Modeling Hunter-Gatherer Decision Making: Complementing Optimal Foraging Theory

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While optimal foraging theory has been of considerable value for understanding hunter-gatherer subsistence patterns, there is a need for a complementary approach to human foraging behavior which focuses on decision-making processes. Having made this argument, the paper proposes the type of modeling approach that should be developed, using decision making during encounter foraging as an example. This model concerns the individual decision maker attempting to improve his foraging efficiency, rather than maximize it, under the constraint of limited information and with conflicting goals. This is illustrated by applying it to the Valley Bisa hunters using computer simulation.

KEY WORDS: Optimal foraging theory; decision making; computer simulation; Valley Bisa.

INTRODUCTION

The study of human foraging behavior has been transformed in recent years by the application of optimal foraging theory (OFT). This has substantially advanced our understanding of subsistence patterns within individual societies and helped explain variability in the foraging behavior between individuals and groups. Perhaps of equal importance, at a time of severe destruction of natural habitats, the evolutionary ecological perspective has stressed the continuities between man and other animals, which in turn emphasizes our responsibilities toward those species and the environment. However, there are serious theoretical and methodological problems with OFT, and constraints in the types and amount of behavioral variability it

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can explain. This is particularly so when applied to human foragers. Such problems inhibit further progress. Consequently, a complementary approach to human foraging behavior is required which preserves the evolutionary basis, answers the valid criticisms of OFT, and allows further areas of foraging behavior to be studied. This paper will expand upon this issue and propose an approach which stresses the active individual striving to improve, not maximize, his foraging efficiency in a context of imperfect information and conflict between long- and short-term foraging goals. This will be illustrated by considering decision making by "encounter" foragers.

OPTIMAL FORAGING: THEORETICAL AND METHODOLOGICAL PROBLEMS

OFT is now well established in both ecological and anthropological fields and has been extensively reviewed (e.g. Pyke, Pullman, and Charnow, 1977; Winterhalder, 1981a; Durham, 1981; Krebs, Stephens, and Sutherland, 1983; Smith, 1983; Foley, 1985; Stephens and Krebs, 1986). These, together with the large number of anthropological and archaeological applications (e.g. Winterhalder and Smith, 1981; Keene, 1981; Hames and Vickers, 1982; Hawkes, Hill, and O'Connell, 1982; O'Connell and Hawkes, 1981, 1984; Beckerman, 1983; Hill and Hawkes, 1983; Webster, 1987; Belovsky, 1987) have made the principals and methods of OFT very familiar to those involved in hunter-gatherer studies.

Along with this work, there is a lively critical debate as to its relevance and appropriate form for anthropological applications (Martin, 1983; Keene, 1983; Jochim, 1983; Smith and Winterhalder, 1985; Sih and Milton, 1985; Hawkes and O'Connell, 1985). From this work, a range of issues have been raised which suggest a complementary approach to human foraging is required, though one that maintains the evolutionary perspective. These issues concern either theoretical and methodological problems or point to areas of foraging behavior which cannot be tackled with an optimal foraging approach. Overall, they suggest that greater attention should be paid to modeling the decision processes of the foragers, rather than enclosing these within a "black box", as is required by OFT. The most important of these issues will be briefly considered.

The Principle of Optimality

The maximization (or minimization) of some currency lies at the heart of OFT, this being claimed as a logical stance in light of the process of natural selection. However, this optimality assumption, which is present in many areas of biological study, has been critized in both the biological and anthropological literature (Lewontin, 1978; Gould and Lewontin, 1979; Maynard-Smith, 1978; Dawkins, 1982, Jochim, 1983). The processes involved in biological evolution themselves impose "limits to perfection" and ultimately there can be no rationale for assuming that humans forage "optimally" other than as a heuristic stance (Smith, 1983). As such, the optimality principal has been, and still is, extremely useful. However, alternative perspectives can also play this role, particularly if they have a greater theoretical validity. As Dawkins (1982) has discussed in a biological context, and Jochim (1983) for human foragers, fitness is defined by doing better than other individuals, not by achieving some optimum. Consequently, the concept of "optimizing" may profitably be replaced with one of "meliorizing." Hence, foragers should be modeled as trying to improve upon, not maximize current foraging efficiencies. This position is also more compatible with knowledge of modern hunter-gatherers. This ethnographic literature suggests frequent competition for prestige which is gained through hunting success (Hill, 1984) but carries no implication that optimal strategies are strived for. Of course, if all other things remain equal, a meliorizing strategy will take the forager toward the optimal foraging pattern.

Information as a Constraint

This is a criticism directed to the form of OFT applications in anthropology, rather than of OFT itself. Any optimal foraging model includes a set of constraints on behavior, but that of imperfect information has received insufficient attention. Most models have been deterministic, in that the values of prey and patch types do not change over time. Consequently, the importance of acquiring information is neglected, though many ethnographies and optimal foraging studies suggests this is central to foraging activity (e.g. Silberauer, 1981; Winterhalder, 1981b; Beckerman, 1983). When temporal, e.g., resource depletion, or stochastic elements are added making the models both more complex and realistic (Stephens and Charnov, 1982; Winterhalder, 1986), the need for foragers to invest time and energy in acquiring and updating their information bank emerges as a central requisite for appropriate models of foraging behavior. This is emphasized by numerous case studies which have interpreted the deviations from predicted foraging patterns as related to information-gathering behavior (e.g. Winterhalder, 1981b; O'Connell and Hawkes, 1981; Beckerman, 1983). This suggests that better predictions may be included by making information acquisition and constraints integral to the model from the outset.

