interpreting lithic raw material variability in Middle Palaeolithic contexts: a modeling approach with applications to the Bau de l'Aubesier (Southeastern France)

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Chapter Four

A network model of local resource selection for evaluating landscape knowledge, navigation, and foraging extents at the Bau de l'Aubesier

Evaluating landscape knowledge and lithic resource selection at the French Middle Palaeolithic site of the Bau de l'Aubesier

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Published in *Journal of Human Evolution (2022) 166: 103152*

DOI: 10.1016/j.jhevol.2022.103152

Journal of Human Evolution 166 (2022) 103152

Contents lists available at ScienceDirect

Journal of Human Evolution

journal homepage: www.elsevier.com/locate/jhevol

Evaluating landscape knowledge and lithic resource selection at the French Middle Paleolithic site of the Bau de l'Aubesier

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ARTICLE INFO

Article history:
Received 16 February 2021
Accepted 9 January 2022
Available online 23 March 2022

Keywords:
Middle Paleolithic
Provisioning strategies
Lithic raw materials
Spatial cognition
Neanderthal

ABSTRACT

We report on the application of a novel approach to exploring the degree of landscape knowledge, wayfinding abilities, and the nature of decision-making processes reflected in the utilization of stone resources in the French Middle Paleolithic. Specifically, we use data from the site of the Bau de l'Aubesier to explore the reasons why a majority of the 350 raw material sources cataloged in the surrounding region appear not to have been utilized, including several located near the site and yielding high-quality lithic materials. To this end, we focus on the spatial relationships between sources as an explanatory variable, operationalized in terms of minimum travel times. Using geographic information system software and a generalized linear model of resource selection derived from the Bau assemblages, we compute source utilization probabilities from the perspective of hominins located off-site. We do so under three optimization scenarios, factoring in the intrinsic characteristics (e.g., quality) and time required to reach each source on the way to the Bau. More generally, we find that in slightly more than 50% of cases, seemingly viable sources may have been ignored simply because the minimum cost path leading back to the Bau passes through or requires only minimal deviations to reach, higher quality options. More generally, we found that throughout the entire region, a cost/benefit analysis of competing sources favors those from source areas known to have been utilized. Virtually all the available information on lithic procurement at the Bau is consistent with a model of landscape utilization premised on detailed knowledge of a very large area, an ability to accurately estimate travel times between locations, and a pragmatic strategy of stone resource exploitation based on minimizing costs (travel and search times) and maximizing utility.

1. Introduction

Our understanding of the lifeways and evolutionary histories of our hominin relatives is premised to a very large extent on the degree to which their relationships with past environments can be elucidated. Indeed, knowledge of the affordances and constraints characteristic of specific landscapes provides essential context for evaluating both individual decisions and overall adaptive strategies. Such knowledge is difficult to acquire, however, as we face two major obstacles. The first involves reconstructing past conditions, such as the physical availability of resources and the presence of barriers and hazards, based on evidence that is fragmentary, biased by differential preservation, and generally available at coarse temporal and spatial resolutions. The second pertains to understanding what hominins could have done given these conditions, in other words, the nature of the physiological but also cognitive constraints—for example, limited spatial memory and information processing abilities—underpinning the relationships with their surroundings.

Among extant primate species, ours is unusual in terms of both our capacity to consciously modify the environment (Lewis and Maslin, 2015) and our abstract spatial reasoning skills. We can, for example, use flexible but cognitively demanding Euclidean mental maps to efficiently navigate to distant, out-of-sight resources (e.g., Dehaene et al., 2006; Trapanese et al., 2018), evidence for which remains elusive in other living species. Our spatial abilities appear to be tied to linguistic faculties and extended developmental trajectories (e.g., Spelke and Lee, 2012) specific to our

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https://doi.org/10.1016/j.jhevol.2022.103152
0047-2484/

genus (but see Normand and Boesch, 2009), and the question of when such abilities developed in our lineage is still a matter of some debate. Essentially modern spatial abilities appear to have already been present in *Homo erectus* prior to ca. 500,000 years ago (Wynn and Coolidge, 2016), but it has been suggested that novel spatial skills gave anatomically modern humans a unique advantage resulting in our worldwide dispersal (Burke, 2012). In brief, when considering hominin species other than our own, caution is warranted in assuming modern capacities to conceptualize and navigate space.

In this context, Neanderthals present an interesting challenge. Very closely related to us (e.g., Sánchez-Quinto and Lalueza-Fox, 2015; Roebroeks and Soressi, 2016), equipped with large brains and able to exploit the harsh mid-latitude Pleistocene environments of western Eurasia (e.g., Hublin and Roebroeks, 2009; Nielsen et al., 2017), these hominins left behind abundant material culture which sporadically comes tantalizingly close to suggesting fully modern human cognition (e.g., Zilhão, 2012; Radovčić et al., 2015; Jaubert et al., 2016; Hoffmann et al., 2018a, b). Yet, although the evidence clearly points to Neanderthals having been highly intelligent, it is far from clear whether they learned and processed information the same way we do. The relatively extensive evidence we have for their lifeways suggests that Neanderthals had a somewhat different relationship with their environment than our anatomically modern ancestors. They appear to have exploited a typically narrower resource base (e.g., Richards and Trinkaus, 2009; Stiner, 2013; Fiorenza et al., 2014; Power et al., 2018; but refer to the study by Henry et al., 2014) perhaps over a smaller territory (e.g., Verpoorte, 2006; Nava et al., 2020) and to have had higher energy requirements (e.g., Sorensen and Leonard, 2001; Macdonald et al., 2009; Sørensen, 2009; Hockett, 2012; Churchill, 2014; also refer to the study by Heyes and MacDonald, 2015), somewhat smaller group sizes and more spatially constrained social networks (e.g., Churchill, 2014; Pearce and Moutsiou, 2014; but refer to the study by Hayden, 2012) as well as a more limited ability to colonize new environments. It also appears that Neanderthals had somewhat different growth curves and that their brains developed along different, more archaic pathways than our own (Gunz et al., 2012; Hublin et al., 2015; Neubauer et al., 2018; but see Rosas et al., 2017). All of these differences have potential bearing on their spatial abilities, including memory and navigation.

Multiple lines of evidence can be used to investigate the spatial abilities of extinct hominins. These include diachronic changes in stone tool complexity, anatomical changes observable in the fossil record, the distribution of archaeological sites, and the patterns of faunal and lithic resource exploitation such sites document. Developments in lithic technology, for instance, provide clues about the evolution of abilities such as mental rotation and, more broadly, visuospatial integration, that is, the functional synthesis of visual and spatial perception (Overmann, 2015; Bruner et al., 2018). Moreover, stone tool complexity may also reflect degrees of landscape knowledge, with greater investment in tool manufacture, including raw material procurement, reflecting greater social knowledge of resource availability (Clark and Linares-Matás, 2020). The neurological and genetic underpinnings of spatial abilities and their ontogeny have been studied in extant humans as well as other primates, and the results can serve as a guide to interpret anatomical features of extinct hominins, including differences in gross neuroanatomy (e.g., Correira, 2013; Bruner and Lozano, 2014; Kuhn et al., 2016; Shakeshaft et al., 2016; Bruner et al., 2018; Hodgson, 2019). Finally, the distribution of sites and patterns of faunal and lithic resource exploitation supply critical information on spatial behaviors and cognition, including wayfinding and landscape learning (e.g., Raynal et al., 2013; Burke, 2015; Guiducci and Burke, 2016; Hussain and Floss, 2016; Kuhn et al., 2016).

In this study, we report on the application of a novel approach to exploring aspects of spatial cognition in Neanderthals using lithic data. Specifically, we investigate the degree of landscape knowledge, navigational abilities, and decision-making processes reflected in Neanderthals' use of regionally available stone resources at the French Middle Paleolithic site of the Bau de l'Aubesier (hereinafter 'the Bau'). We focus on stone because 1) archaeological preservation is not a major concern with this material, 2) it constitutes a predictable fixed resource, and 3) it is often possible to meaningfully narrow down locations from where rocks used to manufacture archaeological artifacts may have originally been collected. Indeed, it is generally acknowledged that evaluating the archaeological incidences of different raw materials in light of their environmental availability and distribution can provide crucial insights into past land use strategies at different scales (e.g., Féblot-Augustins, 2009; Frahm et al., 2016; Turq et al., 2017). At the Bau, this distribution, as well as the individual characteristics of the plentiful sources available within ca. 40 km of the site, are both well known and unlikely to have changed substantially since the initial occupation of the site (Browne and Wilson, 2011). In other words, using lithic provenance data from the Bau allows us to minimize the first of the challenges noted at the onset, that is, the need to reconstruct past conditions (cf. Dibble, 1991), and to focus instead on examining the constraints underlying resource use (also refer to the study by Wilson et al., 2018).

Our approach departs from most other lithic provenance studies in two important ways. First, we focus squarely on evaluating why a majority of the raw material sources available in the region surrounding the Bau were seemingly not used over a period of roughly 100,000 years. Typically, provenance studies concentrate on identifying the location of exploited raw material sources and on explaining their degree of utilization, paying less attention to why plausibly viable procurement options may have been ignored. This is understandable because many factors can explain a lack of use—for example, sources may simply not have been available—but it does mean that a potentially critical source of information on past behaviors may be underutilized. Second, we emphasize the spatial relationships between sources, operationalized here as minimum travel times, as an explanatory variable. It has long been recognized that a source is less likely to have been used if a better procurement alternative exists on the way to a site (e.g., Luedtke, 1976; see also Wilson, 2007a), but the effects of the spatial relationships between potentially usable sources are generally not quantified or modeled. And yet, as shown by Pop (2016), source utilization can be expected to be shaped by the presence or absence of other nearby sources even under entirely neutral mobility and resource exploitation conditions. Considering this, we make such spatial relationships central to our approach by conceptualizing each source as a node in a network of plausible procurement options and propose three possible nested explanations for the systematic, long-term avoidance of sources that may be witnessed at the Bau, differentiated by increasingly complex cognitive requirements.

Our hypotheses are formulated from the perspective of individuals engaged in some unknown off-site activity who are intent on procuring raw materials on their way to a camp and are all premised on Neanderthals having been rational agents who sought to optimize their foraging activity by transporting usable stone to a site from the best sources and along the most efficient routes. This is in line with the selectivity in lithic raw material procurement evidenced at the Bau (e.g., Browne and Wilson, 2011; Wilson and Browne, 2014). Of course, we do not know where Neanderthals made procurement decisions, but a source which is a suboptimal choice at its own location, because a better alternative exists en route to a destination site, cannot have been the best choice at any other location either. Moreover, it is possible to simulate procurement decisions everywhere individuals could have been located when they decided to collect rocks and to investigate where archaeological observations are compatible with the known distribution of used and unused resources under a given procurement scenario. Based on these insights, we use variations of an optimization algorithm, representing our proposed explanations and rooted in archaeologically evidenced selection criteria, to probabilistically classify all known sources in our study region as either exploitable or unexploited. We then evaluate the resulting modeled distributions against the archaeological representation of sources among the nearly 16,000 stone artifacts for which provenance is known. To the best of our knowledge, this constitutes a new approach to inferring wayfinding abilities from the representation of lithic raw materials at archaeological sites and adds to a growing number of novel quantitative studies (e.g., McPherron, 2018; Režek et al., 2018; Oestmo et al., 2020).

Our hypotheses are graphically represented in Figure 1 as simplified scenarios. They vary in terms of 1) the number of procurement options whose location (and characteristics) individuals would have had to accurately recall and 2) the number and complexity of the paths (i.e., straight to the destination, or including a detour to intercept other raw material sources) for which individuals would have needed to accurately estimate minimum travel times. Briefly, they are as follows:

Hypothesis 1. (H_1): Neanderthals optimized procurement at a localized scale, recalling and evaluating the potential of all lithic sources found directly along the least-cost paths to the site and collecting stone only from the best among these (Fig. 1A and B). Under this hypothesis, we classify as exploitable all sources for which no better alternatives exist en route to the Bau (e.g., source 2 in Fig. 1A and source 1 in Fig. 1B) and the remainder as unexploited.

Hypothesis 2. (H_2): Neanderthals optimized procurement at a regional scale by evaluating the potential of all sources in light of all other sources and only exploiting those that offered the best cost-benefit ratios (Fig. 1C). Under this hypothesis, we classify as exploitable sources for which no better procurement alternative is available anywhere in the region and the remainder as unexploited. In the sample scenario illustrated in Figure 1C, source 1 would therefore be classified as unused because a hominin would have found the extra effort required to reach another source (e.g., source 4) to be warranted owing to the greater quality or abundance of materials there; conversely, sources 4 and 5 would both be classified as exploitable (but note that only the evaluation of source 1 is shown in Fig. 1C).

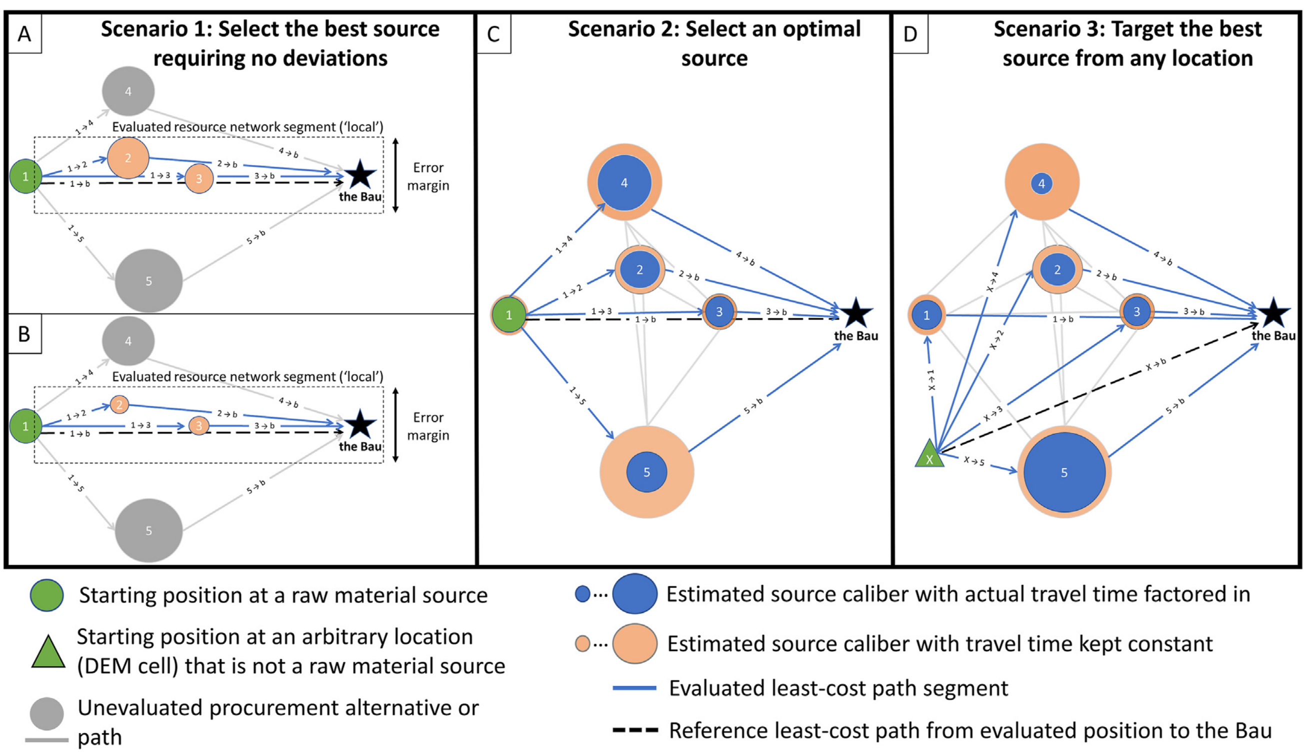

Figure 1. Schematic representation of three procurement optimization scenarios. Subplots A and B illustrate how a hypothetical source (1) would be evaluated under Hypothesis 1, that is, based on the presence or absence of better alternatives along the least-cost path to the destination, the Bau (arrow 1→b; note that we allow here for small uncertainties in travel time estimations). In these cases, sources are compared only in terms of the quality and abundance of their raw materials, represented by the size of the orange circles (larger is better). In the scenario shown in subplot A, source 1 would be classified as unexploited because source 2 is a better option, whereas in the scenario represented by subplot B, source 1 would be classified as exploitable. Note that sources 4 and 5 are not evaluated because they would not be encountered en route to the site. Subplot C illustrates how the same source (1) would be evaluated under Hypothesis 2. In this case, all known options are considered and, in addition to the quality and abundance of their raw materials, minimum required travel times are also taken into account to determine the relative benefits each offers (size of the blue circles; larger is better). Thus, the evaluated source (1) would be classified as unexploited because source 4 is a superior (and the best) procurement option and is expected to have been targeted instead. Note that source 5 has better and/or more abundant materials (compare the size of the orange circles), but the cost of reaching it on the way to the Bau (i.e., travel times along arrows 1→5 and 5→b) is too high to warrant the effort (hence the smaller blue circle). Subplot D illustrates how sources would be evaluated from an arbitrary landscape location (x), represented as a digital elevation model (DEM) cell, under Hypothesis 3. As shown in subplot C, the best procurement option (largest blue circle) when travel costs are factored in is presented by source 5, which is therefore predicted to have been targeted. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Hypothesis 3. (H_3): Neanderthals optimized lithic raw material procurement by optimally targeting the best sources (i.e., those identified as exploitable under H_2) from throughout the region (Fig. 1D). This hypothesis is a generalized version of the second one outlined earlier: for Hypothesis 3, the landscape and potential for exploiting sources are also judged from any other, nonsource points. Thus, for each landscape location (e.g., x in Fig. 1D), we classify a source as exploitable if it represents a good procurement alternative (e.g., source 5 in Fig. 1D) or unexploited if it does not. Under this hypothesis, we would expect the number of lithics procured from specific sources to covary with the number of procurement decisions taken at locations where they constitute the best alternatives.

