GUILÁ NAQUITZ

Archaic Foraging and Early Agriculture in Oaxaca, Mexico

Edited by

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The Modeling of Foraging Strategy: An Introduction to Part VII

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Adaptation is the process of evolutionary change by which the organism provides a better "solution" to the "problem", and the end result is the state of being adapted.
(Lewontin 1978:213)

In Part VI of this volume we dealt with division of labor and partitioning of work space by the group occupying Guilá Naquitz. In Part VII we deal with a pair of questions that are even more difficult: (1) What strategy led the occupants of the cave to select the mix of plants we see on the preagricultural living floors? and (2) How did this strategy change during the period of incipient agriculture?

We stated in Chapter 2 that we intended to give "equal time" to the role of information in the origins of agriculture, and the adaptive computer simulation model designed by Reynolds (Chapter 31) is consistent with that approach. Reynolds rejected the notion of a mechanistic-deterministic simulation, opting instead for a stochastic-probabilistic model in which thousands of alternative decisions could be made on the basis of remembered information.

The approach taken in Chapter 31 owes a lot to our University of Michigan colleague John Holland, whose book *Adaptation in Natural and Artificial Systems* (Holland 1975) explores the mathematical complexities of the process of adaptation. Holland argues that adaptation is a nonlinear phenomenon that is not amenable to the mathematical formulae that are easiest to use. For example, he demonstrates that if adaptation by animals were a simple matter of trying out mutations one by one, taking advantage of the occasional more advantageous allele, there would be insufficient time in the life of the universe to accommodate the progress that has been made. Rather, adaptation deals with "chunks" of information or cooperating sets of genes. Holland's suggestions for modeling such adaptation are incorporated into Reynolds' simulation, along with some of Zeigler's (1976) procedures for simplifying models to increase their tractability, while preserving their essential features with respect to the questions being asked.

In Reynolds' model, a hypothetical microband of 5 foragers, starting from a position of ignorance, "learns" how to schedule its collection of the 11 major plant foods of the Guilá Naquitz environment by trial and error over a very long period of time. They do this by attempting to improve the efficiency of their recovery of calories and protein per area searched during each cycle, or time step, of the simulation. They are confronted with an unpredictable sequence of wet, dry, and average years that change the productivity of the plants; and information on their past performance gradually builds up in the memory of the system, informing their decisions on whether or not to modify their strategy when a similar year comes up again. Each strategy considers the vegetational zone searched, the rank order in which the plants are searched for in each zone, and the size of the harvest area for each. By evaluating *sets* of changes (rather than single modifications, as would be the case if the group were testing "mutations" one by one), the group arrives at what would be called "coadapted sets of decisions" in Holland's framework. As time goes on, increasing amounts of experience are available to inform the microband's decisions, until their performance is so efficient that no new modification has much probability of being an improvement (although thousands of potential modifications are available should the parameters of the group's environment change). At this point, Reynolds compares the model group's strategy to the remains from Zone D of Guilá Naquitz, our last largely preagricultural level.

Agricultural plants (cucurbits, beans, and primitive maize) are introduced into the simulation at this point, and the whole process begins again. Slowly but surely, the microband shuffles its priorities until it develops a new coadapted set of strategies that are hard to improve upon. Here Reynolds can compare the mix of plants generated by this set of collecting strategies with that from Zone B1 of Guilá Naquitz. But the analysis does not stop there, for one of the advantages of a simulation is the possibility of varying the parameters of the model to see what might have happened under different conditions. Reynolds therefore makes several changes in the model:

1. The frequency of wet years is gradually increased to see what effect a climatic improvement might have.
2. The frequency of dry years is gradually increased to see what effect a climatic deterioration might have.
3. The frequency of average years is set at 100% to see what effect reduced climatic variation might have.
4. The population of the group is allowed to (a) increase steadily or (b) fluctuate unpredictably around a mean to see what effect such demographic change might have.

Rather than anticipate Reynolds' results, we withhold comment on his conclusions until Chapter 32.

REYNOLDS' MODEL IN THE CONTEXT OF OTHER COMPUTER SIMULATIONS

Computer simulations have a considerable time depth in archaeology. One of the first archaeologists to simulate a hunting–gathering strategy was David H. Thomas in his dissertation on the Shoshone of Nevada (Thomas 1971). Not long after, Wright and Zeder (1973, 1977) simulated a tribal-level exchange system and Wobst (1974) simulated boundary conditions for Paleolithic social systems. By the late 1970s, whole symposium volumes had been dedicated to simulation (e.g., Hodder 1978; Sabloff 1981).

There are many kinds of simulations, and to put Reynolds' in perspective we may briefly consider some of these. A simulation is an imitation of reality, and the more realistic the data put into it, the closer the imitation should be. At the head of the list we might put such simulations as Paulik and Greenough's (1966) study of Pacific Northwest salmon populations or McCullough's (1979) study of the George Reserve deer herd. After collecting the necessary quantified data on salmon recruitment and mortality, Paulik and Greenough generated 250-year runs on the computer to see what would happen to salmon fisheries under different conditions. After collecting similar data on deer recruitment and mortality over a 12-year period, McCullough generated a series of herd histories to see what would happen under different hunting strategies. Such studies imitate reality well because (1) all variables contain values empirically derived from study of the animals involved, (2) all formulae used are based on recurrence relationships among variables that have been generated by empirical observation, and (3) the number of values "made up" by the investigator are few to none.

More common in archaeology are cases where some of the values are empirically based but others amount to "missing data" and have to be made up by the investigator. In still other cases, the values are derived from the real world but the recurrence relationships among variables are not yet empirically generated in the way the formulae used by McCullough and Paulik and Greenough have been. In Wright and Zeder's (1973, 1977) simulation, for example, the villages participating in the exchange system are fictional but their rates of population gain or loss are taken from actual quantitative accounts in the ethnographic literature on New Guinea.

Finally, one can find simulations in which *all* values have to be made up by the investigator because no one has yet done the basic research necessary to provide reliable quantitative values. For example, a simulation of the Classic Maya collapse by Hosler *et al.* (1977) uses a set of variables not one of whose values could possibly be known. These include the birthrate and death rate for Classic Maya commoners, their average lifetimes, the number of kilograms of crops eaten per person per year, the number of commoners involved in monument construction, the desired number of monuments per commoner, and so on. It will certainly be a long time before archaeologists possess values for those variables that are as empirically generated as the figures one can collect for Pacific Coast salmon or George Reserve deer; and since we still have no idea what the "reality" of the Classic Maya collapse was, we cannot yet evaluate the extent to which it is imitated by the model.

Reynolds' simulation in Chapter 31, like that of Thomas (1971), lies somewhere between McCullough's and Wright and Zeder's. By far the majority of the values used come from our decade-long study of the natural vegetation near Guilá Naquitz (described in Chapters 4, 18, 23, and 24) and are therefore empirically generated. Occasionally we have to deal with missing data, such as the piñon nuts that no longer occur in the Guilá Naquitz environment; in such cases, values have been taken from the literature. Because it is impossible for us to specify how many calories preceramic foragers expended while harvesting the foods of the eastern Valley of Oaxaca, we have used square meters of area harvested—a variable for which we *do* have quantified data—as our measure of work effort. To make the model more realistic, Reynolds has presented his hypothetical band of foragers with a succession of wet, dry, and average years that occur in the frequency displayed by Oaxaca's rainfall records, but in random and therefore unpredictable order. These years change the plant resources of the model in the ways we have observed them to change the Mitla area vegetation in real life. In other words, while hampered by our inability to observe and interview the preceramic occupants of the cave, we have done everything we could think of to make the model realistic.

ALTERNATIVE WAYS OF MODELING HUNTER-GATHERER SUBSISTENCE STRATEGIES

There are many alternative ways in which we might have modeled the use of plants by the preceramic inhabitants of Guilá Naquitz. Two that have been used and discussed in the recent literature are optimal foraging theory (Winterhalder and Smith 1981) and linear programming (Keene 1981a, 1981b; Reidhead 1979, 1981). While we have no objection to either of these approaches, we chose to use an alternative method and therefore feel that we should explain that choice. Our reasons had to do with (1) the diachronic nature of our data, which included strategies changing through time; (2) our desire to give information equal time with energy and matter; and (3) our suspicion that resiliency or risk reduction might have been more of a goal than optimization in the Guilá Naquitz case.

Optimal foraging theory is derived from evolutionary ecology, which we regard as a point in its favor. As pointed out by Durham (1981), however, it was largely developed for animals where competition occurs not only with other species but also between individuals of the same species—even between mated males and females, and between parents and their offspring. It is grounded in the notion that where organisms compete for resources, selective advantage is conferred on those organisms having the more efficient techniques for acquiring energy. Hence, foragers should attempt to maximize the number of calories (energy) they acquire per unit of time. Reynolds' model overlaps to the extent of measuring efficiency in terms of calories and protein acquired per hectare searched. However, Cashdan (1982) points out that while there are good ecological reasons for focusing on energy, anthropologists can easily think of situations where some other optimization goal might be more appropriate, such as "reliability of energy capture."

Winterhalder and Smith measure the extent to which Cree Indians and Inuit Eskimos meet the expectations of an optimal foraging model, but since their studies are ethnographic they do not face the diachronic problems we face. Zones E, D, C, and B1 of Guilá Naquitz present us with a history of changes in foraging strategy, and while we could presumably have tested each living floor against an optimization model, we strongly suspected we should try to simulate the changes as a long-term learning process.

In contrast to optimal foraging theory, linear programming analysis was developed in economics. It uses a computer program to arrive at the one single combination of available resources that both satisfies the subsistence needs of a group and does so at the lowest possible cost of time and risk. Its major advantage over optimal foraging theory lies in the fact that it considers more variables than caloric needs and time constraints. Reynolds' simulation is similar in the sense that it considers both calories and protein, and indeed we wish we could have included even more variables—for example, deer hunting, for which we have "missing data" because of a lack of deer in the Guilá Naquitz region today.

Keene's (1981a, 1981b) linear program for the prehistoric Saginaw Valley suggests that energy was a binding constraint only during the low-sunlight months of March, April, September, and November; during other months there were different limiting factors such as calcium, ascorbic acid, thiamine, and hides. Keene's results remind us that we are prevented from modeling a whole calendar year at Guilá Naquitz because the preceramic occupants moved on to other campsites from January to August.

Among the problems posed by linear programming is the fact that it, like optimal foraging theory, presents us with one, static, optimal solution to what is for us a diachronic problem. Moreover, that solution requires what Moore (1981) calls the "all-knowing, computationally perfect decision maker." In other words, linear programming can tell us the best way to exploit an environment, but it does not tell us how to get there from a position of ignorance; and there is some reason to believe you might not get there without a computer, or else a high level of competition combined with intense selection pressure.

How often did prehistoric people arrive at the optimum solution? In his linear programming study of prehistoric Indiana, Reidhead (1981) found that behavior observed in the archaeological record "departed from a pure optimizing strategy in a few notable ways" (p. 95) and that "strict effort minimization. . . does not seem to have been the end nor the goal of food procurement" (1981:103). Keene (1981b:237) goes so far as to ask, "Are optimization models realistic?" He concludes that "a perfect correspondence between an optimal solution and real behavior should not be expected," but that "optimizational modeling provides a baseline against which observed behavior can be compared with a theoretical optimum" (1981b:237). Significantly, he adds that "in benevolent environments, when resources are abundant and when risk is minimal, there is greater leeway to deviate from the optimal pattern of behavior without risk to security and survival" (Keene 1981b:237–238). Without giving away the results of Reynolds' analysis (Chapter 31), I suggest the reader make note of the way our hypothetical microband behaved during wet years when risk was reduced.

THE RATIONALE FOR OUR APPROACH

It should be clear by now that our approach to the foraging strategy of the Naquitz phase is one that focuses on adaptation through learning by trial and error, relies on memory to inform decisions, and concerns itself more with resiliency in the face of unpredictable variation than with optimizing energy capture. We might summarize our rationale for this approach as follows:

1. In linear programming and optimal foraging theory, time is not a factor. The programs yield brilliant solutions to foraging problems; but linear programming does not tell you exactly how to get there, while optimal foraging theory tells you to get there by competition. If you are an ethnologist dealing with contemporary peoples, this lack of time depth is not a problem, but if you are an archaeologist faced with a sequence of changes, it is. Reynolds' simulation tells us how

to get to the adaptations seen in Zones D or B1 of Guilá Naquitz, starting from a position of ignorance and without assuming competition from another group. Looking back over the output, one can see just what decisions were made to get to a certain point because the program is process oriented.

2. Both optimal foraging theory and linear programming descriptions of foraging lean heavily on energy and matter, while Reynolds' hypothetical microband also relies on information and through experience gets better and better at making decisions over time.

3. In Reynolds' model, not all changes are improvements; some make things worse. Slowly changing by means of "chunks," or "coadapted sets of decisions," the model group increases its efficiency to the point where there is a low probability that any new change will be an improvement; yet even at this stage, there is a tremendous reservoir of potential variation available to the group in case of unpredictable stress. This is what we mean by "preserving resiliency," and it seems to us to be at least as realistic an imitation of the prehistoric world as the solution of an "all-knowing, computationally perfect decision maker."

4. We wanted to be able to vary the parameters of the model to see what would happen if population grew or fluctuated or if the climate got wetter, drier, or more uniform. Reynolds' simulation allows us to do this.

5. We wanted our scheduling model to be a systems model, with feedback relationships within it, and we wanted to be able to test the importance of those feedback relationships. In Chapter 31, Reynolds experimentally disconnects the feedback loop between the memory bank of past performances and the present-day decision makers, and we learn something about the effects of such feedback within the system.

6. No deer herd or school of salmon has the kind of multigenerational memory constructed by Reynolds for his adaptive model; hence the latter's responses should be more like those of a human group, which is, after all, what we are trying to model.

Finally, the approach taken in Chapter 31 is only one alternative—one that we felt met our goals and the nature of our data but far from the only alternative. While we have given our reasons for not using linear programming or optimal foraging theory here, we would be curious to see what the results of such analyses would be. Indeed, we hope that we have included enough information in the earlier chapters of this volume so that some of our colleagues with expertise in optimization models will be tempted to apply them to our data. Only in this way can the Guilá Naquitz data transcend the parochiality of our analyses and contribute to the general discussions of foraging theory carried on by our colleagues.

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An Adaptive Computer Model for the Evolution of Plant Collecting and Early Agriculture in the Eastern Valley of Oaxaca

Robert G. Reynolds

PART 1: INTRODUCTION

One aspect of all interesting social systems would seem to be the need to synchronize reliably sets of concurrent or parallel social processes. While many observers will readily admit to the existence of mechanisms to meet this need, few have attempted to model them. Some years ago, Flannery (1968) suggested that such processes of synchronization were instrumental in the gradual evolution of primitive agricultural systems in central Mexico, drawing most heavily on MacNeish's work in the Tehuacán Valley of Puebla.

While many of the crucial processes involved in agricultural evolution involve exchanges of *matter* and *energy*, Flannery argued that they were synchronized by exchanges of *information*. In a later paper, he and Marcus argued that most paleoecological studies in archaeology had dealt only with exchanges of matter and energy and that this was "distressing because it is the information exchanges which regulate many of the matter–energy transactions" (Flannery and Marcus 1976:374).

The widespread bias toward the modeling of human ecosystems in terms of matter and energy reflects a corresponding bias in the nature of the available data. That is, aspects of a prehistoric society's material culture, such as tools, animal bones, and plant remains, are more likely to be preserved in the archaeological record than evidence concerning its information-processing and decision-making structure. The archaeologist is, therefore, in a situation somewhat akin to that of the computer scientist who is given a detailed description of the hardware for a particular computing system and then asked to make inferences about the structure of the programs that are most often run on it. Making inferences in such situations often involves "leaps of faith" that most researchers are hesitant to make.

Flannery's 1968 model for agricultural evolution can be briefly described as follows. Given the seasonal aspects of the semiarid Mexican highlands, many edible plants and animals are available only at certain times of the year. For example, some species bear fruit at the end of the dry season, which lasts from November to May, so that their seeds can germinate during the rainy season to follow. A large number of other species fruit at the end of the rainy season so that their seeds lie dormant during the following dry season and sprout when the rains begin in June. As a result, a number of plant and animal resources are available simultaneously in large amounts at certain times of the year and not at others. This situation produces scheduling conflicts such that a small group of hunter–gatherers with limited time and labor capabilities must decide what to collect, when, and how. Since they are effectively competing with other animals, what is not collected immediately is often lost to the group.

Incipient agriculture, Flannery suggested, began as an extension of efforts to increase the local density of desirable plants. While the scope of these new activities was initially quite restricted, even then scheduling conflicts began to arise. These conflicts were especially important during the months from August to November. This is the peak time for the collection of most of the seasonal wild plants recovered at Guilá

Naquitz. Any harvesting of newly cultivated plants would have to compete with these other collecting activities for the group's time. Therefore, the achievement of a sedentary agricultural system from one based principally on the collection of wild plants with some incipient agriculture involves the gradual rescheduling of a group's activities over time. In the Valley of Oaxaca, this process would have taken place between 9000 and 1500 B.C., by which time the first permanent village settlements had appeared.

One driving force behind this rescheduling process was the fact that repeated planting of maize and cucurbits increased the plants' availability, first by increasing their density and later by selecting for favorable genetic changes. Therefore, while the yields associated with the hunting and collecting sector of the economy remained approximately the same, those associated with certain domesticates increased. If rescheduling by the group was based at least in part on the schedule's observed performance, one would then expect over time a gradual but directed shift toward scheduling strategies that emphasized the agricultural component.

While the overall model deals with the set of adaptations that led to sedentary agriculture from a system based entirely on the collection of wild plants, it can be divided into several different stages: (1) collection of exclusively wild plants, (2) an early form of agriculture that simply involved altering the distribution of available species, (3) a gradual production of higher-yielding strains due to genetic change and selection, and (4) sedentary agriculture. In this chapter I am concerned mainly with modeling the first two stages, which took place during the period 9000–6500 B.C. Extension of our basic model to cover the remaining stages should be a subject for future research.

With regard to these two early stages, Flannery argues that some of the most important pressures involved in producing the initial series of adaptive changes were *internal* ones based on decision-making problems. This provides a contrast with some other models for the origins of agriculture, in which *external* pressures such as climatic change were seen as crucial. Our intent here is to operationalize those portions of the 1968 model dealing with agricultural incipience and to test them against the data presented in earlier sections of this volume. In the process, we test two basic claims: (1) that scheduling decisions based on a number of different criteria served to structure the group's preagricultural collecting behavior and (2) that these scheduling considerations regulated the manner in which the group adjusted its existing collecting behavior to accommodate new activities dealing with incipient agriculture. Since Flannery's 1968 model was based largely on MacNeish's 1960–1964 work in Tehuacán, and the data in this volume result largely from Oaxacan analyses completed subsequent to 1968, no tautology is involved.

Another of my purposes in undertaking this analysis is to challenge the notion that systems models cannot be quantified or operationalized. For example, Doran (1970:289) has already questioned whether Flannery's 1968 model could be made operational:

> Flannery can, for example, point to an example of positive feedback in the ecosystem of Mesoamerica in the period he considers. But there is little he can do to quantify that observation. And if he could, by some miracle, attach meaningful figures to the various food-procurement systems he studies, what would happen then? Although there certainly is a solid body of mathematical theory and techniques labelled "system theory", it forms a branch of control engineering and is most unlikely to be of practical use in such a context.

Doran thus sees two obstacles that stand in the way of operationalizing a model such as Flannery's: (1) the lack of mathematical techniques to aid in the modeling and eventual computer simulation of such a system and (2) the lack of archaeological data against which the model could be tested.

In the decade since Doran made these comments, a number of advances in both of the above areas have been made. For example, in the realm of control theory, Holland (1975) has developed a sophisticated framework in which to model adaptation in both natural and artificial systems. Holland's framework is employed here as a formal basis in which to embed Flannery's model. However, this initial formal model still needed to be simplified somewhat before it could be simulated on a computer. Zeigler (1976) has dealt extensively with techniques for translating a formal "base" model into a simpler "lumped" model whose behavior preserves certain desirable properties of the original. We employ Zeigler's approach here to generate a simpler version of our initial formal model, one that is amenable to computer simulation and produces results that can be compared with current archaeological data.

While these mathematical techniques were being worked out, new quantitative data were being collected on the seasonality, productivity, and nutritional makeup of the eastern Valley of Oaxaca. These data, which were presented and analyzed in Chapters 18–24 of this volume, were not available in 1968 and thus effectively prevented Flannery from quantifying his model. It is these newly collected Oaxaca data that can now be combined with Holland's and Zeigler's mathematical approaches to operationalize a model originally generated from Tehuacán data.

With the above background in mind, the remainder of this chapter is structured as follows. The first portion, consisting of Parts 2–6, deals with the developing and testing of the scheduling model for the preagricultural system. We begin in Part 2 by formally demonstrating that a group of hunter–gatherers in a semiarid environment like that of the Valley of Oaxaca are faced with a number of complex problems in information processing. These problems are felt to have generated internal pressures that helped to orient the group's scheduling of resource acquisition activities.

In Part 3 we begin our modeling of preagricultural scheduling activities by looking first at the available archaeological and environmental data. The nature of these data motivates us to make certain initial assumptions about the structure of our model. In Part 4 we derive an informal characterization of our scheduling model. In Part 5 this informal model description is given formal interpretation as a network of adaptive systems. This basic formal model is then simplified to allow for computer simulation. It is shown that the behavior of this simplified system formally preserves certain desired aspects of the original model. As a result, simulation of this simpler model can be expected to produce behavior like that of the original, more complex one. The results of this simulation are then presented in Part 6. Our intent there is to characterize the general set of resource scheduling adaptations acquired by the model group in the process of attaining an equilibrium set of scheduling strategies. The properties of these strategies are then compared with the archaeological data.

Having developed our adaptive computer model of preagricultural scheduling activities and characterized its steady state behavior, we proceed to make a number of experimental structural changes to the system in Part 7. These changes correspond to the acquisition of incipient agriculture in the manner suggested earlier in this chapter. In Part 8, this new system is simulated. Starting with the system in its preagricultural steady state, we observe what happens as it begins to experiment with incipient agriculture. It will be interesting to see whether the basic preagricultural scheduling adaptations previously acquired by the group are retained in the wake of these changes. Also, we want to see what forms of rescheduling are produced by the simulated system and how well these changes conform to the corresponding changes in the archaeological record over time. In Part 9, we alter the parameters of the model in order to see what effect different regimes of climate and population might have had on the rate of acquisition of incipient agriculture.

Finally, in Part 10 we summarize our results, draw conclusions about the behavior of our model group in both preagricultural and early agricultural times, and set forth what we see as the wider implications of our study.

PART 2: MODELING HUNTER–GATHERER DECISION MAKING

Introduction

In this section, we examine a formal mathematical model that suggests that consensus-based egalitarian hunter–gatherers (especially those living in mosaic environments such as those in the Near East, highland Mesoamerica, and the Andes) were faced with a number of significant problems dealing with acquisition of reliable information about the location of necessary resources. By concentrating on problems of information acquisition, we also suggest that agriculture could have arisen in some areas as a solution not to climatic change or population problems but to the predictable problems of resource search and scheduling encountered by any group lacking a decision-making hierarchy.

We are concerned with modeling the decisions made by a group of hunter–gatherers about how to best utilize a two-dimensional distribution of resources. In particular, we are concerned with the following problems:

1. the ability of each member to collect and process information about the resource distribution,
2. the extent to which information is shared among members,
3. the specific sets of decisions available to each member, and
4. the way in which the individual decisions are integrated to produce a group decision.

In this context, it is formally demonstrated that constraints on the communication between individuals impose limitations on the utilization that any egalitarian group can make of the spatially distributed resources accessible to it.

Our basic model of group decision making is that of the "linear threshold" or "voting" type that demands only minimal communication facility by its members. By relating our model to the perceptrons studied by Minsky and Papert (1969), we are able to employ some of their fairly deep results on the limitations of perceptron recognition in our own context.

Our specific aim here is to characterize formally certain aspects of egalitarian decision-making systems and to demonstrate within the context of the model that it is hard for such a group to answer certain questions about its environment. In particular, we demonstrate that the group's ability to decide on the direction to take for maximum resource exploitation is strongly limited by the information gathering of its individual members and *not* by the number of individuals in the group.

More concretely, let the area searchable by an individual be bounded by some constant M. Then no matter how large the group, or how complex the information-processing power of the individual (limited of course to the search area), there is a maximum region size N, determined by M, in which the group can decide the following question: In which region is the largest supply of resources concentrated? We stress that this is not a trivial limitation due to limited accessibility (since with a sufficient number of individuals an area of any size can be fully searched) or to individual processing capacity but a genuine limitation imposed by the structure of the decision-making process.

We show that, by augmenting the basic group model with a centralized decision maker[1] so that the structure is now of the pandemonium form (see Minsky and Papert 1969), the limitation on maximum region disappears. In fact, very little in the way of information collection capacity is required of the individual members to solve the "best-direction" problem, though mental capacity by the decider for perception and comparison of directional proposals is now necessary.

[1]This term refers to a simple pattern-recognizing scheme in which the model's components vote on the presence or absence of a particular pattern. The final decision is a weighted linear sum to the components' individual decisions.

Some Preliminaries: The Modeled Environment

We begin by providing a formal characterization of the environment with which our several decision-making models must deal.

Definition: Let R represent an arbitrary set of cells in the standard two-dimensional cellular space (i.e., a planar region divided into R discrete subregions [cells] of unit area).

Here it will be convenient for us to think of R as the catchment area, or current set of locations about which the group can acquire information. Each location i will refer to a particular cell in the two-dimensional space. With each cell in this space is associated a finite set of properties or attributes. At this point it is best to think of these properties as being resources of interest to the group. For our purposes, all we need to know is whether a certain resource is present (coded here as 1) or absent (coded as 0) in a specific location at a certain time t. No assumption is made about the nature of these properties except that they can be recognized by an individual scanning the location. Therefore, if resource Z is present at location i, then an individual looking for resource Z at location i will observe it.

The subset of all locations in which a resource Z is found at time t exhibits a certain distribution over the space R, as does the set of all locations at which it is not found. We denote by Z_t the subset of cells in R at which resource Z is found at the time t. Since time plays no role in our current discussion we drop the t subscript and refer directly to distributions as subsets Z or R.

In order to exploit a resource distribution Z, a group must be able to categorize it in various ways. The most fundamental categorization is of the binary kind in which the subset Z is determined to have some property P (such as being empty) or not.

Definition: A configurational predicate is a function that assigns to each subset of the catchment set R one of two possible values.

If the distribution of cells in R that possess resource Z is characterized by a property P, then $\Psi_P(Z)$ takes the value of 1; otherwise it has the value of -1.

There are essentially two general classes of predicates:

1. Position-dependent predicates are defined precisely with reference to specific points in R. For example, the query, "Are there nut crops in the canyon on the south side of the river?" is defined relative to a particular subarea of R.
2. Position-independent predicates are concerned with the recognition of general classes of patterns independent of where they occur within the region R. One example would be the predicate Ψ_{connect}, which serves to identify the class of all connected regional distributions. Other position-independent predicates that might be of concern are whether any grove of trees within its territory R has ripe fruit or whether there are any potential predators within the region R.

We now specify what it means for a group potentially to recognize a distributional predicate.

Definition: A distributional predicate is potentially recognizable by a group if there exists a decision-making algorithm or procedure executable by the group whereby it can decide with absolute certainty whether or not the predicate is true for any given distribution.

The Group Theoretic Framework

In the preceding sections we developed a formalism in which to phrase both the distribution of resources and the properties of these distributions over the space R. Now we develop our basic model in which each individual is able only to vote for or against a particular question that is posed to the group. He or she is not, however, able to express to the rest of the group the specific information used to form his or her opinion.

The following assumptions are made about the behavior of any member:

1. The region of interest R is larger than the area over which the member can collect data. This is certainly a reasonable assumption when one is concerned with hunter–gatherers, where walking is the principal form of transportation.
2. If an observable resource is present within a cell, then an individual looking there will observe it.

Although the latter assumption is particularly optimistic, since more realistically some erroneous data might be collected, the presence of this assumption in the model serves a good purpose. We show that even these hypothetical groups composed of error-free individuals cannot recognize certain types of distributions without some additional processing. More realistic models with the same decision-making structure but employing error-prone individuals can at best only hope to do as well.

With the above in mind, we express the data collection activities of any one individual X as δ_X, a predicate whose domain of reference is a subset of points in R. This subset of points is termed the *support* of the local predicate δ_X. For example, suppose an individual X searches a subregion S_X at time t in order to check whether there are any cells containing a resource Z. Formally, if $S_X \cap Z$ is not empty, $\delta_X(Z) = 1$, otherwise $\delta_X(Z) = -1$. The support of δ_X is then the subset of locations within R that are checked by an individual.

Local predicates of this kind, called *masks*, are basic to perception studies, but the theory is not limited to their use.[2] Supports of local predicates can overlap, so a location may be checked by more than one individual. Moreover the support of a local predicate need not consist of contiguous cells. The requirement of contiguity is a natural one in our context, but since we are interested in showing limitations

[2]The restriction to masks turns out not to limit perceptron capabilities according to a theorem of Minsky and Papert (1969).

of the primate group decision model under even the most optimistic circumstances, we do not restrict supports to contiguous sets or local processing to the mask type.

It now remains for us to discuss how the several individual decisions are woven together by the group to produce an overall decision.

The Decision Function

As already indicated, we initially consider the case in which an individual can only communicate his or her opinion, either favorable or not, with respect to a question (predicate) posed to the group.

First we take the localized predicate δ_X, which symbolizes the individual's decision based on his or her particular experience. With each individual X is associated a weight W_X that reflects the relative influence his or her opinion has on the group's decision about the particular class of problems. Every member is able then to vote on the matter, with some opinions counting more than others and some counting not at all ($W_X = 0$).

Now the group decision Ψ_{GROUP} can be expressed as a weighted linear function of the individual ones, where

$$\Psi_{\mathrm{GROUP}}(Z) = \begin{cases} 1 \text{ if } \sum_{X \in \mathrm{GROUP}} W_X\, \delta_X(Z) > \theta \text{ and} \\ \\ -1 \text{ otherwise.} \end{cases}$$

The constant θ represents a certain level of confidence that must be attained before consensus is reached. If the sum of the weighted individual opinions taken together exceeds this level, a positive consensus is attained. Otherwise the consensus is a negative one. Note that the threshold θ is problem specific. It can therefore take small values for unimportant questions and larger values for more important ones.

We refer to the above models as *voting groups*. Such models belong to the class of linear threshold devices and are formally isomorphic to the one-level perceptrons of Minsky and Papert (1969).

A predicate Ψ is potentially recognizable by a group if there are weights W_X, $X \in$ GROUP, and a threshold θ such that for each subset Z in R, $\Psi_{\mathrm{GROUP}}(Z) = \Psi(Z)$.

Individual Decision-making Capabilities

An individual can recognize a class of position-dependent predicates, namely those whose reference cells fall within his or her support. If his or her domain is relatively small, this class of predicates is correspondingly restricted. Moreover, in such a case, the individual is incapable of recognizing any nontrivial translation-invariant predicates. A *translation-invariant predicate* is a special case of position-independent predicate in which the defining property is preserved under all spatial translations.

Theorem: An individual searching a maximum area of size L within a sufficiently large region R cannot recognize any nonconstant translation-invariant regional predicates.

Proof: Suppose Ψ is a translation-invariant predicate on R that is recognizable by X. Then any two distributions that agree on L are Ψ equivalent (i.e., assigned the same Ψ value). Let R be large enough so that a translation L' of L can be found disjoint from L. Let d_{empty} be the distribution with all zeros in R. Let $d_{L'}$ consist of any arbitrary assignment of zeros and ones to L' and zeros everywhere else. Translate d_{empty} and $d_{L'}$ so that L' is placed over L. Since d_{empty} and d_L agree on L, they are Ψ equivalent; and since Ψ is translation invariant, their translates are also Ψ equivalent. Thus Ψ assigns the same value to all distributions over L and hence to all distributions over R, that is, Ψ is constant predicate (Ψ_{TRUE} or Ψ_{FALSE}) Q.E.D. With our intuition concerning the limits of individual capability thus reinforced we turn to group decision capabilities.

Recognition Capabilities of Voting Groups

Minksy and Papert (1969) have established certain capabilities and limitations of perceptron models. In our context, the most relevant strength of perceptrons is their ability to do certain kinds of counting and their ability to perform certain kinds of numerical comparison. To make this precise, we need to introduce the notion of "order." The order of a local predicate δ_X is the size of its support (i.e., the number of cells it looks at). The order of a perceptron or voting group employing a set of predicates $\{\delta_X | X \in \mathrm{GROUP}\}$ is the maximum of the orders of its local predicates. Finally, the order of a predicate Ψ_R on region R is the smallest order of all the perceptrons that can recognize Ψ_R.

We have just now purposefully emphasized that a predicate always refers to a particular region. The reason is that even though this is true, we often think of the same predicate being applied to any arbitrary region. Technically, such a predicate is really a *predicate scheme* (i.e., a rule that associates to each region R a particular predicate Ψ_R). For example, the predicate scheme $\Psi_{\mathrm{everywhere}}$ assigns to any region R the predicate $\Psi_{\mathrm{everywhere}}$, where $\Psi_{\mathrm{everywhere}}(Z) = 1$ if and only if Z is a distribution on R and $Z = R$.

With this in mind we can define the *order of a predicate scheme* to be the smallest of the orders of all the predicates defined by the scheme. If this order is finite, all the predicates, no matter what the size of the underlying region, are recognizable by perceptrons of this order or less; if the order is infinite, then the order of perceptrons needed to recognize the predicate Ψ_R grows without bound as the size of the region increases.

We summarize some results of Minsky and Papert (1969) in Table 31.1. Let us interpret the table in terms of the voting group model. Our hunter–gatherer group can decide whether or not a region has any resource. To do this, it need only have enough individuals to cover the entire region, with each individual examining a subset of cells for presence of the resource. The weights can be all -1 for Ψ_{empty}, and all $+1$ for $\Psi_{\mathrm{somewhere}}$, with thresholds $|R|$ and $-|R|$ respectively ($|R|$ is the size of R). More usefully it can decide whether one region is more profitable to utilize than a second region. It can recognize $\Psi_{A|>|B}$ by weighting individuals sampling A by +1 and those sampling B by −1. All the results above the dashed line in the table are variations on this theme except for $\Psi_{=N}$. This last result has an interesting implication in our context:

Observation: The predicate $\Psi_{A=B}$ (regions A and B contain the same number of resource cells) is of Order 2. Moreover, at least one local predicate must have support in both A and B.

Proof: $\Psi_{A=B}$ is true if and only if $\Psi_{A \geq B}$ and $\Psi_{B \geq A}$ are both true or both false (i.e., $\Psi_{A=B} = \Psi_{A \geq B} \cdot \Psi_{B \geq A}$). By substitution of the linear forms, or by Theorem 1.5.4 of Minsky and Papert, the order of $\Psi_{A=B}$ is seen to be no greater than 2. If the order were 1, then the order of $\Psi_{=N}$ would also be 1, since we could set up a distribution of N cells in A and recognize when any distribution in B had this same number of nonempty cells using $\Psi_{A=B}$.

Now suppose $\Psi_{A=B}$ is recognizable with predicates having supports restricted to either A or B but not both. Then the sum in the linear form splits into two disjoint parts. By a familiar argument, we can show that the following four situations lead to a contradiction:

1. $|A \cap Z| = |B \cap Z| = 0$,
2. $|Z \cap Z| = 1, |B \cap Z| = 0$,
3. $|A \cap Z| = 0, |B \cap Z| = 1$,
4. $|Z \cap Z| = |B \cap Z| = 1$.

Q.E.D.

Thus, to check the equality of resources in two disjoint regions at least one member of the group must sample both regions, in effect doing a comparison. In fact, in the realization with Order 2, many individuals make elementary comparisons of pairs of cells.

From Table 31.1, we see that counting Modulo 2 (Ψ_{parity}) is not easy for perceptrons. In fact, Minsky shows that *all* cells must be examined by at least one individual in the group (meaning that the individual must be smart enough to do the calculation!). Also noteworthy is the fact that $\Psi_{connected}$ is not of finite order, so that for any group of individuals there is a largest region in which the group (voting model) can handle the concept of connectivity. A more meaningful limitation is that of the infinite order of the minimization predicate $\Psi_{A>C,\,P>C}$. This implies that deciding which of more than two alternative regions is best is hard for our voting model. But to see this requires that we formulate the notion of choice of direction for our model.

TABLE 31.1
Predicate Schemes and Their Orders

Predicate	Definition	Order
Ψ_{empty}	Resource absent in region.	1
$\Psi_{somewhere}$	Resource present somewhere in region.	1
$\Psi_{everywhere}$	Resource is found everywhere.	1
$\Psi_{>N}$	At least N cells have the resource.	1
$\Psi_{<N}$	No more than N cells have the resource.	1
$\Psi_{=N}$	Exactly N cells have the resource.	2
$\Psi_{A>B}$	Subregion A contains at least as much resource as subregion B.	1
$\Psi_{A>C,\,B>C}$	Subregion C has less resource than both A and B each do.	∞
Ψ_{parity}	An odd number of cells have the resource.	∞
$\Psi_{connected}$	The resource distribution is connected.	∞

Group Directional Decision Making

While we have so far formulated our decision problem in binary form, much field observation suggests that hunter–gatherer groups are very concerned with directional choices. Finding itself located at some point in a large region, with which its members have some experience, the group must decide among the diverse proposals which direction to move. The essence of this problem, we feel, is capturable by our voting model extended as follows to enable directional decisions:

Let a point in a region R be designated as the origin of a rectangular co-ordinate system (this is to represent the group's current position). Let QUAD designate the set of quadrants represented counterclockwise by the points (1,1), (−1,1), (−1,−1), and (1,−1), respectively.

Definition: A directional function Ψ is a mapping from the subsets of R to QUAD. Thus Ψ assigns to each distribution Z an element $\Psi(Z)$ in QUAD that represents a direction in which to move.

Our primary example is the maximization function Ψ_{max} defined as $\Psi_{max}(Z) = (i^*, j^*)$, where (i^*, j^*) represents the quadrant having the largest number of resource cells. Formally, $|Q_{(i^*,j^*)} \cap Z| = \max_{(i,j)\in \text{QUAD}} |Q_{(i,j)} \cap Z|$, where $Q_{(i,j)}$ is the quandrant represented by (i,j). (If there is a tie for the most profitable quadrant, we allow an arbitrary choice.)