Mental Computation or "Rules of Thumb"?

Related to the availability of information is the issue of how much information is required and how it is processed. The extent to which individuals make calculations to estimate the returns from the available resources. or simply use "rules of thumb" is a matter of some debate (Jochim, 1983; Sih and Milton, 1985; Hawkes and O'Connell, 1985). Outside of hunter-gatherer studies, several anthropologists have emphasized the limited computational powers of the human mind, or at least the absence of computation when making decisions (Quinn, 1978; Gladwin and Murtaugh, 1984). Others, however, have stressed that even without writing, the human mind can and is used to make complex calculations when assessing which course of action to choose (O'Frake, 1985). The most realistic stance is that both computation and "rules of thumb" are used, each in the appropriate context. The former may be limited to occasions when information recall is stimulated by story telling or discussion with other individuals, while simple noncomputational rules of thumb may be employed when there is less time for reflection, and/or stimuli to aid information recall are absent.

The Role of the Individual

OFT was developed in relation to the individual forager, rather than the combined activities of the group. However, the majority of anthropological applications have used aggregated data from the behavior of all members of the group, or in a few cases one specific sex (e.g. Hurtado, Hawkes, and Kaplan, 1985; Hill, Kaplan, Hawkes, and Hurtado, 1985). Since the foraging goals, the currency adopted, and the behavioral constraints are likely to vary between individuals, such aggregated data may be of little value (Smith, 1983). Using such data removes the underlying theoretical justification for optimal foraging models.

In addition, due to the great behavioral flexibility of the human species, we should expect the individual to switch between goals, currencies, and constraints. These may change over the long term with age or changing seasons, and in the short term, such as during one single hunting episode. With respect to the latter we may imagine how short-term goals, such as the acquisition of food for one evening meal may conflict with longer term goals of increasing foraging efficiency. Similarly, during a hunt, a successful kill may impede further hunting (due to carrying the carcass) or make such hunting superfluous to current needs, allowing time to be spent on other activities. Such multiple and conflicting goals are not necessarily held by the individual decision maker, but models of foraging behavior must be such that this possibility can be examined.

Decision-Making Processes

These issues may be seen as either suggesting that optimal foraging models must be more complex (in terms of introducing further constraints and multiple goals), or as directing attention to the processes of decision making themselves. These may be modeled by simpler, and hence preferred, mathematical models. The importance of considering decision-making processes is also highlighted by the very success of certain optimal foraging applications in terms of significant similarities between observed and predicted behavior (Hames and Vickers, 1982; Hill and Hawkes, 1983; O'Connell and Hawkes, 1984). These have tended to be diet breadth models and pose the question of how the foragers are managing to achieve such efficient foraging patterns and track the environment as it changes. A simple answer is that they possess a "capacity for adaptive decision making" (Smith and Winterhalder, 1981, p. 7) which is related to Boehm's (1978) concept of rational pre-selection. Hence, to fully understand foraging behavior, the decision processes must be considered. Clearly, those employed by humans are extremely complex and the role of models must be seen as heuristic tools to help understand and describe this complexity. As with optimal foraging models, the patterns predicted by a decision rule model should be seen as providing a base line or template against which to compare the observed behavior (Foley, 1985). There will also be considerable heuristic benefit in constructing a decision rule model in terms of developing our understanding of the decision-making process.

DECISION RULE MODELS AND ENCOUNTER FORAGING

In order to suggest the type of modeling approach that may be useful in overcoming the problems and tackling the issues identified, the "diet breadth" problem faced by encounter foragers will be used, since this has been the most frequent OFT application in anthropology. This approach may be termed a "decision rule" model and although it lacks the elegance of optimal foraging models, it enables the decision processes to be explored with the use of computer simulation. The specific model described is just one of numerous alternatives that might be developed. Greatest progress will no doubt be made by building and comparing a range of different models (Jochim, 1983).

Encounter foraging has been characterized by Binford (1980) as one pole of a spectrum of hunter-gatherer settlement systems. Such systems involve high residential mobility, little or no food storage, and are most frequently found in low latitudes. The Ache of Paraguay (Hill and Hawkes, 1983), the Agta of the Phillipines (Esticko-Griffen, 1986), and the Gwi of the Kalahari (Silberauer, 1981) are predominantly encounter foragers. Groups who are "logistically" organized may use encounter foraging methods on some occasions (Binford, 1978, p. 268). To simplify the discussion, an "ideal" version of encounter foraging will be assumed in which individuals hunt by themselves during the day, encounter potential resources at random and share their kills with the other group members at a camp in the evening. During that time, or in the morning before hunting starts, the hunters discuss the merits of stalking the animals which may be encountered.

