

# A NEUTRAL MODEL OF STONE RAW MATERIAL PROCUREMENT

P. Jeffrey Brantingham

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*Stone tool assemblage variability is considered a reliable proxy measure of adaptive variability. Raw material richness, transport distances, and the character of transported technologies are thought to signal (1) variation in raw material selectivity based on material quality and abundance, (2) optimization of time and energy costs associated with procurement of stone from spatially dispersed sources, (3) planning depth that weaves raw material procurement forays into foraging activities, and (4) risk minimization that sees materials transported in quantities and forms that are energetically economical and least likely to fail. This paper dispenses with assumptions that raw material type and abundance play any role in the organization of mobility and raw material procurement strategies. Rather, a behaviorally neutral agent-based model is developed involving a forager engaged in a random walk within a uniform environment. Raw material procurement in the model is dependent only upon random encounters with stone sources and the amount of available space in the mobile toolkit. Simulated richness-sample size relationships, frequencies of raw material transfers as a function of distance from source, and both quantity-distance and reduction intensity-distance relationships are qualitatively similar to commonly observed archaeological patterns. In some archaeological cases it may be difficult to reject the neutral model. At best, failure to reject the neutral model may mean that intervening processes (e.g., depositional time-averaging) have erased high-frequency adaptive signals in the data. At worst, we may have to admit the possibility that Paleolithic behavioral adaptations were sometimes not responsive to differences between stone raw material types in the ways implied by current archaeological theory.*

*Se considera la variabilidad de las colecciones de lítica como una medida confiable de la variabilidad de las adaptaciones al medio ambiente. La diversidad de materias primas, la distancia a sus yacimientos y la tecnología empleada reflejarían (1) la selección de la materia prima con base en su calidad y abundancia, (2) la optimización de gastos de tiempo y energía empleados en la obtención de materia lítica de yacimientos dispersos; (3) la integración anticipada de las visitas a los yacimientos con actividades de caza y recolección, y (4) una estrategia de reducción de riesgos que consiste en transportar la lítica en las cantidades y formas más eficientes del punto de vista energético y menos susceptibles al desgaste. En este trabajo prescindimos de suponer que el tipo y la abundancia de materia prima hayan jugado un papel en la organización de estrategias de obtención de ésta y de los desplazamientos en general. En su lugar, partimos de un modelo conductualmente neutral basado en el agente (individuo), como sería un cazador que se desplaza al azar en un medio ambiente uniforme. La obtención de materia prima depende entonces únicamente de hallazgos fortuitos de yacimientos de lítica y la cantidad de material que el cazador pueda agregar a su equipaje. La simulación de la relación entre la diversidad y el tamaño de la muestra, así como de la frecuencia de uso, la cantidad y la reducción del volumen en función de la distancia al yacimiento, revelan patrones que se asemejan, de manera cualitativa, a los que arroja a menudo el registro arqueológico. En algunos casos arqueológicos resultaría entonces difícil descartar tal modelo. En el mejor de los casos la imposibilidad de descartarlo señalaría que los procesos post-deposición (p.ej. la combinación de artefactos de distintas épocas en una sola colección) han borrado todos los indicadores de la adaptación. En el peor de los casos, nos veríamos obligados a reconocer que las adaptaciones del comportamiento paleolítico a veces no obedecían a las diferencias entre los tipos de materias primas de la lítica de la manera que sugieren las teorías vigentes en arqueología.*

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*It is easy to invent a selectionist explanation for almost any specific observation; proving it is another story. Such facile explanatory excesses can be avoided by being more quantitative.*

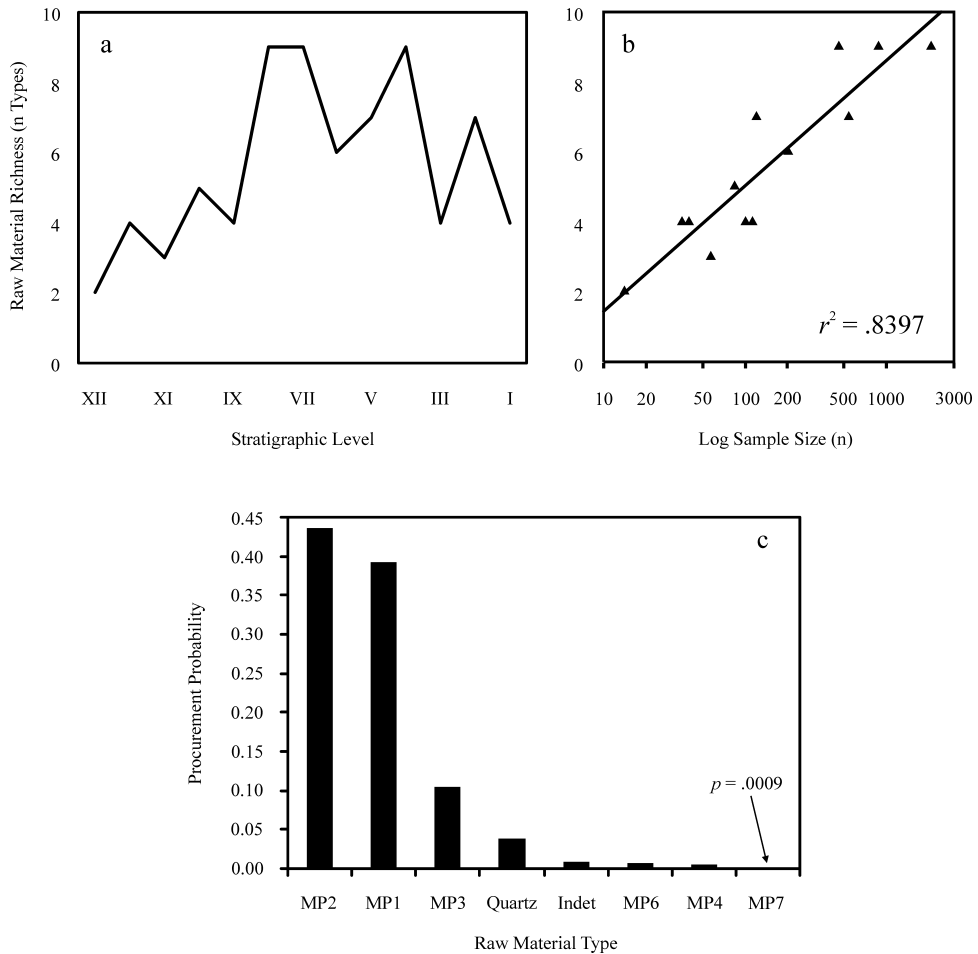
Motoo Kimura (1983:xiv)  
*The Neutral Theory of Molecular Evolution*

**T**he richness of stone raw material types in an archaeological assemblage, the geographic distances over which those materials were transported, and the technological forms in which they were transported have provided empirical benchmarks for inferring the organization of Paleolithic adaptive strategies (Féblot-

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American Antiquity, 68(3), 2003, pp. 487-509  
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**Figure 1.** Raw material richness in assemblages from the Middle Paleolithic site of Grotte Vaufray, approximately 204,000–74,000 B.P. Richness changes through time (a) but is heavily dependent upon sample size (b). Procurement probabilities estimated from the observed raw material proportions (c) illustrate the structure of the distribution underlying procurement behaviors. The primary question is whether this probability distribution is derived from the environmental densities of different raw materials, or whether a biased behavioral strategy is responsible. Data from Geneste (1988) with revisions.

Augustins 1993, 1997a, 1997b, 1997c; Gamble 1986, 1999; Geneste 1988, 1989; Kuhn 1995; Melars 1996; Morala and Turq 1990; Potts 1994; Rensink et al. 1991). Such inferences make appeals to optimization of mobility and technological strategies, depth of planning in landscape use, and risk minimization.

One family of models focuses on differences between generalist and specialist strategies of raw material utilization as inferred from the richness (i.e., number of types) of stone raw materials found in archaeological assemblages: generalists exploit many different raw material types, while specialists exploit only a few types. To complicate mat-

ters, observed assemblage richness is frequently—if not universally—constrained by sample size (Grayson 1984; Hayek and Buzas 1997; Shott 1989). Consider, for example, the Middle Paleolithic site of Grotte Vaufray in the Aquitaine Basin of France, which spans the time interval from 204,000–74,000 B.P. (Geneste 1988, 1989). Despite the appearance of changes in raw material richness through time, a single sample size–richness relationship is apparent at this site (Figure 1a, b) (Geneste 1988). Changes in stone raw material richness, from only two unique raw material types to as many as nine, do not necessarily diagnose switching between specialist and generalist strate-

gies, but rather imply an unvarying set of raw material procurement behaviors (Figure 1c) (see Grayson and Delpech 1998, 2002; Shott 1989).

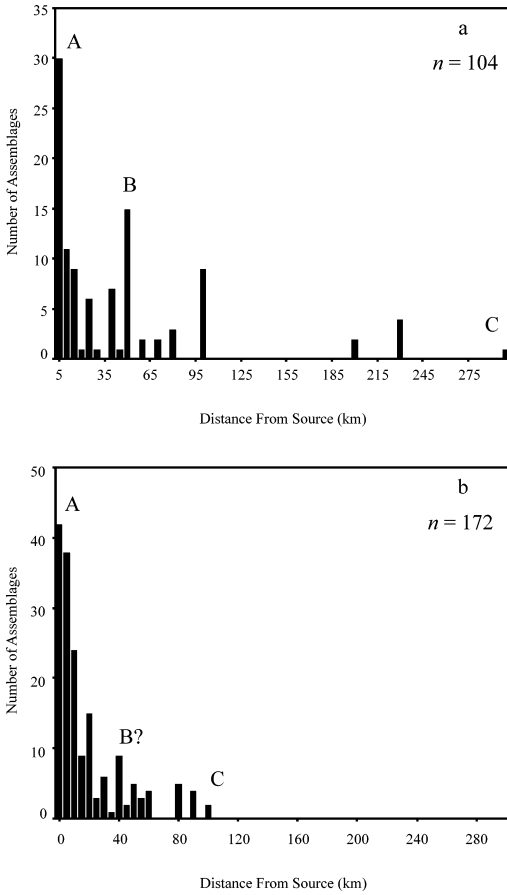
There are two alternative, though not mutually exclusive, behavioral inferences that can be made about the nature of the underlying set of procurement behaviors. First, procurement could simply be keyed to the natural densities of raw materials in the environment (see Grayson 1984:116); some materials are environmentally very abundant, have a higher probability of being procured, and therefore will be observed at small sample sizes (e.g., material types MP1 and MP2); other material types are very rare, less likely to be procured, and therefore will be observed only at very large sample sizes (e.g., material types MP4 and MP7). Second, stone procurement strategies could be biased toward some raw material types and away from others; differences in raw material quality, for instance, could lead to such procurement biases (Andrefsky 1994; Brantingham et al. 2000). The anticipated outcome of a biased procurement strategy would be higher probabilities of observing certain raw material types at small sample sizes, independent of their environmental densities. The first situation is thought of as an “opportunistic” strategy of stone raw material procurement, while the second is taken to imply intentional raw material selectivity. Given that observed maximum richness at Grotte Vaufrey is very low relative to the number of known sources, numbering close to one thousand (Geneste 1985), it may be safe to assume that procurement behaviors were in some way biased. Current theory would lead us to conclude that raw material procurement was non-opportunistic, involved a significant measure of planning depth to execute, and was, in fact, adaptive (Geneste 1989).

