HUMAN BEHAVIOURAL ECOLOGY IN THE MIDDLE PALAEOLITHIC: A COMPARATIVE STUDY BASED ON HOW WE QUANTIFY THE USE OF RAW MATERIAL

by

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A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of

Bachelor of Science with Honours in Marine Biology

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April, 2020

ABSTRACT

Resource Selection Function (RSF) analyses can be used to understand what variables influenced hominin choices for selection of lithic raw materials. Previous work examined stone tool assemblages from the Bau de l'Aubesier (Vaucluse, France), quantifying raw material use by the number of lithics from a particular source area. My study compares this to quantifying use by the weight of those pieces, using Generalized Linear Models that describe the sources of raw material used in each archaeological layer. Independent variables describe raw material characteristics or the surrounding terrain. In the older layers of the site, terrain variables contribute more towards source area use. In the younger layers, raw material characteristics drive source use, but less so in models that quantify lithics by their weight. *k*-fold cross-validation analyses suggest the best method of quantifying lithic artefacts for use in RSFs may vary depending on the hominin behaviour that led to the assemblage.

ACKNOWLEDGEMENTS

I wish to express a deep gratitude to my supervisors, Lucy Wilson and Connie Browne, whose abundant enthusiasm and warm encouragement have made this project both fascinating and enjoyable. Additional thanks to Lucy for the hospitality during my time spent in France.

I would also like to thank the University of New Brunswick for the funding opportunities that have allowed me to work on this project as an undergraduate research assistant and attend the 2019 Developing International Geoarchaeology conference in Vancouver.

STATEMENT OF RESEARCH CONTRIBUTION

I was given the excavation raw data as a file of 11 Microsoft Excel sheets, representing each of the archaeological layers at the Bau de l'Aubesier, which I reorganised to reflect the weight of lithic material. Then I matched these values with a petrographic series and assimilated this with further data that described each of the 122 source areas in terms of 10 independent variables. I reproduced 33 previously published Generalized Linear Models that used the number of lithic pieces as a dependent variable, and then ran the same models with my lithic weight data for comparison. I plotted both sets of models according to a series of proportional Wald χ^2 values and then completed *k*-means cluster analyses and *k*-fold cross validation on the results, determining an optimal α for significance for use in the *k*-fold analyses. Finally, I led the interpretation of these results, under the guidance of my supervisors.

Project milestones	Date
Discovery of cave site 'Bau de l'Aubesier'	1901
Beginning of serious scientific investigation	1987
Locating of lithic sources	1987 to 2007
Publication of petrographic series	2007
Various applications of Browne & Wilson resource selection function	2011 to present
Description of source area variables in their current form	2014
Reorganisation of raw data to reflect weight of lithic material	Sep to Nov 2019
GLMs completed and proportional Wald χ^2 values plotted	Dec 2019
Post-hoc analyses carried out and analysed	Jan 2020

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LIST OF ABBREVIATIONS

AIC: Akaike Information Criterion

BP: Before Present

GLM: Generalized Linear Model

ka: thousand years

kg: kilogram

km: kilometre

RSF: Resource Selection Function

VIF: Variance Inflation Factor

INTRODUCTION

Modern humans are defined as much by their behaviour as by their anatomy, but the determination of 'modern' behaviour – what it means, when it began, and how it developed – is a real challenge, requiring input from a multidisciplinary field of researchers. The behavioural ecology of extant species can be studied using field observations, but to understand that of our prehistoric human ancestors we rely on proxies for the evidence of their interactions with the environment: their material remains. Through these we can come to understand not only how they were capable of living, but also the cognitive reasoning that they demonstrated in the face of environmental pressures as they became *us*.

Over the past 2.5 million years or more, human species have distinguished themselves from other primates by their emphasis on the manufacture and use of tools (de Lumley, 2006; Haslam et al., 2009; Semaw et al., 1997). This fundamental aspect of the human lifeway, central to its evolution (Ambrose, 2001; Key and Lycett, 2011; Stout et al., 2008), was highly reliant upon stone as a raw material until only very recent millennia. Flint was especially prevalent, being widespread and common across many landscapes, easily worked and capable of producing a razor-sharp edge (Luedtke, 1994). In an archaeological context, the chemical and physical composition of flint also give it a durability that can make it among the most lasting and useful evidence of prehistoric societies (Luedtke, 1994; Schmid, 1986; Wilson, 2007a). The types of tools present at a prehistoric archaeological site can tell us much about the hominins that left them there: their technological capability and manual skills, for example (Cahen et al., 1979; Menras, 2009). Use-wear analysis of these tools can show that wood, hides and other substances were also used, suggesting the types of tool that were considered fit to purpose (Binford and Binford, 1969). In many cases, specific

stone tool assemblages have been used to define specific prehistoric periods, and some of those periods are more or less closely associated with specific hominin types (Foley, 1987). For instance, the Middle Palaeolithic is not only a time period, it is a time period during which particular combinations of tool types existed and certain tool-making techniques were common. In western Europe, the Middle Palaeolithic is characterized by the Mousterian industry (generally rich in sidescrapers, with common use of the Levallois technology), and the Mousterian industry is, in turn, associated with the hominins known as Neanderthals (Bordes, 1961; Carrión and Walker, 2019; Dibble, 1987; Richter, 2011).

In the ecology of animal species, the concept of resource selection can refer to a broad range of objects or conditions with which an animal might be associated, and which ultimately influence the animal's fitness, due to the behavioural choices leading to its use or avoidance of them (Buskirk and Millspaugh, 2006). For prehistoric hominins, resource selection refers to strategies for obtaining the resources they needed: food, water, shelter, tools, etc. Since stone tools persist in the environment, they are useful evidence for tracing various aspects of how people lived and what they were doing. In particular, the rock type can be traced back to its source in the landscape, so we can begin to determine patterns of mobility and landscape use (Soto et al., 2018; Stout et al., 2005). This allows us to build a picture of hominin resource selection and make interpretations about what factors might have influenced it, broadening our understanding of how prehistoric groups used the environment around them and lived their lives. Archaeologists have been trying to reconstruct and understand the lives of our prehistoric ancestors in this way for over half a century (Kuhn, 1995; Renfrew et al., 1966; Vukosavljević and Perhoč, 2017; Wilson, 1988). However, the vast majority of studies have tended to focus on highly detailed descriptions of the artefacts themselves and then simply the Euclidian distance 'as the crow flies' to the source of

their raw materials. This fails to account fully for a number of concepts centered around the mobility strategies of hominin groups, which deserve consideration if we are to add any sort of breadth to our interpretations.

Some attempts to understand raw material use in concert with human mobility include the *chaîne opératoire* approach, which recognises that lithic technology does not necessarily equate to lithic typology, and the items found at an archaeological site may represent a tool at any point in a chain of operations from its raw material procurement to its abandonment (Bar-Yosef and Van Peer, 2009). Related to this, distance-decay models propose that as the distance increases from the site of procurement, stone tools are expected to exhibit a greater degree of processing (Beck, 2008). In other words, the tool will show more evidence of having been 'touched-up', perhaps repurposed or otherwise more used, potentially accounting for apparent technological variation within assemblages (Dibble, 1995; Rolland and Dibble, 1990). We can also consider the archaeological site where a stone tool assemblage was found as a spatially and temporally dynamic reflection of one or many procurement strategies, such as what Kuhn (1995) describes as a 'provisioning of place': a site where a group might have stockpiled materials knowing they would revisit it.

Ultimately, given the myriad intersecting factors that influence all lives, most lithic studies do not fully account for a pattern of source use in a stone tool assemblage, and still less explain the rationale behind the behaviour that led to it. In order to understand more about the behaviour of prehistoric groups, and even get at *why* they behaved the way they did, we need a method that integrates source use not only with the characteristics of the tools themselves, but also with their environmental context. Additionally, as we have no way of equating our own behaviourally evolved tendencies to those that governed prehistoric hominin behaviour and daily life, this must be carried out in a way that is free of *a priori* assumptions. In other words, if we want to understand

how extinct species, who were not us, behaved, we cannot do so by assuming they behaved like us, and we equally cannot assume that they did *not* behave like us.

C. Browne and L. Wilson have developed a new method to investigate prehistoric lithic raw material choices (Browne and Wilson, 2013, 2011; Wilson, 2008; Wilson et al., 2018; Wilson and Browne, 2014) that uses multivariate statistical techniques adapted from wildlife ecology (Boyce et al., 2002; Browne and Paszkowski, 2014). The work is a well-established and highly detailed account of the contributions made by many descriptive variables towards patterns of stone tool raw material abundance at a large, multi-layered archaeological site in southern France. It has synthesised a vast amount of descriptive raw data and placed it into context with its prehistoric regional environment, providing a more objective insight as to the basis on which hominin behavioural choices were made. Although models in general are never completely objective, because they are based on the variables that have been selected as relevant, the method nevertheless delivers a critical and quantitative interpretation of the behaviour of prehistoric hominin groups, based on the material remains that they left behind.

However, as progress is made with research that uses more descriptive variables and complicated statistical techniques, there remains the underlying and fundamental question of how to quantify stone tool use. That is, do we describe the presence of a particular type of stone tool raw material by its quantity of pieces in the assemblage, or by its total weight? After all, this is what we are modeling any descriptive variables against. Usually this is taken as a measure of the number of pieces, which are categorised according to geologic and archaeological criteria, as is the case in the relevant provenance studies cited so far. But with the wide variety of stone tool sizes that might be found at a given archaeological site, and ranging sizes of raw material in a given landscape, the idea that weight would serve as a better measure of use is pertinent. It is

particularly relevant from a cost-benefit perspective in relation to the previously discussed mobility strategies, where carrying rocks is a cost and carrying a heavier amount of rocks increases that cost. Carrying a greater number of pieces, regardless of its implication, does not measure this cost of transport as directly as weight does. In fact it has the clear potential to be ambiguous and misleading, given that one rock might easily be larger and heavier than several smaller ones.

The weight of lithic material has been a popular and often heated point of discussion in the general field, but typically centered on functionality: how tools were used and managed. As an example we have Kuhn (1994) challenged by Morrow (1996), in two papers that attempt to model the optimal means of reducing weight while maximizing the potential utility of stone tools, amongst mobile populations of hominins. Or, in simple terms, is it better to carry more smaller artefacts or a few larger ones, and how this is reflected by what is actually seen in the archaeological record? Other examples of weight being discussed in a prehistoric behavioural context include experimental butchery studies, such as Merritt's (2012) paper that builds on a large body of work attempting to infer ancient tool preference from bone surface modifications made by modern replicates. But weight as a means of *quantifying* use, overall from artefacts found collectively in a large stone tool assemblage, is a little, if at all, explored concept.

The work described here compares two different ways of quantifying a Middle Palaeolithic stone tool assemblage in the Vaucluse region of southern France. It compares the number of stone tool pieces to the weight of those same artefacts, by modelling them against an identical set of descriptive variables, according to previously published research (Wilson and Browne, 2014). This is important because they are both ways of measuring how much a particular type of raw material was used by the prehistoric hominins that left them there, and this value is central to the output of any statistical model and the conclusions that can be drawn from it. The objective then, is to

evaluate whether we should reconsider how previous models have been used to interpret the prehistoric economic behaviour and raw material procurement strategies of Middle Palaeolithic hominins in the Vaucluse.

MATERIALS AND METHODS

The study area

The Vaucluse is a western interior district of Provence, southern France, with a considerable prehistory that includes over 30 archaeological sites from the Middle Palaeolithic alone (Buisson-Catil, 1994). Among these, the large rock shelter site known as the Bau de l'Aubesier (hereinafter referred to as "the Bau") provides the lithic assemblage that forms the basis of the work described here. It is located approximately five kilometers to the south of the Mont Ventoux, with other regional topography including the Monts de Vaucluse and Luberon mountains to the south, and the Ouvèze, Calavon and Durance rivers that flow westward to eventually meet the Rhône at Avignon (Fig. 1). The region has never been glaciated and consequently the major features of the landscape have remained relatively unchanged for several million years (Rouire, 1975). While this by no means makes the present day landscape an exact reconstruction of the past 300,000 or so years (our time period of interest) it can be considered a justifiable proxy (Browne and Wilson, 2011). Importantly this means that the many flint outcrops and deposits, along with the major topographical features that surround them (mountains, rivers, valleys, etc.) are as they were when they were being negotiated by the hominins that left us the stone tool assemblage at the Bau. Therefore, using the present day landscape as a tool to make inferences about Middle Palaeolithic raw material selection strategies provides valid (if never completely exact) results (Browne and Wilson, 2011).

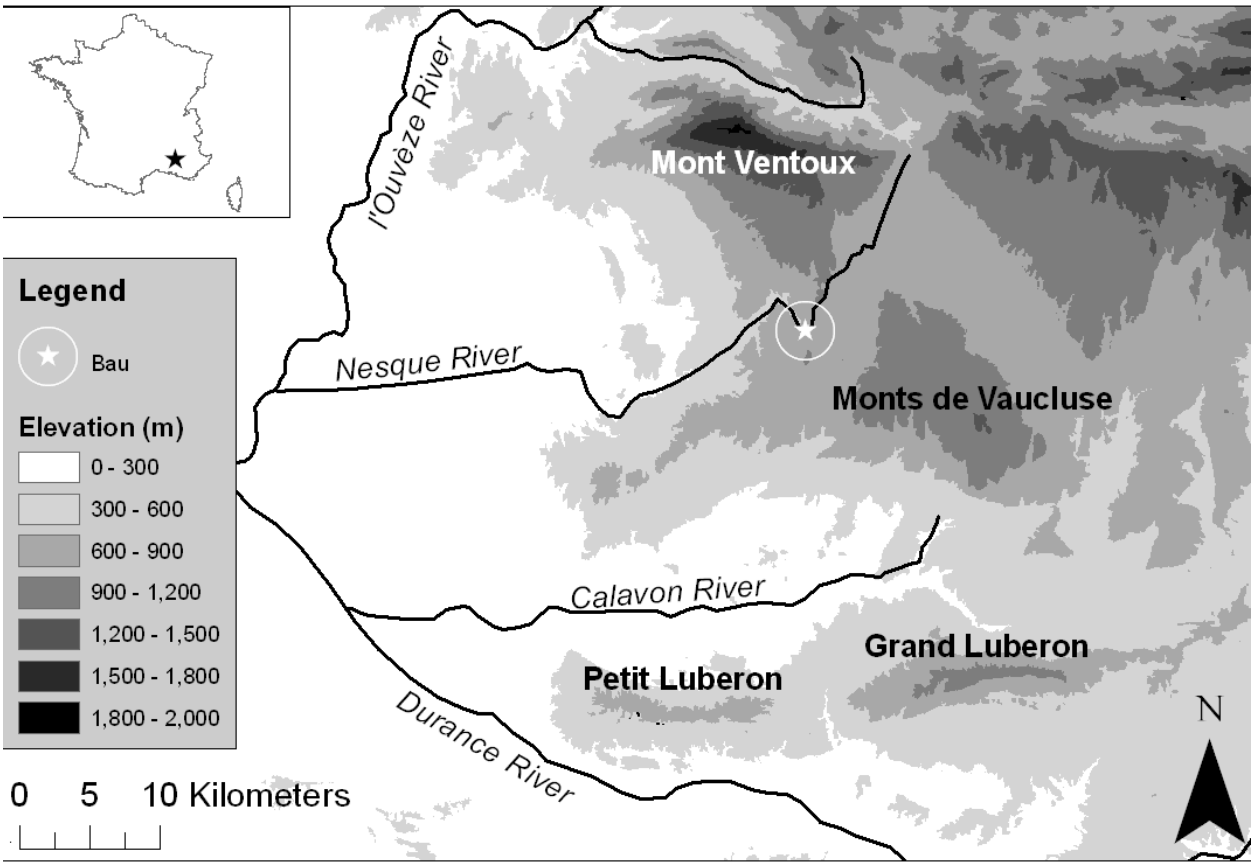

Figure 1. The study area (after Wilson and Browne, 2014).