The central decision facing an encounter forager is whether or not to exploit a potential resource upon encounter. "Exploit" may refer to initiating a stalk and attempted kill if the resource is an animal, in which case the encounter may be with spoor rather than the animal itself, or to the gathering of a particular plant resource. For simplicity, I will consider hunting and the forager will be referred to as male, though the discussion and model developed might equally refer to plant gathering or hunting by women.

The optimal foraging approach to this decision is the diet breadth model (Charnov, 1976; Winterhalder, 1981a). This simply ranks the resources with respect to their cost/benefit ratio and defines which of these should be exploited and which ignored to maximize foraging efficiency. Probabilities are defined, lying at either 1.0 or 0.0, for the exploitation of potential resources upon encounter.

Consider this decision from the perspective of the decision-making processes of the individual. These may also be seen as defining "Stalk probabilities", though not necessarily at 1.0 or 0.0, since there may be some uncertainty as to the merits of stalking an encountered animal. First consider the foraging goals. The meliorizing equivalent of "energy maximizing" is "energy increasing", or more appropriately "utility increasing" (UI) since this takes into account the acquisition of raw materials as well as, or instead of, food. This goal simply states that the hunter will stalk the animal if he considers that it will increase, not necessarily maximize his current foraging efficiency. This may be considered as a long-term goal which, together with the information available, defines the stalk probabilities. However, in the short term, during a single hunting trip, this goal and hence the stalk probabilities may be modified by the influence of additional goals. For instance, there may be a need to ensure that some kill is made on each hunting trip, even if this reduces overall hunting efficiency, i.e., a "risk-reducing" (RR) goal. This may lead to the increase of stalk probabilities for animals which are easy to kill, but provide a low return. Second, a "satisfying" (S) goal, or rather a constraint, may lead to a reduction in stalk probabilities, possibly to zero, i.e., the end of the hunt, following a sufficiently-sized kill so that time may be spent on tasks other than hunting.

Now consider the information available to the forager and the manner in which it may be processed. For the long-term, UI goal, the forager may compare his estimate of current foraging efficiency with those expected from exploiting each encountered animal to define a set of stalk probabilities at the start of the hunt. These estimates will be based on his past experience. This "model" can be justified in terms of the large quantities of information stored by hunter-gatherers about their environment and resources (for instance, see Blurton-Jones and Konner, 1976; Silberauer, 1981). However, he may also use information from other individuals, most probably those who have had better hunting success and appear to make better decisions. Such information exchange may take place at the end of a day when experiences are recounted which themselves act as stimuli for further information recall (e.g. Blurton-Jones and Konner, 1979; Silberauer, 1981; Hames and Vickers, 1982; Hill and Hawkes, 1983).

During the day, however, when foraging by himself, the probabilities so defined may be modified due to short-term goals. In this context, it is most likely that "rules of thumb" are used (Jochim, 1983), rather than a quantified assessment of sudden increases in foraging effeciency following a kill, or gradual declines as no kills are made. In relation to the risk-reducing goals, the amount of time that has been spent foraging without a kill may act as a cue for the amount to raise stalk probabilities (for those less than 1.0). Similarly, following a kill, the amount of meat acquired may indicate the degree to lower stalk probabilities with respect to the satisfying goal. Consequently, upon encountering an animal the hunter's decision to pursue it or not is influenced by both long- and short-term goals, between which there may be some conflict, by information from his own and others past experience, and by the circumstances of that particular hunt, i.e., whether any kills have been made.

From this discussion we can begin to develop the mathematical model by formalizing these factors relating to the critical decision, whether or not to stalk an encountered animal.

First we can define Prob_{ijtd} as the probability that the i_{th} individual will stalk the j_{th} animal if encountered during the t_{ih} minute of the d_{th} day.

$$1 \geq \operatorname{Prob}_{ijtd} \geq 0$$

This is partly, or totally determined by the individual's long-term experience. We can therefore define F_{ijd} as the probability that the i_{th} individual will stalk the j_{th} animal if encountered on the d_{th} day, using information from his own past experience.

$$1 \geq F_{ijd} \geq 0$$

Since past experiences are exchanged we can define X_{ikjd} as the influence of the long-term experience of the k_{th} individual over the i_{th} individual concerning the j_{th} animal on the d_{th} day, with the constraints that:

$$0 \geq X_{ikjd} \geq 1.0$$

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$$\sum_{k=1}^{m} X_{ikjd} = 1.0$$

m = number of hunters in the group

Consequently, the probability for individual i to stalk an encountered animal on day d, using past experience is:

$$\operatorname{Prob}_{ijtd} = \sum_{k=1}^{m} X_{ikjd} F_{kjd}$$

which will lie between zero and one. Thos constitutes the model for the longterm utility-increasing (UI) hunting goal.