A second family of models focuses on a generally recognized “decay-like” pattern in the frequencies of stone raw material transfers from sources at different distances from sites (Blades 1999; Féblot-Augustins 1993, 1997a, 1997b, 1997c; Morala and Turq 1990; Potts 1994). Maximum raw material transport distances are taken to reflect the geographic range of the populations in question (Roebroeks et al. 1988), with distinctions sometimes made between the “local” portion of the range, less than 5 km away, and the “distant” portion of the range, beyond 20–30 km (Féblot-Augustins 1993:214–215; Gamble 1999:88;

Geneste 1988, 1989). Two assumptions are necessary to infer geographic range from these data, namely that raw material procurement is embedded within other foraging activities (Binford 1979; Rensink et al. 1991), and that the maximum recorded transport distance for a material translates approximately into the maximum radius of the foraging area (Roebroeks et al. 1988:30). Thus, in the Central European Middle Paleolithic, the maximum recorded distance for raw material transfers is around 300 km, while in the Middle Paleolithic of Aquitaine Basin the maximum distance is approximately 100 km (Figure 2) (Féblot-Augustins 1993). The differences between regions are presumed to reflect range sizes adapted to different ecological settings. Nonetheless, in both cases the decline in the frequencies of transfers from greater distances is taken to indicate minimization of the costs associated with raw material procurement and transport (see below).

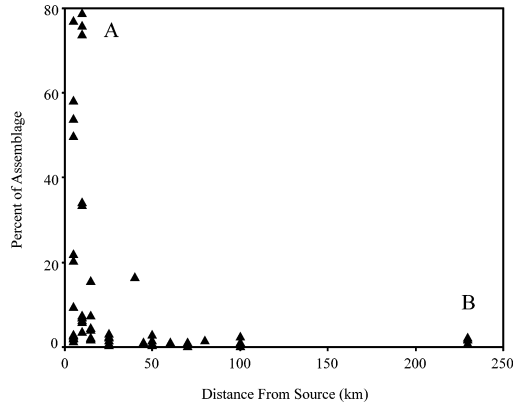
More interesting perhaps is Féblot-Augustins’ (1993:243–245) interpretation of “internal modes” deviating from the decay-like trend for raw material transfers overall (Figure 2a) (see also Féblot-Augustins 1997b, 1997c). She views “unexpectedly” high frequencies of raw material transfers from distant sources as indicating either logistical (*sensu* Binford 1980) use of distant ecological patches by specialized task groups, or seasonal residential moves to non-core areas in the search for migratory prey (see also Blades 1999; Féblot-Augustins 1997a, 1997b, 1997c; Rensink et al. 1991). This inference implies extensive depth of planning in landscape use.

A final family of models focuses in greater detail on the decay-like relationship between the quantities of specific stone raw materials found in an assemblage and the distance from the sources of those materials. In general, the closest stone raw material sources contribute the greatest quantities to an assemblage (60–80 percent from sources <5 km away), while the most distant sources contribute diminishingly small quantities (1–2 percent from sources >20 km away) (Féblot-Augustins 1993; Geneste 1988). In Central Europe, Middle Paleolithic assemblages show a dramatic decline in the percentage frequency of stone materials from sources beyond 50 km from the site (Figure 3). At Kulna (Layer 11), a Moravian Middle Paleolithic cave site, 87 percent of the assemblage is com-



**Figure 2.** Frequency histograms of raw material transfer distances for Middle Paleolithic assemblages in (a) Central Europe and (b) the Aquitaine Basin. High frequencies of short-distance transfers (A) are interpreted in terms of optimization of time and energy costs associated with raw material procurement. Internal modes (B) are interpreted in terms of logistical or seasonal use of distant ecological patches. Raw material transfers from very distant sources (C) are thought to mark the maximum extent of the geographic range of the populations in question. Data from Féblot-Augustins (1993).

prised of materials from sources within 15 km of the site, while .7 percent (*n* specimens = 12) are from a source 230 km away (Féblot-Augustins 1993:Table 4). This general pattern is thought to reflect optimization of the time and energy trade-offs inherent in the procurement of stone raw materials from geographically adjacent *vs.* geographically distant sources (Féblot-Augustins 1993:220; Gamble 1999:88; see Metcalfe and Barlow 1992). As an extension of this decay-like pattern, the tendency for materials from distant sources to be introduced to sites as small, heavily reduced



**Figure 3.** Percentage frequencies of specific stone raw material types in Middle Paleolithic assemblages from Central Europe as a function of distance from source. A general contrast between (A) high quantities of minimally reduced materials from nearby sources and (B) low quantities of heavily reduced materials from distant sources is thought to reflect time-energy optimization, depth of planning in raw material acquisition, and formal technological strategies that minimize the risk of technological failure. Data from Féblot-Augustins (1993).

technological forms—representing the end stages of lithic reduction sequences as opposed to early-stage unmodified blocks or minimally utilized cores—is thought to signal depth of planning and formal risk management strategies (Geneste 1989). In particular, technologies are expected to be formally designed from the outset to be small, light weight, and resistant to failure if they are to be transported over long distances (Beck et al. 2002; Kuhn 1994; Nelson 1991; Torrence 1989). According to Geneste (1989:80), these archaeological patterns diagnose real behavioral adaptations and dynamic economic strategies.

Here I would like to introduce the possibility that much of the variation in the representation of stone raw materials, both within and between lithic assemblages, could be of no functional or adaptive significance whatsoever. Ultimately, our ability to determine whether adaptive variability is (or is not) measured by lithic assemblage variability is dependent upon having a null model for what assemblage variability should look like under completely neutral assumptions. With this goal in mind, I develop an agent-based model involving a forager engaged in a random walk in a uniform food-resource environment. Different stone raw material types occur at equal densities, but are distributed randomly in the environment. Simulated raw material procure-

ment, consumption, and discard are independent of raw material type designations and therefore comprise an unbiased stone raw material procurement strategy. The model provides a baseline for comparison where we can be certain that adaptation is *not* responsible for observed patterns in raw material richness, transport distances, and both quantity-distance and reduction intensity-distance relationships (see Gotelli and Graves 1996:6).

### Elements of a Neutral Model

The core premise of any neutral model is that all *same-level* components of a system are equivalent both in terms of their innate behaviors and the impact that the environment has on the expression of those behaviors (Bell 2001; Gotelli and Graves 1996). It is uncontroversial to note that some genetic systems are accurately described by neutral dynamics, that nucleotide or gene sequences change in a stochastic manner because all *same-level* components (i.e., nucleotides or genes), exposed to the same environment, have equal probabilities of undergoing mutation or experiencing sampling drift (Kimura 1983). Indeed, geneticists now rarely object to the notion that natural selection—a non-stochastic evolutionary force—sometimes does not distinguish between purines and pyrimidines, or between one allele and its alternatives, despite the fact that these differences are empirically verifiable and are sometimes evolutionarily salient.

By contrast, neutral models of community ecology have been received with much greater skepticism (Abrams 2001; Bell 2001; Gotelli and Graves 1996). In the most extreme “per capita” neutral models (e.g., Hubbell 2001), individual organisms are posited to have equivalent demographic properties—probabilities of birth, death, and migration—regardless of species affiliation. This is a controversial starting point in that it dispenses with all assumptions about the unique functional or adaptive characteristics of clearly defined species and places the root cause of community ecological dynamics in the hands of purely stochastic mechanisms operating at the level of the individual. However astonishing this may seem, such extreme neutral assumptions provide reasonably accurate descriptions of some universal patterns seen in ecological communities such as species-area and range-abundance relationships (Bell 2001;

Hubbell 2001). Such models thus call into question the ultimate role of ecological assembly rules—especially interspecific competition—in establishing and maintaining community-level ecological diversity (Connell 1980; MacArthur and Levins 1967; Roughgarden 1983; Schoener 1983; Weiher and Keddy 1999).

A neutral model of lithic technological organization based on similar first principles offers a radical point of departure from traditional approaches (but see Neiman [1995] and Shennan and Wilkinson [2001] for related discussions of “cultural drift”). The neutral model of stone raw material procurement developed here jettisons the assumption that differences between stone raw materials necessarily influence both procurement decisions and how stone toolkits are maintained and materials ultimately discarded. The alternative, neutral starting point is to assume that all stone raw materials are equivalent on a *per unit* basis. For example, each unit weight of raw material, regardless of whether we classify it as chert, obsidian, or quartzite, is assumed to be equivalent in terms of probabilities of procurement, consumption, and discard. The dynamics of stone procurement, use, and discard in this neutral framework are therefore independent of how we might label raw material types and any unique functional qualities we might attribute to them.

It is pertinent to ask whether the patterns of raw material diversity observed in the archaeological record are consistent with procurement strategies modeled using such extreme neutral assumptions. If they are consistent, then we must confront the difficult possibility that empirically observable features of the archaeological record such as raw material richness and transport distances may not be telling us much of anything about optimization of procurement behaviors, depth of planning, risk management strategies, and, ultimately, adaptive variability. Of course, one may reject the neutral model if observed archaeological patterns are found to be inconsistent with its expectations. Interpretations linking patterns of raw material diversity to specialized behavioral adaptations would be more robust as a result.

