Archaeological Survey as Optimal Search

E. B. Banning

Department of Anthropology

University of Toronto, Toronto, Canada M5S 3G3

Phone: +1-416-978-2315 - Fax: +1-416-978-3217 - E-mail: banning@chass.utoronto.ca

Abstract: The research designs of many archaeological surveys suffer from a failure to distinguish between the goals of prospection, estimation, and pattern recognition. Often surveyors expect sampling methods, which are designed for estimation, to act as detection tools, or use predictive models without regard for their purpose. This paper shows how many problems of archaeological detection are suited to the principles of optimal search in Operations Research, and illustrates this with an example of optimal allocation of search effort.

Key words: archaeological survey, Bayesian probability, detectability, Game Theory, optimal search, Operations Research, prospection, purposive survey, spatial sampling

Introduction

It is easy to find examples of archaeological surveys that failed to detect a Teotihuacán (Cowgill 1975: 260, Flannery 1976: 133-134), that provided biased estimates of site density, or that yielded none of the economic or contextual information needed to investigate a particular research problem. Yet surveys are also uniquely able to provide some kinds of important data, and especially ones at the regional scale. The key to more useful surveys is to tailor surveys' designs to their objectives. The following paper will introduce a set of tools that can improve the effectiveness and reliability of one type of survey in particular, while also having more general implications.

Types and goals of archaeological survey

I classify surveys broadly into three categories, on the basis of their principal goals, although some surveys certainly combine aspects of more than one.

Today, most surveys are of the sampling variety, designed to estimate parameters, such as site density, mean edge angles, population size, or the proportion of sites that are Saxon settlements. These surveys can also be used to test statistical hypotheses or to devise predictive models for the location of archaeological materials. A common design for such a survey is to divide some region of space into regular, geometric spatial units, which serve as the sampling elements. In that case, sampled artifacts or sites typically constitute a cluster sample of the population of sites or artifacts in the region. Note that here I use the term "sample" in its narrower, statistical sense, and not merely to describe some subset of a larger whole.

Other surveys are meant to detect and understand spatial structure, such as Christalleran settlement lattices, rank-size distributions, the scale of artifact clustering over continous space, or the organization of road or canal networks. Usually such goals would be ill-served by a spatial sample because it would not provide sufficiently continuous coverage of the region for the patterns of interest to be recognizable. Some archaeologists, consequently, have argued for so-called "total survey" in these situations (e.g., Ebert 1992, Fish and Kowalewslei 1990).

Finally, what I call here "prospection" is survey meant to find particular targets or kinds of targets, to test hypotheses that predict the specific locations of targets in space, or to ensure that the other two types of survey are sufficiently thorough to achieve their goals. Effective or successful prospection, or "purposive survey," as it is sometimes called, finds sites, features, or artifacts. In other words, its purpose is detection. Here you will note that I use "prospection" quite broadly, and not only to refer to geophysical remote sensing.

Many archaeologists have shunned purposive survey and used sampling as a discovery method, apparently out of fear of seeming unscientific. Statistical or sampling surveys are, however, a poor way to find rare or specific targets, as archaeologists have known for a long time, because sampling is meant to find typical or common ones, or to represent central tendency in a population (cf. Cowgill 1975: 260).

Prospection, by contrast, takes advantage of information that may improve our chances of finding the archaeological materials of interest, even when they are rare, but may be a poor basis for statistical generalizations. Prospection also allows us to balance the costs of survey and risks of missing these materials, which for convenience I will call "sites" or "targets," although they can be "non-site" evidence or individual artifacts (e.g., Dunnell and Dancey 1983, Ebert 1992, Foley 1981). Among the goals that prospection may face are minimizing costs or search time, operating within resource constraints, or minimizing the risk of missing targets. Where prior information is available, purposive survey is more productive than a sample (Cowgill 1975: 260, 27, Read 1975: 45, Schiffer et al. 1978: 18).

Prospection can involve searching for specific, historically documented targets or, more generally, can help us find examples of some class of sites, especially rare or unusual ones, which random sampling and its variations tend to miss unless sample size is unusually large.

Prospection of the former type is perhaps most familiar in maritime applications, when we know the date and sometimes even the cargo of a shipwreck, but not its exact location. For example, historical documents explicitly describe the orientation and approximate location of ships of the Chesapeake Fleet, which the Americans scuttled in the Patuxent River in 1814 to keep the ships from falling into the hands of British forces (Shomette and Eshelman 1981). Prospection builds such information into a search strategy to improve our chances of finding the ships with limited resources. Such a strategy helped Tommy Thompson, a non-archaeologist, locate the SS Central America in 1986, which was known to have sunk in the Atlantic in 1857 (Kinder 1998).

Prospection of this type is also applicable, however, to some examples of terrestrial survey, such as cases where historical documentation refers to some fort or settlement, the precise location of which has been forgotten. For many years archaeologists have used historical information to narrow such a search, as in the search for Columbus's settlement at La Navidad (Deagan 1989), the search for Mission Santa Catalina de Guale, or even Schliemann's search for Troy. Yet, although recognizing the need for "a systematic approach to prospection, reducing the area of search and thereby incrementally increasing the probability of success" (Garrison et al. 1985: 302), searchers have rarely selected near-optimal strategies for this purpose, and sometimes even begin with a random sample that does not take advantage of prior information. In a more productive vein, Lolley (1996) used historic maps to predict the locations of Upper Creek Muskogee settlements in Alabama. He combined this prior information to make a more accurate map on which he marked the predicted locations of these sites with circles whose areas represented the uncertainty of location, and used these to recommend the distribution of survey effort.