Turning now to the influence of short-term experience the first factor, the increase in probabilities due to decreasing time is modeled as an additive component. This is the risk-reducing element (RR) of the decision rule. A_{ir} = increase in probability that the i_{th} individual will stalk animals if encountered due to the value of t. Consequently, the model now has the form:

$$\operatorname{Prob}_{ijtd} = \left(\sum_{k=1}^{L} X_{ikjd} F_{kjd} + A_{it}\right)$$

with the constraint that:

$$1.0 \geq \operatorname{Prob}_{ijtd} \geq 0.0$$

The second factor of short-term experience, the reduction in probabilities due to the utility already gained, or the satisfying (S) element, will introduced as a multiplicative component. E_{it} = proportional decrease in stalk probabilities for the i_{th} individual due to the utility gained up to the t_{th} minute, with the constraint that:

$$1.0 \geq E_{it} \geq 0.0$$

Consequently, the model now has the form:

$$\operatorname{Prob}_{ijtd} = \sum_{k=1}^{k} X_{ikjd} F_{kjd} + A_{it} E_{it}$$

with the constraint that:

$$1.0 \geq \operatorname{Prob}_{ijtd} \geq 0.0$$

The next section describes how the four elements of this equation can be modeled.

The Influence of Long-Term Experience

The fundamental character of this component rests upon the idea that to achieve their goals, the foragers must make estimates of their expected foraging efficiency based on their past experience, and the efficiency of stalking the different animals. Consequently, there is an information component to this rule, the way in which these estimates are arrived at and a decision aspect, the way they are used to make the decision. The first step is to differentiate between "stored" and "acquired" types of information. The estimate of current foraging efficiency will be acquired information since this will change from day to day and hence must be regularly updated. In contrast, the mean estimate of the return to be gained from stalking an encountered animal may be considered to be stored information, under conditions of stable environment and technology, since this will be approximately the same each time a stalk is made. From this basis, a decision rule model is described for a forager with a long-term utility-increasing goal.

The expected payoff from a successful kill can be modeled as in the optimal diet breadth model as:

$$P_j = U_j / (C_s \operatorname{Pur}_j + C_b \operatorname{Pro}_j)$$

Where P_j = payoff from killing animal j, U_j = Utility of animal j, Pur_j = Pursuit time of animal j, Pro_j = Processing time of animal j, C_s = Cost per minute pursuit, and C_b = cost per minute processing.

However, since not every kill will be successful, the expected payoff from choosing to stalk an encountered animal will be:

$$AP_{j} = \frac{U_{j} * PS_{j}}{C_{s} Pur_{j} + (PS_{j} * C_{b} Pro_{j})}$$

where AP_j = expected payoff from stalking animal *j*, and PS_j = Probability of killing animal *j*.

This simply reduces the utility gain and the processing time by the proportion of kills which are successful. The pursuit time is not effected since all stalked animals are by definition pursued, whether successfully or not. The hunter stores the AP_i values for each animal.

If we now turn to the expected return from foraging in general this consists of acquired information and must be updated each day. This is modeled simply as a weighted average of his previous day's foraging efficiency. On one single day the efficiency will be:

$$TP_{id} = TU_{id}/TC_{id}$$

where TP_{id} = payoff gained by the i_{th} individual on the d_{th} day, TU_{id} = utility gained by the i_{th} individual on the d_{th} day, and TC_{id} = cost of foraging by the i_{th} individual on the d_{th} day,

where:

$$TC_{id} = [C_r S_{id} + C_s PU_{id} + C_b Po_{id}]$$

 $C_r = \text{cost per minute searching or passive, } C_s = \text{cost per minute pursuit,}$ $C_b = \text{cost per minute processing, } S_{id} = \text{minutes spent searching or passive,}$ $Pu_{id} = \text{minutes spend pursuing, and } Po_{id} = \text{minutes spent processing. Now}$ if the expected foraging efficiency was modeled simply as an average of the previous days efficiency, this would result in a model of the form:

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$$ETP_{id} = \frac{\sum_{c=1}^{d-1} TU_{ic}}{\sum_{c=1}^{d-1} TC_{ic}}$$

The unsatisfactory nature of this can be realized when one appreciates the changing nature of the environment. The general efficiency may be either increasing from day to day, due to learning about the environment, or decreasing due to depletion of the game. Whatever trend there is, and even if there is no trend, the meliorizing hunter will be wanting to improve on the more recent days efficiency, that is, the more recent days activity and experience will play a greater role in determining the expected efficiency. In addition there may be biological constraints which prevent the perfect recall of previous days experience. Consequently a more useful model is one that uses a weighted average of the following form:

$$ETP_{id} = \frac{\sum_{c=1}^{d-1} A^{d-c-1} TU_{ic}}{\sum_{c=1}^{d-1} A^{d-c-1} TC_{ic}}$$

where A = attention factor, 0 > A > 1.

The form of the weighting is taken from Harley's (1981) ESS learning rule. "A" is simply an attention factor which takes a value between zero and one. At the extreme value of one, the equation returns to the non-weighted form and the expected efficiency is derived from all previous days equally. A value less than one however puts greater weight on recent days, and as it approaches zero the expected efficiency is increasingly a function of the most recent days experience. Consequently if, for instance, there is a falling rate of returns and the attention factor has a value less than one, the expected efficiency will be less than the average, whereas if efficency was increasing that expected will be greater than the average. Note that this does not allow the identification of a trend. If efficiencies were decreasing in a regular fashion, then the expectation may be a continuation of this trend and a value less than that of the previous day.