The first hypothesis is thus a special case of the second, which in turn is a special case of the third. As already noted, the main difference lies in the number and complexity of paths (blue arrows in Fig. 1) and the range of alternatives that must be considered to determine whether a given source ought to be ignored or not. Collectively, these hypotheses enable us to ascertain, based on the degree to which each fits archaeological observations, whether Neanderthals were able to target a set of locally (H_1) or globally (H_2) optimal sources, and whether they could do the latter efficiently throughout the region (H_3). Alternatively, failure of our hypotheses to explain archaeological observations would signal that our fundamental assumptions regarding Neanderthal (optimizing) behavior are problematic or, possibly, that the lithic landscape that exists today is substantially different from what would have existed in the past. As discussed in the following part of the article, this does not appear to be the case at the Bau.

2. Materials and methods

2.1. Data

We rely on previously published data on lithic resource availability and use at the Bau de l'Aubesier (Wilson, 2007a, b, c; Browne and Wilson, 2011, 2013; Wilson and Browne, 2014). Compiled over the course of more than 25 years and including systematic characterizations of 350 raw material sources and nearly 41,000 archaeological pieces, they constitute one of the most comprehensive and consistent datasets available for a Middle Paleolithic site. These data, as well as the site and its regional context, are described in the following subsections.

The Middle Paleolithic site of the Bau de l'Aubesier The Bau de l'Aubesier is a large rock shelter located in the Vaucluse department of southeastern France. Known since the turn of the 20th century (Moulin, 1903), it has yielded a complex and rich archaeological sequence, approximately 13-m thick, which was deposited over the course of roughly 100,000 years or more ($\geq$200 kya to $\leq$100 kya; see Blackwell et al., 2000, 2001; Lebel et al., 2001; Wilson, 2021). The site is found at the intersection of multiple types of ungulate home ranges (Fernandez, 2001) in a region of variable topography and abundant sources of knappable materials (Fig. 2). The total number of lithics recovered from the partially excavated deposits, virtually all flint, amounts to at least 85,000; they are classified as Typical Mousterian of Levallois facies (de Lumley-Woodyear, 1969; Texier, 2004). Although early analyses (concerning only the upper deposits) had suggested substantial techno-typological homogeneity across the layers (e.g., Moulin, 1903; de Lumley-Woodyear, 1969), more recent work has highlighted diachronic changes that included important shifts in lithic raw material selection (Wilson and Browne, 2014; Wilson, 2021). Specifically, although the same major raw material types were exploited throughout, their proportions do vary by layer, and some layers show a greater diversity of types than others (see Supplementary Online Material [SOM] S1). In addition to lithics, the site has also yielded combustion features, more than 2700 identifiable ungulate remains resulting from anthropic accumulation and representing a minimum of 241 individuals (Fernandez, 2001, 2006) and isolated deciduous and permanent Neanderthal lineage teeth as well as a partial (pre-)Neanderthal mandible with substantial pathologies (e.g., Lebel et al., 2001; Wilson, 2021).

The study region The study region is defined here as a rectangular area of ca. 87 by 55 km that includes all raw material sources documented by Lucy Wilson near the Bau, regardless of whether or not they were utilized. Its limits are therefore arbitrary and not intended to represent home ranges or a discrete geographic entity with clear physical boundaries; indeed, the region is characterized by variable topography and resource availability. Importantly, however, and despite the presence of steep and inaccessible cliffs in certain areas, it is not partitioned by any major physical barriers that would have impeded human mobility. The region is home to several other important Middle Paleolithic sites, including the Baume des Peyrards, La Combette, and the rich stratified open-air site of Berigoule (see Texier, 2004) and was never glaciated. In fact, there is no evidence for major changes to the geomorphology of the landscape over the last 200,000 years. Thus, while it is probable that the characteristics of some raw material sources did change through time, it is reasonable to consider the overall lithic landscape that exists today as representative of that exploited by hominins during the deposition of the Middle Paleolithic levels at the Bau.

Regional raw material sources A total of 350 individual landscape locations with naturally occurring, potentially usable lithic raw materials have been cataloged to date, including both primary (outcrop) and secondary (alluvial or colluvial) localities. Throughout this article, we refer to such locations as sources. Some of these yielded abundant, high-quality rocks over a relatively large area, whereas others yielded only poor-quality stone in low quantities, in a variety of combinations of quality, extent, and abundances. These characteristics, as well as geographic coordinates, are among the variables that have been systematically collected and recorded for each source by Lucy Wilson since 1987.

Geological samples collected at these locations were characterized for the purposes of sourcing archaeological materials based primarily on their macroscopically visible features and petrographic thin sections. Analyses were supplemented by limited geochemical data and focused on properties that are useful in identifying materials by age and depositional environments (Wilson, 2007a; Browne and Wilson, 2011). Because the available information does not always allow for sources to be distinguished in terms of archaeologically visible properties, they have been classified into 122 groups, or 'source areas' (e.g., Browne and Wilson, 2013). Each such source area is characterized by a specific, archaeologically identifiable raw material type and may include one or more discrete sources (minimum = 1, median = 1, maximum = 15). The convex hulls that define these source areas vary in size and, as shown in Figure 2, at times overlap. With archaeologically represented raw material types that are procurable at multiple locations, it is impossible to say which location was in fact targeted, and to what extent.

Archaeological raw material variability A total of 15,674 of the 40,770 lithic artifacts examined to date for provenance purposes have been assigned to the source areas described earlier by Lucy Wilson using mainly visual and petrographic criteria (Browne and Wilson, 2011; Wilson and Browne, 2014). These artifacts include pieces of all types and sizes. The rest of the materials either were procured from sources that have not yet been identified ($n = 171$, or ca. 0.5%) or have been altered to such an extent by patination and burning as to prevent reliable classification (Browne and Wilson, 2011). The sourced lithics, which come primarily from 11 different archaeological layers that span the entire sequence (Wilson and Browne, 2014; see also SOM S1), are made from materials collected at a minimum of 17 and a maximum of 101 sources comprising 17 source areas; hereinafter, we refer to all sources assigned to these source areas as belonging to a set S_1. A large number of possible procurement locations ($n = 249$, from 105 source areas) therefore appear not to have been utilized at all, and hereinafter, we refer to these as belonging to a set S_0. Four of the seemingly nonutilized sources were situated on steep terrain (slope >60%) and were therefore not easily accessible, but many others are located in relatively close proximity to the site, on relatively gentle slopes (Fig. 2).

Overall, the archaeologically observed raw material variability and the distribution of possibly exploited sources suggest that the Bau was fairly centrally located within its raw material supply zone, with most artifacts being made from stone found within 13 km of the site. It must be noted, however, that archaeologically represented raw materials are rarely found in close proximity to the site—75% of their sources are found at 6.3 km or more from the Bau, and the average Euclidean distance is 10.9 km (minimum = 0.2, maximum = 47.3).

2.2. Analytical methods

Our approach to evaluating procurement alternatives can be conceptualized as involving a complete directed edge- and node-weighted network where accessible sources and the Bau constitute the nodes and least-cost paths constitute the edges (two for each pair of nodes). These edges have associated weights, which we define as the minimum walking times required to traverse them, while nodes have weights (see orange circles in Fig. 1, whose size remains constant across the different scenarios) that correspond to a combination of attributes (i.e., quality, extent, raw material abundance); hereinafter, we refer to the weight of the directed edge connecting a given node (or vertex) v to another node v' in the network of sources as $w_{v \to v'}$ and that of the edge connecting v' to v as $w_{v' \to v}$ (see blue arrows in Fig. 1 and Table 1 for a summary of all key variables and sets that are referenced in this study). As discussed in the rest of this section, we evaluate the relative merits of procuring materials from sources found along different network

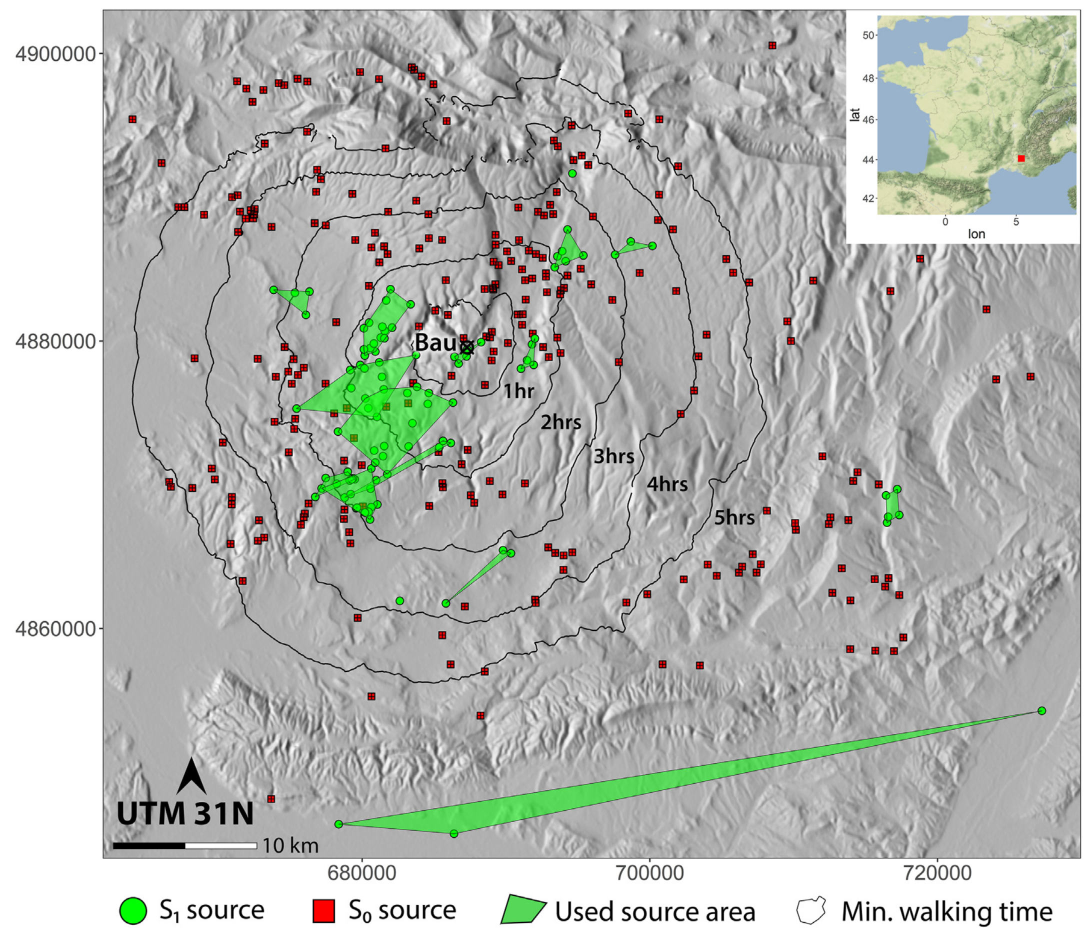

Figure 2. Study area and lithic resource distribution around the Bau de l'Aubesier. Sources of archaeologically represented raw materials (set S_1) are indicated by green circles, and sources of nonrepresented materials (set S_0), by red squares. Green polygons represent convex hulls encompassing sources from different archaeologically exploited source areas; note that these vary in size and at times overlap. Concentric rings show GIS-computed distances that can be covered while walking away from the site, in 1-h increments (minimum walking times). Note that several S_0 sources are located close to the site and that most S_1 sources are located at relatively substantial distances from the Bau. Two distant S_0 sources included in the dataset are not shown in this figure; one is located far to the west, and the other beyond the area's eastern limits. Coordinates are given in UTM zone 31N. Min. = minimum. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Table 1
Definitions of key variables and sets discussed in the text.

Key	Definition
b	The Bau, considered as the end destination for a procurement trip.
E	The extent of a source, approximated to four values: 20 m^2, 706 m^2, 4416 m^2, and 17,663 m^2.
H_1	Hypothesis 1. Figure 1A and B illustrate how sources are evaluated under this hypothesis.
H_{2a}	Hypothesis 2. When sources with the highest $P_{S1\ (v')}$ values (i.e., 'optimal') at one or more nodes (i.e., sources) are predicted to be used (i.e., S_{1p}) and the rest are predicted to be unused (i.e., S_{0p}). Figure 1 C illustrates how sources are evaluated under this hypothesis.
H_{2b}	Hypothesis 2. When sources with $P_{S1\ (v')}$ values within the 95% confidence interval of the highest (i.e., 'good') at one or more nodes (i.e., sources) are predicted to be used (i.e., S_{1p}) and the rest are predicted to be unused (i.e., S_{0p}).
H_3	Hypothesis 3. Sources are evaluated as under H_2, but from all cells of the digital elevation model (DEM) which are reachable within 5 h of walking from the Bau. Figure 1D illustrates how sources are evaluated under this hypothesis.
L	The abundance of large rocks at a raw material source, expressed in terms of the approximate percentage of a source's surface area. Takes values of 0 (absent), 1 (<5%), 2 (5–24%), 3 (25–50%), and 4 (>50%).
P_{S1}	The probability that a source with a given combination of attributes and access costs belongs to the set of sources from utilized source areas (S_1), when access costs refer to minimum required travel times from the Bau. Can take values between 0 and 1.
$P_{S1\ (tc)}$	Same as P_{S1}, but with access costs kept at a constant value for all sources.
$P_{S1\ (v')}$	The probability that a source (v') belongs to the set of sources from utilized source areas (S_1) when the access costs factor in the minimum travel time from another source (v) to it and then to the Bau. Unlike P_{S1} and $P_{S1\ (tc)}$, this value will vary depending on which other source is considered. Under H_2, each source will have up to 346 $P_{S1\ (v')}$ associated values, corresponding to the number of accessible sources within the study area (see Fig. 1C, D for more details).
Q	The average quality or suitability for toolmaking of the raw materials found at a source. Recorded on a scale consisting of the following values: 0 (very poor), 1 (poor), 2 (fair), 4 (good), 8 (very good), and 16 (excellent).
S_0	The set of sources for which no evidence of exploitation is preserved at the site.
S_1	The set of sources from utilized source areas.
S_{0p}	The set of sources predicted to belong to the set S_0 under various scenarios.
S_{1p}	The set of sources predicted to belong to the set S_1 under various scenarios.
T	Access costs, defined as minimum walking times. In Eq. (1), T refers to the time required to reach a given source (v) from the Bau, and is equivalent to the weight ($w_{b\rightarrow v}$) of the path or network edge connecting the Bau to the node/source.
v	A raw material source, when considered as a node or vertex in the network of sources in the study area.
v'	A raw material source, when representing a potential procurement alternative being evaluated from another source (v), or from an arbitrary landscape location (x).
$w_{v\rightarrow v'\rightarrow b}$	Minimum travel time from source v to source v' and then to b (the Bau). Substitutes for variable T in Eq. (1).
$w_{v\rightarrow b}$	Minimum travel time from source v to b (the Bau). Substitutes for variable T in Eq. (1).
x	A digital elevation model cell reachable within 5 h from the Bau, and from where procurement alternatives (v') are evaluated under Hypothesis 3. Each x will have 346 associated $P_{S1\ (v')}$ values, one for each procurement option (v').

paths using a generalized linear model (GLM) that aims to reflect the relative importance given to these weights by the hominin inhabitants of the site.

Unless otherwise noted, all analyses described in this paper were conducted in Microsoft R Open, v. 4.0.2 (R Core Team, 2020) with the aid of a number of packages including 'car,' v. 3.0.8 (Fox and Weisberg, 2019), 'caret,' v. 6.0.86 (Kuhn, 2020), 'data.table,' v. 1.12.8 (Dowle and Srinivasan, 2019), 'ggplot2,' v. 3.3.2 (Wickham, 2016), 'raster,' v. 3.3.7 (Hijmans, 2020), and 'rgdal,' v. 1.5.12 (Bivand et al., 2020). Prior to performing these analyses, the random number generator was seeded with a predetermined value (corresponding author's birthday) to ensure the replicability of the results. Relationships between variables were evaluated using nonparametric Spearman's rank order correlation tests because they were not normally distributed, and significance throughout this study is given at an alpha level of 0.05. The R code is available on Zenodo (https://doi.org/10.5281/zenodo.5813254), whereas data on lithic resource use at the Bau are available from L. W. upon request.

Spatial data processing and edge weights All travel costs discussed in this study were computed based on digital elevation models (DEMs) using the processing tools provided by the GRASS, v. 7.4.0, open-source GIS package (GRASS Development Team, 2018). For reproducibility, we scripted all GIS operations with the GRASS Python library v. 2.7.5, and GNU bash, v. 4.2. We used 3 arc-seconds postprocessed Shuttle Radar Topography Mission (SRTM) DEMs, v. 4.1, provided by the International Center for Tropical Agriculture (Jarvis et al., 2008) as our data source because the resolution of SRTM DEMs has proven adequate for route calculations in this region (Browne and Wilson, 2013). Because the study area, defined here as 45°N, 43°N, 4°E, and 6°E (WGS84), spans two SRTM tiles, we merged these with the r.patch module. After importing previously published information on sources (WGS84; https://gisgeography.com/wgs84-world-geodetic-system/), we reprojected the spatial data to UTM zone 31N (EPSG 23031) with datum transformation 3 (France: 2-m horizontal accuracy). For this, we used the r.proj module, using bicubic interpolation (with fallback) for reprojection and for resampling of the DEM to a resolution of 80 m (from ca. 92.57 m by 71.15 m). We also filtered out areas with slopes greater than 60%, deemed inaccessible (Browne and Wilson, 2013), by first creating slope maps with the r.slope.aspect module (default precision parameter) and removing cells with values above the threshold using the r.mapcalc module.

From these data, we created anisotropic least-cost maps using the r.walk GRASS module and a maximum value of 20 hours. For this, we used the default cost and slope parameters, as proposed for modern hikers by Langmuir (1984) based on Naismith's rule, the 'knight's move' option for higher accuracy and constant friction values. While Henry et al. (2017) have published r.walk parameters specific to Neanderthals and anatomically modern humans, we considered empirically derived values as a more appropriate baseline. We generated such least-cost maps for all sources as well as for the site and queried these maps for travel times between locations. Thus, to determine minimum travel times from a source v to a source v', which would correspond to the weight $w_{v\rightarrow v'}$ of the network edge connecting v to v', we queried the value of the raster cell corresponding to the location of source v' on the map created for source v.