As an example of the second type, searching for some class of sites rather than a particular site, some researchers (e.g., Storck 1978, 1982, 1984) have long used the tendency of previously known Paleoindian sites to occur on particular landforms, such as fossil beach ridges, to narrow the search for undocumented Paleoindian sites. Today the use of GIS predictive modelling (discussed below) has refined this kind of approach.

In spite of such applications, archaeologists have been largely unaware of a large body of theory explicitly devoted to searches of these kinds, found in Operations Research, that could help them improve the effectiveness of their surveys. Sometimes they have also reinvented tools that had already been available for several decades.

Operations Research

Operations Research began with efforts by Koopman (1980) and other mathematicians to optimize the US Navy's

searches for German U-Boats almost 60 years ago. These researchers also worked out near-optimal ways to conduct search-and-rescue operations (Richardson and Discenza 1980), including transect spacing and orientation and distribution of search effort, and to track multiple moving targets (Stone et al. 1999). The principles were later extended to fields such as petroleum exploration and mineral exploration (e.g., Cozzolino 1972, Drew 1967, 1979, Harbaugh et al. 1977, McCammon 1977, Savinskii 1965, Singer 1975, Singer and Drew 1976, Singer and Wickman 1969), which share many of the same problems that survey archaeologists face, and especially the need to detect subsurface targets.

Archaeologists have rarely referred to any of this literature, in spite of previous archaeological interest in Optimal Foraging Theory, which uses some of the same principles and concepts, including encounter rate, patchiness, and cost functions (see Winterhalder and Smith 2000 for a recent review).

The one area in which Operations Research has had some archaeological impact is in the optimal arrangement of augers, cores, and test pits and the evaluation of their detection probabilities, including work by Kintigh (1988), Krakker et al. (1983), and Zeidler (1995), all of whom cite geological applications in this area. Other research of this kind (e.g., Nance 1979, 1983, Nance and Ball 1989; Shott 1985) and work on the edge effects of transects and other geometric survey units by Plog et al. (1978) progressed independently and apparently without benefit of the earlier publications in Operations Research or earth sciences. Even archaeologists working for the US Department of Defense seem unaware of the US Navy's substantial and long-standing contributions to search theory.

Approaches to optimal search in Operations Research

Broadly speaking, "classic" optimal survey strategies have emphasized one of two approaches. Koopman (1980), Stone (1989), and others who pioneered Operations Research emphasized Bayesian approaches (Dobbie 1968, Washburn 1981). Corwin (1981), Gal (1980, 1989) and others explored the Game Theory approach. Recent advances in search theory have brought novel methods, including application of genetic algorithms (see Reynoso and Jezierski, this volume) to search problems, and some of these may conceivably have potential in archaeological searches.

The Bayesian approach uses prior probabilities based on existing information, analysis of expert opinion (Morris 1977, Savage 1971), or even educated guesses, to try to optimize the allocation of search effort over space (Koopman 1980, Stone 1989, see also Buck et al. 1996). It can also adapt to new information as survey progresses to refine the survey strategy. Typically it assumes some probability distribution for the target's location, such as a bivariate normal distribution over a potential shipwreck. In the worst-case scenario, it might assume a uniform distribution, with all parts of the survey space equally likely to contain the target or targets. In such instances we end up with a strategy resembling the long-familiar sampling surveys.

Game Theory uses some methods already familiar from

Optimal Foraging Theory, such as the Minimax approach, and treats the search as a two-person, zero-sum game between the searcher (the archaeologist) and the hider (the target or site). This is like Optimal Foraging Theory's focus on foragers trying to optimize their encounters with prey (e.g., Paloheimo 1971). Often the goal is to find the trajectory or sequence of search spaces that will probably find the target most quickly. Sometimes, alternatively, it is to ensure against the risk of not finding the target at all. As in Optimal Foraging Theory, it uses a cost function to evaluate the risks and benefits of various strategies. Generally it assumes that search consists of movement through a sequence of spaces or a continuous sweep of space, as in the transects that archaeologists typically use for surface survey by visual inspection.

Factors affecting discovery (detectability)

In both Bayesian and Game-Theory approaches to search, we also need to assure ourselves that interception of the target will probably lead to its detection. However, as archaeologists are well aware, many factors can confound detection, even when we are standing right on a site. Archaeologists (McMannamon 1984, Plog et al. 1978, Schiffer et al. 1978) have identified some of these factors as visibility, obtrusiveness, intensity, and so on. Others have stressed the distinction between the probability of intersecting a site and the probability of detecting it, given that one is present (e.g., Krakker et al. 1983, Lightfoot 1986, Zeidler 1995). Operations Research addresses these same issues, although usually under different names, and provides a framework to minimize the risk that we will fail to detect a site we intersect, and the converse risk that we will mistake a "false target" for a site.

Among the factors that affect discovery are ones concerning the properties of the target. Archaeologists have summarized these as "obtrusiveness" (Schiffer et al. 1978: 6). In fact obtrusiveness is a function of both the target's properties and those of the target's immediate environment. Successful detection depends on a contrast between these. For example, during a magnetic survey, an iron cannonball is highly obtrusive if it is buried in typical soil or sediment, but it would escape detection if it were buried in iron filings because there would be no magnetic contrast between it and its environment. For artifact scatters detected by visual inspection, test-pitting, or augers, obtrusiveness is largely a function of artifact density (Krakker et al., 1983, Stone 1981) and artifact clustering (Nance and Ball 1986, 1989), although other factors come into play.

Another factor that affects detectability is the type of signal that communicates information about these properties from the target to a sensor. For example, the signal could be seismic, magnetic, or electromagnetic, and includes visible light.