### Modeling Stone Raw Material Procurement

The neutral agent-based model of stone raw material procurement developed here assumes that (1)

the foraging environment is uniform with respect to food resources (i.e., it is a single-resource megapatch); (2) stone raw materials occur as point sources distributed randomly within the environment and each point source is arbitrarily labeled as a unique raw material type; (3) foragers follow a “random walk” foraging path; (4) each forager has a “mobile toolkit” of fixed size (i.e., a forager can carry a maximum amount of stone material); (5) if a material source is encountered, raw material is collected contingent upon the amount of empty space there is in the toolkit; and (6) if the mobile toolkit contains raw material, then a fixed amount is selected at random with respect to raw material type, consumed and discarded from the mobile toolkit.

Assumptions 1 and 3 ensure *mobility-neutral* foraging patterns. A random walk through a uniform environment is neither logistical nor residential (*sensu* Binford 1980). More technically, a random walk does not seek to optimize any specific currency associated with movement, involves no depth of planning in that all move directions are equally likely, and is risk insensitive in that the results of previous move decisions have no impact on the probability of the next move direction. Assumption 2 ensures *source-neutrality* in that all raw material sources occur at equal densities and are randomly distributed in the environment. In other words, there are no abundance biases or non-random spatial clusters of individual raw material types. Moreover, the random-walk foraging strategy employed by the forager ensures that each raw material source has, in the limit, a probability equal to one of being encountered and that each unique source ultimately will be encountered an equal number of times. Assumptions 5 and 6 are *unit raw material-neutral*. Assumption 5 ensures that all raw materials have an equal probability of procurement when encountered. Since all raw materials are alike, save for an arbitrary label, they are necessarily collected if there is empty space in the mobile toolkit (assumption 4). Once raw materials have been procured from a source, assumption 6 ensures that each unit of material in the toolkit has a probability of being consumed and discarded dependent *only* upon its relative frequency in the toolkit.

#### Technical Meanderings

The simulation is based on the RePast agent-based

modeling platform (<http://repast.sourceforge.net>). The simulated “world” consists of a two-dimensional grid (500 x 500 cells) that holds all of the raw material sources and a single forager engaged in a random walk through the environment. Each grid cell is assumed to contain a uniform, infinite food supply, ensuring that there are no patch choice decisions to be made in forager movement (see below). The world can contain a variable number of raw material sources (Figure 4). In most simulations, the world is seeded with 5,000 point sources of stone raw material and each of these sources is arbitrarily assigned a unique type label  $i = 1, 2, \dots, 5,000$ . The coordinate location of each raw material source on the grid is chosen at random from a uniform distribution  $(x, y) = [1, 500]$ , without replacement. There are 250,000 cells that could potentially hold a unique raw material source. The probability that any one cell contains stone raw material is approximately .02 (i.e., 5,000 sources / 250,000 cells) and, since each point source represents an arbitrarily unique raw material type, the probability that any one cell contains a specific raw material type is approximately  $4.0 \times 10^{-6}$  (i.e., 1 type / 250,000 cells). Alternatively, these numbers may be thought of as the environmental densities of all stone raw materials and specific raw material types, respectively.

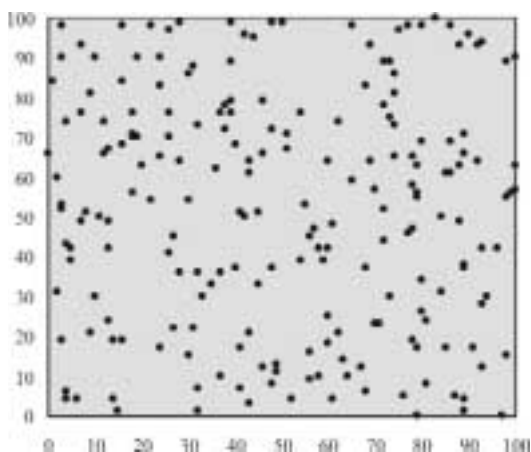


Figure 4. A snapshot of a 100-x-100 cell area of the simulation world (total size 500 x 500 cells) showing the random distribution of raw material sources in the environment. The mean distance between nearest neighboring raw material sources is 3.72 grid cells (standard deviation = 1.85 cells; minimum = 1.0 cells; maximum = 8.25 cells). The entire simulated world contained 5,000 raw material sources each arbitrarily assigned a unique type label.

The initial coordinate position of the single forager in the environment is chosen in a manner similar to the positioning of raw material sources, namely from a uniform distribution  $(x, y) = [1, 500]$ . At each time step, the forager moves to one of the nearest eight neighboring cells (i.e., the Moore neighborhood) or stays in the present cell, with equal probability ( $p = 1/9$ ). This movement rule defines a random walk wherein there are no first- or higher-order correlations in move directions (Turchin 1998:78).

When a raw material source is encountered, the forager evaluates the present size of the mobile toolkit and collects only as much raw material as is necessary to provision the toolkit up to the maximum size. The mobile toolkit is simulated as a vector  $v_i$  where each element represents the amount of stone raw material in the toolkit of unique type  $i$ . In most simulations, the maximum amount of material that can be carried in the mobile toolkit is arbitrarily set at 100 units. Accordingly, the mobile toolkit must always meet the constraint:

$$\sum_i v_i \leq 100 \tag{1}$$

The amount of raw material procured when a source of type  $i$  is encountered is given by:

$$a_i = 100 - \sum_i v_i \tag{2}$$

The theoretical maximum richness  $k_{max}$  of the mobile toolkit is simply the maximum toolkit capacity. In the baseline case, the mobile toolkit is maximally rich when each unique material type is represented by only one unit and the left side of equation (1) sums to 100. The mobile toolkit is minimally rich when only one raw material type  $i$  is represented, regardless of the sum from equation (1).

At each time step, a fixed amount of raw material from the mobile toolkit is consumed, even if the forager has not moved from its current position and provided that the toolkit is not empty. In all simulations, the consumption rate  $r$  is fixed at one unit of material per time step. Importantly, each material type  $i$  is consumed with a probability dependent *only* upon its relative frequency within the mobile toolkit:

$$c_i = \frac{v_i}{\sum_i v_i} \tag{3}$$

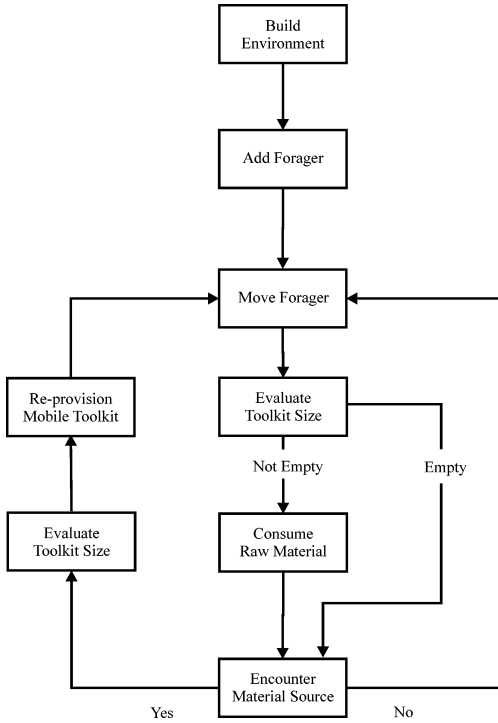
where  $c_i$  is the probability that a material of type  $i$  is consumed at a single time step. If all materials are equally represented in the toolkit, then they will each have an equal probability of being consumed in the next time step. This is an important observation because it ensures that the type  $i$  of raw material does not influence the probability of consumption. For example, if there are five raw material types equally represented by one unit in the mobile toolkit, then there are equal probabilities  $c_i = .2$  (or  $c_i = 1/5$ ) that type  $i$  is consumed. Alternatively, if type  $i = 1$  in the mobile toolkit is represented by 10 units and the remaining four types each by one unit, then the probabilities of consumption shift to  $c_1 = 10/14$  and  $c_{1-4} = 1/14$ , respectively.

Each unit of raw material consumed is immediately discarded from the mobile toolkit. Because the choice of material to consume is independent of raw material type, discard is similarly independent of raw material type. This is a critical point to recognize since any archaeological evaluations of the model developed here are dependent on a clear understanding of the mechanism by which stone raw materials become part of the archaeological record. Substantial effort has been invested in modeling the discard process (e.g., Schiffer 1987; Shott 1989; Varien and Potter 1997), and there is much to recommend these models. In the spirit of the neutral approach taken here, however, discard is considered simply to be a random sampling mechanism that operates on the mobile toolkit independent of raw material type designations. Individual archaeological assemblages may be treated as repeated random samples of different sizes from the mobile toolkit. In the aggregate, multiple archaeological assemblages should provide a reasonably complete picture of stone raw material procurement dynamics.

Figure 5 presents a schematic diagram of the structural and dynamic components of the simulation, and Table 1 lists the variables and parameter settings that define the baseline model. In all cases, the simulation is allowed to run until either 200 unique sources have been encountered, or the forager reaches the “edge” of the simulation world.

### Simulation Results

The simulation seeks to establish a set of neutral expectations for trends in stone raw material representation within the mobile toolkit. Baseline data

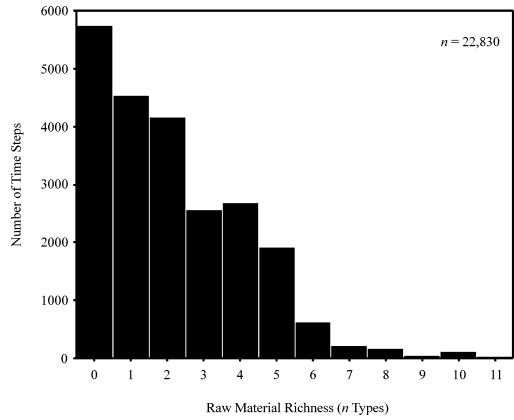


**Figure 5.** Structural and dynamic components of a neutral model of stone raw material procurement. Building the simulation environment entails defining the size of the simulation world and adding a fixed number of unique raw material sources. A single forager with a mobile toolkit of fixed maximum capacity is then added to the environment. At each time step, the forager moves to one of the eight nearest neighbors, or remains in its current location, with equal probability, and a fixed amount of raw material is consumed dependent only upon its frequency in the mobile toolkit. If a raw material source is encountered, the toolkit is replenished up to its maximum capacity before moving again at random. If no raw material source is encountered, the forager moves immediately at random. Simulations are run until 200 unique raw material sources are encountered, or the edge of the simulation world is reached.

are generated on raw material richness, quantities of unique raw material types, and transport distances for unique raw material types contained in the mobile toolkit. These data combine to provide additional expectations for the relationship between the quantity of a material in the toolkit and the distance from its source and the intensity of raw material reduction as a function of distance from source.