While we work with four directions, our results are easily extendable to an arbitrary number of directions.

We now extend our voting model to enable directional decision making.

Definition: A vector voting model specifies a linear threshold directional function: $\Psi_{GROUP} = \text{QUAD}[\sum_{X \in GROUP} W_X\, \delta_X(Z)]$, where each δ_X is a local directional function mapping Z into QUAD $\cup$ (0, 0) and QUAD maps the region R into quadrants—namely QUAD(x,y) = [bin(x), bin(y)], where

$$\text{bin}(x) = \begin{cases} 1 \text{ if } x > 0 \text{ and} \\ -1 \text{ otherwise.} \end{cases}$$

Our vector voting model is truly an extension of the basic voting model. In the vector model each individual can propose a direction based on the region he has explored. Each direction is treated as a unit vector, the associated weight gives a magnitude to the vector and then the vectoral sum is taken. The resultant vector is then categorized according to the quadrant in which it lies. No generality is lost by not including a threshold explicitly since this may be included as one of the local functions. In these terms the basic voting model is a one-dimensional version of the extended model of the form $\Psi_{\text{GROUP}} = \text{bin}[\sum_{X \in \text{GROUP}} W_X \, \delta_X(Z)]$.

Definition: A vector voting model computes a directional function Ψ if $\Psi_{\text{GROUP}} = \Psi$.

We now establish the promised limitation on the vector model's directional decision capabilities.

Theorem: The directional function $\Psi_{\max}$ is not of finite order in the class of all vector voting models.

Proof: Suppose to the contrary that the directional function is of finite order M. Let R be an arbitrary region with designated origin and let a vector model of order M compute $\Psi_{\max}$.

$$\begin{aligned}\Psi_{\max}(Z) &= \text{QUAD}\,[\textstyle\sum_{X \in \text{GROUP}} W_X\delta_X(Z)]\\ &= \text{QUAD}\,[\textstyle\sum_{X \in \text{GROUP}} W_X(\delta^1_X(Z),\, \delta^2_X(Z)]\\ &\quad \text{(where } \delta^1 \text{ and } \delta^2 \text{ are the projections of } \delta \text{ on the}\\ &\quad \text{first and second co-ordinates, respectively)}\\ &= \text{QUAD}\,[\textstyle\sum_{X \in \text{GROUP}} W_X\delta^1_X(Z),\ \sum_{X \in \text{GROUP}} W_X\delta^2_X(Z)]\\ &= \text{bin}[\textstyle\sum_{X \in \text{GROUP}} W_X\delta^1_X(Z)],\ \text{bin}[\sum_{X \in \text{GROUP}} W_X\delta^2_X(Z)]\\ &= [\Psi^1_{\text{GROUP}}(Z)\Psi^2_{\text{GROUP}}(Z)],\end{aligned}$$

where Ψ^1_{GROUP} and Ψ^2_{GROUP} are of Order M. (The projections have the same order as the original functions.)

Thus $\Psi^1_{\text{GROUP}}(Z) = 1 \Leftrightarrow \Psi_{\max}(Z) = (1,1)$ or $\Psi_{\max}(Z) = (1,-1)$. Now restrict Ψ^1_{GROUP} to quadrants $(1,1)$, $(-1,1)$, and $(-1,-1)$. Then

$$\begin{aligned}&\Psi^1_{\text{GROUP}}(Z) = 1 \quad\Leftrightarrow\quad \Psi_{\max}(Z) = (1,1)\\ &\Leftrightarrow\quad |Q_{(1,1)} \cap Z| = \max\{|Q_{(1,1)} \cap Z|,\ |Q_{(-1,1)} \cap Z|,\\ &\qquad |Q_{(-1,-1)} \cap Z|\}\\ &\Leftrightarrow\quad |Q_{(1,1)} \cap Z| > |Q_{(-1,1)} \cap Z|\\ &\qquad \text{and } |Q_{(1,1)} \cap Z| > |Q_{(-1,-1)} \cap Z|.\end{aligned}$$

Thus it is possible to decide which of three quadrants has the largest concentration of resources. But by defining $\overline{\Psi}(Z) = \Psi^1_{\text{GROUP}}(\overline{Z})$, where $\overline{Z}$ is the complementary distribution to Z, we then have

$$\begin{aligned}\overline{\Psi}(Z) = 1 \quad\Leftrightarrow\quad &|Q_{(1,1)} \cap Z| < |Q_{(-1,1)} \cap Z| \text{ and}\\ &|Q_{(1,1)} \cap Z| < |Q_{(-1,-1)} \cap Z|;\end{aligned}$$

and thus the minimization predicate $\Psi_{A > C,\, B > C}$ is of finite order M, a contradiction. Q.E.D.

We conclude that for every vector voting group there is an upper bound on the size of the region in which the group can decide in which direction to go to find the largest concentration of resources. This upper bound is determined by the area sizes accessible to group members.

Decision Capabilities of Groups with a Central Decision Maker

Consider now the vector model augmented with a maximizer D. The direction function computed by such a pandemonium structure is

$$\Phi(Z) = (i^*, j^*)$$

where

$$\text{MAG}_{(i^*,j^*)}(Z) = \max_{(i,j) \in \text{QUAD}} \text{MAG}_{(i,j)}(Z),$$

where

$$\text{MAG}_{(i,j)}(Z) = |\delta_X(Z) = \textstyle\sum_{(i,j)}(i,j) W_X|.$$

In other words, the output direction is the one in which the magnitude of the associated vector is largest. Note that this requires that proposals of each of the members be classified into directional categories, the strength in each category totaled, and the results perceived by the demon D who selects the category with greatest strength. Clearly much more in the way of intragroup communication is required to realize this structure.

It is easy to see, however, that pandemonium models can compute the maximization function with finite order local functions. Indeed, let each cell (x,y) in R be scanned by a first-order local function

$$\delta_{(x,y)}(Z) = Z(x,y) \cdot \text{QUAD}\,(x,y);$$

that is, if resource is present at cell (x,y), then a proposal is made for motion toward the quadrant in which it lies. Using unit weights the resultant proposals in the four alternative directions are equal to their respective concentrations of resources. The maximizer thus selects the most promising direction.

While we have shown how a group making decisions in the manner described by our model can theoretically compute a number of spatial predicates and functions presented to them by the environment, there is no guarantee that it will. In terms of the model, the following criteria must be met in order for a model computable function to be actualized:

1. There must be a set of expected values for the pertinent variables corresponding to locations within the environment.
2. The search areas must be coordinated so that all cells in the space necessary to the recognition of the pattern are scanned.
3. The weights for individual opinions regarding a problem must be coordinated with their experience and the level of consensus needed to obtain a group decision.

Note that Criterion 2 requires there be a sufficient number of members in the group so that the region is covered. Our limitation results show that even if this is the case, there are limitations on the group's decision-making ability. It is conjectured here that the coordination of weights is fostered by the presence of a relatively fixed set of social niches or roles that group participants might play. Such roles are often structured with respect to age and sex in egalitarian societies. Therefore, if a conflict between members arises and the one is able to displace the other, the principal effect is merely to change roles. If each role is characterized by an associated set of weights in the decision-making process, then the group by insuring the presence of a certain set of roles is maintaining an associated set of weights as well. This increases the likelihood of a good decision being duplicated in the future, even though the individuals who made the initial decision may no longer be present.

Predictions and Open Questions

Our results suggest that the size of the region in which resources may be maximally exploitable by hunter–gatherer groups that do not possess centralized decision making is strictly limited by the individual's abilities to gather information. In semiarid environments where the distribution of resources is mosaic, with these patches scattered over a large area, this limitation could be an important one. In this situation, a group in order to collect sufficient resources is often forced to forage over an area so large that members can only make educated guesses about the locations of available resources. Since we have shown that the group cannot always make decisions with certainty, it is important that they be able to increase their probability of making good decisions.

The remainder of this chapter is concerned with modeling the way individuals acquire and adjust their resource collecting strategies based on experience. In particular, we want to see how this process affects the way in which the group members incorporate agricultural innovations into an economy based principally on the collection of wild plants. Here we are concerned only with modeling this process within the Valley of Oaxaca, although aspects of the model may be applicable to other situations.

PART 3: THE EASTERN VALLEY OF OAXACA DATA

Introduction

In Part 2 it was suggested that good resource collecting schemes are not easy to generate since many decisions within them are based on collected information that is inherently unreliable. As a result, not all the strategies employed by the group will necessarily be good ones. It is therefore important that the group be able to find out, over time, which strategies are less successful than others. Accordingly, the model developed here deals with how a hunter–gatherer group acquires and uses performance information to restructure its repertoire of strategies.

Although the task of generating such a model is made difficult by the fact that the real system no longer exists, some archaeological data concerning the nature of the Guilá Naquitz group's behavior and its environment have been presented in the earlier chapters of this volume. Here we use that information to make certain suggestions about the model's design.

The Environment

The environment of the Guilá Naquitz area has been described in Chapters 3 and 4. In Chapters 15 and 16, Schoenwetter and Smith and Flannery and Wheeler have suggested on the basis of pollen and microfauna data that the present-day environment is a useful guide to the past. In that present-day environment, there is both (1) *predictable* variation in rainfall between the May–November wet season and the December–April dry season and (2) *unpredictable* variation in rainfall from one year to the next (Kirkby 1973:Figs. 9, 10, 58). Available precipitation data suggest that over a 40-year period about half the years will have "average" rainfall (between 420 and 600 mm), while a quarter of the years will be significantly drier than average and a quarter will be significantly wetter than average. In Chapter 18, the effects of "good" and "bad" years on the productivity of wild plants was documented. In our model, a hypothetical band of hunter–gatherers are presented with an unpredictable (randomly patterned) sequence of years 50% of which are "average," 25% of which are "rainy," and 25% of which are "dry." As suggested in Chapter 18, the effect of such years may be that there is a 25% decline in productivity in dry years and a 25% increase in productivity in wet years, which may be augmented if two wet or two dry years occur in succession (see Part 5). Since comparable data on animal resources are not available, our model is confined to the use of plants.

Vegetational zones in the vicinity of Guilá Naquitz have been presented in Chapter 4 (see especially Fig. 4.6) and their productivity estimated in Chapter 18. Virtually all the plant foods used at Guilá Naquitz were available within 4 km of the cave, and we possess data on (1) how far one would have to walk to each vegetational zone today and (2) how many square meters of that zone would have to be harvested to produce a specified amount of a given vegetal food. In Chapter 23 we have been given data on the nutritional makeup of the most important plants, and in both Chapters 23 and 24 we have reconstructions of hypothetical daily intakes. These are the raw data on the basis of which we attempt to model which zones our foragers used, the priorities they assigned to certain plants, and the extent of their success in terms of calories and protein recovered.

Even if we restrict the problem to one of scheduling a sequence of autumn plant collection activities, the task facing our group is not an easy one. This is evident from Fig. 18.1 in Chapter 18, which depicts the large number of plants available from August through November. Not only are there a number of potentially available plants but they also exhibit differing densities and distributions, especially as these parameters vary from year to year as a function of available rainfall.

The inhabitants of Guilá Naquitz were faced then with a rather complex problem, but one that had to be effectively dealt with if the group were to survive. The plant remains deposited on the living floors of the cave reflect the extent to which the real-life group solved this problem. It is the ultimate goal of our model to help us determine how. In order to do this we need to compare our hypothetical group's behavior with the archaeological data that we presently have about the real Guilá Naquitz group's solution.

The Archaeological Data

The excavation of Guilá Naquitz has already been described in Chapter 5, and the raw counts of major plant foods have been given in Chapter 25. These are the data against which the performance of our model must be evaluated. To what extent will the hypothetical group of hunter–gatherers in our simulation come up with the same plant frequencies displayed by living floors E, D, C, and B1 at Guilá Naquitz? To what extent will they display, over time, the changes in plant collecting documented for the Zone E–D–C–B1 sequence in Chapter 24?

Basic Assumptions

On the basis of the data presented in early chapters of this volume, we make the following assumptions for the purposes of our model.

1. The environment of the valley today is sufficiently similar to that during the period of study so as to allow us to use current environmental data in the model.
2. The distribution and density of wild plants in sample transects near the cave are sufficiently similar to what was present between 9000 and 6500 B.C. (There are a few exceptions to this, such as piñon nuts.)
3. During the period in question the cave was occupied principally between August and November by a group of at most four to five persons.
4. At this time, the group's focus was mainly on the collection of available wild resources. Due to the difficulty of evaluating the relative amounts of time spent hunting versus plant collecting, our model considers only the scheduling of plant collecting activities by the group.
5. Archaeological data from the cave support the assumption of behavioral continuity between the groups that successively occupied the cave. In other words, the data do not suggest the intrusion of another group with different patterns of resource exploitation.
6. There was no increase in the size of the group that occupied Guilá Naquitz from Zone E (9000 B.C.) through Zone B1 (6700 B.C.).

With these basic assumptions in mind, we begin the task of generating the preagricultural resource acquisition model in Part 4.

PART 4: THE INFORMAL PREAGRICULTURAL MODEL

Introduction

We are now ready to construct a model for the preagricultural foraging behavior of our hypothetical group of four to five hunter–gatherers in the eastern Valley of Oaxaca. In Part 4 that model is presented informally, in plain English. In Part 5, we present it formally in order to facilitate its implementation as a simulation program.

However, before proceeding, it may be beneficial to look at the experience of others who have used a systems perspective in modeling hunter–gatherer subsistence. Thomas (1971), in particular, has employed this approach in order to develop a model of subsistence for the precontact Shoshone in the Great Basin of Nevada. There he used ethnographic data collected by Steward (1938) to characterize the group's resource procurement and decision-making subsystems. Simulation of this model on the computer produced results that were then compared with the available archaeological data. This was done in order to test the ability of the model based on current ethnographic information to explain the group's behavior prior to first contact with Europeans. In the next section, we describe this excellent study in some detail. This will not only help us to characterize our own system but also provide us with some benchmarks against which our model can be compared.

Thomas's Model

The Great Basin of Nevada is a vast area of interior drainage that lies mainly between the Wasatch Mountains of Utah and the Sierra Nevada range of California. The landscape is characterized by large arid valleys nestled among mountain ranges that run from north to south (Steward 1955:103). These valleys lie between 4000 and 6000 feet above sea level and receive from 5 to 20 inches of rainfall in a year. Such low rainfall, coupled with high evaporation, supports largely drought-resistant vegetation. Much of the vegetation has limited nutritional value to animals or men. The largest concentrations of roots and edible seeds are found along the banks of streams that etch the landscape. However, in the extensive sandy areas between these streams, the quantity of edible plants is low and their distributions vary from year to year and place to place, depending on rainfall. This paucity of vegetation severely restricted the numbers of available game. Hunting was therefore an intermittent activity conducted on a communal basis. Fish were an additional source of food, but their runs were seasonal.

The second major vegetational zone was characterized by stands of piñon and juniper trees. This zone occurs at elevations from 6000 to 9000 feet above sea level, largely along the sides of the mountain chains. Increased rainfall at these altitudes resulted in more available seeds, roots, grasses, and game (especially deer) than along the valley floor. However, the most important available resource was the nut of the piñon pine. These were available seasonally in large numbers and were intensively collected. Large quantities of the nuts were cached and used for food during the winter months.

These biotic communities served to structure the spatial and temporal activities of the area's hunter–gatherers. Foragers, therefore, moved seasonally from one zone to the next depending on the availability of local resources. Steward described the typical movements of a Shoshone family in the following way:

> The typical Shoshoni family living in the piñon area of Nevada traveled alone or with one or two related families during the spring and summer, seeking seeds, roots, various small mammals, rodents, insects, larvae, and other edible items. In the late summer when a family heard reports that the pine nuts seemed very promising in a certain portion of a mountain range, it arranged its travels so as to arrive in that locality in late October or early November, when the first frosts would have opened the cones and made the nuts ready to harvest. Other families who had also been foraging for food within a radius of perhaps twenty to thirty miles of that locality came there for the same reason.
>
> In gathering the pine nuts, each family restricted itself by common understanding to a limited area, because there were so many pine nuts in the locality as a whole that no one could gather them all before they dropped and because each family could harvest more if it worked alone. The different families remained from several hundred yards to a mile or more apart. Each gathered pine nuts as rapidly as it could and stored them in earth caches. If the harvest was good, it might support the family throughout most of the winter.
>
> The winter encampment consisted of perhaps twenty or thirty families within easy visiting distance of one another. Early spring generally found the people suffering more or less acutely from hunger. The families then had to go their separate ways to forage for greens, game, and any other foods they could find. Throughout spring and summer, the migrations of a particular family, although limited in general to the terrain it knew well, were determined almost week to week by its knowledge of available foods. It might learn that sand grass seeds were promising in one place, rabbits numerous elsewhere, fly larvae abundant in a certain lake, and antelope ready for a communal hunt under a shaman or medicine man over in the next valley. (Steward 1955:105–106; reprinted by permission of the University of Illinois Press)

Steward's observations were taken by many anthropologists to be representative of Shoshonean lifestyles prior to their first contact with the white man. Since the environment has changed considerably as a result of this contact, one can only hypothesize that such a correspondence exists. Thomas undertook to test this hypothesis in the following manner. He first developed a computer program that simulated the seasonal round of activities for a "typical" family in an "average" year based on Steward's observations. The purpose of this simulation was to estimate the relative portions of artifacts deposited in an average year by a group that behaves in the manner suggested by Steward.

> The concern is not to chart change over a cultural trajectory, but rather to establish the "equilibrium basin" for the Great Basin Shoshonean technoeconomic system. The simulation model does not employ time in the conventional sense; that is, a 1000 year simulation model does not attempt to array systemic behavior over 1000 continuous years. Rather, a computer run simulating 1000 years simply repeats the artifactual deposition for the *same* year, 1000 times. (Thomas 1971:12)

In order to do this, Thomas embedded Steward's theory in a systems structure (Thomas 1971: Fig. 2.1). Each box in his flowchart represented a particular resource-acquisition strategy with respect to a certain resource. The decision-making scheme dealt only with how these different subsystems are selected during a year; in fact, Thomas constrained the sequence of selected activities to be that suggested by Steward. He was not, therefore, concerned with modeling change in resource procurement strategies over time, but rather with modeling the result of a particular seasonal scheduling strategy at one point in time (specifically A.D. 1840).

Significantly, in Thomas's Fig. 2.1 there are no connections between the different resource procurement subsystems. That is, each set of activities is seen to be done independently of all others:

> *BASIN I* obviously ignores interactions between subsystems. In more advanced simulation models, the interaction effects may be more significant than any of the main effects (Watt 1968:151). But *BASIN I* is not yet in such complex form. The attempt here has been to simplify an intricate extractive system into component subsystems, so that artifactual deposition can be simulated. (Thomas 1971:38–39)

As Thomas indicates, this assumption was quite consistent with the goal of his simulation. However, in developing our model of daily decision making and resource scheduling, these interaction effects have to be included.

Thomas was therefore primarily concerned with modeling a particular schedule of seasonal activities, the one proposed by Steward. As a result, the decision-making subsystem consists of the single seasonal sequence of activities. Associated with each of these activities is a set of artifacts deposited on the ground as a result of that activity. The model therefore generates a spatial pattern of artifacts that is then compared with what is known archaeologically about the distribution of these artifacts. Data were then collected from the Reese River in order to test the model. As it turns out, 75% of the predicted frequencies were verified by the archaeological data. From this, Thomas was led to conclude the postcontact Shoshone behavior, as described by Steward, well represented subsistence activities in the prehistoric Reese River valley.

Thomas's systems model was designed to model the spatial distribution of artifacts produced by one set of annual procurement strategies at a particular point in time. He suggests, however, that such a basic model could be extended to describe changes in resource procurement strategies over time. "Goal-directed systemic change (cultural trajectories) could perhaps also be studied if key variables could be integrated" (Thomas 1971:21).

In order to test our Oaxaca model, we have to simulate the types of changes suggested above by Thomas. This is what we begin to do in the next section.

Operationalizing the Oaxaca Model

The work of Thomas described in the previous section suggested that the seasonal scheduling of activities observed by Steward was also employed by prehistoric populations in the Reese River valley. While such patterned behavior is most readily observed in terms of seasonal shifts in resource use, local scheduling of collecting activities over a shorter period (say, several days) should be important as well. For example, Leakey and Lewin point out the importance of local decision making in describing the foraging activities of the !Kung bushmen:

> The real skill of food gathering is knowing where to go and when to go there. With a wide range of fruits, nuts, roots, and shoots coming into season at different times of the year and in different places, food gatherers must balance up the probability of success in traveling, say, three miles in one direction to a potentially good source of food, against going four miles in the opposite direction to an even richer source, but perhaps with a lower probability that it is ready to collect just yet.
>
> To make a success of a food-gathering economy you need highly efficient mental maps, not just of space but of time; you have to know where to go and at what time. . . . So, the key to this type of economy lies in the information and analytical skills inside the head, rather than in fancy technology wielded in the hand. (Leakey and Lewin 1978:109; reprinted by permission of Anchor Press)

As a result we might easily conceive of a resource collection schedule as a sequence of activities, where each activity consists of searching a number of locations in a particular vegetational zone for a certain resource. The principal resource of interest is termed the *focus* of the activity. While looking for this resource at the specified locations, an individual may collect small amounts of other associated resources found at the same location or on the way to that location. Such practices, however, contribute only small amounts to the overall yield for an activity and therefore are not explicitly dealt with here.

In our model, an activity is defined as occurring within one of the four vegetation zones (Thorn Forest A and B and Mesquite Grassland A and B) described in Chapter 4. This is because each vegetational zone in the vicinity of Guilá Naquitz has a distinct set of component species and associated densities. Therefore, the set of species associated with a focal resource changes from zone to zone, as do the densities of that resource. This implies that the nature of collecting activities will also vary from zone to zone. In fact, this variation is well documented by Steward for the Shoshone. By restricting the location of an activity to points within a vegetational zone, these distinctions can be taken into account.

A resource collecting schedule or strategy is a sequence of these activities that represent the behavior of the group over a certain period of time. In our model we look at collecting activities over a period of 10 days. During this 10-day period, group members execute each of the proposed activities in turn. At the end of this period, it may happen that not all of the planned-for activities have been carried out. These "intended activities" are still associated with that schedule, and together with those completed activities they describe the whole collecting strategy. Later, we describe the mechanisms that allow the schedule to be restructured. One possible result of this restructuring is to allow the use of activities that the group previously did not have time for.

In terms of our present approach, it is not important how the schedule is represented in the minds of the group members. By describing an activity on the basis of the resources collected and locations searched, we are really characterizing a strategy in terms of the observable results it produces when used. It is, therefore, not important whether it is specified by a single individual or jointly specified by several members; what counts is the fact that it is specified and used.

To this point we have talked only in terms of one generalized scheduling strategy. However, Flannery has suggested that there are probably a number of possible strategies that are available to the group: "The outlines of a schedule, albeit with conflicts, were present. . . . 'scouting reports' helped resolve conflicts and give precision to the dates of each kind of resource exploitation, depending on individual variations in growing season from year to year" (Flannery 1968:90). That is, at any point in time a number of alternative, possibly conflicting, schedules were available to be used. Exactly which one was selected depended on the current state of the environment. Collected information about the environment was then used to select a strategy to employ.

In our model, we presume that there were no more than 10 basic alternative strategies available to our group during a 4-month period between late August and early December, which seems reasonable for a group of five persons. From this set of 10, a strategy is selected for use based on environmental data. Since each strategy spans only a 10-day interval, a number of strategies could each be used several times during the period from late August to early December. In terms of our model, the plant materials found on the living floors of Guilá Naquitz cave were the result of applying a number of small-scale scheduling strategies over time. The more frequently a strategy is used, the more likely it is to influence the relative amounts of plant material deposited. While certain strategies may be used more often than others, our model assumes that it is the interplay of a number of strategies that contributes to the group's subsistence in any given year. It would, therefore, be very interesting to see what the equilibrium mix of strategies is for our model system. If our model is a good one, then the relative proportions of plant materials collected by this equilibrium mix should resemble the proportions found in the cave. For this reason we need to transform our present verbal description into a formal model. The equilibrium behavior of this formal model can then be simulated on the computer and the results compared with the archaeological data from the cave.

Associated with each strategy is information about its performance that is used when deciding whether or not to use the strategy. We now discuss, in turn, the types of information used to describe a schedule's performance in our present model.

Starting sometime in August and continuing into early December, the group selects a number of the currently available schedules to structure its collecting activities. Every time a strategy is used it allows the group to acquire a certain amount of food material, measured here in terms of protein and calorie yield. These measures represent the extent to which the energetic needs of the population are satisfied. While hunter–gatherers obviously do not evaluate a strategy directly in terms of the acquired grams of protein or number of calories, there is a distinct correspondence between the strategies' ability to satisfy the group's energetic needs and the group's physical well-being over the course of a season. During the season, the group members produce an estimate of the ability of each strategy to acquire food resources, based on the number of times that it is used. In our model, this estimate is based on the total amount of protein and calories acquired over the season. These estimates are then used to evaluate the relative performance of each strategy for the season.

Along with estimates of total yield, group members also form an impression about the amount of effort it took to collect that much food. Such considerations have been observed among present day hunter–gatherers. For example, the !Kung bushmen of the Kalahari "tend to cut only the most attractive foods available at a given season and bypass the less desirable ones in terms of taste and/or ease of collection" (Lee 1972:343).

Also, Silberbauer argues that conservation of collecting effort is important among the G/Wi bushmen. "In choosing from among a number of available species . . . [the G/Wi's] criteria of preference are, in order of importance, the thirst and hunger alloying properties of the plant food, the ease with which it may be exploited, and lastly its flavor" (Silberbauer 1972:283).

Therefore, the effort expended by group members in the course of employing a particular resource collecting schedule should be taken into account when evaluating its performance. In our model, estimates of the total amount of protein and calories acquired per unit area searched are used as a reflection of the effort needed to acquire them. The data needed to derive these estimates are drawn from Chapters 18 and 24 of this volume.

In addition to the specific impressions of each strategy's performance given above, an overall impression of the scheduling strategy's performance, relative to the other strategies used for the season, is developed. The factors that enter into the development of this impression are the following:

1. The strategy must satisfy certain minimal energetic needs for the group. The fact that hunter–gatherers seem to be well aware of this has been noted by Sahlins (1968), among others. Jochim expresses this principle quite nicely when he says that:

> The minimum number of calories necessary for the biological viability of the population provides a minimum aspiration level. The lack of large surplus accumulation and of large-scale redistribution systems in most hunter–gatherer societies, and the presence of conflicting demands on time and energy indicate that the actual aspiration level is not far above this minimum. (1976:16)

2. The strategy must continually be able to provide yields above the minimum even in the worst possible years. This is obviously important for hunter–gatherers in semiarid environments, as mentioned by Lee with reference to the !Kung: "During the dry season the [!Kung] diet becomes much more eclectic. . . . It is this broad base that provides an essential margin of safety during the end of the dry season when the mongongo nut forests are difficult to reach (1968:35)." Flannery (1968:90) also notes that consistent performance above the starvation level must have been important for hunter–gatherers in Oaxaca as well. Here the ability of a strategy to perform better than others in terms of both yield and required effort is taken to be a good indicator of relative reliability.

3. A strategy must take into account the state of the environment in which it was last employed. As described in Chapter 4, the state of the environment is primarily a function of rainfall, which will determine the density and distribution of relevant plants. Associated with each available collecting schedule is information that determines the "state" of the environment in which the strategy was last used. The extent to which this state agrees with the current year is undoubtedly one factor in determining whether to use a given strategy.

All of the above factors play a part in determining whether a schedule will be used and whether it will be modified. In our Oaxaca model, the group must select between 10 available strategies. This involves comparing the strategies on the basis of their relative merits. For our purposes, two comparisons are made in order to select a strategy: (1) What is the degree to which the present "state" of the environment matches the "state" in which the strategy was last used? (2) What is the group's impression of the strategy's performance relative to those employed the last season in which it was used? Taken together, these two criteria determine the likelihood of a particular strategy's being used at least once during a season.

A second major function of the decision making system is to "reschedule" a strategy, based on its performance. Once a schedule has been selected and its performance observed, the group members may elect to alter its structure. If the schedule performs well there is little need to alter its structure; indeed, tampering with it may do more harm than good. Therefore, it is more likely that a poorly performing schedule would be altered (since it is doing poorly already, the group has little to lose by making an adjustment).

Given that the likelihood of a schedule's being changed is associated with its performance, what manner of adjustments can be made to it? We program into our model a number of alternative ways in which changes can be made, based on suggestions by Flannery (1968):

1. Change the focal resource for an activity.
2. Change the vegetational zone in which the activity is carried out.
3. Change the set of locations over which to search for the resource.
4. Given two activities in a schedule, change the order in which they are executed.
5. Exchange activities between two schedules.
6. Replace an activity on one schedule with an activity from a more productive schedule. (This is equivalent

to imitating a successful activity associated with another strategy.)

7. Given two activities in a schedule that occur in the same vegetational zone, exchange their focal resources. (This means that the locations of the two resource collecting activities are shifted.)
8. Given two activities in a schedule that are in the same zone, exchange subsets of locations between them.
9. For two activities in a schedule, exchange their zones of execution and location sets, on the proviso that the new activities are defined. (In order for an activity to be defined, the resources must be present in the vegetational zone to be searched.)

Notice that each of these decisions involves at most two activities in two schedules. However, by applying a number of these decisions at the same time, one can represent more complicated decisions dealing with multiple activities over a number of schedules. In this way, the model group can create "its own decisions" out of these simple parts.

A rescheduling strategy assigns to each of these basic decisions a certain likelihood that it will be used to alter a given collecting strategy. This set of likelihoods develops as the result of past decision-making experience. In particular, those combinations of local decisions that have produced improvements in the relative performance of a schedule from one year to the next will have an increased likelihood of being used with the strategy again. Combinations of decisions that reduce the observed relative performance for a schedule will be less likely to be used again to modify the schedule. Therefore, the group uses observed changes in relative performance for a strategy to adjust its rescheduling policy for that strategy. As the structure of the group's collecting strategies changes with experience over time, so will the structure of its rescheduling decisions associated with each of them. That is, there will be a tendency to use only those decisions that are most likely to improve the performance of the current strategies.

In this section we have taken a first step toward operationalizing our model for the eastern Oaxaca Valley by providing a structural framework on which to build our formal model in Part 5. This structure contains a number of basic rules by which the group is able to alter its resource collecting strategies based on its experience. As a result of the operation of these decision-making rules over a period of time, the system should attain a relatively stable structure with some basic properties. What we attempt to do in Part 6 is to simulate the long-term behavior of the model and compare its structure with that of the real world. If the model adequately represents the real system, the simulation results should bear some similarity to the data from the real world, that is, the living floors in Guilá Naquitz.

There is still another way to verify our model. We can introduce a change in the model that corresponds with a known change in the real system and see if the two systems produce similar responses. If they do, we will have constructed a strong argument for the model's ability to represent the real system. Since the real system is known to have acquired incipient agriculture sometime between 8750 and 6800 B.C., we allow the model group to experiment with incipient agriculture and see if the model undergoes the same changes in resource use that the real system did. This is our task in later sections of this chapter.

Recapitulation

In Fig. 31.1, we present a simplified diagram that suggests how our model operates over time. Our model begins with the entry of a hypothetical family of five hunter–gatherers into the eastern Valley of Oaxaca. The area they enter consists of four vegetation zones that resemble Thorn Forest A and B and Mesquite Grassland A and B as defined earlier in this volume. Those zones are characterized by the differing frequencies of piñon nuts, acorns, *susí* nuts, agaves, nanches, wild beans, mesquite, hackberry, prickly pear, *guaje*, and wild cucurbits already described for them in earlier chapters; each of these foods is assigned the protein and calories it was found to contain in Chapters 23 and 24.

It is not assumed that our hypothetical group has as yet worked out any efficient way of using these resources. To begin with, they are assigned a 10-day strategy in which the order in which they utilize these resources, the vegetational zones they go to, and the amount of time spent in each zone are selected randomly. Then, over the course of a 4-month collecting season, they are allowed to modify their strategies at 10-day intervals; this procedure is followed year after year as the simulation continues to run.

Our hypothetical group is presented with an unpredictable (randomized) succession of years in which about 50% are average, 25% are wet, and 25% are dry. Plant yields are adjusted to year type as suggested earlier in this chapter. The system has a memory, so that the group can remember how a particular strategy worked in each type of year. The "efficiency" of a strategy is measured in terms of calories and protein recovered versus square meters of vegetation searched; the smaller the effort required to produce 2000 cal and 40 g of protein per person per day, the more efficient the strategy. We feel that considerable "realism" is introduced into the model through the fact that the group cannot predict in advance what kind of a year to expect.

Over the course of a season, the group uses a subset of plant collecting schedules to structure their resource acquisition activities. A schedule is selected to be used based on its past performance relative to other schedules, and the current state of the environment. Associated with the use of a schedule is a notion of its relative performance that is derived from a number of different considerations, such as reliability, yield, and expended effort. For those schedules that had been changed since they were last used, their new relative performances are contrasted with their old. If the schedule's performance increased as a result of the past rescheduling decision, then the rescheduling policy for the strategy is adjusted to make this decision more likely in the future. On the other hand, if the change produced an observed reduction in performance, then the rescheduling policy is adjusted

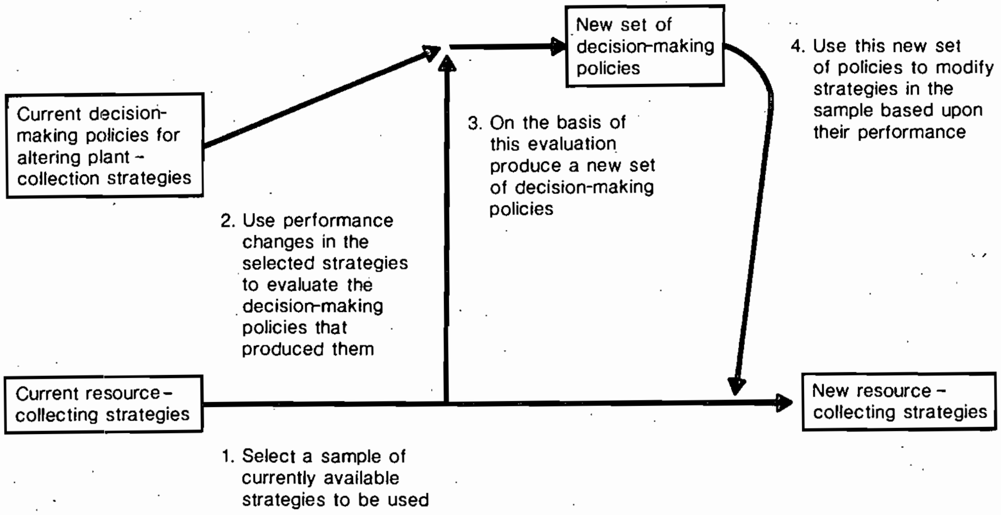

Fig. 31.1. Interaction between the two adaptive systems.

in order to make it less likely that the same type of change will be made again.

These adjusted rescheduling policies are then used to alter the structure of the utilized schedules on the basis of their relative performance. This serves to generate a new set of schedules that will then be available for the next year. It is this general sequence of processes that form the basis for the formal model described in Part 5.

While no simulation could exactly imitate a system that existed 8000–10,000 years ago, we feel that ours includes a number of elements that add to its realism:

1. The environment is based on quantified data that are believed, on the basis of paleoenvironmental studies, to be like those of the past.
2. With the exception of piñon nuts, the nutritional data are based on studies of plants collected within 5 km of Guilá Naquitz.
3. Our group must adjust to year-to-year variations in rainfall based on the best available precipitation data for the area.
4. The group can choose from a wide variety of strategies during any 4-month period (more than 1,000,000 possible sequences of collecting activities), making it impossible to "stack the deck" in favor of any one strategy.

PART 5: DEVELOPING THE FORMAL MODEL

Introduction

In Part 5, the informal base model presented in the preceding pages is given a formal interpretation. Since the informal model is concerned with the decision-making adaptations that served to structure the collecting activities of preceramic hunter–gatherers in the Valley of Oaxaca, any formal version should necessarily highlight the model's adaptive aspects. Along these lines, Holland (1975) has developed a formal mathematical framework in which to describe complex systems exhibiting adaptation. This framework has been used in a number of situations to describe adaptation in both natural and artificial systems (Cavicchio 1970; De Jong 1975; Holland and Reitman 1978). It is, therefore, well suited to our present purposes.

We begin the following section by providing a general overview of how the informal model is represented in terms of Holland's basic framework. It is convenient to view our model as comprising two interacting adaptive systems. The first deals with the specification and use of the various existing strategies for plant resource collection by the group. The second deals with the formulation of policies whereby the group can alter these strategies based on experience. In the subsequent 5 sections the formal specification for both subsystems is presented.

Given that we can rephrase our informal base model in terms of a formal adaptive system, the fact remains that our base model, as pointed out previously, makes predictions that cannot be verified using presently collectible data. We would, therefore, like to be able to translate the formalized base model into yet another simplified model, one that utilizes currently available data and can be tested via computer simulation. Recent work on the theory of modeling and simulation (Zeigler 1976) suggests that in certain situations precise formal inference can be made about the properties of a model even when the collected data are insufficient to test the model in all its aspects. This is done by generating a simplified or *lumped* version of the original model that preserves selected structural and behavioral properties.

The formal connection between the base and lumped model is termed a *system homomorphism*, and its existence guarantees that (1) there is a precise relationship between the structure of both models and (2) there is a similarity between the behavior of both models when subjected to corresponding sequences of inputs. In other words, the existence of a system homomorphism guarantees that the lumped model, designed to make predictions comparable to known data, responds to input in the same fashion as does the original.

The key to insuring such a correspondence is to ascertain that each change made in producing the simplified model preserves the particular behavioral and structural correspondences sought by the modeler. In the section titled, "Simplifying the Base Model," we state the structural properties we wish to preserve in the simplification process, as well as the type of simplifications we want to make. Next, a sequence of lumped models is produced by the successive application of these model simplifications. The end result is a model that uses only currently collectible data and makes predictions easily comparable with existing data. In addition, we are able to prove formally that this lumped model preserves the desired set of structural and behavioral properties found in the original. Once this can be substantiated we need only to simulate *this lumped model* and observe its behavior with regard to the properties of interest.