The site

The Bau is nestled in the steep south wall of the gorge of the Nesque river (Fig. 2a). It covers an area of approximately 400 square metres and contains over 13 vertical metres of stratified sedimentary deposits. These deposits form a series of archaeological layers that range in age from approximately 100 ka (thousand years) to over 200 ka BP (before present) (Blackwell et al., 2001; Lebel et al., 2001). The site was discovered and first excavated in modern times at the beginning of the twentieth century (Moulin, 1904), resulting in an irregular trench, about two meters deep, along the west wall of the rock shelter: the Moulin Trench (Fig. 2b) (Wilson and Browne, 2014). After sporadic short-term investigations during the 1950s and 1960s, research

using modern methods of excavation began in 1987 (Wilson, 2007b) that included some work in the Moulin Trench but was largely focused on a second trench in the central part of the site: Trench L (Fig. 2c). The site was at this point divided up according to a metre-square grid system, with metres labelled alphabetically from west to east, and numerically from south to north (Fig. 3). Also around two metres deep, Trench L mostly comprises bands K, L and M but extends to bands I through P in places (Wilson and Browne, 2014). The site has an upper plateau area, within which the Moulin Trench and Trench L were excavated, and a lower slope, that slopes steeply from about band 14 towards the outside of the site (Wilson and Browne, 2014). Beginning in 1987, a part of this lower slope in front of the Moulin trench was also excavated (Fig. 2d) (Wilson and Browne, 2014). Excavation seasons were undertaken during the summer months between the years 1987 and 2000, in addition to work carried out in 2006 in zones H5, I5 and J5 that aimed to connect the two trenches, although the relationship between their archaeological layers is still not entirely clear (Lebel, 2006). Separate terminology is used for the archaeological layers in each part of the site: letter-names (with Layer A at the top) in the Moulin Trench and lower slope, and Arabic numerals (starting with 1 at the top) in Trench L (Fig. 4) (Wilson and Browne, 2014).

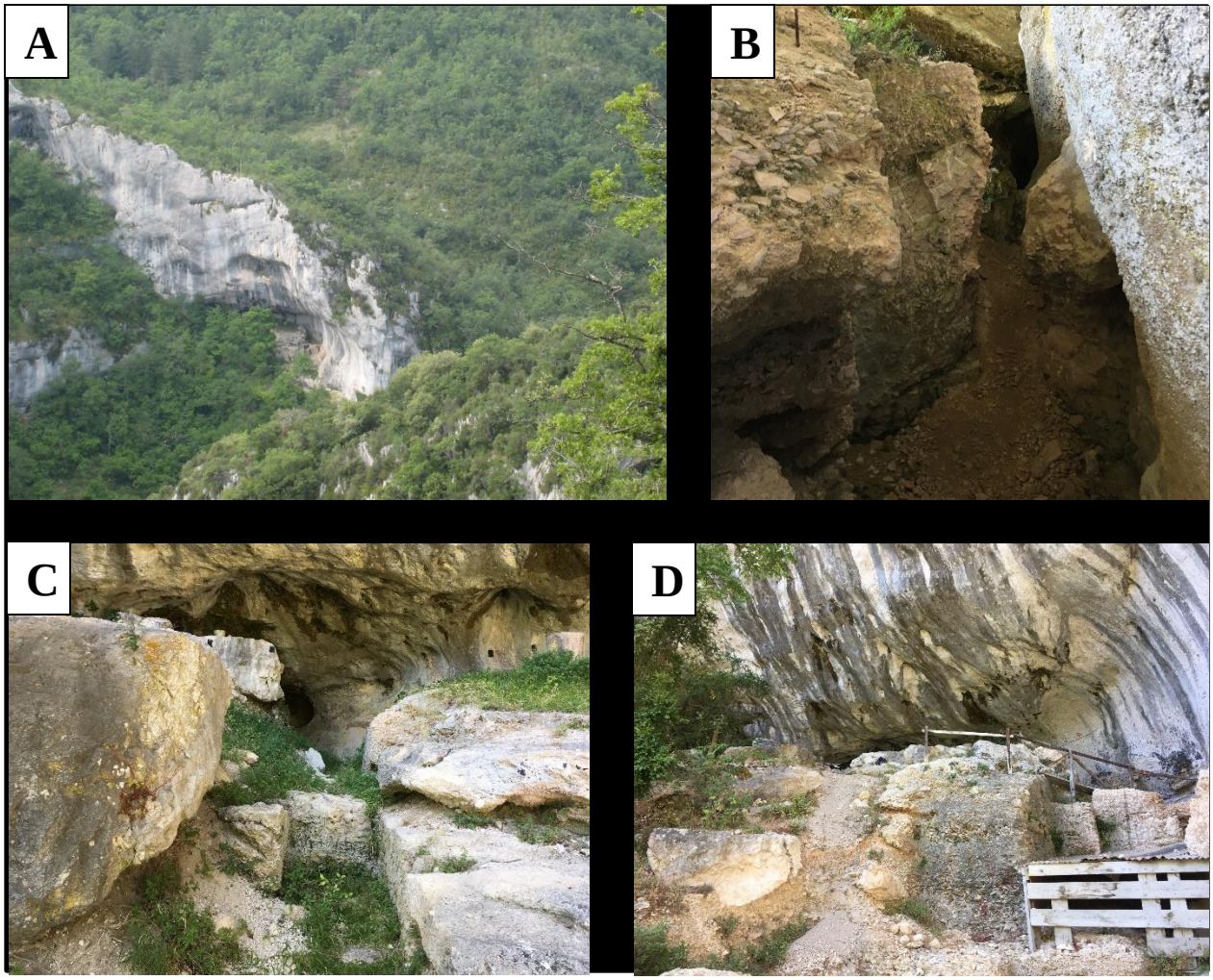

Figure 2. Recent photographs, following a number of years of inactivity at the site, showing (**A**) the Bau in relation to the steep north-facing wall of the gorge of the Nesque river, (**B**) the Moulin Trench, (**C**) Trench L, and (**D**) the view south towards the interior of the Bau, from the bottom of the lower slope.

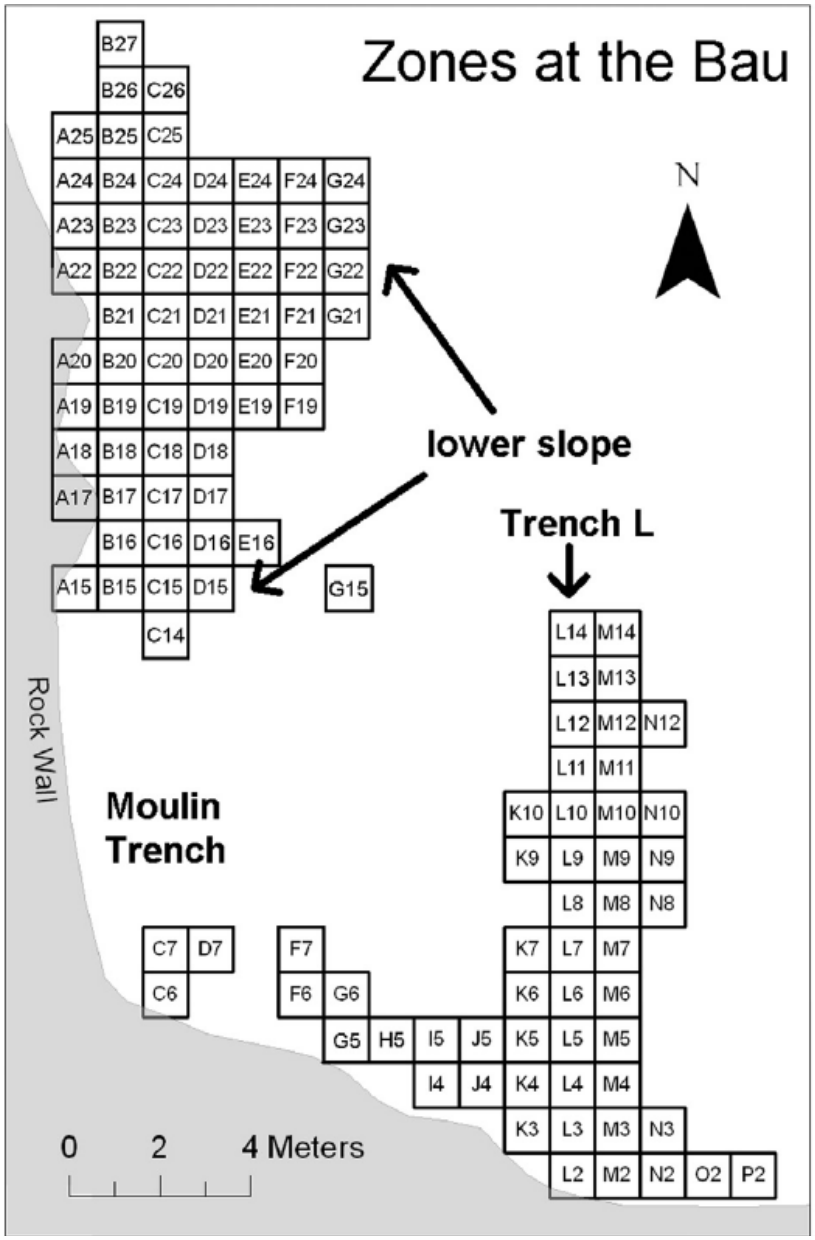

Figure 3. Major zones excavated at the Bau (after Wilson and Browne, 2014)

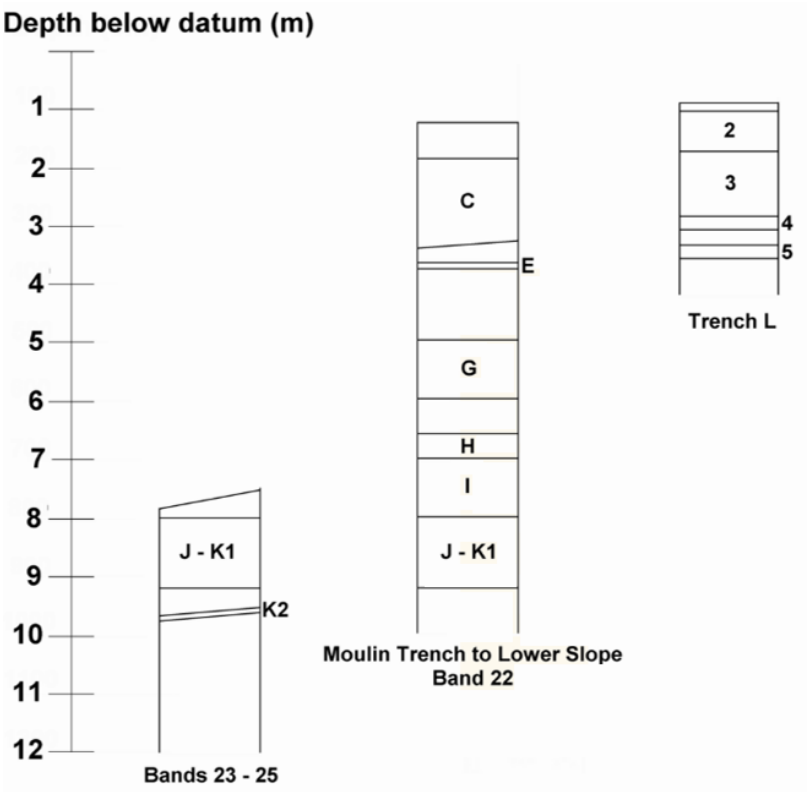

Figure 4. Stratigraphy at the Bau (after Wilson and Browne, 2014)

The sources of lithic raw material

Starting in 1987, and continuing annually to the present, L. Wilson has led the Vaucluse Raw Material project, prospecting for sources of lithic raw material in the region and analysing the implications of their use. This long term geological survey has led to a detailed database of 354 sources of flint, describing not only details of the sources themselves (size, quality and abundance of available raw material, etc.) but also of their geographic relationship to the Bau (distance, terrain difficulty, etc.) (Wilson, 2008, 2007a, 2007b; Wilson and Browne, 2014). These have been grouped into 122 source areas that contain one or more sources, since it may not always be possible to say from which precise outcrop or deposit a particular type of flint originated (Fig. 5) (Browne and Wilson, 2011).