*Raw Material Richness*

The simulated mobile toolkit spends variable periods of time in different richness states (Figure 6).



**Figure 6.** Frequency histogram showing mobile toolkit richness for one complete simulation run of 22,830 time steps. These simulation results provide empirical probabilities of observing a given raw material richness within the mobile toolkit. In this representative simulation run the mobile toolkit contained no raw material approximately 25 percent of the simulation time, between one and four unique raw material types 61.1 percent of the time, and five or more types only 13.7 percent of the time. On average, one would expect to see different richness states in roughly those proportions. Model parameters: world size = 500 x 500; number of unique sources = 5,000; mobile toolkit size = 100; consumption rate = 1.

Most often the toolkit contains few raw material types, 25 percent of the time containing no material at all. Occasionally the toolkit sustains richness levels of more than 10 unique types. Ten separate simulation runs using baseline parameters establish a median raw material richness within the mobile toolkit of two unique material types and maximum raw material richness of 11 unique types. These values are not significant in any global sense, though the general shape of the distribution may be (see Hayek and Buzas 1997; Hubbell 2001). What is interesting, however, is that richness levels are always very low relative to the theoretical maximum, determined by the size of the mobile toolkit (equation [1] above). In Figure 6, the simulated maximum richness is only 11 percent of the theoretical maximum of 100 unique types.

The proportion of time spent in various richness states and the observed maximum richness of the mobile toolkit are dependent on the density of raw materials in the environment, the maximum capacity of the mobile toolkit, and the raw material consumption rate. A few analytical steps are required to explicate these constraints.

Consider first the number of time steps *N* it takes



Table 1. Variables and Baseline Parameter Settings.

Variable description	Variable	Units	Baseline Parameter Setting/Range
Simulated world size in $X$ dimension	$X$	grid cells	500
Simulated world size in $Y$ dimension	$Y$	grid cells	500
$x$ -coordinate position of raw material/forager	$x$	grid cells	random from uniform = [1, 500]
$y$ -coordinate position of raw material/forager	$y$	grid cells	random from uniform = [1, 500]
Number of unique raw material sources	$n$	sources	5,000
Raw material type label	$i$		1, 2, ... 5,000
Quantity of material from source $i$ in mobile toolkit	$v_i$	arbitrary units	minimum = 0; maximum = 100
Total material of all types in mobile toolkit; maximum toolkit capacity	$\sum v_i$	arbitrary units	minimum = 0; maximum = 100
Amount of material collected from source $i$	$a_i$	arbitrary units	minimum = 1; maximum = 100
Probability of consuming material of type $i$ in mobile toolkit	$c_i$		[0.0, 1.0]
An observed number of simulation time steps	$N$	time steps	
Estimated distance traveled in $N$ time steps; effective foraging radius	$d$	grid cells	minimum = 0; maximum = 707
Maximum forager move length at each time step	$l$	grid cells	1
Raw material consumption rate	$r$	arbitrary units / time step	1
Raw material richness in mobile toolkit	$k$	number of types	minimum = 0; maximum = 100
Quantity of material discarded in making room for newly procured material	$q_i$	arbitrary units	minimum = 1; maximum = 100
Most abundant material in the mobile toolkit at a given time step	$\max\{v_i\}$	arbitrary units	minimum = 1; maximum = 100

to get from one raw material source to the next randomly encountered raw material source. This is approximately:

$$N \cong \left(\frac{d}{l}\right)^2 \tag{4}$$

where  $d$  is the distance between the two sources and  $l$  is the move length at each time step (see Denny and Gaines 2002:110–114).<sup>1</sup> When  $l$  is unity, the number of time steps it takes to travel a given distance  $d$  is approximately the square of the distance. Remembering that a fixed amount of material is consumed at each time step, it is possible also to establish the relationship:

$$N = \frac{\sum v_i}{r}, \quad r > 0 \tag{5}$$

where the sum of  $v_i$  is the total amount of raw material in the mobile toolkit at a given point in time and  $r$  is the consumption rate. Equation (5) defines the toolkit “clearing rate,” the number of time steps it takes to consume all of the raw material presently in the mobile toolkit at a consumption rate  $r$ .

Substituting into equation (4) and rearranging yields:

$$d \cong l \sqrt{\frac{\sum v_i}{r}} \tag{6}$$

Equation (6) states that the distance that can be traveled before all materials in the mobile toolkit are consumed is approximately the square root of the present toolkit size divided by the consumption rate, assuming again that the step length  $l$  is unity. With a consumption rate of one unit of material per time step, the distance that can be traveled before the toolkit is “cleared” is simply the square root of the amount of material in the toolkit: a toolkit filled to a maximum capacity of 100 units would be “cleared” of all materials by the time the forager had traveled approximately  $d = 10$  cells from the current position, provided no other material sources were encountered along the foraging path. The foraging area around a raw material source that can be effectively exploited with material from that source is thus defined by radius  $d$ .

Additional material sources encountered before the toolkit is “cleared” increase mobile toolkit richness. Maximum toolkit richness can be estimated empirically from the maximum number of unique sources that might be found within a foraging area of radius  $d = 10$ . Table 2 lists the minimum nearest neighbor distances between raw material sources for two simulated worlds with different global raw material densities.<sup>2</sup> Minimum nearest neighbor distances are calculated by measuring, for each source, the distance to all  $n - 1$  other sources in the environment and then selecting the

Table 2. Minimum Nearest Neighbor Distances between Raw Material Sources and Predicted Maximum Toolkit Richness for Two Simulated Environments.

	5,000 Unique Sources minimum distance to source (grid cells)	3000 Unique Sources minimum distance to source (grid cells)
Nearest source rank 1	<b>1.00</b>	<b>1.00</b>
Nearest source rank 2	<b>1.00</b>	<b>3.00</b>
Nearest source rank 3	<b>2.24</b>	<b>4.24</b>
Nearest source rank 4	<b>3.61</b>	<b>6.08</b>
Nearest source rank 5	<b>4.47</b>	<b>6.40</b>
Nearest source rank 6	<b>6.40</b>	<b>8.49</b>
Nearest source rank 7	<b>7.07</b>	<b>9.22</b>
Nearest source rank 8	<b>7.07</b>	11.18
Nearest source rank 9	<b>7.81</b>	12.04
Nearest source rank 10	<b>8.00</b>	12.73
Nearest source rank 11	<b>9.22</b>	14.21
Nearest source rank 12	10.20	14.56
Nearest source rank 13	10.82	16.03
Nearest source rank 14	11.18	17.49
Nearest source rank 15	11.31	18.25
Nearest source rank 16	12.53	19.03
Nearest source rank 17	13.00	19.31
Nearest source rank 18	13.34	19.92
Nearest source rank 19	13.60	21.02
Nearest source rank 20	14.14	21.21
Nearest source rank 21	14.32	22.02
Nearest source rank 22	15.52	22.67
Predicted maximum tool kit richness	11	7
Observed maximum toolkit richness	11 <sup>a</sup>	6 <sup>b</sup>
Average distance to a neighbor within the foraging area	5.69	5.49

Note: Toolkit size is 100 and  $d = 10$  in both cases; boldface numbers mark the minimum nearest neighbors that fall within the effective foraging radius  $d$ .

<sup>a</sup>Ten separate simulation runs.

<sup>b</sup>Five separate simulation runs.

observed minima for the population of sources overall. Two sources chosen at random from the environment, for example, each have nearest neighbors of rank 1, 2, 3 . . . 5,000. The corresponding distances to neighbors of each rank may be, hypothetically, 1.0, 1.25, 4.3 . . . 698, and 1.2, 1.3, 2.6 . . . 687 grid cells for each source, respectively. In this hypothetical case, the first- and second-order minimum nearest neighbors are defined on the basis of source 1, while the third and 5,000th nearest neighbors are defined on the basis of source 2. This process yields the set of minimum nearest neighbors 1.0, 1.25, 2.6 . . . 687, which subsequently defines the maximum possible packing of resources into a local foraging area. When the simulated world contains 5,000 unique sources—a global density of .02 sources/grid cell—the set of minimum nearest neighbors will on average include 11 sources within the boundaries of a foraging area of

radius  $d = 10$ . With a total of 3,000 sources—.012 sources/grid cell—on average there are seven unique sources within a foraging area of radius  $d = 10$  (Table 2). These sets provide reasonable estimates of maximum attainable raw material richness under different raw material density conditions.

In general, increasing the global density of raw materials in the environment, which increases probabilistically the maximum number of materials found in a foraging area of radius  $d$ , will also increase the maximum attainable richness for the mobile toolkit. Similarly, increasing maximum toolkit capacity, leaving both the environmental density of resources and raw material consumption rate unchanged, effectively increases the foraging radius  $d$ . For example, from equation (6), doubling the maximum capacity of the mobile toolkit to 200 units of material increases the foraging radius  $d$  to 14.1 grid cells. This expands the area over which

Table 3. Procured Raw Material Package Sizes and Expected Consumption Rates.

Toolkit Richness	Number of Occurrences	Package Size Procured (Arbitrary Units)			
		Mean	Std. Deviation	Minimum	Maximum
1	160	63.6	45.1	2	100
2	104	30.3	29.0	2	95
3	93	29.7	30.0	2	95
4	49	26.6	25.8	2	95
5	54	14.9	18.6	2	70
6	18	20.8	19.2	3	66
7	3	6.7	4.7	3	12
Total	481	38.7	38.5	2	100
		Expected Amount Remaining At Distance $d^a$			
		$d = 10$	$d = 20$	$d = 30$	$d = 40$
		20.7	9.0	3.9	1.7

Note: Data are for one simulation run using baseline parameters.