The Formal Base Model: An Overview

As suggested by Lewontin (1978), "the modern view of adaptation is that the external world sets certain 'problems' that organisms need to 'solve' . . . . [a]daptation is the process of evolutionary change by which the organism provides a better and better 'solution' to the 'problem'." Holland (1975) has extended this biological notion of adaptation in order to develop a formal framework in which to pose a problem in adaptation for any arbitrary system. Within this framework a problem is considered to be well posed if a formal specification can be given of the system undergoing adaptation, the specific problems posed by its environment to which the system can adapt, the set of available policies that can generate new adaptations, and some criterion by which to evaluate the system's adaptive success.

The two major problems facing our group of hunter–gatherers are what collecting strategies to use and how to change them based on their performance. It is possible, however, that the group may adapt to each of these problems concurrently. Also, the two problems are interdependent in the sense that adaptations made in one problem domain may affect the nature of subsequent adaptations in the other. In most interesting problems in evolution, parallel adaptations will play an important part in determining the way in which a system develops. It is, therefore, quite important that we be able adequately to model such parallelism formally. In the remainder of this section we examine Holland's framework for adaptation in some detail, as well as suggest how our problem in concurrent adaptation might fit into such a framework.

The basic paradigm around which Holland's formalism is developed, concerns a system (S) that is able to alter its structure and/or behavior based on experience in some set of performance environments (E). Such a system can be specified as a collection of mathematical objects in the following way:

> by the set of objects $(\mathscr{A},\Omega,I,\tau)$ where
> $\mathscr{A} = \{A_1,A_2, \ldots\}$ is the set of attainable structures, the domain of action of the adaptive plan,
> $\Omega = \{\omega_1,\omega_2, \ldots\}$ is the set of operators for modifying structures with $\omega \in \Omega$ being a function of $\omega:\mathscr{A} \rightarrow \mathscr{P}$, where $\mathscr{P}$ is some set of probability distributions over $\mathscr{A}$,
> I is the set of possible inputs to the system from the environment, and
> $\tau:I \times \mathscr{A} \rightarrow \Omega$ is the adaptive plan which, on the basis of the input and structure at time t, determines what operator is to be applied at time t.
> Under the intended interpretation
>
> $$\tau(I(t), \mathscr{A}(t)) = \omega_t \in \Omega \text{ and } \omega_t(\mathscr{A}(t)) = \mathscr{P}(t+1)$$
>
> where $\mathscr{P}(t+1)$ is a particular distribution over $\mathscr{A}$. $\mathscr{A}(t+1)$ is determined by drawing a random sample from $\mathscr{A}$ according to the distribution $\mathscr{P}(t+1)$. Given the input sequence $<I(1), I(2), \ldots>$, τ completely determines the stochastic process. (Occasionally, when the adaptive system is to be deterministic with $\mathscr{A}(t+1)$ being uniquely determined once $I(t)$ and $\mathscr{A}(t)$ are given, τ will be defined without the use of operators so that $\tau:I \times \mathscr{A} \rightarrow \mathscr{A}$. The structure of the adaptive system at time t, $\mathscr{A}(t)$, will be required to summarize whatever aspects of the input history are to be available to the plan. Hence it will often be useful to represent $\mathscr{A}$ as $\mathscr{A}_1 \times \mathscr{M}$, where $\mathscr{A}_1$ is the set of structures to be directly tested and $\mathscr{M}$ is the set of possible memory configurations, for retaining past history not directly incorporated in the tested structures. (Holland 1975:28, reprinted by permission of the University of Michigan Press)

Now that we have a general notion of what it takes to describe formally an adaptive system, just how can we express our informal model in this framework? It was mentioned earlier that the group of hunter–gatherers must be concerned not only with the problem of when to use a collecting strategy but also with the problem of when and how to change it. Each of these problems characterizes a different set of adaptations, and this suggests that we construct a specific adaptive system for each. These problems are not independent in the sense that the system's responses to one affects its responses to the other. So it is necessary that we model the interaction between these systems as well. A schematic diagram of the proposed system and interactions is given in Fig. 31.1. The interactions are of the following form:

1. At the beginning of each model cycle or iteration the group selects a subset of available strategies to use between August and November. The relative performances of each in terms of bulk plant material acquired and the effort taken to acquire it is gauged.
2. Changes in the relative performances of strategies that have been modified since they were last used are noted. These changes are then used to evaluate the effectiveness of the decision-making policy that produced them.

Those policies that produced improvements are more likely to be preserved than those that do not.
3. This information about strategy performance is then used to generate a new set of adjusted decision-making policies.
4. These new decision-making policies are used to alter selected members of the current sample of strategies.

With this general scheme in mind, let us now see how much of these two systems might be defined in terms of the informal model given in Part 4. The most natural subsystem to start with is the one dealing with the specification and selection of collecting strategies. This system, (S^C), is represented formally as a collection of mathematical objects $\{\mathscr{A}^C, \Omega^C, I^C, \tau^C\}$, where each formal object characterizes portions of the informal model in the following ways.

The set of possible collecting strategies available to the group is represented by $\mathscr{A}^C$. Each strategy specifies a sequence of collecting tasks over a 10-day period from August through November. At any one point in time only a subset of those possible strategies are actually in use.

The set of mechanisms by which the system alters the structure of its collecting strategies based on experience is represented by Ω^C. Here the mechanisms are effectively decisions to alter certain aspects of the current set of strategies.

The information available to members of the group at each model time step is specified by I^C. In our model, this information concerns the relative performance of strategies that are selected for use by group members, as well as some information about the state of the environment when the strategy was last used.

The transition function τ^C describes two basic processes. The first, τ_1^C, models the selection of a set of strategies to be used based on their past relative performances and how well the climate in which they were last used matches the current climate. The second, τ_2^C, describes the changes made to each of the sampled strategies based on their performance. The exact nature of these changes depends on the current decision-making policies held by group members with regard to each of these strategies. How the group members are able to generate these policies based on experience is the concern of the next subsystem we discuss.

The decision-making subsystem, S^D, can be specified by the set of mathematical objects $\{\mathscr{A}^D, I^D, \Omega^D, \tau^D\}$. Here $\mathscr{A}^D$ represents the set of possible decision-making policies that could be held by group members regarding a strategy. At any point in time, only a subset of these are actually used. Every policy is expressed in terms of the probability of applying each one of the basic decisions.

The set I^D represents the possible information that could be used by members of the group to evaluate the effectiveness of their current policies. At each time step the group acquires information about the effects of past decisions on the current performance of the sampled strategies. The policies associated with each of these may then be adjusted depending on whether the policy has produced an increase or decrease in the performance of the strategies since last used.

The basic adjustments that can be made to a decision-making policy based on its peformance is described as Ω^D. The nature of these adjustments was discussed in Part 4.

The transition function for the decision-making subsystem, τ^D, details how the above operators are used based on their performance. In general, the better the schedule's relative performance, the less likely it will be subject to change by the group.

Given the two subsystems, it now remains for us to specify the set of environments, E, in which they can perform. As in the informal model, the current plant densities and distributions are seen to be a function of annual rainfall. Three general classes of performance environments are then defined to be wet, dry, and average on the basis of total rainfall. The basis for this classification was given earlier in this chapter. Associated with each type of year is a characteristic distribution of plant densities that is conditional on the preceding year type. Since there are three basic year types, it follows that there will be 3^2, or 9, possible performance environments. The exact nature of the differences between each are discussed later.

We have now given a general overview of how our informal model can be rephrased formally as a set of problems in parallel adaptation. Our new perception of the basic model can be seen in Fig. 31.2. Note that our entire system can be described in terms of two interacting adaptive subsystems. Taken together their associated transition functions represent the transition function for the whole system.

In addition we have indexed each aspect of the model by the variable referred to as "model time." That is, $\mathscr{A}^C(t)$ can be referred to as the current set of collecting strategies at time t. Applying the transition function τ^C to $\mathscr{A}^C(t)$ produces a new set of strategies that is now designated as $\mathscr{A}^C(t + 1)$. Note that the model time is just a method of indexing the succession of group structures generated by the model. It does not necessarily have to have any direct correspondence to real time. In actuality, the length of time between each evaluation cycle may vary, and there is no information that presently allows us to describe such variation. However, since the main purpose of the model is to discern the equilibrium mix of strategies, the time between evaluations is not important here. Thus a model time of 1 between each successive transition is used for convenience.

Even though the model time does not directly correspond to real time, if the model is a valid representation of the decision-making adaptations of the group, then the changes in equilibrium structures produced by the model when incipient agriculture is introduced should correspond in some reasonable fashion to what we know from the archaeological record. This is a topic of interest later in this chapter.

Formal Model Development: Strategy Specification

Now that we have a general impression of what the model's structure will look like, it is time to construct a more specific realization of the base model. First we must have a way to

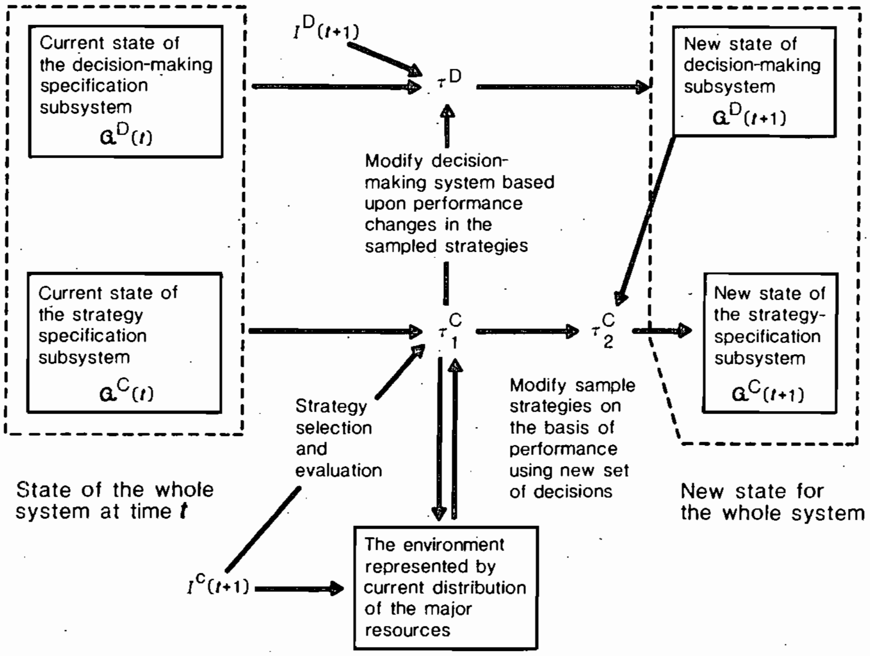

Fig. 31.2. Revised specification of the resource scheduling system.

represent the structure of our adaptive system. The representation should be sufficient to describe all relevant changes to the system during the period of interest. To construct such a representation the system can be thought of as comprising subsystems, where each of these is described via a corresponding set of descriptive variables. Thus, if we subdivided an arbitrary system into N subsystems, each resulting system S_i (where $i \in \{1, \ldots N\}$) would have an associated set of M_i descriptive variables. The number of descriptive variables for subsystem S_i is represented by M_i, since not all components will necessarily have the same variable set. The sum of these terms

$$\sum_{i=1}^{N} M_i,$$

is the total number of variables used to describe the entire system. We refer to this number as K. Each of these M_i variables will be indexed so that the jth descriptive variable in the ith subsystem is referenced as D_{ij}. Associated with this variable is its *range set*, which is the range of measured values that the variable can have for the system. The range set for an arbitrary variable D_{ij} is represented as R_{ij} and corresponds then to a set of allowable values for the variable.

An arbitrary system that was first decomposed into an indexed set of n interconnected systems, can now be respecified by replacing each subsystem with its associated descriptive variables as shown below.

$$\begin{gathered} S \\ \Downarrow \\ S_1, S_2, \ldots, S_n \\ \Downarrow \\ D_{11}, D_{12}, \ldots, D_{1m_1}, D_{21}, \ldots, D_{nm_n} \end{gathered}$$

The Cartesian product, or cross product of this collection of sets, denoted by $D_{11} \times D_{12} \times \ldots D_{nm_n}$, is the set of all K-tuples $\{< d_{11}, d_{12}, \ldots > | d_{ij} \in R_{ij}\}$ formed by selecting a particular measured value d_{ij} for each descriptive variable. This stands for the set of all states that our system might have during the course of our observation.

In the previous section we initially decomposed our system into two subsystems, each representing a certain type of adaptation. Now we develop the descriptive variables for both systems, beginning with the strategy-specification subsystem. These descriptive variables together characterize the elements of $A^C(t)$, the current set of strategies.

As mentioned previously our descriptive variables should detail the *observable* results of using a strategy or making a decision. They describe to us the current behavior of the system and, therefore, can be expressed via our choice of measurements. For example, we can describe the area searched by a strategy in terms of hectares even though the group members probably represented this in a much different manner. We do presume, however, that there exists a correspondence between the internal structuring of this information and the external behavior.

First, recall that in our base model a scheduling strategy is represented by a set of activities, or *tasks*. Associated with each task is information about the vegetational zone in which it occurs, what the focal resource is, which locations are to be searched, and how much of the resource is present at each location. In addition, this set of tasks is ordered, where the ordering reflects their relative sequence of execution. These tasks when taken together specify a sequence of collecting activities for the group over a 10-day period from August into November.

The model, therefore, presupposes that this collection of variables is effectively specified for each task. It means that the information used to specify a collecting activity effectively associates with that activity certain properties. These are properties that characterize the task's execution and may not be directly represented in the mind of an individual member of the group. They are, however, the observable results of the mentally specified task and therefore constitute the descriptive variables for our strategy-specification subsystem.

Since we are dealing with a segment of the behavioral repertoire of a small group, it is to be expected that certain limits will exist in terms of the total number of tasks and associated strategies that can be specified by the group. The model assumes that at any one point in time there is an upper bound on the number of strategy specifications retained by the group; we designate this MAX_STRAT. Here the maximum number of schedules is set equal to 10. We might expect, also, that an individual strategy will consist of no more than some maximum number of tasks since the strategy's specification is over a very limited period of time—10 days. This maximum is designed as MAX_TASKS in the model.

We are now in a position to list the descriptive variables that represent the strategy-specification subsystem for the model. The strategy-specification component descriptive variables are as follows:

1. MAX_STRAT is the maximum number of currently active strategies. Here the maximum number of currently active strategies is taken to be 10.
2. MAX_TASKS is the maximum number of tasks associated with a given strategy. The maximum number of tasks for this model is taken to be 25.

For every STRAT(i) • TASK(j) where $i \in \{1, \ldots$ MAX_STRAT$\}$ and $j \in \{1, \ldots$ MAX_TASKS$\}$ the following variables are included in the model:

3. STRAT(i)•TASK(j)•ZONE specifies the vegetation zone in which the activity is carried out. It can take values from the set {Mesquite Grassland B, Thorn Forest A, Thorn Forest B, Mesquite Grassland A}.
4. STRAT(i)•TASK(j)•RESOURCE represents the focal resource for the collecting activity. Depending on the zone, this variable can take values from the set of major plant resources {piñon nuts, hackberries, *susí* nuts, nanche fruit, *Opuntia* nopales, *Opuntia* fruits, acorns, *guaje* pods, mesquite pods, *Agave*, beans}.
5. STRAT(i)•TASK(j)•LOCATIONS_TO_SEARCH represents the set of locations in a particular zone that are searched during the collecting activity. This takes values from the set of all allowable subsets of locations with respect to the cave for each zone. The total area encompassed by these locations cannot refer to more than 0.33 ha. Since 0.33 ha is the maximum area that the group is allowed to search in a day, this means that one task can specify no more than one day's activities. Also we presume that the locations searched for each task in a strategy are not included in tasks found either in that strategy or in other current strategies. Since the minimum size of a location is taken to be 0.001 ha, this condition seems quite reasonable.

In addition to the set of variables that describe the sequence of plant collecting activities, a strategy can also be specified in terms of its performance. Recalling the informal base model, two pieces of information were found to be important in determining which strategies to employ during any one year. In making such a decision, one would first need to know how well a strategy performed the last time it was used. Since the performance for a strategy is a function of the environment, one also needs information about the type of environment in which it was last used in order to compare its performance with other strategies. Therefore, for each strategy i there is a variable STRAT(i)•LAST_USED that stores the last year type in which the strategy was used. Accordingly, there will be information about how the strategy performed the last time it was used, STRAT(i)•LAST_PERF. A discussion of the exact nature of this performance index is deferred until later when we discuss the performance function.

Since a strategy has been selected for use at time t, we need to record its current performance. This variable is labeled STRAT(i)•PERF and takes on a value for those strategies used at time t. As mentioned in the previous chapter, this represents a derived impression of the schedule's relative performance in terms of a number of criteria. While we have no information as to how these impressions were derived, it is quite conceivable that they were generalized descriptions of each strategy's performance. Over the course of the season, a general set of expectations regarding the performance of a strategy is developed. Here we represent such expectations by the strategy's average performance. For each utilized strategy i, the following expectations are produced:

1. STRAT(i)•CALORIES is the average yield in terms of calories
2. STRAT(i)•PROTEIN is the average yield in terms of protein
3. STRAT(i)•CALORIES_EFFORT is the average effort expended relative to the amount of calories acquired. Here this is represented by dividing the number of acquired calories by the area searched, STRAT(i) •CALORIES/STRAT(i)•AREA_SEARCHED. STRAT(i)•AREA_SEARCHED is computed by adding together all the individual locations searched
4. STRAT(i)•PROTEIN_EFFORT is the average effort expended relative to the amount of protein acquired. This is represented by dividing the amount of acquired protein (in grams) by the area searched, STRAT(i)• PROTEIN/STRAT(i)•AREA_SEARCHED.

In this model we are not concerned with specifying the precise set of circumstances that produce a decision, only its likelihood of occurrence given certain key variables. Here this likelihood is expressed in terms of probabilities. Each rescheduling decision is conceived of as a stochastic process with a certain probability of occurring. Associated with each process is an ideal random number generator with a state set in the interval [0,1] and having a transition function of the form RAND:[0,1] → [0,1]. Given an initial seed r_0, this function will produce a sequence of numbers $< r_0, r_1, r_2, r_3, \ldots >$ that appear to be uniformly distributed throughout the interval [0,1]. Every number in this sequence appears to be unrelated to those previously sampled. This number is translated into an associated model event by a random variable that takes the form of a function mapping the numbers in [0,1] into a set of outcomes. Here the set will be {yes, no}. Once a decision to reschedule a strategy has been made, a number of other random variables may come into play depending on the exact nature of the decision. We now specify each of these decisions in detail, beginning with the recombination operators.

ω_1 = SWAP__EXTERNAL: This operator represents the exchange of tasks between strategies. This exchange is a stochastic process mediated by three random variables in the following way:

1. Given a pseudorandom number generator with the transition function RAND:[0,1] → [0,1], apply this mapping to the current value for the SWAP__EXTERNAL__SEED to produce a real number between [0,1], r_1. In addition, it will generate a new value for EXTERNAL__SEED.
2. Next apply the SWAP__EXTERNAL__DECISION map to r_1 to obtain the sampled SWAP__EXTERNAL__DECISION. SWAP__EXTERNAL__DECISION is, therefore, a random variable that takes real numbers in [0,1] into the set {yes, no} in the following way:

$$\text{STRAT}(i) \cdot \text{OPER(1)}\cdot\text{USED} = \begin{cases} \text{“yes” if} \\ r_1 \leq \text{STRAT}(i)\cdot \\ \text{OPER(1)\_\_PROB and} \\ \\ \text{“no” if otherwise.} \end{cases}$$

   STRAT(i)•OPER(1)__PROB is the current probability that the swap external operation will be performed on this strategy.
3. If the decision is yes then the following processes occur. First a new random number, r_2 is produced, RAND:(PARTNER__SEED) → $r_2 \in [0,1]$. This value is used to determine which other member of the current sample is to participate in the exchange by applying the SWAP__PARTNER map to r_2. SWAP__PARTNER:[0, 1] → set of sampled strategies excluding STRAT(i). This map corresponds to dividing the unit interval into K subintervals of equal length, where K is the cardinality of the range set. The index of the subinterval into which r_2 falls is the index of the strategy to be selected.
4. Next a third random number, r_3, is generated. The ORDER map is applied to r_3 in the same manner as above. ORDER[0,1] → {1, . . . MAX TASKS}. This determines the execution order of the tasks to be exchanged.
5. Finally, the selected tasks with a given execution ORDER are exchanged between STRAT(i) and STRAT(PARTNER) in a manner that depends on their performance indices. If the two strategies have similar performance indices, |STRAT(i) • PERF__STRAT (PARTNER)•PERF| ≤ 2, then the selected tasks are exchanged between them. However, if their difference is 3 or more, it means that one performed better in at least two of the three basic performance categories (effort, yield, and minimal yield). As such, this represents more than just a slight difference in performance. In this situation the poorer performer replaces its current task with a copy of a task from the other strategy.

$$\text{SWAP\_EXTERNAL} = \begin{cases} \text{If |STRAT}(i)\text{•PERF–STRAT} \\ \quad \text{(PARTNER)•PERF|} \leq 2\text{|,} \\ \text{then} \\ \quad \text{(STRAT}(i)\text{•TASK(ORDER), STRAT} \\ \quad \text{(PARTNER)•TASK(ORDER))} \rightarrow \\ \quad \text{(STRAT}(i)\text{•STRAT(PARTNER)} \\ \quad \text{•TASK(ORDER), STRAT(PARTNER)} \\ \quad \text{•(STRAT}(i)\text{•TASK(ORDER))).} \\ \text{else if} \\ \quad \text{STRAT}(i)\text{•PERF} > \\ \quad \text{STRAT(PARTNER)•PERF,} \\ \text{then} \\ \quad \text{(STRAT}(i)\text{•TASK(ORDER),} \\ \quad \text{STRAT(PARTNER)•TASK(ORDER))} \rightarrow \\ \quad \text{(STRAT}(i)\text{•STRAT(PARTNER)•TASK(ORDER),} \\ \quad \text{STRAT(PARTNER)•TASK(ORDER));} \\ \text{else} \\ \quad \text{(STRAT}(i)\text{•TASK(ORDER), STRAT(PART-} \\ \quad \text{NER)•TASK(ORDER))} \rightarrow \\ \quad \text{(STRAT}(i)\text{•TASK(ORDER), STRAT(PART-} \\ \quad \text{NER)•(STRAT}(i)\text{ •TASK (ORDER))).} \end{cases}$$

This operator is described schematically for two arbitrary strategies in Fig. 31.3.

One might suggest that our operator is overly restrictive since, realistically, exchanges can presumably be made between TASKS at different levels of priority. We show later that our system, by combining this operator with other elementary operations, can represent these types of decisions as well as more complicated ones. Thus we are able to generate a hierarchy of increasingly complex decision-making rules based on our elementary operators in Ω^D. This provides us with a very powerful tool in the analysis of the model's decision-making behavior.

If their performances are similar	A	$T_1\ T_2\ T_3\ T'_4\ T_5\ T_6 \ldots T_{MAX\_TASKS}$
	B	$T'_1\ T'_2\ T'_3\ T_4\ T'_5\ T'_6 \ldots T'_{MAX\_TASKS}$
If one, B, performs much better than the other	A	$T_1\ T_2\ T_3\ T'_4\ T_5\ T_6 \ldots T_{MAX\_TASKS}$
	B	$T'_1\ T'_2\ T'_3\ T'_4\ T'_5\ T'_6 \ldots T'_{MAX\_TASKS}$

Fig. 31.3. The SWAP__EXTERNAL operator exchanges TASKS with the same order of execution between two strategies with similar performances. If one strategy is a much better performer, then a copy of its TASK is made.

ω_2 = SWAP__INTERNAL: This stochastic operator performs an exchange of tasks within a strategy. Intuitively, it reflects a decision to exchange the order of execution between two tasks. One reason for doing this is to reorder the schedule so that several activities in the same zone are executed in sequence. This could lead to a reduction in the distance traveled by the group members involved.

The SWAP__INTERNAL operator is mediated by three random variables, each of which specifies an aspect of the overall process in the following way:

1. Input an initial seed, SWAP__INTERNAL__SEED, into the pseudorandom number generator, which maps this into $r_4 \in [0,1]$.
2. Next, apply the SWAP__INTERNAL__DECISION map to r_4 to obtain the sampled decision SWAP__INTERNAL__DECISION. This map represents a random variable that takes numbers in [0,1] into the set {yes, no} in the following way for a sample strategy i:

$$\text{STRAT}(i)\cdot\text{OPER(2)\_\_USED} = \begin{cases} \text{“yes” if } r_4 \leq \text{STRAT}(i)\cdot \\ \text{OPER(2)\_\_PROB and} \\ \text{“no” otherwise.} \end{cases}$$

   STRAT(i) • OPER(2)__PROB is the current probability of performing this rescheduling operation on strategy i.
3. If SWAP__INTERNAL•(STRAT(i) = yes, the process continues; otherwise no exchange is made. Assuming that the decision is in the affirmative, we now must select the two tasks to exchange. Using another seed, TASK__1__SEED, we derive a new random number r_5. Next, we define TASK__1 to be a random variable that maps r_5 into the set of available tasks for Strategy i: TASK__1: $[0,1] \rightarrow \{T_1, T_2, \ldots T_{\text{MAX\_\_TASKS}}\}$.
   This is done by subdividing the unit interval [0,1] into 10 subintervals of equal length, where the jth subinterval corresponds to the probability of selecting the jth task. The index of the subinterval into which r_5 falls is then the index of the task to be selected.

   The second task to be exchanged is selected in the same manner as above using the variables TASK__2__SEED, r_6, and TASK__2.
4. The SWAP__INTERNAL operator then exchanges the ORDER of execution for the two selected tasks in STRAT(i) as shown schematically in Fig. 31.4.

ω_3 = SHUFFLE__LOCATION: This operator symbolizes the decision to exchange locational specifications between two activities in a strategy. Associated with each activity is a set of locations where the activity is carried out. This operator exchanges subsets of locations between activities on the same schedule, providing that these activities are located in the same zone. It is a stochastic operation that is specified in the following way for a given strategy i:

1. First, SHUFFLE__LOCATION__SEED is used to generate a random number r_7. SHUFFLE__LOCATION__DECISION is defined to be a random variable that maps r_7 into the set {yes, no} for a given strategy i.

$$\text{STRAT}(i)\cdot\text{OPER(3)\_\_USED} = \begin{cases} \text{“yes” if } r_7 \leq \text{STRAT}(i)\cdot \\ \text{OPER(3)\_\_PROB and} \\ \text{“no” otherwise.} \end{cases}$$

   STRAT(i) • OPER(3)__PROB represents the current probability of making this decision for Strategy i.
2. Next the two tasks that are to be involved are determined stochastically in the same manner as given for the SWAP__INTERNAL operator defined previously. Here SHUFFLE__TASK__1__SEED and SHUFFLE__TASK__2__SEED are used to generate random numbers r_8 and r_9, respectively. These are then mapped by their respective random variables, SHUFFLE__TASK__1 and SHUFFLE __TASK__2, into the set of available tasks for Strategy i as before.
3. Now the SHUFFLE__LOCATION operator is applied to exchange the LOCATION sets associated with the two selected tasks for Strategy i.

$$\boxed{T_1 \cdot T_2 \cdot T_3 \cdot T_4 \cdot T_5 \cdot T_6 \cdots T_{MAX\_TASKS}} \xrightarrow{\omega_2} \boxed{T_2 \cdot T_1 \cdot T_3 \cdot T_4 \cdot T_5 \cdot T_6 \cdots T_{MAX\_TASKS}}$$

Fig. 31.4. The SWAP__INTERNAL operator describes the exchange of execution priorities between TASKS. Here the execution sequence for the first two TASKS is reversed.

$$\text{SHUFFLE\_\_LOCATION:} \begin{cases} \text{STRAT}(i)\bullet\text{TASK(SHUFFLE\_\_TASK\_\_1)} \\ \quad \bullet\text{LOCATIONS} \rightarrow \text{STRAT}(i)\bullet\text{TASK} \\ \quad \text{(SHUFFLE\_\_TASK\_\_2)}\bullet\text{LOCATIONS} \\ \qquad\qquad \text{and} \\ \text{STRAT}(i)\bullet\text{TASK(SHUFFLE\_\_TASK\_\_2} \\ \quad \bullet\text{LOCATIONS} \rightarrow \text{STRAT}(i)\bullet\text{TASK} \\ \quad \text{(SHUFFLE\_\_TASK\_\_1)}\bullet\text{LOCATIONS.} \end{cases}$$

In order to perform the mapping, it is presumed that the resulting tasks are well defined. In other words, the operator is constrained to exchange locations that make sense for the currently specified TASKS, since one does not want to allow exchanges that associate a plant species with a location where it does not grow. Therefore, this operator changes only allowable combinations of TASK variables into other allowable combinations. Such constraints apply not only to this operator but also to all that follow.

While SHUFFLE__LOCATION does serve to change the nature of an activity, the change is somewhat conservative in that it only involves information already used in some form to specify the schedule. For example, the shifts in locations produced by SHUFFLE__LOCATION for a schedule will only be in terms of locations already associated with the schedule. This is the type of change represented by each of the shuffle operations to be described next.

ω_4 = SHUFFLE__ZONE: This stochastic operator represents the exchanging of zone specifications between compatible activities in the same schedule. Since the location set is zone specific, this operator involves more than just exchanging zones. For each participating task, if the new zone differs from the old then a new set of locations in the new zone must be produced. The total area encompassed by these new locations is constrained to be the same as before for each strategy. The process for some strategy i goes as follows:

1. Initially the SHUFFLE__ZONE__SEED is used to produce a random number r_{10} that is then mapped by SHUFFLE__ZONE__DECISION into the set {yes, no}.

$$\text{STRAT}(i)\bullet\text{OPER(4)\_\_USED} = \begin{cases} \text{“yes” if } r_{10} \le \text{STRAT}(i)\,\bullet \\ \text{OPER}(j)\text{\_\_PROB and} \\ \text{“no” otherwise.} \end{cases}$$

   As before, STRAT(i)•OPER(j)__PROB represents the probability that the group will decide to make the change in light of its current policy for Strategy i.
2. If the decision is to reschedule the strategy in this way, then the tasks involved are determined stochastically. This is done via two seeds, SHUFFLE__ZONE__TASK__1__SEED and SHUFFLE__ZONE__TASK__2__SEED. These seeds generate random numbers r_{11} and r_{12} which are then mapped into the sets of available tasks by the random variables SHUFFLE__ZONE__TASK__1 and SHUFFLE__ZONE__TASK__2 in the same manner as for SHUFFLE__LOCATION.
3. This is followed by the application of the SHUFFLE__ZONE operator that exchanges the zones where these tasks are carried out.

$$\text{SHUFFLE\_\_ZONE:} \begin{cases} \text{STRAT}(i)\bullet\text{TASK(SHUFFLE\_\_ZONE\_\_} \\ \quad \text{TASK\_\_1)}\bullet\text{ZONE} \rightarrow \text{STRAT}(i)\bullet\text{TASK} \\ \quad \text{(SHUFFLE\_\_ZONE\_\_TASK\_\_2)}\bullet\text{ZONE} \\ \qquad\qquad \text{and} \\ \text{STRAT}(i)\bullet\text{TASK(SHUFFLE\_\_ZONE\_\_} \\ \quad \text{TASK\_\_2)}\bullet\text{ZONE} \rightarrow \text{STRAT}(i)\bullet\text{TASK} \\ \quad \text{(SHUFFLE\_\_ZONE\_\_TASK\_\_1)}\bullet\text{ZONE.} \end{cases}$$

4. In addition, if the two zones that are exchanged are different, then two random numbers r_{13} and r_{14} are generated from AREA__SEED__1 and AREA__SEED__2. Each of these is mapped into a subset of points for the new zone that encompasses the same amount of area as the previous set. Each subset of available points is assigned a subinterval of equal length over the real line between 0 and 1. The new subsets are the ones whose intervals overlap with the numbers r_{13} and r_{14}, respectively.

ω_5 = SHUFFLE__RESOURCE: This operator exchanges the focal resources between two compatible activities on the same schedule. The process is mediated by three random variables that determine the basic characteristics of this decision for a strategy i:

1. The current SHUFFLE__RESOURCE__SEED is used to produce a random number r_{15}. The random variable STRAT(i)•OPER(5)__USED maps r_{15} into the set {yes, no} and is the same as for the previous operator.
2. If the value for STRAT(i)•OPER(5)__USED is yes, then SHUFFLE__RES__SEED__1 and SHUFFLE__RES__SEED__2 are used to generate two random numbers r_{16} and r_{17}. These are mapped into the set of available tasks for Strategy i by the random variables SHUFFLE__RES__TASK__1 and SHUFFLE__RES__TASK__2.
3. Finally, the SHUFFLE__RESOURCE operator is applied to these two selected tasks to produce the required scheduling change:

SHUFFLE__RESOURCE: { STRAT(*i*)•TASK(SHUFFLE__RES__TASK__1)•ZONE → STRAT(*i*)•TASK(SHUFFLE__RES__TASK__2)•ZONE
and
STRAT(*i*)•TASK(SHUFFLE__RES__TASK__2)•ZONE → STRAT(*i*)•TASK(SHUFFLE__RES__TASK__1)•ZONE.

This closes out our discussion of those rescheduling decisions that involve recombining existing information within and between strategies. Now we turn our attention to a set of operators that represent the outright change of a descriptive variable associated with a strategy.

ω_6 = ALTER__RESOURCE: This operator models those rescheduling decisions that consist of replacing the focal resource for an activity with another that is compatible with the current vegetation zone for the activity. Unlike previous operators, this allows the introduction of resources that are previously not employed within any current strategy into a schedule. Formally, it can be described as follows for some strategy *i*:

1. ALTER__RES__SEED is used to generate r_{18}. STRAT(*i*)•OPER(6)__USED then maps r_{18} into the set {yes, no} in the same fashion as with the previous operators.
2. If STRAT(*i*)•OPER(6)__USED = yes, then we proceed. Another seed ALTER__RES__TASK__SEED is used to produce r_{19}, which is mapped into the set of available tasks for Strategy *i* by ALTER__RES__TASK. This designates the task to be changed.
3. Then RES__VALUE__SEED is used to derive r_{20}. This value is mapped by NEW__RES__VALUE into a resource compatible with the present location specification by assigning each compatible resource to a subinterval in [0,1] of equal length. The index of subinterval into which r_{20} falls is, therefore, the index of the new resource. This NEW__RES__VALUE is then assigned to STRAT(*i*)•TASK(ALTER__RES__TASK)•RESOURCE.

ω_7 = ALTER__ZONE: The function of this rescheduling operator is to represent a change in the vegetation zone for the task. This is only possible if the present resource is found in another zone. The operator is able, therefore, to describe decisions that shift resource collecting activities from one zone to another.

1. For a given strategy (*i*), employ ALTER__ZONE__SEED to get r_{21}, which is then mapped by STRAT(*i*)•OPER(7)__USED into the set {yes, no} in the same manner as the other operators.
2. If the decision is yes, then we proceed to select a task to be changed. This is done using the ALTER__ZONE__TASK__SEED to produce r_{22}, which is then mapped by ALTER__ZONE__TASK into one of the available tasks. If the focal resource for that acitivity can be found in another zone, we continue by generating r_{23} via NEW__ZONE__SEED. This number is then mapped into the set of zones compatible with the focal resource in our standard manner.
3. Once this is done we use NEW__ZONE__LOCATION__SEED to get r_{24}. The random variable NEW__ZONE__LOCATION maps this number into a set of locations with the same amount of area in the new zone. The details of this mapping need not concern us now.

ω_8 = ALTER__LOCATION: This represents rescheduling changes that involve the relocation of a collecting activity within a zone. Given a current set of locations the operator can modify a subset of these to produce a new set in the following way.

1. First, the decision is made in light of current policy for the strategy regarding whether or not to shift locations. Here this decision is represented stochastically by the generation of a random number, r_{25}, from ALTER__LOC__DECISION__SEED. If the value of r_{25} is less than or equal to the current probability of such a decision being made for this strategy, then the random variable STRAT(*i*)•OPER(8)__USED is assigned the value "yes"; otherwise it is given the value "no."
2. Provided that the decision is in the affirmative, the task to be changed is selected at random. ALTER__LOC__TASK__SEED produces r_{26}, mapped into the set of 25 available tasks by the random variable ALTER__LOC__TASK.
3. Next ALTER__LOC__VALUE__SEED is input to the pseudorandom number generator and r_{27} is produced. This random number is then mapped into a new subset of available locations where each subset is assigned a subinterval in [0,1]. The new subset is the one whose interval overlaps with the value for r_{27}.

The above set of stochastic operators represents the basic set of decisions that we can expect a group to make with respect to modifying its collecting strategies. However, these are not the only decisions that *can* be represented in the model. For example, by applying these decisions in sequence, we can represent more-complex operations as demonstrated in Fig. 31.5. These two operators are applied in sequence to a strategy, and the resulting strategy can be thought of as being produced by $\omega_1 \bullet \omega_2$. We signify this sequential application of operators by a "•", which signifies the successive composition of the basic operations. By this means we can represent more-complex modification decisions in terms of our original set.

Therefore, rather than specify the types of complex decisions available to the group, we have defined a simple set of basic decisions and allow the group to combine them in any manner. The group through its own experience is able to generate complex decisions that prove to be advantageous. As illustrated in Fig. 31.6, these complex operators can be

$$\begin{bmatrix} T_1 \cdot T_2 \cdot T_3 \cdots T_{MAX\_TASKS} \\ T'_1 \cdot T'_2 \cdot T'_3 \cdots T'_{MAX\_TASKS} \end{bmatrix} \xRightarrow{\omega_1} \begin{bmatrix} T'_1 \cdot T_2 \cdot T_3 \cdots T_{MAX\_TASKS} \\ T_1 \cdot T'_2 \cdot T'_3 \cdots T'_{MAX\_TASKS} \end{bmatrix} \xRightarrow{\omega_2} \begin{bmatrix} T'_1 \cdot T_2 \cdot T_3 \cdots T_{MAX\_TASKS} \\ T'_2 \cdot T_1 \cdot T'_3 \cdots T'_{MAX\_TASKS} \end{bmatrix}$$

Fig. 31.5. The composition of two operators $\omega_1 \bullet \omega_2$ for two strategies.