A third factor is the medium of signal propagation, which archaeologists have summarized as "visibility" (Schiffer et al. 1978: 6). Visibility through a medium such as sediment or air may be poor or even zero for some types of signal while the same medium is perfectly transparent to some other type of signal.

Another factor is the kind of sensor or method of inspection. For example, we might use our unaided eyes to conduct survey for surface artifacts, but a magnetometer to detect anomalies in the magnetic field due to buried iron objects or sediments whose magnetic susceptibilities contrast with that of their environment.

Yet another major factor is our ability to recognize the signal and correctly classify or identify it. In practical situations, there are often "false targets." These are phenomena that send signals we find difficult to distinguish from those of targets of interest. For example, some buried natural irregularity in the bedrock could produce a magnetic or electromagnetic signal that we mistake for that of a buried pithouse, or the discovery of a single artifact in a test pit may be ambiguous evidence for the presence of a site (or cluster of artifacts). The incidence of false targets can cause us to waste valuable time digging test trenches to investigate ambiguous remote-sensing anomalies or putting additional test pits in the area around isolated artifact discoveries to see if more evidence for a site is forthcoming (e.g., Lightfoot 1986).

Some of the many other factors we need to consider are resource constraints, crew training and motivation, accessibility, density of survey effort, and even weather and time of day.

Factors in optimization

Some of the factors that Operations Research considers in order to optimize searches include cost (in search time or effort), resource constraints, the area or number of spaces to be searched, the expected number of targets, the likelihood of false targets, and the relationship between point or transect spacing (or sweep width), the range of our eye or other sensor, and the probability of detection. Archaeologists have usually used the term "intensity" to refer to the cost or effort involved in searching a space, but the term tends to be confusing because it can refer to total effort, to amount of effort per unit area (density of effort), or to the spacing (resolution) of transects, auger holes, or magnetometer measurements. Operations Research treats these separately, and cost refers to the total effort devoted to a search space, usually measured in either time or person-hours. The range is often conceptualized as the lateral (or perpendicular) distance between a transect and a target but, in remote-sensing applications, can also refer simply to the distance between the target and a sensor.

Unlike U-boats and antelopes, and fortunately for archaeologists, archaeological targets are stationary, which makes the search problem much easier. However, we still need to consider whether it makes more sense to conceive of the search space as a set of discrete spaces, such as topographic features of the landscape, arbitrary geometric spaces, or the pixels of a GIS Digital Terrain Model, or as continuous space, such as part of the open sea over a shipwreck. Our way of sensing the archaeological remains can also be discrete or continuous. Resistivity measurements, crew visits, auger holes and test pits involve discrete "peeks" at what lies below, while surface survey and Ground-Penetrating Radar may involve virtually continuous scans or sweeps of the ground.

Discrete peeks or glimpses run the risk of missing remains that lie between observation points. Some of the literature concerns ways to minimize this risk, and several authors have published on the optimum spacing and pattern of points to detect circular (e.g., Kintigh 1988) and elliptical targets (e.g., Drew 1979, McCammon 1977, Singer 1969).

Sweeping the ground, however, does not always assure detection either. Sometimes it is convenient to assume that detection is assured as long as the target comes within range R of a transect, sometimes called the discovery radius. In that case, a transect spacing of 2R makes a "clean sweep" of an area or region. So-called total survey depends on this assumption, which Operations Research describes as the "Law of Definite Detection" (fig. 1, Koopman 1980: 82-83). Of course, different kinds of sites have different discovery radii, and it may only be possible to make a clean sweep of the more obtrusive sites.

In many instances, furthermore, we know that the probability of detection falls off rapidly with distance. Often, the Inverse-Cube Law pertains, with detectability of targets inversely proportional to the cube of the range (fig. 1b, Koopman 1980: 57-67). Consequently, in these cases, we could fail to detect sites even when they are quite close to a transect. This has led to surface surveys with narrow transect intervals, or even crawling on the ground, to minimize the maximum distance between observer and target.

Archaeologists have also sometimes tried to address this problem with a variety of search geometries, or by surveying each space with two complementary geometries (fig. 2). For example, in surface survey, "wavy" transects are intended to decrease the systematic omission of between-transect observations (e.g., Mortensen 1974), but make it more difficult to evaluate detectability. In surface survey or distributional archaeology (Ebert 1992), a second set of transects is often at right angles to the first, the rationale being that repeating the survey from a different angle (and with different lighting conditions) will reveal some artifacts missed in the first pass. Operations Research has also investigated this problem and found that, for double sets of transects, it is optimal for the second set to be diagonal to the first (fig. 2d), rather than at right angles, because it maximizes the area of new ground covered .

In the Bayesian approach, meanwhile, some situations (namely when the prior probabilities make a circular normal density function) call for a spiral trajectory expanding from the point of highest prior probability, as in the case of a shipwreck or historic settlement whose approximate coordinates can be estimated. For practical reasons, it is usual to approximate this with an Expanding Square centered on the Point of Fix (mode of the probability distribution; fig. 3, Koopmans 1980: 214-227), and with a spacing interval (S) that depends on the distribution's standard deviation (σ) and the sweep width (W) or "effective visibility" (E) of the detector. E is half the sweep spacing that results in a detection probability of 0.5. For definite detection, W = E, but for inverse-cube detection, W = 1.076E (Koopman 1980: 76-77, 217). We can then define the spacing interval as

$$S = 0.75 \sqrt{E\sigma}$$

Note that, if definite detection applies, posterior probabilities fall rapidly to zero as search progresses without finding anything, so that the posterior probability distribution can quickly become doughnut-shaped (Koopman 1980: 216), rather than bivariate-normal.