Resource selection model Previous research has successfully examined how source characteristics and access costs have shaped degrees of raw material exploitation at the Bau (Wilson, 2007b; Browne and Wilson, 2011; Wilson and Browne, 2014), demonstrating that it is possible to provide objective measures of what the Neanderthal inhabitants of the site considered important, and to what extent. Here we adopt a similar approach in that we use a GLM to quantify the benefits of targeting sources from the Bau based on the available archaeological information. However, instead of modeling the relationship between source attributes and artifact quantities, we use a simple logistic model with binomial error structure and logit link function (McCullagh and Nelder, 1989) to assess the probability P_{S1} that a source with a given combination of attributes and access costs belongs to the set S_1 of sources from utilized source areas (shown in green in Fig. 2) rather than to the set S_0 of sources for which no evidence of exploitation is preserved at the site (shown in red in Fig. 2); in other words, we model the relationship between the attributes of the known sources and the presence or absence at the Bau of the type of raw materials such sources yield. With each source, P_{S1} can therefore take a value between 0 and 1, with values closer to 1 ostensibly denoting more attractive targets from the perspective of a hominin located at the Bau.

Downscaling the data to a binary response may seem like an odd choice, but it has the distinct advantage of preserving information on source area membership, and therefore on degrees of archaeological utilization, as an external variable that should in no way shape the resulting probabilities. Indeed, as discussed in the next subsection, we use this variable to test whether our assumption regarding the meaning of P_{S1} values holds true. It should also be noted that our model is built on the combined archaeological information available for the entire sequence; that is, we do not distinguish between archaeological layers. Given our goals, using such aggregated data is advantageous because it increases confidence in the proposition that sources assigned to the set S_0 were intentionally ignored or avoided rather than simply unknown or unavailable to hominins inhabiting the site.

Because the available dataset includes multiple potential predictors, some of which are strongly correlated (Browne and Wilson, 2011), we performed an initial exploratory analysis of the data and formulated our model by selecting four predictors that showed the clearest separation between sets S_0 and S_1 (see SOM S2): 1) the quality of the raw materials (Q); 2) the approximate extent over which raw materials may be found at the sources (E); 3) the abundance of large rocks (L); and 4) access costs, defined as minimum walking times required to reach the sources from the Bau (T). Other available variables, such as the caloric expenditure required to reach the Bau from the various sources, the difficulty of the routes linking sources to the site, and the abundances of small, medium, and very large rocks were therefore excluded from consideration. Moreover, because our basic units of analysis are individual sources rather than source areas, we did not factor in source area characteristics (e.g., extents over which sources of a given raw material type can be found—'area of the source area' [AOSA] in the study by Browne and Wilson, 2011, 2013).

As detailed in previous publications (e.g., Browne and Wilson, 2011, 2013), quality, recorded on a scale from 0 to 16 (see Table 1), refers to a subjective measure of the suitability for toolmaking of the average rocks found at a given source; it was determined by Wilson (2007b, c) based on criteria such as the homogeneity, granulometry, and toughness of the materials, as well as the presence or absence of cracks, aspects which also impact functional performance (e.g., Pop, 2013). Extent, on the other hand, refers to the approximate size of a source, originally recorded on a scale from 1 (<10 m in diameter) to 4 (>100 m in diameter) and given here in square meters (see Table 1). The abundance of large rocks refers to the approximate percentage of a source covered by knappable rocks 16–35 cm in size and takes values from 0 (absent) to 4 (>50% of the area). Finally, the minimum walking times were computed based on SRTM DEMs as outlined earlier. We note that we used elevation data as the sole source for estimating movement costs owing to its availability and low expected variability over the time period considered here. We recognize that land cover affected minimum travel times, but presently neither the paleoenvironmental data available for the region nor the chronology of the site are sufficiently well understood to allow for the inclusion of this variable.

Prior to inclusion in the model, we applied a log transform to the quality variable (Q) and a square root transform to the extent and access cost variables (E and T) to minimize distribution skewness (and therefore the likelihood of influential cases). We also scaled (z-transformed) all covariates, so they comprise directly comparable units (see SOM S2 for descriptive statistics on individual variables). Our estimations of P_{S1} values for each of the 346 accessible sources (i.e., those not located on steep terrain) were therefore based on the following formula, where $_t$ denotes a transformed variable and β the coefficients estimated based on the observed archaeological presence or absence of the raw materials each such source yields. The probability that a source belongs to the set S_1 of sources from archaeologically represented source areas is thus given by

$$P_{S1} = \frac{\exp(\beta_0 + \beta_1 Q_t + \beta_2 E_t + \beta_3 L_t + \beta_4 T_t)}{1 + \exp(\beta_0 + \beta_1 Q_t + \beta_2 E_t + \beta_3 L_t + \beta_4 T_t)} \quad (1)$$

We assessed the model's validity and stability through various diagnostics and established that it met the relevant assumptions (see SOM S3). Finally, we established the significance of the full model by using a likelihood ratio test (Dobson, 2002) to compare its deviance with that of a null model containing only the intercept.

Cross-validation and performance To test the model's predictive ability, we used a repeated fivefold cross-validation procedure with stratification. This involved splitting the data into five groups (i.e., folds) of approximately equal size ($n \approx 69$ per group) and assigning an approximately equal number of randomly selected sources from S_1 and S_0 to each group so that they are representative of the overall population (i.e., a ratio of ~1:2.43 per group). P_{S1} values for sources within each fold were predicted using models trained on data from the other four folds. We repeated this cross-validation procedure 100 times to achieve more robust estimates for individual source probabilities and assigned to each source the average of the estimates. These average P_{S1} values were reclassified as '1' or '0' predicting membership in sets S_1 and S_0, respectively, with '1' being assigned to sources with values greater than 0.5 (50%). To avoid confusion, from this point forward, we refer to all predicted S_1 and S_0 sets as S_{1p} and S_{0p}, respectively.

The accuracy of the predictions was then assessed through a confusion matrix, a tool commonly used in the field of machine learning to evaluate the performance of classifiers. A confusion matrix has two dimensions—observed and predicted classes—and summarizes the degree to which these match. With binary classes (e.g., positive and negative, or classes that may be designated as such), the confusion matrix has four cells containing the number of true positives, false positives, true negatives, and false negatives. On the basis of these numbers, several performance measures can be derived, including accuracy, sensitivity, and specificity. Accuracy refers to the overall ability to classify cases correctly, whereas sensitivity and specificity refer to the ability to correctly classify true positives and true negatives, respectively (e.g., Kuhn, 2008; Kotu and Deshpande, 2014; Ting, 2017).

We further evaluated the predictions by means of Kvamme's gain statistic (Kvamme, 1988), often used to evaluate the performance of predictive models of site location. The statistic is calculated as 1—p_i/p_s, where p_i is the proportion of the study area identified as a zone of interest and p_s is the proportion of sites within that zone of interest. Values can range from −1 to 1, with zero indicating performance at the level of chance and high values indicating good performance in the zone of interest. Because we consider sources rather than sites here, we define p_i as the proportion of the total sources that are predicted to have been used (i.e., having cross-validated P_{S1} values above the 0.5 threshold) and p_s as the proportion of sources from exploited source areas that are predicted to have been used.

Finally, we investigated whether the computed P_{S1} values are meaningful proxies for the degree to which specific sources were desirable exploitation targets. To this end, we tested for a significant correlation between P_{S1} values obtained for sources from exploited source areas and the number of archaeological artifacts derived from those source areas. Because information on source area membership did not factor into our model, the most parsimonious explanation for a significant positive correlation would be that P_{S1} values are indicative of source attractiveness, with the strength of the correlation providing an indication of the degree to which this is true.

Network navigation and the evaluation of procurement alternatives Preliminary results (presented in Section 3.2) indicated that the resource selection model described earlier enables us to quantify the caliber (P_{S1}) of a procurement alternative based on the attributes of a source and the cost of reaching it from the Bau. This alternative can be expressed in terms of a network node and path as $v_{b\rightarrow v}$, where v denotes the node (i.e., source) whose characteristics are considered (i.e., variables Q, E, and L in Eq. (1)), and $_{b\rightarrow v}$ denotes the network path (here, one edge) whose weight (i.e., $w_{b\rightarrow v}$) is factored in as variable T in Eq. (1). We suggest that this model can be used to evaluate procurement alternatives along other network paths as well, that is, using any edge weights that do not fall substantially (here, ≤5%) outside the range of values on which the model was formulated. We assume that 1) this can be done symmetrically, with either the start or the end of an evaluated path representing the Bau—in other words, that valid P_{S1} values can be calculated for $v_{b\rightarrow v}$ as well as for $v_{v\rightarrow b}$ using the same model (although the resulting values would, of course, be different). We also assume, out of necessity (see below), that 2) the costs of travel between nodes do not vary substantially depending on whether rocks are carried or not.

Because we defined a complete network, the node b representing the Bau is reachable from any other node either directly or passing through one or more additional nodes. Under the premise that raw materials would have been procured by an individual from only one source at a time, we restrict our evaluation of possible routes to the Bau to those involving at most two distinct network edges. If the two assumptions outlined earlier can be provisorily accepted, P_{S1} values for a given source accessed along different network paths can be computed by adding the weights (i.e., minimum travel times) of the network edges along those paths. Thus, the P_{S1} value of a procurement alternative that involves traveling from a node v to another node v^1, collecting materials at v^1, and then carrying those materials to the Bau, can be computed by replacing T in Eq. (1) with ($w_{v\rightarrow v1} + w_{v1\rightarrow b}$); hereafter, we refer to this alternative as $v'_{v\rightarrow v'\rightarrow b}$ and to the P_{S1} values computed for it as $P_{S1\ (v')}$, so as to avoid confusion; the sizes of the blue circles in Figure 1 represent these $P_{S1\ (v')}$ values. The same can be done to assess the alternative whereby materials are procured at v (i.e., where v and v' represent the same source) and are carried straight to the Bau (i.e., $v_{v\rightarrow b}$); in that case, T would be replaced by $w_{v\rightarrow b}$. The $P_{S1\ (v')}$ values obtained for these two alternatives can then be compared to assess which one ranks higher.

We acknowledge that the first assumption (disregarding direction of travel) may introduce some uncertainty, but our analyses focus on the relative ranks of the alternatives, not on absolute differences in computed P_{S1} values, and the resulting ranking should be relatively robust. If substantial errors are nevertheless introduced by this uncertainty, we would expect these to compromise our ability to explain the available data under our second and third hypotheses, not to improve it. The degree to which the second assumption (cost of load carried) holds is difficult to determine. There is clearly a cost associated with carrying additional weight, so this is not an irrelevant variable, but estimating that cost also requires making a series of assumptions. Put simply, we know of no reliable method for determining the cost difference between a path traversed empty-handed and one traversed carrying rocks, not least because we do not know how much lithic material Neanderthals may have been willing or able to carry at any given point. However, the consequences of any violations of our second assumption are predictable; they would introduce two types of bias, which should be considered when evaluating the results:

1) Bias 1—$P_{S1\ (v')}$ values calculated for $v_{v\rightarrow b}$ will be inflated relative to those calculated for $v'_{v\rightarrow v'\rightarrow b}$. This is because the assumed costs of traveling from node v to node v' and then to node b (the Bau) are higher than the real cost because materials would only have been carried part of the way ($v'\rightarrow b$).
2) Bias 2—If two sources v^1 and v^2 are evaluated as procurement alternatives for a source v, and v^1 is farther from the Bau than v^2, the $P_{S1\ (v')}$ value computed for $v^1{}_{v\rightarrow v1\rightarrow b}$ will be inflated relative to the value for $v^2{}_{v\rightarrow v2\rightarrow b}$.

Assessment of the proposed hypotheses To assess H_1, we evaluated each source (v) as follows. First, we isolated a local network segment by identifying a set of alternative sources requiring no or minimal deviations from the path to the Bau—that is, all v' where ($w_{v\rightarrow v'} + w_{v'\rightarrow b}$) is within 5% of $w_{v\rightarrow b}$. Next, we estimated, for each v and each v' in the local network segment, P_{S1} values using a non-scaled variant of our model, with T in Eq. (1) set to a constant equal to the minimum observed in the dataset. This enables us to compare the relative benefits afforded by the evaluated sources and their possible alternatives while controlling for access costs; to avoid confusion, from this point forward, we refer to P_{S1} values where access costs are controlled for as $P_{S1\ (tc)}$ (see also Table 1); these values are represented in Figure 1 by the size of the orange circles. For each source v, we then identified alternatives with greater relative benefits (i.e., greater $P_{S1\ (tc)}$ values), if any (see Fig. 1A and B).

We assessed H_2 by defining the relative benefits of each source and its alternatives as $P_{S1\ (v')}$ values that are computed for all valid procurement paths from each source to the Bau (i.e., $v_{v\rightarrow b}$, and $v'_{v\rightarrow v'\rightarrow b}$ for every alternative v'), using the procedure discussed in the previous section, concerning network navigation. For each source, we then identified the alternative with the highest $P_{S1\ (v')}$ value (i.e., optimal) as well as those ('good') alternatives whose $P_{S1\ (v')}$ values fall within the 95% confidence interval of the highest, to account for estimation uncertainties. We contend that although the sources we identify as optimal based on currently available data may not be identical to the set of true optimal sources (e.g., they might constitute a subset), the latter are likely to be included among the sources we identify as 'good.' This would be expected if source characteristics remained similar over time and our model performed well but not perfectly. We also performed the assessment on isolated subsets of the network that expand radially from the Bau to include nodes whose $w_{b \to v}$ edge weights (i.e., minimum walking times from the Bau) fell within cutoffs that increase in 10-minute increments. This allowed us to investigate the possibility that the evaluation of procurement alternatives may have been contingent on distance from the site and the area over which least-cost paths (i.e., network edges) must have been known. If this were the case, we would expect an increase in the ability to explain the data under H_2 up to a certain network size, followed by a steady decrease due to the addition of noise (i.e., nodes and paths that would have been too far to be considered in procurement decisions).

To assess H_3, we first identified all DEM cells reachable within 5 hours from the Bau, temporarily adding each as a node (hereinafter referred to as node *x*) to the network of sources. We chose a 5-hour cutoff somewhat arbitrarily, to keep computations manageable, but preliminary findings suggest that adding more distant locations would not have been informative (see Section 3.4). For each cell, we then evaluated all valid procurement paths to the Bau (i.e., $v'_{x \to v' \to b}$ for each cell *x*, and for each *v'* representing an accessible raw material source; see Fig. 1D), identifying optimal alternatives (i.e., highest $P_{S1\ (v')}$ value per cell) as well as 'good' alternatives whose $P_{S1\ (v')}$ values fell within the 95% confidence interval of the highest, to account for estimation uncertainties. We examined the proportions of S_0 sources among the 'good' alternatives at each DEM cell across the region, to determine the degree to which different landscape locations are compatible with H_3, and investigated any spatial patterning. Finally, for each raw material type, we also summed the number of DEM cells where their sources are identified as good or optimal procurement targets, that is, we calculated the areal extent over which a hominin could be expected to have targeted a given material and tested for a correlation with the frequency (i.e., number of lithics) with which the different raw materials are represented at the site.

3. Results

3.1. Resource selection model and P_{S1} estimation

A null model comparison indicates that the evaluated characteristics of the available sources have a highly significant combined influence on their probabilities (P_{S1}) of yielding raw material types that are also archaeologically represented at the Bau ($\chi^2 = 69.51$, $df = 4$, $p < 0.001$). As shown in Table 2 (see also SOM S4), the quality of the raw materials, the size of the area over which these are found, and the abundance of large nodules all had a positive effect. However, the strongest and most significant predictor is the minimum walking time required to reach the sources from the Bau, and its effect is negative; the higher the access costs of a source are, the less likely it is to provide raw material types represented at the site. These results are consistent with previous findings (e.g., Browne and Wilson, 2011) as well as theoretical expectations.

The estimated P_{S1} values for individual raw material sources are quite variable (minimum = 0.01, maximum = 0.89, mean = 0.29, SD = 0.2), and this is true even for sources assigned to the same source area. Estimated probabilities for the seven locations assigned to source area 55, for example, which yields the most common raw material type in the Bau assemblage (4981 artifacts), vary between a minimum of 0.27 and a maximum of 0.74, having a mean of 0.52. This variability is expected given the substantial differences in the characteristics of the sources (see SOM S2), including access costs (see Fig. 2) and the overall quality of the available nodules. It is nevertheless noteworthy because it strongly suggests that not all locations within a given source area represented at the Bau were exploited to the same extent and, indeed, some may not have been utilized at all. Also noteworthy, particularly given our present goals, is that several sources which are not represented at the Bau ($n = 17$, or 7%) were assigned high probabilities by our model ($P_{S1} > 0.5$, maximum = 0.87).

A confusion matrix analysis of cross-validated P_{S1} values indicates that our model can be used to classify sources as containing archaeologically represented raw material types with significantly more accuracy (76%, balanced = 65%, $p = 0.018$) than would be expected by chance alone based solely on the incidence of non-represented sources (245, or 70.8% of the 346 accessible sources) when using a threshold of 50% for the classification (that is, when sources with P_{S1} values greater than 0.5 are classified as used, and the rest unused). These results (Fig. 3) are driven mostly by the correct identification of sources with nonrepresented stone types (specificity = 0.91), as the sensitivity is low (0.39). In other words, the model performs well in assigning low probabilities to non-represented sources but also assigns low probabilities to many sources that provide stone types known to have been utilized at the Bau. This is not necessarily indicative of poor performance, however, because we do not know how many of these latter sources were in fact exploited by hominins inhabiting the site. It is quite likely that many were not, because a given raw material type could have come from a different source within its source area, so these results may well represent a worst-case scenario. Still, with eight of the 17 exploited source areas, all sources (22 in total) are assigned probabilities that fall below the threshold of 0.5, although their overall contribution to the Bau is only 104 lithics (0.7% of the provenanced pieces). Regardless, these results indicate that the model can be used to meaningfully predict likelihoods for new cases within the region, such as known sources being evaluated from different landscape locations and therefore having different access costs. For reference, the Kvamme gain (Kvamme, 1988) value here is 0.551.

3.2. P_{S1} as a proxy measure of relative benefit

P_{S1} values appear to be good proxy measures of the relative perceived benefits afforded by different procurement alternatives. A Spearman's rank correlation test revealed a strong and significant positive relationship between the number of stone artifacts produced from different raw material types and the maximum cross-validated average (across the 100 replications) P_{S1} values predicted for individual sources where such materials can be obtained (r_s

Table 2
Scaled logistic resource selection model coefficients with unscaled means and standard deviations.

