was therefore tested using five-fold cross validation. Despite the small sample size for the number of used source areas, the new combination of variables had very good predictive ability, with a value of 0.762 for \( r_s \), and \( p = 0.147 \), which is lower than our cut-off of \( p < 0.2 \) for statistical significance. This confirms that these variables were important to hominins when they were selecting lithic raw materials. It is likely that the equation including 'small rocks' would have given even better values, had we been able to test it, because it had a lower AIC value.

Conclusions

The work reported here aims to quantify aspects of the lithic landscape within which Middle Palaeolithic hominins in the Vaucluse lived, and to see how important various aspects were in conditioning resource choices. We acknowledge that the models developed here do not account for all of the factors that influenced choice of resources. In particular, the more 'human' factors (as opposed to geologic or geographic ones) are not explicitly included. This includes potential factors such as procurement and residence strategies, hunting strategies, territorial limits, direction of travel, the need for other resources besides lithics, etc. However, we believe that the models developed here have yielded important insights into the geologic and geographic factors that mattered to the prehistoric groups that created the lithic assemblages, and by doing so contribute to developing a better understanding of the overall picture, including other aspects of their organization of economic behaviour.

The best model that we obtained showed that hominins were more inclined to use sources with high quality raw material, especially if those sources were large (in extent) and relatively densely populated with raw material sources (higher AOSISA, lower AOSA). Sources where the available raw material pieces were mainly small or medium in size were avoided, whereas ones with larger pieces were preferred. Sources that were hard to get to (high Calories and difficulty) were also less likely to be used. In short, then, hominins seemed to have obtained the most good quality raw material for the least effort expended in getting to or searching for the source, or searching for usable raw material at the source. They also seem to have preferred to work with larger pieces of raw material, rather than struggling to deal with small pieces.

It is interesting to see this work in the context of selection of other resources, too, such as fauna. At the Bau, the faunal analyses have been able to not only determine which animals were selected as prey, but also that they were in fact selected (not just encountered) and that they were hunted (not scavenged) (Fernandez et al., 1998; Fernandez, 2006). In fact, the faunal assemblage provides evidence of at least two distinctly different selective hunting strategies within a single layer (Fernandez et al., 1998), showing that the hominins were capable of exploiting their environment to suit themselves, and were flexible in their strategies. In this case, too, they maximized their 'return on investment'.

The results reported here come from considering all layers at the Bau combined and therefore must reflect an overall tendency through time. Our next study will be to apply this analysis to each individual layer (sample sizes permitting) to see how they differ. It may be that the model explains more of the behaviour in some layers than in others and this will lead us to consider what other factors (such as residence strategies) may have been playing a more important role in those layers. After that, we intend to look at data from other sites in the region, and if possible beyond. The data sets required for this work are formidable, but we do hope that other researchers will also try this approach on their own data. This can be done either by running GLMs as described in this paper, or by applying the equation given above (although other researchers may want to consider including extrac tion cost). Although that equation was derived for the data sets used here, applying it to multiple and varied data sets should point up interesting similarities and differences between archaeological assemblages.

The model presented here therefore has two main contributions to make. It has predictive ability, giving us concrete results that will allow us to work towards a better understanding of prehistoric economic behaviour. In addition, this technique can be applied to any appropriate data set, of any age or geographic origin, to see how well those results match ours. This may point to differences between times or regions, and give us a meaningful way of comparing the behaviour of different groups of hominids, whether modern human or not. This means that we can finally start to tease out what prehistoric humans were really like, how they were different from more (or less) modern groups, what some of the fundamental traits (in terms of organizing economic behaviour and survival strategies) of human beings are, and how long those traits have been around.

Acknowledgements

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Appendix. Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jhevol.2011.08.004.
References