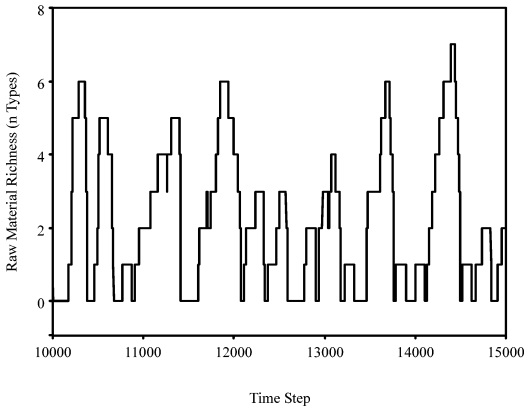
<sup>a</sup>Expected amount (arbitrary units) calculated from the equation  $y = 47.726e^{-0.0834x}$  given in Figure 11.

raw material sources may be encountered and concomitantly increases the maximum attainable toolkit richness. Using Table 2, maximum attainable richness increases to  $k_{max} = 19$  in the case of 5,000 unique sources in the environment and  $k_{max} = 10$  in the case of 3,000 unique sources. Finally, increasing the consumption rate  $r$  reduces the effective size of the mobile toolkit and therefore lowers the maximum attainable toolkit richness.

Note that there is a tradeoff between toolkit richness and the amount of time spent at a richness state. From equation (5),  $N = \max[v_i]/r$  is the amount of time it takes to “clear” the most abundant material type from the mobile toolkit. The dynamic behavior of the mobile toolkit is similar to a zero-sum game (see Hubbell 2001; MacArthur 1960). When all of the most abundant material is consumed, the richness state of the toolkit will decrease by 1. If the toolkit is completely full (i.e.,  $\sum v_i = 100$ ), any increase in richness of the toolkit—from  $k$  to  $k+1$ —must be accompanied by a decrease  $q_i$  in a quantity of material already in the toolkit. The most abundant material type in the toolkit is usually the one that must yield space since the probability of consuming a material type is dependent only upon its frequency in the toolkit (equation [3] above). The estimated time spent at the new richness state  $N$  is necessarily lower since  $\max[v_i - q_i] < \max[v_i]$ . Consider the situation where the mobile toolkit is completely full and contains only one raw material type (i.e.,  $\sum v_i = 100$ ,  $k = 1$ ). The expected amount of time spent at this richness state is  $N_{k=1} = \max[v_i] = 100$ . To accommodate exactly one unit of a new

raw material, the material already in the toolkit must be reduced by at least one unit (e.g.,  $q_i = 1$ ). Consequently, the expected time spent at the new richness state is reduced relative to the original richness state by a finite amount  $N_{k=2} = \max[v_i - q_i] = 99$ . If it were possible to encounter 100 unique raw material sources within a foraging area of radius  $d = 10$ , then a richness state  $k = 100$  would require  $\max[v_i] = 1$  for all raw material types in the toolkit. If no further raw material sources were encountered after time step 100, then the expected time at each richness state would be exactly  $N_{k=100} = N_{k=99} \dots = N_{k=1} = 1$ . Thus, the probability of observing a given richness state within the mobile toolkit decreases as richness increases (Figure 6; see also Table 3).

It is also important to note that the probability of observing a given richness state is not distributed evenly in time or space, but is dependent on the local environmental distribution of raw material sources (Figure 7). Rapid increases in toolkit richness will occur only in those local environments where the number of stone sources is high; where the local set of nearest neighbors approaches the minimum set. Random walk paths carrying the forager away from these local clusters of raw material sources rapidly decrease toolkit richness. While Table 2 illustrates that it is possible to predict global maximum toolkit richness simply on the basis of the density of stone raw material in the local environment, and given additional assumptions about maximum toolkit capacity and raw material consumption rate, individual observations of the



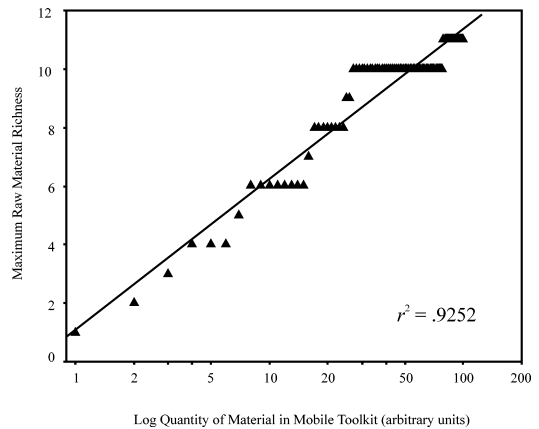
**Figure 7.** Time series showing changes in raw material richness within the mobile toolkit of a single forager. Data represent observations over 5,000 time steps from a simulation run lasting 24,294 time steps. Model parameters: world size = 500 x 500; number of unique sources = 5,000; mobile toolkit size = 100; consumption rate = 1.

mobile toolkit in space and time may deviate substantially from these expectations.

Finally, maximum toolkit richness increases systematically with the log of the amount of material in the toolkit (i.e., sample size) (Figure 8). When the mobile toolkit contains low quantities of material, the limit on richness is trivial; it is only possible to have one unique raw material type if there is only one unit of raw material in the toolkit. This trivial limit appears to hold up through four units of raw material. When the mobile toolkit contains greater than four units of material, however, maximum richness increases at a much slower rate than the amount of transported raw material. Above this level, the environmental density of raw materials, combined with the constraints of toolkit size and consumption rate, is increasingly responsible for determining maximum toolkit richness: in theory it is possible to have 100 different stone sources packed into a foraging area of radius  $d = 10$ , but in practice this never occurs. In the base model, the maximum richness value of 11 unique types is observed only when the mobile toolkit is filled to near its maximum capacity. Note also that this sample size–richness relationship emerges in spite of the equal densities of different raw material types in the environment.

#### *Transport Distance*

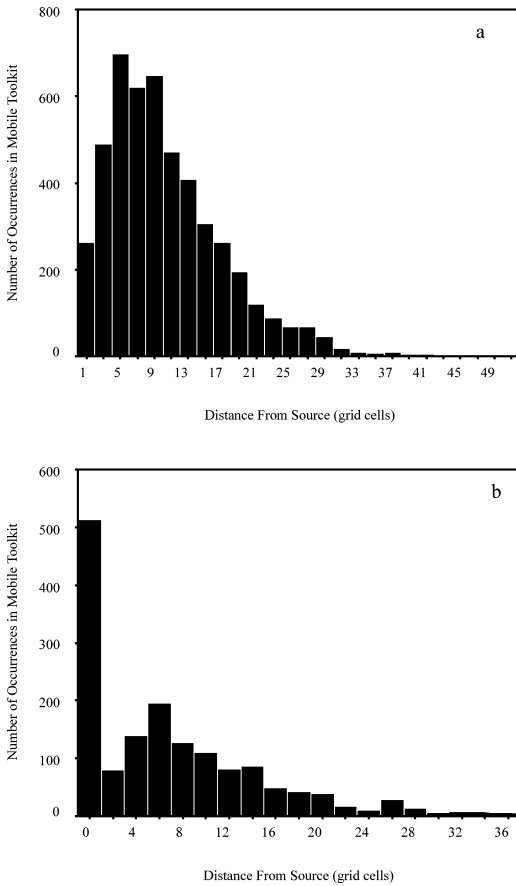
At each time step in a simulation, it is possible to evaluate how far the forager is from the procure-



**Figure 8.** Maximum raw material richness (number of types) is strongly correlated with the log of the quantity of material in the mobile toolkit. Model parameters: world size = 500 x 500; number of unique sources = 5,000; mobile toolkit size = 100; consumption rate = 1.

ment point for each unique raw material type present in the mobile toolkit. This procedure provides an effective measure of how far a raw material type has been transported from its source. Figure 9 presents frequency histograms of distances from source for materials in the mobile toolkit measured in two different spatial contexts. Figure 9a shows a random sample of approximately 10 percent of all raw material occurrences in the mobile toolkit for one simulation run lasting 24,294 time steps. Represented are the number of time steps in which a material present in the mobile toolkit is found a specified number of grid cells from the point source, regardless of whether the forager is presently at a source of material. Figure 9b, in contrast, shows the distance from source for materials in the mobile toolkit observed only at the points of encounter with raw material sources. The two spatial contexts display some interesting similarities.

When observations of the mobile toolkit are made independent of spatial location, the frequency distribution of distances displays an “internal mode” with a long right skew (Figure 9a). The internal mode indicates that the mobile toolkit most often contains material types from sources in relatively close proximity to the spatial location where the toolkit is observed. The median transport distance (9 cells) represents 1.2 percent of the maximum possible linear distance between two sources, the diagonal distance of 707 grid cells across the simulation world. The modal transport distance (5



**Figure 9.** Frequency histograms of the distance from source for stone raw materials occurring in the mobile toolkit. (a) Distance from source measured at points both at and away from raw material sources. Data represent approximately 10 percent sample of the total number of raw material occurrences in the mobile toolkit from a simulation run lasting 24,294 time steps. (b) Distance from source for stone raw materials occurring in the mobile toolkit measured at encounters with raw material sources. There were a total of 513 separate encounters with raw material sources over the entire simulation run lasting 24,294 time steps. Model parameters: world size = 500 x 500; number of unique sources = 5,000; mobile toolkit size = 100; consumption rate = 1.

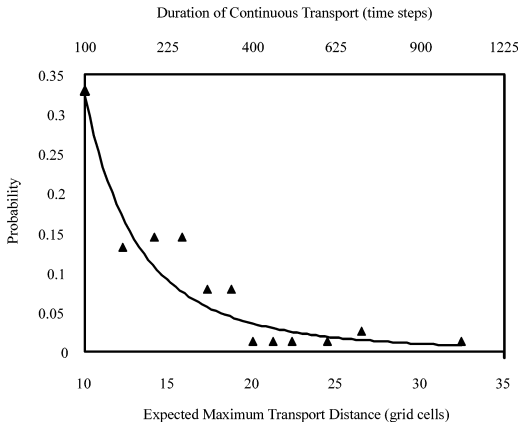
cells) represents only .7 percent of the maximum. The median and mode are influenced, respectively, by distance to the edge of the foraging area, given by radius  $d$ , and the average expected distance to neighboring raw material sources *within* the foraging area, which is approximately  $d/2$  (see Table 2). The median and modal transport distances do not change appreciably with different environmental raw material densities. Rather, as raw material density decreases toward zero, the distribution

loses its right skew and clusters more tightly around the interval  $[d/2, d]$ .