	.	.	.
	.	.	.
n+1 order	.	.	.
	.	.	.
	.	.	.
Third order	$\omega_8 \cdot \omega_6 \cdot \omega_4$	$\omega_1 \cdot \omega_2 \cdot \omega_3$	$\omega_6 \cdot \omega_1 \cdot \omega_2$
Second order	$\omega_6 \cdot \omega_8$	$\omega_1 \cdot \omega_1$	$\omega_1 \cdot \omega_6$
First order	ω_6	ω_1	-none
Type	**Mutation**	**Recombination**	**Hybrid**

Fig. 31.6. Hierarchy of higher-order decisions achieved by the successive application of operators. The order of a decision represents the number of basic operations required to produce it. While only three orders are illustrated here, many more are possible.

of three types. In the first class all decisions in the sequence are recombination-type operators. Their composition produces a more complex recombination decision. Similarly the second group stands for more-complicated mutation operations. The third class, however, is new. It is a hybrid of the first two. In it one finds decisions that contain both mutation- and recombination-style operators. The *order* of a decision reflects in model terms the minimum number of basic decisions required to represent it. Later, in analyzing the simulation results we are able to observe the exact nature of the hierarchy generated by the group during each phase of its adaptation.

Model Group Rescheduling Policies

Now having described the set of operators, Ω^D, we again turn our attention to the specification of a decision-making policy. Implementing such a policy means that certain operators will be applied more freqently than others. In the model, a policy is specified in terms of the relative probabilities with which each of the basic set of operators is to be used to modify a particular strategy. Therefore, with every current strategy we associate a set of descriptive variables that reflect the probability that each operator will be applied to it under the current policy.

In addition, the group members must recall the operators involved in the last rescheduling decisions for each strategy. This information is used to apportion credit for an increase or decrease in performance among the operators that participated in a decision. For example, if a decision to modify a particular strategy was third order (e.g., $\omega_1 \bullet \omega_2 \bullet \omega_6$) and it resulted in an improvement in the strategy's performance, the group would want to modify the operator probabilities for each of the three operators so that this favorable decision can be repeated more often.

We can now list the descriptive variables associated with the model's decision-making policy component. The decision-making policy-specification descriptive variables are as follows:

1. For every strategy, STRAT(i), where $i \in \{1, \ldots \text{MAX\_STRAT}\}$, and OPERATOR ($j$), where $j \in \{\omega_1, \ldots \omega_8\}$, we have STRAT($i$) • OPERATOR($j$) • PROB.

   This represents the probability that the current decision-making policy will apply Operator $\omega(j)$ to Strategy i. The range of values taken by this variable are from the real numbers in [0,1].
2. The variable STRAT(i)•OPERATOR(j)•USED reflects the participation of operator j in the last decision to reschedule strategy i. This variable will take values from the set {yes, no}.

One important point worth noting here is that the effects of these rescheduling operators discussed above are not necessarily additive. For example, a successful higher-order decision involving several operators may fail to produce improvements altogether if one of them is not used in conjunction with the rest. The presence of such nonlinearities means that adaptation for the model group becomes in part a search for coadapted sets of operators—operators that when applied together produce improvements in a schedule's performance. This search is complicated by the large number of potential combinations of available operators and the ability of the group to store information about the performance or only a subset of these combinations.

Holland, however, has investigated certain means by which a system can cope with these problems. To illustrate his approach, let us take the set of all third-order decisions. Any one of the eight available operators can be used in each of the three decisions. This means that there are 8^3 basic types of decisions that can be made. We can denote subsets of these decisions that have attributes in common using the following notation: $\omega_1 \cdot \square \cdot \square$, for example, represents all those third-order decisions beginning with ω_1, where a $\square$ stands for a "don't care." These representations are called schema, and 9^3 such schemata exist for third-order decisions. A schema is said to be defined on those positions not specified by "don't care" symbols.

Any given third-order decision (e.g., $\omega_1 \cdot \omega_3 \cdot \omega_8$) is an instance of 2^3 possible schema that can be defined by substituting $\square$'s for one or more of three attributes. Therefore, when we look at the performance for $\omega_1 \cdot \omega_3 \cdot \omega_8$ we are really acquiring information about the performance of 2^3 constituent schemata. This situation is called intrinsic parallelism. Algorithms that are able to exploit such parallelism have been shown to exist by Holland and Reitman (1978:313). These algorithms are able to test many schemata with a single trial and implicitly store the results in the current population of available structures. We now proceed to develop the transition function for the model that determines how the group is able to alter both its resource collecting schedules and their associated decision-making policies over time. In this context the current set of available schedules and their associated rescheduling policies can be thought of as the data base in which information acquired from experience is stored. Holland refers to this set of existing information as $B(t)$ for some time t (Holland 1975:91). The transition function for the model group describes how this data base is updated by the group members over time based on input from the environment. As we see in the following, certain portions of this transition function possess the intrinsic parallelism discussed above and facilitate the search for compatible resource schedules and rescheduling policies.

The Basic Transition Function

Having specified the structure of both the resource collecting schedules and their associated decision-making policies, it now remains for us to describe the transition function that allows the group to change these structures based on its experience in the environment. The transition function for a typical cycle can be viewed as the composition of a number of basic processes.

1. Initially the state of the environment is determined stochastically.
2. The next process deals with the selection of the subset of strategies that group members intend to use. Schedules are selected for use on the basis of current environmental information as well as past performance.
3. This process models the day-to-day foraging activities for the group members.
4. As the season ends, an impression of the expected total performance for each selected schedule is developed.
5. The performance of each strategy is compared with the others used, as well as with certain minimal standards of performance. The result of these comparisons is a relative impression of the schedule's performance.
6. If the strategy has been rescheduled since it was last used, the two relative performances are compared. If the change was associated with an improvement in relative performance, then the probabilities of all the decision-making operators that were combined to produce the decision are increased. If, on the other hand, there was a reduction in performance, the probability of applying each of the associated operators is reduced.
7. Next, a decision to apply each of these updated rescheduling policies to its associated schedule is made based on the schedule's current relative performance.

Together, these processes characterize the changes made to the system during one cycle in the model. We now describe each of the constituent processes in turn.

1. The previous state of the environment is mapped by δ_1 into a new state. Here this is represented by a random variable, CURRENT_YEAR. From data on current rainfall patterns in the Valley of Oaxaca (Kirkby 1973), the following environmental states and their associated probabilities were derived:

   a. A "wet year" has rainfall in excess of 600 mm. The probability of this is approximately .25.
   b. Years with rainfall less than 420 mm are designated "dry years." The possibility of this occurring is .25.
   c. A year that is neither wet nor dry with rainfall between 420 and 600 mm is termed "average" and has a .50 probability of occurrence.

   CURRENT_YEAR, therefore, assigns a random number generated by YEAR_SEED into the set {wet, dry, average} in the following fashion:

   $$\text{CURRENT\_YEAR} = \begin{cases} \text{dry if } r_{28} \leq .25, \\ \text{average if } .25 < r_{28} \leq .75, \text{ and} \\ \text{wet otherwise.} \end{cases}$$

   Note that the current rainfall does not depend on the rainfall for previous years. This assumption was made on the basis of Kirkby's analysis of current rainfall data in the Valley of Oaxaca.
2. After having determined the climatic conditions for the current year, the next phase represents the process of selecting a set of strategies that the group intends to use. This set is generated on the basis of the group's current information and needs. The function δ_2 maps STRAT(i) • USED into the set {yes, no} for each $i \in \{1, \ldots 10\}$. It stochastically represents the selection of a subset of currently available strategies to be used in the following manner:

   $$\text{STRAT}(i)\text{\_USED} = \begin{cases} \text{yes if RAND(EVAL\_SEED)} \geq \\ \quad (\text{STRAT}(i) \cdot \text{PERF} * .14 + .08 \text{ and} \\ \text{if RAND(CLIM\_SEED)} \leq \\ \quad \text{COMPATIBILITY (CURRENT\_YEAR,} \\ \quad \text{STRAT}(i) \cdot \text{LAST\_USED), and} \\ \text{no otherwise.} \end{cases}$$

TABLE 31.2
Probabilities for Selecting a Strategy Given the Current Year Type and the Type in Which It Was Last Used

Current year type	Strategy (i) last used in year type	Probability of selection on basis of climate compatibility
Dry	Dry	1.0
Dry	Average	.5
Dry	Wet	.25
Average	Dry	.5
Average	Average	1.0
Average	Wet	.5
Wet	Dry	.25
Wet	Average	.5
Wet	Wet	1.0

RAND(EVAL__SEED) represents the random number obtained by applying the EVAL__SEED to RAND, the pseudorandom number generator. Notice that the probability of selecting a strategy is based on two factors. First, the better the performance impression associated with a strategy, the more likely it is to be used. The best performance has a .92 probability of use in terms of performance, while the worst has only a .08 probability. However, the type of year in which the strategy was last used is important too. The more compatible the present environment is with that in which the strategy last performed, the more likely that its past performance reflects its current potential. The index of compatibility employed here assigns the probabilities listed in Table 31.2 for selecting a strategy, given the current year type and the type in which it was last used. If the two year types agree, then the strategy's performance is the critical factor in making the decision. The more they disagree, the more influence these environmental considerations have on the decision not to use a strategy.

3. The third part of the transition function, δ_3, deals with the use of these selected strategies throughout the period from August to November. Initially, each strategy can be used a number of times within the 120-day period when it is initiated. For the next 10 days after each initiation, the collecting activity of the group is governed by this strategy. The exact times at which the strategy will be used depends stochastically on the distribution and availability of the focal resources associated with the schedule. Based on scouting reports, the group is able to get some idea of the current status of its evironment so that it can employ the collecting strategy it feels is best suited to the situation. In other words, the group has a fixed probability of knowing the amount of plant materials currently found at a location x at time t. For each accessible location x, there is a random variable KNOWLEDGE__OF(x) that maps into the set {yes, no} with fixed probabilities at time t. The group's perception of its environment at time t then consists of information for all those locations x with the value KNOWLEDGE__OF(x) = yes. If it is time to select a new strategy, the strategies that have been intended for use this year are compared with the group's current information. Each strategy then has a certain probability of being selected based on the results of this comparison. The strategy that contains the most locations about which the group has current knowledge is the one selected. If there is a tie, they pick the one with the highest relative performance. Since the group intends to use each of the strategies selected by δ_2, we presume that over the course of the season subsets of location will be searched in such a manner as to allow each intended strategy to be used at least once. This is accomplished by altering the KNOWLEDGE__OF(x) probabilities over the season. In the base model, the probability of gaining information about location x is a function of the number of times that it is referenced in the set of intended strategies. At the onset of the season, the probability that the group will have knowledge about location x is the number of times it is referenced by the strategies the group intends to use divided by LOCATION__TOTAL. LOCATION__TOTAL represents the maximum number of references that can be made to the location in terms of the intended strategies. Since a location can be referenced once by each of the 25 tasks in a strategy, LOCATION__TOTAL = 25 × number of intended strategies. Once a strategy has been used, the probabilities for searching the available locations are adjusted. Such an adjustment is due to the depletion of resources at those locations as a result of the activity. This means that the probability of searching other locations is higher. In the model, the adjustment is accomplished for each location x by removing the total number of references made to it by the strategy and dividing by a new value for LOCATION__TOTAL, where LOCATION__TOTAL = (old)LOCATION__TOTAL − 25. This does not rule out the possibility of the strategy being used again. It only says that the strategy is less influential in governing the information collecting activities of the group in the near future. This readjustment of the probabilities occurs only after the initial use of each intended strategy. Subsequent use of a strategy does not serve to readjust the probabilities until each of the intended strategies has been used at least once. At this point, the original probabilities that prevailed at the beginning of the season are reinstated and the process begins anew, selecting a strategy every 10 days until the 120-day duration of the season is reached. These probabilities are reinstated because now most of the referenced locations have been visited at least once and locations that have been searched previously may again begin to look attractive.

Each of the intended strategies is used, therefore, at least once by the group. We now discuss the foraging activities of the group based on a particular strategy *i* at time *t* as described in the model.

Starting at Guilá Naquitz in Thorn Forest A, the collectors proceed to the zone specified by the first activity, STRAT(*i*)•TASK(1) • ZONE. There they search each of the specified locations, STRAT(*i*) • TASK(1) • LOCATIONS, for the focal resource STRAT(*i*) • TASK(1) • RESOURCE. Associated with each location at time *t* is the amount of the resource available there, which is expressed in terms of proteins and calories. This amount is added to the variables STRAT(*i*)__PROTEIN and STRAT(*i*)__CALORIES. The area encompassed by the locations searched is added to STRAT(*i*)__AREA as well as to DAY__AREA, a variable that keeps track of the area searched in a day. Each of these variables was set to 0 before the strategy was used. In addition, the distance traveled to get to the zone from the cave is represented by a generalized index, DISTANCE, in the following way. At the start of each collecting day DIST is set to 0. Each time the collectors move from one zone to an adjacent zone, the index is incremented by 1. This represents not only the movement between zones but also the distance traveled within the specified zone searching for the focal resource. If the collectors must first move through other zones to get to the one specified by the task, then the index is incremented by 1 for each zone crossed into. Thus, if the group moved from Thorn Forest A to Mesquite Grassland B in order to collect mesquite, the index would be increased by 3 since the collectors would travel through Thorn Forest B, Mesquite Grassland A, and Mesquite Grassland B. A collecting day is measured in terms of both the area searched by the group and the distance traveled. It was mentioned earlier that the maximum area the group can search in a day (DAY__AREA) is 0.33 ha; the maximum distance that it can travel in a day is here set to a value of 6. To provide an idea of just how far this is, movement by the group down from the cave to the river in Mesquite Grassland B and back would be of Order 6. While moving directly to and from Mesquite Grassland A will take less than a day by itself, we must remember that the distance travled within a zone in order to check the specified locations also contributes to the total distance traveled.

Therefore, beginning with the first activity in a schedule, the group collects a certain amount of resources, as well as having to travel a certain DISTANCE and search a certain AREA. If the potential increments to both DISTANCE and AREA associated with the next task in the sequence will not cause either total to exceed its daily limit, then the group proceeds with the next task. Otherwise, the next task will begin on a new day, DAY+1, while the day indices DAY__AREA and DISTANCE are reset to 0.

This cycle of activities continues until the addition of a new task would cause the DAY index to be in excess of 10 (DAY was initially set to 0 when the group began to use the strategy). At that point, STRAT(*i*)__PROTEIN and STRAT(*i*)__CALORIES will represent the total plant resources collected, while STRAT(*i*)__AREA stands for the total area searched. Every time a strategy is used during the season the acquired yield is added to STRAT(*i*) • PROTEIN and STRAT(*i*) • CALORIES, respectively. By the end of the season both of these variables represent the total yield for the strategy. STRAT(*i*)•AREA represents the area encompassed by the tasks employed over the 10-day period. This value is constant for the strategy over the season.

4. At the end of the season a general expectation of the performance for each utilized strategy is produced by δ_4. Each estimate of total yield, STRAT(*i*) • PROTEIN and STRAT(*i*) • CALORIES, is divided by STRAT(*i*) • AREA to produce STRAT(*i*) • PROTEIN__EFFORT and STRAT(*i*) • CALORIES__EFFORT. These variables measure the effort taken to acquire the total yield for the strategy.
5. The subsequent formation of an expectation about the overall performance of the sample of strategies used is symbolized by δ_5. In the model, this is produced by taking an average over the expectations for each of the individual strategies used. Therefore, SAMPLE__PROTEIN stands for the average expected protein yield over the set of utilitized strategies. The same holds true for SAMPLE__ CALORIES, SAMPLE__CALORIE__EFFORT, and SAMPLE__PROTEIN__EFFORT.

   Next, the expected performance for each strategy is compared with that for the sample in order to generate an impression of the strategy's relative performance, STRAT(*i*)__PERF. The basis of this comparison has been described previously and is not repeated here.
6. Those utilized strategies that had been altered since they were last used are now scrutinized. If the state of the environment is the same now as it was the last time the strategy was tested, CURRENT YEAR = STRAT(*i*) • LAST__USED, and STRAT(*i*) • PERF–STRAT(*i*) • LAST__PERF ≠ 0, then the rescheduling decision has definitely affected the strategy's performance. The corresponding adjustment of the probabilities for the decision-making operators that contributed to the decision is represented by δ_6. The nature of the adjustment depends on whether an improvement in performance was achieved. For a particular strategy *i* the process works as follows:
   a. Generate a random number RAND(MODIFY__SEED). The random variable MODIFY__DECISION maps this number into the set {yes, no} such that

MODIFY__DECISION = "yes" if RAND(MODIFY__SEED) ≤ (|STRAT(*i*)•PERF–STRAT(*i*)•LAST__PERF|*.14 + .08 and CURRENT__YEAR=STRAT(*i*)•LAST__USED, and "no" otherwise.

Note that even if no change was produced, the strategy's resource scheduling policy still has some chance of being altered, although that chance is rather small.

b. If the decision is yes, then the following procedures are carried out for each of the eight operators associated with the strategy's policy: For each $j \in \{1, \ldots 8\}$ if STRAT(i) • OPER(j) • USED = yes, stochastically adjust the probability of using that operator upward if the change resulted in an improvement and downward if the change produced a decrease in performance.

$$\delta_6: (\text{STRAT}(i)\cdot\text{OPER}(j)\cdot\text{PROB}) = \begin{cases} \text{If STRAT}(i)\cdot\text{PERF\_STRAT}(i)-\text{LAST\_PERF}<0 \\ \quad \text{then GENERATE RAND(OPER\_SEED)}\in[0, \text{STRAT}(i)\cdot\text{OPER}(j)\cdot\text{PROB}] \\ \text{else} \\ \text{if STRAT}(i)\cdot\text{PERF\_STRAT}(i)\cdot\text{LAST\_PERF}\geq 0 \\ \quad \text{then GENERATE RAND (OPER\_SEED)}\in[\text{STRAT}(i)\cdot\text{OPER}(j)\cdot\text{PROB},1] \end{cases}$$

LAST_PERF ≥ 0.

Here RAND(OPER_SEED) is mapped into the uniformly distributed set of numbers between the designated end points. Next the STRAT(i) • OPER(j) • USED is reset to no for each of the operators in Strategy i.

Notice that by incrementing the probability for an operator that participated in a decision to improve a schedule, we are increasing the probability of every schema for which that operator is a defining element. For example, if the probability of ω_1 is increased, so is the probability $\omega_1\square$, $\square\omega_1$, $\omega_1\square\square$, $\square\omega_1\square$, $\square\square\omega_1$, etc. Therefore, by increasing the probability of an operator, one also increases the expected number of instances for its associated schema. This property was referred to earlier as intrinsic parallelism and allows the model group to test implicitly and store information about a number of related schemata simultaneously. Those schema that are associated with improvements will become more common while those that produce reductions will become less frequent.

b. If the decision to reschedule the strategy is in the affirmative, the following procedures are performed on each of the eight decision-making operators: Generate a random number RAND(OPERATOR(j) _SEED). STRAT(i) •OPER(j)•USED is then the random variable that maps this number into the set {yes, no} such that

$$\delta_7: \text{RESCHEDULE} = \begin{cases} \text{"yes" if} \\ \text{RAND(RESCHEDULE\_SEED)} \leq \\ \text{STRAT}(i)\cdot\text{PERF}^{*}\ .14 + .08) \text{ and} \\ \text{"no" otherwise.} \end{cases}$$

Therefore, the probability of a strategy being rescheduled is a linear function of its performance. Notice that even the best performance, STRAT(i) • PERF = 0, results in some possibility of change.

b. If the decision to reschedule the strategy is in the affirmative, the following procedures are performed on each of the eight decision-making operators: Generate a random number RAND(OPERATOR(j) _SEED). STRAT(i) •OPER(j)•USED is then the random variable that maps this number into the set {yes, no} such that

$$\text{STRAT}(i)\cdot\text{OPER}(j)\text{USED} = \begin{cases} \text{"yes" if} \\ \text{RAND(OPER}(j)\text{\_SEED} \leq \\ \text{STRAT}(i)\cdot\text{OPER}(j)\cdot\text{PROB) and} \\ \text{"no" otherwise.} \end{cases}$$

Therefore, on the basis of the current rescheduling policy for strategy i, a decision is made regarding use of the operator. If the decision is in the affirmative, then STRAT(i)•OPER(j)•USED is set to "yes" and the appropriate stochastic operator is applied to the system according to the specifications given earlier.

The Modeled Environment

This completes our discussion of the basic adaptive subsystems that comprise the model. Now we turn our attention to the environmental subsystem with which they interact. The initial state of this subsystem, at the beginning of each season, is a function of both the present and past year types. Associated with each location is the average total collectible yield for the current combinations of year types—PROTEIN_YIELD•RES(i)•LOC(j) and CALORIE_YIELD•RES(i)•LOC(j). In general, the yield at every location relative to sequences with two "average" years in a row is as shown in Table 31.3. This relative yield is assumed to apply to every resource in that location.

The yield for a location in two average years is defined to be the average measured yield for that location observed in the field.

Every time the group chooses to search a specific location j for a resource i, a random variable YIELD is assigned a value between MIN_COLLECT and REMAIN_PERCENT_RES(i)•LOC(j). That is, the group can potentially collect no less than some minimum amount, MIN_COLLECT, and no more than the total remaining yield. If REMAIN_PERCENT_RES(i)•LOC(j) is less than MIN_COLLECT, then YIELD is assigned the value for REMAIN_PERCENT_RES(i)•LOC(j). YIELD represents the fraction collected, and REMAIN_PERCENT_RES(i)•LOC(j) stands for the percentage remaining. This latter variable is initially set equal to 1. Every time the location is searched, the group collects some fraction, YIELD, of this total. The value for REMAIN_YIELD_RES(i)•LOC(j) is then decremented by the fraction collected. The number of proteins and calories associated with the collected fraction is added to STRAT(i) •PROTEIN and STRAT(i)•CALORIES.

TABLE 31.3
The Yield at Every Location Relative to Sequences of Two "Average" Years in a Row

Previous year	Present year	Relative yield
Average	Wet	1.25 as much
Avg.	Dry	.75 as much
Wet	Dry	1.0 as much
Wet	Wet	2.0 as much
Wet	Avg.	1.25 as much
Dry	Dry	.5 as much
Dry	Wet	1.0 as much
Dry	Avg.	.75 as much

The value for MIN__COLLECT is determined by the group from experience and is large enough to insure that the group acquires all of the resource available at the location.

We have now finished our description of the basic model. The model is quite detailed, and would be too expensive to simulate on the computer. Therefore, we developed a simplified version in the next section that preserves this model's behavior but is easier to simulate on the computer.

Simplifying the Base Model

While the base model presented in the previous section well characterizes those aspects of the system we are interested in, testing the model requires data about the total yield of each major plant resource in every location during the season. The only data that are presently available is the total yield for each major plant species per hectare. What we must do, therefore, is simplify our base model so that it uses these available data. However, we must do this in such a way so as to produce a new model whose behavior corresponds with the original. We begin by describing the changes made to the base model and then demonstrate that this new model behaves in much the same manner as the original.

Turning first to the resource scheduling component, the following changes are made: If we are going to use the average yield per 0.001 ha for each resource in each zone, we no longer need specific information about the locations. Instead, we replace the location specificiation with a variable that represents the total area encompassed by these locations. Therefore, for every STRAT(i)•TASK(j)•LOCATIONS__TO__SEARCH, we substitute a new variable STRAT(i)•TASK(j)•AREA that represents the area encompassed by the locations searched.

The corresponding changes are now made for the rescheduling adaptive system in terms of each operator:

1. With ω_1 = SWAP__EXTERNAL, there is no real change except that the tasks that are exchanged use STRAT(i)• TASK(j)•AREA instead of STRAT(i)•TASK(j)• LOCATIONS__TO__SEARCH.
2. With ω_2 = SWAP__INTERNAL there is no change aside from that mentioned with ω_1.
3. Here ω_3 = SHUFFLE__LOCATION symbolizes not the exchange of location sets between tasks on the same strategy, as before, but the exchange of area specifications between tasks. However, the mechanism of the process is the same as before.
4. With ω_4 = SHUFFLE__ZONE there is no real change except that it is no longer necessary to specify a new set of locations for each participating task. As a result, Step 4 in the specifications can now be omitted.
5. With ω_5 = SHUFFLE__RESOURCE there is no change.
6. With ω_6 = ALTER__RESOURCE there is no change.
7. The modification of ω_7 = ALTER__ZONE is the same as that of ω_4. Since it is no longer necessary to regenerate a new set of points with equal area for a new zone, Step 4 can be omitted.
8. With ω_8 = ALTER__LOCATION, rather than selecting a subset of new locations, we need only to select a different amount of area to search. Perhaps the easiest way to visualize this is to select a subset of locations as done previously and assign to STRAT(i)•TASK(j)•AREA the area covered by this subset. In our lumped model it is therefore not the specific locations that are important but the area that they cover.

With these basic structural alterations in mind, let us now look at changes made in the transition function for the system:

1. The determiner of the new environmental state, δ_1, is not changed.
2. The manner in which the strategies to be used during the season are selected, δ_2, is also not changed.
3. The only process that is changed significantly is δ_3. Previously, δ_3 modeled the day-to-day foraging activities for the group. The result of these activities was the production of a performance estimate based on total yield. However, this requires estimates of the yield for every major resource in each location in an "average" year. Since our present data consist of estimates of the total yield for an average location in each zone during an average year, we restructure δ_3 so that these data can be used.

Given that the total yield for an arbitrary collecting task is the sum of the total yields for each location that comprises the strategy, this sum can be rephrased as in the following:

1. The average total yield for Resource i at n locations in Zone j, where n is the number of locations searched for the task, is represented as n^{*}. As n increases, the average yield for the n locations approaches the average yield over all locations in the zone. In ad[illegible]n, since the tasks are defined to be locationally independent (no one location is referenced more than once over all currently used tasks), the average total yield for each task

that uses a particular resource, i, in a certain zone j is m^*.

2. Given that m^* is the average total yield for resource i in n locations for zone j where n is the total number of such locations in the strategy, then if m is large, the average yield for the n locations will be very close to the average yield over all locations in the zone. It is shown elsewhere that as long as n is of a certain minimum size, using average yields to represent the performance of each unit area rather than using the yield for each individual unit area will produce the same average performance values for a strategy (Reynolds 1979). Since the remaining portions of the transition function are only influenced by the relative performance index, this means that the substitution of the one set of calculations for the other will not affect the system's overall behavior.

   So our new version of δ_3 emphasizes the average total yield per strategy and does not attempt to deal with the variability of foraging activities. The process therefore takes the following form: For each strategy selected to be used by the group, the total yield for each is calculated. This is done by finding out which tasks will actually be used over the 10-day period in the same way as the base model. Once this set of tasks has been delimited, then the total yield for each task is computed. This is done by multiplying the average total yield for Resource i per 0.001 ha in Zone j by the number of 0.001-ha units searched for the task. The yields for each of these tasks are then added together to get the total yield for the strategy.
3. The process of deriving a generalized performance expectation, δ_4, for each strategy is equivalent to that in the base model.
4. The formation of expectations about the overall performance of the entire sample of strategies (δ_5) is unchanged as well.
5. The process of changing the rescheduling policy for a strategy based on its performance is the same as before, although the operators' function, as mentioned previously, has changed slightly.
6. The basic process of rescheduling each utilized strategy based on its performance is the same as before, although the specific rescheduling decisions have been altered slightly, as mentioned earlier.

It can be shown in fairly straightforward fashion that the above model exhibits the same average behavior as our base model, when both are started in corresponding states and are exposed to the same sequence of inputs. Given that we have a formal description for each, it remains only to construct a correspondence between the two. Zeigler (1976:267) has specified certain relations that must hold between two systems in order for them to exhibit the same behavior. It is shown in detail elsewhere that such relations can be constructed between our present models (Reynolds 1979). As a result, we can be assured that the results obtained by simulating our simplified model in the next chapter also characterize the more detailed base model as well.

PART 6: THE PREAGRICULTURAL SIMULATION

Introduction

The early stages of agricultural evolution in the southern Mexican highlands have been characterized by Flannery (1968) as featuring a series of positive feedback loops that allowed successively greater divergence from the preagricultural pattern. These loops were seen as taking a series of small (and perhaps initially accidental) deviations in the preexisting hunter–gathering subsistence system and magnifying them to the point where they began to effect widespread changes in some of their fellow subsystems.

In this section, we suggest that these later cycles of deviation amplification were made possible by a preexisting pattern of systemic interaction that had been "primed" by certain adaptations that encourage the system to search for and exploit sources of positive system change. For example, we see in Fig. 31.7 the basic set of interactions between the adaptive subsystems. Notice that there is a potential for both positive and negative feedback cycles. The exact nature of these interactions depends on the current state of the model and its environment. What we do in the next section is to begin with a random set of resource scheduling strategies that will allow the rescheduling subsystem plenty of room in which to make improvements. Initially, we would expect the group to generate and maintain a directed sequence of performance improvements over time. If the group can do this, it will be interesting to characterize the pattern of behavior associated with this positive feedback loop, as well as any adaptations that the group might acquire to sustain such a loop. When the schedules have been improved to the point where the current information is not sufficient to allow for continued success in rescheduling the available strategies, the interaction between the two systems changes gradually so that a negative feedback loop comes to dominate. In this way, the group's rescheduling policy becomes more conservative and avoids the risk of losing the performance improvement that it already has made.

However, the decision-making adaptations acquired during the positive feedback cycle are retained by the group. These adaptations "prime" the system so that its search for improvements can still go on as an undercurrent within an otherwise conservative decision-making environment. In the event that an improvement is found, these adaptations can serve to restart the positive feedback cycle. This is, in fact, exactly what happens with the introduction of incipient agriculture in Part 8.

We then compare the performance of our preagricultural model against data from the same period, Zone E and Zone D at Guilá Naquitz. Such a comparison allows us to see how well the behavior of our model group matches that of the real world. If they correspond, we will have good reason to believe that it is the result of corresponding rescheduling behavior over time.

Finally, we alter the network of interactions between the subsytems in the model in order to see how the system's per-

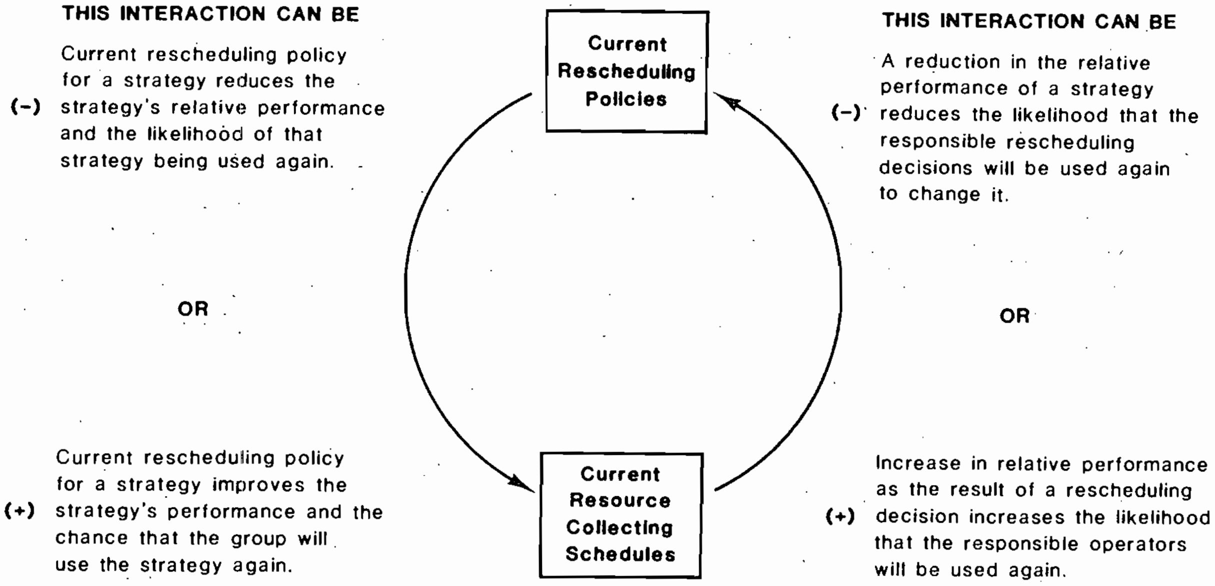

Fig. 31.7. Basic interaction between the system's components.

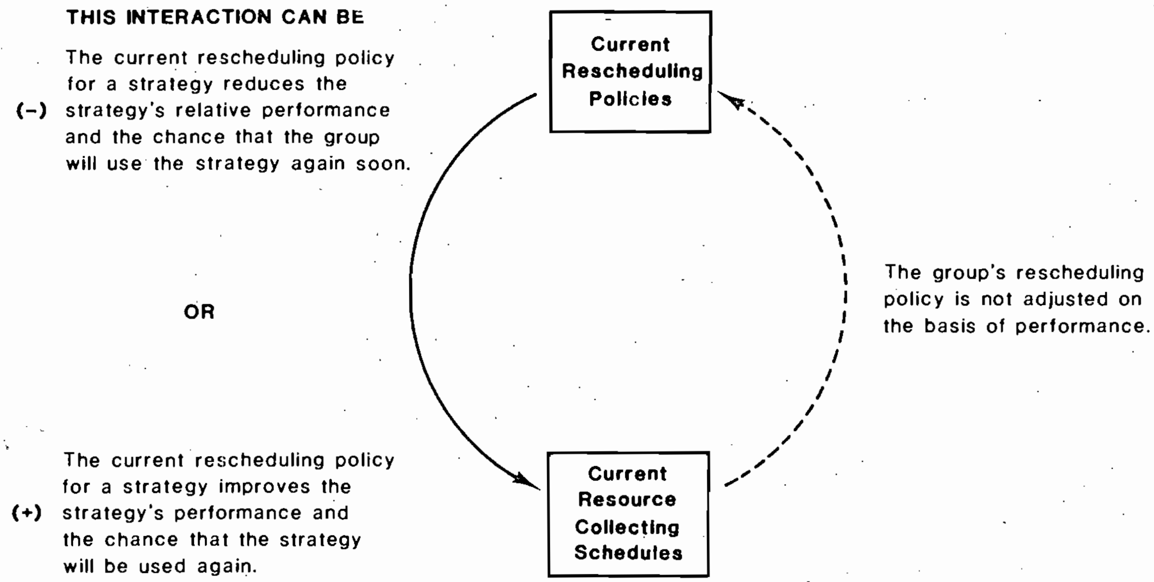

Fig. 31.8. Removing the feedback cycle. (Those interactions that have been disabled are given as dashed lines.)

formance is affected. In particular, we no longer allow the rescheduling system to adjust its decision-making policies based on their performance. This disables the feedback loop as shown in Fig. 31.8.

The extent to which this adjusted system is able to mirror the archaeological data provides insight into the importance of these feedback mechanisms in the functioning of the real system.

Behavior of the Model Group: Learning To Adapt within a Challenging Environment

Since our interest is in seeing how well our model group is able to assimilate information from its environment into its decision-making structure over time, we start off the basic set of structures in an undifferentiated, random fashion. The same sequence of random activities is assigned to each of the

TABLE 31.4
The 25 Tasks that Were Each Used Once in Each Initial Strategy

Resource	Zone	Area (ha)
Acorns	Thorn Forest A	.075
Piñon nuts	Thorn Forest A	.075
Nanches	Thorn Forest A	.075
Nanches	Thorn Forest B	.075
Wild beans	Thorn Forest A	.075
Wild beans	Thorn Forest B	.075
Susí nuts	Thorn Forest A	.075
Susí nuts	Thorn Forest B	.075
Susí nuts	Mesquite Grassland A	.075
Agave hearts	Thorn Forest A	.075
Agave hearts	Thorn Forest B	.075
Agave hearts	Mesquite Grassland A	.075
Opuntia nopales	Thorn Forest A	.075
Opuntia nopales	Thorn Forest B	.075
Opuntia nopales	Mesquite Grassland A	.075
Opuntia nopales	Mesquite Grassland B	.075
Opuntia fruits	Thorn Forest A	.075
Opuntia fruits	Thorn Forest B	.075
Opuntia fruits	Mesquite Grassland A	.075
Opuntia fruits	Mesquite Grassland B	.075
Mesquite pods	Thorn Forest B	.075
Mesquite pods	Mesquite Grassland A	.075
Mesquite pods	Mesquite Grassland B	.075
Hackberries	Mesquite Grassland A	.075
Hackberries	Mesquite Grassland B	.075

10 initial strategies, where the basic tasks used are as described in Table 31.4. A fixed search area of 0.075 ha is associated with each of the tasks in every strategy.

This assignment of strategies is taken to represent the knowledge that the group initially has of its environment when exposed to it for the first time. Corresponding to this lack of scheduling experience is a lack of decision-making experience as well. In this situation, each of the basic rescheduling decisions has a 50–50 chance of being used. If our model at all characterizes the adaptive aspects of the group's scheduling system, the structure of the model group's behavior should change over time based on its experience.

If the model group can indeed learn from its experiences, its performance over time should become better. In order to gauge changes in the group's performance, an index was formed by adding together the following variables:

3*SAMPLE_PROT_AVE+SAMPLE_CAL_AVE+3*
SAMPLE_PROT_EFFORT+SAMPLE_CAL_EFFORT

These represent the four variables used by the group to judge each strategy's performance in a given season. Thus, for a given season, the index represents the overall performance of the sample strategies, based on the average amount of protein and calories acquired along with the effort expended to acquire these amounts. The variables associated with the acquisition of protein were both multiplied by a factor of three, so that the contribution of all four variables to the index would be of the same order of magnitude.

In Figs. 31.9–31.11, the changes in the above index are displayed over 500 time steps for each of the 3 year types. Notice that the group improves its performance in all 3 situations over time, although the greatest rate of improvement is associated with both dry and average year types. In these years, the reduced yield in many species put a certain amount of pressure on the group to survive. This selective pressure apparently leads to rapid improvements in the group's collecting activities in these year types.

It is also interesting that the group seems to treat both dry and average year types alike in terms of performance. Notice, for example, that the group is able to effect few performance improvements in either year type after about 300 iterations. Perhaps this is because there is still too much selective pressure on groups in an average year to allow them to treat such a year any differently from a dry year.

Wet years, on the other hand, are associated with relatively high yields, and survival is much easier in such a context. This reduction in performance constraints means that a wider variety of collecting strategies can be utilized in such an evironment. As a result, the group's performance in wet years takes a much longer time, almost twice as long, to level off. This is because there is less concern with improving performance in a situation that is favorable already. Also, the lack of long-term storage technology meant that there was little incentive to collect more than the group could consume within a reasonable length of time.