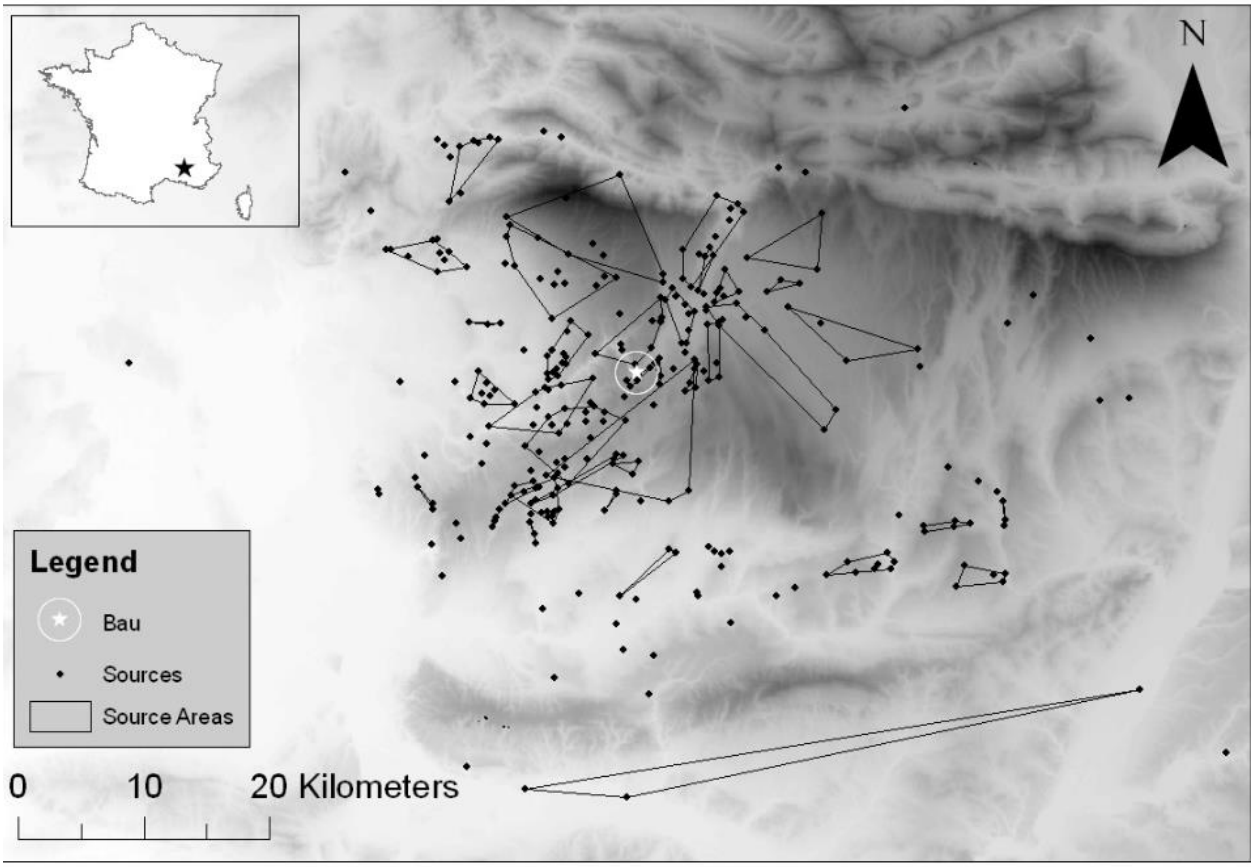

Figure 5. The Bau and surrounding sources of lithic raw material (after Browne and Wilson, 2011)

The lithic assemblage

The assemblage at the Bau includes 39,142 lithic pieces identified by raw material. These have been categorised according to a variety of geologic criteria (colour, cortex, sub-cortical colour variations, fossils, etc.) in a petrographic series of 46 types that has then been used alongside the lithic raw material source data to establish their geographic origins (Wilson, 2007b). Patination (surface alteration due to post-depositional weathering) and burning make it impossible to determine the original source of a majority of these pieces, leaving 15,674 from 11 different

archaeological layers that are statistically usable (Fig. 6) (Wilson and Browne, 2014). Wilson and Browne (2014) have explored several methods of determining whether certain types of flint may have been affected preferentially by factors that exclude them from being used in the data (weathering processes, etc.) but have found no indication that a bias has been introduced and therefore conclude that the sample is reliably representative of the overall lithic assemblage.

Figure 6. Examples of stone tools excavated at the Bau, showing (**A**) a patinated piece from Layer 4 (N9 4 60) and (**B**) a larger artefact excavated in Layer J-K1 (D22 J4 22), which was provenanced to a source of raw material.

Browne and Wilson's analytical methods

Browne and Wilson (Browne and Wilson, 2013, 2011; Wilson et al., 2018; Wilson and Browne, 2014) describe each source area using a Generalized Linear Model (GLM): a form of multivariate regression that uses a link function to predict a constant rate of change (Guisan et al., 2002). Each source area (n = 122) is represented by one source within the area and described in terms of 10 independent variables that detail either the characteristics of the raw material itself, or

terrain characteristics that relate to the source as part of the landscape (Table 1) (Wilson and Browne, 2014). The model then calculates which combination of variables best accounts for the actual pattern of raw material use seen in the lithic assemblage, including the specific contribution of each variable (Wald χ^2 value: higher means more important) and whether its contribution results in a positive or negative pattern of source use (Beta value: a negative value indicates that the variable contributes to a source not being used, and vice versa). The model is able to test many combinations of variables as long as they are not significantly correlated to each other (Guisan et al., 2002), so the independent variables were collectively screened for collinearity using Pearson's correlations and variance inflation factor (VIF) values before the model was created.

Table 1. Summary descriptions of the ten independent variables in the model, and their attribution to subsets 'Raw Material' and 'Terrain' (after Wilson and Browne, 2014)

Variable	Subset	Description
Quality	Raw Material	The suitability of the raw material for tool-making. Based on criteria including homogeneity, the presence or absence of cracks, granulometry, and toughness or ease of breaking.
Extent	Terrain	The size of the outcrop or deposit according to a numerical scale from 1 (<10 m diameter) to 4 (> 100 m in diameter).
Difficulty	Terrain	A value in Calories per km (see below for Calories) calculated for each route from source to site, using a straight-line path except for deviations around areas that have slopes greater than 60%.
Small rocks	Raw Material	The abundance of small rocks (0 – 5 cm) ranked using a numerical scale from 0 to 3.
Medium rocks	Raw Material	The abundance of medium rocks (6 – 15 cm) ranked using a numerical scale from 0 to 3.
Large rocks	Raw Material	The abundance of large rocks (16 - 35 cm) ranked using a numerical scale from 0 to 3.
Very large rocks	Raw Material	The abundance of very large rocks (> 35 cm) ranked using a numerical scale from 0 to 3.
Calories	Terrain	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%. Note that 'Calories' is capitalized because it is the measurement equal to 'kilocalories', one thousand calories.
AOSA	Terrain	Area Of the Source Area: the surface area in m^2 of a minimum convex polygon made using the locations of sources within each source area.
AOSISA	Terrain	Area Of Sources In the Source Area: the total of the surface area covered by the individual sources within a source area.

The model was run on each of the 11 archaeological layers, first as an overall model including all 10 independent variables, then with each of the two subsets of those variables (Raw Material and Terrain), respectively (Wilson and Browne, 2014). An Akaike Information Criteria (AIC) value was taken from the output of each GLM and plotted to determine which of these 3 model types produced the most parsimonious explanation of the data within each layer, with a lower number being better (Wilson and Browne, 2014). In order to compare the results of each model between layers, Wilson and Browne (2014) devised a technique where each of the Wald χ^2 values in each of the overall models are summed and converted to percentages which, when added together for each subset, make it possible to directly compare the percent contributions of the Raw Material and Terrain variables to source area use between each layer at the site.

The comparative study

The first stage of this work was to reorganise the raw data in order to make it possible to run the same analytical procedure using weight of stone types rather than number of pieces of stone types. After that, I ran the GLM analyses using both of these datasets. The third stage was then to analyse the data in terms of the Raw Material and Terrain subsets.

I was given the raw data as a Microsoft Excel file, with each archaeological layer on a separate sheet. Artefacts were listed alongside basic descriptive details (location within the site where they were excavated, tool type, dimensions, etc.) and matched to one of the 46 rock types in the petrographic series. I manually adjusted this, piece-by-piece, so that the weight in grams of each lithic was now the recorded value that corresponded to its matching petrographic type. In some instances, this was complicated by weight values that described more than one lithic piece. During excavations, individual artefacts are “coordinated” before being removed: their precise

position and orientation within a square metre zone, and their "z", or depth, value are recorded. However, when large numbers of similar pieces occur within a small area, they may be coordinated collectively. These 'collectives' were weighed as a whole, and although the individual pieces were later separated for geologic classification, their respective individual weights were not recorded. To account for this lack of data, I divided the weight of each collective by the number of pieces in it. I then proportionally distributed this value, according to how many pieces were present of a particular petrographic type. This was carried out rather than striking the Bau collectives from the data because (1) it avoided a major departure from the results of the published data on which the original interpretations were made, to which this study is being compared, and (2) collectives, by their very nature, tend to be composed of relatively small pieces of a similar size, so any bias introduced by dividing their collected weight equally is likely to be slight, and preferable to eliminating a large number of very small pieces from the dataset. As an example, Layer 4 contains 7439 usable pieces of data, of which 3356 were found in a total of 348 collectives. On 882 occasions, no weight value was recorded for an artefact, presumably as an oversight. In these cases there was no alternative but to remove the entire datapoint from both datasets, reducing the usable number of stone tool pieces by just over 5%, to 14,792.

I summed the weight data for each petrographic type, giving its overall measure of contribution to the archaeological layer, then exported this data to another Excel document listing the 122 source areas and the values of the 10 independent variables for each of them. Each petrographic type was matched to its corresponding source area and its weight value (the dependent variable) added to the row alongside the independent variables. Before completing the analysis by weight of raw material, however, I re-ran Wilson and Browne's (2014) 'number-of-pieces' data (minus those data points for which there was no weight information), in order to replicate a version

of the published models (see Appendix I). The benefits of doing so were to (1) form the basis for a fair comparison between the same number of datapoints, where only the nature of the dependent variable (weight, as opposed to the number of pieces) was changed, (2) confirm that those alterations made to the original dataset did not lead to a meaningful departure from Wilson and Browne's (2014) results, and (3) ensure that the methodology was being executed correctly, preventing the possibility of a false comparison being drawn. Subsequent to this, I followed the same procedure using the weight data, according to Wilson and Browne's (2014) methodology described above (see Appendix II), and also calculated the Wald χ^2 values as percentages for both sets of GLM outputs (see Appendix III).

Post-hoc analysis and testing the predictive ability of the models

To give a preliminary idea of any differences in the data that could potentially drive change in the results, I made a descriptive statistical summary of the distribution of weight within each layer, providing average stone tool sizes throughout the site. I also compared the average size of tool present in the useable weight data to that of the complete dataset (including pieces that were unable to be sourced due to patination).

I ranked, according to layer age, each set of 11 models showing the relative contribution of both the Raw Material and Terrain variable subsets towards source area use. Then I compared the percentage values for each variable subset to the ranked age of the layer using *k*-means cluster analysis, to determine whether there was any grouping in the data and, more importantly, provide a statistical basis for direct comparison between the two datasets.

Finally, I examined the predictive power and internal consistency of the models using *k*-fold cross validation (Boyce et al., 2002). I randomly split the data into '*k*' number of folds ($k = 5$

for Layer 4, for example, with a single fold representing approximately 20% of the data). As the sample size of used source areas was relatively small (17 out of 122 source areas were used across all layers), I stratified the random data so that each fold featured an equivalent number of used source areas. In cases where this division could not be made equally, I biased the placement of data towards the lower numbered folds, against the likelihood of a strong correlation. By doing this, the analyses were less likely to produce significant results and therefore made my subsequent interpretations more conservative. One fold, the 'validation' data, was used to test the predictive ability of the model, and the remaining $k - 1$ folds were used to fit a new model as the 'training' data for this purpose. I carried out this process k number of times, with each fold serving as the validation data once. Then I used Spearman's rank correlation coefficient to determine the relationship between predicted and observed values in the test data (r_s value and associated p value), with the averaged results of each iteration providing an overall estimation. Initially I had intended to plot k-fold values for each of the 11 models, for both the weight and number-of-pieces datasets. However, this was not feasible for a majority of the layers because of the small number of source areas that were used and other issues with collinearity in the data (only four source areas had a value of other than 1 for the 'small rocks' variable). This created a Hessian matrix singularity when the analyses were run on the partitioned dataset and, while there was definitely justification for excluding the 'small rocks' variable (running the model without it gave a comparable AIC result), the relatively low number of used source areas remained a problem. Consequently, I was only able to run k-fold cross validation effectively on both sets of data for Layer 2 (13 source areas used, $k = 4$), Layer 4 (16 source areas used, $k = 5$), Layer I (12 source areas used, $k = 4$), Layer J-K1 (12 source areas used, $k = 4$), and also the combined layers of the complete assemblage (17 source areas used, $k = 5$). To accommodate the high probability of making a type II statistical error

due to the low used source area sample size (n = 3 or 4 per fold), I determined an optimal α for significance and carried out post-hoc power analyses using G*Power v 3.1.9.4 software (Faul et al., 2009).

RESULTS

The replicated versions of Wilson and Browne's (2014) models (see Appendix I), using the number of stone tool pieces as a dependent variable, showed no departure from the overall trends that were observed in the previously published material. Consistent with these results, the GLMs using the stone tool weight data as a dependent variable produced Beta values that indicated the same positive or negative correlation between source area use and each of the 10 independent variables (Table 2).

Table 2. Positive or negative correlation between 10 independent variables and source area use, as determined by Beta values in the output of Generalized Linear Models. Results for using both the weight and number of stone tool pieces as the dependent variable.

Independent Variable	Correlation with source area use	
	Positive	Negative
Quality	✓	
Extent	✓	
Difficulty		✓
Small rocks		✓
Medium rocks		✓
Large rocks	✓	
Very large rocks	✓	
Calories		✓
AOSA		✓
AOSISA	✓	

In each of the 11 layers for both datasets, the AIC values that compared the performances of the two subsets were always lower for Terrain, rather than Raw Material, variables (Table 3). However, the overall model, which includes all 10 independent variables, outperformed both subsets in all cases.

Table 3. Comparing the performance of model variable subsets using both the number-of-pieces and weight datasets. A lower AIC value indicates a more parsimonious model. AICs are comparable only within layers using the same dependent variable. Best outcome is shown in bold font.

Layer	AIC values					
	Model variable subsets using the Number-of-pieces dataset			Model variable subsets using the weight dataset		
	Overall	Raw material	Terrain	Overall	Raw material	Terrain
C	**80.87**	136.77	105.29	**54.49**	91.42	69.01
2	**184.34**	271.42	231.84	**321.37**	553.15	413.83
3	**104.01**	154.34	137.68	**172.34**	308.65	238.28
4	**288.46**	453.12	378.14	**487.66**	861.09	710.17
5	**76.56**	134.29	95.10	**130.35**	281.45	188.78
E	**96.14**	163.09	107.98	**149.83**	232.73	180.22
G	**76.59**	146.11	99.91	**87.25**	145.56	107.67
H	**180.87**	318.97	225.97	**305.81**	699.18	386.56
I	**163.97**	257.84	197.64	**419.63**	736.37	472.26
J-K1	**170.48**	275.74	222.03	**295.14**	637.82	450.16
K2	**122.90**	215.55	144.39	**219.27**	455.27	243.08

Wilson and Browne's (2014) most striking result was in the relative contributions of the variable subsets towards the Wald χ^2 percentages within the overall model, reproduced in Fig. 7a (and see Appendix III). A substantial shift occurs in the weighting of these between what corresponds to Layers 5 and E of the site. The contribution of the Terrain variables is always relatively greater in the oldest 6 layers of the site (E to K2), while in the youngest 5 layers (C to 5) it is the Raw Material variables that contribute more. In contrast, in the results that plot the weight dataset using the same technique, although there are similarities in the greater contribution of the Terrain variables in the lower, older layers, there is more of a convergence of subset Wald χ^2 values in the upper layers. Thus, we do not find the same distinct switch, or role reversal, between subsets in the two groups of layers (Fig. 7b, Appendix III). In these layers the

contributions made towards to the Wald χ^2 percentages by the variable subsets take on more of an equivalence in comparison to the Wilson and Browne (2014) models.