Observing the mobile toolkit only at the spatial locations where a raw material source is encountered predictably inflates the observed number of occurrences where the distance from source is equal to zero (Figure 9b). This is a trivial outcome determined by the spatial bias in the sample of observations. What is perhaps more interesting is that the internal mode is still evident even when the forager is at raw material sources. Moreover, the mode is in approximately the same location; as above, this is approximately the interval  $[d/2, d]$ .

Raw materials are also transported over distances much greater than the radius of the local foraging area. For the baseline parameters used here, the maximum transport distance (43 grid cells) is approximately a factor of four greater than the foraging area radius  $d = 10$ . To see why, consider what happens following an encounter with a raw material source where the forager collects 100 units of material. At this point, the forager is guaranteed at least 100 time steps of movement. This allows the forager to move an average distance of approximately 10 grid cells (see equations [4]–[6]). If no additional raw material sources are encountered in the foraging area, then the maximum distance of raw material transport would be approximately  $d = 10$  grid cells. If, on the other hand, additional raw material sources are encountered before 100 time steps have passed from the initial procurement event, then transport distances can be extended greatly beyond the standard foraging radius.

Consider again the situation where a forager encounters a raw material source and procures 100 units of raw material. Imagine that the forager then moves for 99 time steps, or a distance of approximately 9.95 grid cells, before encountering a second source. Encountering the second source “rescues” the mobile toolkit from being cleared for at least 100 more time steps. There is thus a finite probability that the one unit of material remaining in the toolkit from the first source will be transported over another 100 time steps, giving a cumulative transport distance of 19.95 grid cells from source. This distance may increase to approximately 30 grid cells from source if a third source is encountered just before the next 100 time steps have elapsed. However, the probability that at least one raw material source is encountered every 100



**Figure 10.** The probability that a stone raw material will be transported at least a distance  $d$  is a negative exponential function of the distance from the source. Most materials procured have a relatively high probability ( $p = .33$ ) of being transported approximately 10 grid cells from their point of procurement. This probability drops to  $p = .14$  for distances of around 15 grid cells. The probability that a material is transported greater than 30 grid cells from source falls below .02. Transport distances are estimated using the relationship  $N \approx d^2$  from observed durations of continuous raw material transport. Note that the scale for plotting the duration of continuous transport is the square of the transport distance and is therefore nonlinear in this figure.

time steps, and thus the probability that the mobile toolkit will continuously hold raw material beyond each block of 100 time steps, declines rapidly (Figure 10).

At the environmental density of materials, toolkit size and consumption rate specified in the base model, it is quite common for the toolkit to contain some amount of material continuously for 200, 300, or even 400 sequential time steps. Using these simulated results and the relationship  $N \approx d^2$ , we should expect raw materials frequently to be transported distances between 14 and 20 grid cells from source, or 1.4 to 2 times the standard foraging radius  $d = 10$  grid cells (Figure 10). It is uncommon, however, for material to be continuously transported for more than 1,000 sequential time steps. The longest period of continuous raw material transport observed in the base model is 1,050 time steps, which leads to an estimated maximum transport distance of 32.4 grid cells. This analytical result is a reasonable approximation of the maximum transport distance of 43 grid cells observed in the stochastic, discrete time case.<sup>3</sup> In general, the neutral model predicts that maximum raw mater-

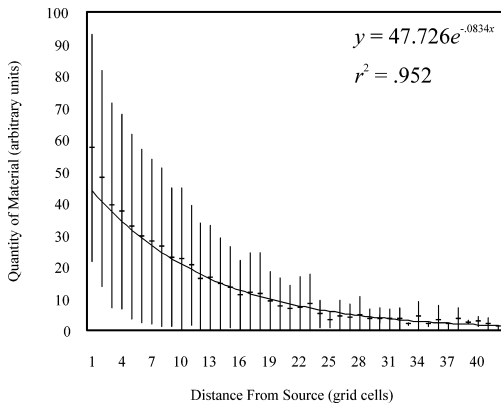
ial transport distances should be three to four times the foraging radius  $d$ . Of course, any modifications to the maximum capacity of the mobile toolkit, or the raw material consumption rate, necessarily change  $d$  and also the absolute maximum transport distance. Importantly, however, these “behavioral” modifications to the nature of the mobile toolkit do not alter the maximum transport distance *relative* to  $d$ .<sup>4</sup>

#### *Technology of Transported Materials*

The simulation also provides neutral expectations for the quantity and technological character of materials in the mobile toolkit transported from sources at different distances. Figure 11 illustrates that the quantity of material  $i$  in the mobile toolkit as a function of distance from the source of  $i$  follows an exponential decline of the form  $y = b \cdot e^{-ax}$ . Materials from the closest sources are usually represented in the greatest quantities, while those from the most distant sources are represented in the smallest quantities. Note, however, that variation around the mean increases with increasing proximity to the source of the material. Thus, materials from nearby sources are frequently procured and transported either both in high and low quantities. At greater distances from source, raw materials are more uniformly represented by low quantities.

The high variance in the quantities of materials transported over short distances stems from the influence that materials already in the toolkit have on the size of raw material packages procured. For example, if raw material sources are close to one another in space, then there is a high probability that the toolkit will be nearly full when a unique source is encountered. Because precedence is given to materials already in the toolkit—there is no discard of excess material—the quantity of material procured from the newly encountered source will be relatively low. If material sources are spaced far apart, however, then the mobile toolkit will be nearly or completely empty when a unique source is encountered. In this case, the size of the raw material package procured from the newly encountered source will approach maximum toolkit size.

The low variance in material quantities transported from distant sources reflects a different mechanism: materials transported from greater distances display the effects of repeated consumption events, dampening out any effect of initial package



**Figure 11.** The quantity of a material (mean  $\pm$  1 standard deviation) in the mobile toolkit is a negative exponential function of the distance from the raw material source. The reported equation is a least-squares fit to the mean values only. Data represent approximately a 10 percent sample of the total number of raw material occurrences in the mobile toolkit from a simulation run lasting 24,294 time steps, or the time necessary for the simulated forager to encounter 200 unique raw material types. Model parameters: world size = 500 x 500; number of unique sources = 5,000; mobile toolkit size = 100; consumption rate = 1.

size. In essence, raw materials transported from the most distant sources have been “at risk” for consumption the longest and therefore occur consistently in the smallest quantities within the mobile toolkit. Table 3 presents data on the sizes of raw material packages procured when the mobile toolkit is at different richness levels. Mean package size procured decreases as richness increases, illustrating that materials already in the mobile toolkit place certain limits on the amount of material that can be procured from a newly encountered source.

Table 3 also illustrates, as alluded to above, a fundamental relationship between distance from source and intensity of material consumption. Quantities of materials in the mobile toolkit from nearby sources generally have spent the least amount of time in the toolkit and have therefore been exposed to limited risk of consumption. Predictably, these materials are not intensively reduced. Risk of consumption increases with the amount of time a material type has spent in the mobile toolkit, which equations 4–6 show is directly related to raw material transport distance. Materials from more distant sources are thus predictably more intensively reduced. This pattern is independent of raw material type designations. For example, for a starting mobile toolkit of richness  $k$

= 1, the mean procured raw material package size is 63.6 units (Table 3). After traveling a distance of 10 grid cells, the expected remaining amount of material from that source is 20.7 units, representing consumption and discard of 60 percent of the material originally procured. By the time the forager has traveled 20 grid cells the remaining amount of material in the mobile toolkit is 9 units (70 percent consumed), and by 40 grid cells only 1.7 units remain (~97 percent consumed).

### Archaeological Parallels

Several important observations and predictions are derived from the neutral model developed above. First, raw material richness within the mobile toolkit should be expected to vary dynamically as a function of both spatial location and time, but in all cases richness is constrained to be much less than the maximum richness theoretically attainable. The signature of this process is a dependence of maximum toolkit richness on sample size. Remembering that all materials in the simulated environment occur at equal densities, it is clear that the biases in the representation of raw materials within the toolkit arise solely from a neutral, non-adaptive raw material procurement strategy. The fact that some materials present in the environment are never procured, others are only rarely procured, while a few are commonly procured need not imply raw material selectivity on the part of the forager.

Second, the frequency distribution of raw material transport distances displays an internal mode and a long right skew. Maximum transport distances are expected to be three to four times the distance represented by the internal mode. The ratio of the maximum to the modal raw material transport distance is largely unaffected by changes in mobile toolkit size, consumption rate, or the natural densities of raw materials in the environment. Maximum transport distances may translate into the “utilization range” of a given raw material type, but are equivocally related to the “geographic range” of the forager.

Finally, the quantity of material of a given type within the mobile toolkit generally follows an exponential decline with increasing distance from source. As an extension of this pattern, materials from the most distant sources are expected to be represented consistently (i.e., with low variance) in small quantities and be heavily reduced relative to

mean size of procured raw material packages. In contrast, materials from the closest sources are expected to display high variance in both the quantities represented and the intensity of reduction. In large part, these patterns may be explained as resulting from the “zero-sum” behavior of the mobile toolkit, which gives precedence to materials already procured over those newly encountered, and the length of time a material in the mobile toolkit has been exposed to risk of consumption. Neither optimization of raw material procurement strategies to minimize time and energy expended in finding and transporting stone, nor risk reduction strategies for managing the consumption of stone, play a role in the generation of these patterns.

Each of these above predictions finds direct parallels in the archaeological record. Here I return to the example cases discussed at the beginning of this paper but emphasize that I do not intend the following observations to be restricted to these cases (see below).

The Middle Paleolithic site of Grotte Vaufrey provides a familiar example of changes in raw material richness through time that are dependent on the sizes of the archaeological samples examined (Geneste 1988, 1989). Rather than indicating shifts between generalist and specialist raw-material procurement strategies, the data from Grotte Vaufrey suggest a single, remarkably stable set of procurement strategies persisting for perhaps 130,000 years. The primary question is whether this richness–sample size relationship can be distinguished from the neutral model expectations.