While our hypothetical group was given three year types to work with, they reduced this to a binary classification (wet versus dry or average) based on the relative selection pressures in each. This is interesting, since many Zapotec speakers in the Valley of Oaxaca today seem to perceive of all years within recent memory as belonging to one of two classes, "wet" or "dry" (see for example Kirkby 1973:Appendix I). Thus Zapotec farmers, given a wide variety of actual annual rainfall patterns, behave as if there were only two kinds of years. The fact that our model group does the same may suggest that there is a functional basis for such environmental perception.

The model group is able to produce a number of modifications in its resource collecting activities that, at first, lead to marked increases in performance. However, over time, it becomes much harder for the group to effect new improvements with the information provided. As a result, the group reaches a stable performance state by 500 iterations. The use that the group makes of the plant resources at this stage is evident from Table 31.5. In it, the average area searched per task for each major resource is given. Notice that both acorns and hackberries are given the most emphasis. This is a good sign, since we have already seen in Chapter 19 that these were the two most abundant resources in Zones E and D of Guilá Naquitz. In the following section we discuss correspondence between these data and those from the cave in more detail.

The majority of activities carried out by the group at this

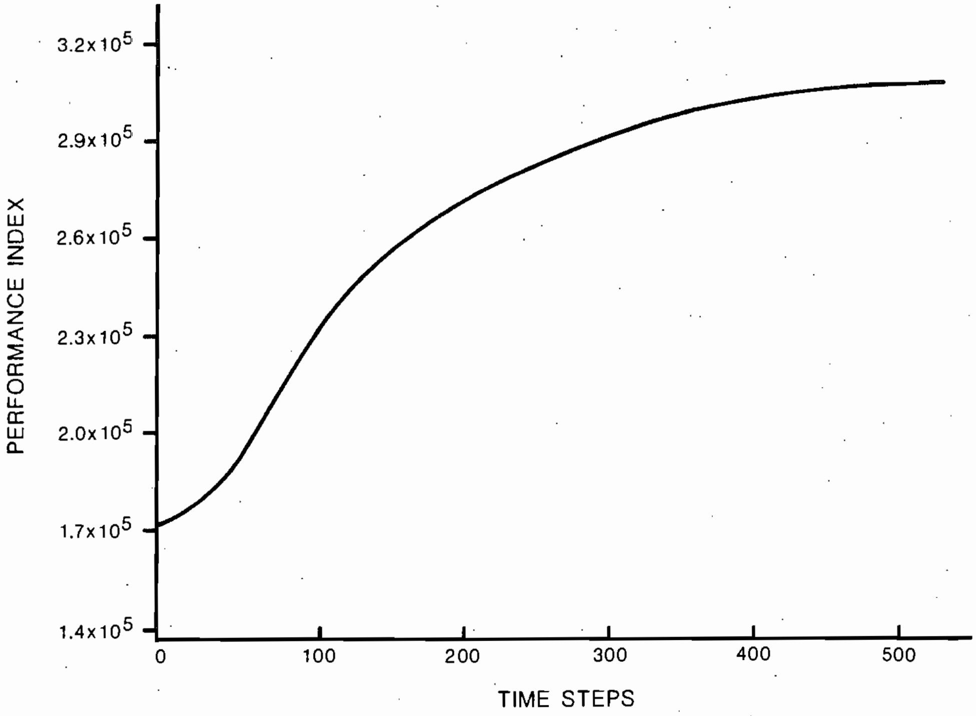

Fig. 31.9. Changes in the model group's performance in "dry" year types over time.

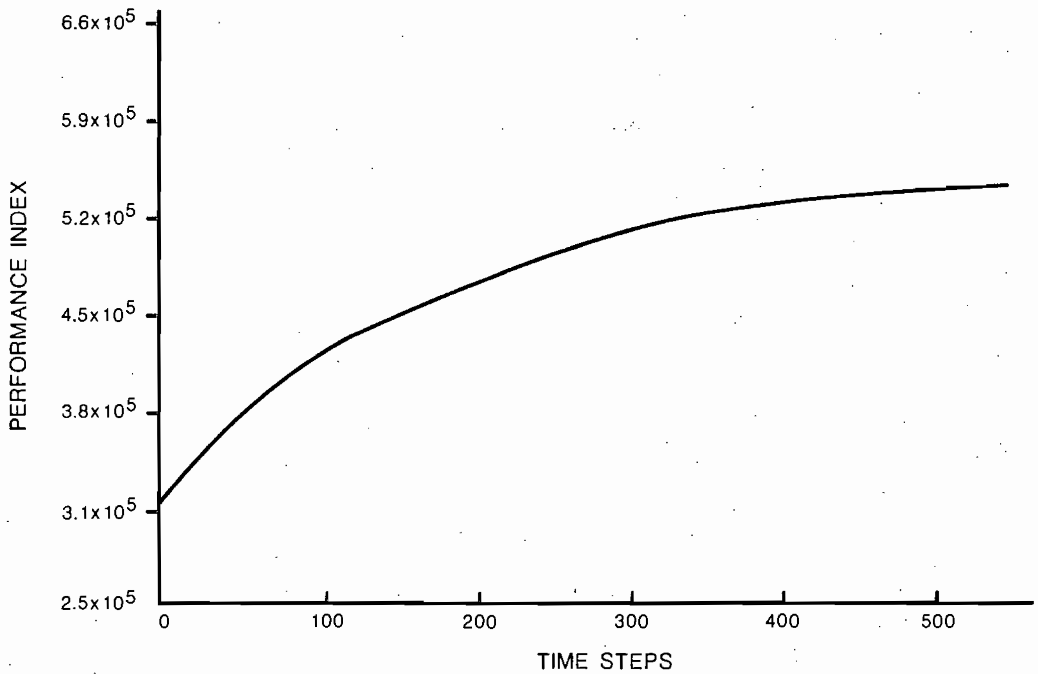

Fig. 31.10. Changes in the model group's performance in "average" year types over time.

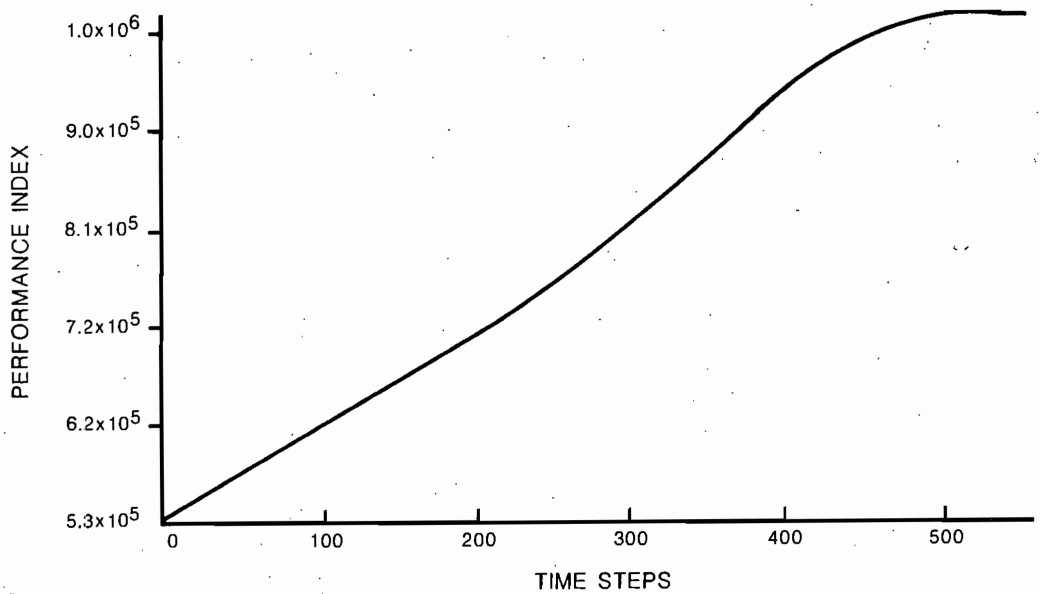

Fig. 31.11. Changes in the model group's performance in "wet" year types over time.

TABLE 31.5
Average Area Searched per Activity Involving Each Major Resource after 500 Time Cycles

Resource	Average area used (ha)	Rank based on average area
Piñon nuts	.133	3
Acorns	.164	2
Guaje	.104	10
Susí nuts	.115	9
Agave	.1175	8
Nanche fruits	.123	6
Wild beans	.080	12
Mesquite	.1275	5
Cucurbits	.129	4
Hackberries	.171	1
Opuntia fruits	.121	7
Opuntia nopales	.106	11

time centered around the Thorn Forest zones near the cave. Of the 10 strategies, only 1 had more activities outside of these zones than within them. That strategy emphasized tasks in the Mesquite Grassland. While there were not as many activities carried out in the Mesquite Grassland zones, those that were carried out involved a much larger share of the day's activities than most tasks from other environments. This is due, perhaps, to the time that the group would have to spend to get to the Mesquite Grassland from the cave in the first place.

The rescheduling policies for the group also changed as its experience with the environment increased. These trends are shown in Fig. 31.12. Notice that all the operators exhibit an initial decrease in use. At this point, the group has no experience on which to base its decision. It therefore takes a number of cycles before the policies become adjusted to their associated schedules. Once this occurs, there is then a chance for improvement to take place.

The first operators to exhibit increased use are those that recombine existing specifications rather than creating new ones. The use of these operators alone explains the slow-growth phase of the performance curve for dry years. However, after about 150 cycles, the mutation-type operators come into play as well. Together, the two account for the fast-growth phase of the performance curves for dry years. Next, certain recombination operators begin to be used less; and by 300 cycles, the alter operators exhibit a similar change. From here on the group's rescheduling policy becomes more and more conservative, and with this the performance curves start to flatten out.

In other words, schema consisting of recombination-style operators were the first to exhibit major increases. As the model group's experience with rescheduling decisions increased, the group began to use high-order schema more often. By 350 model time steps, all the mutation-style operators have been brought into play along with the recombination operators. However, it becomes harder for any of these schema to effect improvement in the performance of the majority of available strategies sampled. As a result, the overall complexity of available schema for the set of sampled strategies begins to decrease by 400 iterations. This does not mean, however, that the policies for particular strategies are necessarily reduced in complexity.

While on the average the rescheduling policies of the group tend to become more conservative over time, there are exceptions. These exceptions are strikingly obvious by 500 time

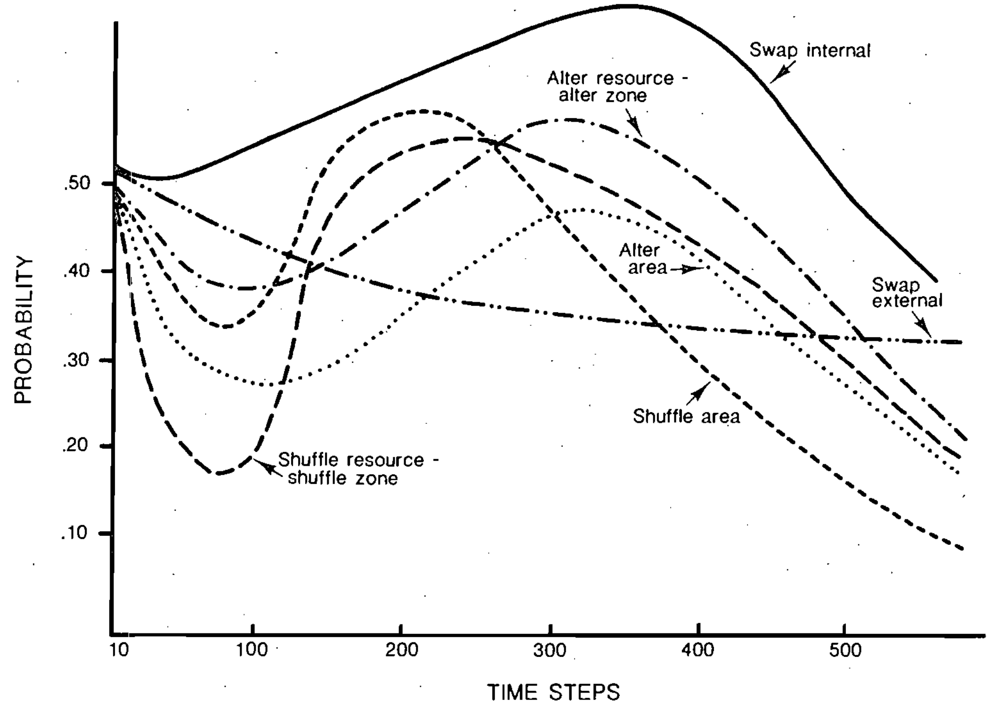

Fig. 31.12. Changes in average probability for each operator based on the sampled strategies. "Alter resource" and "alter zone" are shown together, as are "shuffle resource" and "shuffle zone".

cycles. In particular, a small number of strategies develop rescheduling policies that encourage experimentation. One strategy, after 500 model cycles, has a .75 average probability for each rescheduling operator. This means that it is probably changed every time that it is used.

At first glance, this does not appear to be consistent with our earlier statement that the group's rescheduling behavior had become more conservative. It turns out, however, that this strategy is a relatively poor performer and is used very infrequently. Unlike most of the available strategies, the majority of its tasks (18 out of 25) occur in the 2 least-productive zones, Thorn Forest B and Mesquite Grassland A. Accordingly, it tends to use less-productive species in less-productive zones.

What is interesting here is really not the schedule's productivity but when it is used. This below-average strategy, with a rather unusual collection of tasks and a high probability of being modified, is used primarily in wet years. This tactic makes a good deal of sense. In doing this, the system is able to continue its experimentation even while it becomes more conservative. Changes are made, not to those strategies that have a lot to lose if they are unsuccessful, but to poor performers such as the one described, which have little to lose and more to gain. In addition, the group hedges its bets by making such changes predominantly in wet years, when plant densities are high and rescheduling mistakes would not be felt as much.

Therefore, the group, in associating specialized decision-making policies with poorer performing strategies, can introduce changes into the system via years in which selective pressure is reduced. This consistent process of change generates a schedule whose structure is unique to wet years. These wet-year strategies, therefore, provide for an undercurrent of change within a system that is becoming more conservative.

This notion of experimenting with schedules in wet years is an interesting one, and examples of it can still be found among present day agriculturalists in the valley. Kirkby (1973:94), in describing planting strategies among Zapotec farmers, state that "marginal land provides an area in which opportunities for gambling on wet years takes place." It may even be that this modern behavior includes an extension of resource collecting policies developed in preagricultural times.

Comparing the Model's Performance with the Archaeological Data

We have seen in the previous section that the group acquired a number of decision-making adaptations before achieving a stable performance level. In this section, we want to see how well the strategies generated by the group using these adaptations characterize the resource collecting behavior of the real group. In order to do this, we compare the relative emphasis placed on each of the major plant species in the model group with the relative frequency of each plant in Zones E and D of Guilá Naquitz. Both of these zones, as mentioned in earlier chapters, are the results of human

TABLE 31.6
Raw Counts, Relative Frequency, Rank Order of Relative Frequency, and Corresponding Rank Order Predicted by the Model for Each Major Plant in Zone E

Resource	Raw frequency counts	Relative frequency	Rank order based on relative frequency	Predicted rank order in model
Piñon nut hulls	155	.042	4	3
Acorns	1846	.511	1	2
Susí seed coats	98	.027	6	8
Agave quids and leaves	8	.002	8	7
Nanche seeds	6	.001	9	5
Bean pod valves	161	.044	3	10
Mesquite seeds	32	.008	7	4
Hackberry seeds	1166	.322	2	1
Opuntia seeds	135	.037	5	6
Opuntia nopales	3	.0008	10	9

occupation prior to 7500 B.C. and represent the preagricultural activities of the hunter–gatherers of the valley.[3]

We begin with Zone E, the earliest occupational zone found in the cave. In Table 31.6 the raw counts for each of the major species found in the zone are given, as well as their relative frequency. A rank ordering based on their relative frequency was computed and given as well. It is with this rank ordering that we compare the model results.

For each of the major resources in the model that correspond to those in Zone E, a ranking was given, on the basis of the average area allocated to it by each task in which it occurred, for all the existing schedules at Time Step 500. This time slice was chosen because by then our model group had achieved a stable performance state, as discussed earlier. This rank ordering, therefore, reflects the relative emphasis placed on each resource by the model group at this time.

In comparing the two sets of rankings, we notice a great deal of correspondence between them. Indeed, 7 of the 10 plant resources have rankings that differ by 2 or less. Only mesquite, nanche fruits, and wild beans exhibit any greater discrepancy.

Although it seems quite apparent that the two sets of trends correspond, can we quantify this correspondence statistically? This can be done using a nonparametric statistic that tests the agreement between K sets of observations. In our case, the rank correlation between the predicted and observed changes is computed. The *concordance statistic* is a linear function of these paired comparisons and represents the goodness of fit between them (Gibbons 1971). This statistic is used to test the hypothesis that the model makes predictions that are independent of the observed rank ordering of plant use based on the archaeological data from Zone E. If the value for the concordance statistic differs enough from the value that would be expected, given that the two sets were not related (i.e., they are independent), then we would have good reason to reject this hypothesis of independence.

The concordance statistic was computed for this case and found to be 0.75, where 1.00 denotes a perfect correspondence. The probability that the two orderings were generated by independent processes, given the present level of agreement, is .07. This is sufficient grounds for us to reject our original hypothesis in favor of one that postulates a correspondence between the model and the real system.

While the similarities between the two systems are important, their differences can be instructive as well. The fact that mesquite and nanche fruit are found less often in the cave than predicted, while wild beans are found more often, is interesting. From Fig. 18.1 we learn that both mesquite and nanche are available earlier in the season (by August), while beans become available slightly later (September). It is possible, therefore, that the difference between the two systems lies in the fact that the real group arrived at the cave slightly later than presumed in the model (see also discussion in Chapter 24).

Looking next at Table 31.7, we see the frequency data for Zone D. At this time, there are 12 major resources present, rather than just the 10 found in Zone E. The 2 new plants include cucurbits as well as *guajes*. The corresponding ranks for each of the 12 resources generated by the model are given as well. By inspection, we observe that 9 out of the 12 pairs of rankings differ by at most 2 positions. The concordance statistic for these 2 sets of rankings was .78 and the associated level of significance was .03. Again, according to our criteria, this leads to a rejection of our original hypothesis that the two rankings were independent.

Therefore, the relative frequency of the plant resources collected by the model group does not differ much from the rank ordering of materials actually found in the cave for both

[3]One possible *Cucurbita pepo* seed occurred in Zone D, but it was so heavily outnumbered by wild plant remains that Zone D can be considered preagricultural for our purposes.

TABLE 31.7
Raw Counts, Relative Frequency, Rank Order and Corresponding Rank Order Predicted by the Model for Each Major Plant in Zone D Based on Relative Frequency

Resource	Raw frequency counts	Relative frequency	Rank order based on relative frequency	Predicted rank order in model
Piñon nut hulls	94	.020	5	3
Acorns	3182	.707	1	2
Susí seed coats	237	.052	4	9
Agave quids and leaves	53	.011	7	8
Nanche seeds	49	.010	8	6
Bean pod valves	17	.003	10	12
Mesquite seeds	59	.013	6	5
Hackberry seeds	416	.092	2	1
Opuntia seeds	348	.077	3	7
Opuntia nopales	28	.006	9	11
Guaje pods	11	.002	11	10
Cucurbit remains	6	.001	12	4

Zones D and E. On this basis, it seems quite likely that rescheduling processes of the kind modeled here are of fundamental importance in the formation of the preagricultural group's resource collecting activities over time.

Testing the Feedback Cycle Assumption

In order to substantiate our assumption that feedback cycles played a necessary part in the development of the real group's collecting activities, we can disable the basic cycle in our model as shown in Fig. 31.8. We then start our simulation using the same set of strategies and rescheduling policies as before. However, this time the group is not able to alter its basic rescheduling policy based on experience. This situation is somewhat akin to what happens within more complex societies when the decision-making system either is not able to keep tabs on the very subsystems it is supposed to be controlling or has become too inflexible in its policy making. What happens is that the modified system exhibits a sequence of initial improvements in somewhat the same manner as the original system did. This is because almost any change in this initial set will represent an improvement. Not only does the group's performance peak earlier than before, but its performance in each of the three year types also peaks concurrently. This suggests that the distinction made between wet and dry climatic types in our original model is not made here. This makes sense, because the group now cannot adjust its rescheduling policies to take advantage of the differences in selection pressure in the different year types. As a result, it cannot generate either the decision-making or resource collecting specializations found in the other model.

In addition, our group is not able to adjust its rescheduling policy to fit the structure of the existing schedules. This means that it will make unnecessary and perhaps unwise adjustments in the current schedules. It is because of this and the other problems mentioned above that the group's performance begins to exhibit wild oscillatory behavior soon after experiencing its initial increases. Such unstable behavior continues on for over 2000 iterations, although only part of that is graphed here (Fig. 31.13).

Not only did the lack of articulation between the two component subsystems result in intrinsic performance instability, but also, the overall performance got progressively worse. For example, Table 31.8 gives the relative emphasis placed on each of the major plant resources by this model compared with the relative amounts of collected resources found in Zone D of the cave. A number of high-yielding plants, such as acorns and mesquite, are deemphasized and replaced instead by less-productive genera.

Additional runs were made not only with this set of fixed policies but with other fixed policies as well. In every case, the system exhibited inherent instability after a certain period of time. Not only is there no evidence for such instability archaeologically, but the mix of resources produced does not correspond with existing data either. For example, when the ranked preferences produced by this model were compared with the actual rank observed for the plants in Zone D, the concordance statistic took the value of .35. This degree of association was not significant statistically. These results strongly suggest that feedback cycles within the group's decision-making system had to be present in the preagricultural period in order for the group to exhibit the observed scheduling behavior.

Conclusions

Analysis of the simulation results described in this part of the chapter has revealed a number of interesting points. First, it seems that the basic feedback cycle between the two decision-making subsystems articulated in our model is needed to insure performance comparable with the real

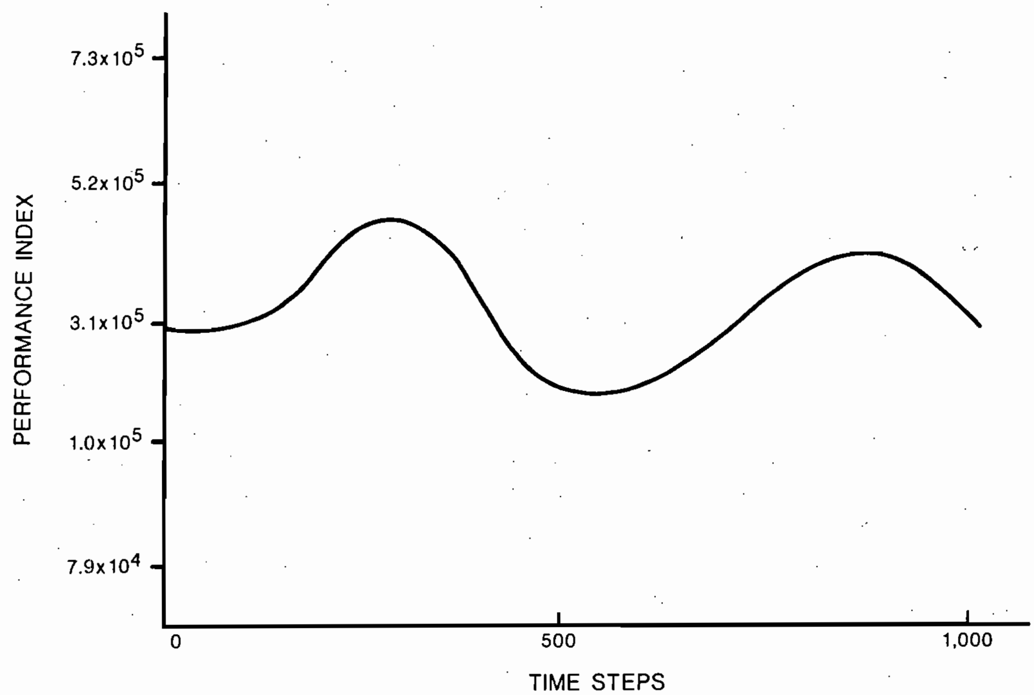

Fig. 31.13. Performance trends for the modified group model in "average" year types.

TABLE 31.8
Comparative Rank Ordering of Collected Plants between the Adjusted Model and Actual Remains from Zone D[a]

Resource	Rank order based on relative amounts in adjusted model	Rank order based on relative amounts in Zone D
Piñon nut hulls	7	5
Acorns	9	1
Guaje pods	3	11
Susí seed coats	12	4
Agave quids and leaves	8	7
Nanche seeds	2	8
Bean pod valves	4	10
Mesquite seeds	10	6
Cucurbit remains	11	12
Hackberry seeds	5	2
Opuntia seeds	6	3
Opuntia nopales	1	9

[a]The value 1 denotes the most important and 12 the least important.

system. This feedback loop allows both experimentation and system stability at the same time. This is accomplished through the aid of a number of adaptations acquired by the group over time. Such adaptations appear designed to deal with differences in selective pressure exhibited by the different environmental states encountered by the group. Among these adaptations we find the following:

1. The group tends to make rescheduling decisions more frequently in wet years, when the overall yields are greater than normal. These decisions are associated with strategies that possess relatively poor performance. By doing this, the group is able to make rescheduling decisions under favorable circumstances. That is, since the target strategy is not as good as the others, there is less to lose by changing it; and even

if the change produces a reduction in performance, it is least likely to be noticed in a wet year, when yields are increased for most species.

2. This differential decision-making produces a set of wet-year strategies that exhibit more variability in collecting behavior than those used in other year types. For example, the more successful strategies could be termed "general purpose" and focus their activities on the most-productive species in the most-accessible zones. Wet-year strategies, on the other hand, are more likely to use less-productive species as well.

3. Although the group is given information regarding three different year types, it behaves as if there are only two. This binary classification corresponds to the traditional Zapotec dichotomy between wet and dry years. It turns out that the average year type does not possess enough selective advantage over dry years to permit specialized decision-making as with wet years. As a result, dry and average years are effectively lumped together.

Employing the above adaptations, the group is able to produce resource collecting behavior that corresponds significantly with data from Zones E and D of Guilá Naquitz.

The entire basis for the above behavior is performance information acquired from the environment. It may be that the rate of system change is in some sense limited by the amount of information provided to the group by its environment. The more information available to the group, the more adjustments it is able to make if needed.

The climate of the valley is such that the sequence of year types is unpredictable over time. It is perhaps this unpredictable succession of climatic types with different selective pressures that provides the context in which the group can acquire a good deal of information about its existing schedules through experimentation. It will be our goal in Part 9 of this chapter to see just how important this climatic sequence is to the rate of system change. By varying the associated probabilities for each year type, we can hypothetically change the climate to which the group is exposed and measure the corresponding achievement of the group.

PART 7: MODELING INCIPIENT AGRICULTURE

Introduction

In Part 6, we demonstrated that considerations of foraging efficiency in the face of annual variation are by themselves sufficient to generate a pattern of collecting behavior that corresponds well with the archaeological data on preagricultural plant use. The relatively stable pattern of collecting seen after Time Step 500 did not, however, last throughout the preceramic era. Part way through the Naquitz phase came hints that incipient agriculture was now part of the subsistence pattern.

Perhaps the first group of plants to come under domestication were the cucurbits. The bottle gourd was represented by rind fragments as early as Zone C of Guilá Naquitz; 1 possible *Cucurbita pepo* seed was present in Zone D, and this squash was even better represented in Zones C–B1, where 14 seeds and/or peduncles were present (Chapter 20). Small black runner beans were also present in large numbers at Guilá Naquitz. While the species involved is one that has left no domestic descendants, the beans were present in such unexpectedly high quantities relative to more common plants that it is possible the occupants of the cave were experimenting with their cultivation (Chapter 24). Finally, pollen grains of the genus *Zea* were present in Zones C–B1 of Guilá Naquitz (Chapter 15). While it cannot be determined whether teosinte or early domestic maize was the source of the pollen, tiny but indisputable cobs of maize have been recovered from sixth-millennium B.C. levels near Tehuacán, not far to the north of Guilá Naquitz.

For all these reasons, we decided it would be interesting to model incipient agriculture in the eastern Valley of Oaxaca by adding maize, beans, and squash to the group of plants already present in the preagricultural simulation and observing how the preexisting collecting schedule was modified to accommodate them.

The Mechanisms of Incipient Agriculture

This chapter is not the place to speculate on why the first seed was planted in the Valley of Oaxaca. In our model, incipient agriculture is viewed as a process by which (1) the density of certain useful plants was artificially increased and (2) the location of these atypically dense stands within the overall Guilá Naquitz environment was made more predictable. Judging from the archaeological record, any increases in productivity associated with these early agricultural activities were small compared to later periods (after 5000 B.C.), when genetic changes in some of the plants produced substantial increases in productivity. However, the initial changes probably produced certain shifts not only in the group's collecting activities but also in the type of rescheduling decisions that were likely to be made. These adjustments favored continued experimentation[4] with incipient agriculture, which ultimately led to the "fixing" of genetically modified strains.

Our purpose here is to introduce the potential capability for incipient agriculture into the preagricultural group model at equilibrium in order to discern the nature of these initial shifts in scheduling. In terms of our preagricultural lumped model, this entails the following adjustments. First, associated with each task in every strategy is a new descriptive variable STRAT(i)•TASK(j)•DENSITY. This variable denotes the extent to which the density of the focal resource has been altered by the group for the associated locations. It effectively represents the results of effort spent in the preceding months

[4]We use the term *experimentation* here in the vernacular sense only, as in the "trying out" of various subsistence strategies over a long period of time.

TABLE 31.9
The Distribution and Maximum Density for
Maize, Beans, and Squash as the Result of Incipient Agriculture[a]

Plant	Mesquite Grassland B	Mesquite Grassland A	Thorn Forest B	Thorn Forest A
Maize	.33	1	1	.16
Beans	5.0	1	3	4.0
Squash	5.0	.2	2	4.0

[a]Each figure represents the maximum relative increase in density that can be attained by incipient agriculture. A 1 represents a zone in which the density is not appreciably affected by incipient agriculture.

to adjust the distribution of the focal resource at the prescribed locations. These distributional shifts will have the same relative effect on the yield of the focal resource throughout the season.

While it might be expected that a number of resources could have their distributions adjusted, only three—cucurbits, beans, and maize—are dealt with here. These are the plants that were to become the backbone of the later sedentary agricultural systems in the valley. Although the densities of other plants may have been affected as well, the adjustments made to them are relatively minor in comparison and therefore are not considered.

Each of the three plants—maize, beans, and squash—has a characteristic range of possible densities for each of the four vegetational zones. In Table 31.9, the maximum potential increase in yield as the result of incipient agriculture is given for the three species. The greatest improvements in yield are to be made in Thorn Forest A and in Mesquite Grassland B, as the result of increased moisture availability. Of these two, Mesquite Grassland B has the higher potential yields because of the availability of good alluvial soils.

Therefore, in a given year, the distribution of certain plants may be altered during the spring and summer by the group. The degree to which this is done will affect the character of the strategies that the group intends to use in the fall, since their knowledge of and interest in these areas will be increased. The STRAT(i) • TASK(j) • DENSITY variable serves to associate with the collecting task the amount of prior effort taken to produce the observed yield. If no prior effort was given to altering the associated distribution, then the variable takes a value of 1. Otherwise, it can have a value up to the maximum potential increase for the particular resource in the particular zone. These values represent, in model terms, the increase in yield as the result of the group's activities, where yield is said to be directly related to prior effort.

The only additional structural change that needs to be made in the model is with regard to the basic set of rescheduling operators. Now that the group can potentially alter the density of the three plants, new sets of decisions must be made by the group members. These new decisions are represented by two new stochastic operators in the following way:

ω_9 = ALTER__DENSITY: This represents a decision to alter the density of the focal resource for a task. For an arbitrary strategy i and task j, the process is modeled stochastically in two stages:

1. Generate a random number RAND(ALTER__DENSITY__SEED) and apply this number to the random variable STRAT(i) • OPER(9) • USED that maps it into the set {yes, no}, where

$$\text{STRAT}(i)\cdot\text{OPER}(9)\cdot\text{USED} = \begin{cases} \text{“yes” if} \\ \text{RAND(ALTER\_DENSITY\_} \\ \quad\text{SEED} \le \text{STRAT}(i)\cdot\text{OPER}(9) \\ \text{PROB} \\ \qquad\qquad \text{and} \\ \text{“no” otherwise.} \end{cases}$$

2. If the decision is in the affirmative, then RAND (ALTER__DENS__TASK__SEED) is produced and mapped by ALTER__DENS__TASK into the set {1, . . . 25} of indices for the available tasks.
3. Next ALTER__DENS__VALUE__SEED is used to provide a new random number that is then mapped into the set of $R^+ \epsilon$ [1, MAX__DENS__ZONE]. MAX__ DENS__ZONE is taken from Table 31.9 and represents the maximum potential increase in yield as the result of incipient agriculture for the focal resource in the designated zone.

ω_{10} = SHUFFLE__DENSITY: This operator stands for the exchange of density specifications between two compatible tasks in a strategy i. It is determined stochastically by the following sequence of processes:

1. First a random number, RAND(SHUFFLE__DENS__SEED), is mapped into the set {yes, no} by the random variable STRAT(i) • OPER(10) • USED such that

$$\text{STRAT}(i)\cdot\text{OPER}(10)\cdot\text{USED} = \begin{cases} \text{“yes” if} \\ \text{RAND(SHUFFLE\_DENS\_} \\ \quad\text{SEED)} \le \text{STRAT}(i)\cdot \\ \quad\text{OPER(10)}\cdot\text{PROB} \\ \qquad\qquad \text{and} \\ \text{“no” otherwise.} \end{cases}$$

   STRAT(i)•OPER(10)•PROB stands for the probability that a favorable decision will be made to modify the strategy in this way, given the current rescheduling policy for the strategy.
2. If the decision is yes, then the seeds SHUFFLE__DENS__SEED__1 and SHUFFLE__DENS__SEED__2 are used to generate two random numbers. These are mapped into the set of available tasks for the strategy by SHUFFLE__DENS__TASK__1 and SHUFFLE__DENS__TASK__2 in the same manner as described for the previous shuffle operators.

3. If the two tasks are performed in the same vegetational zone and involve the same resource—either maize, beans, or squash—then the density specifications are exchanged such that

$$\text{SHUFFLE\_DENS:}\begin{cases}\text{STRAT}(i)\cdot\text{TASK(SHUFFLE\_DENS\_TASK\_1)}\cdot\text{DENS} \rightarrow \text{STRAT}(i)\cdot\text{TASK(SHUFFLE\_DENS\_TASK\_2)}\cdot\text{DENS} \\ \text{and} \\ \text{STRAT}(i)\cdot\text{TASK(SHUFFLE\_DENS\_TASK\_2)}\cdot\text{DENS} \rightarrow \text{STRAT}(i)\cdot\text{TASK(SHUFFLE\_DENS\_TASK\_1)}\cdot\text{DENS}\end{cases}$$

Aside from the above changes, the rest of the model for incipient agriculture is the same as with the preagricultural model.

Conclusions

After having made the above structural adjustments to our preagricultural model, we are now in the position to simulate the development of incipient agriculture by the group. In Part 8, we describe the results of running the agricultural model, where initially all the values for the resource collecting schedules defined in the preagricultural model are the same as they were at equilibrium for that model. The new density specification for each task is initialized to 1. This means that no distributional change has yet been made to any of the focal resources. In addition, since the group has had no experience with making decisions that affect the density specification, the initial probability of making each of the new decisions is initially set to 50-50.

The group, while initially displaying the scheduling behavior described in Part 6, is now in a position to employ these new agricultural procedures as well. It is our goal in Part 8 to see whether the group is able to develop incipient agriculture in this context. If it does, it will be interesting to see the manner in which these rescheduling processes will take place and the new mix of resource acquisition strategies produced.

PART 8: SIMULATING THE ACQUISITION OF INCIPIENT AGRICULTURE

Introduction

In Part 6 we observed that our preagricultural model, which was based on a very simple set of decision rules, achieved a stable level of performance. The relative mix of plants collected by the model group compared well with the existing archaeological data for the last essentially preagricultural level (Zone D) in Guilá Naquitz. This correspondence suggests that the occupational remains found in the cave represent the results of collecting activities for a group that had attained a stable performance relationship with its environment. Since the model group achieved this relationship via a series of gradual adjustments in its resource collecting and policy-making behavior, it is possible that the real inhabitants could have achieved it in this way as well.

This stable performance level was maintained by the group through a specific set of decision-making and resource collecting adaptations. These adaptations focus on the sequence of different performance environments observed by the group. Since critical resources are more available in wet years than in dry ones, it is to be expected that the group members should adjust their resource collecting and decision-making strategies in order to reflect these differences. In particular, the group developed specialized collecting strategy for both wet and dry climatic types. While a third category (average years) was included, the group effectively behaved as if these were dry years. Thus, given three possible categories, the group only used two. As it turns out, a binary classification scheme not only is consistent with local ethnological data, but also reduces the probability that the group will employ a specialized collecting strategy in the wrong year type. Indeed, if the group was not able to reduce the probability of misapplication in this way, it would be hard to develop and maintain these specialized collecting strategies.

Therefore, in addition to a set of general purpose strategies that were used by the group in any type of year, there were two classes of special purpose strategies. *Dry-year strategies* used relatively fewer available species and emphasized plants with high yields. In *wet-year strategies*, a greater variety of plant species were used and less emphasis was placed on high-yield resources. This increased flexibility exhibited by wet-year collecting strategies was mirrored by their associated policy-making schemes. Wet-year strategies were more likely to be altered if they performed poorly than were dry-year strategies. The decision-making policies associated with wet-year types were much more complex than those of dry-year types. At the stable performance level, there is little turnover between wet-year strategies and general-purpose strategies. That is, special-purpose strategies rarely become general-purpose strategies, and vice versa. This is because few changes will lead to improvements in performance. While increased performance will allow a specific wet-year strategy to be employed in other types of years, there is little likelihood that this will occur once the system has achieved a stable level of performance. Such specialization effectively allowed the group to take advantage of good years through increased experimentation with certain resource collecting strategies.

Specialized strategies constituted 30% of the total number of currently available strategies. The remainder were general purpose in the sense that they had a good probability of being used, regardless of the type of year, because of their high performance. Since general-purpose strategies are relatively successful, their associated decision-making policies are quite conservative. Their focus is on resources with high yields in the vicinity of the cave. The mix of resources collected with these strategies compares very well with the cave remains.

These are the strategies that seem to determine the basic character of the cave remains and that represent in performance terms the best results of the group's experiences. It is important to note, however, that the special-purpose strategies that are archaeologically less visible still play an important part in the development of incipient agriculture.