Term (scaled)	Estimate	SE	Lower CL	Upper CL	Mean	SD	*p*-value
Intercept	− 1.122	0.144	− 1.414	− 0.849	N/A	N/A	<0.001
Q_t	0.449	0.134	0.190	0.718	0.785	0.486	<0.001
E_t	0.351	0.141	0.077	0.629	64.888	50.332	0.013
T_t [a]	− 0.889	0.158	− 1.212	− 0.592	107.837	33.387	<0.001
L_t	0.376	0.136	0.110	0.646	0.887	0.882	0.006

Abbreviations: Q_t = quality (log), E_t = extent (square root), T_t = time from Bau (square root), L_t = large rock abundances, SE = standard error of the estimate, CL = confidence limit, SD = standard deviation, N/A = not applicable.

[a] Corresponds to the minimum travel times required along least-cost routes from the Bau.

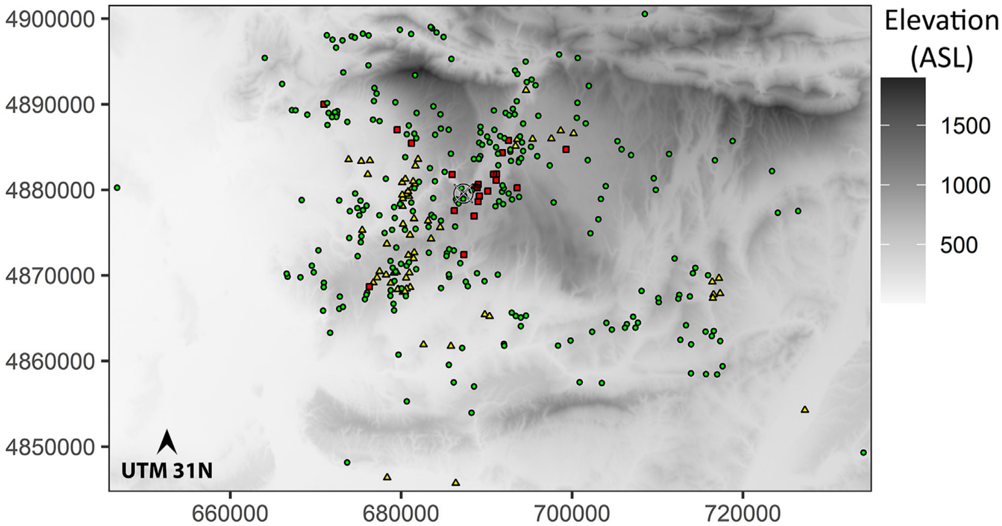

Figure 3. Compatibility of archaeological observations and source classification based on cross-validated P_{S1} values. Sources correctly classified as S_0 ($n = 224$) or S_1 ($n = 39$) when using a threshold of 0.5 are shown by green dots. Red squares identify unused (i.e., S_0) sources incorrectly classified as S_1 ($n = 21$). Yellow triangles identify S_1 sources (i.e., from exploited source areas) incorrectly classified as S_0 ($n = 62$). Note that most sources can be classified correctly based on their cross-validated P_{S1} values alone, but several misclassified unused sources with high values (i.e., unexplained) are located close to the site. In fact, most of the sources in the vicinity of the site (within ca. one hour of walking; see also Fig. 2) are incorrectly classified as yielding archaeologically represented materials. Coordinates are given in meters for UTM zone 31N, and elevation values are given in meters above sea level (ASL). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

[15] = 0.757; $p < 0.001$). This relationship remains significant if the mean (r_s [15] = 0.612, $p = 0.009$) or median (r_s [15] = 0.488, $p = 0.047$) estimates for source areas are used, but it is considerably weaker than observed with maxima, which to us suggests that exploitation was driven by the preferential use of the most desirable (i.e., highest P_{S1} value) sources; accounting for sources with relatively low P_{S1} values seems to add noise, likely because many such sources were not actually used. The strength of this relationship, which is visually represented in Figure 4, is consistent with a good overall performance of our model as well as with substantial uniformity in criteria shaping the management of lithic resources: factors that rendered specific sources of stone desirable from the perspective of the Neanderthal inhabitants of the Bau seem to have proportionally influenced the quantities of raw materials collected from these sources and/or the degree to which they were reduced before discard.

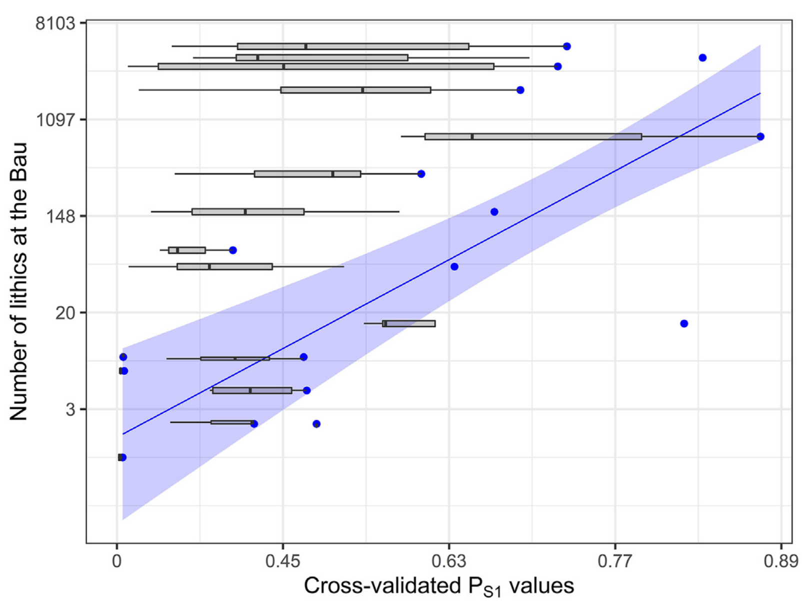

Figure 4. Cross-validated P_{S1} values as proxies for archaeological representation. The number of lithics at the Bau is significantly and positively correlated with P_{S1} values (maximum cross-validated averages; blue dots) estimated for source areas represented at the Bau. Blue line and shaded area show a fitted negative binomial model and its 95% confidence limits. Boxplots represent the range of variation in P_{S1} values per source area. Note that P_{S1} values are computed with access costs set to minimum walking times from the Bau. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

3.3. Evaluation of Hypothesis 1—Exploitation of the best sources available directly en route to the site

The data do not support our first hypothesis (H_1). Although this hypothesis can explain the lack of exploitation of a substantial proportion of the unused sources (at least 134, or 54.7%, and plausibly as many as 190, or 77.6%; see Table 3), a larger proportion (224, or 91.4%) can be accounted for simply by classifying all sources with a cross-validated P_{S1} value below 0.5 (i.e., 50%) as unused. Moreover, the sources which we cannot explain under this hypothesis (red squares in Fig. 5; see also Table 3) also cover a larger area than sources incorrectly classified based exclusively on their cross-validated P_{S1} values, and several are located close to the site (compare Figs. 3 and 5). Sources identified as exploitable under H_1—that is, those sources for which we found no better procurement alternatives on the way to the Bau—do explain a slightly larger fraction of the artifacts than sources with cross-validated P_{S1} values above 0.5, but the difference is negligible (15,574 lithics made from 10 of the 17 raw material types represented at the Bau, versus 15,570 made from nine such raw materials). In any case, the evaluation of this hypothesis does reveal an important fact: at most unused sources (54.7%), the best procurement option en route to the Bau would not have been the source itself, but rather a source from an exploited source area.

3.4. Evaluation of Hypothesis 2—Exploitation of the best sources available in the region

Full source network Overall, the available data provide support for our second hypothesis. Under this hypothesis, and if we consider only optimal procurement alternatives (hereinafter, H_{2a}), all but eight sources are predicted to have been ignored in favor of exploiting even better sources (see Fig. 1C for an explanation). Those eight optimal sources, for which we could identify no alternatives with higher $P_{S1\ (v')}$ values, include six S_1 sources (i.e., from exploited source areas) and two unused ones (i.e., S_0). The sources which cannot be explained under this hypothesis, namely the two optimal sources that should have been used but were not, and the 34 other sources where these constitute, according to our algorithm, the best procurement options (Table 4) are all located far from the site (Fig. 6). Conversely, all sources located within 17 km from the Bau can be explained: these are sources from where, according to our algorithm, the six optimal S_1 sources should have been targeted. The latter can account for five raw material types, or 12,986 (83%) of the lithics found at the site. It should be noted that reaching them from sources where they are identified as optimal procurement choices would have required substantial deviations from the direct, least-cost paths to the Bau (median = 9%, or 16 minutes; interquartile range

Table 3
Summary of the fit between observed and predicted source classification under Hypothesis 1.[a]

Actual set	Predicted S_0 (S_{0p})	Predicted S_1 (S_{1p})	S_{0p} with S_1/S_{1p} options	S_{0p} with S_1/S_{1p} best option	Misclassified as S_{1p}	S_{0p} and no S_1 options
S_0	217	28	190[b]	134	28	24
S_1	77	24	75	71	N/A	2

[a] Hypothesis 1 (H_1). S_0 = set of sources that are not represented at the Bau; S_1 = set of sources from archaeologically represented source areas; S_{0p} = set of sources predicted to be unused under H_1; S_{1p} = set of sources predicted to be used under H_1; N/A = not applicable. Options refer to better alternatives available enroute to the Bau. Columns 2 and 3 show the predicted versus observed source classification; columns 4 and 5 indicate unused or likely unused sources that are explainable under H_1; columns 6 and 7 indicate sources that cannot be explained under H_1.

[b] Excludes three cases where an S_1 option exists but is predicted to have been unused.

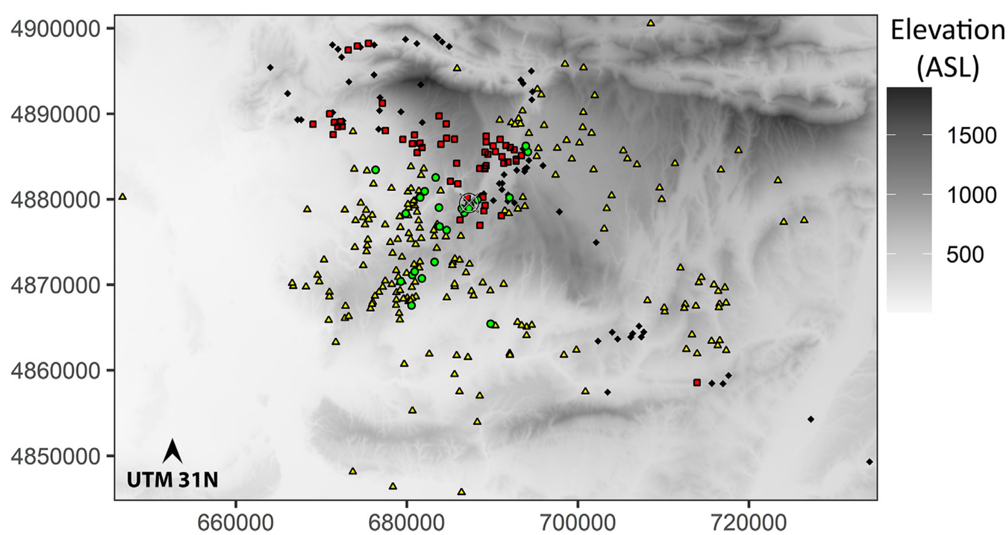

Figure 5. Compatibility of raw material sources with archaeological observations under Hypothesis 1 (H_1). Sources that cannot be explained under H_1 are identified by red squares (high confidence) if the only options from their locations are unused, S_0 sources, or black diamonds (lower confidence) if the best procurement option is an unused, S_0 source, but S_1 sources are identified among the possible alternatives. Sources that can be explained are identified by green dots or yellow triangles. The former denote sources predicted to have been exploited and which yield archaeologically represented materials; sources indicated by yellow triangles are predicted to have been bypassed in favor of sources identified by green dots. Note that fewer unused (S_0) sources can be explained under this hypothesis than if spatial relationships between sources are ignored and cross-validated P_{S1} values are used for classification (see Fig. 3). Note also that unexplained sources cover a large area around and to the northwest of the site. The location of the Bau is indicated by the circle with crosshairs. Coordinates are given in meters for UTM zone 31N, and elevation values are given in meters above sea level (ASL). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Table 4
Summary of the fit between observed and predicted source classification under Hypothesis 2a.[a]

Actual set	Predicted S_0 (S_{0p})	Predicted S_1 (S_{1p})	S_{0p} with S_1/S_{1p} best option	Sources with misclassified S_{1p} best options[b]
S_0	243	2	210	35
S_1	95	6	94	1

[a] Hypothesis 2 (H_{2a}) with optimal alternatives. S_0 = set of sources that are not represented at the Bau; S_1 = set of sources from archaeologically represented source areas; S_{0p} = set of sources predicted to be unused under H_{2a}; S_{1p} = set of sources predicted to be used under H_{2a}. Options refer to better alternatives available on the way to the Bau. Columns 2 and 3 show the predicted versus observed source classification; column 4 indicates sources that are explainable under H_{2a}; column 5 indicates sources which are not.

[b] Sources where an unused source (S_0), wrongly predicted to have been used by our algorithm (column 3), was identified as the top procurement option.

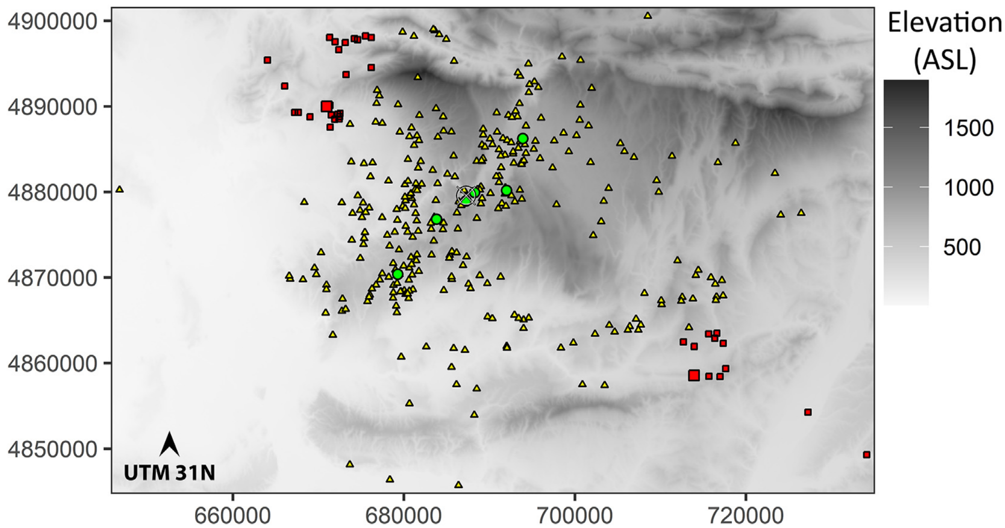

Figure 6. Compatibility of raw material sources with archaeological observations under Hypothesis 2, with optimal alternatives (H_{2a}). Sources that cannot be explained under H_{2a} are shown as red squares. Large squares denote optimal procurement choices that were not used; small squares denote sources where unused sources (large squares) are predicted to be top alternatives. Sources that can be explained are shown as green dots (sources predicted to have been used and which yield archaeologically represented materials) or yellow triangles (sources predicted to have been bypassed in favor of procuring materials from sources identified by green dots). The location of the Bau is indicated by the circle with crosshairs. Note that all unused sources found within 17 km of the site can be explained under this hypothesis, and the identified optimal exploitation targets (green dots) can account for 83% of the lithic materials found at the site. Coordinates are given in meters for UTM zone 31N, and elevation values are given in meters above sea level (ASL). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

[IQR] = 17.75%, or 32 minutes; with 25% of cases necessitating deviations of >20% or 38+ minutes).

If, to increase the likelihood of including all true optimal sources in the set of sources classified as S_{1p} (i.e., exploitable) under H_2, we also consider other 'good' options available at each evaluated location, the sources predicted to have been unused number 272. Of the sources thus classified as S_{0p} under this implementation of H_2 (hereinafter, H_{2b}; see Table 1), 70 are from exploited source areas (i.e., S_1) and 202 are unused (S_0) ones. Conversely, 31 of the 74 sources classified as S_{1p} are in fact S_1 and 43 are S_0. The latter are distributed throughout the region (pink squares in Fig. 7) and, although we cannot account for their lack of exploitation under H_{2b}, at no evaluated location do they constitute the only 'good' alternatives. Indeed, of the 'good' procurement options identified at each source (median = 8, IQR = 6, maximum = 33), one or more of the 31 S_1 sources typically constitute the majority (minimum = 17%; median = 63%; maximum = 100%). These S_1 'good' alternatives belong to 14 of the 17 archaeologically represented source areas and can account for 15,659 (99.9%) of the lithic artifacts recovered at the site.

The three raw material types whose presence at the Bau cannot be explained under H_{2b} can only be found at substantial distances from the site (minimum = 3.9 hours). One is represented by a flake made of a volcanic rock collected along the Durance River, which could have reached the site by simple chance, as an unusual component of a mobile toolkit (see Brantingham, 2003; Pop, 2016). The other two consist of Oligocene flints collected in the eastern part of the study region from sources located at more than 5 hours from the Bau (Fig. 2) and silicified crust that formed on top of ochre deposits at Roussillon, closer to the site. While the presence of these materials is noteworthy, it is important to keep in mind that they contribute negligibly to the assemblage (15 artifacts, or ca. 0.1%). Overall, we find that when the entire network of sources is considered, H_2 fails to explain why up to 43 S_0 sources were never exploited, but also that it could explain them all, and that it may account for a larger proportion of archaeological artifacts and archaeologically represented raw material types than H_1.

Expanding source networks The ability to explain the available data under H_2 is likely contingent on the area covered by the evaluated resource network: the inclusion of very distant resources is likely to add noise, whereas the exclusion of all but the closest sources is likely to leave a large portion of the data unexplained. We therefore expected to see an increase in the ability to explain the data with a growing resource network, up to a point that reflects the size of the area over which procurement decisions were likely taken by hominins using the Bau, and then a gradual decline with the inclusion of sources located further away.