Target detection

Not surprisingly, the conditional probability of detecting a target, given that the target is present, increases with the amount of time we devote to searching for it. For continuous searches with definite detection and accurate transect trajectories, this relationship is linear. For discrete searches with uncertain detection, however, the quantity, g, is the instantaneous probability of detection by one glimpse. Thus g summarizes the factors, including visibility and obtrusiveness, that contribute to detectability. If each glimpse is independent of the others, the probability of each failed glimpse is $(1 - g)$ and we multiply this n times to find the probability of not detecting the target in n glimpses. The converse of this, that is, the probability of detection in n glimpses, is then

$$P_n = 1 - (1 - g)^n$$

More generally, the probability of detection in the time interval dt is

$$p(t) = 1 - e^{gt}$$

This is one way to express the exponential detection function, where g and $g\sigma$ depend on physical conditions of visibility and obtrusiveness, and t is the amount of time devoted to search. Although the exponential detection function it is somewhat unrealistic, in that it assumes that glimpses are randomly distributed and independent of one another, it actually is a conservative detection function (fig. 4 and Stone 1983: 218) because it predicts a lower detectability than either definite detection or inverse-cube detection.

The important thing, for our purposes here, is that the exponential detection function describes a curve that levels off. This means that we can expect the payoff for increasing search effort to show diminishing returns (fig. 4). At some point, it may be more profitable to search elsewhere, rather than continue searching in the same space, under these circumstances. As it turns out, a wide variety of circumstances can lead to an exponential detection function, including inaccurate placement of survey transects and exponential falloff in the probability of "seeing" the target as range increases. The inverse-cube detection function also has diminishing returns, but is more optimistic than the exponential function (fig. 4).

Steps in planning prospection

There is not space here to discuss optimal search plans in detail. Once searchers have identified the goal of search,

however, the search involves a number of tasks (modifed after Stone 1983: 208):

1. Estimating the prior distribution of the target location ,
2. Characterizing the target or targets and selecting appropriate sensing methods,
3. Estimating the capabilities of sensors to detect targets,
4. Estimating the impacts of visibility,
5. Estimating the impact of false targets,
6. Determining a detection function, including estimated detectability under various circumstances,
7. Developing a search plan and estimating its cost and probability of success,
8. Updating the plan as the search yields new information, and
9. Evaluating the search's effectiveness.

Note that many of these steps would apply equally to surveys of the sampling variety. In fact, one could well question whether we can justify extrapolating from a sample to a population without estimating some of the impacts included in this list.

Examples of prospection problems

This section will briefly present some examples of search problems that could benefit from the approaches of Operations Research. In the interest of brevity, I will concentrate on allocation of effort, as this is a problem integral to all kinds of surveys.

As an example of discrete search, but in cells that are small enough to approximate continuous search, we could use Bayesian methods to find the optimal allocation of effort among the pixels in a GIS predictive model, such as Minnesota's Archaeological Predictive Model.[1] The pixels, each 30 m x 30 m in size, have been classified to eight levels of prior probability. Commonly, archaeologists make little use of this information except to warn planners of probable CRM impacts, yet more specific models of this type can also guide survey for rare targets or what Altschul (1990) calls "red flags": surprising results rather than the typical and highly predictable ones that sampling surveys normally report.

Another example that could benefit from optimal allocation of effort is Florida State University's survey for Paleoindian sites on Florida's continental shelf, flooded by rising Holocene sea levels (Faught and Donoghue 1997). The FSU survey has focussed on geological outcrops along drowned river valleys that are likely to contain chert sources, which in turn have relatively high prior probabilities of having prehistoric sites in their vicinities. This is an intuitive application of the principles of optimal search, yet does not take advantage of the theory available to optimize search effort explicitly (cf. Mangel 1983).

In both these cases, and ones like them, where we can reduce space to a set of discrete, smaller spaces, each with different areas and probabilities of containing targets, the optimum densities of search effort are equal to the logarithms of quantities proportional to the probability densities of the

spaces (Koopman 1980: 149). When we are looking for a single target, and it can only be in one of the spaces, all the probabilities sum to 1.0. In cases where we are only looking for a class of targets, and do not even know how many targets there are, the probabilities are independent. The total density of search effort (fo) in the i-th space of n spaces in a region of area A, is:

$$\varphi_i = \log \rho_i - \frac{1}{A}(A_1 \log \rho_1 + A_2 \log \rho_2 + \ldots + A_n \log \rho_n) + \frac{\phi}{A}$$

Here ρ_i is the probability density of space i (the prior probability that space i contains the target divided by the area of space i), n is the number of spaces in the search area, A_i is the area of space i, ϕ = total search effort, expressed as area covered (for transects $\phi = WL$), and ϕ_i is the "coverage" or "sampling fraction" of area i:

$$\varphi_i = \frac{WL_i}{A_i}$$

where W and L are respectively the width and total length of transects. ϕ/A, then, is what archaeologist's have usually called "coverage." This can be expressed just as easily with the total area of test pits, augers or cores.

It turns out that, when the total amount of search effort is very small relative to the region surveyed, it is optimal to devote the entire search effort to the space or spaces with the highest probability density. This is much like what happens in typical use of predictive models in Cultural Resource Management today. With middling amounts of search effort available, we distribute it among the spaces according to the expression above. We can test each space to see whether it meets the threshold for allocation of space. If, for any two spaces,

$$\rho_1 \leq \rho_2 e^{-\phi/A}$$

then no search effort is allocated to space 1 (Koopman 1980: 149). When search effort is very large, however, the amounts of effort per unit area for all spaces become equal; this amounts to a simple, proportionally stratified sample, a type of survey strategy with which archaeologists are very familiar. Unfortunately, we usually do not have the luxury of nearly unlimited survey effort.