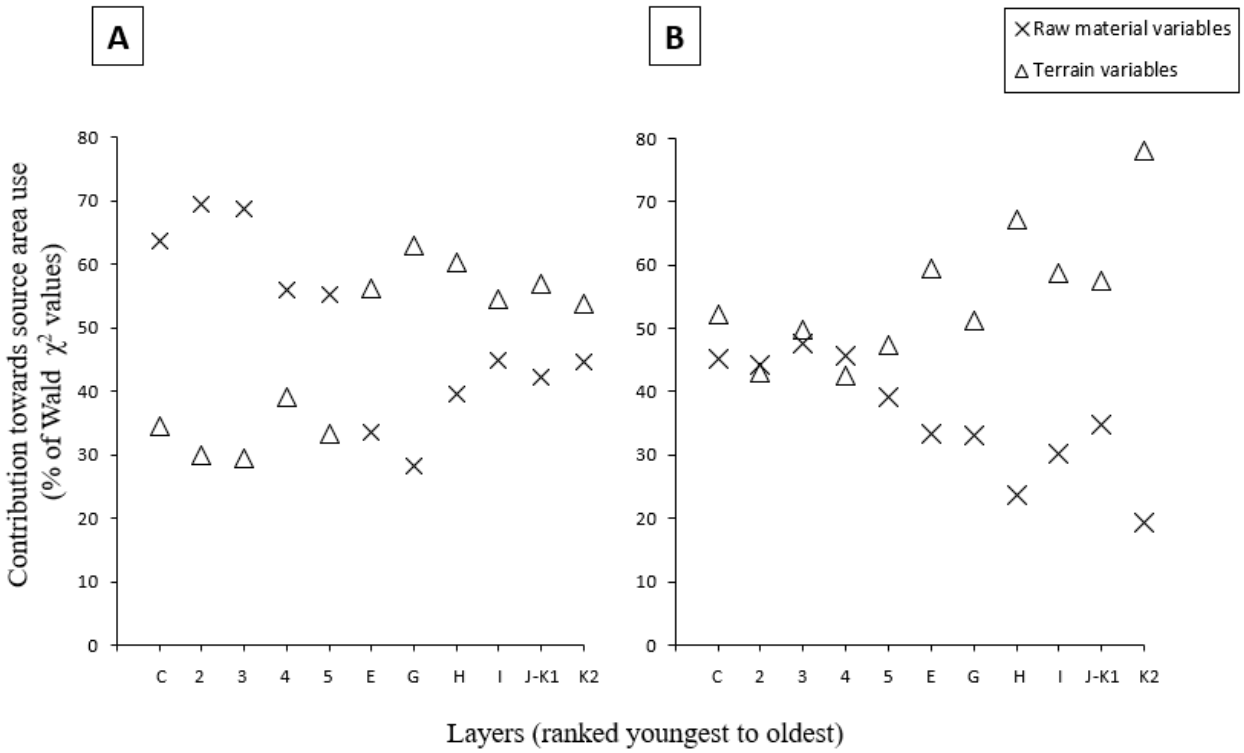

Figure 7. Percent contribution towards source area use of the Raw Material and Terrain variable subsets by layer for the stone tool assemblage, described in terms of (**A**) the number of pieces per source area and (**B)** the collected weight of those pieces. Note: due to the inclusion of the Wald χ^2 values for the model intercepts, the percentages do not total 100.

The *k*-means cluster analyses confirmed the strength of these observed groupings in the Wald χ^2 percentage data. Two statistically significant clusters were identified in the reproduced Wilson and Browne (2014) models for both the Raw Material subset (Cluster 1: Layers E - K2, Cluster 2: Layers C - 5; final cluster centers: 1 = 40.83, 2 = 62.65; $F_{1,9}$ = 45.530, $p < 0.001$) and Terrain subset (Cluster 1: Layers E - K2, Cluster 2: Layers C - 5; final cluster centers: 1 = 58.68, 2 = 33.21; $F_{1,9}$ = 103.405, $p < 0.001$), separated at the point between Layers 5 and E. This 5 - E boundary was not as distinctly identified by *k*-means analysis in the models that were plotted using

the weight of stone tools as the dependent variable. In this case, statistically significant groupings were identified in the Raw Material subset between upper Layers C to 5 but including lower Layer J-K1, with the remaining lower layers forming a separate group (Cluster 1: Layers C - 5 and J-K1, Cluster 2: Layers E – I and K2; final cluster centers: 1 = 42.81, 2 = 27.93; $F_{1,9}$ = 20.005, p = 0.002). However, no comparable grouping was observed for the Terrain variable subset (Cluster 1: Layers H and K2, Cluster 2: Layers C - G and I - J-K1; final cluster centers: 1 = 42.81, 2 = 27.93; $F_{1,9}$ = 20.005, p = 0.002).

The optimal α thresholds for statistical significance in the *k*-fold analyses were calculated at α = 0.286 for Layers 2, 4, and all layers collectively, and α = 0.316 for Layers I and J-K1 (Table 4). The *k*-fold analyses for Layer 2 suggested that the weight model had a superior predictive ability (average r_s = 0.747, average p = 0.253, power = 0.994) to the model using the number-of-pieces dataset (average r_s = 0.689, average p = 0.311, power = 0.991). In contrast, the number-of-pieces model had better internal consistency for Layer 4 (weight dataset: average r_s = 0.603, average p = 0.302, power = 0.968; number-of-pieces dataset: average r_s = 0.682, average p = 0.220, power = 0.970). A more closely equivalent predictive ability between the weight and number-of-pieces models was indicated in the lower Layers I and J-K1 and, especially in the case of Layer J-K1, these tended to have a stronger predictive ability than the upper layer models. Results for the collected layers showed that weight was a significantly superior dependent variable, although this model had the least predictive power of all those that were considered statistically significant (weight dataset: average r_s = 0.637, average p = 0.273, power = 0.971; number-of-pieces dataset: average r_s = 0.488, average p = 0.418, power = 0.958).

Table 4. Summary of *k*-fold cross validation analyses carried out for both the number-of-pieces and weight datasets in Layers 2, 4, I, J-K1, and all layers collectively. Significant *p* values shown in bold font.

Layer	Optimal α	*p* value		r_s		Post-hoc power	
		Pieces	Weight	Pieces	Weight	Pieces	Weight
2	0.286	0.311	**0.253**	0.689	0.747	0.991	0.994
4	0.286	**0.220**	0.302	0.682	0.603	0.970	0.968
I	0.316	**0.253**	**0.262**	0.747	0.738	0.967	0.967
J-K1	0.316	**0.138**	**0.182**	0.862	0.818	0.931	0.953
All layers	0.286	0.418	**0.273**	0.488	0.637	0.958	0.971

Large skews towards smaller stone tools were observed in the data that described the average size of stone tool pieces within each layer, driven by a high quantity of outliers, particularly in lower Layers H, I and J-K1 (Fig. 8). The mean size of artefact was shown to be greater in the combined lower layers (E to K2: 20 g) than the combined upper ones (Layers C to 5: 13 g), $t(8716) = 9.44$, $p < 0.001$.

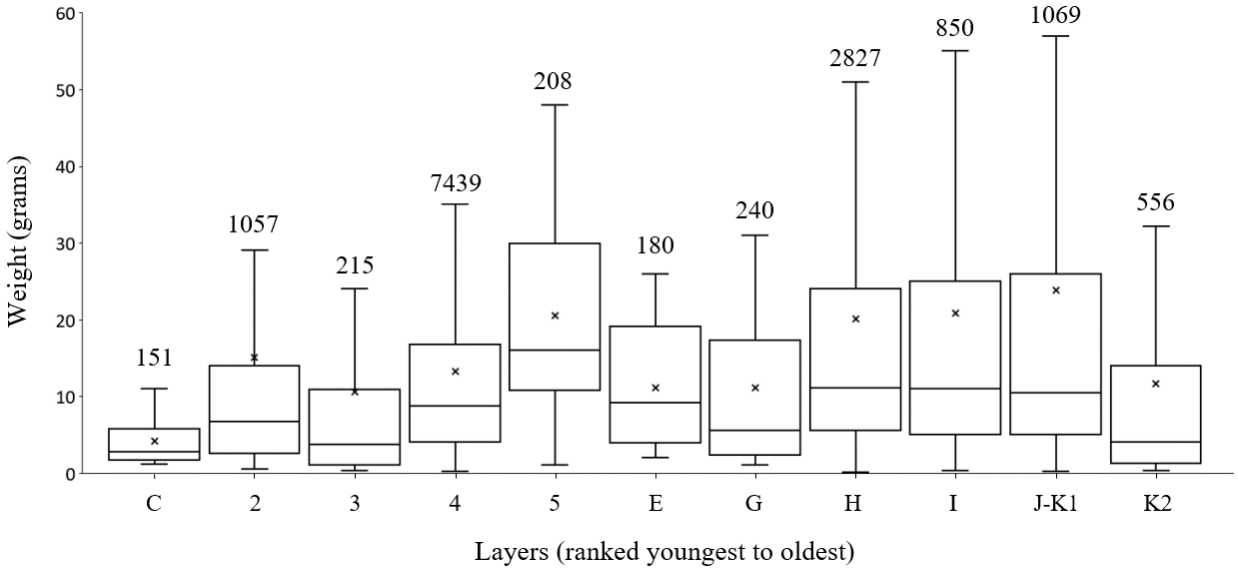

Figure 8. Boxplots showing the number of stone tools and their distribution of sizes within each archaeological layer, determined by weight. Crosses indicate the mean and show a skew towards smaller pieces in the data. Note: Outliers are excluded.

In the comparison between the average sizes of stone tool pieces in the usable data and the total dataset, there was a trend of larger pieces in the usable data in all layers, with the exception of Layer C (Fig. 9). Biases towards heavier pieces in the usable data were found to be statistically significant ($\alpha = 0.05$) in the case of five archaeological layers (Layer 4: $t(11429) = 6.49$, $p < 0.001$, Layer 5: $t(407) = 2.67$, $p = 0.004$, Layer H: $t(4715) = 4.24$, $p < 0.001$, Layer I: $t(1353) = 2.43$, $p = 0.008$, Layer J-K1: $t(22894) = 1.79$, $p = 0.037$), and the assemblage as a whole, $t(1983) = 8.10$, $p < 0.001$.

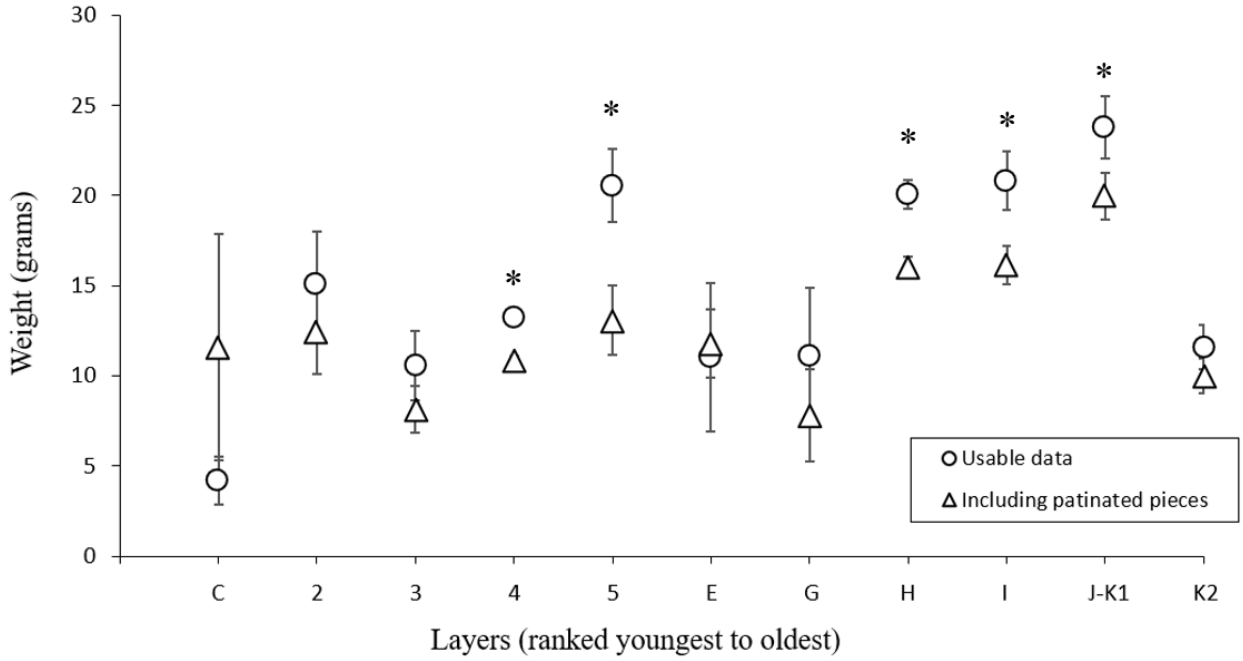

Figure 9. Mean sizes of stone tools ± SE per archaeological layer, as determined by weight. Significant biases towards larger (heavier) pieces are observed in the usable data in five layers marked with asterixis. A significant bias towards heavier artefacts is also reported in the usable data across all layers combined (Two Sample t-Test, $t = 8.10$, $df = 22893$, $p < 0.001$)

DISCUSSION

My study builds upon the contributions of many researchers (Binford and Binford, 1969; Kuhn, 1995; Vukosavljević and Perhoč, 2017; Wilson and Browne, 2014) and in particular offers a novel insight into a highly pertinent, though little explored, concept. To my knowledge, this is the first account of an existing archaeological model being reproduced and subjected to a direct and rigorous comparison that examines multiple ways in which data from the same lithic assemblage can be described. Importantly, the work demonstrates key differences in the output of this model that are dependent on how the concept of source area use is quantified, providing scope for different interpretations to be drawn.