Having now defined the informational components of the long experience component F_{ijd} , we can turn to the decision part. Assuming a meliorizing strategy, the model will simply state that if the expected payoff from stalking an animal is greater than the expected payoff from foraging in general, the forager will choose to stalk the animal. Mathematically:

$$F_{ijd} = \begin{cases} 1 \text{ IF } AP_j > ETP_{id} \\ 0 \text{ OTHERWISE} \end{cases}$$

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We can note here that this rule follows a similar criterion as that in the optimal diet breadth model in which any resource which provides a payoff greater than that from foraging in general should be taken. In this case, however, the general foraging efficiency is acquired information and only assessed at the start of the day, rather than being continually updated.

The Influence of Other Individual's Long-Term Experience

The second component of the model concerns the exchange of information, the influences of each individuals' past experience upon others. There are, as with the other components, several ways to model this. One of the simplest involves the assumption that the influence of one member of the group is the same over all other members, over himself, and is the same for all game. Hence, rather than considering the parameter, X_{ikjd} , we need only consider the parameter X_{id} .

The model states that the influence of each individual will depend upon his previous success as a hunter, as compared to that of the other individuals. This returns therefore, to the initial position that hunting success brings prestige, which is related here to influence over decision making. Consequently, we can simply use the relative amount of utility provided by the forager, averaged over the previous days foraging. Hence:

$$X_{id} = \frac{\sum_{c=1}^{d-1} TU_{ic}}{\sum_{k=1}^{m} \sum_{c=1}^{d-1} TU_{kc}}$$

As before, however, a weighted average may be more appropriate. For instance, a hunter who had been successful during the first hunting trips from a site may not be as rapid a learner as other hunters. He may not be as proficient in adjusting his stalk probabilities to account for prey depletion and hence his initial high influence ought to be weighted against decisions taken during later hunting trips from that site. Consequently, we can use the attention factor again and define:

$$X_{id} = \frac{\sum_{c=1}^{d-1} A^{d-c-1} TU_{ic}}{\sum_{k=1}^{m} \sum_{c=1}^{d-1} A^{d-c-1} TU_{ic}}$$

In this manner, all the influences will sum to one. Since in this model the influence of one hunter does not vary between the other hunters, at the start of the day, that is, before the "particular circumstances" arise, each hunter will have the same probabilities for stalking each of the animals. This is defined by the value:

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$$\operatorname{Prob}_{ijd} = \sum_{k=1}^{m} X_{kd} F_{kjd}$$

Note, however, that because the F_{kjd} value (1 or 0) for each animal may differ between the individuals, due to their own previous experience, the probabilities for certain species after this "discussion" has taken place may lie between 0 and 1, not necessarily at one of these extremes. This means that upon encounter the forager will sometimes choose to stalk these animals, and sometimes ignore them.

Considerably more sophisticated models of information exchange could be constructed in which the influence of one individual varies over different members of the group. In that case, a consensus-reaching model such as described by DeGroot (1974) would be appropriate.

The Influence of Short-Term Experience

This section considers the influence of short-term experience, the gain and processing of information when the individual is by himself during the day. Two types of circumstances were previously described which will affect the foragers' assessment of the worth of pursuing different animals.

The first factor relates to the amount of time left for foraging. Assuming there is a limited amount of time available each day, there may be an increase in the probabilities for stalking encountered game as time passes due to the decreased chance of encountering others. This will occur if the forager has a short-term risk-reducing goal. The role of this factor can be appreciated if we consider the last minute of the day. If an animal is encountered in that minute there will be no chance to encounter another if it is passed up and consequently the probability for stalking it will be one, given that no kills have already been made on that day. An encounter early in the day however, would have much less influence over the stalk probabilities. Consequently, we can develop the model in the following manner:

$$\operatorname{Prob}_{ijrd} = \sum_{k=1}^{m} X_{kd} F_{kjd} + A_{in}$$

where $A_{it} = (1 - \sum_{k=1}^{m} X_{kd} F_{kjd})(h^t/h^{tmax})$, Tmax = total number of minutesavailable for foraging in day d, and h = model constant, h > 1

The model now states that at the start of the day, t = 0, the probability for stalking an encountered animal is solely defined by the long-term experience, since $A_{it} = 0.0$. As t increases, and hence less time to encounter other animals, A_{it} will increase in an exponential manner. At tmax, the last minute of the day and after which no other game can be encountered, $A_{it} = 1 - \sum_{k=1}^{m} X_{kd} F_{kjd}$ and, consequently, $\operatorname{Prob}_{ijtd} = 1.0$. Figure 1 illustrates the



Fig. 1. Increases in stalk probabilities with time due to the presence of a risk-reducing, short term-goal.

pattern of increase in probabilities during the day with two different values of the model constant h and with a starting stalk probability of 0.5. Of course, if $\sum_{i=1}^{m} X_{kd} F_{kjd} = 1$ when t = 1, then A_{it} will always remain at zero.