Simplified examples of optimal allocation

To provide a more concrete example, let us assume a simple case with a survey region stratified into three spaces with areas of 3 ha, 2 ha and 1 ha, respectively. Let us furthermore assume that we are searching for a historic fort, but have no prior information about it other than that it should occur somewhere in the region we are surveying. A common archaeological plan is to divide search effort in proportion to the three areas, which amounts to assigning the three spaces prior probabilities of 0.50, 0.3333, and 0.1667. In that case the value of ρ_i for every space will be the same: 0.1667, and most of the terms in the equation cancel out (Table 1A). Thus, the result is simply a proportionally stratified sample with equal coverage of each stratum. Let us assume, furthermore, that poor surface visibility and low expected

artifact density leads us to survey with test pits, each 1 m² in size, and the amount of survey effort available (ϕ) is 3000 m² (3000 test pits, or roughly 1500 person-days of effort [Zeidler 1995:5.5]). Dividing this admittedly huge resource by the total survey area A, then gives us ϕ/A of 0.05 (5% "coverage"), so that a total of 3000 test pits would be allocated as 1500, 1000, and 500 test pits, respectively.

An alternative, if there is no reason to think it more likely that the fort would occur in any one of these spaces is to assign them all equal prior probabilities. This may seem strange, but the practice in the last paragraph actually makes the untested assumption that large spaces are more likely to contain the fort even though we know that strategic locations for forts, such as hilltops or fords, often occupy very small proportions of space. Since the fort can only be in one place, the probabilities have to sum to 1.0, so the priors are all 0.3333. In that case, however, the probability density of the smallest space is so great relative to the others that we would allocate all search effort to it (Table 1B). Neither space 1 nor space 2 meets the threshold given in (6). Needless to say, assuming equal probabilities in cases where we know nothing except that the spaces vary considerably in size would usually be risky, so it makes sense to try to estimate probabilities more carefully.

Sometimes we have statistics from previous surveys and background research that gives us a basis for estimating the fort's probability of being in various kinds of location. For example, a sample of a dozen similar forts in the broader region or information from historic maps might allow us to estimate prior probabilities of 0.45, 0.35, and 0.20, respectively (Table 1D). In that case, dividing by their surface areas, the probability densities (ρ_i), are 0.15, 0.175 and 0.2 respectively. Note that the probability *densities* are ordered quite differently than the ordinary probabilities on which they are based. This results in a ϕ_1 of 0.007 (206 test pits spread over 3 ha), ϕ_2 of 0.074 (1476 test pits over 2 ha), and ϕ_3 of 0.132 (1318 test pits). A more generous, if unrealistic, total effort allocates a much greater number of test pits to areas 1 and 2 (Table 1C). Note, however, that if our resources only allow us to dig 1200 test pits (ca. 600 person-days), then the "coverage" becomes 2% and space 1 no longer meets the threshold of probability density. Consequently, no effort is allocated to space 1 in this scenario because its probability density of 0.15 is simply too low. We now include only spaces 2 and 3 in the calculation, so that ϕ_2 becomes 0.021 (413 test pits), and ϕ_3 becomes 0.0.079 (787 test pits)(Table 1E). Note how the proportions of effort change when the resources decrease, and how the greatest amount of effort, somewhat counter-intuitively, is concentrated in space 3, even though it had the lowest prior probability (but highest probability density).

It is important to keep in mind that adopting a strategy like this does not mean that the target is most likely to occur in space 3 - after all, we have estimated that there is a 45% chance that it is in space 1 - but only that looking in space 1 is more likely to be productive, given our resource constraints. Allocating a small amount of effort to such a large area as space 1, by contrast, is quite unlikely to find the fort even if it is there. We must remember that in this case

the goal is to find the fort as quickly as possible, when resources are limited. Had the goal been to characterize the three spaces, obviously the allocation would have been very different.

More realistic allocations are made incrementally, using information from a previous, unsuccessful search with effort ϕ to plan the next increment with effort ϕ' (Koopman 1980:150). Stone (1975:108-109) has shown that incremental plans that always put the next search in the space with the highest ratio of detection probability to search cost will be optimal in this situation.

Conclusions

It is important for the designs of surveys to be suited to their goals. Where the goal is to find particular targets or kinds of targets, rather than to make parameter estimates, build predictive models, or detect spatial structure, we should use prospection, by which we try to optimize the recovery or detection of those targets.

> There is little question that purposive selection is preferable to sampling whenever selection is feasible, sufficient for one's research objectives, and not wasteful. One of the reasons why improved techniques of data detection ... are so important is that they offer new possibilities for feasible and effective data selection. (Cowgill 1975: 260).

Here I have tried to provide a taste of the tools that Operations Research, and particularly optimal search methods, can offer to help archaeologists accomplish this. With its emphasis on measuring and evaluating detectability, this kind of research also has implications for the other kinds of survey. Sampling surveys, for example, will provide biased estimates of population parameters if their practitioners employ unrealistic assumptions about the detectability of targets that are supposed to be included in the sample.

Operations Research is underexploited as a source of well-developed tools for survey archaeologists and can help us with all three kinds of surveys, including more efficient "total survey" and "non-site survey."

To conclude, we should take prospection, or "purposive survey," seriously where it is warranted, and not treat it as a haphazard "poor cousin" to sampling space. Prospection provides some kinds of information sampling cannot, such as documenting the presence of rare sites. It allows us to test hypotheses that make specific predictions about the locations of archaeological materials much more efficiently than a sampling survey (Cowgill 1975: 260-261). Its tools also help ensure that sampling surveys do not omit parts of the intended sample, creating bias, or at least allow us to evaluate the seriousness of such bias.