Wilson and Browne's (2014) interpretation of hominin economics at the Bau revealed a distinct change in selection criteria at some point between the time of formation of Layers 5 and E. In the older layers, from E to K2, the subset including terrain variables was much more important for describing patterns of raw material use: an emphasis was placed on the ease of obtaining raw material rather than on its inherent properties (Wilson and Browne, 2014). In the younger layers of the site (C to 5) the subset including characteristics of the raw materials became more central to hominin subsistence activities: a greater concern was shown for the quality and size of available raw material (Wilson and Browne, 2014). Nonetheless, the models' AIC values show that no matter which variable subset explains more of source area use, the subsets always explain more when combined than they do independently – hominin source use was always influenced by both (Wilson and Browne, 2014). An initial comparison with the results of my weight data analyses suggests similarities: an overall model combining both variable subsets always provides a better match to raw material source selection, and the boundary between Layers 5 and E also marks a change in selection criteria (Fig. 7). The older layers reflect a comparable –

and in fact even stronger – trend of source use being driven by the Terrain variable subset. However, the results are somewhat different in the younger layers. Rather than a switch in importance of the subsets, we see a convergence in their relative contributions at the 5 - E boundary, such that in the younger layers they are broadly equivalent in importance. While the overall pattern still shows an increasing concern for raw material characteristics, when we judge by weight the terrain stays (in most cases) slightly more decisive in hominin resource selection. Only Layers 2 and 4 have the Raw Material subset variables surpassing the Terrain variables.

To examine these differences, we must first consider the types of hominin behaviour that could have shaped them, because the weight and number-of-pieces models will detect their effects differently. For example, if hominins always prepared their tools at a raw material source area and only brought back finished products to the Bau directly, then a comparison of their weight and number would seemingly be unbiased by behavioural strategy. If, however, some of those tools were processed at the Bau, either from raw material that was brought back or existing tools that were reworked, there would be more artefacts (more small flakes and knapping debris) while the weight of their material type would be unchanged. This is further complicated by the possibility that hominins prepared their tools in the field more from certain sources (e.g., the farther ones) than others. Even if this was not strictly the case, a tool arriving at the Bau from a relatively distant source area is more likely to be further along the *chaîne opératoire*, resulting in it being a smaller (i.e., lighter) piece than it started out as. According to this principle, which underpins the distance-decay model, a more distant source area could end up underrepresented by the weight of its pieces, while its number of them would remain unchanged.

The distribution of tool sizes between the layers at the Bau offers some explanation for how they were being used or prepared at the site. There is a greater amount of knapping debris

present in the younger layers of the site compared to the older ones (Wilson and Browne, 2014) and the artefacts in them have a significantly smaller average size. This indicates that stone tool use at the Bau was more intensive as these younger layers were being formed. Given the greater importance of the Raw Material variables in the younger layers, this resembles what Kuhn (1995) describes as a 'provisioning of individuals', where a lightweight and reliable tool kit that can be maintained and reworked to purpose is carried by mobile populations of hominins. In this case, the cost of transporting these raw materials would show up better if they are quantified by weight, because it would avoid wrongly detecting an increased measure of their presence (more individual pieces) due to on-site stone tool use, maintenance or repurposing. The particular prominence of the Raw Material subset in the upper-layer, number-of-pieces models could thus be due to an "over-counting" of those types, in comparison to the models where source area use is quantified by weight.

The older layers (notably H, I and J-K1), while heavily skewed towards smaller pieces (Fig. 8), show a higher abundance of larger stone tool sizes in their overall distribution, relative to the younger layers. This could reflect a greater 'provisioning of place' (Kuhn, 1995) at the Bau during the formation of these layers: a strategy of low mobility, short-range foraging and stock-piling of resources, made possible in areas of rich subsistence opportunities. This idea gathers further support from Wilson and Browne's (2014) investigation into prey size through time at the site, which shows a significant positive relationship between older layers and large animal carcasses of 500 kg to 1500 kg. An emphasis towards this kind of lifeway may have been possible in the older layers, but less so in the upper ones, due to climatic change. As the lower layers were being formed, conditions were becoming colder and harsher, with the boundary between layers 5 and E appearing to correspond to the very coldest part of the end of the Middle Pleistocene, about

140 ka (Blackwell et al., 2001; Fernandez, 2006; Lebel, 2006; Lebel and Trinkaus, 2002). In this increasingly hostile climate, the conditions required to meet Kuhn's (1995) 'provisioning of place'– dependable nearby resources in a predictable landscape – were less likely to be met, for reasons ranging from the impact on prey availability, to the perennial snow covering sources of raw material. The 5 - E boundary may have marked a fundamental turning point in hominin economic behaviour, where they were forced to be more reliant on fewer resources, which they had to carry around, thus prioritising lighter weight. If this accounts for a larger average size of artefact in the lower layers, and a greater abundance of larger pieces in those layers generally, then it is basic descriptive weight data that support the argument. This heavier size of artefact might also explain the increased importance of older-layer Terrain variable signals in the weight dataset: the quantity being measured is proportionally greater for an individual piece that is heavier rather than lighter, and the variables that relate to it are therefore more important.

Remembering that the models were run using the "usable" (i.e., identifiable to source area of raw material) artefacts, we might wonder whether this creates any bias. Wilson and Browne (2014) have attempted many different methods to determine whether any raw materials are more or less susceptible to patination, and have not been able to detect any bias. While there is thus no evidence to suggest that the useable portion of the assemblage data contains any bias towards a specific type of material, the basic descriptive weight data do show a bias towards larger stone tool sizes. This is to be expected, as smaller artefacts, with a larger surface area to volume ratio, are more likely to suffer a greater degree of patination than those with a smaller ratio (Wilson, 2007b). This bias has a more pronounced bearing on the weight data analyses, because use in this case is being quantified by the same measure that is preferentially excluding some pieces. Patination removes smaller pieces, which weigh less, from our usable assemblage. This means that in contrast

to counting the number of pieces – where size is irrelevant – we will observe a proportionally intensified importance of variables that are associated with larger artefacts, which has the greater potential to affect layers where the discrepancy between the usable and patinated data is higher. However, although we can be confident that patination does not affect certain rock types preferentially (Wilson and Browne, 2014), we cannot know whether the smaller pieces that are excluded were selectively chosen by hominins from specific sources.

The *k*-fold cross validation analyses allow us to directly compare the suitability of the two dependent variables, and my findings show that the weight variable produces a model with stronger predictive ability in some layers (i.e., Layer 2), while number-of-pieces is more appropriate for others (i.e., Layer 4). The Spearman's rank correlation coefficients and associated high level of statistical significance in models from the two older layers (I and J-K1) suggest a strong predictive ability in the case of both dependent variables, particularly in Layer J-K1. On the other hand, the r_s values in the upper layers are generally more moderate, and the insignificant *p* values of the weight model in Layer 4 and number-of-pieces model in Layer 2 indicate a poor internal consistency. In other words, quantifying source area use by the quantity of lithics produces a better model in Layer 4 and weight is a better means of describing Layer 2. The dissimilarity of these layer assemblages supports the idea that a 'best' solution may be determined by the nature of the assemblage itself – that certain types of independent variable, being more descriptive of certain kinds of subsistence behaviour, are better expressed by either the weight or the quantity of lithics, depending upon circumstance.

The standout feature of the Layer 2 assemblage is its diversity in featuring 13 source areas, which is second only to Layer 4 where 16 source areas are represented. However, Layer 4 comprises 7439 lithic pieces, whereas Layer 2 only has 1057. As a proportion of its overall number

of pieces, this makes Layer 2 far more diverse and could suggest a group of hominins that were more highly mobile, perhaps not returning to the Bau as frequently as the hominins that occupied Layer 4 (Wilson, 1998). On the basis that the cost of transport is measured more directly by the weight of lithic raw material carried, rather than its number of individual pieces, we would expect weight to be the more robust dependent variable in models that describe hominins foraging over wider distances or more extensively. The results of the *k*-fold analyses for Layer 2 support this interpretation, which draws additional strength from a comparison of the individual Wald χ^2 variable percentage contributions. In the weight model, the 'Calories' variable from the Terrain subset (that quantifies the amount of energy required for travel from source area to site) is considerably more prominent than in the other upper layers (see Appendix III), a trend that is not shared with its number-of-pieces counterpart. As this variable is negatively related to source area use, it suggests that Layer 2 hominins particularly economised energy expenditure in collecting lithic resources, perhaps by using closer sources, or by following easier paths. The increased importance of the Raw Material subset in the younger layers implies, however, that the diversity of source area use was related to specific characteristics of the flint at those sources, rather than a lack of discretion. It is interesting to note that in the number-of-pieces model, the reduced prominence of the 'Calories' variable is largely offset by a much higher 'Quality' value. This suggests that source areas requiring more Calories to reach were used for a similar number of pieces, but those pieces tended to be smaller (shown by using weight as a dependent variable) and of a higher quality of flint. This would make sense for a more mobile population that was carrying and using tools over any considerable distance (Kuhn, 1995). However, given that weight performs much better as a dependent variable in Layer 2, it appears that these more distantly sourced pieces make an exaggerated contribution to the Raw Material subset and potentially mask Terrain signals

in the number-of-pieces models. There are many other implications from these results, and the next stage of this work will explore them by examining the specific sources that were used and the types of tools that were made from their materials.

Measuring the cost of transport more accurately does not mean that the related variables will necessarily contribute *more* towards source area use, but in the case of Layer 2 there is a conspicuous difference between the output of the two models, one of which (the weight model) is statistically shown to perform much better than the other. However, even if the cost of transport is measured more directly by weight, it is clearly not the only important factor at play, and it does not help us understand the *k*-fold results from Layer 4. Whereas for all layers the 'Calories' variable is diminished in the number-of-pieces models, the 'Quality' variable is, in general, more important. In Layer 4, 'Quality' is the only variable that shows any substantial difference between the two models – certainly not the contributions of the 'Calories' variables, which are separated by less than 1% (see Appendix III). An explanation for the Layer 4 number-of-pieces model significantly outperforming its weight counterpart could be that the very large Layer 4 assemblage reflects many separate occupations of differing kinds and subsistence strategies, the evidence of any one of them being swamped or intercut with features of another. Archaeologists refer to this as a 'palimpsest', and it might be that weight in grams is somehow less suited to dealing with these conflicting signals. Future work on the tool type characteristics versus their raw material sources will aim to explore this issue.

Although I was not able to run *k*-fold analyses on every layer due to limited sample sizes, I attempted to assess the relative importance of the two dependent variables by using the complete assemblage data with all layers combined. It seems surprising that while the weight model only has a moderate r_s correlation and falls just inside the threshold for statistical significance, it also

substantially outperforms its theoretical number-of-pieces counterpart (Table 4). The fact that the full dataset shows an opposite trend from Layer 4 (which consists of just over 50% of the full dataset) suggests that other layers may also be better explained by the weight data. However, the strongest models, whether using the weight or the number of lithic pieces, are still found on a layer-by-layer basis, supporting the basic notion that isolating hominin groups and their subsistence strategies as much as possible provides clearer indications of the factors that influenced their behavioural choices.

CONCLUSIONS

The work described here shows that the interpretations drawn from Browne and Wilson's modelling techniques (Browne and Wilson, 2013, 2011; Wilson, 2008; Wilson et al., 2018; Wilson and Browne, 2014) deserve a continued consideration, if not necessarily a reconsideration. After all, weights and the number of pieces do not give exactly the same results in the context of quantifying lithic source area use, but those results do display enough similarity to confirm the correlative relationship that they undoubtedly share. The wider question of which is better or, perhaps more specifically, which is better applied to a given set of circumstances, is left largely unanswered. Even so, that these dependent variables are both ostensibly suitable, and yet perform variously well, is a key point in itself.

Certainly, lithic material was being used differently through time by the Middle Palaeolithic hominins of the Vaucluse, as they made complex and increasingly evolved behavioural decisions to negotiate their world in the face of changing environmental pressures. Further research towards better uncovering those decisions, in turn arriving at a more complete understanding of why they were taken, might include approaching the question from the perspective of tool typology – do the quantities of materials maintain the same pattern in different typological categories? For instance, if it turns out that one source area produces larger pieces of a specific tool type within a layer, then that is something only weights would tell us. Following on, a source area could be reevaluated in those terms, giving a more refined idea of what it was providing and why it was used.

My study challenges not only the nature of previous archaeological models that have sought to explain prehistoric human behaviours, but also how they are used. It is of particular value because the modelling technique described here represents a move away from more subjective

interpretation and idealistic optimal foraging theory approaches, and it has the enormous additional benefit of being easily applicable to other appropriate datasets, regardless of their age or geographic origin. This means that we are brought objectively closer to knowing what our prehistoric ancestors were really like: the capability and reasoning they demonstrated as a part of the environment where they made the choices that would determine their survival. Further, we may begin to trace and unravel the origins and development of the behavioural traits that define us as modern humans.

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Appendix I. GLM output for the number of stone tool pieces data

Results for each layer: 1) Overall (ten-variable) Model, 2) Raw Material subset, and 3) Terrain subset. Significant variables are indicated with bold font (using α = 0.05 to determine statistical significance).