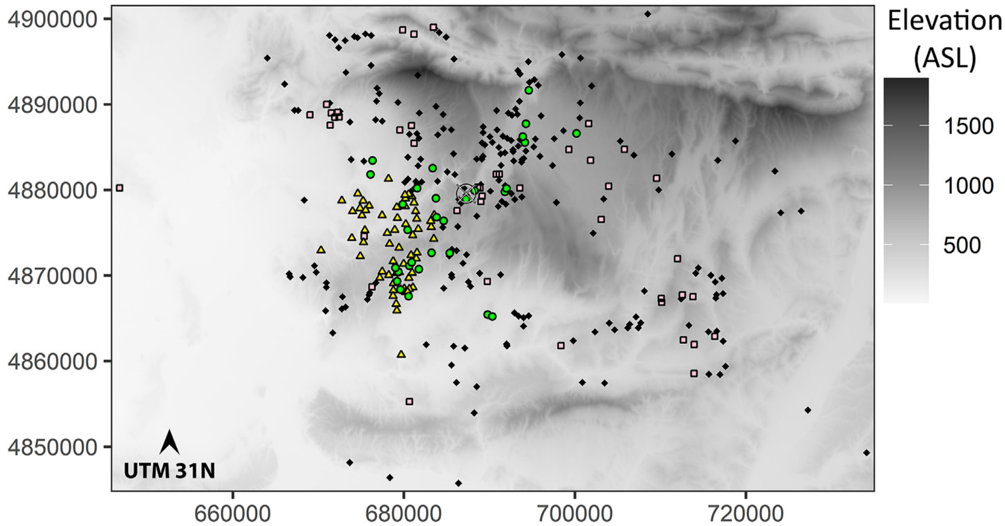

Figure 7. Compatibility of raw material sources with archaeological observations under Hypothesis 2, with 'good' alternatives (H_{2b}). Sources explainable under H_{2b} with high confidence are indicated by green dots (S_1 sources identified as 'good' alternatives) and yellow triangles (sources predicted to have been bypassed in favor of those 'good' alternatives; no 'good' S_0 alternatives identified). Sources explainable under H_{2b}, but with lower confidence, are indicated by pink squares (43 unused sources predicted to have been 'good' procurement options) and black diamonds (sources where 'good' alternatives could have included unused sources). Note that 'good' procurement alternatives from exploited source areas (green dots) exist for all sources in the region; in other words, the lack of archaeological representation of all unused sources may be explainable if we allow for some uncertainties in the identification of optimal procurement alternatives (cf. Fig. 6). The location of the Bau is indicated by the circle with crosshairs. Coordinates are given in meters for UTM zone 31N, and elevation values are given in meters above sea level (ASL). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Our results, summarized in Figure 8, indicate that this is indeed the case. The few sources found within 30 minutes of the site explain the data very poorly because 1) they can account for a maximum of 768 provenanced lithics (ca. 5%), 2) under H_{2b} we can only predict with relative confidence the lack of exploitation for ca. 33% of the S_0 sources available within this restricted resource network (black line 'A' in Fig. 8), and 3) only ca. 50% of the available 'good' targets identified under H_{2b} are S_1 sources (red dashed line 'B' in Fig. 8). From this minimum of explanatory power seen with sources found within 30 minutes of the Bau, the proportions of S_0 sources that can, with some confidence, be predicted to have been ignored under H_{2b} increases steadily as we increase the size of the evaluated network, and so does the proportion of 'good' procurement alternatives that are S_1 sources and, importantly, the number of explainable lithics (i.e., those that could have been procured from those S_1 sources).

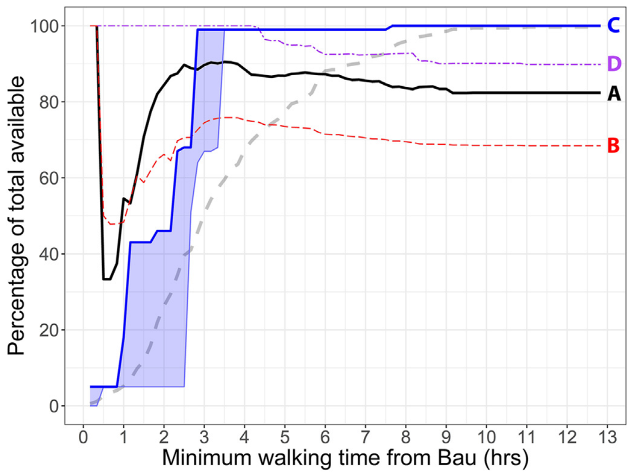

Figure 8. Hypothesis 2 with increasing resource network sizes. The ability to explain the data improves as more distant sources are added, up to the inclusion of sources requiring minimum walking times of ca. 3.5 h from the site, and then declines. The threshold (ca. 2.5–3.5 hours) likely represents the limits of the regular active resource exploitation area around the site. Note that the resource network is expanded radially from the Bau in 10-minute increments (minimum walking times) to include sources with increasingly greater access costs (proportion of the total [346] indicated by grey dotted line). Line A (black) represents the proportion of unused sources (S_0) predicted to have been ignored under H_{2b} at different network sizes. Also shown is the proportion of 'good' alternatives made up of S_1 sources (B, red dashed line), the minimum and maximum quantities of archaeological artifacts these good S_1 procurement alternatives can explain (C, blue line, with the range denoted by the shaded area), and the proportion of optimal procurement alternatives (H_{2a}) made up of S_1 sources (D, purple dashed line). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

This increase in the ability to explain the data can be observed until the weights of the network edges connecting the Bau to sources (i.e., minimum walking times) reach values of ca. 3.5 hours, at which point the resource network comprises 206 nodes/sources, or ca. 60% of the total. Within this network, optimal procurement targets identified under H_{2a} are S_1 sources in 100% of cases (purple line 'D' in Fig. 8) and can account for the utilization of 5 of the 17 exploited raw material types as well as 12,986 of the sourced lithics. Procurement alternatives identified as 'good' under H_{2b}, on the other hand, are mostly S_1 sources (76%; red dashed line 'B' in Fig. 8) and can account for 15,574 (ca. 99.4%) of the sourced artifacts and 11 of the 17 exploited source areas. Moreover, the proportion of available S_0 sources whose lack of utilization is confidently explainable under H_{2b} reaches 91%. The inclusion of sources located at more than 4 h from the site adds considerable noise, resulting in the identification of some unexploited (S_0) sources as optimal procurement targets (see purple line 'D' in Fig. 8) and a decrease in the proportion of 'good' candidates that are S_1 of sources (to ca. 68% if sources located at more than 10 hours from the Bau are considered), but it does not improve our ability to explain the archaeological data except very marginally (two additional raw material types, and 81 additional provenanced artifacts). In brief, under H_2, the available data are most consistent with an excellent knowledge of the best-available procurement options for locations reachable within 2.5–3.5 hours from the site; within this radius, H_2 can explain the lack of utilization of at least 91% of the available S_0 sources (possibly all), as well as the presence of most (99.4%) of the sourced lithics recovered at the site.

3.5. Evaluation of Hypothesis 3—Optimal exploitation of the best sources available in the region

The set of sources predicted to have been ignored or avoided under Hypothesis 3 (H_3), and consequently the set of sources deemed to have been exploitable, is identical to that predicted under H_2 for any given maximum cutoff value for travel times from the Bau (see Section 3.4). When this cutoff is set to 5 hours, six S_1 sources are identified as optimal alternatives over 96.2% of the area (ca. 1305 km^2 of 1356 km^2), and a lone S_0 source (ID 223) is identified as the optimal procurement choice over the remaining 3.8%—in other words, H_3, similar to H_2, can account for the lack of utilization of 99.4% of 175 unused (S_0) sources available within 5 hours of the site. The number of locations (i.e., DEM cells) where these S_1 and S_0 optimal alternatives are expected to have been targeted has a predictable but not statistically significant relationship with the number of lithics made from materials that can be procured at these, with one exception (Spearman's r_s [3] = 0.9, $p = 0.083$ with source ID 48 excluded; r_s [4] = 0.37, $p = 0.497$ with it included). This exception, which is identified as an optimal choice over ca. 31% of the area, only accounts for up to 16 of the provenanced lithics found at the site and may be explainable by a lack of utilization of certain areas or, possibly, by an incorrect (over-)estimation of its $P_{S1\ (v')}$ value. Be that as it may, optimal resource selection based on knowledge of the relative benefits afforded by the available sources (i.e., nodule sizes, quality of the materials, and extent over which they may be found) and the cost of accessing them, fit the data well, although not necessarily equally well, regardless of where a hominin might have been located when deciding where to procure raw materials on their way to the Bau.

The set of 'good' alternatives identified for locations (i.e., DEM cells) within 5 hours of the Bau includes 51 unique sources. Of these, 28 belong to the set S_1 that yields archaeologically exploited raw materials, representing 12 of the utilized source areas and accounting for up to 15,578 of the provenanced lithics (i.e., 99.4%) at the site. The other 23 are sources that are not represented at the

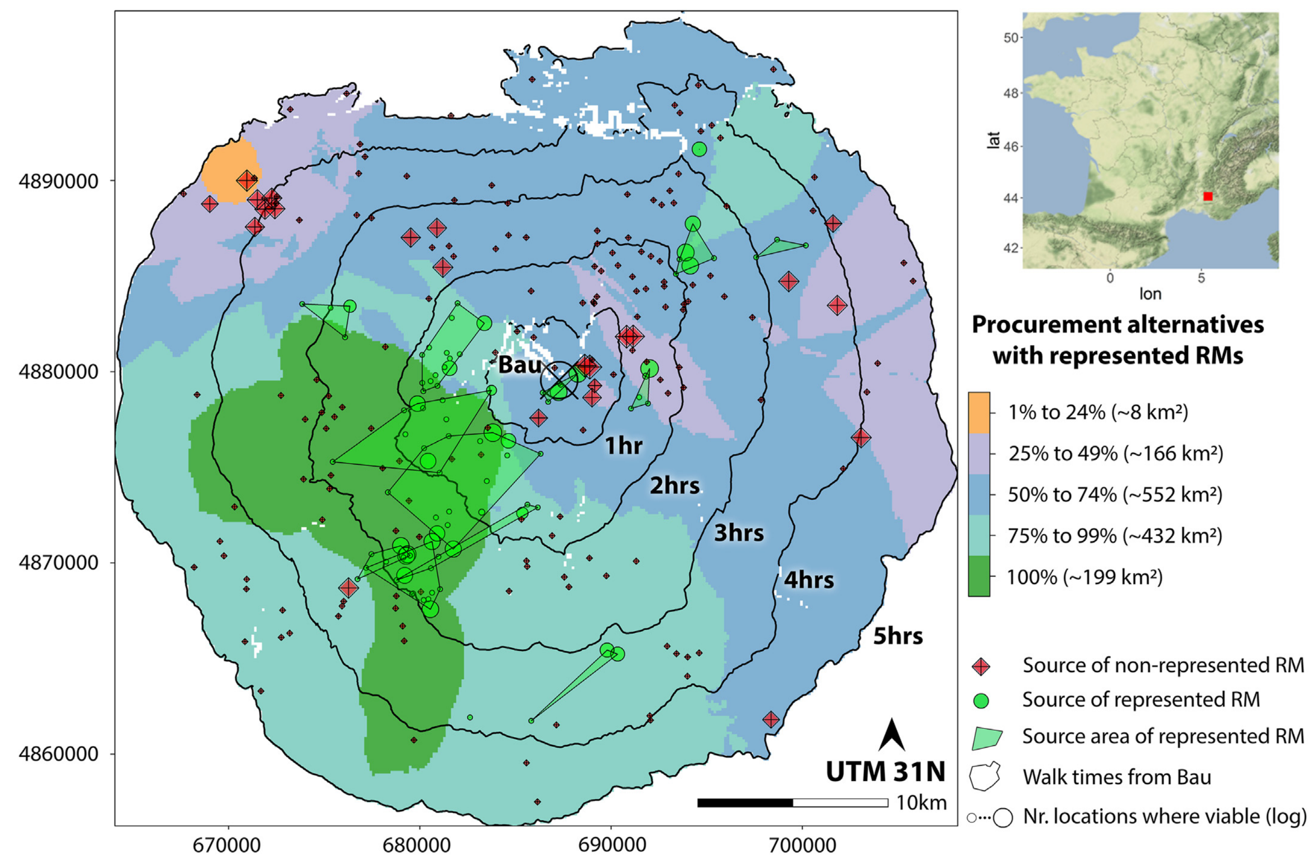

Figure 9. Predicted resource selection across the landscape. The different colors indicate the proportions of good procurement options consisting of raw material (RM) sources from exploited source areas (i.e., S_1 sources), as computed for every location (i.e., digital elevation model [DEM] cell; 80-m resolution) under Hypothesis 3. Locations (i.e., DEM cells) where these proportions reach minimal (1–24%) and maximal (100%) values are shown in orange and dark green, respectively, whereas cells with intermediary values are shown in purple, blue, and teal. Green circles represent S_1 sources available within 5 h of the site, whereas red diamonds represent S_0 (i.e., unused) sources; the size of the circles and diamonds indicates the size of the area (i.e., number of DEM cells) over which the respective sources are identified as good procurement alternatives, on a logarithmic scale. Green polygons represent convex hulls encompassing sources from individual exploited source areas, and concentric rings show GIS-computed distances that can be covered walking away from the site, in 1-hour increments (minimum walking times). Note that throughout the region the identified good procurement options are mostly sources from exploited source areas; some unused sources (red diamonds) located close to the site are identified as good procurement alternatives from a large number of locations, but from those same locations good alternatives also include S_1 sources, the latter accounting for a majority of options in most cases. Nr. = number. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Bau and set an upper limit to the number of seemingly unused sources (of the 175 available within 5 hours) that cannot be explained under H_3. The number of 'good' alternatives identified per DEM cell varies (mean = 9, SD = 3, maximum = 22), and as shown in Figure 9, they typically consist of S_1 sources (mean = 71.8%, minimum = 14%, maximum = 100%). At most locations (78.3%), these constitute half or more of the alternatives, and no 'good' S_0 options can be identified over an area of some 199 km^2 (14.7%).

Digital elevation model cells where specific sources are identified as 'good' options form areas of variable size (mean = 239.1 km^2, median = 90.3 km^2, maximum = 1310.3 km^2). A Spearman's rank correlation test indicates that when these areas are summed for each of the 23 raw material types represented by the 51 unique options, they are moderately and positively correlated with the number of sourced artifacts made from those materials (r_s [21] = 0.49, $p = 0.017$). If we assume the identification of nonutilized sources among the 'good' alternatives represents an error, and therefore only consider the areas serviced by alternatives from exploited source areas, the correlation becomes much stronger (r_s [10] = 0.76, $p = 0.004$). We interpret these correlations as indicating that 1) in the aggregate, and based solely on the lithic data, we cannot reject the possibility of a relatively uniform utilization of the region by the hominins responsible for the accumulation of the Bau assemblages and 2) that, regardless of where they might have been located, these hominins could identify and target sources that would have been optimal or close to optimal procurement choices.

4. Discussion

The idea that the probability of observing raw materials from a given source at an archaeological site depends not only on the characteristics and accessibility of the source itself but also on the presence of alternatives which may be intrinsically better, more accessible, or both, is certainly not new (e.g., Wilson, 2007b and references therein; Pop, 2016). Nevertheless, most lithic sourcing studies consider the impact of such alternatives only in terms of the position of different sources vis-à-vis a site, without considering spatial relationships between the sources themselves. Our results highlight the importance of such spatial relationships because several sources that may seem attractive when considered on an individual basis may turn out to be poor choices when considered in light of the alternatives. In this same vein, the results presented here highlight the interpretive potential of directly addressing another aspect that is seldom the explicit focus of sourcing studies, namely, why certain resources were not utilized at all.

At the French Middle Paleolithic site of the Bau de l'Aubesier, Neanderthals appear to have ignored many of the lithic resources available to them for some 100 millennia. In this study, we set out to evaluate three potential explanations for why this may have been the case, all premised on rational decision-making but requiring increasingly sophisticated spatial knowledge and navigational skills. To this end, we modeled the resource selection criteria evidenced in the archaeological assemblages and applied these to assess what procurement options would have been viable under the different scenarios if sources are considered as embedded in a network of potential alternatives. We found that most unused sources (55–77.5%) could be explainable by the simple fact that resources which would have been considered to be better, and which yield archaeologically represented raw material types, were available along the least-cost paths to the site (H_1).

We also found that a larger proportion of the unused sources (82–100%) may be explained if we allow for the possibility that hominins were able to identify and procure materials from globally (i.e., with all alternatives considered) optimal, or close to optimal, procurement targets (H_2). Indeed, if we further allow for the possibility that procurement was largely restricted to a 3.5-hour radius from the Bau, we can explain between 91% and 100% of the unused sources, while simultaneously accounting for 83–99.4% of the provenanced lithics recovered at the site. The identification of such globally optimal or close to optimal procurement targets would have required good knowledge of the available sources, including minimum travel times between each. However, the set of such targets is relatively small—a minimum of 14 optimal or close to optimal sources, or one per distinct raw material type, and a maximum of 31—and it is therefore possible that knowledge of their viability could have been transmitted socially, resulting in fixed reference points in foraging 'mental maps' (see Roebroeks et al., 2011). In fact, our second hypothesis is not informative with regards to how these optimal resources might have been targeted and exploited from the Bau.

We did, however, consider a scenario in which procurement decisions were taken, at least occasionally, while foraging for nonlithic resources within a 5-hour radius of the site (H_3), and we assessed whether the available archaeological data are consistent with an optimal targeting of lithic resources under such a scenario. If, in such an embedded procurement context (sensu Binford, 1979) trips to collect raw materials on the way to the Bau had an equal chance of being initiated anywhere in the region, reflecting a uniform utilization of the environment, raw material types identified as optimal alternatives over larger areas would be expected to be represented proportionally more frequently at the site. This is precisely what is observed at the Bau, where the correlation between these variables is in fact rather staggeringly strong, given the underlying assumptions. Such capacity to identify optimal procurement targets at arbitrary locations across large portions of the study region implies an ability to not only accurately recall the characteristics of nearby resources but also estimate access costs on demand, regardless of one's location; in other words, it implies more than simple knowledge of which resources are worth exploiting in the region, and which are not.