Prospection succeeds through the combination of basic mathematical principles and archaeologists' experience and prior knowledge. Background research should not be "a

mechanical task, a token interlude between the signing of a contract and the beginning of fieldwork…" (Wobst 1983: 58). We can focus background research on the goals of a survey by using it to model the expected distribution of archaeological materials (Wobst 1983: 62) or to estimate the prior probabilities that particular kinds of targets will occur in particular locations. Operations Research provides the framework with which to make a fruitful partnership of background research and survey design.

References

Altschul, J. H. 1990. Red flag models: The use of modelling in management contexts. In Allen, K. M. S., Green, S. W., and Zubrow, E. B. W. (eds.), *Interpreting Space: GIS and Archaeology*. Taylor and Francis, London: 226-238.

Buck, C. E., Cavanagh, W. G., and Litton, C. D., 1996. *Bayesian Approach to Interpreting Archaeological Data*. John Wiley & Sons, New York.

Corwin, T. L., 1981. Search for a moving target under Minimax estimation. *Journal of Applied Probability* 18: 167-180.

Cowgill, G. L., 1975. A selection of samplers: Comments on archaeo-statistics. In Mueller, J. W. (ed.), *Sampling in Archaeology*. University of Arizona, Tucson: 258-274.

Cozzolino, J. M., 1972. Sequential search for an unknown number of bjects of nonuniform size. *Operation Research* 20: 293-308.

Deagan, K. A., 1989. The search for La Navidad, Columbus' 1492 settlement. In Milanich, J. T., and Milbrath, S. (eds.), *First Encounters: Spanish Explorations in the Caribbean and the United States, 1492-1570*. University of Florida Press, Gainesville: 41-54.

Discenza, J. H., 1980. A solution for the optimal multiple rectangle search. In Haley, K. B., and Stone, L. D. (eds.), *Search Theory and Applications*. Plenum Press, New York.

Dobbie, J. M., 1968. A survey of search theory. *Operations Research* 16: 525-537.

Drew, L., 1967. Grid-drilling exploration and its application to the search for petroleum. *Economic Geology* 62: 698-710.

Drew, L., 1979. Pattern drilling exploration: Optimum pattern types and hole spacings when searching for elliptical shaped targets. *Mathematical Geology* 11: 223-254.

Dunnell, R. C., and Dancey, W. S., 1983. The siteless survey: A regional scale data collection strategy. *Advances in Archaeological Method and Theory* 6: 267-287.

Ebert, J. I., 1992. *Distributional Archaeology*. University of New Mexico Press, Albuquerque.

Faught, M. K., and Donoghue, J. F., 1997. Marine-inundated archaeological sites and paleofluvial systems: Examples from a karst-controlled continental shelf setting in the Apalachee Bay, northeastern Gulf of Mexico. *Geoarchaeology* 12: 417-458.

Fish, S., and Kowalewslei, S. (eds.), 1990. *The Archaeology of Regions: A Case for Full-coverage Survey*. Smithsonian Institution Press, Washington, DC.

Flannery, K. V. (ed.), 1976. *The Early Mesoamerican Village*. Academic Press, New York.

Foley, R., 1981. Off-site archaeology: An alternative approach for the short-sited. In Hodder, I., Isaac, G., and Hammond, N. (eds.), *Patterns of the Past: Studies in Honour of David Clarke*. Cambridge University Press, Cambridge: 157-183.

Gal, S., 1980. *Search Games*. Academic Press, New York.

Gal, S., 1989. Continuous search games. In Chudnovsky, D. V., and Chudnovsky, G. V. (eds.), *Search Theory: Some Recent Developments*. Marcel Dekker, Inc., New York: 33-53.

Garrison, E. G., Baker, J. G., and Thomas, D. H., 1985. Magnetic prospection and the discovery of Mission Santa Catalina de Guale, Georgia. *Journal of Field Archaeology* 12: 299-313.

Harbaugh, J. W., Doveton, J. H., and Davis, J. C., 1977. *Probability Methods in Oil Exploration*. John Wiley & Sons, New York.

Ives, J., 1982. Evaluating the effectiveness of site discovery techniques in boreal forest environments. In Francis, P., and Poplin, E. (eds.), *Directions in Archaeology: A Question of Goals*. University of Calgary, Alberta: 95-114.

Kinder, G., 1998. *Ship of Gold in the Deep Blue Sea*. Random House, Toronto.

Kintigh, K. W., 1988. The effectiveness of subsurface testing; A simulation approach. *American Antiquity* 53: 686-707.

Koopman, B. O., 1980. *Search and Screening: General Principles with Historical Applications*. Pergamon Press, New York.

Krakker, J. J., Shott, M. J., and Welch, P. D., 1983. Design and evaluation of shovel-test sampling in regional archaeological survey. *Journal of Field Archaeology* 10: 469-480.

Lightfoot, K. G., 1986. Regional surveys in the eastern United States: The strengths and weakness of implementing subsurface testing programs. *American Antiquity* 51: 484-504.

Lightfoot, K. G., 1989. A defense of shovel test sampling: A reply to Shott. *American Antiquity* 54: 413-416.

Lolley, T. L., 1996. Ethnohistory and archaeology: A map method for locating historic Upper Creek Indian towns and villages. *Journal of Alabama Archaeology* 42: 1-81.

Lynch, M., 1980. Site artifact density and the effectiveness of shovel probes. *Current Anthropology* 21: 516-517.

Mangel, M., 1983. Optimal search for and mining of underwater resources. *SIAM Journal of Applied Mathematics* 43: 99-106.

McCammon, R. B., 1977. Target interception probabilities for parallel-line and continuous-grid types of search. *Mathematical Geology*: 9: 369-382.