Layer C (Sample: 151 pieces from 7 source areas):

Overall:

Omnibus test: likelihood ratio chi-square = 296.483, df = 10, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	2.162	0.8313	6.767	**0.009**	80.872
Extent	1.470	0.9195	2.555	0.110	
Difficulty (Cal/km)	-0.069	0.0498	1.911	0.167	
Small rocks	-8.163	4.3168	3.576	0.059	
Medium rocks	-5.663	2.4697	5.258	**0.022**	
Large rocks	5.032	1.4695	11.726	**0.001**	
Very large rocks	0.970	1.6614	0.341	0.559	
Calories	-0.002	0.0011	0.145	0.703	
AOSA	-3.3 e-7	1.9 e-7	2.979	0.084	
AOSISA	0.000	4.0 e-5	7.380	**0.007**	
(Intercept)	-6.490	7.1582	0.822	0.365	

Raw Material:

Omnibus test: likelihood ratio chi-square = 230.589, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	2.022	0.4104	24.283	**<0.001**	136.767
Small rocks	-8.972	2.5972	11.935	**0.001**	
Medium rocks	-3.647	1.236	8.603	**0.003**	
Large rocks	4.297	0.8935	23.126	**<0.001**	
Very large rocks	2.210	0.6734	10.772	**0.001**	
(Intercept)	-2.236	3.1211	0.513	0.474	

Terrain:

Omnibus test: likelihood ratio chi-square = 262.062, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Extent	0.776	0.4012	3.743	0.053	105.293
Difficulty (Cal/km)	-0.144	0.0379	14.349	**<0.001**	
Calories	-0.002	0.0009	4.062	**0.044**	
AOSA	-1.8 e-7	5.9 e-8	9.078	**0.003**	
AOSISA	3.1 e-4	2.0 e-5	32.445	**<0.001**	
(Intercept)	5.887	2.8432	4.287	**0.038**	

<u>Layer 2 (Sample: 1057 pieces from 13 source areas):</u>

Overall:

Omnibus test: likelihood ratio chi-square = 566.524, df = 10, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	2.001	0.3967	25.445	**<0.001**	184.342
Extent	1.127	0.4919	5.251	**0.022**	
Difficulty (Cal/km)	-0.006	0.0190	0.085	0.770	
Small rocks	-10.140	2.6402	14.750	**<0.001**	
Medium rocks	-5.193	1.4135	13.495	**<0.001**	
Large rocks	1.843	0.5152	12.793	**<0.001**	
Very large rocks	1.207	0.8187	2.173	0.140	
Calories	-0.002	0.0006	10.586	**0.001**	
AOSA	-2.1 e-7	9.2 e-8	5.047	**0.025**	
AOSISA	5.5 e-5	1.9 e-5	8.485	**0.004**	
(Intercept)	3.174	4.0589	0.612	0.434	

Raw Material:

Omnibus test: likelihood ratio chi-square = 469.443, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	1.998	0.2512	63.229	**<0.001**	271.423
Small rocks	-10.337	1.8821	30.163	**<0.001**	
Medium rocks	-3.566	0.8035	19.699	**<0.001**	
Large rocks	2.598	0.3111	69.739	**<0.001**	
Very large rocks	2.136	0.4575	21.790	**<0.001**	
(Intercept)	3.967	1.8383	4.657	**0.031**	

Terrain:

Omnibus test: likelihood ratio chi-square = 509.023, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Extent	0.929	0.2839	10.701	**0.001**	231.843
Difficulty (Cal/km)	-0.016	0.0167	0.870	0.351	
Calories	-0.003	0.0005	30.269	**<0.001**	
AOSA	-1.6 e-7	4.1 e-8	15.206	**<0.001**	
AOSISA	9.7 e-5	1.1 e-5	75.872	**<0.001**	
(Intercept)	-1.186	1.9464	0.371	0.542	

<u>Layer 3 (Sample: 215 pieces from 10 source areas):</u>

Overall:

Omnibus test: likelihood ratio chi-square = 333.992, df = 10, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	1.940	0.5012	14.976	**<0.001**	104.014
Extent	1.829	0.7316	6.253	**0.012**	
Difficulty (Cal/km)	-0.048	0.0295	2.643	0.104	
Small rocks	-6.780	2.7480	6.087	**0.014**	
Medium rocks	-4.501	1.5671	8.250	**0.004**	
Large rocks	3.737	0.9450	15.638	**<0.001**	
Very large rocks	0.542	0.9908	0.299	0.585	
Calories	-0.001	0.0009	1.667	0.197	
AOSA	-2.1 e-7	1.3 e-7	2.701	0.100	
AOSISA	6.8 e-5	2.8 e-5	6.098	**0.014**	
(Intercept)	-5.639	5.1571	1.195	0.274	

Raw Material:

Omnibus test: likelihood ratio chi-square = 273.664, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	1.894	0.3497	29.323	**<0.001**	154.342
Small rocks	-8.301	2.2927	13.111	**<0.001**	
Medium rocks	-3.022	1.0834	7.780	**0.005**	
Large rocks	3.458	0.6182	31.293	**<0.001**	
Very large rocks	1.454	0.5903	6.068	**0.014**	
(Intercept)	-1.161	2.4516	0.224	0.636	

Terrain:

Omnibus test: likelihood ratio chi-square = 290.324, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Extent	0.841	0.3294	6.524	**0.011**	137.682
Difficulty (Cal/km)	-0.106	0.0274	15.116	**<0.001**	
Calories	-0.002	0.0007	8.839	**0.003**	
AOSA	-1.6 e-7	4.3 e-8	13.917	**<0.001**	
AOSISA	9.5 e-5	1.3 e-5	52.358	**<0.001**	
(Intercept)	4.721	2.3782	3.941	**0.047**	

<u>Layer 4 (Sample: 7439 pieces from 16 source areas):</u>

Overall:

Omnibus test: likelihood ratio chi-square = 882.238, df = 10, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	1.990	0.2937	45.907	**<0.001**	288.463
Extent	0.997	0.3086	10.445	**0.001**	
Difficulty (Cal/km)	-0.032	0.0169	3.687	**0.005**	
Small rocks	-10.395	2.0230	26.404	**<0.001**	
Medium rocks	-5.532	1.0739	26.539	**<0.001**	
Large rocks	1.284	0.3781	11.538	**0.001**	
Very large rocks	1.212	0.7370	2.703	0.100	
Calories	-0.002	0.0004	25.649	**<0.001**	
AOSA	-2.2 e-7	6.2 e-8	12.089	**0.001**	
AOSISA	6.6 e-5	1.3 e-5	27.036	**<0.001**	
(Intercept)	8.974	2.8426	9.966	**0.002**	

Raw Material:

Omnibus test: likelihood ratio chi-square = 707.578, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	1.848	0.1807	104.621	**<0.001**	453.123
Small rocks	-8.764	1.5628	31.451	**<0.001**	
Medium rocks	-3.184	0.5512	33.360	**<0.001**	
Large rocks	2.861	0.2509	130.083	**<0.001**	
Very large rocks	2.122	0.4247	24.954	**<0.001**	
(Intercept)	4.067	1.5494	6.890	**0.009**	

Terrain:

Omnibus test: likelihood ratio chi-square = 782.562, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Extent	0.365	0.2023	3.254	0.071	378.139
Difficulty (Cal/km)	-0.022	0.0125	3.140	0.076	
Calories	-0.002	0.0004	35.769	**<0.001**	
AOSA	-2.0 e-7	3.8 e-8	27.905	**<0.001**	
AOSISA	2.4 e-5	9.3 e-6	131.592	**<0.001**	
(Intercept)	2.034	1.4689	1.918	0.166	

<u>Layer 5 (Sample: 208 pieces from 8 source areas):</u>

Overall:

Omnibus test: likelihood ratio chi-square = 355.587, df = 10, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	2.988	1.7050	3.071	0.080	76.556
Extent	1.647	1.2272	1.802	0.179	
Difficulty (Cal/km)	0.012	0.0487	0.056	0.812	
Small rocks	-11.252	8.5261	1.742	0.187	
Medium rocks	-6.786	5.3217	1.626	0.202	
Large rocks	5.650	2.2338	6.397	**0.011**	
Very large rocks	2.591	2.6185	0.979	0.322	
Calories	-0.002	0.0019	0.014	0.905	
AOSA	-4.2 e-7	3.1 e-7	1.894	0.169	
AOSISA	3.3 e-5	6.2 e-5	4.554	**0.033**	
(Intercept)	-16.455	9.7435	2.852	0.091	

Raw Material:

Omnibus test: likelihood ratio chi-square = 287.857, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	1.462	0.2829	26.694	**<0.001**	134.286
Small rocks	-5.328	2.1610	6.078	**0.014**	
Medium rocks	-0.772	0.9566	0.651	0.420	
Large rocks	3.227	0.7787	17.168	**<0.001**	
Very large rocks	3.221	0.6284	26.273	**<0.001**	
(Intercept)	-5.724	3.2014	3.196	0.074	

Terrain:

Omnibus test: likelihood ratio chi-square = 327.043, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Extent	0.805	0.4690	2.948	0.086	95.101
Difficulty (Cal/km)	-0.057	0.0286	4.029	**0.045**	
Calories	-0.003	0.0010	7.318	**0.007**	
AOSA	-2.2 e-7	5.8 e-8	14.833	**<0.001**	
AOSISA	7.6 e-5	1.8 e-5	44.633	**<0.001**	
(Intercept)	-1.407	2.6313	0.286	0.593	

<u>Layer E (Sample: 180 pieces from 7 source areas):</u>

Overall:

Omnibus test: likelihood ratio chi-square = 308.822, df = 9, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	0.683	0.3780	3.266	0.071	96.139
Extent	1.878	0.7422	6.401	**0.011**	
Difficulty (Cal/km)	-0.066	0.0334	3.901	**0.048**	
Medium rocks	-0.991	1.2747	0.604	0.437	
Large rocks	3.167	0.9691	10.682	**0.001**	
Very large rocks	-0.412	0.8912	0.214	0.644	
Calories	-0.001	0.0009	0.918	0.338	
AOSA	-1.2 e-7	7.6 e-8	2.487	0.115	
AOSISA	8.6 e-5	2.6 e-8	11.084	**0.001**	
(Intercept)	-10.749	5.0333	4.560	**0.033**	

* Small rocks removed because of Hessian matrix singularity

Raw Material:

Omnibus test: likelihood ratio chi-square = 231.875, df = 4, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	1.177	0.2165	29.547	**<0.001**	163.086
Medium rocks	-1.041	0.7695	1.832	0.176	
Large rocks	2.930	0.5431	29.097	**<0.001**	
Very large rocks	1.469	0.5089	8.329	**0.004**	
(Intercept)	-8.140	1.4322	32.307	**<0.001**	

*Small rocks removed because of Hessian matrix singularity

Terrain:

Omnibus test: likelihood ratio chi-square = 288.980, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Extent	1.216	0.4809	6.393	**0.011**	107.981
Difficulty (Cal/km)	-0.135	0.0308	19.153	**<0.001**	
Calories	-0.002	0.0009	4.062	**0.044**	
AOSA	-1.6 e-7	4.8 e-8	10.792	**0.001**	
AOSISA	7.6 e-5	1.8 e-5	42.472	**<0.001**	
(Intercept)	3.628	2.3808	2.322	0.128	

<u>Layer G (Sample: 240 pieces from 5 source areas):</u>

Overall:

Omnibus test: likelihood ratio chi-square = 379.152, df = 9, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	5.514	4.7487	1.348	0.246	76.589
Extent	8.484	6.6590	1.623	0.203	
Difficulty (Cal/km)	-0.189	0.1227	2.371	0.124	
Medium rocks	-5.363	5.3435	1.007	0.316	
Large rocks	19.928	15.6939	1.612	0.204	
Very large rocks	4.444	6.2795	0.501	0.479	
Calories	-0.006	0.0046	1.525	0.217	
AOSA	3.9 e-8	2.2 e-7	0.030	0.861	
AOSISA	7.6 e-5	3.6 e-5	4.421	**0.035**	
(Intercept)	-71.491	60.2640	1.407	0.236	

* Small rocks removed because of Hessian matrix singularity

Raw Material:

Omnibus test: likelihood ratio chi-square = 299.633, df = 4, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	1.547	0.3346	21.390	**<0.001**	146.108
Medium rocks	-1.032	1.1586	0.794	0.373	
Large rocks	4.704	1.0565	19.828	**<0.001**	
Very large rocks	0.515	0.6603	0.609	0.435	
(Intercept)	-12.652	2.7450	21.245	**<0.001**	

* Small rocks removed because of Hessian matrix singularity

Terrain:

Omnibus test: likelihood ratio chi-square = 347.834, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Extent	1.585	0.6455	6.026	**0.014**	99.907
Difficulty (Cal/km)	-0.202	0.0478	17.834	**<0.001**	
Calories	-0.002	0.0012	3.394	0.065	
AOSA	-2.5 e-7	7.7 e-8	10.494	**0.001**	
AOSISA	3.4 e-5	2.6 e-5	36.581	**<0.001**	
(Intercept)	5.833	3.4207	2.908	0.088	

<u>Layer H (Sample: 2827 pieces from 10 source areas):</u>

Overall:

Omnibus test: likelihood ratio chi-square = 779.580, df = 10, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	1.561	0.3902	16.003	**<0.001**	180.873
Extent	1.848	0.5345	11.959	**0.001**	
Difficulty (Cal/km)	-0.093	0.0236	15.537	**<0.001**	
Small rocks	-6.722	2.3825	7.961	**0.005**	
Medium rocks	-3.657	1.4379	6.468	**0.011**	
Large rocks	2.344	0.6546	12.826	**<0.001**	
Very large rocks	0.517	0.7170	0.520	0.471	
Calories	-0.001	0.0006	1.755	0.185	
AOSA	-1.7 e-7	6.5 e-8	7.171	**0.007**	
AOSISA	8.9 e-5	1.6 e-5	30.183	**<0.001**	
(Intercept)	1.412	3.9890	0.125	0.723	

Raw Material:

Omnibus test: likelihood ratio chi-square = 631.481, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	1.858	0.2168	73.466	**<0.001**	318.973
Small rocks	-9.102	1.7336	27.564	**<0.001**	
Medium rocks	-2.766	0.7020	15.528	**<0.001**	
Large rocks	3.092	0.3452	80.246	**<0.001**	
Very large rocks	2.932	0.4846	36.607	**<0.001**	
(Intercept)	2.004	1.8621	1.158	0.282	

Terrain:

Omnibus test: likelihood ratio chi-square = 724.487, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Extent	1.013	0.3306	9.394	**0.002**	225.966
Difficulty (Cal/km)	-0.173	0.0249	48.414	**<0.001**	
Calories	-0.002	0.0006	7.225	**0.007**	
AOSA	-2.0 e-7	3.8 e-8	29.036	**<0.001**	
AOSISA	2.6 e-6	1.2 e-5	113.325	**<0.001**	
(Intercept)	9.177	2.0807	19.453	**<0.001**	

<u>Layer I (Sample: 850 pieces from 12 source areas):</u>

Overall:

Omnibus test: likelihood ratio chi-square = 541.538, df = 10, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	1.031	0.2573	16.059	**<0.001**	163.967
Extent	1.965	0.5068	15.033	**<0.001**	
Difficulty (Cal/km)	-0.066	0.0204	10.593	**0.001**	
Small rocks	-3.816	1.8912	4.071	**0.044**	
Medium rocks	-1.520	0.8507	3.193	0.074	
Large rocks	1.905	0.5643	11.397	**0.001**	
Very large rocks	0.082	0.7798	0.011	0.917	
Calories	-0.001	0.0006	5.240	**0.022**	
AOSA	1.4 e-8	4.4 e-8	0.093	0.760	
AOSISA	4.0 e-5	1.2 e-5	11.150	**0.001**	
(Intercept)	-2.004	3.5126	0.325	0.568	

Raw Material:

Omnibus test: likelihood ratio chi-square = 437.660, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	1.463	0.1895	59.553	**<0.001**	257.844
Small rocks	-7.742	1.6844	21.125	**<0.001**	
Medium rocks	-1.881	0.6255	9.047	**0.003**	
Large rocks	2.448	0.3436	50.737	**<0.001**	
Very large rocks	2.540	0.4688	29.357	**<0.001**	
(Intercept)	1.390	1.8468	0.566	0.452	