It should be noted that the degree to which H_2 and H_3 can account for archaeological observations at the Bau may be underestimated because violations of the assumptions that are built into our approach, and which are likely to some degree, should result in a lower-than-warranted fit. For instance, we would expect weak results if the resource selection model cannot be applied symmetrically, that is, regardless of which end of an evaluated procurement path represents the Bau. Similarly, violations of our null assumption regarding the effects of transporting rocks would reduce our chances of explaining nonutilized (S_0) sources under these hypotheses because $P_{S1(v')}$ values for evaluated sources, most of which belong to the set S_0, would be inflated relative to the $P_{S1(v')}$ values of the alternatives (see Bias 1 in Methods). The impact of a second potential bias (i.e., that sources located farther from the Bau may have inflated $P_{S1(v')}$ estimates compared to ones located closer by—see Methods) is more difficult to evaluate, but it is unlikely to result in more favorable findings, that is, in more S_0 sources being accounted for than warranted under H_2 and H_3.

Overall, we find that the lithic data from the Bau are most consistent with the direct (i.e., from the site) acquisition of raw materials over an active exploitation area of ca. 306–650 km^2 (a radius of 2.5–3.5 hours of walking). Only a few raw material types, accounting for a virtually negligible quantity of archaeological artifacts (n = 102), are better explained by indirect procurement through other sites. This is because we identified optimal candidates by computing access costs under the assumption that the Bau was the end destination of procurement journeys—from the perspective of other sites, the set of optimal candidates could indeed be very different. The results are therefore surprising because the distances involved extend beyond the daily foraging radius of five to perhaps 10 km normally seen with ethnographic hunter-gatherers (e.g., Kelly, 1995), and the exceptional circumstances under which larger distances are recorded for the latter (e.g., Bailey and Davidson, 1983) likely do not apply. Indeed, the active exploitation area at the Bau falls well within the range reported by Marlowe (2005) for minimum hunter-gatherer home ranges ethnographically documented across the world, which encompass all areas exploited by local groups and not just individual site exploitation territories sensu Bailey and Davidson (1983). It is possible, however, that allowing for inaccuracies in the detection of optimal candidates fits the data best because the former reflect the influence of procurement while at other camps. This is an alternative we are currently investigating through simulations of a minimally realistic, agent-based model of lithic raw material management for the region, which aims to evaluate the potential effects of residential mobility on raw material variability. Regardless, the lithic data from the Bau do not support the notion that Neanderthals exploited smaller territories than is typically seen with anatomically modern humans (cf. Verpoorte, 2006; Macdonald et al., 2009; Henry et al., 2017).

Our results indicate that Neanderthals were probably not at a disadvantage in terms of their spatial abilities, at least not in environments they were well acquainted with (cf. Burke, 2012; also refer to the studies by Raynal et al., 2013 and Wynn and Coolidge, 2016). As noted earlier, the avoidance of certain resources in the area surrounding the Bau is consistent with not only an excellent knowledge of the location, characteristics, and least-cost paths linking different resources to each other and to the site but also the ability to identify optimal or close to optimal procurement alternatives from arbitrary locations on the landscape. This would have presupposed accurate estimations of access costs, implying a location-specific awareness of directions and distances to different options that we contend is most easily explained in terms of Euclidean mental representations of space. Navigation using Euclidean mental maps is based not on salient landmarks and the reuse of paths but on comprehensive 'birds-eye' (Wynn and Coolidge, 2016) metric knowledge of the environment that allows access costs to be computed from any possible direction. Such navigational skills, proposed for chimpanzees (*Pan troglodytes verus*) by Normand and Boesch (2009) but generally considered to be absent today in species other than our own, represent the most efficient but also most cognitively demanding wayfinding mechanism (Normand and Boesch, 2009; Trapanese et al., 2018). Without the ability to use Euclidean mental maps, however, the surprising strength of the correlation reported in Section 3.5 is difficult to explain. The presence of such spatial abilities in Neanderthals, who began diverging from our lineage some 600–800 kyr ago or more (Prüfer et al., 2014; Gómez-Robles, 2019; Petr et al., 2020), would add support to the view that modern spatial cognition already existed by 500 kyr ago (Wynn and Coolidge, 2016, and references therein). However, although selectivity and optimization in raw material procurement are known from the Oldowan onward (e.g., Stout et al., 2005; Braun et al., 2009; Key et al., 2020), the kind and degree of optimization evidenced at the Bau remains, to our knowledge, undocumented in earlier contexts.

A conceivable alternative is that the topography of the landscape could have directed Neanderthals through source areas which are, as a result, more frequently represented at the site. While the mobility potential of the landscape likely did play a role, as highlighted in fact by the evaluation of our first hypothesis, we do not think it can explain the available data. In part, this is because under such a scenario, we would expect utilized source areas located closer to the site to be represented more frequently than sources further afield, yet this is clearly not what we see at the Bau. Nevertheless, examining the structuring effects of terrain on movement throughout the region is a research avenue well worth pursuing in the future, through the application of either White and Barber's (2012) 'From Everywhere to Everywhere' approach or Llobera et al.'s (2011) focal mobility networks. At the very least, it could lead to the incorporation of additional variables, such as source accessibility, resulting in a more refined model. A similarly promising avenue of research involves exploring the effects of carried load, and potentially the incorporation of this variable into a future iteration of the model presented here.

The use of stone resources at the Bau reflects overall pragmatic, rational, and informed choices aimed at optimizing returns. The strong correlation between P_{S1} values computed for the available sources and the number of artifacts made from materials that may be found at those sources further indicates remarkable consistency in raw material management strategies (from procurement to discard), in turn pointing to an essentially fully utilitarian use of stone. Indeed, the frequencies of lithic raw materials at the Bau appear to be largely explainable without consideration of how tools were used, curated, or reduced, without consideration of toolkit sizes or lengths of occupation, or other factors that may be expected to have played an important role in explaining specific instances of technological organization (e.g., Dibble, 1991; Kuhn, 1995; Andrefsky, 2008). We suggest that this is due, on the one hand, to the richness of raw material sources in the region, which placed no special constraints on the use of stone, and, on the other hand, to the fact that we considered the material consequences of human behaviors averaged over a time span of some 100,000 years. This meant that any workable explanation had to reflect fundamental and enduring principles rather than behaviors specific to individuals, groups, or time periods. In other words, we are not suggesting that individual Neanderthals or Neanderthal groups exploited the landscape uniformly, always striving to procure raw materials from optimal sources in accordance with some universal criteria, and producing implements from these in an identical manner. That was clearly not the case. When the archaeologically visible outcomes of all actions performed by every individual who spent some time at the Bau over a period of 100,000 years are considered together, however, such variability becomes little more than noise. This is a strength, rather than a weakness, of dealing with large-scale time-averaged palimpsests in human evolution because the physiological and cognitive affordances underlying such variability can become easier to distinguish. As it has long been recognized by proponents of time perspectivism, different processes and phenomena may become apparent depending on the chosen temporal scale and resolution, and, depending on the questions asked, coarser resolutions can be an advantage rather than a handicap (see Bailey, 2007; see also the study by Holdaway and Wandsnider, 2008).

It is important to note, however, that our results reflect solely the use of lithic materials at the site. They need not apply to the exploitation of other resources, which may well reflect different territorial extents, for instance (Cole, 2002). Regardless of the resource being examined, however, what our results do demonstrate is the importance of considering all alternatives available in an area, not just those for which we have clear evidence of utilization. They also warn against the hasty dismissal of nonutilized resources as simply unavailable in the past, or to their attribution to cultural factors (e.g., prohibitions against accessing certain areas). Finally, they underscore the fact that the purposeful selection of resources is compatible with embedded procurement, which need not presuppose chance encounters with raw material sources (also refer to the study by Elston, 2013).

5. Conclusions

Our analyses of the comprehensive stone resource utilization dataset available for the French Middle Paleolithic site of the Bau de l'Aubesier indicate that Neanderthals had excellent spatial knowledge and navigational abilities. These data suggest a detailed knowledge of a large area, an ability to accurately navigate the environment using Euclidean mental maps, and a pragmatic strategy of lithic exploitation based on minimizing costs (travel and search times) and maximizing utility. Virtually all the available information can be accounted for under this framework, including the exploitation of certain sources, the avoidance of others, and the degree of archaeological representation of different raw material types. While alternative explanations could undoubtedly be formulated, it is difficult to envision one of comparable simplicity and consistency with the entirety of the available resource procurement data.

Declaration of competing interest

The authors declare no known conflict of interest.

Acknowledgments

We would like to thank the Max Planck Society and Jean-Jacques Hublin for supporting this research and Shannon McPherron for his encouragement, advice, and suggestions on earlier versions of this manuscript. We would also like to thank the anonymous reviewers whose insightful and constructive comments have resulted in a substantially improved article. This work was supported by the Max Planck Society.

Supplementary Online Material

Supplementary Online Material to this article can be found online at https://doi.org/10.1016/j.jhevol.2022.103152.

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Supplementary Online Material (SOM):

Evaluating landscape knowledge and lithic resource selection at the French Middle Paleolithic site of the Bau de l'Aubesier

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SOM S1

Raw material distribution across the Bau sequence

The stratigraphy of the site is complex, and a large number of layers and sub-layers have been identified to date (Wilson, 2021). Some of the layers are substantially richer in archaeological materials than others, and this is reflected in the number of lithics with known provenance (SOM Table S1). As shown in SOM Table S2, the proportions and diversity of raw materials also vary (see also SOM Fig. S1).

SOM S2

Exploratory analyses

Access costs Previous work has suggested that site/source transfer costs measured along a straight-line route (allowing for deviations around inaccessible terrain, i.e., >60% slope) are better predictors of source utilization than those measured along least-cost routes (Browne and Wilson, 2013). However, here we target a different response (probabilities of belonging to the set S_1 of sources from archaeologically represented source areas) and calculate the cost of traversing least-cost paths in terms of minimum walking times rather than caloric expenditure (see also Browne and Wilson, 2011). Consequently, we re-examined the likely effects of easily computed access cost variables through simple descriptive statistics so as to identify the one resulting in the clearest separation of the data. Ease of computation was an important criterion because some of the analyses presented here involved a large number of evaluations (see section *3.5.* of the main text), and we envisioned our model being usable in agent-based simulations for future studies. Four highly and significantly correlated ($r_{min} = 0.975$, $p_{min} < 0.001$)

variables were investigated: 1) Euclidean distances, 2) surface distances on Shuttle Radar Topography Mission (SRTM) Digital Elevation Models (DEMs), 3) minimum walking times from the Bau, and 4) minimum walking times to the Bau. The latter two are not identical because the cost of walking downhill is not the same as the cost of walking uphill (e.g., Langmuir, 1984).

The strongest differentiation between seemingly non-utilized (set S_0) and potentially used (set S_1) sources was observed with walking times along least-cost routes from the Bau to the sources, although distance measures appear to perform similarly well (SOM Fig. S2). This result was surprising, as we had expected, under the assumption that the cost of carrying rocks back to the site would have been a substantial concern, that walking times to the Bau would outperform walking times from the Bau. Overall, SOM Figure S2 suggests that the ability to reach specific areas within a reasonable time was a more important driver of selection than the cost of carrying materials back to the site and, indeed, that sources located at a walking distance of over four hours from the site were typically not exploited (see also SOM Table S3). There is indeed a clear gap in source utilization beyond a four-to-five hours of walking radius (or ca. 20 km) from the Bau, there being no sources classified as potentially utilized over a further two-to-three hours of walking. Exploited sources beyond this gap are represented by very few archaeological pieces (n = 7, or 0.04%), and it may be that the latter were procured indirectly, while residing at a different site.

<u>Source extents</u> As shown in SOM Table S4, there is no visible pattern in the non-utilized (S_0) sources in terms of their extent, although a likely trend can be observed with potentially utilized (S_1) sources. With S_1 sources, the data suggest a preference for larger sources or, conversely, an avoidance of smaller ones. Indeed, the largest differences are seen with the

smaller sources, which appear to have been seldom (if ever) exploited. More details on the distribution of source extents across exploited source areas are provided in SOM Table S3.

Rock size abundances In terms of the abundance of different rock sizes at the sources, no obvious trends that would allow for meaningful discrimination between potentially used (S_1) and non-utilized (S_0) sources are observable with small and very large rock size classes (SOM Table S5). The abundance of medium-sized rocks appears to be a more promising differentiator, but the distribution of frequencies across abundance classes is very imbalanced, with over 75% of the sources, regardless of their utilization category, falling under the 'scarce' classification. The most promising variable in this class, then, is the abundance of large rocks, which shows a more even spread of observations.

Raw material quality There are clear differences in the quality of raw materials found at seemingly non-utilized (S_0) and potentially utilized (S_1) sources (SOM Fig. S3). Non-utilized sources show a positively skewed distribution with most sources clustering at lower quality values, the median falling below the lower confidence interval of the median quality observed for potentially utilized sources. The distributions do show considerable overlap, however, and there are several high-quality sources which do not appear to have been utilized. Overall, raw material quality appears to be a good discriminator between the source utilization categories, but likely played a more modest role in determining the usability of a source than the access costs of the latter, since the median walking times from the Bau for potentially utilized sources fall outside the interquartile range for non-utilized ones (see SOM Fig. S2B).

SOM S3

Logistic model diagnostics

An examination of variance inflation factors (VIFs) revealed that collinearity was not an issue (maximum VIF = 1.12). Despite the imbalance in the frequency of the two response alternatives, the model also appears to be stable, as case-wise deletions do not substantially affect individual estimated coefficients (SOM Table S6; see also SOM Fig. S4 for standardized dfbeta values, which indicate the standardized difference between coefficient estimates with cases excluded one at a time).

We did identify 13 influential cases (SOM Table S7), defined here as having leverage values above a threshold of two times the number of predictors plus one divided by the number of cases (i.e., 2*6/346, or 0.035). However, removal of these influential cases does not have a major effect on the results: all coefficients remain within their standard error as observed in the full model with no cases removed, no coefficients change signs and no critical changes in the significance of individual predictors can be observed (see SOM Table S8). Most affected by the removal of influential cases is the estimate for the quality variable, which is not surprising given that the removed cases have some of the highest quality values in the dataset.

SOM S4

Logistic model results

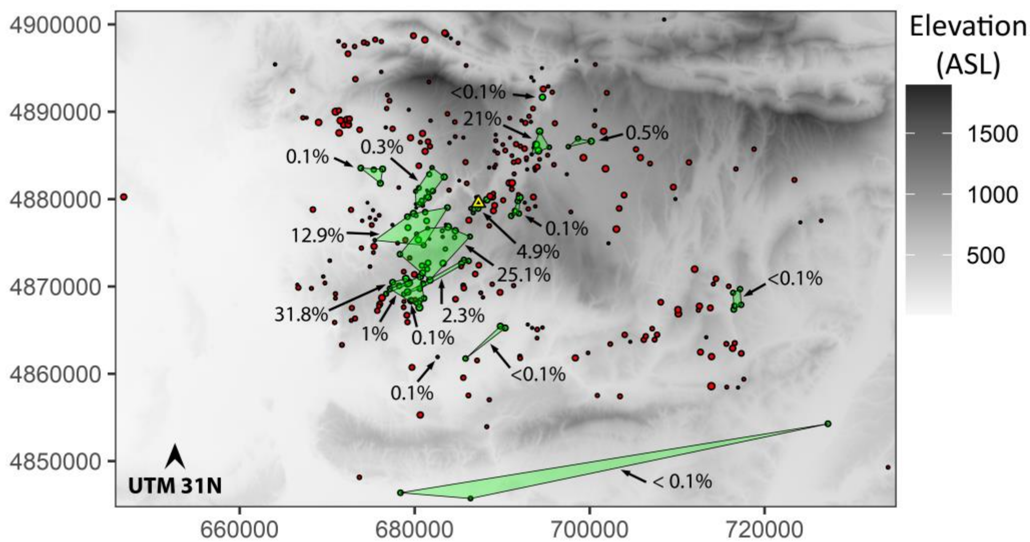
A null model comparison revealed that our logistic model of the influence of the four tested variables on the likelihood of sources being classified as potentially utilized or not is highly significant ($\chi^2 = 69.51$, df = 4, $p < 0.001$). As illustrated in SOM Table S8 and discussed below, the quality of the raw materials, the size of the area over which these are found and the degree to which they are present as large nodules (more flexible in their potential for reduction), all have a positive and significant impact on the likelihood of sources being classified as potentially utilized. However, the strongest and most significant influence is that of the time it takes to reach a source from the Bau, and its effect is negative—the higher the access costs of a source, the less likely it is to be classified as potentially exploited. These results are consistent with previous findings (Browne and Wilson, 2011) as well as theoretical expectations.

Minimum walking times from the Bau Supplementary Online Material Figure S5 shows the influence of the cost of reaching a source from the Bau on its likelihood of classification as potentially utilized, when controlling for the effects of the other variables considered. Sources of an average size (ca. 4210.47 m^2), yielding raw materials of average quality for the region (ca. 2.19), and characterized by an abundance of large rocks that is also typical for the study area (i.e., absent or scarce), have a probability of being classified as potentially utilized of about 78% (61–88 at 95% confidence level) if in the vicinity of the Bau (i.e., where the closest source classified as potentially utilized is located, or 6 minutes from the Bau). This probability falls below 50% if located at more than about 73 minutes from the site. Note that these probabilities do not account for the spatial relationship between sources.