The neutral model anticipates the low observed richness relative to the environmental density of sources, as well as the temporal changes in raw material richness and the dependence of these changes on sample size (compare Figures 1a, 1b, 7, and 8). The model also suggests an alternative interpretation of the differences in raw material procurement probabilities seen at Grotte Vaufrey (Figure 1c). One may view the distribution in Figure 1c as specifying the probabilities that the mobile toolkit contains a given raw material type, and no other types, at the time of arrival at Grotte Vaufrey (i.e., richness  $k = 1$ ). Thus, the mobile toolkit would contain only material type MP2 with probability  $p = .43$ , and only MP7 with probability  $p = .0009$ . Although the simulated mobile toolkit spends the majority of its time dominated by only one raw

material type (see Figure 6), repeated samplings of the toolkit—yielding a large aggregate archaeological sample size—would nevertheless be necessary to detect those times the toolkit contained only MP7. Less-frequent sampling of the mobile toolkit—leading to a small archaeological sample size—would most often detect material types MP2 and MP1.

The neutral model reinforces the observation that the differences in raw material procurement probabilities at Grotte Vaufrey represent a bias introduced by hominid behavior. The question surrounds the nature of this behavioral bias. The neutral model indicates that biased procurement probabilities can arise out of the path dependence of a random walk. As a consequence, biased raw material representation at Grotte Vaufrey need not imply necessarily specialized procurement strategies keyed to raw material quality. More specifically, the neutral model suggests that, to arrive at a site with a single material type “in hand,” the forager must traverse the distance between source and site before the toolkit has “cleared” (see equation [6]). With increasing distance between source and site, the foraging path must become increasingly linear to meet this condition. In the base model, for example, the forager must follow a perfectly linear path to traverse the distance between a source and a site located 100 grid cells away. Any deviation from this path would ensure that the toolkit is cleared of material before arrival at the site. Given the mathematical properties of a random walk, the probability that the path chosen between two points is perfectly linear becomes infinitesimally small as the distance between the points increases.<sup>5</sup> In other words, the probability of path-dependent biases in raw material representation increases dramatically with increasing distance between sources.

The higher expected procurement probabilities for materials MP2 and MP1 at Grotte Vaufrey may reflect a situation where many different foraging paths were feasibly executed without danger of clearing the toolkit (i.e., low-path dependence). Indeed, both material sources are found in relative close proximity to the site (Geneste 1988). In contrast, the lower expected probabilities for procuring MP6, MP4, and MP7 may indicate that only a limited number of random walk paths would have allowed for successful transport of materials to the site before toolkit clearing (i.e., high-path depen-



dence). This argument would appear to hold for MP6 and MP7, which are both >40 km from the site, but may fail to explain the low expected procurement probability for MP4, which is substantially closer (Geneste 1988, 1989). As a first approximation, the differential representation of these materials may simply reflect different probabilities of finding viable (i.e., “pre-clearing”) random walk paths between sources and sites, and not necessarily raw material selectivity.<sup>6</sup>

Raw material transfers within the Middle Paleolithic of Central Europe and the Aquitaine Basin of France display distributions characterized by high frequencies of transfers from nearby sources, within the “local” portion of a foraging range, and a dramatic decline in the occurrence of transfers from greater distances. In the former region, but less so in the latter, there are also “internal modes” representing relatively high frequencies of transfers from sources beyond the “local” portion of the range (for individual Middle Paleolithic cases see Geneste [1989]; for individual Upper Paleolithic cases see Féblot-Augustins [1997a, 1997b, 1997c] and Morala and Turq [1990]). The longest distance transfers (230–300 km) within the Middle Paleolithic in Central Europe are between 4.6 and 6 times distance represented by the primary internal mode (50 km). The longest distance transfers within the Aquitaine Basin would be only twice this modal distance.

The neutral model generates frequency distributions displaying similar characteristics (compare Figures 2 and 9). In particular, when observations of the simulated mobile toolkit are spatially biased toward procurement points, there is a frequency peak at very low distances from source. There remains, however, an internal mode corresponding to raw material transfers from intermediate distances. The modeled maximum stone transfer distances in this case are between three and four times the distance represented by the internal mode. The neutral interpretation is that the spike in short-distance transfers is primarily a result of a spatial bias in the sample of sites toward those located at or near raw material sources. The “internal modes” define the effective foraging radius  $d$  around raw material sources: generally, how far a forager can travel in a random walk with material from a source. These “internal modes” are controlled by the clearing rate for the toolkit and need not imply special-

ized logistical or seasonal exploitation of patches. Finally, the archaeologically observed maximum transport distances in these cases are qualitatively similar to those predicted by the neutral model. It remains to be seen whether the quantitative differences between observed and predicted maximum transport distances are robust under further testing. As a first approximation, however, the similarity between the Middle Paleolithic data and the neutral model suggests that raw-material transfer distances of this order need not reflect optimization of stone procurement and transport. Moreover, there is no necessary reason to invoke social exchange to explain maximum transport distances in these instances.<sup>7</sup> More generally, it is not clear that maximum raw material transport distances translate in any direct way into geographic territory size.

Lastly, the Central European Middle Paleolithic also illustrates that materials from nearby sources are transferred in relatively large quantities, while materials from distant sources are transferred in small quantities (Féblot-Augustins 1993; Geneste 1988, 1989; but see Féblot-Augustins 1997c). Normally this pattern is paralleled by increasing reduction intensity (and/or design formality) with increasing distance from source. The neutral model similarly anticipates both of these empirical observations (compare Figures 3 and 11). Materials from nearby sources are usually transferred in large quantities, but with a high degree of variability, and these materials are usually minimally consumed relative to the initial quantities procured. In contrast, materials from distant sources are invariably found in small quantities and have been heavily consumed relative to initial raw material package sizes. The modeled relationship is accurately described by an exponential function of the form  $y = b * e^{-ax}$ . The neutral interpretation is that the quantity of material transferred is constrained by a fixed toolkit size, precedence given to materials already in the toolkit and a fixed consumption rate.<sup>8</sup> Similarly, reduction intensity may simply be a function of the length of time a material has spent in the mobile toolkit and thus degree of exposure to “consumption risk” (see Dibble 1995). Quantities of materials transferred and reduction intensity in this case are independent of specific raw material types and, because the mechanism driving toolkit dynamics is entirely stochastic, these patterns need not

imply any depth of planning, optimization, or risk-management strategies.

### Discussion

Many an ethnography—and common sense—tells us that foragers employ complex optimal foraging strategies (Binford 2001; Kelly 1995; Smith 1991). It is assumed that optimal foraging strategies must influence and, therefore, be diagnosed by stone raw material procurement patterns. The present model, however, is based on assumptions that foragers do not optimize any specific currency associated with movement, do not depend on any form of planning depth, and are risk insensitive in all of their movement and procurement decisions. Surprisingly, these extreme assumptions lead to patterns in raw material richness and transport that are qualitatively similar to commonly observed archaeological patterns. What should we conclude from these results?

There are at least two answers to this question. First, it is possible that the processes of archaeological site formation—especially time-averaging—may eradicate the fine details of discrete procurement events leaving a palimpsest of behavioral traces indistinguishable from the neutral model. In general, time-averaging occurs whenever events that happened at different points in time appear synchronous in the geological record (Kowalewski 1996). It influences our understanding of behavioral, ecological, or evolutionary processes whenever the sedimentation rate is slower than the time scale of the process in question (Bush et al. 2002; Kowalewski et al. 1998; Stern 1994). Stone procurement strategies were implemented on time scales of minutes to perhaps months, if seasonal planning was in play, while sedimentation is generally a much slower process. Moreover, geochronological controls rarely offer such fine-scale resolution. There is thus little question that time averaging will be a concern in interpreting most cases of stone raw material procurement and transport (but see Close 2000). It may be the case that discrete stone procurement events were highly adaptive in all of the ways suggested by current archaeological theory, but in some cases it may not be possible to distinguish the aggregate patterns of procurement behavior from the neutral alternative.

Second, it is conceivable—though perhaps unlikely in many environments (but see Branting-

ham et al. 2003; Brantingham et al. 2001; Turchin 1998)—that random-walk foraging and a raw-material procurement strategy that is indifferent to stone types could be optimal. The conclusion here would be that the *absence* of both planning depth and explicit risk management strategies would yield higher fitness than their more complex alternatives.

It is perhaps more likely that other aspects of foraging behavior were subject to optimization, depth of planning, and risk management in the ways suggested by contemporary archaeological theory, but that stone raw material procurement and transport were not, at least as reflected in the empirical measures discussed here.<sup>9</sup> Foraging strategies optimized with respect to mobile prey, or seasonally distributed plant resources, may be entirely stochastic with respect to raw material source encounters and raw material procurement. Moreover, whether or not stone procurement behaviors were optimized (or sensitive to risk) may have had little or no impact on the optimality of food procurement strategies. The conclusion here would be that a random-walk stone procurement strategy and indifference to stone raw material type may not entail the fitness penalties commonly assumed and, importantly, that the more complex alternatives may not necessarily yield higher payoffs. This is a logical extension of arguments suggesting that stone raw material procurement was completely embedded within other foraging activities (Binford 1979). Absent any direct fitness consequences, stone procurement and transport behaviors would be neutral with respect to selection and would be free to vary in a stochastic manner.

The present model, like many neutral models in community ecology (Gotelli and Graves 1996:5–6), raises questions about how we infer adaptation from empirical patterns. This said, there will be temptation for critics to reject the model outright by claiming that foragers “would” never engage in a random walk and “would” never make raw-material procurement decisions without considering raw material type. Similarly, motivated objections have been voiced over neutral models discounting the importance of interspecific competition in structuring ecological communities (see Connell 1980; Conner and Simberloff 1979; Roughgarden 1983; Simberloff 1983). In this latter case, conventional wisdom suggests that competition is *the* critical determinant of whether

species can coexist on given a limited resource (MacArthur and Levins 1967). Many researchers have rejected competition-free neutral models in community ecology only because they seemed to deny the unique behavioral and morphological characters considered adaptively important to, if not definitive of, biological species. That a neutral model contradicts orthodox theory, however, is not sufficient grounds for rejecting the model (Gotelli and Graves 1996:13).

A related criticism might concede that the neutral model works for the Middle Paleolithic and behaviorally archaic hominids, but that behaviorally modern humans “would” never have employed such strategies. The choice of examples discussed here was not motivated by a desire to paint archaic hominids as “acultural” automatons engaged in random behavioral strategies. Rather, the Western and Central European Middle Paleolithic archaeological records offer some of the best (and most explicit) treatments of long-term, regional patterns of stone raw material procurement and transport. The models and behavioral interpretations made explicit in these studies are also commonly invoked in Lower Paleolithic (e.g., Féblot-Augustins 1997b, 1997c; Kimura 2002; Martinez 1998; Potts 1994), Upper Paleolithic (e.g., Blades 1999; Féblot-Augustins 1997a, 1997b, 1997c) and even Holocene contexts (see Bamforth 2002). The neutral model provides a baseline for comparison in all of these contexts. It may be rejected in some, or perhaps even most empirical tests (see Féblot-Augustins 1997c:Tables 62 and 64). In those cases we will be more confident that observed archaeological patterning does reflect some form of adaptation. However, rejection of the neutral model is not assured *a priori* simply because of an assumption of behavioral modernity.