Terrain:

Omnibus test: likelihood ratio chi-square = 497.864, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Extent	1.177	0.3224	13.327	**<0.001**	197.641
Difficulty (Cal/km)	-0.076	0.0205	13.699	**<0.001**	
Calories	-0.002	0.0005	11.313	**0.001**	
AOSA	-9.0 e-8	3.6 e-8	6.142	**0.013**	
AOSISA	8.9 e-5	1.0 e-5	78.551	**<0.001**	
(Intercept)	1.512	2.0925	0.522	0.470	

<u>Layer J-K1 (Sample: 1069 pieces from 12 source areas):</u>

Overall:

Omnibus test: likelihood ratio chi-square = 582.745, df = 10, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	1.572	0.3821	16.924	**<0.001**	170.484
Extent	2.512	0.6382	15.490	**<0.001**	
Difficulty (Cal/km)	-0.083	0.0224	13.852	**<0.001**	
Small rocks	-7.945	2.5164	9.968	**0.002**	
Medium rocks	-3.240	1.5041	4.641	**0.031**	
Large rocks	2.540	0.7650	11.023	**0.001**	
Very large rocks	-0.326	0.9289	0.123	0.725	
Calories	-0.003	0.0009	16.680	**<0.001**	
AOSA	-1.3 e-7	7.4 e-8	3.029	0.082	
AOSISA	4.6 e-5	1.6 e-5	8.227	**0.004**	
(Intercept)	3.506	3.8643	0.823	0.364	

Raw Material:

Omnibus test: likelihood ratio chi-square = 467.493, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	1.461	0.1837	63.179	**<0.001**	275.736
Small rocks	-9.406	1.8657	25.418	**<0.001**	
Medium rocks	-1.824	0.5993	9.257	**0.002**	
Large rocks	2.449	0.3023	65.609	**<0.001**	
Very large rocks	1.440	0.4232	11.579	**0.001**	
(Intercept)	3.582	1.9532	3.363	0.067	

Terrain:

Omnibus test: likelihood ratio chi-square = 521.013, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Extent	1.364	0.3232	17.806	**<0.001**	222.032
Difficulty (Cal/km)	-0.079	0.0211	13.840	**<0.001**	
Calories	-0.004	0.0007	23.298	**<0.001**	
AOSA	-1.6 e-7	3.7 e-8	19.042	**<0.001**	
AOSISA	9.4 e-5	1.0 e-5	80.138	**<0.001**	
(Intercept)	3.485	2.1386	2.655	0.103	

<u>Layer K2 (Sample: 556 pieces from 9 source areas):</u>

Overall:

Omnibus test: likelihood ratio chi-square = 496.015, df = 10, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	1.346	0.3932	11.723	**0.001**	122.902
Extent	2.136	0.6955	9.433	**0.002**	
Difficulty (Cal/km)	-0.064	0.0259	6.143	**0.013**	
Small rocks	-4.662	2.2776	4.191	**0.041**	
Medium rocks	-2.818	1.3003	4.698	**0.030**	
Large rocks	2.803	0.8151	11.828	**0.001**	
Very large rocks	-0.298	0.8529	0.122	0.727	
Calories	-0.002	0.0009	3.188	0.074	
AOSA	-1.5 e-7	7.5 e-8	4.002	**0.045**	
AOSISA	7.8 e-5	1.9 e-5	16.493	**<0.001**	
(Intercept)	-4.884	4.5019	1.177	0.278	

Raw Material:

Omnibus test: likelihood ratio chi-square = 393.366, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	1.586	0.2340	45.946	**<0.001**	215.552
Small rocks	-7.728	1.8433	17.576	**<0.001**	
Medium rocks	-2.033	0.7663	7.037	**0.008**	
Large rocks	2.767	0.4113	45.269	**<0.001**	
Very large rocks	2.001	0.4926	16.491	**<0.001**	
(Intercept)	0.248	2.0388	0.015	0.903	

Terrain:

Omnibus test: likelihood ratio chi-square = 464.528, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Extent	1.284	0.3965	10.480	**0.001**	144.390
Difficulty (Cal/km)	-0.127	0.0294	18.724	**<0.001**	
Calories	-0.002	0.0009	8.505	**0.004**	
AOSA	-1.9 e-7	4.3 e-8	18.572	**<0.001**	
AOSISA	2.8 e-8	1.4 e-5	73.327	**<0.001**	
(Intercept)	4.139	2.4898	2.763	0.096	

Appendix II. GLM output for the weight of stone tool pieces data

Results for each layer: 1) Overall (ten-variable) Model, 2) Raw Material subset, and 3) Terrain subset. Significant variables are indicated with bold font (using α = 0.05 to determine statistical significance).

Layer C (Sample: 151 pieces from 7 source areas):

Overall:

Omnibus test: likelihood ratio chi-square = 148.604, df = 10, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	0.660	0.6242	1.117	0.291	54.486
Extent	0.479	0.8164	0.344	0.558	
Difficulty (Cal/km)	-0.035	0.0649	0.292	0.589	
Small rocks	-0.383	4.3362	0.008	0.930	
Medium rocks	-4.440	10.6043	0.175	0.675	
Large rocks	4.816	2.6510	3.300	0.069	
Very large rocks	-3.474	2.4922	1.943	0.163	
Calories	-0.002	0.0019	0.917	0.338	
AOSA	-1.730E-7	1.3500E-7	1.642	0.200	
AOSISA	9.650E-5	4.6277E-5	4.348	**0.037**	
(Intercept)	-8.992	15.1330	0.353	0.552	

Raw Material:

Omnibus test: likelihood ratio chi-square = 101.673, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	0.989	0.2041	23.491	**<0.001**	91.417
Small rocks	-3.285	1.8629	3.109	0.078	
Medium rocks	-2.740	1.3822	3.931	**0.047**	
Large rocks	2.507	0.6407	15.312	**<0.001**	
Very large rocks	0.304	0.4611	0.434	0.510	
(Intercept)	-3.103	2.5820	1.444	0.229	

Terrain:

Omnibus test: likelihood ratio chi-square = 124.084, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Extent	-0.096	0.3928	0.059	0.807	69.006
Difficulty (Cal/km)	-0.099	0.0439	5.079	**0.024**	
Calories	-0.001	0.0010	1.875	0.171	
AOSA	-5.643E-8	6.0752E-8	0.863	0.353	
AOSISA	7.227E-5	2.0360E-5	12.598	**<0.001**	
(Intercept)	3.940	2.6514	2.208	0.137	

<u>Layer 2 (Sample: 1057 pieces from 13 source areas):</u>

Overall:

Omnibus test: likelihood ratio chi-square = 890.654, df = 10, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	1.521	0.2364	41.394	**<0.001**	321.369
Extent	0.217	0.2569	0.715	0.398	
Difficulty (Cal/km)	-0.003	0.0004	8.627	**<0.001**	
Small rocks	-10.861	1.8031	36.283	**<0.001**	
Medium rocks	-4.758	0.8630	30.401	**<0.001**	
Large rocks	1.553	0.3377	21.158	**<0.001**	
Very large rocks	-0.150	0.4018	0.139	0.709	
Calories	-0.044	0.0150	57.681	**0.003**	
AOSA	-3.519E-7	6.6423E-8	28.072	**<0.001**	
AOSISA	8.167E-5	1.4591E-5	31.328	**<0.001**	
(Intercept)	14.869	2.4309	37.415	**<0.001**	

Raw Material:

Omnibus test: likelihood ratio chi-square = 648.875, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	1.415	0.1529	85.656	**<0.001**	553.148
Small rocks	-7.790	1.4554	28.649	**<0.001**	
Medium rocks	-2.426	0.4915	24.357	**<0.001**	
Large rocks	3.537	0.2328	230.815	**<0.001**	
Very large rocks	-0.078	0.2471	0.101	0.751	
(Intercept)	3.490	1.4475	5.812	**0.016**	

Terrain:

Omnibus test: likelihood ratio chi-square = 788.195, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Extent	0.196	0.1989	0.967	0.325	413.828
Difficulty (Cal/km)	-0.039	0.0120	10.349	**<0.001**	
Calories	-0.003	0.0004	67.393	**<0.001**	
AOSA	-2.294E-7	4.5894E-8	24.990	**<0.001**	
AOSISA	9.615E-5	1.1348E-5	71.782	**<0.001**	
(Intercept)	5.002	1.2187	16.848	**<0.001**	

<u>Layer 3 (Sample: 215 pieces from 10 source areas):</u>

Overall:

Omnibus test: likelihood ratio chi-square = 633.411, df = 10, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	0.967	0.2774	12.150	**<0.000**	172.338
Extent	0.816	0.4391	3.452	0.063	
Difficulty (Cal/km)	-0.082	0.0318	6.604	**0.010**	
Small rocks	-6.138	1.8791	10.669	**<0.001**	
Medium rocks	-1.858	0.9815	3.582	0.058	
Large rocks	2.368	0.5691	17.317	**<0.000**	
Very large rocks	-0.775	0.7208	1.155	0.283	
Calories	-0.003	0.0008	10.538	**<0.001**	
AOSA	-1.571E-7	6.1713E-8	6.480	**0.011**	
AOSISA	6.296E-5	1.4131E-5	19.849	**<0.001**	
(Intercept)	6.111	3.9777	2.360	0.124	

Raw Material:

Omnibus test: likelihood ratio chi-square = 487.099, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	1.189	0.1714	48.123	**<0.001**	308.651
Small rocks	-5.536	1.6437	11.345	**<0.001**	
Medium rocks	-0.824	0.6184	1.776	0.183	
Large rocks	3.347	0.4463	56.237	**<0.001**	
Very large rocks	1.481	0.4257	12.100	**<0.001**	
(Intercept)	-2.244	2.1267	1.113	0.291	

Terrain:

Omnibus test: likelihood ratio chi-square = 557.471, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Extent	0.223	0.2382	0.873	0.350	238.279
Difficulty (Cal/km)	-0.133	0.0236	31.799	**<0.001**	
Calories	-0.002	0.0006	13.159	**<0.001**	
AOSA	-1.247E-7	3.7336E-8	11.151	**<0.001**	
AOSISA	7.810E-5	9.1545E-6	72.780	**<0.001**	
(Intercept)	9.771	2.0130	23.560	**<0.001**	

<u>Layer 4 (Sample: 7439 pieces from 16 source areas):</u>

Overall:

Omnibus test: likelihood ratio chi-square = 1245.654, df = 10, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	2.094	0.2475	71.585	**<0.001**	487.658
Extent	1.137	0.2490	20.856	**<0.001**	
Difficulty (Cal/km)	-0.065	0.0149	18.971	**<0.001**	
Small rocks	-12.935	1.8756	47.563	**<0.001**	
Medium rocks	-7.131	0.9773	53.237	**<0.001**	
Large rocks	1.474	0.3360	19.257	**<0.001**	
Very large rocks	-0.958	0.5336	3.226	0.072	
Calories	-0.002	0.0003	56.862	**<0.001**	
AOSA	-3.811E-7	6.8891E-8	30.597	**<0.001**	
AOSISA	2.656E-6	1.3597E-5	54.452	**<0.001**	
(Intercept)	16.680	2.3715	49.471	**<0.001**	

Raw Material:

Omnibus test: likelihood ratio chi-square = 862.225, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	1.651	0.1380	143.139	**<0.001**	861.088
Small rocks	-8.075	1.3536	35.585	**<0.001**	
Medium rocks	-3.017	0.4105	54.028	**<0.001**	
Large rocks	3.692	0.2879	164.503	**<0.001**	
Very large rocks	0.308	0.3982	0.598	0.439	
(Intercept)	5.405	1.3015	17.247	**<0.001**	

Terrain:

Omnibus test: likelihood ratio chi-square = 1013.148, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Extent	0.163	0.1504	1.176	0.278	710.165
Difficulty (Cal/km)	-0.060	0.0100	36.584	**<0.001**	
Calories	-0.002	0.0002	54.635	**<0.001**	
AOSA	-2.348E-7	4.0859E-8	33.012	**<0.001**	
AOSISA	7.269E-5	9.9234E-6	118.007	**<0.001**	
(Intercept)	6.987	1.0578	43.628	**<0.001**	

<u>Layer 5 (Sample: 208 pieces from 8 source areas):</u>

Overall:

Omnibus test: likelihood ratio chi-square = 774.750, df = 10, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	1.518	0.5154	8.678	**0.003**	130.348
Extent	1.951	0.6839	8.137	**0.004**	
Difficulty (Cal/km)	-0.032	0.0312	1.029	0.310	
Small rocks	-0.509	3.1027	0.027	0.870	
Medium rocks	-0.618	1.8447	0.112	0.737	
Large rocks	6.794	1.7679	14.767	**<0.001**	
Very large rocks	1.057	0.6826	2.398	0.121	
Calories	-0.003	0.0009	8.740	**0.003**	
AOSA	-1.966E-7	1.2190E-7	2.600	0.107	
AOSISA	9.272E-5	2.8013E-5	10.955	**<0.001**	
(Intercept)	-22.382	7.4938	8.921	**0.003**	

Raw Material:

Omnibus test: likelihood ratio chi-square = 614.245, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	1.305	0.2093	38.874	**<0.001**	281.453
Small rocks	-0.961	2.1285	0.204	0.652	
Medium rocks	1.373	0.9729	1.992	0.158	
Large rocks	6.322	1.2651	24.970	**<0.001**	
Very large rocks	2.961	0.4633	40.853	**<0.001**	
(Intercept)	-16.115	4.8374	11.097	**<0.001**	

Terrain:

Omnibus test: likelihood ratio chi-square = 706.918, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Extent	1.396	0.3674	14.442	**<0.001**	188.780
Difficulty (Cal/km)	-0.084	0.0261	10.253	**<0.001**	
Calories	-0.004	0.0008	19.996	**<0.001**	
AOSA	-1.689E-7	4.0678E-8	17.231	**<0.001**	
AOSISA	2.855E-7	1.1453E-5	90.256	**<0.001**	
(Intercept)	1.725	2.3993	0.517	0.472	

<u>Layer E (Sample: 180 pieces from 7 source areas):</u>

Overall:

Omnibus test: likelihood ratio chi-square = 510.448, df = 9, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	0.566	0.3001	3.558	0.059	149.827
Extent	1.484	0.5547	7.162	**0.007**	
Difficulty (Cal/km)	-0.070	0.0316	4.938	**0.026**	
Medium rocks	-0.765	1.1155	0.470	0.493	
Large rocks	3.329	0.8769	14.410	**<0.001**	
Very large rocks	0.164	0.5784	0.080	0.777	
Calories	-0.001	0.0008	3.308	0.069	
AOSA	-1.145E-7	5.7454E-8	3.973	**0.046**	
AOSISA	8.687E-5	2.3474E-5	13.695	**<0.001**	
(Intercept)	-8.339	4.1600	4.018	**0.045**	