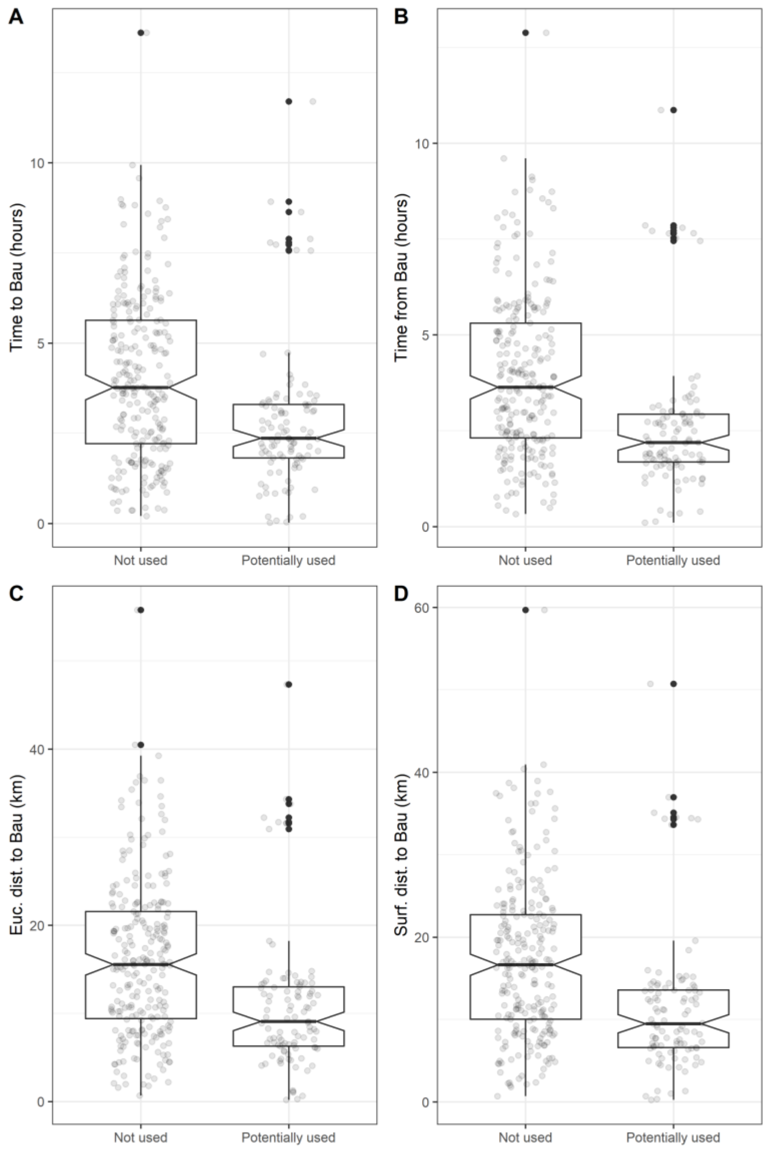
The influence of raw material quality The influence of raw material quality on the likelihood of sources being classified as potentially utilized when other variables are controlled for is shown in SOM Figure S6. As indicated in subplot A, these likelihoods are above 50% for sources with otherwise average characteristics for the region (i.e., scarce large nodules and a surface area of roughly 4210 m^2) and located in the vicinity of the Bau (i.e., ca. 6 minutes) in all but the lowest raw material quality cases. On the other hand, similar sources that are only reachable in ca. 3.2 hours or more from the Bau (the adjusted mean for the region) would have to yield materials of the highest quality (ca. 8) to have a greater than 50% probability of being classified as potentially utilized (subplot B).

The influence of source extent For otherwise average sources located in the vicinity of the Bau, the size of the area over which raw materials may be found somewhat shapes but certainly does not fundamentally determine their probabilities of classification as potentially utilized, which in all cases are above ca. 70% (SOM Fig. S7A). This variable has a somewhat clearer effect when access costs become a greater concern (SOM Fig. S7B), but in all cases the probability of classification as potentially utilized for otherwise average sources (scarce large rocks, relatively low-quality raw materials, ca. 3 hours away from the Bau) is well below 50%. Assuming classification probabilities are adequate proxies for selection probabilities, these data suggest that, when other criteria were met, larger sources were preferred, possibly because of a combination of factors such as being easier to find, easier to intercept on the way back to the site, and easier to casually procure materials from (having to work less to find suitable stone).

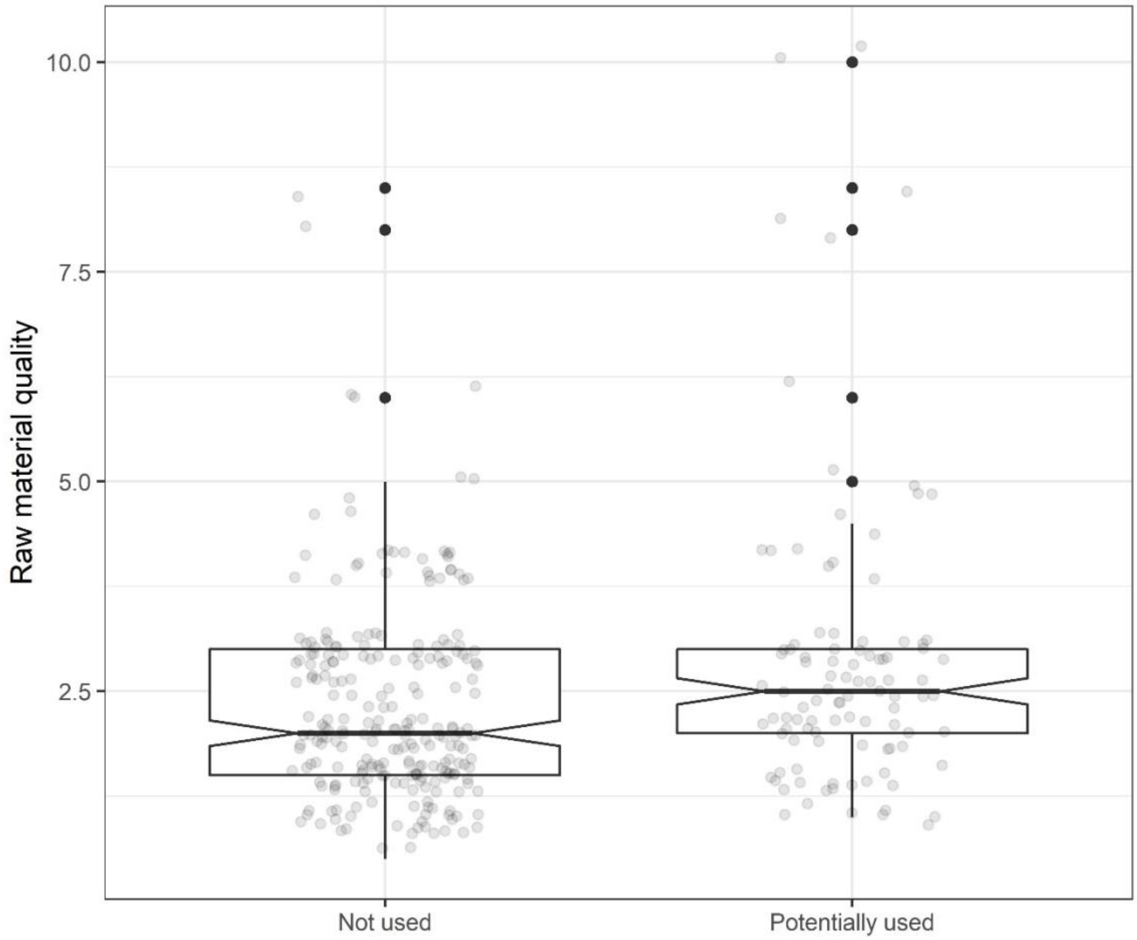
The influence of large rock abundances As shown in SOM Figure S8, and as with source extent, the overall effect of this variable with otherwise average sources located in the vicinity of the Bau is minor (above 50% in all cases, and there is overlap in the 95% confidence intervals of the maximum and minimum probabilities). For sources where access costs are greater the influence of this variable becomes more critical. All else being equal, a source which is average for the region in all respects (relatively low-quality materials found over a reasonably large area at ca. 3 hours from the Bau), has a very low probability of being classified as potentially utilized if it yields no or only few large rocks. However, for such a source the effect of having an abundance of large rocks is far more uncertain, as shown by 95% confidence intervals which, for the maximum predicted probability, span almost half of the possible range. If probabilities of classification can be taken as reliable proxies for source selection, these data suggest, overall, that when access costs were a concern sources with few large rocks were avoided, while for sources where the abundance of large rocks was not an issue, other variables played a more important role in determining their likelihood of selection.



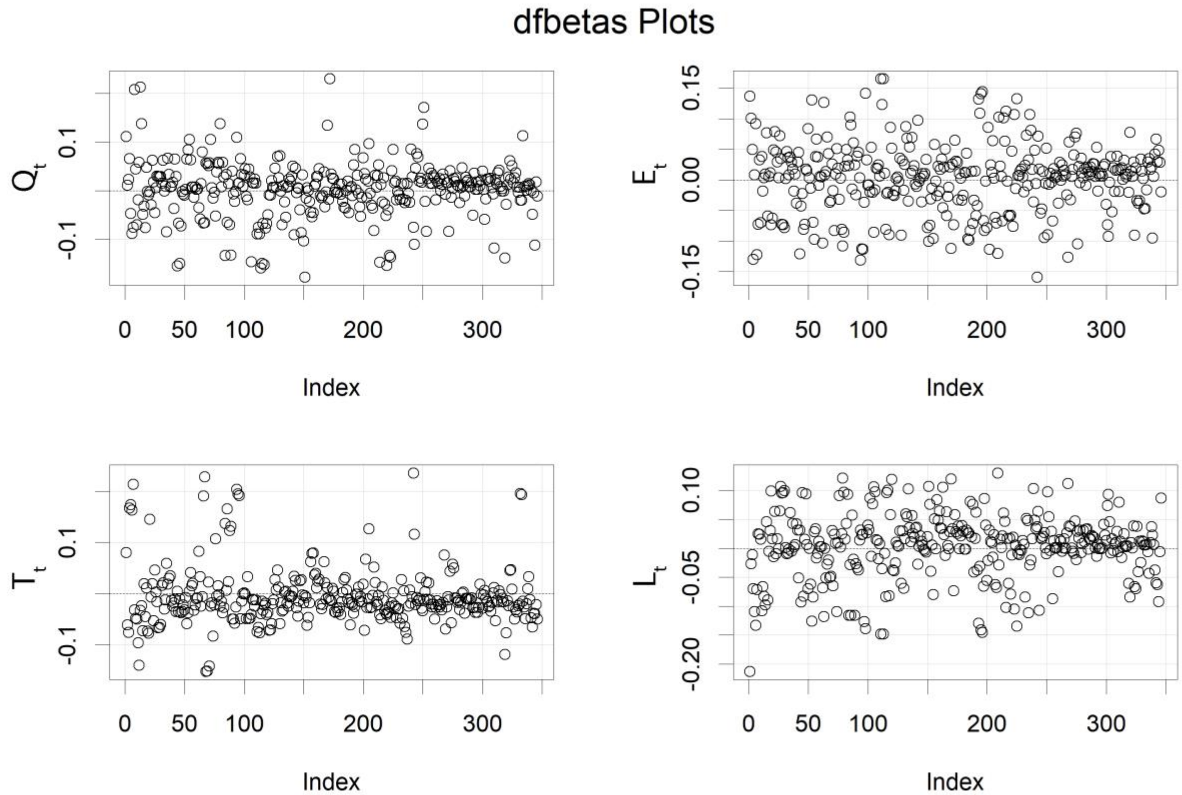
SOM Figure S1. Distribution of raw material sources near the Bau de l'Aubesier rock shelter. Unused sources (S_0) and sources that were potentially exploited from the Bau (S_1) are indicated by red and green dots respectively, while the location of the site is indicated by the yellow triangle. The size of the dots represents relative differences (cubed) in time controlled P_{S1} values ($P_{S1(tc)}$; see Table 1 in the main text), which are a proxy for overall source quality. Green polygons represent convex hulls encompassing sources from used source areas, and percentages represent the contributions of those source areas to the total number of lithics with established provenance recovered at the site. Note that most raw materials were procured from relatively distant sources and several good sources located close to the site (large red dots) were apparently not used. Coordinates are given in meters for UTM zone 31N, and elevation values are given in meters above sea level (ASL).



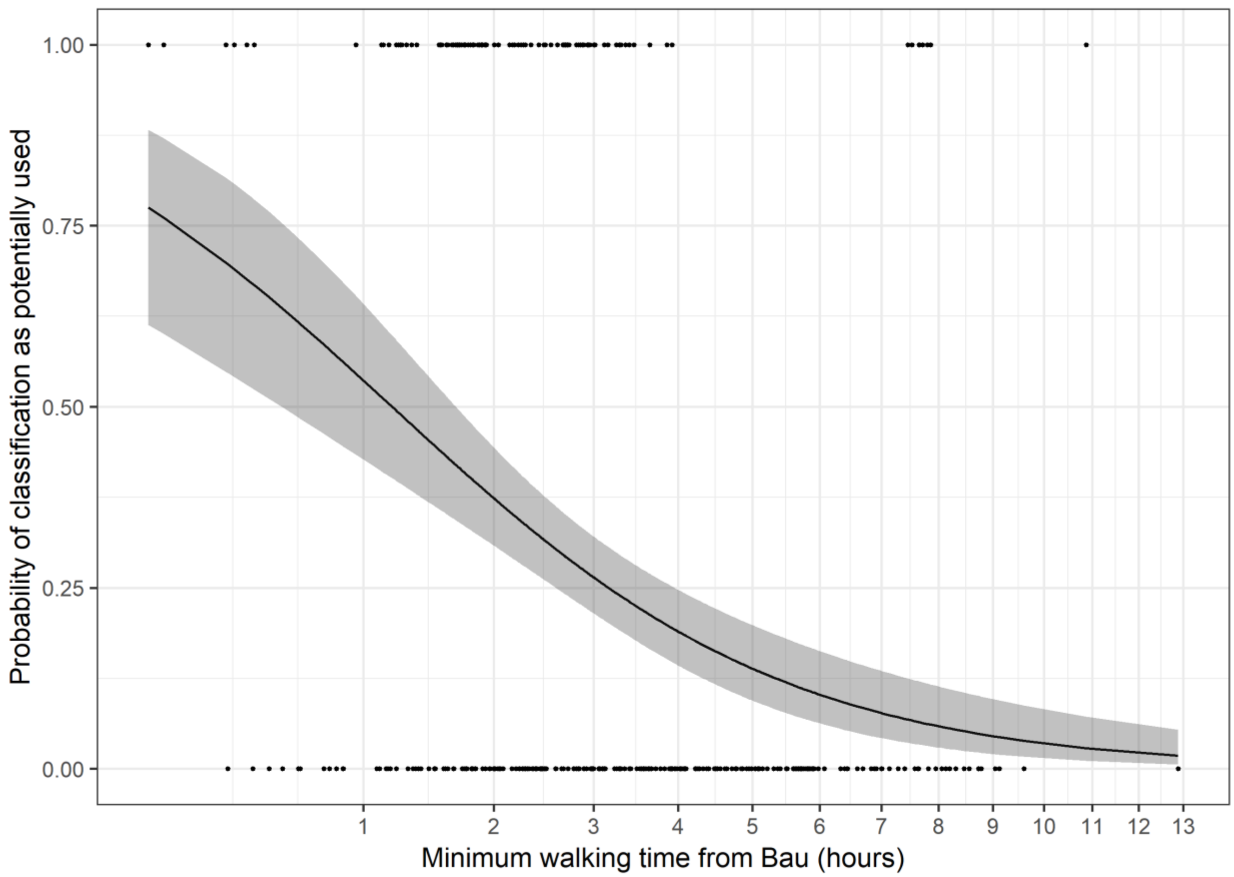
SOM Figure S2. Distribution of access costs across reachable (slope < 60%) potentially utilized (set S_1, n = 101) and non-utilized sources (set S_0, n = 245), defined as A) minimum walking times required to reach the Bau from the sources, B) minimum walking times required to reach the sources from the Bau, C) Euclidean distances (Euc. dist.) between the sources and the site, and D) minimum distances along the surface of the terrain (Surf. dist.). Black dots denote outliers (1.5 times the interquartile range) while grey dots indicate individual sources, with random horizontal jitter added to enhance visualization. Note that all four access cost variables discriminate well between unused (S_0) and potentially used (S_1) sources, but the best differentiation is seen with minimum walking times from the Bau (B).



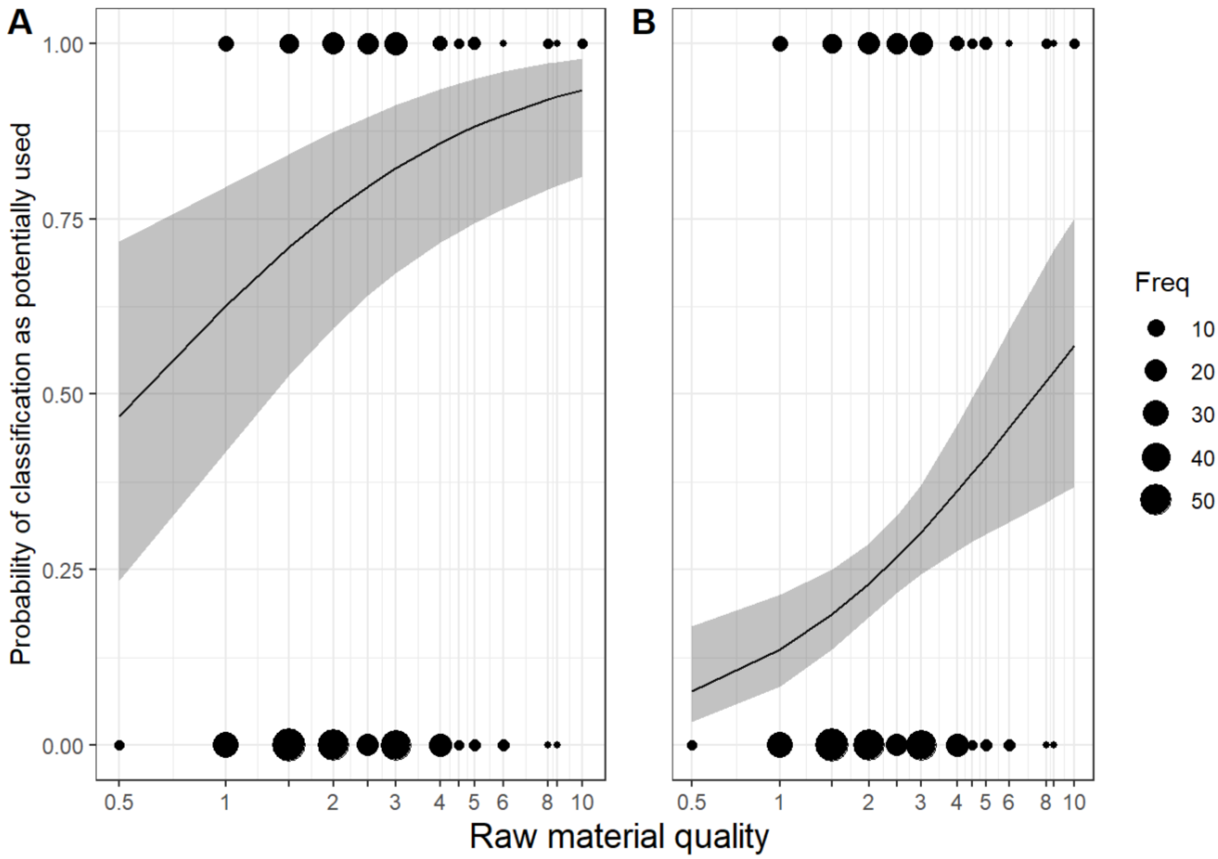
SOM Figure S3. Raw material quality at accessible (n = 346) non-utilized (S_0) and potentially utilized (S_1) sources. Black dots denote outliers (1.5 times the interquartile range) while grey dots indicate individual sources, with random horizontal jitter added to enhance visualization. Note that for both sets of sources the quality values span a similar range, but S_0 sources (Not used) are somewhat more variable, and both the median and maximum quality value for that set is lower than for S_1 sources (Potentially used). The lack of overlap in the notches (approximate confidence intervals for the medians) suggests raw material quality is a useful discriminator between the source utilization categories.