In this chapter, we see if a group possessing the above specializations is able to incorporate incipient agriculture into its structure. Specifically, we want to know how the preexisting adaptations affect the way in which the group acquires these new agriculturally based tasks. Also, in the wake of these changes, we would like to know if the group is able to retain the decision-making and resource collecting specializations acquired earlier.

Acquiring Incipient Agriculture

Earlier we characterized the first stages of incipient agriculture as attempts to alter explicitly the densities of particular plants. Now we begin with a group in the stable performance state described above and simulate their acquisition of this new activity. We first observe how the group's current resource collecting and decision-making structures will affect this process. It might be expected that the initial experimentation will take place in wet years, since only wet-year decision-making policies are flexible enough to allow for such changes. It was mentioned previously that at the stable performance level there was little chance of a wet-year strategy improving its performance and displacing a current general-purpose strategy. However, wet-year strategies that incorporate useful innovations into their structure will have a decided advantage. Their increased performance should allow them to displace existing general-purpose strategies, and they will therefore be used more often in drier years. With increased use, these strategies will become more visible and certain aspects of their structure are likely to be copied by their competitors. This is in fact what the model group does.

As the simulation progresses, the frequency of use for each of the strategies begins to change over time (Fig. 31.14). These changes are shown in Table 31.10. Strategy 1, which characterized the group's basic preagricultural routine, was still used most often. However, after 100 time steps a number of changes had occurred. In particular, Strategy 2, which was a wet-year strategy in the preagricultural phase, was used much more frequently. Its policy was one of experimentation. Therefore, it was modified almost every time it was used.

These early modifications to Strategy 2 introduced a number of tasks associated with the incipient cultivation of beans in Thorn Forest A. Since this is the vegetation zone in which the cave is located today, it meant a refocusing of collecting strategies nearer the cave. This allowed the individuals to travel less but collect more by increasing the density of beans through cultivation in the zone near the cave. Such an adaptation would seem to be advantageous, in terms of both increasing the total yield and reducing the amount of effort spent collecting those resources. Indeed, judging from the associated performance curves, this is exactly what happened (Figs. 31.15–31.17). In each figure, the performance gradually improves from the onset of the simulation until tapering off after 90 time steps for the sample strategies in each year type.

Since Strategy 6 was also initially a wet-year strategy, we would expect to see a similar increase in its performance. This happened between Time Steps 100 and 150. During this period, Strategy 6 was used 27 times and was second only to Strategy 1 in usage (see Table 31.10). The increased performance of both wet-year strategies allowed them to be used more frequently. It also meant that they would displace other strategies in terms of frequency of use. This happened after approximately 150 time steps. By that time, the relative performance advantages of Strategies 3 and 9 had eroded to the point that they were used predominantly in wet years. Again, as their relative performances decreased, their corresponding probability of being modified increased. Since they were in a performance environment that was slightly different from that of the original wet-year strategies, one might expect differences in their modification policies as well. Now that other strategies had the innovations, the exchange of tasks between and within strategies was quite advantageous. As a result, the schema involving the recombination operations were employed more often in Strategy 3 to produce improved scheduling changes.

These changes produce an increase in the performances of both Strategies 3 and 9. This makes it possible for them to displace other strategies, and the cycle continues. The presence of this cycle of gradual improvement can be seen in Fig. 31.18. The figure compares the probability of modification of strategies selected to be used in wet years with those selected to be used in dry years. In the latter year type, this probability remains around .32. However, that for wet years is consistently higher. This reaffirms our earlier observations that increased experimentation takes place in wet-year types. In addition, the probability of modification for wet years seems to oscillate in a fairly regular way. This oscillation is due to the replacement of the current wet-year strategies (with their high probabilities of modification) by new ones. As they begin to produce successful changes, their probabilities of use increase as well. Once they become good enough, they displace other strategies, their decision policies become more conservative and the cycle continues. Through this cycle of improvement and displacement, the group gains experience in the scheduling of these new agricultural tasks.

After 450 time steps, all strategies in the population have become involved in this cycle, including Strategy 1. Strategy 1 was the most frequently used during the preagricultural phase and the last to become involved in the displacement cycle. As long as it performed well, there was no need to make substantial adjustments. Although agricultural tasks were initially associated with this strategy, they were assigned a low priority of use. In fact, their priority was so low they were never actually used. This is shown in Table 31.11. From the table we can also see that they were not actively employed by the strategy until about 250 iterations. At this point in time, other agriculturally based strategies were beginning to

```
STRAT              1  DAY               2  STARTED AT            2  DAY              3  STARTED AT           3  DAY          4  ST
ARTED AT              4  DAY               5  STARTED AT            5  DAY              6  STARTED AT           6  DAY          7
STARTED AT               7  DAY               8  STARTED AT           10  DAY              9  STARTED AT          11  DAY
            10  STARTED AT             12
STRAT              2  DAY               2  STARTED AT            3  DAY              3  STARTED AT           5  DAY          4  ST
ARTED AT              7  DAY               5  STARTED AT            8  DAY              6  STARTED AT          10  DAY          7
STARTED AT              13  DAY               8  STARTED AT           15  DAY              9  STARTED AT          16  DAY
            10  STARTED AT             18
STRAT              4  DAY               2  STARTED AT            3  DAY              3  STARTED AT           4  DAY          4  ST
ARTED AT              6  DAY               5  STARTED AT            7  DAY              6  STARTED AT           8  DAY          7
STARTED AT               9  DAY               8  STARTED AT           10  DAY              9  STARTED AT          11  DAY
            10  STARTED AT             12
STRAT              8  DAY               2  STARTED AT            2  DAY              3  STARTED AT           3  DAY          4  ST
ARTED AT              4  DAY               5  STARTED AT            5  DAY              6  STARTED AT           6  DAY          7
STARTED AT               8  DAY               8  STARTED AT            9  DAY              9  STARTED AT          10  DAY
            10  STARTED AT             11
PROT_EFF  5488.3590000  SAM_CAL_EFF238668.1000000  CAL_AVE584058.0000000  PROT_AVE 13430.8700000  AREA_AVE     2.4471550
CULTIV_AREA AVE. TFA      0.1780000
CULTIV AREA AVE TFB      0.1741436
CULTIV AREA AVE MGA      0.0000000
CULTIV AREA AVE. MGB      0.0000000
STRAT              2  MODIFIED
ALTER_RES            2               8
ALT_AREA            2              10
SWAP_EXT_1            2               1               2
SWAP_INT            2               8              19
SHUFFLE_AREA            2               2               6
SHUFFLE_RES            2              16               1
CURRENT_YR_TYPE            3
SAMPLE_SIZE            4
THE STRATEGIES IN THE SAMPLE ARE            1              2              4              8
TOTAL CULTIVATED AREA FOR TFA IS      0.7119999  TOTAL CULTIV AREA TFB     0.6965745
TOTAL CULTIV AREA MGA      0.0000000  TOTAL CULTIVATED AREA FOR MGB IS     0.0000000  TFBB     0.3010000  TFBC     0.3955745  MGAC
     0.0000000  TFAM     0.4340000  TFAB     0.2779999  TFAC     0.0000000  MGBM     0.0000000  MGBB     0.0000000  MGBC
     0.0000000
STRAT_NO            1  STRAT_CAI680202.2000000  STRAT_PROT 17037.0300000
STRAT_PROT_EFFORT  7066.3750000  STRAT_CAL_EFFORT282124.7000000
STRAT_LAST_USED            3  STRAT_PERF     0.0000000  STRAT_TRIP_DIST     22.0000000  TASKS     12.0000000
STRAT_OPERATORS FOR            1     0.5000000     0.0110000     0.2010000     0.0620000     0.4480000     0.0090000

     0.5000000     0.1280000
STRAT_NO            2  STRAT_CAI643794.0000000  STRAT_PROT  9891.0080000
STRAT_PROT_EFFORT  3814.6240000  STRAT_CAL_EFFORT248289.3000000
STRAT_LAST_USED            3  STRAT_PERF     2.0000000  STRAT_TRIP_DIST     26.0000000  TASKS     19.0000000
STRAT_OPERATORS FOR            2     0.8200000     1.0000000     0.9899999     1.0000000     0.9000000     0.8300000
     0.7800000     0.9000000
STRAT_NO            3  STRAT_CAI118991.2000000  STRAT_PROT  6719.2500000
STRAT_PROT_EFFORT  3070.8900000  STRAT_CAL_EFFORT 54382.3800000
STRAT_LAST_USED            2  STRAT_PERF     4.0000000  STRAT_TRIP_DIST     32.0000000  TASKS     17.0000000
STRAT_OPERATORS FOR            3     1.0000000     0.9000000     0.9899999     1.0000000     0.9800000     0.5100000
     0.9400000     0.8300000
```

Fig. 31.14A. One time step from a sample computer run for the incipient agricultural simulation. This was Time Step 66 in the simulation, which falls early in the process of adding incipient agricultural tasks to the model group's repertoire. "CURRENT_YR_TYPE:3" indicates that this was a "wet" year. In this time step, Strategies 1, 2, 4, and 8 were selected to be used.

```
STRAT_NO              4  STRAT_CAI66246O.3000000  STRAT_PROT 10383.2000000
STRAT_PROT_EFFORT  4090.6170000  STRAT_CAL_EFFORT260986.2000000
STRAT_LAST_USED            3  STRAT_PERF       2.0000000  STRAT_TRIP_DIST     20.0000000  TASKS     12.0000000
STRAT_OPERATORS FOR           4        0.5000000        0.1250000        0.3600000        0.0400000        0.1140000        0.3900000
     0.5000000        0.1500000
STRAT_NO              5  STRAT_CAI242694.2000000  STRAT_PROT  3202.6500000
STRAT_PROT_EFFORT  1451.1750000  STRAT_CAL_EFFORT109968.8000000
STRAT_LAST_USED            2  STRAT_PERF       4.0000000  STRAT_TRIP_DIST     30.0000000  TASKS     17.0000000
STRAT_OPERATORS FOR           5        0.8300000        0.7100000        0.5500000        0.9899999        0.9200000        0.5200000
     0.5000000        0.8300000
STRAT_NO              6  STRAT_CAI 76158.1200000  STRAT_PROT  1644.0970000
STRAT_PROT_EFFORT   671.8040000  STRAT_CAL_EFFORT 31119.4100000
STRAT_LAST_USED            1  STRAT_PERF       5.0000000  STRAT_TRIP_DIST     29.0000000  TASKS     20.0000000
STRAT_OPERATORS FOR           6        0.5599999        0.5300000        0.7000000        0.9200000        0.8699999        0.5300000
     0.6000000        0.5300000
STRAT_NO              7  STRAT_CAI246940.6000000  STRAT_PROT  2715.9860000
STRAT_PROT_EFFORT  1005.8930000  STRAT_CAL_EFFORT 91456.9400000
STRAT_LAST_USED            2  STRAT_PERF       4.0000000  STRAT_TRIP_DIST     26.0000000  TASKS     16.0000000
STRAT_OPERATORS FOR           7        0.3370000        0.0030000        0.4000000        0.4710000        0.1760000        0.0010000
     0.5000000        0.2620000
STRAT_NO              8  STRAT_CAL349776.5000000  STRAT_PROT 16412.2700000
STRAT_PROT_EFFORT  7305.9960000  STRAT_CAL_EFFORT155704.6000000
STRAT_LAST_USED            3  STRAT_PERF       2.0000000  STRAT_TRIP_DIST     21.0000000  TASKS     11.0000000
STRAT_OPERATORS FOR           8        0.5360000        0.1100000        0.1350000        0.3090000        0.0170000        0.6100000
     0.5000000        0.5450000
STRAT_NO              9  STRAT_CAL106438.3000000  STRAT_PROT  6058.1450000
STRAT_PROT_EFFORT  2458.0090000  STRAT_CAL_EFFORT 43185.8600000
STRAT_LAST_USED            2  STRAT_PERF       4.0000000  STRAT_TRIP_DIST     30.0000000  TASKS     18.0000000
STRAT_OPERATORS FOR           9        0.0570000        0.5000000        0.0680000        0.1479999        0.1370000        0.0010000
     0.5000000        0.0110000
STRAT_NO             10  STRAT_CAI239865.9000000  STRAT_PROT  8091.3400000
STRAT_PROT_EFFORT  3648.3750000  STRAT_CAL_EFFORT108155.2000000
STRAT_LAST_USED            2  STRAT_PERF       2.0000000  STRAT_TRIP_DIST     31.0000000  TASKS     15.0000000
STRAT_OPERATORS FOR          10        0.0160000        0.6799999        1.0000000        0.3830000        0.2399999        0.0030000
     0.5000000        0.9400000
CURR_TIME             66
SAMPLE OPER.  PROB             1        0.5889997
SAMPLE OPER.  PROB             2        0.3114998
SAMPLE OPER.  PROB             3        0.4214995
SAMPLE OPER.  PROB             4        0.3527496
SAMPLE OPER.  PROB             5        0.3697495
SAMPLE OPER.  PROB             6        0.4597497
SAMPLE OPER.  PROB             7        0.5699999
SAMPLE OPER.  PROB             8        0.4307497
THE SAMPLE OPERATOR AVE. IS       0.4381247
```

Fig. 31.14B. In this, the second half of the same time step shown in Fig. 31.14A, the current performance averages for the strategies are printed out so that the analyst can observe any changes in performance.

TABLE 31.10
Changes in the Frequency of Use
for Each of the Ten Strategies (1–10) over 450 Time Steps[a]

50 time steps	100 time steps	150 time steps	200 time steps	250 time steps	300 time steps	350 time steps	400 time steps	450 time steps
1	1	1	1	1	1	1	3	1
10	8	6	10	7	10	10	1	10
8	2	10	3	9	9	9	6	8
3	4	8	7	10	3	8	10	2
4	10	4	5	5	4	3	7	6
9	3	2	8	3	7	7	2, 4, 8, 9	9
5	5	5	4	8	5	2	—	7
7	7	7	6	4	8	6	—	3
6	9	9	2	2	6	4	—	5
2	6	3	9	6	2	5	5	4

[a]Strategies are listed in order of decreasing frequency of use.

TABLE 31.11
The Position of Agricultural Tasks in Strategy 1 over Time[a]

Time step	Strategy (tasks used from left to right)
50	[(0 0 0 0 0 0 0 0 0 0 0 0) 0 0 0 0 0 0 0 0 0 0 C 0 0] used
250	[(0 0 0 0 0 0 0 0 0 0 0 0) 0 0 0 0 0 0 C 0 0 0 C C 0] used
550	[(0 B 0 0 0 C 0 0 0 0 0 B B) 0 0 M 0 0 0 0 0 0 0 C B] used

[a]An agricultural task is specified by either B (beans), C (cucurbits), or M (early maize); all other tasks are represented by 0.

erode the performance advantage of Strategy 1. As its relative performance decreased, it became more likely to be changed. These early changes were successful and led to policy changes that encouraged experimentation. By Time Step 550, Strategy 1 had again become the most frequently used strategy. Now, however, it included an agricultural component.[5]

Table 31.11 also provides a good example of how a particular strategy incorporates agricultural tasks into its structure. Beginning at a position of low priority, they are seldom used. As time goes on, they increase in frequency and priority of use. At Time Step 550, incipient agriculture is employed through the strategy. It would be interesting to know what policy changes were involved in producing these shifts. More generally, is there a difference in the way that the innovation is accepted by a strategy at this stage as compared to earlier ones?

We have already seen that the policy at 200 iterations favored both the generation of new tasks and the rescheduling of existing ones. The mutation operators produce new tasks, and the recombination operators attempt to reschedule the existing sequence of tasks to accommodate these changes. However, by the time Strategy 1 is in a position to be modified (about 300 iterations), the situation is somewhat different. A number of agricultural tasks are already available and in regular use by other strategies at that time. Strategy 1 also has associated with it a number of agricultural tasks that it just has not used. As a result, one would expect that the strategy's policy would be modified to favor the recombination-type operators. Such operators can function to alter the priority of execution for a task, as well as allowing the "copying" of tasks from other, more successful strategies. Looking at Table 31.12, this possibility seems confirmed. Both "swap external" and "swap internal" (exchanging the priorities of tasks in the same strategy) increase in probability by 550 iterations. This increase is preceded by a corresponding increase in the tendency to change the zone or resource associated with a task. While this pattern is similar to the succession of operators at the start of the

[5]In Strategy 1 (preagricultural version), the group spent nearly 80% of its time in Thorn Forest A, not even leaving it until Day 6; the second most frequently visited vegetational area was Mesquite Grassland B, where they spent nearly 20% of their time. About 8 days out of every 10, they concentrated on only 1 major resource per day, typically harvesting an area of 1700–2900 m^2/day. Less frequently, they might devote a day to harvesting 2–3 minor resources. When incipient agriculture was added to Strategy 1, the harvest of 900–1400 m^2 of domestic squash became an additional task. This is about half the area per day over which they had to range for wild products, illustrating the way agriculture further reduces search area.

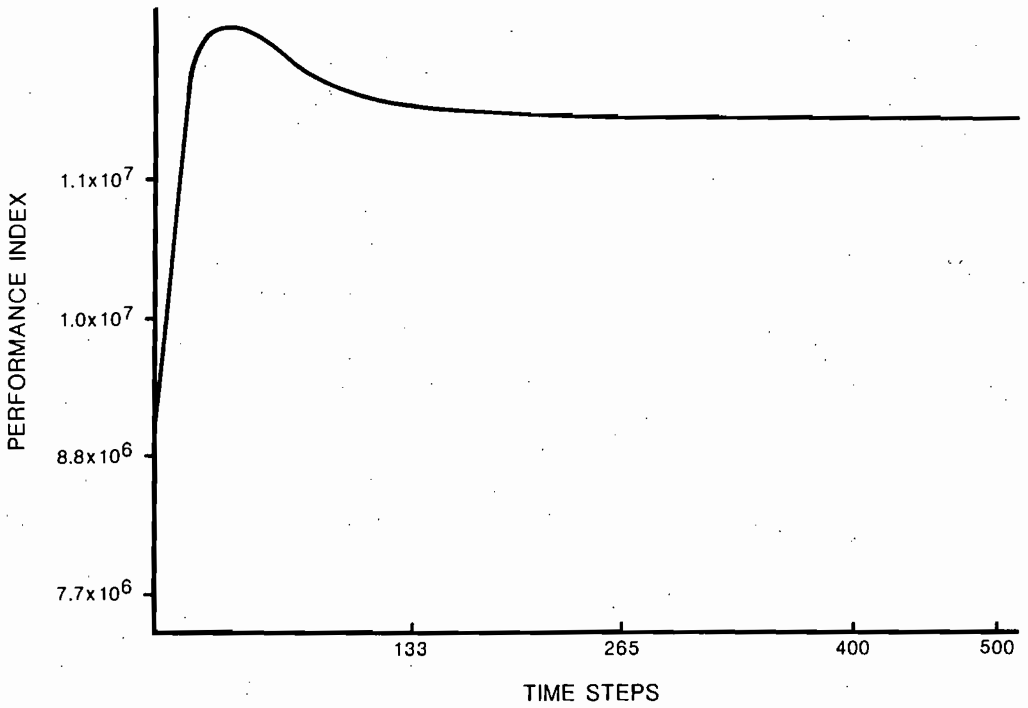

Fig. 31.15. Changes in the performance index for "wet" years brought about by experimentation with incipient agriculture.

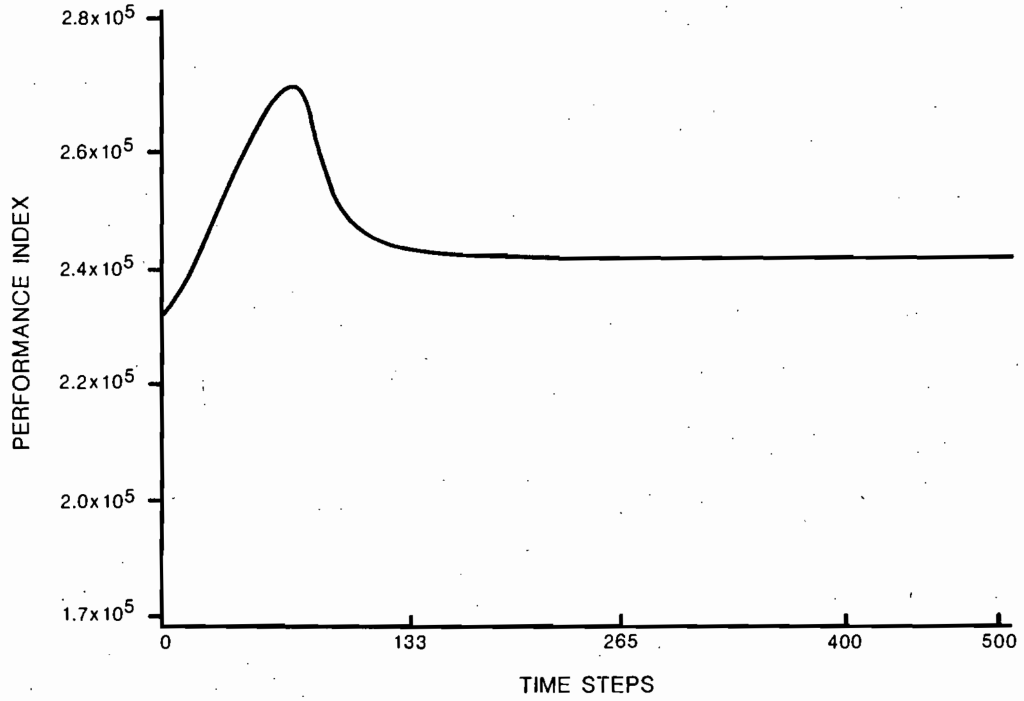

Fig. 31.16. Changes in the performance index for "dry" years brought about by experimentation with incipient agriculture.

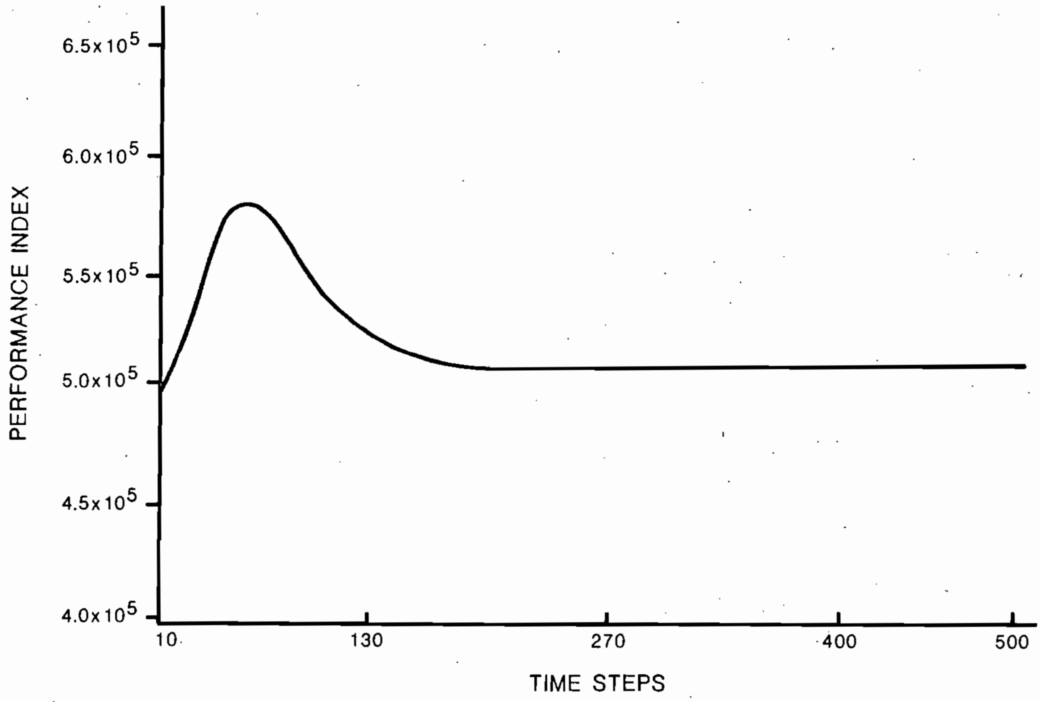

Fig. 31.17. Changes in the performance index for "average" years brought about by experimentation with incipient agriculture.

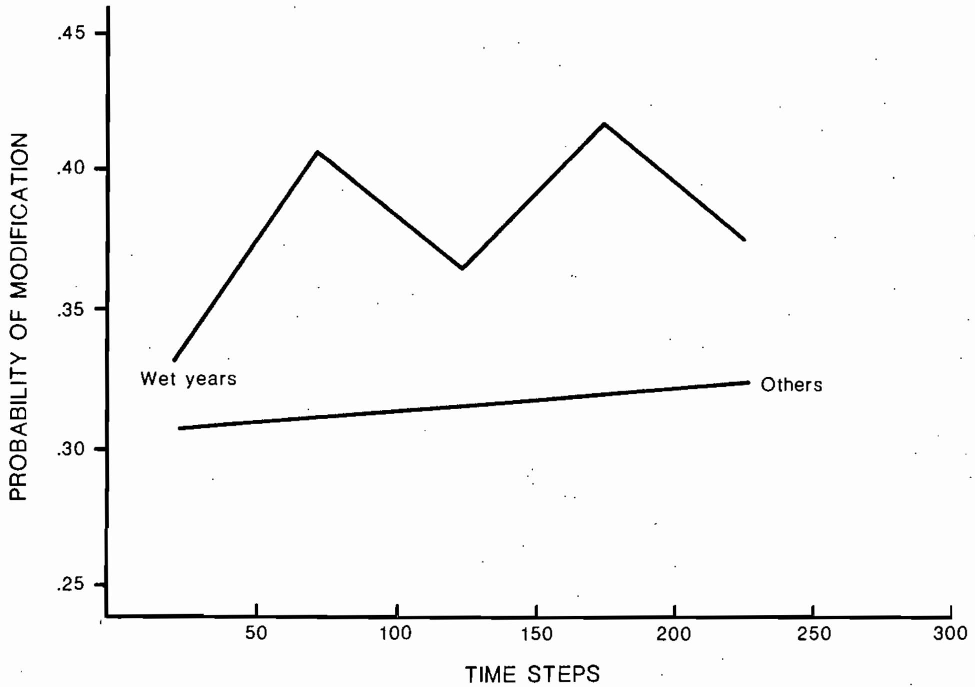

Fig. 31.18. The probability of modifying sample strategies in "wet" years as opposed to other year types.

TABLE 31.12
Changes in Operator Probabilities for Strategy 1 over Time

Time step	Alter resource	Alter zone	Alter area	Swap internal	Swap external	Shuffle resource	Shuffle zone	Shuffle area	Shuffle density	Alter density
50	.5	.5	.01	.20	.06	.44	.44	.009	.12	.5
250	.5	.5	.01	.20	.06	.44	.44	.009	.12	.5
550	.003	.003	.01	.86	.86	.065	.065	.062	.94	.14

simulation, the tendency to change resources is not as high now as it was. This is to be expected, since there are already a number of agricultural tasks available to the strategy. The problem here is not so much to generate new tasks but to schedule efficiently the ones already available.

Once the above operators have supplied the strategy with several viable agricultural tasks, then the shuffle operators come into play. These recombination operators then "fine tune" the strategy by exchanging resource, zone, and density specifications among the group of agricultural tasks for the strategy. Therefore, the policy shifts required to change strategies after the group has had some experience with the innovation are significantly different from those initially used. The emphasis in the latter stages is on rescheduling the original sequence to accommodate the new tasks. This rescheduling takes the form of large-scale shifts of tasks between and within strategies, as well as fine tuning the sequence of agricultural tasks.

We have, therefore, been able to observe a gradual shift in wet-year policies over the course of the simulation. Initial emphasis is on those operators that can generate new tasks. As these new tasks become more common, increased emphasis is on operators that efficiently reschedule the strategy in order to accommodate the new tasks. It soon becomes harder to make successful "coarse-grained" adjustments, so the emphasis shifts to operators that produce "fine-grained" changes within the group of agricultural tasks for a strategy. After 500 iterations, the system again achieves a stable performance state, with Strategy 1 again being the most frequently used strategy. At this point, few changes are made to the set of scheduling strategies (less than 12% of the operators have more than a 50% chance of being applied).

It is interesting to note that the incipient agricultural system takes around 550 iterations to reach a stable level of performance, while it took only 300 iterations to reach stability in the preagricultural phase. This slowdown has to do with the decision-making adaptations acquired by the group during the preagricultural phase. Such adaptations seem designed to maintain the majority of structures intact, while deferring experimentation to wet years. This made the system much more conservative. Since the current structures represent the results of a long period of experience with the environment, it seems "logical" that the system would be reluctant to change. Such logic is represented in the model by a low probability of making successful changes, and therefore a low probability of making adjustments. As a result, major policy shifts were not made by group members until after they had been exposed to the innovation for over 50 iterations. Even then, the changes diffused through the population quite slowly. It turns out, however, that this acceptance process has a number of advantages. In order to appreciate what these are, we need to know a bit more about the external results of the processes just described. In particular, we want to find out how these processes change the relative emphasis placed on each of the available resources by the group. This allows a direct comparison between the sequence of model changes and the corresponding changes in the archaeological record. If they match up, we will then have reason to believe that the model's behavior is a good characterization of the real system.

Spatial and Temporal Changes in Resource Use

In the previous section, we focused on the general adjustments made by each component in our network of adaptive systems to the presence of the new innovation. Here we look in more detail at the specific changes in resource use exhibited by the model. These changes are then compared with the related archaeological data.

We begin by tracing changes in the total number of tasks associated with the 3 species involved in incipient agriculture. These changes are displayed graphically in Fig. 31.20. Notice that initially, 32 out of the 250 available tasks are ascribed to these 3 species. Of these, only 13 are actually of high enough priority to be used in their respective strategies. In general, it would seem that initially the 3 species played a rather minor role in the group's resource collecting activities. However, after approximately 50 iterations, the number of tasks involving maize, beans, and squash began to increase. At this point, the group began to increase its experimentation during wet years as the result of initial successes. The current wet-year strategies improve their performance and temporarily displace other strategies whose relative performance is now worse. These strategies are relegated to infrequent use during wet years and are subject to increased experimentation. Such changes produce new incipient agricultural tasks that improve their relative performance. These, in turn, displace others and the cycle continues. These developments produce an almost linear increase in the number of tasks for the 3 species through 350 time steps. Over this interval, a new task is generated every 8 time steps.

After 350 iterations, agricultural tasks are present in every strategy, and the slope of the curve approaches 0. At this

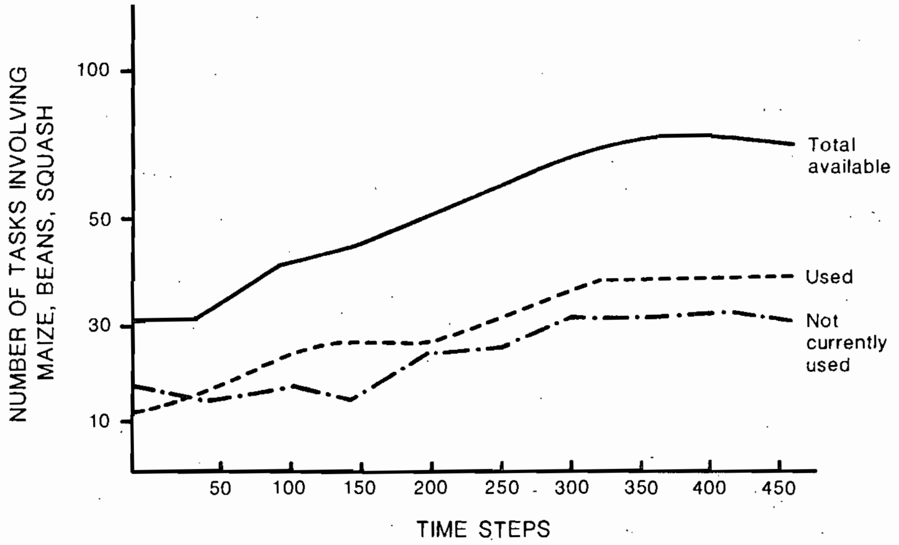

Fig. 31.19. Changes in the total number of tasks involving maize, beans, or squash through time.

point, the probability of generating a new task that is better than the one it must replace also is reduced. Thus, as the system approaches a stable performance state, almost 30% of all the available tasks relate to incipient agriculture.

Since the individuals only have a limited amount of time to apply a strategy, they may only be able to complete a portion of the tasks they have scheduled. In Fig. 31.19, the total number of tasks for the three species is broken down into two categories. The first represents the number of these tasks that are important enough to be used. In the second, the number of tasks that are specified but not used is given. Notice that after the first 50 iterations, the number of agricultural tasks used is always greater than the number of those tasks that are not. This relationship continues to hold as the system attains a stable state. There, 60% of all available tasks for these three species are used. Also, they represent about 30% of the number of tasks used by the group.

While we have seen that the use of agricultural tasks increases over time, it is important that we discern the relative contribution made by each of the three species. In Figs. 31.20–31.22, the changes in the number of tasks for each species is displayed. It is apparent that both beans and cucurbits account for a major share of the observed increase. Maize is used to a significantly lesser extent. Since the yield per unit area of this early maize is quite low, it is interesting that the group uses it at all. In fact, because of its low original productivity, the group uses it, for the most part, in wet-year strategies. In this situation, its yields are high enough to make it competitive. This result suggests that early experimentation with maize was performed in wet years and that this fostered its continued use for a long period of time. This would guarantee its availability for repeated use and set the stage for the emergence of new, more-productive forms in the future via genetic modification.

It is now quite apparent that group members are slowly incorporating agricultural tasks into their repertoire. But in doing so, what changes are they making in their relative use of other resources? The answer to this is given in Table 31.13. In this table, the change in the total number of tasks for each seasonally available resource used in the model is given. Notice first that the total number of tasks has increased. Since the maximum distance that individuals can travel in the 10-day period is constant, the reason for this must lie in the group's increased ability to consolidate resource collecting tasks over time. This corresponds well with earlier observations that particular strategies maintained incipient agriculture primarily within Thorn Forest A, the vegetation zone that is nearest to the cave in our model (just as it is under today's climatic conditions in the eastern Valley of Oaxaca). This trend served to refocus collecting activities in Thorn Forest A; in fact, it seems that one of the advantages for this earliest agriculture rests in its ability to encourage such shifts.

More evidence for the subsequent refocusing of collecting activities is provided by Fig. 31.23. There we see that in the preagricultural phase, collecting was done primarily within the three vegetation zones nearest the cave, with only slight preference given to collecting resources in Thorn Forest A. With the onset of incipient agriculture, there is a shift in emphasis towards Thorn Forest A and away from the other two zones, which are farther from the cave. Thorn Forest A is also the principal zone in which the group practices incipient agriculture. Mesquite Grassland B, which is the farthest zone from the cave, exhibits little change as far as the number of nonagricultural tasks executed there is concerned. Since this zone was furthest from the cave, activities that caused the individuals to travel this distance had to be of relatively high preference. For example, the collection of mesquite was quite important to the survival of the group and represents a sizable

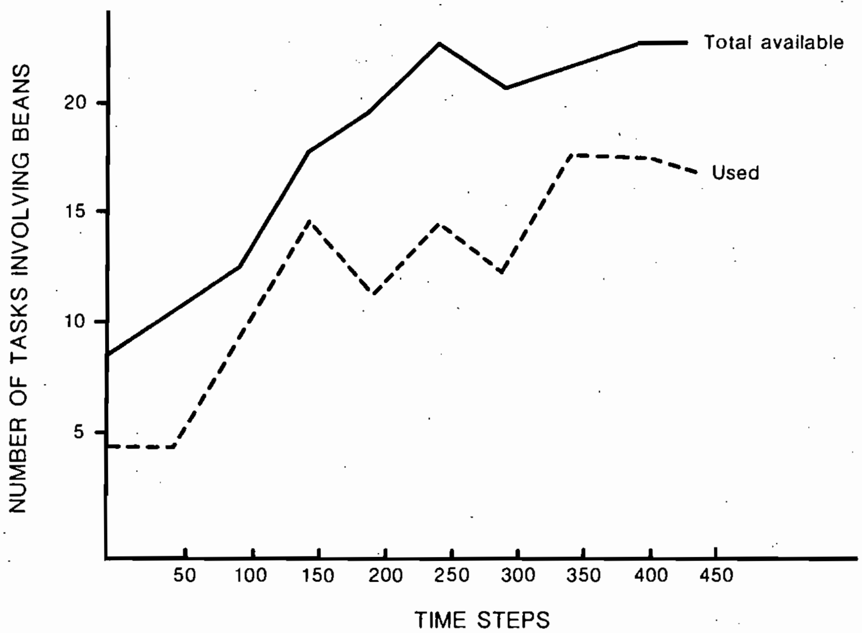

Fig. 31.20. The number of tasks allocated to beans through time.

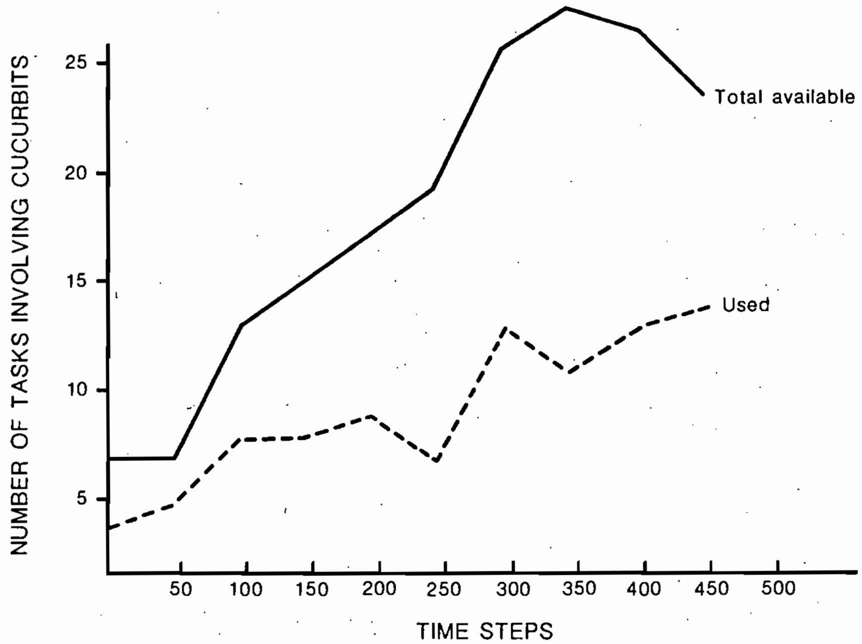

Fig. 31.21. The number of tasks allocated to cucurbits through time.