The second factor of short-term experience is how stalking probabilities decrease due to the value of animals already exploited. This is required for two reasons. First, the hunter may have a constraint on the amount of meat/raw material that can be carried back to the camp and further processed there, if it is not left and collected later. Second, it must be recognized that foraging is only one of the activities to be accomplished by an individual and consequently there may be a short-term satisfying element interacting with the long-term goals. It is a satisfaction that the meliorizing goal has been reached, however, rather than a satisfying goal in itself. Once the longterm goal has been sufficiently achieved on one day, the hunter may invest his time in the other essential activities such as tool manufacture, social visiting, and ritual acts. Consequently, we need a component in the model to decrease the stalk probabilities as kills are made. We can introduce this in the following manner. The model now has the form:

$$\operatorname{Prob}_{ijtd} = (\sum_{k=1}^{m} X_{kd} F_{kjd} + A_{it})E_{it}$$

where $E_{it} = \exp(-q \sum_{c=1}^{i} TU_{icd})$, q = model constant, 1 > q > 0, and t = number of minutes spent foraging.

This reduces the stalk probabilities for all game by an equal rate. As with the previous component it uses a model constant, q, to determine the rate of decrease. The hypothetical graphs in Fig. 2 show the changes in exploitation probabilities with an initial value of 0.5, an h parameter of 1.02,



Fig. 2. Increases and decrease in stalk probabilities due to the interaction between a risk-reducing short-term goal and a satisfying element. "Kills" with utility values of 200 and 500 units are made at t = 100 and t = 250, respectively.

utility gains of 200 and 500 units at t = 100 and t = 250, respectively, and two alternative q values of 0.001 and 0.005. As is evident, the larger value of q leads the forager to reduce his exploitation probabilities by a larger amount for the same kill, than does a smaller q value. As will be discussed the simulation model considers that if all exploitation stalk probabilities fall below a critical threshold, then the forager is no longer considered to be motivated for hunting and enters a passive state.

The graphs in Fig. 2 illustrate the conflict between the role of the two short-term experience components. One works to increase, and the other to decrease the stalk probabilities within the same day. In this, the model begins to capture the often conflicting pieces of information and the need to reach a compromise between them when decisions are taken. When exploring the model in the following, one, both, or neither of the short-term elements (RR and S) may be included with the long-term element (UI) when modeling the stalk probabilities.

EXPLORING THE MODEL

The behavior resulting from this decision rule can be explored via computer simulation. For this we need to model the encounter foraging process, during which prey are encountered and decisions as to whether or not to stalk them are taken.

The framework for this is a fixed number of hunters foraging by themselves for a fixed number of days from one central hunting camp to which

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they return each evening. The number of hunting days are not necessarily consecutive in the calendrical state, but are simply days on which hunting takes place. Each day is modeled in the following manner. Hunting activity is divided up into six separate states and the simulation defines the "state" of each hunter at each minute of the day. A hunter moves from one state to another according to the encounters with game, the decisions he takes concerning stalking these, and his successes at killing those he stalks. The six states are named "searching", "encountering", "pursuing", "killing", "processing", and "passive".

At each minute of the day, the simulation examines the state of each hunter and takes various action according to that state. In the first minute, each hunter is in a "searching" state. Using a set of probabilities for encountering game, the model tests whether the hunter encounters a potential resource (the animal itself or a sign of one). If so, he enters "encountering" state for the next minute, otherwise he remains searching. The hunter only remains in the "encountering" state for 1 minute during which the decision is taken whether or not to stalk the animal. This is taken using the "stalk probabilities" defined by the decision rule. If the hunter chooses to ignore the animal he returns to searching state for the next minute. Otherwise he enters "pursuing" state.

He remains in pursuing state for a time equal to the pursuit time of the animal now being hunted. At the end of this time he enters "killing" state. As with "encountering," this only lasts 1 minute and in this the probability for successfully killing the animal is used to define the outcome of the pursuit. If unsuccessful, the hunter returns to "searching," otherwise he enters "processing" state and remains there for the processing time of the animal plus 1 additional minute for the kill itself. After that he returns to "searching".

If while searching the hunter's stalk probabilities all fall below some predefined value, e.g., 0.1, then the hunter enters the "passive" state. This is modeling the hunter's loss of interest in taking more game and he remains in this state for the rest of the day. In it he invests no time in searching and can make no encounters. In effect, it models his return to the camp and engagement in other activities.

After the last minute of the day all the hunters are considered to return to the camp, if not already there due to being "passive". If, during that last minute, the hunter was engaged in either "pursuing" or "processing," then the simulation allows them to spend extra foraging time to finish these activities (if the hunter was "pursuing", and successfully kills the animal, then the simulation also allows him to process it). At the end of the day, the simulation models information exchange and the formation of the stalk probabilities for the game if encountered during the next days hunting, in the manner described.