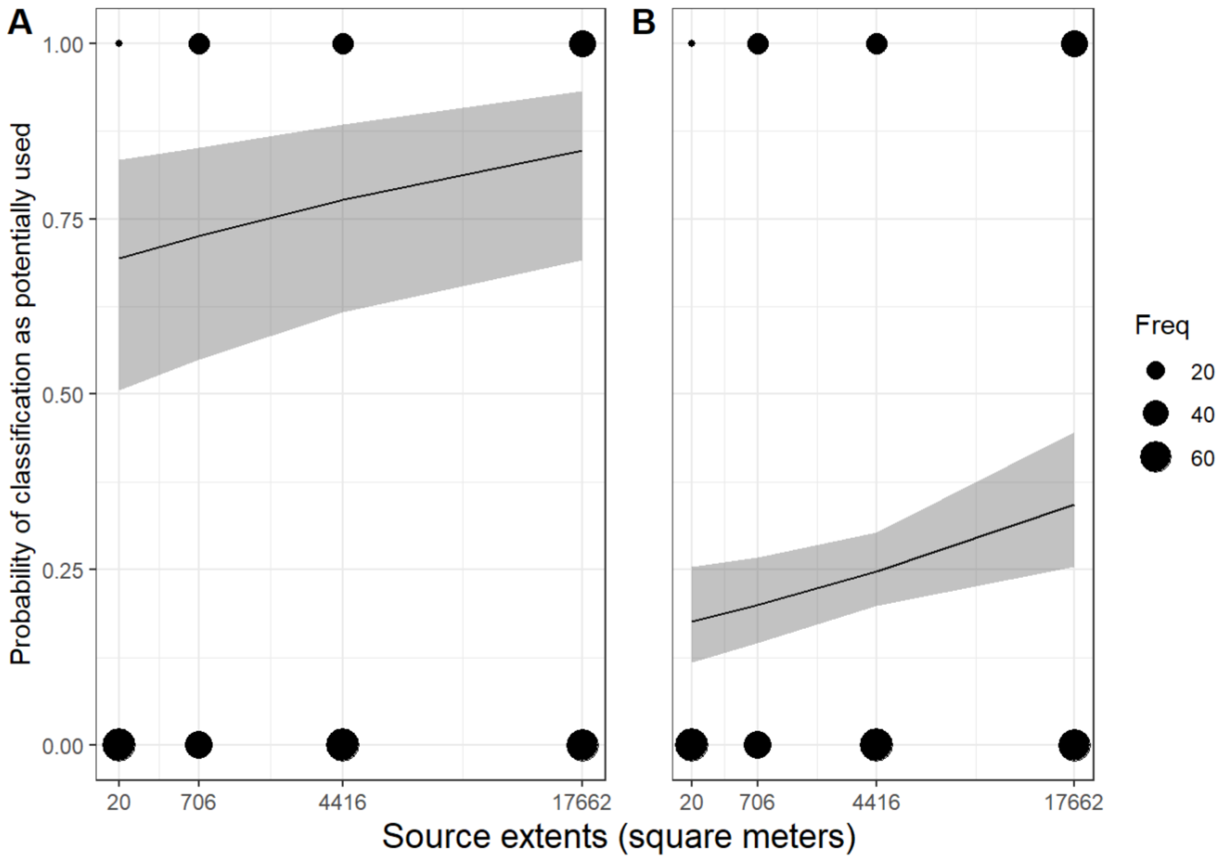
SOM Figure S4. Plot of standardized dfbeta values for individual scaled predictors. Q_t = quality (log), E_t = extent (square root), T_t = time from Bau (square root), L_t = large rock abundances. Low absolute values indicate that deletions of individual observations do not have a major effect on the estimated coefficients.



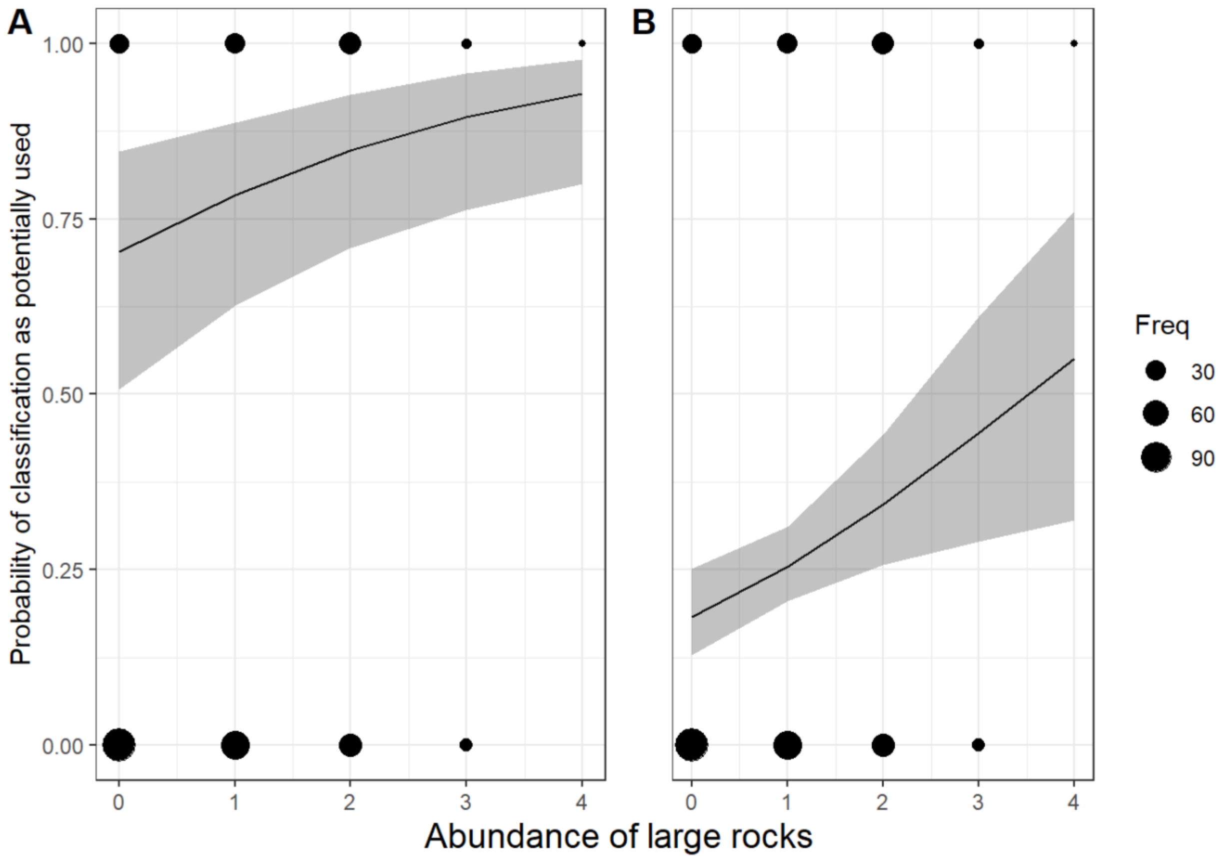
SOM Figure S5. Modeled probabilities of source classification (0 = unused; 1 = potentially utilized) based on the minimum walking times required to reach them from the from Bau, when all other source characteristics are kept at the mean values observed throughout the region. Black dots represent actual observations: sources from exploited source areas have values of 1.00, and unused sources values of 0.00. Note that this variable has a major effect on classification probabilities, with estimates ranging from more than 0.75 with average sources located close to the site to almost zero with average sources located at ca. 13 hours from the Bau.



SOM Figure S6. Modeled probabilities of source classification (0 = unused; 1 = potentially utilized) based on raw material quality, with minimum walking times (from the Bau) kept constant either at the observed minimum (A) or at the average for all sources in the region (B), and all other variables kept constant at their mean. Actual observations are represented by black dots whose size is proportional to the number of unused or potentially used sources with specific raw material quality values. Note that the presence of high quality raw materials plays an important role, but more so with sources that are not in the immediate vicinity of the site (B).



SOM Figure S7. Modeled probabilities of source classification (0 = unused; 1 = potentially utilized) based on source extents, with minimum walking times (from the Bau) kept constant either at the observed minimum (A) or at the average for all sources in the region (B), and all other variables kept constant at their mean. Actual observations are represented by black dots whose size is proportional to the number of unused or potentially used sources with specific extent values. Note that source extent plays a role, with larger sources being more likely to be classified as potentially utilized, but the influence of this variable is relatively minor.



SOM Figure S8. Modeled probabilities of source classification (0 = unused; 1 = potentially utilized) based on the abundance of large usable rocks, with minimum walking times (from the Bau) kept constant either at the observed minimum (A) or at the average for all sources in the region (B), and all other variables kept constant at their mean. Abundance values are given on a scale from 0 (absent) to 4 (very abundant; see also variable L in Table 1 of the main text). Actual observations are represented by black dots whose size is proportional to the number of unused or potentially used sources with specific abundance values. Note that the abundance of large rocks substantially and positively influences the likelihood estimates with sources that are not located in the immediate vicinity of the site (B).

SOM Table S1

Number of lithics assessed for provenance purposes, by layer (data from Wilson, 2021). Layers K2–C represent the stratigraphic sequence along the western wall of the rock shelter, with K2 being the oldest, while layers 5–2 correspond to the sequence observed towards the center of the rock shelter. The complete site assemblage used in the present paper also includes pieces from minor layers not shown here, and from test pits whose stratigraphic positions were not given layer attributions.

	K2	**J–K1**	**I**	**H**	**G**	**E**	**D**	**C**	**5**	**4**	**3**	**2**
Total	1290	2084	2077	7004	224	1998	147	860	546	19332	648	1962

SOM Table S2

Percentage of pieces by source area and layer (data from Wilson, 2021). Layers K2–C represent the stratigraphic sequence along the western wall of the rock shelter, with K2 being the oldest, while layers 5–2 correspond to the sequence observed towards the center of the rock shelter. The complete site assemblage used in the present paper also includes pieces from minor layers not shown here, and from test pits whose stratigraphic positions were not given layer attributions.

Source Area	K2	J–K1	I	H	G	E	D	C	5	4	3	2
Unidentifiable	53	41	58.4	58.2	14.4	90.1	92.5	75.8	61.5	63.1	66.7	47
Unknown	3.8	0.5	0.2	0.4	0.9	0.1	0	0.3	0	0.2	0.3	1.4
Faraud	9.9	8.8	12	14.4	8.1	3	2	7.3	4	9	7.3	10
Méthamis	5.3	3.8	9.1	7.7	0.5	1.3	0.7	2.7	8.8	4.6	1.4	1.6
Les Sautarels	0.3	0.2	0.1	0.2	0	0	0	0.3	0.4	0.5	0.8	0.5
Sault	8.1	10.9	4.6	6.4	35.1	3	4.8	9.4	2.2	8.3	11.9	14.1
Murs	17.7	27.9	13.1	11.1	39.2	2.1	0	3.3	22	11	8.2	15
Local	0.1	2	0.5	0.3	0	0	0	0.1	0.5	2.6	0	7.8
St. Jean de Sault	0	0.2	<0.1	0	0	0	0	0	0	<0.1	0	0.1
Roussillon	0	0	<0.1	0	0	0	0	0	0	<0.1	0	0.1
Murs-Bezaure	1.2	3.4	1.2	1.1	1.8	0.4	0	0.6	0.4	0.3	2	1.9
Ravin de la Treille	0.3	0	<0.1	0.1	0	0.1	0	0	0.2	0.1	0.2	0.3
St. Trinit	0.2	1	0.5	0.1	0	0.1	0	0	0	0.12	0.2	0.1
Durance	0	0	<0.1	0	0	0	0	0	0	0	0	0
Tertiary Calavon	0	0	0	0	0	0	0	0.1	0	<0.1	0	0
Tertiary Murs VdeV	0	0.1	<0.1	<0.1	0	0	0	0	0	<0.1	0.2	0
Mormoiron	0	0	0	0	0	0	0	0	0	<0.1	0	0.2
R de Guérin	0	0	0	<0.1	0	0	0	0	0	<0.1	0	0.1
N. Aurel	0	0	0	0	0	0	0	0	0	<0.1	0	0

SOM Table S3

Distribution of source extents across exploited source areas, as well as associated degrees of utilization (i.e., number of attributable archaeological lithics) and minimum/maximum access costs for sources of the latter, defined as minimum walking times (in hours) from the Bau.

Area	20 (m^2)	706 (m^2)	4416 (m^2)	17662 (m^2)	Lithics	Time (min)	Time (max)
55	0	1	2	4	4981	2.7	3.5
82	0	5	5	5	3935	1.1	2.8
45	1	1	1	3	3286	2.0	2.2
57	0	1	2	7	2015	1.0	3.6
53	2	2	0	2	768	0.1	0.2
36	0	2	4	1	355	1.6	3.4
61	0	4	0	4	162	2.4	3.6
47	0	1	1	1	73	3.0	3.1
59	4	1	5	5	52	1.5	2.5
58	0	3	0	2	16	1.2	1.0
37	0	2	0	0	8	3.0	3.3
76	1	0	0	0	8	3.9	4.7
75	0	3	2	0	6	7.5	7.9
35	0	0	1	3	4	2.7	4.1
64	0	0	0	1	2	3.2	3.1
67	0	0	2	1	2	3.3	4.7
13	0	0	0	3	1	7.5	11.7

Abbreviations: min = minimum, max = maximum.

SOM Table S4

Frequencies of source extents across reachable (n = 346) potentially used (set S_1) and non-utilized (set S_0) sources.

Factor	20 (m^2)	706 (m^2)	4416 (m^2)	17662 (m^2)
Potentially used	8	26	25	42
Not used	68	46	67	64

SOM Table S5

Frequencies of abundance values for different nodule sizes at the accessible sources (n = 346).

Type	Factor	None	Scarce	Relatively scarce	Abundant	Very abundant
Small rocks	Not used (S_0)	0	240	2	3	0
	Potentially used (S_1)	0	98	1	0	2
Medium rocks	Not used (S_0)	21	187	28	3	6
	Potentially used (S_1)	2	79	14	5	1
Large rocks	Not used (S_0)	115	80	43	7	0
	Potentially used (S_1)	28	31	38	3	1
Very large rocks	Not used (S_0)	209	25	11	0	0
	Potentially used (S_1)	86	13	0	1	1

SOM Table S6

Baseline scaled (z-transformed) logistic model coefficients with minimum and maximum ranges with case-wise deletions.

Coefficient	Slope estimate	Minimum	Maximum
Intercept	−1.1218	−1.1306	−1.1016
Q_t	0.4490	0.4249	0.4801
E_t	0.3506	0.3281	0.3741
T_t[a]	−0.8886	−0.9129	−0.8511
L_t	0.3760	0.3466	0.3939

Abbreviations: Q_t = quality (log), E_t = extent (square root), T_t = time from Bau (square root), L_t = large rock abundances

[a] Corresponds to the minimum travel times required along least-cost routes from the Bau.

SOM Table S7

Characteristics (unscaled) of influential cases with leverage values above selected threshold, ordered by their leverage values.

Source	Area	Classification	Minimum walking time from Bau (hr)	Quality	Extent (m^2)	Large rock abundances	Leverage
1	84	Not used	0.8	1.0	20	Abundant	0.0577
324	124	Not used	8.2	8.5	17662	Rel. scarce	0.0546
8	61	Potentially utilized	2.4	10.0	706	Scarce	0.0481
153	12	Not used	4.0	8.0	17662	None	0.0449
254	55	Potentially utilized	2.7	8.0	706	Rel. scarce	0.0447
325	73	Not used	7.6	4.0	20	Abundant	0.0437
69	53	Potentially utilized	0.1	3.0	20	None	0.0424
68	53	Potentially utilized	0.1	3.0	20	None	0.0413
13	55	Potentially utilized	2.7	8.5	4416	None	0.0407
174	61	Potentially utilized	2.9	8.0	706	None	0.0388
253	55	Potentially utilized	2.7	10.0	17662	Scarce	0.0383
207	41	Not used	0.3	1.0	20	Scarce	0.0375
226	12	Not used	4.0	6.0	706	Rel. scarce	0.0364

SOM Table S8

Baseline scaled (z-transformed) logistic model coefficients with and without influential cases removed.

Model	Coefficient	Estimate	SE	Z.value	*p*-value
All cases (n = 346)	Intercept	−1.12	0.14	−7.80	<0.001
	Q_t	0.45	0.13	3.35	<0.001
	E_t	0.35	0.14	2.49	0.013
	T_t[a]	−0.89	0.16	−5.63	<0.001
	L_t	0.38	0.14	2.76	0.006
High leverage cases removed (n = 333)	Intercept	−1.12	0.14	−7.74	<0.001
	Q_t	0.34	0.15	2.21	0.027
	E_t	0.35	0.15	2.41	0.016
	T_t[a]	−0.83	0.16	−5.07	<0.001
	L_t	0.44	0.14	3.07	0.002

Abbreviations: Q_t = quality (log), E_t = extent (square root), T_t = time from Bau (square root), L_t = large rock abundances, SE = standard error.

[a] Corresponds to the minimum travel times required along least-cost routes from the Bau.

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