* Small rocks removed because of Hessian matrix singularity

Raw Material:

Omnibus test: likelihood ratio chi-square = 417.547, df = 4, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	1.116	0.1433	60.676	**<0.001**	232.728
Medium rocks	-0.946	0.5683	2.770	0.096	
Large rocks	2.898	0.4241	46.709	**<0.001**	
Very large rocks	0.454	0.3603	1.589	0.208	
(Intercept)	-7.260	1.0898	44.377	**<0.001**	

* Small rocks removed because of Hessian matrix singularity

Terrain:

Omnibus test: likelihood ratio chi-square = 472.056, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Extent	4.613	1.9995	5.322	**0.021**	180.219
Difficulty (Cal/km)	-0.131	0.0258	25.680	**<0.001**	
Calories	-0.002	0.0007	9.275	**0.002**	
AOSA	-4.276E-8	4.2723E-8	1.002	0.317	
AOSISA	8.260E-5	1.2806E-5	41.600	**<0.001**	
(Intercept)	1.725	2.3993	0.517	0.472	

<u>Layer G (Sample: 240 pieces from 5 source areas):</u>

Overall:

Omnibus test: likelihood ratio chi-square = 292.205, df = 9, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	0.566	0.3001	4.288	0.059	87.246
Extent	0.969	0.4679	3.222	**0.038**	
Difficulty (Cal/km)	1.107	0.6165	1.161	0.073	
Medium rocks	-0.049	0.0451	0.148	0.281	
Large rocks	-0.399	1.0389	6.299	0.701	
Very large rocks	5.885	2.3446	0.149	**0.012**	
Calories	0.445	1.1522	3.094	0.699	
AOSA	-0.002	0.0012	1.323	0.079	
AOSISA	-9.178E-8	7.9799E-8	8.047	0.250	
(Intercept)	-16.326	7.2335	5.094	**0.024**	

* Small rocks removed because of Hessian matrix singularity

Raw Material:

Omnibus test: likelihood ratio chi-square = 223.888, df = 4, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	1.007	0.1644	37.567	**<0.001**	145.563
Medium rocks	-0.450	0.7673	0.344	0.557	
Large rocks	3.932	0.9713	16.390	**<0.001**	
Very large rocks	0.945	0.4367	4.682	**<0.030**	
(Intercept)	-10.681	2.6324	16.464	**<0.001**	

* Small rocks removed because of Hessian matrix singularity

Terrain:

Omnibus test: likelihood ratio chi-square = 263.780, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Extent	0.536	0.3676	2.122	0.145	107.671
Difficulty (Cal/km)	-0.114	0.0332	11.863	**<0.001**	
Calories	-0.001	0.0008	3.266	0.071	
AOSA	-4.620E-8	4.2339E-8	1.191	0.275	
AOSISA	7.690E-5	1.5043E-5	26.129	**<0.001**	
(Intercept)	3.996	2.1670	3.400	0.065	

<u>Layer H (Sample: 2827 pieces from 10 source areas):</u>

Overall:

Omnibus test: likelihood ratio chi-square = 1301.446, df = 10, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	1.487	0.3891	14.602	**<0.001**	305.813
Extent	2.685	0.5115	27.552	**<0.001**	
Difficulty (Cal/km)	-0.189	0.0304	38.433	**<0.001**	
Small rocks	-8.226	2.3545	12.207	**<0.001**	
Medium rocks	-4.389	1.4889	8.692	**0.003**	
Large rocks	2.347	0.7127	10.846	**<0.001**	
Very large rocks	-1.508	0.8871	2.889	0.089	
Calories	-0.005	0.0010	25.181	**<0.001**	
AOSA	-2.634E-7	7.2127E-8	13.332	**<0.001**	
AOSISA	3.924E-8	1.6922E-5	34.930	**<0.001**	
(Intercept)	15.208	3.5278	18.583	**<0.001**	

Raw Material:

Omnibus test: likelihood ratio chi-square = 898.076, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	1.406	0.1397	101.191	**<0.001**	699.184
Small rocks	-7.160	1.3879	26.618	**<0.001**	
Medium rocks	-1.701	0.4375	15.124	**<0.001**	
Large rocks	3.510	0.3253	116.461	**<0.001**	
Very large rocks	1.391	0.4349	10.227	**<0.001**	
(Intercept)	2.844	1.4362	3.921	**0.048**	

Terrain:

Omnibus test: likelihood ratio chi-square = 1210.703, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Extent	1.317	0.2895	20.703	**<0.001**	386.557
Difficulty (Cal/km)	-0.214	0.0196	119.232	**<0.001**	
Calories	-0.004	0.0007	29.863	**<0.001**	
AOSA	-1.454E-7	4.7297E-8	9.446	**0.002**	
AOSISA	5.90E-6	1.0730E-5	102.741	**<0.001**	
(Intercept)	15.055	1.8888	63.529	**<0.001**	

<u>Layer I (Sample: 850 pieces from 12 source areas):</u>

Overall:

Omnibus test: likelihood ratio chi-square = 967.978, df = 10, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	1.271	0.2053	38.347	**<0.001**	419.634
Extent	1.635	0.2525	41.939	**<0.001**	
Difficulty (Cal/km)	-0.110	0.0155	50.495	**<0.001**	
Small rocks	-7.217	1.7109	17.793	**<0.001**	
Medium rocks	-3.573	0.7232	24.407	**<0.001**	
Large rocks	0.416	0.3255	1.630	0.202	
Very large rocks	-0.675	0.4169	2.618	0.106	
Calories	-0.003	0.0005	33.773	**<0.001**	
AOSA	9.574E-8	2.2132E-8	18.712	**<0.001**	
AOSISA	3.450E-5	7.7136E-6	20.003	**<0.001**	
(Intercept)	13.347	2.3913	31.153	**<0.001**	

Raw Material:

Omnibus test: likelihood ratio chi-square = 641.244, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	0.930	0.1060	76.950	**<0.001**	736.368
Small rocks	-4.312	1.1406	14.295	**<0.001**	
Medium rocks	-1.121	0.3600	9.699	**0.002**	
Large rocks	3.205	0.2582	154.097	**<0.001**	
Very large rocks	-0.262	0.3545	0.547	0.460	
(Intercept)	1.826	1.1873	2.367	0.124	

Terrain:

Omnibus test: likelihood ratio chi-square = 905.356, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Extent	1.179	0.1833	41.391	**<0.001**	472.256
Difficulty (Cal/km)	-0.111	0.0137	66.122	**<0.001**	
Calories	-0.002	0.0003	33.248	**<0.001**	
AOSA	3.557E-8	1.6321E-8	4.750	**0.029**	
AOSISA	6.324E-5	5.9844E-6	111.687	**<0.001**	
(Intercept)	7.087	1.1935	35.256	**<0.001**	

<u>Layer J-K1 (Sample: 1069 pieces from 12 source areas):</u>

Overall:

Omnibus test: likelihood ratio chi-square = 1146.940, df = 10, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	1.608	0.3600	19.954	**<0.001**	295.144
Extent	2.995	0.5238	32.690	**<0.001**	
Difficulty (Cal/km)	-0.149	0.0366	16.599	**<0.001**	
Small rocks	-8.706	2.2439	15.054	**<0.001**	
Medium rocks	-4.015	1.3907	8.333	**0.004**	
Large rocks	2.969	0.7674	14.971	**<0.001**	
Very large rocks	-2.266	0.9906	5.233	0.022	
Calories	-0.007	0.0012	32.477	**<0.001**	
AOSA	-2.259E-7	7.1303E-8	10.039	**0.002**	
AOSISA	5.553E-5	1.5312E-5	13.149	**<0.001**	
(Intercept)	13.392	3.6078	13.779	**<0.001**	

Raw Material:

Omnibus test: likelihood ratio chi-square = 794.266, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	1.327	0.1385	91.784	**<0.001**	637.818
Small rocks	-8.143	1.4055	33.563	**<0.001**	
Medium rocks	-1.490	0.4276	12.136	**<0.001**	
Large rocks	3.210	0.2880	124.217	**<0.001**	
Very large rocks	-0.283	0.3687	0.589	0.443	
(Intercept)	4.290	1.4259	9.051	**0.003**	

Terrain:

Omnibus test: likelihood ratio chi-square = 981.924, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Extent	0.945	0.1953	23.426	**<0.001**	450.159
Difficulty (Cal/km)	-0.141	0.0196	51.342	**<0.001**	
Calories	-0.005	0.0006	76.955	**<0.001**	
AOSA	-1.806E-7	3.4991E-8	26.635	**<0.001**	
AOSISA	7.572E-5	7.9055E-6	91.749	**<0.001**	
(Intercept)	14.202	2.0044	50.202	**<0.001**	

<u>Layer K2 (Sample: 556 pieces from 9 source areas):</u>

Overall:

Omnibus test: likelihood ratio chi-square = 872.857, df = 10, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	1.047	0.3544	8.729	**0.003**	214.268
Extent	2.706	0.6381	17.988	**<0.001**	
Difficulty (Cal/km)	-0.169	0.0321	27.583	**<0.001**	
Small rocks	-3.401	2.1917	2.407	0.121	
Medium rocks	-2.559	1.2855	3.963	**0.047**	
Large rocks	1.580	0.7788	4.117	**0.042**	
Very large rocks	-1.214	0.9203	1.741	0.187	
Calories	-0.004	0.0010	14.530	**<0.001**	
AOSA	-1.709E-7	6.9678E-8	6.013	**0.014**	
AOSISA	7.784E-5	1.7807E-5	19.107	**<0.001**	
(Intercept)	6.882	4.1008	2.816	0.093	

Raw Material:

Omnibus test: likelihood ratio chi-square = 621.855, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Quality	1.185	0.1409	70.771	**<0.001**	455.270
Small rocks	-4.803	1.3838	12.045	**<0.001**	
Medium rocks	-1.123	0.4478	6.293	**0.012**	
Large rocks	2.820	0.2704	108.802	**<0.001**	
Very large rocks	0.243	0.3625	0.449	0.503	
(Intercept)	0.012	1.4714	0.000	0.993	

Terrain:

Omnibus test: likelihood ratio chi-square = 834.044, df = 5, p = <0.001

Variable	Beta	S.E.	Wald Chi-Square	P-value	AIC
Extent	1.947	0.3391	32.960	**<0.001**	243.081
Difficulty (Cal/km)	-0.209	0.0269	60.518	**<0.001**	
Calories	-0.004	0.0007	23.143	**<0.001**	
AOSA	-1.641E-7	4.0098E-8	16.745	**<0.001**	
AOSISA	5.205E-8	1.1948E-5	86.477	**<0.001**	
(Intercept)	10.400	2.0334	26.160	**<0.001**	

Appendix III. Wald χ^2 percentage contributions towards source area use

Number of stone tool pieces data:

Variable	Layer										
	C	2	3	4	5	E	G	H	I	J-K1	K2
Quality	15.57	25.77	22.76	22.73	12.29	7.40	8.51	14.48	20.81	16.79	16.06
Extent	5.88	5.32	9.50	5.17	7.21	14.51	10.24	10.82	19.48	15.37	12.92
Difficulty	4.40	0.09	4.02	1.83	0.22	8.84	14.96	14.06	13.73	13.74	8.42
Small Rocks	8.23	14.94	9.25	13.07	6.97	-	-	7.20	5.28	9.89	5.74
Medium Rocks	12.10	13.67	12.54	13.14	6.51	1.37	6.36	5.85	4.14	4.61	6.44
Large Rocks	26.98	12.96	23.76	5.71	25.60	24.21	10.17	11.61	14.77	10.94	16.20
Very Large Rocks	0.78	2.20	0.45	1.34	3.92	0.49	3.16	0.47	0.01	0.12	0.17
Calories	0.33	10.72	2.53	12.70	0.06	2.08	9.62	1.59	6.79	16.55	4.37
AOSA	6.85	5.11	4.10	5.99	7.58	5.64	0.19	6.49	0.12	3.01	5.48
AOSISA	16.98	8.59	9.27	13.39	18.23	25.12	27.90	27.31	14.45	8.16	22.59
(Intercept)	1.89	0.62	1.82	4.93	11.41	10.34	8.88	0.11	0.42	0.82	1.61
Raw Material subset total	**63.66**	**69.54**	**68.76**	**56.00**	**55.29**	**33.47**	**28.20**	**39.62**	**45.01**	**42.35**	**44.61**
Terrain subset total	**34.45**	**29.84**	**29.42**	**39.07**	**33.30**	**56.19**	**62.92**	**60.27**	**54.57**	**56.83**	**53.78**

Weight of stone tool pieces data:

Variable	Layer										
	C	2	3	4	5	E	G	H	I	J-K1	K2
Quality	7.74	14.12	12.90	16.80	13.08	6.40	13.06	7.05	13.65	10.95	8.01
Extent	2.38	0.24	3.67	4.89	12.26	12.88	9.82	13.29	14.93	17.93	16.50
Difficulty	2.02	2.94	7.01	4.45	1.55	8.88	3.54	18.54	17.98	9.11	25.31
Small Rocks	0.06	12.37	11.33	11.16	0.04	-	-	5.89	6.33	8.26	2.21
Medium Rocks	1.21	10.37	3.80	12.49	0.17	0.85	0.45	4.19	8.69	4.57	3.64
Large Rocks	22.85	7.22	18.39	4.52	22.25	25.91	19.19	5.23	0.58	8.21	3.78
Very Large Rocks	13.46	0.05	1.23	0.76	3.61	0.14	0.45	1.39	0.93	2.87	1.60
Calories	6.35	19.67	11.19	13.35	13.17	5.95	9.43	12.15	12.02	17.82	13.33
AOSA	11.37	9.57	6.88	7.18	3.92	7.14	4.03	6.43	6.66	5.51	5.52
AOSISA	30.11	10.68	21.08	12.78	16.51	24.63	24.51	16.85	7.12	7.21	17.53
(Intercept)	2.44	12.76	2.51	11.61	13.44	7.23	15.52	8.97	11.09	7.56	2.58
Raw material subset total	**45.31**	**44.12**	**47.66**	**45.74**	**39.15**	**33.30**	**33.16**	**23.76**	**30.19**	**34.86**	**19.23**
Terrain subset total	**52.24**	**43.12**	**49.84**	**42.65**	**47.41**	**59.48**	**51.32**	**67.28**	**58.72**	**57.58**	**78.19**