A more appropriate criticism of the present model would suggest that a forager “could” never engage in a random-walk foraging strategy and “could” never ignore the differences between stone raw material types. In this case, the model would be behaviorally irrelevant. I contend, however, that the neutral model of stone raw material procurement developed here is both behaviorally explicit and behaviorally realistic. Regarding the first point, there are no hidden variables and there should be no confusion about the behavioral mechanics underlying the model. Regarding the second point,

the model offers a simplest-case scenario for the form and sequence of behaviors involved in raw material procurement.

Use of the word “realistic” is likely to raise some hackles. Nonetheless, it is critical to recognize that the simulation does not intend to capture all features of Paleolithic foraging adaptations, but rather only those behaviors directly involved in raw material procurement. If anthropologists accept as reasonable and realistic that Paleolithic foragers had the adaptive capacity to implement patch choice strategies and even long-term seasonal foraging plans, should it not also be within their capacity to not implement these behaviors? Similarly, if anthropologists accept that foragers are able to distinguish between raw material types and make further choices about which materials to transport and in which forms, should we not also attribute to them the ability not to make these distinctions and decisions? If the answers to these questions are affirmative, as I believe they are, then a neutral modeling strategy is appropriate and both a random-walk foraging strategy and the absence of raw material selectivity offer simplest-case starting points.

One may also object to the appropriateness of parsimony as a principal for choosing between alternative hypotheses that generate similar, or even equivalent, results. In truth, there is no guarantee that the simplest explanation is the correct one. In defense of parsimony, I would suggest that the probability of producing a Type II error (i.e., false positive) is minimized by favoring the simplest model available and also that the opportunity for identifying and rectifying such an error is greater.

Finally, it is clear that a general neutral model of stone raw material procurement is only a first step. Rigorous, quantitative development of the observations presented herein requires calibration of the agent-based model to run in simulated “worlds” built around the known geographic distributions of actual raw material sources. Such integrated GIS agent-based models are the subject of current endeavors. Subsequent to this, it will be important to begin systematically modifying the neutral assumptions of the model to explore how different assumptions influence results. For example, it will be important to explore the impact of partial- or fully non-random walk-foraging strategies on mobile toolkit dynamics, holding the other assumptions about unit raw material neu-

trality constant. Similarly, it will be instructive to modify the assumptions concerning raw material selectivity by, for example, rank ordering stone materials in the environment according to quality. Ultimately, the goals of these future models will be to establish whether changes in assumptions lead to quantitatively or qualitatively different results from the neutral model. Perhaps more importantly, the goal will be to establish whether these extended results find empirical support in the archaeological record.

### Conclusions

The richness of raw materials, transport distances, and character of the transported materials found in archaeological assemblages are often interpreted in terms of adaptive optimization, depth of planning, and risk minimization. In many instances, however, these patterns may be qualitatively indistinguishable from a non-adaptive model of Paleolithic foragers engaged in a random-walk foraging strategy and procuring stone raw materials without any regard for raw material type. The neutral model of stone raw material procurement developed here provides the simplest-case behavioral interpretations of (1) richness-sample size relationships; (2) a “decay-like” pattern in the frequencies of raw material transfers from sources at different distances from site; and (3) the tendency for materials from distant sources to be imported in low quantities and as heavily reduced technological forms. Though provocative in its challenge of conventional theory, the model is nonetheless explicit and, more importantly, behaviorally realistic. The primary implication of the neutral model is that our inferences about adaptive variability based on patterns of raw material richness and transport may be difficult to prove. The neutral model provides an alternative set of expectations where we can be sure that adaptation is not in evidence. In principle, patterns in raw material richness and transport that deviate from the neutral baseline expectations may indicate where optimization, depth of planning, and risk management are potentially elements of raw material procurement adaptations.

*Acknowledgments.* This research was supported in part by a postdoctoral fellowship from the Santa Fe Institute. Many thanks to John Pepper, Van Savage, Cosma Shalizi, and Todd

Surovell for guidance along the way. I am grateful to David Madsen, David Rhode, J. Féblot-Augustins, and two anonymous reviewers for comments on earlier drafts of this paper. I thank Alex Borejsza for translating the abstract.

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## Notes

1. A two-dimensional random walk on a lattice is commonly used as a discrete approximation of spatial diffusion.  $N \approx (d/l)^2$  is the mean squared distance of spread (the variance) after  $N$  time steps for an ensemble of particles undergoing diffusion. Denny and Gaines (2002) provide a straightforward derivation of this formula for the one-dimensional case. The derivations for the two- and three-dimensional cases yield the same fundamental relationship (Denny and Gaines 2002:163–167).
2. This analysis is based on the limiting case where raw material sources are encountered only within the 100 time steps following a first encounter, and not subsequently (i.e.,  $d = 10$  using equation [4]). Of course, raw material sources may be encountered over time intervals greater than  $N = 100$ . The results are comparable to this limiting case because of a trade-off between time spent at different richness states and the amount of material represented by the most abundant type in the toolkit (see discussion in text).
3. The discrepancy between the observed and expected maximum transport distances reflects the path dependence of a random walk. The analytical form  $N \approx d^2$  may substantially under- or over-estimate the actual distance traveled on any

given sequence of steps in a random walk. The approximation becomes more accurate with increasing number of observations.

4. Increasing the density of stone raw materials towards the environmental maximum also does not fundamentally alter the relationship between  $d$  and the maximum transport distance. Consider the situation where every grid cell contains a unique stone raw material source and, for simplicity, the forager must move from its current position at each time step. One unit of raw material is consumed at each time step and is immediately replaced by another unit of material from a different source located in an adjacent cell. Under these conditions, the mobile toolkit remains at its maximum capacity and very quickly approaches an equilibrium richness near the theoretical maximum; each raw material type in the toolkit is represented by only one unit of material (see equation [1]). The probability that a raw material  $i$  is consumed at a given time step is therefore a constant  $c_i = 1/\Sigma v_i$  (see equation [3]). The probability that a unit of raw material entering the toolkit is transported a number of time steps  $N$  (and distance  $N \approx d^2$ ) is given by the binomial probability distribution:

$$p(n = N) = \frac{N!}{j!(N-j)!} c_i^j (1-c_i)^{N-j}$$

where  $j$  (the number of successes in  $N$  trials) is defined as the consumption of the one unit of material  $i$  present in the toolkit (i.e.,  $j = 1$ ). Given a toolkit size of  $\Sigma v_i = 100$ , raw material foraging radius  $d = 10$  and a constant probability of consumption  $c_i = 1/\Sigma v_i = .01$ , there is a probability  $p = .001$  that material  $i$  will be transported 30 grid cells from its source (three times  $d$ ) and a probability  $p = 1.68 \times 10^{-6}$  that the material will be transported 40 grid cells from its source (four times  $d$ ).

5. On a two-dimensional lattice, allowing for the possibility of remaining in the same location, a step in any one direction occurs with probability  $p = .11$ . Two and three consecutive steps in the same direction occur with probabilities  $p = .012$  and  $p = .0013$ , respectively. The probability of 100 consecutive steps in the same direction is  $p = 3.7 \times 10^{-96}$ .

6. Alternatively, the inferred procurement probabilities from Grotte Vaufrey may be taken to represent the “partition sizes” for a mobile toolkit that had a standing richness of nine types. In this case, material types MP2 and MP1 would together take up 83 percent of the available space in the fixed-size mobile toolkit, while MP6, MP4 and MP7 combined would comprise only 1.4 percent. Such partition sizes could arise because of the indiscriminant “zero-sum” behavior of the mobile toolkit, not necessarily because of raw material selectivity (see Table 3). Remembering the neutral condition that raw materials are consumed and discarded using a simple frequency dependent rule, we may conclude that a large number of consumption-discard events—yielding larger archaeological sample sizes—would be needed to detect the presence of MP6, MP4 and MP7 within the toolkit.

7. In the absence of a spatial bias towards procurement points (see Figure 9a), the modeled frequency distribution displays only the single internal mode with a long right skew. This distribution more closely describes the pattern observed for marine shell transfers within the European Upper Paleolithic where there is primary internal mode at approximately 250 km (Gamble 1999:321, after Floss 1994).

Maximum transfer distances for marine shells are between five and ten times farther for shell than for stone. The neutral model can account for both of these differences. First, it is reasonable to suppose, given the linear geometry of coastal margins, that the archaeological recovery of marine shell shows less of a bias toward procurement points than is the case for stone raw materials found in continental interiors; sites can cluster more tightly around continental stone raw material sources than around coastal shell sources. This could explain the absence of a frequency spike for short distance shell transfers. Second, the underlying cause of the greater maximum transfer distances may simply be that marine shells are at lower risk for consumption (i.e., destruction) compared with stone. This implies that the “clearing rate” for shell is lower than for stone and therefore that the effective foraging radius  $d$  for marine shell is also substantially greater (see equations 4–6). It is interesting that the maximum distance for marine shell transfers (1,500 km) (Gamble 1999: 321) is 6 times the primary mode, the same as observed for stone transfers in the Central and Eastern European Middle Paleolithic, and not orders of magnitude farther than the internal mode.

8. In the Central European Middle Paleolithic, the observed relationship between quantity of material transferred and distance from source is better described overall by a power distribution of the form  $y = b \cdot x^{-a}$ . However, the better fit of a power function is the result of the substantial variance in quantities of materials transferred from sources within 15 km of the study sites. High variance in the quantities of materials transferred from nearby sources is anticipated by the neutral model.

9. Technological design enters into the neutral model only as regards the role reduction intensity plays in establishing, maintaining or modifying designs. Clearly, formal core and tool designs may respond to optimization, risk and depth of planning in ways not anticipated by the model.

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*Received June 10, 2002; Revised November 25, 2002;  
Accepted December 2, 2002.*

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