McManamon, F. P., 1984. Discovering sites unseen. *Advances in Archaeological Method and Theory* 8: 223-292.

Morris, P. A., 1977. Combining expert judgments: A Bayesian approach. *Management Science* 23: 679-693.

Mortensen, P., 1974. A survey of prehistoric sites in northern Luristan. *Acta Archaeologica* 45: 1-47.

Nance, J. D., 1979. Regional subsampling and statistical inference in forested habitats. *American Antiquity* 44: 172-176.

Nance, J. D., 1983. Regional sampling in archaeological survey: The statistical perspective. *Advances in Archaeological Method and Theory* 6: 289-356.

Nance, J. D., and Ball, B. F., 1986. No surprises? The reliability and validity of test pit sampling. *American Antiquity* 51: 457-483.

Nance, J. D., and Ball, B. F., 1989. A shot in the dark: Shott's comments on Nance and Ball. *American Antiquity* 54: 405-412.

Paloheimo, J. E., 1971. On a theory of search. *Biometrika* 58: 61-75.

Plog, S., Plog, F., and Wait, W., 1978. Decision making in modern surveys. *Advances in Archaeological Method and Theory* 1: 384-421.

Read, D. W., 1975. Regional sampling. In Mueller, J. W. (ed.), *Sampling in Archaeology*. University of Arizona, Tucson: 45-60.

Richardson, H. R., and Discenza, J. H., 1980. The United States Coast Guard computer-assisted search planning system (CASP). *Naval Research Logistics Quarterly* 27:659-680.

Reynoso, C., and Jezierski, E., this volume. A genetic algorithm problem solver for archaeology. In xxx (ed.), *Archaeological Informatics — Pushing the Envelope.* Computer Applications and Quantitative Methods in Archaeology. BAR International Series. Hadrian Books, Oxford: xxx-xxx.

Savage, L. J., 1971. Elicitations of personal probabilities and expectations. *Journal of the American Statistical Association* 66: 783-801.

Savinskii, I. D., 1965. *Probability Tables for Locating Elliptical Underground Masses with a Rectangular Grid.* Consultants Bureau, New York.

Schiffer, M. B., Sullivan, A. P., and Klinger, T. C., 1978. The design of archaeological surveys. *World Archaeology* 10: 1-28.

Shomette, D. G., and Eshelman, R. E., 1981. A developmental model for survey and inventory of submerged archaeological resources in a riverine system: The Patuxent River, Maryland. In Watts, G. P. (ed.), *Underwater Archaeology: The Challenge Before Us.* Fathom Eight, San Marino, CA: 159-171.

Shott, M. J., 1985. Shovel-test sampling as a site discovery technique: A case study from Michigan. *Journal of Field Archaeology* 12: 458-469.

Shott, M. J., 1989. Shovel test sampling in archaeological survey: Comments on Nance and Ball, and Lightfoot. *American Antiquity* 54: 396-404.

Singer, D. A., 1975. Relative efficiencies of square and triangular grids in the search for elliptically shaped resource targets. *United States Geological Survey Journal of Research* 3: 163-167.

Singer, D. A., and Drew, L. J., 1976. The area of influence of an exploratory hole. *Economic Geology* 71: 642-647.

Singer, D. A., and Wickman, F. E., 1969. *Probability Tables for Locating Elliptical Targets with Square, Rectangular and Hexagonal Pointnets.* Pennsylvania State University Mineral Science Experiment Station Special Publication 1-69.

Stone, G. D., 1981. Artifact density and shovel probes. *Current Anthropology* 22: 182-183.

Stone, L. D., 1975. *Theory of Optimal Search.* Academic Press, New York.

Stone, L. D., 1983. The process of search planning: Current approaches and continuing problems.*Operations Research* 31: 207-233.

Stone, L. D., Barlow, C. A., and Corwin, T. L., 1999. *Bayesian Multiple Target Tracking.* Artech House.

Storck, P. L., 1978. Some recent developments in the search for early man in Ontario. *Ontario Archaeology* 29: 3-16.

Storck, P. L., 1982. Palaeo-indian settlement patterns associated with the strandline of glacial Lake Algonquin in southcentral Ontario. *Canadian Journal of Archaeology* 6: 1-31.

Storck, P. L., 1984. Glacial Lake Algonquin and Paleo-indian settlement patterns in southcentral Ontario. *Archaeology of Eastern North America* 12: 286-298..

Washburn, A. R., 1981. *Search and Detection.* Operations Research Society of America, Arlington, VA.

Winterhalder, B., and Smith, E. A., 2000. Analyzing adaptive strategies: Human behavioral ecology at twenty-five. *Evolutionary Anthropology* 9: 51-

Zeidler, J. A., 1995. *Archaeological Inventory Survey Standards and Cost-estimation Guidelines for the Department of Defense.* US Army Corps of Engineers Research Laboratories Special Report 96/40.

Endnotes

[1] The use of the Minnesota Archaeological Predictive Model is courtesy of Minnesota's Department of Transport and the US Federal Roadway Authority. I thank Michael Faught and Joe Donoghue for the use of information from the FSU survey of Florida's continental shelf. The author's research has been supported by the Social Sciences and Humanities Research Council of Canada.