The collection of field butchered animals and their further processing and consumption are not modeled. It is assumed that this occurs either dur-



Fig. 3. Hunters states and transitions.

ing the time when hunters are "passive" or between hunting trips. Figure 3 illustrates the hunting states and their transitions. For the initial days foraging, the simulated hunter will not have any acquired information upon which to base his stalk probabilities. Consequently, for a pre-defined number of days, five was chosen in practice, the F_{ijd} values were simply defined as one, for animals with a greater than average AP value, and zero for the rest. This simply creates the starting conditions for the hunting and allows the hunters to acquire a store of information. In the real world, this will have been acquired from earlier foraging experiences in the area or by observations upon the natural environment. Since the simulation was run over a further 50 days, these starting conditions have little influence on the overall foraging patterns.

AN ETHNOGRAPHIC EXAMPLE

To illustrate this decision rule and simulation model, the Valley Bisa (Marks, 1976) who use encounter foraging methods for hunting large game in Zambia will be briefly considered (the most important of which were impala, zebra, buffalo, waterbuck, and warthog). Of course, the simulation of the encounter foraging process is an extreme simplification of that engaged in by the Valley Bisa. Nevertheless, it captures the essential features and is sufficient for the principally theoretical aims of this paper. Due to the nature of encounter foraging and the simulation model, each of the five game species needs to be modeled by five characteristics: (1) probability of encounter, (2) pursuit time, (3) probability of a successful kill, (4) processing time, and (5) meat weight.

Marks (1976; Appendix C) provides data on relative encounter frequencies, but one is unable to put absolute values on these from his description of the Valley Bisa and their environment. His records of game observations (1976, Table 33 and 34) refer to sightings of game rather than "encounters" from which a hunter may initiate a stalk. Consequently, two values for overall encounter frequencies, i.e., of all game species, of 0.1 and 0.01 encounters/minute will be initially explored. These values can then be divided up according to the relative encounter frequencies for each species, as in Table 1. Marks does however provide data on mean pursuit times, meat weights, and the probability of making a successful kill following a stalk (1976, Table 17, Appendices B and C). Meat weights are used as the measure of utility, ignoring the role of raw materials. He gives little data on field butchery and hence processing times must be estimates. A time of 10 minutes for each type is assumed, irrespective of species. Table II summarizes these data. The final data required by the model concern the cost of the different activity states, searching/passive, pursuit, and processing. For these, values of 3.0, 9.5, and 7.0 Kcal/min are used, respectively. These are taken from Pyke (1970) and relate to energy expenditure in the analogous activities of walking, walking fast, and sawing wood.

A simulation program for the encounter foraging process and the use of decision rules was written in Pascal and run on the University of Cam-

Species	Relative envounter rate ^a	Encounter probabilities ^b		
		0.1	0.01	
Impala	0.38	0.038	0.0038	
Zebra	0.24	0.024	0.0024	
Bullalo	0.17	0.017	0.0017	
Waterbuck	0.10	0.01	0.001	
Warthog	0.11	0.011	0.011	

Table I. Resource Envounter Probabilities

^eFrom Marks, 1976, Appendix C.

^bOverall number of encounters/minute.

Species	Probability of successful kill ^a	Pursuit time ^b	Meat value ^c	Processing time ^d	
Impala	0.028	7.0	73.5	10.0	
Zebra	0.091	7.0	289.0	10.0	
Buffalo	0.26	31.0	703.0	10.0	
Waterbuck	0.103	11.0	247.5	10.0	
Warthog	0.18	8.0	99.5	10.0	

Table II. Resource Attributes

"From Marks, 1976, Appendix C.

^bFrom Marks, 1976, Table 17.

From Marks, 1976, Appendix B (averaged over both sexes).

^dEstimated (see text).

bridge IBM 3081 mainframe. Each run of the simulation modeled a group of five hunters, foraging for 5 hours a day for 50 days (with an additional 5 days of foraging to build up an information store). Four versions of the decision rule were explored to investigate which, if any, resulted in foraging patterns which match those adopted by the Valley Bisa. In this context, foraging patterns refer to the frequency with which species are stalked upon encounter.

The first version simply had the long-term UI goal without any shortterm influences (UI rule). Hence, the stalk probabilities did not alter during the day while the hunter foraged by himself. The second and third versions had the RR and S short-term goals added, respectivley (UI + RR and UI) + S rules), while the fourth version had both of these added together (UI + RR + S rule). All of these took the same values for the model parameters: A = 0.8, h = 1.02, q = 0.005. For each version and encounter frequency, three runs were made each with a different seed for the random number generator in the simulation. This affects factors such as the sequence of game encounters and which animals were chosen when stalk probabilities lay between one and zero. By this means the effect of purely stochastic factors on foraging patterns could be assessed. Overall, therefore, 24 runs of the simulation model were made. The results, along with comparisons with the observed foraging patterns are given in Fig. 4.