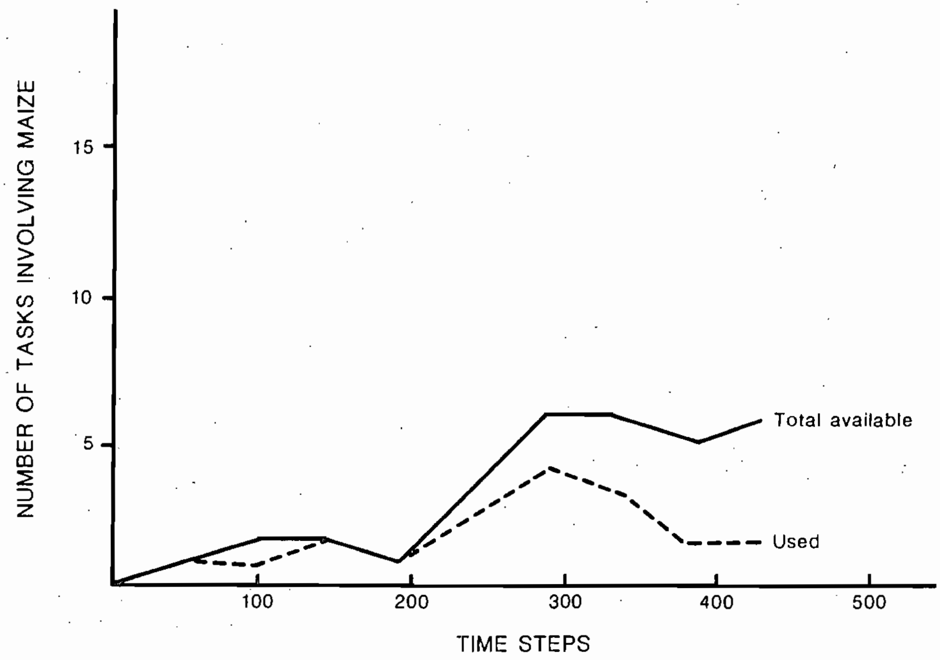

Fig. 31.22. The number of tasks allocated to maize through time.

TABLE 31.13
Changes in the Number of Tasks Used for
Each of the Seasonally Available Resources in the Model

Plant	Number in the pre-agricultural phase (0 time steps)	Number at stable performance state for incipient agriculture (450 time steps)	Change in the total number over the period 0–450
Piñon nuts	6	3	−3
Hackberries	17	11	−6
Susí nuts	24	16	−8
Nanches	13	5	−8
Opuntia fruit	46	37	−9
Opuntia nopales	41	31	−10
Acorns	5	9	+4
Guajes	5	7	+2
Mesquite	17	21	+4
Agave	29	32	+3
Beans	9	23	+14
Cucurbits	7	23	+16
Maize	0	7	+7

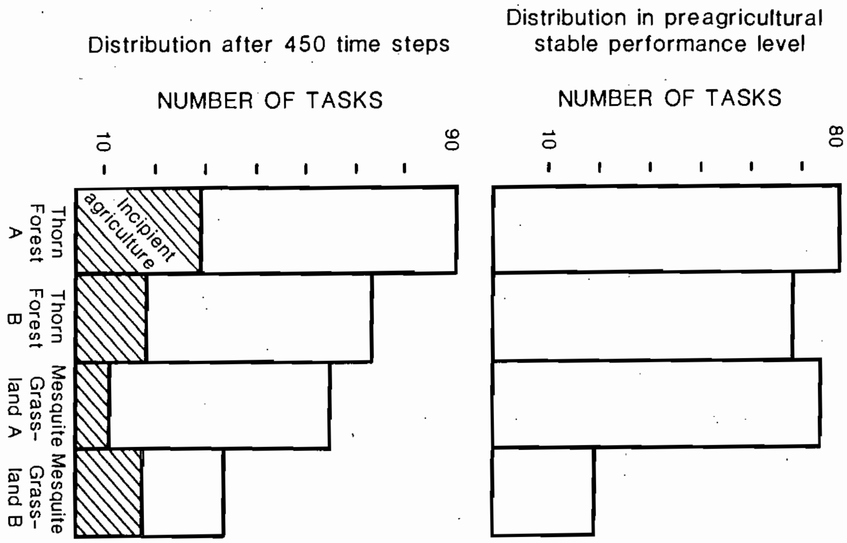

Fig. 31.23. The number of tasks per vegetation zone in all current strategies.

fraction of the available tasks for this zone. In this version of the model, the yields associated with incipient agriculture were originally not enough to produce substantial changes in activities in Mesquite Grassland B. However, in Part 9, when additional variability is added to the model, such changes are observed.

While the number of nonagricultural tasks remains about the same for Mesquite Grassland B, the number of agricultural tasks represents a large fraction of the activities carried out there. It appears that even now, the group is beginning to realize the advantages of agriculture in this zone nearest the river. (This zone would in later periods become the site of the first sedentary villages in the valley, as the group's activities shifted away from Thorn Forest A.)

Incipient agriculture, by allowing higher densities of plants nearer the cave, surely allows the individual to spend more time collecting and less time traveling. As a result, the group is able to increase the number of collecting activities. These increases are most marked in those species found closest to the cave in our model. For example, acorns—which are found principally in Thorn Forest A—are increasingly emphasized; this is true as well for *guaje*, nanche, and agave. Mesquite also increases, presumably because the group is now spending more time in Mesquite Grassland B. Whether this is because they are now trying out agriculture on the riverine alluvium or for other reasons, it is significant.

Another effect of adding incipient agriculture to this system is that the individuals will now spend less time on marginal (low density, low-yield) resources in return for increased emphasis on beans, squash, and maize. Since the yields associated with those early methods of cultivation are relatively low, only four wild species exhibit a reduction in use. These are piñon, hackberry, nanche, and *susí*. The number of tasks involving *susí* decrease by 34%, those involving hackberry by 36%, those involving piñon by 50%, and those involving nanche by 62%. *Susí*, while very productive in Thorn Forest A, is much less so in Thorn Forest B and Mesquite Grassland A. Therefore, we see a decrease in tasks for *susí* collection outside of Thorn Forest A, perhaps due to reduced yields and increased travel distance.

While the use of highly productive resources such as *susí* was cut back along the margins of their ranges, less-productive species experienced a reduction throughout their ranges; this was true of nanches, piñon, and hackberries. (Piñon and nanches are today found primarily in Thorn Forest A.) Of the resources employed in the model, only wild beans were less productive than piñon and nanche; and when the yields associated with incipient agriculture surpassed both of these, their relative use decreased.

Hackberries are in a similar situation in Mesquite Grassland B. Of the four major resources available there, hackberries are the least productive. It is therefore understandable that they are the only species in this zone to exhibit a decrease in use.

In other words, the main impact of adding incipient agriculture to the system was to refocus collecting activities to vegetation zones nearer the cave. Secondarily, it caused a decrease in the use of both productive species along the margins to their ranges and marginally productive species near the center of their range.

In terms of the model, adding agriculture meant that the group could increase the densities of selected plants near the cave. This increase in efficiency allowed the group more time to collect plants nearby. Also, the yields associated with incipient agriculture ultimately made it more productive than collecting certain other species. Since it would take time for the group to achieve such yields, one might expect that the first changes in use observed in the model resulted from the increases in efficiency. Because the individuals do not have to travel quite as far to collect what they did before, they have additional time in which to accomplish more activities. This results in an increase in the number of tasks allocated to certain species. As the group's experience increases, the yield associated with incipient agriculture continues to increase as well. In addition, certain activities are no longer as productive relative to incipient agriculture, and they are done less often. Therefore, the model predicts that decreases in the use of piñon, hackberries, *susí*, and nanches should follow initial increases in other species such as acorns, *guaje*, and cucurbits.

The model predicts not only the expected shifts in the use of the major resources but the order in which these shifts will take place as well. Now it remains for us to see how well these predictions correspond to the archaeological data from the cave. In Table 31.14, the raw frequency counts for each of the major plant resources found in the cave are given for Zones D, C, and B1. The relative frequency of every plant in terms of the total in each of the zones is given in Table 31.15, as well as the net change between Zones D and B1. Table 31.16 compares the net changes in the observed total counts and relative frequencies with the predicted changes.

In Table 31.16, notice that for 10 of the 12 resources, the predicted changes match those changes in total frequency observed between Zones D and and B1. Only acorns and nopales exhibited trends not consistent with the model. This represents an 83% agreement between the model and the data for these resources. It also suggests that the process that produced the changes in the model group may also be the principal factor affecting the changes in the behavior of the real group. Therefore, what appears on the surface to be a very complicated pattern of resource shifts can be characterized quite parsimoniously in terms of the few basic adaptations discussed above.

The concordance statistic between the two sets of predictions was computed and found to have a value of .83, where 1.00 denotes complete correspondence. The probability that the two sequences were generated by independent processes, given the present level of agreement, is .009. This is sufficient to reject our original hypothesis in favor of one that postulates dependence between the model and the real system.

Up to this point we have dealt only with changes in raw frequencies. What happens to our correspondence if we compare the observed changes in *relative frequency* with our model's predictions? From Table 31.16 we note that 9 out of the 12 changes in relative frequency were predicted by the model. Acorns and nopales again do not correspond with the model's predictions. Also, nanches exhibited an increase in relative frequency, contrary to what the model would predict.

Still, 75% correspondence is quite good, especially since relative frequencies are a much more conservative index of change than raw counts. With this in mind, the null hypothesis that the observed changes in relative frequencies shown by the real system do not correspond with those for the model was tested. This time the concordance statistic had a value of .75 and the probability that this would be produced by two independent processes is .04. Given that we stated that any probability less than .10 would be sufficient ground for rejection, the null hypothesis that the two sets of values are unrelated is rejected.

While the general shifts in resource use for the model compare well with the changes in the archaeological record between Zones D through B1, what about the *order* in which these shifts occur? The model suggests that the initial effects of incipient agriculture would be to increase the use of a number of species, particularly in the vegetational zone nearest the cave. As the yields associated with early agriculture improve, there will be a decrease in the use of some plants whose yields are less than those associated with incipient agriculture. Does the sequence of changes hold true for the archaeological data as well? Looking again at our tables, one notices that 9 of the 12 changes in relative frequency from Zone D (8750–7840 B.C.) to Zone C (7450–7280 B.C.) were increases. *All* of the 6 species predicted to exhibit increases do just that. In the later transition fron Zone C (7450–7280 B.C.) to B1 (6910–6670 B.C.), the opposite trend occurs. During this period, 9 of the 12 species exhibited decreases. In addition, 5 out of the 6 species that were predicted to increase do increase.

From this it is quite apparent that the shifts in the archaeological record bear a remarkable correspondence to those predicted by the model. To illustrate just how well they match up, let us now rank each of the 12 species in ascending order of predicted increase, with the species with the largest predicted increase ranked Number 12. The species can next be ranked in ascending order based on the observed increase in relative frequency between Zones D and B1. The two rankings are then compared in Table 31.17. The question now is, How well do they correspond?

Again we use the concordance statistic to test the null hypothesis that the two data sets were generated by unrelated processes. The observed concordance was computed to be .70. The probability that two statistically unrelated processes could have generated sequences that match this well is .08. This is low enough for us to again reject the null hypothesis. As a result we conclude that the processes governing the behavior of the real group and the model must be quite similar. Not only does the model predict the general behavior of the group in terms of changes in resource use, but it emulates the relative magnitude of these changes as well.

This correspondence between the changes in the archaeological data and the real system can be used to verify another aspect of the model. It was assumed originally that the basic cycle of evaluation and modification was performed annually by the group. The fact that the sequence of predicted changes over a particular number of time steps matches the observed changes in the dated archaeological record allows us to estimate, in a very general way, the average length of time required by one cycle in the model. In other words, we can estimate what the length of time between cycles would be if the model were to generate its changes over the same period of time as the real system. It turns out that the length

TABLE 31.14
Raw Frequency Counts for Each of the Major Plant Species in Zones D through B1

Plant	Zone D	Zone C	Zone B1	Net change from D to B1
Agave quids and leaves	53	216	56	+3
Hackberry seeds	416	969	240	−176
Cucurbit remains	6	50	21	+15
Susí seed coats	237	68	22	−215
Guaje pods	11	247	105	+94
Nanche seeds	49	196	46	−3
Opuntia seeds	348	751	143	−205
Opuntia nopales	28	49	45	+17
Bean pod valves	17	43	111	+94
Piñon nut hulls	94	80	31	−63
Mesquite seeds	59	554	1833	+1774
Acorns	3181	1570	892	−2290
	4500	4793	3545	

TABLE 31.15
Relative Frequency of Occurrence of Each Major Species in Zones D through B1

Plant	Zone D	Zone C	Zone B1	Change in relative percentage from D to B1
Agave quids and leaves	.0117	.0450	.0157	+.0040
Hackberry seeds	.0924	.2021	.0677	−.025
Cucurbit remains	.0013	.0104	.0059	+.0046
Susí seed coats	.0526	.0141	.0062	−.0462
Guaje pods	.0024	.0515	.0296	+.0272
Nanche seeds	.0108	.0408	.0129	+.0021
Opuntia seeds	.0773	.15669	.0403	−.0370
Opuntia nopales	.0062	.0102	.0126	+.0064
Bean pod valves	.0037	.0089	.0313	+.0276
Piñon nut hulls	.0208	.0166	.0087	−.0121
Mesquite seeds	.0131	.1155	.5170	+.5039
Acorns	.7071	.3275	.2516	−.4555

TABLE 31.16
Comparison of Predicted Changes in Relative Frequency with Actual Changes between Zones D and B1[a]

Plant	Predicted change in frequency	Observed change in total frequency	Observed change in relative frequency
Piñon nut hulls	Decrease	Decrease	Decrease
Hackberry seeds	Decrease	Decrease	Decrease
Susí seed coats	Decrease	Decrease	Decrease
Opuntia seeds	Decrease	Decrease	Decrease
Opuntia nopales	Decrease	*Increase*	*Increase*
Nanche seeds	Decrease	Decrease	*Increase*
Acorns	Increase	*Decrease*	*Decrease*
Guaje pods	Increase	Increase	Increase
Mesquite seeds	Increase	Increase	Increase
Agave quids and leaves	Increase	Increase	Increase
Bean pod valves	Increase	Increase	Increase
Cucurbit remains	Increase	Increase	Increase

[a]Italicized words represent changes that do not match the predictions of the model.

TABLE 31.17
A Comparison of the Predicted Order of Relative Increase for Each Species Relative to the Others with the Observed Order of Increase Between Zones D and B1

Plant	Predicted ranking in ascending order of increase	Observed ranking in ascending order of increase
Piñon nut hulls	2	5
Hackberry seeds	3	4
Susí nut hulls	4	2
Opuntia seeds	5	3
Opuntia nopales	6	9
Nanche seeds	1	6
Acorns	10	1
Guaje pods	9	10
Mesquite seeds	8	12
Agave quids and leaves	7	7
Bean pod valves	11	11
Cucurbit remains	12	8

of time falls generally between 1 and 1.5 years, depending on one's asssumptions. Given the number of assumptions that have to be made in order to do these calculations, the order of magnitude is strikingly close to what would be expected if the real results were actually produced by an annual sequence of local decisions like those in the model. This only serves to confirm our other findings, all of which indicate a detailed correspondence between the observed behavior of the real system and that of the model.

One would expect that this behavioral correspondence stems from a basic similarity between the decision-making structures of the two systems. As we have seen, the behavior of the model is strongly determined by the structure of its acquired adaptations. This suggests a more detailed examination of the performance advantages offered by these adaptations. In particular, it has already been suggested on theoretical grounds in Part 2, and experimentally in Part 6, that changes that reduce the impact of decision-making "mistakes" on the system's performance would be favored. Such mechanisms certainly would reduce the variation associated with the system's performance. This is particularly important in the present situation, where the environment is inherently unpredictable to start with.

Conclusions

While factors such as population pressure may be important at later periods in the Valley of Oaxaca, it was hypothesized in Part 1 that the initial structuring of resource use in the valley was principally the result of information-processing considerations. These considerations would seem to be of special importance in Oaxaca, where the distribution and density of resources fluctuate markedly from year to year. With this in mind, the main goal of the simulation was to see how well a basic model of hunter–gatherer information processing can explain the archaeological data associated with the acquisition of incipient agriculture.

The beginnings of incipient cultivation generated two basic types of changes within the model. First, there was an initial refocusing of activities nearer the cave. The ability to increase the densities of certain plants meant that less effort had to be spent collecting them. This left the group with additional time in which to collect other resources nearby. Also, with experience the yields associated with incipient agriculture began to increase. This made incipient agriculture more productive than certain other resource collecting activities. As a result, the group began to shift its effort away from collecting and toward incipient agriculture.

The main effects of incipient agriculture were, then, to produce a spatial refocusing of collecting activities about the cave as well as a displacement of less-productive strategies. The shifts in resource use resulting from these changes corresponded quite well with the observed changes in relative frequency for the major plants found in the cave. This strong correspondence suggests that the archaeological data may have been produced in a similar fashion.

Information-processing considerations are quite helpful in describing the behavior of the model group in an uncertain performance environment. Decision-making mistakes in such a context tend to produce large-scale system instability, as shown in Part 6. Adaptations that reduced the likelihood of these errors would be quite advantageous. The model group in fact employed a number of adaptations that do just that. It seems highly unlikely that the real system would be able to display such a detailed correspondence with the stable model unless it, too, was able to reduce the possibility of error. In addition, the types of adaptations used by the model correspond with known hunter–gatherer behavior. This suggests that the adaptations used by the real system may not have been too far removed from the ones in the model.

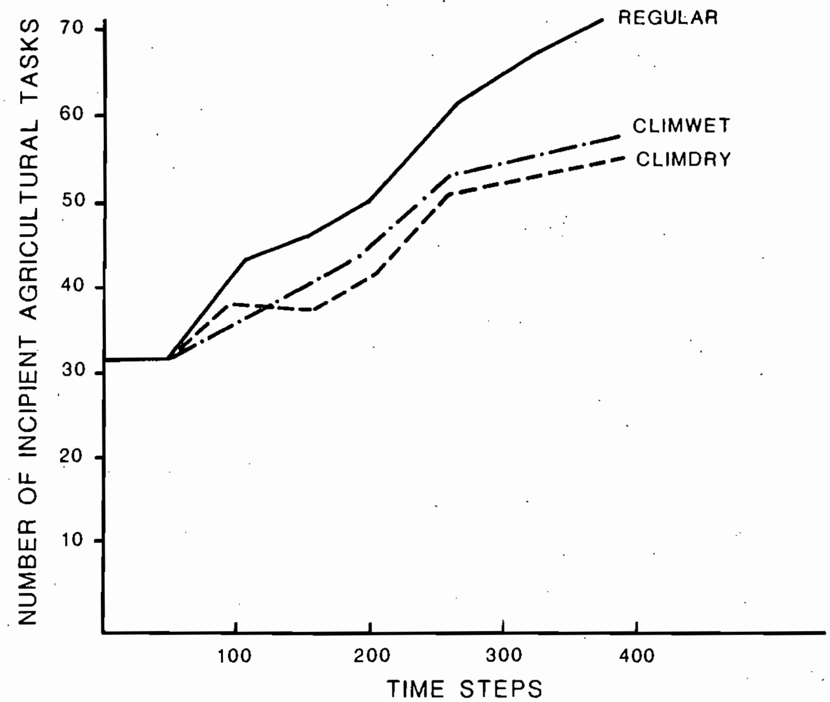

Fig. 31.24. The number of incipient agricultural tasks acquired through time for the three experiments REGULAR, CLIMDRY, and CLIMWET.

PART 9: SIMULATING CLIMATIC CHANGE AND POPULATION GROWTH

Introduction

Having now demonstrated a resonably good fit between the performance of our model and the evidence from the archaeological record, we are in a position to "experiment" by changing one variable of the model and holding all others constant. In Part 9, we simulate changes in two aspects of the model, rainfall and population. There are several reasons for selecting those variables. One reason is that both climatic change and population growth have been suggested as causal factors in the acquisition of incipient agriculture. A second reason is that either, or both, variables might have affected the movement of agriculture from the piedmont barrancas out onto the riverine alluvium. A third reason is that the climate of the Naquitz phase is thought to have been somewhat drier than today's, and we need to see how our model would respond to drier conditions. The latter observations should help make up for the fact that our environmental data were not collected under conditions identical to those of the Naquitz phase.

Prior to Part 9, our simulations were carried out using a fixed group size (five persons) as well as a fixed probability for the occurrence of each year type (wet, dry, average). A year with average rainfall had a .5 probability of occurrence, whereas our wet and dry year types each had a probability of .25. About 550 time steps after the first signs of incipient cultivation, our model group had achieved a stable adaptation, characterized by a mix of resource collecting strategies that correspond well with the plant remains from Zone B1 of Guilá Naquitz. In the model, these strategies emphasized incipient agriculture primarily within Thorn Forest A, the vegetation zone in which the cave is located under today's climatic regime. However, through increased trial and error (and genetic improvement in domesticates), one would eventually find that agriculture is more productive in Mesquite Grassland B, the vegetation belt associated with riverine alluvium. By 1500 B.C., almost all agricultural communities were located so as to take advantage of this alluvium. One of our goals in Part 9, therefore, is to ascertain what variation in model parameters would encourage increased planting in Mesquite Grassland B.

We therefore allow some of the model's basic demographic and climatic variables to change over time, observing their effects on the rate and extent to which the model group develops incipient agriculture. Three fundamental measures are used to estimate the extent to which agriculture is acquired. The first is the number of distinct tasks devoted to incipient cultivation by the group over time. Second, we observe the relative amounts of use of the four vegetation zones (Thorn Forest A and B and Mesquite Grassland A and B) by our model group. Third, we examine the extent to which the group has brought about changes in the density of maize, beans, and squash.

Making the Climate Wetter

In our first experiment, we decided to simulate the gradual onset of a wetter climatic phase. The probability that a wet year (>600 mm) would occur was increased by .0005 each model time step, while the probability that a dry year (<420 mm) would occur was decreased by .0005 each time step. This meant that the climate slowly became wetter and wetter over an extended period of time.

Some results are shown in Fig. 31.24, where REGULAR indicates the acquisition of incipient agricultural tasks under today's "regular" climate (50% average, 25% wet, and 25% dry years) and CLIMWET indicates the same acquisition under our simulated wetter climatic conditions. Note that there is a marked reduction in the rate at which the model group increased its number of incipient agricultural tasks under wetter conditions. There are probably several reasons for this, perhaps including some difficulty on the group's part in recognizing and adjusting to the continual .0005 change. However, one important possibility that emerges from an examination of the output is that pressure for efficiency is lowered. The increased number of wet years allows a lot of trying out of new strategies (many of them representing no improvement), and the decreased number of dry years reduces the rate at which poor strategies are eliminated.

Making the Climate Drier

Our second experiment was the reverse of the first: We increased the probability that a dry year would occur by .0005 each time step while decreasing the probability that a wet year would occur by .0005. In this way we simulated the onset of a drier climatic phase that would gradually become more xeric as time went on. Once again, some results are given in Fig. 31.24, where CLIMDRY indicates the acquisition of incipient agricultural tasks under our simulated drier conditions. Note that the model group did even more poorly than under CLIMWET conditions, apparently because they became more conservative; the reduced number of wet years allowed them fewer opportunities to try out new strategies, while the increased aridity put more pressure on them to be efficient without taking risks. Once again, the difficulty of detecting and adapting to the steady decrease in moisture may have been a contributing factor.

Making the Climate Uniform

Having modeled wetter and drier climatic phases, we found ourselves growing increasingly curious about the tradeoffs between climatic uniformity and variation. From the beginning, our model had featured an unpredictable succession of wet, dry, and average years, and even our simulated wet and dry climates had retained this strong annual variation. This was in keeping with one of the general themes of the whole Guilá Naquitz research project, which was an investigation of the way hunter–gatherers deal with variation. But what if variation had been substantially less?

Our third experiment, therefore, consisted of observing the behavior of the model group in a situation where the two extreme year types—wet and dry—were not present. For each of the computer runs during this experiment, therefore, every time step was programmed to be an average year. Figure 31.25 displays the performance of our model group during 500 time steps of this uniform climate and compares it with the maximum efficiency reached by the group under our original (REGULAR) climatic conditions. Two features of this new graph are particularly interesting. First, the performance of the group under uniform climatic conditions was not as good, on the average, as when all three year types were present. Second, the group's performance oscillated up and down over time, rather than reaching a plateau as it had under our original (varied) climatic conditions. Both these features suggest that lack of climatic variation tends to reduce the group's ability to isolate effective new collecting strategies.

We had not anticipated the results of the uniform climate experiment, but in retrospect they probably should not have been surprising. We had seen earlier that, under "regular" Oaxaca conditions, wet years were used to try out new strategies under low-risk conditions while dry years were used to highlight the more efficient strategies and delete the less efficient ones. In our uniform climate simulation, the loss of wet years reduces the opportunity for new strategies to be tried out and picked up; the loss of dry years reduces the pressure for efficiency, hence the "peaks" in the graph are lower. Without sufficient climatic variation, the group simply oscillates at a level that is well below the performance standards achieved under regular conditions.

There is also another way to view this phenomenon, one that is consistent with the overall theoretical approach of this volume. Variable environments provide a good context in which to develop and test new strategies because they contain so much information. Our new, uniform climate provides much less information about stress, plant productivity, efficiency, and all the other factors the group needs to have in its long-term memory in order to make good decisions. Deprived of this information, the group cannot adapt as well, or as rapidly, as it did under a regime of low-stress–average-stress–high-stress conditions. This discovery does more than confirm our belief that information must be a part of the ecological–evolutionary equation. It also shows us that unpredictable environmental variation, far from being the curse some have considered it, may in fact have been providing early man with a good context for long-term adaptive improvement.

Letting Population Grow

For the fourth experiment, we decided to let our model group begin to grow at a rate that would be reasonable for a foraging population. After looking through the literature for estimates of hunter–gatherer population growth (see, for example, Hassan 1981), we finally decided to let our group increase at a rate of .002% every 100 model time steps. We reasoned that even this small rate of increase, if allowed to continue long enough, should increase human demands on the plant foods of the region. Among other things, we wanted to see if our growing population would speed up its adoption of incipient agricultural tasks.

Some results are shown in Fig. 31.26, which compares our increasing forager population (POPINCR) with the stable group of five persons used in earlier simulations (REGULAR). Notice that the performance of the system in the wake of this gradual, long-term population growth is reduced relative to our original simulation. While there was an initial increase in the adoption of incipient agricultural tasks between Time Steps (or iterations) 50 and 100, the curve soon leveled off and fell some 20 tasks short of the REGULAR curve by Time Step 450. This was true of all computer runs made during this experiment. Evidently, our growing model population met its increasing subsistence needs as much by intensifying its use of certain wild plants as by intensifying agriculture.

This experiment shows that, for our model at least, the addition of population growth does not necessarily speed up the adoption of incipient agricultural tasks. This is significant, but we hasten to add that it should not necessarily be construed as a test of Cohen's (1977) population-pressure model. Cohen argues that population pressure is what caused foragers to turn to agriculture in the first place. Our simulation asks whether foragers, having already been given incipient agriculture as an option, would adopt it more quickly if their population were growing. The two questions are related, but they are not identical.

Letting Population Fluctuate

In our fifth experiment, we took a different approach to demographic change. Instead of letting population grow steadily, we decided to let our model group fluctuate randomly between four and six persons (with a mean of five) from one time step to the next. The underlying distribution of this new random variable was uniform. That is, the probability of a group having four, five, or six members was equally likely. In effect, this meant that an unpredictably variable population had to adapt to an unpredictably variable climatic regime. Although the source of such variability does not concern us here, fluctuations of this magnitude are not uncommon among local groups of hunter–gatherers. The results are shown in Fig. 31.26, where the curve for our varying microband (POPVAR) is compared with that of the REGULAR population.

It is clear that the POPVAR group adopted incipient agricultural tasks at a greater rate than the steadily increasing group (POPINCR), and superficially POPVAR shows a performance profile like that of REGULAR. However, striking differences appear when the output for all POPVAR runs are compared closely with those of REGULAR.

While both the REGULAR and POPVAR simulations accumulated comparable numbers of incipient agricultural tasks, the nature of these tasks differed extensively. In particular, increased short-term variation in population size put additional pressure on the system to generate more productive strategies, strategies able to satisfy a larger-than-average population in a drier-than-average year. As a result, within 150 time steps, the POPVAR group has assigned more than 20 tasks to incipient agriculture in Mesquite Grassland B; it had taken the REGULAR group approximately 500 time steps to achieve the same level of agricultural use of the alluvium. After 150 time steps, the POPVAR group was spending over 50% of its time in Mesquite Grassland B; the REGULAR group had spent less than 25% of its time there, even after 500 model time steps. The POPVAR group also increased crop densities for maize, beans, and squash in Mesquite Grassland B, while the REGULAR group did not.

Looking at the output in detail, it appears that the need to compensate for unpredictable short-term population shifts led to increased wet-year experimentation and dry-year testing, with the result being the production of more efficient strategies. This is not to say that these improved strategies were always necessary, but their existence provided the group with additional access to resources in those stressful times when "six persons" and "dry year" both come up in the same time step. Most significantly, although POPVAR did not adopt quite as many incipient agricultural tasks as REGULAR did overall, it did a far better job of moving agriculture out of the piedmont barrancas and down to the riverine alluvium of Mesquite Grassland B. It also did this better than POPINCR, which suggests that unpredictable annual variation in microband size might select more strongly for valley-floor agriculture than would gradual, long-term population increase. While this is obviously determined in part by the design of our simulation, it could also have implications for Binford's (1968) "density equilibrium model."

Summary

In the course of five separate experiments, we changed one of our model's variables while holding all others constant. First, the climatic regime was altered in three ways: (1) to become wetter, (2) to become drier, and (3) to remain uniformly average. Next, the size of the human population was altered in two ways: (1) to increase at a small, steady rate, and (2) to vary randomly between four and six with a mean of five.

Long-term climatic change, whether toward a wetter or drier climate, did nothing but slow the rate at which agricultural tasks were added to the model's repertoire. Even worse was the model's performance under conditions of climatic uniformity, which reduced the information in the system. Uniformity prevented the development of the binary strategy seen in our original model, where wet years allowed the trying out of new strategies and dry years weeded out the ones that were inefficient.

Our two kinds of demographic change had very different results. Our model group adapted to long-term population growth without increasing its commitment to agriculture; indeed, it failed to acquire as many agricultural tasks as the original model. The small but random fluctuation of the

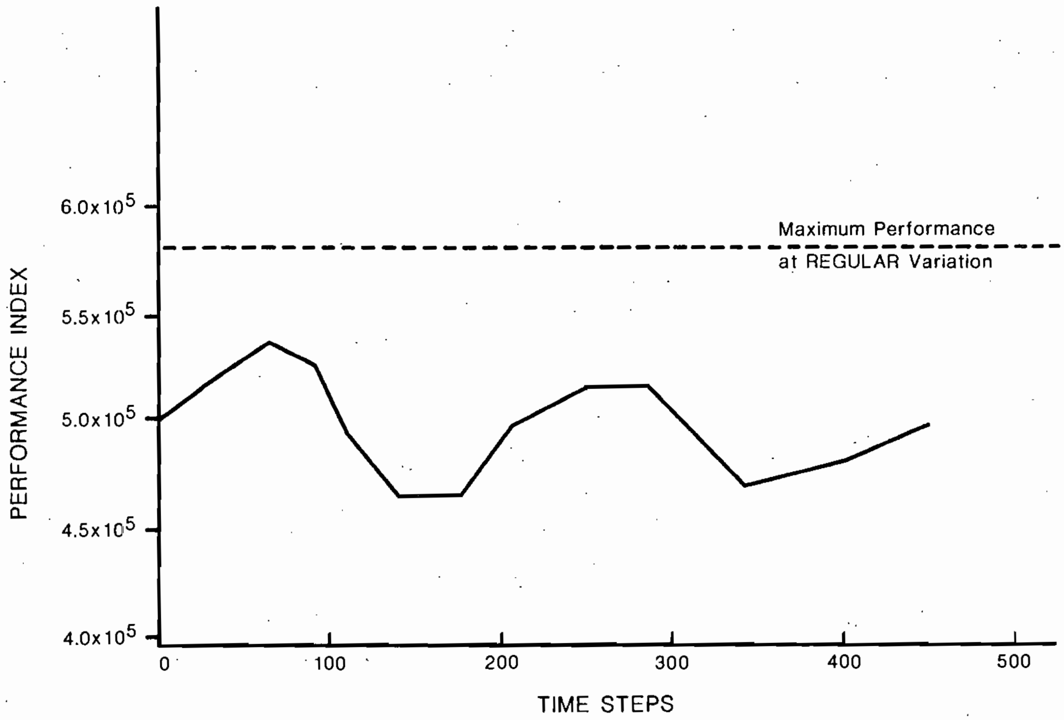

Fig. 31.25. Changes in the performance index brought about by experimentation with incipient agriculture in a situation with greatly reduced climatic variation.

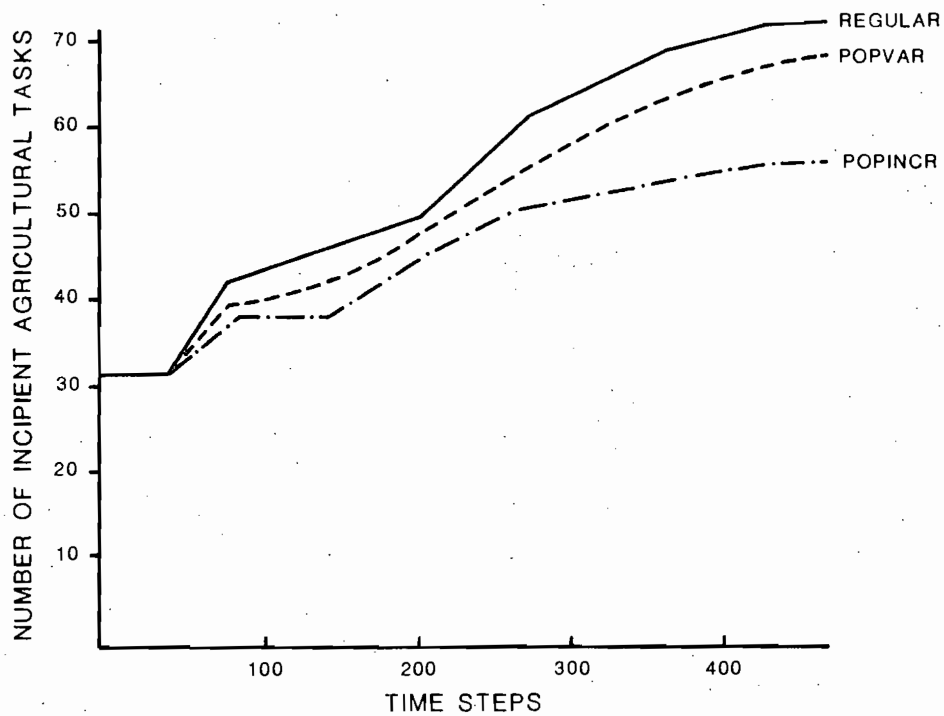

Fig. 31.26. The number of incipient agricultural tasks acquired through-time for the three experiments REGULAR, POPVAR, and POPINCR.

population around a mean, while it led to an overall performance profile similar to that of the original model, shifted agriculture to the alluvium of Mesquite Grassland B more quickly. This is significant, because the increase of maize, bean, and squash densities on the alluvium is thought to have been an important step in the direction of Formative village life.

This allows us a partial answer to our earlier questions about what kind of variation in model parameters would encourage increased planting in Mesquite Grassland B. Given *two* sources of uncertainty—unpredictable climatic fluctuation and unpredictable population fluctuation—the model moved more quickly to increase the density of domestic plants in the environmental zone of their greatest potential productivity. In our experiments, at least, this double dose of uncertainty had a greater effect on the system than steady, predictable population growth. We should perhaps add that two sources of variation also mean two sources of information.

Obviously, there are dozens of other experiments that could be carried out now that we have the model set up, and we hope to explore other possibilities in the future. We content ourselves here with these five additional simulations, which can serve as an example of the way the model can be used to attack some of the questions raised in other sections of this volume.

PART 10: SUMMARY AND CONCLUSIONS

The Preagricultural Simulation

We began by developing an adaptive computer model of hunter–gatherer scheduling and resource collecting activities prior to incipient agriculture. In the model, information on the relative performance of a schedule with respect to other schedules used during the season is "fed back" to the system and used to perform the following functions:

1. Adjust the probability of using the schedule again, based on its performance.
2. Adjust the group's rescheduling policy for a strategy, based on the policy's observed ability to affect the schedule's performance.
3. Adjust the schedule's structure, using the current rescheduling policy associated with it.

Starting with a random sequence of resource acquisition schedules and an arbitrary decision-making policy, our preagricultural group, through this network of interactions, is able to construct a stable set of resource collecting schedules that demonstrate a highly significant correspondence with the results from Guilá Naquitz Cave. In the stable performance state, the relative emphasis placed on the available plant resources by the model schedules demonstrates a marked correspondence (80%) with the relative amounts of these same resources found in the cave for both Zones E and D. Therefore, on the basis of performance information alone, the system is able to develop a quite sophisticated sequence of collecting activities that produce results similar to those produced by the real occupants of the cave.

The key to the continued operation of this feedback cycle is that the measured performance of one strategy is always relative to the performance of the others used during that season. As a result, there are always strategies that do not work as well as others. They are more likely to be modified and therefore provide the grist for our evolutionary mill. If these new modifications improve a schedule's performance, others begin to emulate its successful aspects. Thus, over time, favorable combinations of the basic rescheduling operators are developed and employed more frequently. This acquisition of coadapted sets of decisions is facilitated by the intrinsically parallel nature of the data acquisition process, as described in Part 5. In this way, more and more information is mapped into the group's decision-making structure over time, until the resulting strategies are difficult to improve. Once this happens, rescheduling decisions become more likely to produce decreases in performance and the model group becomes more conservative with regard to change.

At this stable performance level for the preagricultural model, those high-yielding schedules that represent the best results of the rescheduling process are associated with very conservative rescheduling policies. Such "general-purpose" strategies are used often and seem to determine the basic character of the cave remains. While these strategies are used in each possible type of year, another set of "special-purpose" strategies is developed to be used in specific year types. The most interesting of these are the schedules used most often during wet years. They generally incorporate less-productive genera into their collecting repertoire and as a result are relatively poor performers. However, during wet years, the increased environment productivity makes them more productive.