Tables

Space	A_i (ha)	p_i	ρ_i	Φ/A	Φ (ha)	ϕ_i	No. Test Pits	Total
A								
1	3	0.500	0.167	0.05	0.3	0.05	1500	
2	2	0.333	0.167	0.05	0.3	0.05	1000	
3	1	0.167	0.167	0.05	0.3	0.05	500	3000
B								
1	3	0.33	0.111	0.05	0.3	0	0	
2	2	0.33	0.167	0.05	0.3	0	0	
3	1	0.33	0.333	0.05	0.3	1.0	3000	3000
C								
1	3	0.45	0.15	0.10	0.6	0.057	1706	
2	2	0.35	0.175	0.10	0.6	0.124	2476	
3	1	0.20	0.20	0.10	0.6	0.182	1818	6000
D								
1	3	0.45	0.15	0.05	0.3	0.007	206	
2	2	0.35	0.175	0.05	0.3	0.074	1476	
3	1	0.20	0.20	0.05	0.3	0.132	1318	3000
E								
2	2	0.35	0.175	0.02	0.12	0.021	413	
3	1	0.20	0.20	0.02	0.12	0.079	787	1200

Table 1. Examples of allocations to three spaces with unequal areas, proportional (A), equal (B) and unequal probabilities (C-E), and different amounts of total survey effort (F). Note that scenario A is equivalent to a proportionally stratified sample, and that in scenario B spaces 1 and 2 do not qualify for any survey at all.
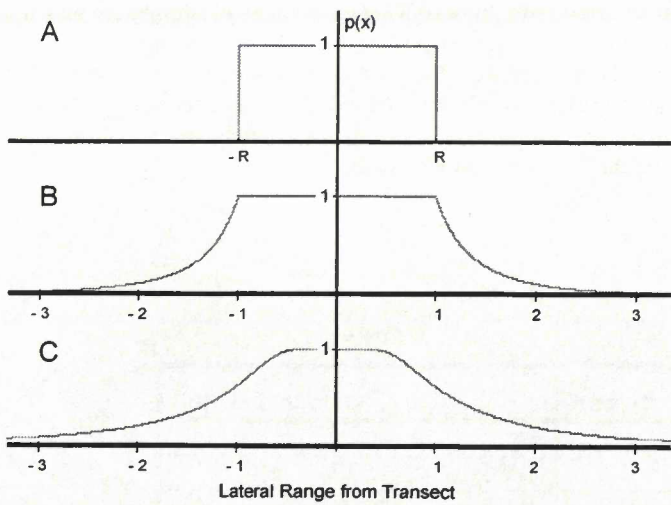
Figures

Figure 1. Cross-sectional plots of the effect of range away from a transect on detection probability: (a) definite detection, (b) inverse-cube detection, and (c) exponential detection.
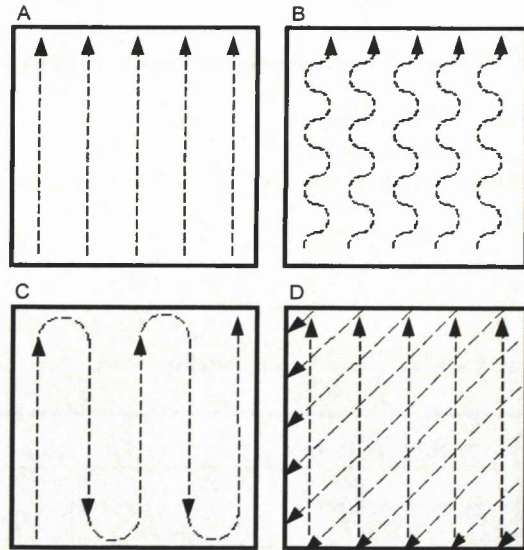

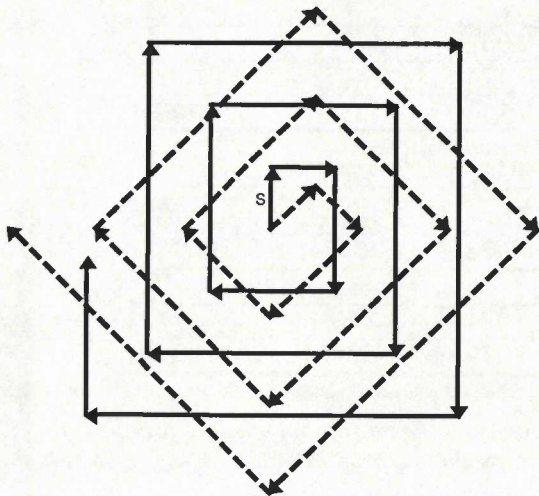Figure 2. A selection of transect geometries (a-c) and two passes by transects oriented 45° (d).

Figure 3. "Expanding square" search over a target with a circular normal prior probability distribution. Note that a repeat search (dashed lines) is optimally oriented 45° to the first (after Koopman 1980:214-221).
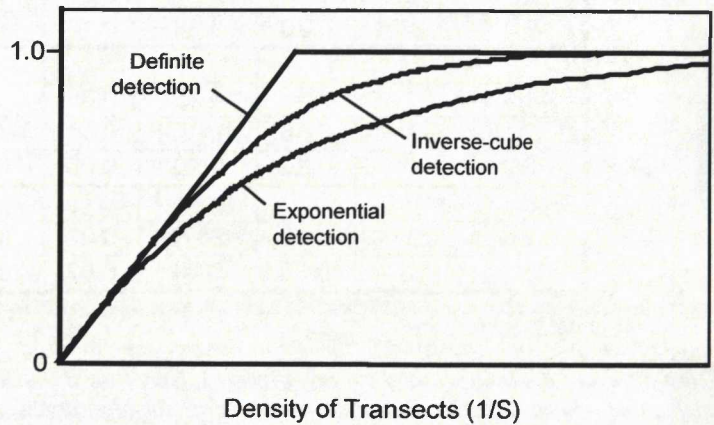

Figure 4. Detection functions for parallel transects with a regular spacing of S, assuming definite detection, inverse-cube detection, and exponential detection (after Koopman 1980:78).