The closest fit between real and simulated foraging patterns are found in rules with an RR short-term goal and in the runs with the lower (0.01)game encounter frequency. Rules without the RR goal, led to patterns which neglected impala, while these were stalked on 36.5% of real encounters. Even with the RR component, impala were stalked on only about 16% of encounters. The UI + RR and the UI + RR + S rules appear indistinguishable in light of these few runs. The simulated runs with the low encounter frequency, with or without the RR goal, led to a better fit than the higher encounter rate in that waterbuck and warthog were stalked on a relatively high number of occasions at frequencies between impala and buffalo. Which of these two species is stalked more frequently appears to be influenced by purely stochastic factors since both were dominant in particular runs. The lower rate of encounter is also validated by the resulting levels of foraging efficiency. Marks (1976; Table 37) quotes the hunting efficiencies for resident individual hunters in terms of meat yield/hour ranging from 0.0-63.2, and with a mean of 22.9. The simulated efficiencies for the UI + RR + S rule were 89.0 and 19.6 for the 0.1 and 0.01 encounter rates, respectively, showing the latter to be more realistic.

In all of these runs with the lower encounter rate, however, zebra was stalked on the majority of occasions while the Valley Bisa rarely hunt this species. In fact, Marks (1976, p. 182) states that he never observed a hunter stalk a zebra. Why zebras should be ignored in this manner is debatable. Marks recognizes their economic worth and rejects the idea that the Valley Bisa are deterred from hunting zebra due to the need for a license elsewhere. He suggests that their refusal to hunt zebra arises from that species' anomalous position in their classificatory system. Zebra flesh may carry the taint of social stigma. This explanation must be followed here since the simulations have supported Marks intuition of the likelihood of exploiting zebra if foraging efficiency is the principal decision-making criterion. While the models and evolutionary ecological view proposed here may be unable to explain attitudes to zebra, they appear adequate in relation to other species.

Indeed, by making some adjustments to the model in the light of the results described, a closer fit should be possible. Those results suggested that the influence of the short-term RR goal may be too low since, while impala had entered the diet when the RR goal was included, they were still relatively infrequently stalked in comparison to the observed patterns. The RR influence can be increased by lowering the value of the *h* parameter from 1.02 to 1.01 (see Fig. 1). In addition we can make the zebra a taboo species by making the probability of stalking it upon encounter a constant zero and also make runs for an intermediate encounter rate of 0.025. The results illustrated in Fig. 5 show that similar real and simulated foraging patterns are found.

Overall, these results have suggested that to explore the Valley Bisa foraging patterns we must refer to both decision-making processes from an evolutionary ecological and from an ideological perspective. These do not appear to interact at all, attitudes to particular species appear to be dominated by one or other of these, with the former defining attitudes to four out of five species. The principal conclusion is that when attitudes to zebra are accounted for, the Valley Bisa foraging patterns can be explained by the use of decision-making processes which include both a long-term utilityincreasing goal and a short-term risk-reducing goal.

Clearly, a more detailed examination of the behavior of the model is necessary to support these conclusions. For instance, a range of "attention" values must be explored and better estimates for parameters such as processing times made. However, this Valley Bisa study has been sufficient in relation

Fig. 4. Stimulated (----) and observed (----) Valley Bisa foraging patterns (A = 0.8, h = 1.02, q = 0.005). Resource types: (1) impala, (2) zebra, (3) buffalo, (4) waterbuck, and (5) warthog.

Fig. 4. (continued).

Fig. 5. Simulated (---) and observed (---) Valley Bisa foraging patterns (A = 0.8, h = 1.01, q = 0.005, zebra tabooed).

to the aims of this paper, as it has illustrated an alternative evolutionary ecological approach to foraging behavior to optimal foraging theory, and shown how this can be realized by using computer stimulation. Elsewhere (Mithen, in press) a detailed and substantial simulation study of Mesolithic foraging has been made using this decision rule model. In that study, which required a model of the postglacial environment and assemblage formation in addition to the hunting and decision-making process, goals without a risk-reducing element were inferred for the foragers of southern Scandinavia, whereas foragers in southwest Germany appeared to include a risk-reducing goal in their decision making. This contrast enabled a series of insights into varying trajectories of social, economic, and technological change across early postglacial Europe to be drawn.

CONCLUSION

The approach to hunter-gatherer foraging behavior presented here seeks to provide a complement to optimal foraging studies. It replaces the concept of maximization with meliorizing, recognizing this as more theoretically valid and more compatible with our knowledge of hunter-gatherer behavior. It also seeks to place informational constraints and multiple, conflicting goals at the center of the model. Similarly, it focuses on the decision-making processes of the individual, rather than the group, but models the process of information exchange between individuals. Clearly, the model described is only one step toward these ends.

The principal manner in which it requires development is to model the individual choosing his goals, whether or not to include an RR and/or S shortterm goal, as well as alternatives to the UI goal over the long term. By this means we shall achieve the variability in goals within the group, rather than attributing to all individuals the same goal, as in this current model. Similarly, the value of the model parameters, A, h, and q, should be seen as variables under the control of the individual, so that they can choose how much attention to pay to past experience or the amount of mean required to satisfy their daily needs. Essentially, this requires modeling "meta-decision"-making activity (Mithen, in press), deciding what decision rule to use and hence how decisions are to be taken (see Brown, 1978 for a discussion of meta-cognition). Once such models are developed, we may begin to be able to describe and gain a greater understanding of the complexity and the flexibility in human foraging behavior.

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