Although wet-year strategies contribute less to the overall productivity than the more visible, general-purpose strategies, they perform an important function nonetheless. Since a wet-year strategy does not perform as well as others, one would expect that its associated rescheduling policy would be less conservative. The model group will make adjustments to such a strategy even when system-wide improvements become less probable. This has several basic implications:

1. There is more variability in resource scheduling behavior in periods of relatively high productivity than in drier years, when the system falls back on tried and true methods.
2. Although most of the group's behavior is determined by relatively high-performing schedules that it is reluctant to change, there is a less visible ongoing undercurrent of change generated within wet years.
3. It is quite possible that the cumulative success of this overall adaptation process is due to the unpredictable variability in rainfall. Wet years, while infrequent, allow more variability in behavior and offer a chance for

trying out new strategies. Dry years, on the other hand, place more selective pressure on the model group, and as a result it employs schedules with relatively high reliability and yield.

The selective pressure placed on the group can vary unpredictably, and it is this variation that may be an important factor in determining the rate of change within the system. If, for example, the group was exposed only to a sequence of dry years that constantly put selective pressure on the group, the wet-year strategies that introduce most of the variation into the system would disappear or never be used. The resource scheduling system as a whole would be extremely conservative. This is, in fact, how most ethnologists describe the scheduling behavior of a number of hunter–gatherer groups that have been pushed into extreme desert environments.

On the other hand, an overbalance of wet years would introduce a good deal of variability into the system, but the group would seldom have an opportunity to test the worth of these adaptations in a more strenuous environment. As a result, a number of adaptations might be acquired that would not stand up well within an environment that is more selective. Between these two extremes stands the environment of Oaxaca. There, wet years occur only about 25% of the time, but this is enough regularity to allow a steady number of new strategies to be tried out over time. On occasion, there is even opportunity to try some of the more successful wet-year schedules in more strenuous environments. If they fail to be competitive, they may well be changed again. This allows the group to maintain only those scheduling changes that do not erode the system's performance.

The Incipient Agriculture Simulation

The same basic adaptations described above continued to hold as the model group was given the opportunity to acquire incipient agriculture. The principal changes made to the existing set of schedules were as follows:

1. Reduce the use of some high-density species along the margins of their range, where the density gets relatively low.
2. Reduce the use of species with characteristically low density in all vegetation zones in which they occur.
3. Concentrate incipient agriculture in the vegetation zone nearest the cave—in our model, Thorn Forest A—with some activity occurring in Mesquite Grassland B near the river.
4. Replace less-productive species with more-productive species that could be planted closer to the cave so that the group had more time to collect additional wild plants in the same vegetation zone.

As a result, the model predicted a sequence of shifts in resource use over time as a result of this gradual acquisition of incipient agriculture. The shifts predicted by the model, based on the above principles, correspond with 80% of the observed shifts in the relative use of the same species from Zone D to Zone B1 of Guilá Naquitz Cave, where only one of the unpredicted shifts involved a species that exhibited a marked change. This correspondence not only is statistically significant but also provides a fairly straightforward explanation of what on the surface appears to be a rather complex unpatterned shift in resource use.

Thus, our predictions concerning wild plant use rescheduling during the initial phases of incipient agriculture in the Valley of Oaxaca correspond remarkably well with the archaeological data. The model's ability to predict the group's resource collecting behavior prior to the onset of incipient agriculture, as well as a significant proportion of the major shifts in resource use that did occur with incipient agriculture, lends strong support to our belief that day-to-day resource scheduling decisions play an important role in the formation of a group's subsistence activities. In this way we are able to construct a sequence of performance curves and associated rescheduling policies that, in turn, can be associated with the different occupational levels within the cave. The occupational levels and their associated remains, therefore, gain a new interpretation as part of a long-term process of cultural adaptation within the valley. Therefore, our model has allowed us to make the necessary connection between the information-processing structure of a group and the archaeological record.

In addition, we have suggested that certain feedback cycles were necessarily present within the real group's decision-making network prior to the advent of incipient agriculture. The presence of such cycles was necessary to generate the basic preagricultural scheduling behavior. They also provided the means by which the group was able to incorporate selected incipient agriculture tasks into its schedule of activities. In fact, it seems quite likely that these cycles formed the nucleus about which the later, more complex feedback cycles, based on genetic changes in maize, came about. In order to test this, we will need to extend our scheduling model to encompass the group's entire seasonal round of activities. This proposed extension will require data on the group's hunting activities, since hunting was an important activity at other times during the year. Data from Cueva Blanca, a slightly later site at which hunting was pursued more intensely than it was at Guilá Naquitz, should provide us with additional information on these activities. This extended decision-making model will form the basis for a more detailed simulation that will ultimately trace both the evolution of sedentary agriculture in the valley and the development of Formative decision-making systems.

Altering the System's Parameters

Finally, we ran a series of five experiments in which certain variables of the incipient agricultural model were changed while all other variables were held constant. In the first, the climate was allowed to become gradually wetter; in the second, it was allowed to become gradually drier. In the third, variation was reduced by making all years average ones. In the fourth experiment, population was allowed to grow slowly but steadily; in the fifth, it was allowed to oscillate around a fixed mean.

Although much work remains to be done, our basic findings were as follows:

1. Gradual, long-term climatic change, whether toward a wetter or a drier climate, did not speed up the rate at which incipient agricultural tasks were adopted.
2. The reduction of annual climatic variation slowed the adoption of agriculture significantly, since the model group no longer had (a) wet years in which to try out new strategies under low-risk conditions, (b) dry years which put pressures on them to be efficient, or (c) as much information available to inform their decisions.
3. Slow, long-term population growth, at a rate reasonable for hunter–gatherers, did not speed up the rate at which incipient agricultural tasks were adopted; nor did the resulting "mix" of resources compare well with that in Zone B1 of Guilá Naquitz.
4. Short-term fluctuation in population around a fixed mean *did* speed up the shift of agriculture from the piedmont (Thorn Forest A) to the river alluvium (Mesquite Grassland B).
5. The latter finding suggests that the prehistoric evolution of agriculture in the Valley of Oaxaca can be more realistically simulated using (a) a model with several sources of short-term uncertainty, even if the sources' ranges of variation are low, than (b) a single long-term "prime mover" process, such as climatic change or population growth, even if that process is allowed to continue for hundreds of time steps.
6. Finally, we do not want to give the impression that we have ignored the importance of long-term unidirectional trends in either climate or population. We are well aware that many parts of the ancient world experienced long-term unidirectional climatic changes such as the retreat of glaciers from Europe at the end of the Pleistocene or demographic trends such as the permanent and dramatic population increases of Formative Mexico. We also know from our simulations that such unidirectional long-term changes are difficult for our model group to adapt to, since the stored data from past situations become increasingly inappropriate for evaluating the group's performance under the permanently changed conditions of the future. Such unidirectional changes may require significant modifications in the group's performance evaluation process, and we hope in the future to investigate how this happened in Formative Mexico. All we are saying here is that (a) no such trends are apparent in the archaeological record for Preceramic Oaxaca, and (b) our computer modeling suggests that it is not necessary to postulate them in order to simulate the adoption of incipient agriculture in the Valley of Oaxaca.

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Adaptation, Evolution, and Archaeological Phases: Some Implications of Reynolds' Simulation

Kent V. Flannery

One reason for undertaking a computer simulation is that it sometimes yields insights that are unexpected, or even counterintuitive. That happens because humans tend to assume the existence of causal relationships between variables that occur close together in time and space; in fact, cause and effect in complex systems may be temporally and chronologically separated. In this chapter we look at some possible implications of Reynolds' adaptive computer model, both expected and unexpected.

THE PREAGRICULTURAL STAGE

Reynolds' model microband starts from a position of ignorance (or better said, no memory of past use of the eastern Valley of Oaxaca), and within 500 time steps achieves a strategy not unlike that of Guilá Naquitz Zone D. It should be stressed that in this model, time steps are *not* years, however analogous they may seem; hence we do not know how long it might have taken a real-life group to achieve the same strategy.

The group is not instructed to "optimize" or to "maximize" any particular variable. They are merely told to make small changes in their foraging strategy each time step, to remember how well each strategy did, and to improve through time by repeating more successful strategies and disdaining less successful ones. The hypothetical group comes up with a two-part strategy, one for dry and average years, another for wet years; the former is more conservative, the latter more experimental, yet both show resiliency when the model parameters are changed. In dry years the group works harder, in wet years less, thereby reducing the difference in productivity between the two year types. They concentrate their efforts in Thorn Forest A and Mesquite Grassland B, suggesting that they are more interested in reducing search area than travel time. Their strategies seem to emphasize calories at the expense of plant protein, but without an optimal foraging analysis we would not want to guess how far short of optimizing either of these nutrients they might have fallen.

IMPLICATIONS

1. Reynolds' model group did best when generating its own decision-making policies, rather than responding to rates set by the computer programmer. Here we may see one of the many evolutionary advantages of a creature with multigenerational memory, logic, detailed perception, and decision-making ability.

2. Further, when Reynolds disconnected the feedback loop between the multigenerational memory and the decision-making apparatus, strategy changes began to wander from gradual improvement toward random fluctuation. This suggests that the use of a systems approach is a perfectly reasonable way to model cultural adaptation, despite the reservations thoughtfully expressed by Doran (1970) and

Salmon (1978). Indeed, when in the future it becomes possible for archaeologists to model human decision-making on a truly serious scale within the context of prehistoric ecosystems, it is hard to imagine how it will be done without some kind of systems approach (see, for example, Thomas 1971).

3. It is noteworthy that Reynolds' simulation gave his hypothetical group more classifications, more options, more tasks, and more possible strategies than they needed to achieve the level of efficiency they eventually displayed. It thus appears that an even simpler model, while less "realistic," might have produced a pattern similar in some of its most basic aspects.

4. One of the most interesting and unexpected results of Reynolds' analysis was the fact that his hypothetical foragers consistently acted as if there were only two kinds of years. Dry years and average years were treated as one type, which required a conservative strategy; wet years, perhaps because of the increased resources alluded to by Keene (1981b:237–238), featured a more experimental strategy. In other words, the group took Reynolds' tripartite year classification and reduced it to the binary opposition, wet–dry. As Reynolds points out, this is just what Mitla Zapotec speakers do today. The Zapotec tend to remember peak rainy or peak drought years, and believe (erroneously) that they can detect cycles in them (Kirkby 1974). If farmers perceive late spring rainfall as "high" (>80 mm in our terms), they predict a wet year and act accordingly. If they perceive late spring rainfall as "low" (<40 mm in our terms), they predict a dry year and act accordingly. Since Zapotec farmers have no rain gauges, they cannot possibly make all the fine distinctions we might make; they have focused on one aspect of local rainfall that allows them to reduce a great deal of ambiguity to a binary decision.

While structuralists and ethnoscientists might well conclude that wet–dry was a cognitive classification based on Zapotec perceptions of the world, the fact that Reynolds' computer did the same thing suggests that there may be perfectly good adaptive reasons for reduction to two strategies, one conservative and one experimental. I like to think that the implications of this discovery are that (a) cultural ecologists should not simply dismiss all native binary oppositions as mentalist epiphenomena and (b) structuralists should not be too quick to argue that the "code" in their informants' minds works independently of ecological adaptation.

5. Improvement of foraging efficiency proceeded more rapidly in dry years, presumably because of tighter selection pressure; it proceeded more slowly in wet years, presumably because of relaxed selection pressure. These findings will not startle those who believe in punctuated equilibrium or stepwise evolution, accelerated by periods of stress. But Reynolds' model also shows that the fastest improvement may take place in the context of an unpredictable stream of wet and dry years, suggesting that the role of annual variation in environmental conditions in setting evolutionary rates may have been underestimated. In Reynolds' simulation, adaptation in dry years benefited from the adoption of improvements that had been tried out first under the relaxed pressure of wet years. This may mean that adaptation moves fastest not simply under conditions of stress, but when its setting combines (a) stressful periods during which conservative and resilient strategies are rigorously selected with (b) more relaxed periods during which the pool of potential innovations can be increased without risk of elimination.

6. As if to underscore this point, one of the most interesting insights came about when Reynolds experimentally instructed the model to present his group with a sequence of exclusively "average" years. Intuitively, one might have expected the group to settle on a uniform and long-term stable adaptation under these conditions. Instead, the group began to wander aimlessly from strategy to strategy rather than progressing toward greater efficiency. Examination of the printout suggested to Reynolds that removing the variation in annual rainfall and vegetational productivity deprived the group of much of the information it needed to make good decisions. If this is so, there can be no clearer evidence for the importance of information in evolving systems.

7. The paragraph above raises one additional question. Could a group presented with an unchanging environment, as is often the case in applications of linear programming or optimal foraging theory, ever reach the point of optimizing its adaptation? Optimal foraging theorists might say "Yes, under conditions of competition, which are lacking in Reynolds' model." Perhaps under those conditions, the necessary stress would come from competition rather than annual variation. But what Reynolds' model suggests is that annual variation can speed adaptation even in the *absence* of competition; and this finding has implications for many human groups that, like the microband at Guilá Naquitz, do not seem to have had much in the way of competition from other humans.

8. As Reynolds' group approaches a stable adaptation similar to that of Guilá Naquitz D, they seem to be sacrificing plant protein in order to gain more calories and reduce their search area. In real life, of course, the group had access to protein from deer, cottontails, birds, and turtles, none of which are included in our simulation. But their sacrifice of plant protein should not be ignored, because it sets up an interesting situation—one in which the cultivation of a high-protein plant that could be grown in a small search area might be selected for.

A glance at Robson and Elias' Fig. 23.1 reveals that the Guilá Naquitz plants highest in protein were cucurbit seeds, followed at a distance by *susí* nuts, *guaje* seeds, and mesquite. When one considers that *susí, guaje,* and mesquite are all perennial trees or woody shrubs that take years to grow to maturity, the case for cucurbit cultivation becomes very strong. Cucurbits are annuals; they are "weedy camp followers" that do well on disturbed soils, such as the talus slope of an occupied cave (Cutler and Whitaker 1967); and they are 33.5% protein. There was probably no way the occupants of Guilá Naquitz could more easily have increased their plant protein, while continuing to lower search area, than by raising cucurbits for the seeds.[1]

[1]In general, wild cucurbits have a distasteful-to-nonexistent flesh; abundant and good tasting flesh is a product of centuries of genetic change following domestication.

9. One could almost phrase the above situation as a testable hypothesis: In cases where increased plant collecting efficiency sacrifices protein in the course of reducing search area, the group may either (a) increase hunting, (b) domesticate a high-protein plant species, or (c) both. In the case of the eastern Valley of Oaxaca, the evidence is still ambiguous. At both Gheo-Shih and Cueva Blanca, two later preceramic sites near Guilá Naquitz, projectile points and other hunting implements are more abundant than at Guilá Naquitz (Flannery *et al.* 1981:56–63); thus we cannot rule out the possibility that deer hunting was intensified in the Jícaras and Blanca phases. On the other hand, given our low estimated densities for deer in the Guilá Naquitz area (Chapter 24), deer hunting would certainly have worked *against* the reduction of search area seen in Reynolds' model. Squash cultivation, by producing localized high-protein patches near Guilá Naquitz, would have facilitated sedentism if this happened to be one of the group's goals; intensive deer hunting might have necessitated frequent moves that prevented sedentism. This may have been one of many factors involved in the long delay between the origins of agriculture and the origins of sedentary life in Oaxaca.

10. One way of accommodating the centrifugal pull of deer hunting and the centripetal pull of horticulture, of course, would be a shift from "foraging" to "collecting" in Binford's (1980) terms—or to a system like that of the San Bushmen, who forage for plants but organize their big-game hunting logistically (Binford 1982). The first alternative could account for 1.5-ha base camps (such as Gheo-Shih) in suitable farming localities, coupled with small hunting camps (such as Cueva Blanca) in the piedmont canyons. It could also be phrased as a testable hypothesis: When there is a conflict between highly localized plant resources and extremely dispersed animal resources, logistically organized collecting is a very likely solution.

11. While we would not want to push the implications of the Oaxaca case too far, we are struck by an interesting contrast between Mesoamerica and the Near East. In Oaxaca, where high-calorie plants are abundant and ungulate species few, one of the first plants domesticated was a protein source. In the Near East, where ungulate species are far more abundant and diversified, two of the first plants domesticated—wheat and barley—were carbohydrate sources.

THE INCIPIENT AGRICULTURAL STAGE

In an earlier section of this book, we discussed the possibility that the first plant domesticated in the New World may have been the bottle gourd (Heiser 1979:81–82; Lathrap 1977). I am intrigued with this hypothesis for two reasons: (1) It could mean that the later domestication of cucurbits (and other plants) in Mesoamerica was partly a long-term consequence of prior gourd domestication, and (2) it could mean that the earliest Mexican agriculture featured a plant used as an artifact, rather than as a food source freeing man from dietary stress or population pressure. This, in turn, would spare us from having to search for phantom population increases or nutritional deficiencies in an archaeological record that so far does not seem to display them.

Because of this uncertainty over the ultimate *causes* of domestication, Reynolds wisely did not attempt to have his model somehow "trigger" cultivation. What he did was to add cucurbits, beans, and primitive maize to the adaptation achieved in late preagricultural times—as if incipient agriculture were introduced into the eastern Valley of Oaxaca from a neighboring region, which could in fact be what happened. He then watched to see (1) if agriculture was adopted, (2) what form that adoption took, (3) how it modified the use of other plants, and (4) how it gradually changed the collecting strategy of his theoretical microband over time.

What Reynolds found is that acceptance of domesticates began as all innovations in his model began: They were used first in wet years, and only later, after they had proved reliable, were they introduced into dry and average years. Little by little, as the use of cultivars increased in importance, the "mix" of wild plants diverged from that seen in Zone D of Guilá Naquitz. In Chapter 24 we made note of the fact that during the transition from Zone E to Zone B1 of the cave, "the use of mesquite pods increased through time, while the use of acorns, piñon nuts, *susí*, and hackberry declined." Reynolds' hypothetical group made virtually the same changes and arrived at a pattern of wild plant use not unlike that seen in Guilá Naquitz B1. The group also gradually began to shift its main focus of activity away from Thorn Forest A (a vegetational zone crucial to preagricultural subsistence) and toward Mesquite Grassland B (a zone crucial to later agricultural adaptation). This supports MacNeish's (1967) Tehuacán model, in which agriculture began in the piedmont barrancas and only later spread to the alluvial valley floor.

IMPLICATIONS

1. Reynolds experimentally altered his model to observe the effects of (a) population increase, (b) a wetter climate, and (c) a drier climate. The results were interesting and have implications for several models of incipient agriculture. First, neither increased humidity nor increased aridity sped up the rate at which cultivars were adopted by the system. The latter increased stress so much that the system became overly conservative, while the first reduced it so much that there was less pressure for efficiency; in both cases, adaptation moved more slowly than under the original rainfall regime.

Second, steady population growth at a rate considered normal for hunters and gatherers did not speed the adoption of cultivars either. There was enough resiliency in the system to accommodate it—even if there were good evidence for population growth in the Oaxaca preceramic, which there is not. Causing the population to fluctuate unpredictably around a mean, while it moved agriculture out of the piedmont and onto the alluvium more effectively, also slowed the overall rate at which incipient agricultural tasks were adopted. Parenthetically, if such local fluctuations (which would be almost invisible archaeologically) did take place, they might be one more factor that would help to explain the incredibly long time it took agriculture to evolve in the Mexican highlands.

Because no trigger to set off agriculture is present in Reynolds' model, we cannot claim to have proven that population pressure or climatic change had nothing to do with the planting of the first squash seed. However, we doubt they had much to do with the planting of the first bottle gourd seed. And on the basis of our discussion in the two preceding paragraphs, we would say this: It is not necessary to invoke either population growth or climatic change to explain the adoption of cultivars in the Valley of Oaxaca. Quite simply, the system does not need them, and they only slow the process down when they are added.

2. Despite the importance of annual variation in giving our hypothetical group both the stress and information they need to reach a new adaptation, the fact that they work harder in dry years and less in wet years suggests a "satisfising" strategy that actually reduces the effect of the differences between years. In Chapter 1 we discussed Richard Ford's suggestion that one of the reasons agriculture was adopted was because it helped to "even out" the effects of annual variation. If anything, Ford's suggestion is strengthened by Reynolds' results. It would make the origins of agriculture not a startling innovation or a response to some new stress, but the extension of a strategy already displayed by the group in preagricultural times.

In Chapter 18 we indicated that the Valley of Oaxaca climate varies along two axes: *predictably* from dry season to rainy season and *unpredictably* from year to year. Preceramic foragers handled seasonal variation by moving from one environment to another, a considerable (but unavoidable) investment in travel time. They handled annual variation by reducing all year types to the binary pair wet–dry, for which they worked out two strategies—one conservative and more labor intensive and one experimental and less labor intensive. In addition to reducing the differences between years, this strategy provided the combination of risk reduction and innovation necessary to achieve an efficient yet resilient adaptation through time.

Squash cultivation increased the efficiency of this adaptation by further reducing the search area for a high-protein plant food. When beans and primitive maize were added, the search area was reduced even further—for Oaxaca Indians, unlike U.S. farmers, did not segregate crops by plot. They grew maize, beans, and squash in the same field, thus concentrating three species in the same patch of vegetation. This was not an Indian invention, since nature had provided the model (see Fig. 1.3, as well as Flannery 1973:291; Flannery and Ford 1972).

However, if nature provided the model, the Indians provided the disturbance. For example, in some thorn forest areas near Chilpancingo, Guerrero, and Valle de Bravo, Estado de México, any patch cleared for the cultivation of squash would ultimately be invaded by teosinte, wild runner beans, and other pioneer weeds of the local succession. It is interesting to speculate on the ways this might have influenced the Indians' choice of plants to cultivate. In such an area, one would not even have to plant to produce a field of *Zea, Cucurbita,* and *Phaseolus*; just clear a hectare of thorn forest, and the next year when you return, nature will already have done the job for you. Of course, if you wanted beans with nonshattering pods and squash with good-tasting flesh, you would have to select and plant.

AGRICULTURE AS AN EXTENSION OF THE PREAGRICULTURAL PATTERN

Let us briefly consider agriculture, then, in terms of the kinds of strategies and ecological relationships we saw in the preagricultural adaptation of the Naquitz phase.

1. As we have seen, agriculture lowers search time; the cultivator knows exactly where the densest stand is, since he created it.
2. It can convert a zonal environment into a patchy environment, where the milpa is the patch.
3. It can produce a patch that is "coarse grained" for maize, beans, and squash in the midst of an environment that is otherwise "fine grained" in MacArthur and Wilson's (1967) terms.
4. It can create a patch in which prehistoric people are likely to (a) spend more time, (b) travel less, and (c) deplete the vegetation more before they move on.
5. If Rindos (1984) is correct, it can also make an *r*-selected plant more *K*-selected, since humans are now investing more "parental care" in the seeds.
6. Rindos has also suggested that agriculture made humans more *r*-selected, but as we have seen, any significant increase in *r* in the Valley of Oaxaca took place millennia after the origins of agriculture and was probably associated with sedentary village life.
7. Agriculture can encourage human groups to move their basic settlement strategy from foraging, or "mapping on to resources" in Binford's (1980) terms, farther along the continuum toward collecting, or "logistically-based food procurement."
8. Agriculture can convert a negative-feedback loop into a positive-feedback loop, thereby setting in motion a series of changes that greatly modify the role of humans within the local ecosystem. One way to illustrate this is to return to one of the simple systems diagrams we used in Chapter 1. That diagram, the one showing the relationship between humans, primitive maize, and mesquite trees, is repeated as Fig. 32.1A of this chapter.

To recapitulate: groves of mature mesquite along the Mitla River yield an average of 183.6 kg of edible portion per ha (Chapter 18), much more than the 60–80 kg/ha estimated for the earliest corncobs of the Tehuacán sequence by Kirkby (1973:Fig. 48). Under such conditions, the best strategy was to continue to cultivate maize in the piedmont barrancas of Thorn Forest A while harvesting mesquite pods on the alluvium of Mesquite Grassland B. The two plants did not compete directly. In May or June, foragers would note the appearance of green mesquite pods and perhaps camp nearby to collect them in July or August. These harvests probably aided in the dispersal of mesquite seeds, since evidence from Guilá Naquitz shows many were never eaten. By September or October, foragers had moved to the piedmont to harvest maize and await the acorns, piñon nuts, and *susí*.

However, as Fig. 32.1 shows, maize steadily increased in productivity as cob length increased. Eventually it reached 250 kg/ha, the lower limit of productivity that Zapotec farmers in the eastern Valley of Oaxaca today require before they will make the effort to clear mesquite forest for agriculture. By the time that point was reached—a point that presumably varied from valley to valley—the Indians were probably well aware of corn's soil and water requirements. The Río Mitla alluvium gets less rainfall than Thorn Forest A, but its soil is considerably richer and more moisture retentive.

Fig. 32.1B attempts to model what happened then. With maize crossing the 250 kg/ha threshold, a new loop in the system was established; mesquite trees were cut down to make way for maize, and although preceramic peoples continued to collect mesquite pods, they were harvesting from ever-dwindling *Prosopis* groves. Instead of propagating mesquite seeds by their collecting and threshing behavior, they were propagating maize kernels by eliminating mature mesquite.

It is particularly interesting to note the way information flow changed between Figs. 32.1A and 32.1B. With primitive maize producing only 80 kg/ha, the most important information foragers could obtain by "reading" mesquite was *an estimate of when its pods would be ready to harvest.* With maize at 250 kg/ha, the most important information obtained from reading mesquite was *the presence of mature trees,* which are considered a sure indication of good corn land. Today's Zapotec say that when fallow land has mesquite trees on it "as thick as a man's arm," it is a sign that that land has recovered enough fertility to be farmed again. Thus, changes in information combined with changes in matter and energy to establish the new feedback loop seen in Fig. 32.1B.

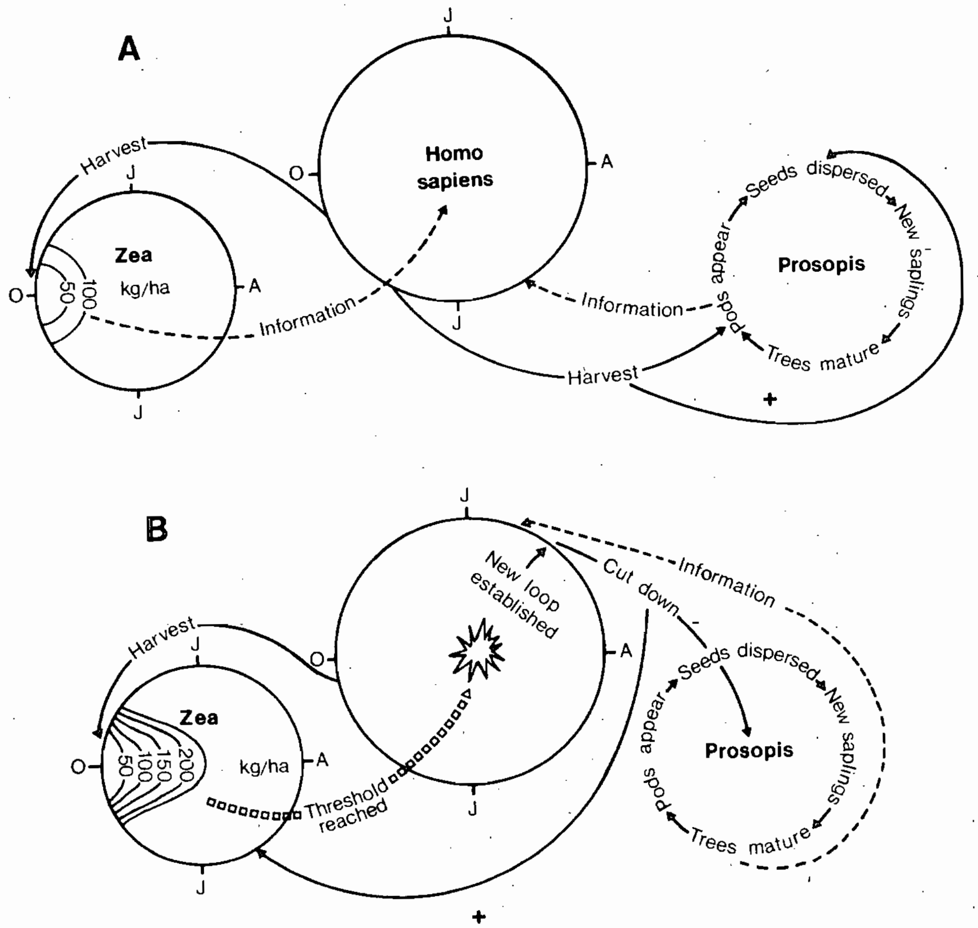

Fig. 32.1. Changes in the systemic relationship of humans and mesquite trees following significant increases in the yield of preceramic maize. A, At 4000 B.C., with maize (*Zea*) yielding only 50–100 kg/ha, mesquite (*Prosopis*) pods are used as food; the appearance of pods is the information triggering a July–August harvest that aided the mesquite's seed dispersal. B, At 2000–1500 B.C., with maize reaching a threshold arbitrarily set by the Indians (perhaps 250 kg/ha in the Oaxaca case), mesquite is now cut down so that corn can be planted on the riverine alluvium; here the appearance of mature *Prosopis* is the information triggering an April–May land clearance that reduces mesquite and increases maize populations (see text).

One other point that should be made is that this systemic change was not forced on our incipient cultivators by the environment, the plants involved, or the increase in productivity. The Zapotec threshold of 250 kg/ha is an arbitrary one, set by the farmers themselves; they could just as easily set a threshold of 100 or 500 kg, depending on how hard they want to work. The notion that a man's arm is an appropriate measure of mesquite thickness, and hence soil fertility, is arbitrary as well. Factors such as human perception and environmental interpretation, a satisfising ethic, and a whole set of notions about how hard one should work are just as important in this model as kilograms and calories. Thus the model illustrates what Harris (1979) might call "feedback between the infrastructure and superstructure of a culture," and it should not be ingenuously applied to some other part of the world where the superstructure was quite different.

9. The long-term consequences of agriculture on Oaxaca peoples' population and protein supply were quite different from the short-term consequences.

This will come as no surprise to those who have watched the long-term evolution of systems, but the details in this case are worth noting. While squash cultivation may have been adaptive in terms of plant protein, it seems to have had little or no effect on population size for thousands of years. If "fitness" is measured by the leaving behind of more offspring, one could legitimately ask how much "fitter" Oaxacan peoples were at 3000 B.C. than at 8000 B.C. Unfortunately, the archaeological record does not tell us whether incipient cultivators in Oaxaca left more offspring than foragers in Coahuila or Durango who remained plant collectors. It tells us only that population densities remained very low until the establishment of village life between 2000 and 1500 B.C.

Ironically, it was not a plant high in protein that changed population rates for the Oaxaca peoples but yet another carbohydrate source—one that could produce 250 kg/ha by the late preceramic and went on to produce 1000 or more kg in later periods. By doing this, maize in fact returned the system to the strategies of (1) increasing calories, (2) sacrificing protein, and (3) reducing search area, which we already observed in the preagricultural era. Indeed, so drastic was the reduction of search area that by Formative times a family of four to five persons could get almost all the calories they needed from a single hectare of land whose location was 100% predictable.

While maize agriculture raised the carrying capacity of the eastern Valley of Oaxaca, that may not even have been the major variable leading to population growth. The decision to become sedentary in hamlets of permanent houses and storage features on the edge of the alluvium in Mesquite Grassland B could have been an equally important factor. For example, Binford and Chasko (1976) have shown that the transition from nomadism to sedentism can have an effect on population growth rates even when agriculture is not involved. It may therefore have been sedentism, rather than agriculture per se, that dramatically increased Oaxacan peoples' fitness.

That population increase, of course, merely worsened the protein sacrifice whose first hints emerged from Reynolds' simulation. A population expanding on the calorie base of maize, beans, squash, and avocados reached levels of 50–700 persons/community by 900 B.C. (Flannery *et al.* 1981:69). There were not enough deer in the Valley of Oaxaca to supply such a population with meat, and the villagers' only domestic animal was the dog. It is therefore no surprise that the system of hereditary ranking that arose in Oaxaca included a restriction of venison to the elite (Whitecotton 1977:143), ameliorating the ruler's protein sacrifice but not that of lower-ranking individuals. In fact, various signs of protein deficiency can be seen in the skeletons of Formative Oaxaca peoples (Richard G. Wilkinson, unpublished data, 1977), who nonetheless continued to display population growth rates (and hence "fitness") that are archaeologically impressive.

ADAPTATION AND TIME

Given the above, we cannot leave Reynolds' simulation without a word about time. If adaptation is the solution of a problem, then time was the greatest ally prehistoric man had on his side. Given a long enough period—thousands of years in the case of the Oaxaca Archaic—even the tiniest incremental changes and growth rates could ultimately be transformed into major cultural changes. This fact makes it unnecessary for us to search for dramatic "revolutions" in the archaeological record: all we need are minor adaptive improvements, and lots of time.

ADAPTATION AND ARCHAEOLOGICAL CHRONOLOGY

Finally, let us consider a major problem with the way we archaeologists deal with time. We can begin by looking again at Reynolds' Figs. 31.9–31.18, which describe the group's gradually improving efficiency both before and after the introduction of cultivated plants.

In Fig. 31.9, for example, improvement in the model group's performance resembles a sigmoid curve. Early Naquitz phase foragers, presented with many alternatives and little experience, improve slowly for a while; then comes a period when their efficiency curve rises steeply for perhaps a hundred time steps; next comes a leveling off at a new adaptive plateau. When our group is presented with a few early cultivated plants, a new curve—less sigmoid but equally striking—arises from the previous plateau and eventually, after several hundred more time steps, levels off at a new plateau of its own (see Fig. 31.16).

As anthropologists, what we claim we most want to know about are the processes underlying these curves. In our grant proposals we talk about "preagricultural adaptation," about agriculture "reaching the takeoff point," about ancient cultures "achieving a new adaptive plateau." One would therefore expect that our preceramic chronologies would be based on the major landmarks of these sigmoid curves. We might expect to hear statements such as, "Guilá Naquitz E lies near the top of the curve's upswing, just before it levels off, while Guilá Naquitz D lies on the stable plateau formed after the upswing levels off." We might expect to hear complaints about how hard it is to find living floors dating to the upswings (which are shorter), and how much easier it is to find occupations from the curve's plateaus (which are longer).

Do we hear such things? We do not. Instead, we have living floors assigned to archaeological phases that are based on projectile point styles. We learn that squash cultivation in the Tehuacán Valley may have begun during the El Riego phase, a period dating from 6500 to 5000 B.C. and defined by the survival of Plainview and Abasolo points, the presence of El Riego, Flacco, Tortugas, Agate Basin, La Mina, Hidalgo, Trinidad, and Nogales points, and the appearance "toward the end of the phase" of San Nicolás and Tilapa points (MacNeish *et al.* 1967:55). Maize cultivation, on the other hand, began in the Coxcatlán phase, which ran from 5000 to 3500 B.C. and was characterized by Abasolo, Trinidad, Nogales, Tilapa, San Nicolás, Abejas, Almagre, and Coxcatlán points (1967:55). We have done things no differently in Oaxaca, since one of the bases for our preceramic chronology is typological overlap with the Tehuacán sequence. In this volume we have learned that squash cultivation in Oaxaca began during the Naquitz phase, which ran from 8900 to 6700 B.C. and was characterized by Lerma(?), Pedernales, and possibly Almagre and Trinidad points.

Thus, the whole sequence of plant collecting, incipient cultivation, and gradually developing preceramic agriculture in the valleys of Oaxaca and Tehuacan has been broken down into time segments based on stylistic changes in deer-hunting equipment. This situation makes no sense in terms of the performance improvement curves we have just looked at, but we are temporarily stuck with it. Radiocarbon dates are too gross to resolve our problems, and most ground-stone artifacts and preceramic flake tools changed too slowly to be useful chronological indicators. We are therefore confronted with a paradox: the processes we wish to document proceed as a series of logistic curves, while our chronologies are composed of linear phases based on stylistic changes in artifacts that may have little or nothing to do with those processes. In Fig. 32.2, I have tentatively tied the living floors of Guilá Naquitz to a series of points along the curve of increasing plant-use efficiency in preceramic Oaxaca. But plant use is only one aspect of human adaptation, and Fig. 32.2 is only a temporary measure; it serves mainly to remind us that so long as our evolutionary sequences are tied to stylistic phases, we have an unresolved dilemma.

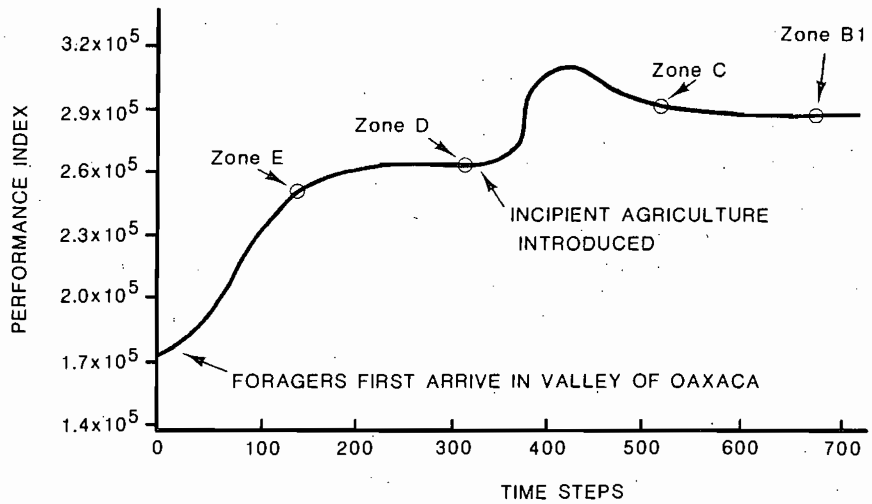

Fig. 32.2. Four living floors from Guilá Naquitz, tentatively fitted to a curve of improving foraging performance like those used by Reynolds in Chapter 31. The purpose is to show what archaeological chronologies might look like if they were based on adaptive or evolutionary processes rather than artifact styles. (While the curve is modeled on Reynolds' Figs. 31.9–31.18, it is not intended to match a specific one of those graphs.)