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Chapter 18

Importance of Sampling Design and Density in Target Recognition

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Abstract

The design and density of surface geochemical sampling programs can significantly influence the interpretability of the survey. Testing hypotheses by purposeful sampling is the most straightforward application of surface geochemistry and the easiest to interpret but requires *a priori* geologic knowledge and provides limited information. Designing a spatial sampling program to produce a map is a much more difficult problem. Two common techniques are line profiles and areal surveys. The interpretation of these techniques, as a function of sampling density, is simulated by examining the relationships of artificial surveys to a known subsurface target. A deterministic model of hydrocarbon migration is used to constrain the randomized mixing of two nonoverlapping populations (anomalous and background). A high-resolution grid of simulated surface measurements is decimated to create lower resolution grids and line profiles. For regional high-grading, a grid with a minimum of two samples across the narrowest expected surface signal (minimum subsurface target width plus a dispersion zone) appears to be adequate. A higher density of four samples is suggested for prospect high-grading. In addition, the sampled area must include sufficient "background" measurements to recognize the existence of an anomaly. About 80% of the samples should be obtained outside the expected area of interest. The most cost-effective sampling program consist of two stages: a low-density regional survey to high-grade the area, followed by a higher density survey within the high-graded area. Undersampling is probably the major cause of ambiguity and interpretation failures involving surface geochemical studies.

INTRODUCTION

Soil gas data, like other natural data, is typically noisy. There is no clear cut spatial or magnitude boundary between anomalously high magnitude sites (above a defined threshold and within a homogeneous compositional class) and lower level (below the threshold) background sites. Methodology to separate background and anomalous sites are covered in Klusman (1993) and Jones et al. (in press). To optimize the recognition of an anomaly (spatial cluster of anomalous sites), while minimizing survey costs, several factors must be considered when planning a survey:

1. The goal of the survey—release of acreage, comparison of two or more separate areas, regional identification of areas of interest, and prospect scale evaluation
2. The size and shape of the expected anomaly—typically assumed to be proportional to the size and shape of the subsurface target (*target* is defined as the subsurface feature that gives rise to a surface anomaly)—and the geologically expected relationship between the two (directly over the target or displaced by dipping faults or stratigraphy)
3. The expected natural variation in surface measurements—both random and those from known geologic factors, such as identified for macroseepage by Link, 1952)
4. The magnitude of the expected signal-to-background ratio.

It is important to recognize that defining background values adequately is required before anomalies can be properly identified. Estimates of background values and signal-to-background ratios are best achieved by pilot studies over nearby producing fields or by a combination of experience and small preliminary surveys in the study area if known producing fields are unavailable. Both pilot and preliminary surveys should include estimates of surface hydrocarbon magnitudes, effect of sample depth, and optimal sample spacing. In practice, these studies are seldom done, except for occasional calibration studies over existing production, performed at the same time as the survey to minimize costs.

It is beyond the scope of this paper to discuss the statistical methods of selecting optimal sample spacing and depth, methods of choosing a threshold between background and anomalously high magnitude measurements, or statistical tests. The reader is referred to several texts covering these techniques, such as Dixon and Massey (1957) or Krumbein and Graybill (1965). Discussions of the use of variograms to estimate the effects of sample spacing by Davis (1973) or Journel and Huijbregts (1978) are recommended. Restricting sampling programs to the vicinity of the expected anomaly is a false economy that is common to the design of most surface sampling programs. It is difficult to characterize an elephant if you only sample its side or leg and never find its limits or other characteristics. Experience at Gulf Research and Development Company suggests that, for each sample taken within an expected anomalous area, more than five times as many samples should be taken in the surrounding area.

The purpose of this paper is to examine the consequences of interpretions made on the basis of sample design and density. Several categories of sampling designs are briefly reviewed, followed by a simulation of the effects of sampling density on line profile and grid designs. This is accomplished through the use of a known subsurface target, defined anomalous and background populations, and a defined relationship between target and seepage measurements at the surface. The method of obtaining these relationships is explained, and the consequences of both line and grid sampling designs are illustrated through simulations of sampling results obtained at different sampling densities along line profiles and regular grids. The effect of both noise and variation in sampling density are considered and related to the ability to define a "known" surface anomaly. The results of one interpretation scheme are then summarized and a cost-benefit analysis presented. Readers are encouraged to examine these simulations using their own style of interpretation. This should be done with respect to the technique's ability to predict the known subsurface target, remembering that it is easier to find something when you know what it looks like than when its shape, size, and location are unknown.

SAMPLING DESIGNS

The goal of the survey determines the nature of the sampling plan. Purposeful selection of sampling sites is a traditional choice of geologists; it maximizes information gained per unit cost and has great use in surface geochemical surveys in circumstances that I group under the umbrella of hypothesis testing. Marine bottom sampling surveys often use purposeful selection of sampling sites due to the high cost of keeping the ship on station during sampling. Typical sample sites include faults, mud volcanoes, sea bottom pockmarks, shallow seismic bright spots, seismically detected gas chimneys, and bubble trains in the water column. Under these circumstances, one is generally trying to determine if hydrocarbon seepage is associated with this feature and what the compositions of any subsurface hydrocarbons are. Prior knowledge of the area is required to properly select the sample locations. Extra samples are generally needed because of the uncertainty between the sampling location determined on a map and the actual position obtained in the field.

It cannot, however, be emphasized enough that the information gained by purposeful sampling pertains only to that particular sample site and should not be used to infer anything about areas not sampled. For instance, if a fault is sampled by taking a sample at three widely separated locations in the vicinity of the fault trace, and no seepage was found, it would be incorrect to say that the fault does not leak. It is possible that at some sample locations the fault was missed and at the unsampled locations seepage was occurring. Seepage is known to occur in spots along fault traces (Wakita, 1978; Preston, 1980) rather than uniformly along their length. A better approach would be to take several samples in a cluster (to minimize the risk of missing the fault's surface trace) at several locations along a fault where reservoir leak points would be expected to occur, such as near the crest and expected spill points of the trap. Then, if no seepage was found, it would be more reasonable to infer that the fault was not leaking hydrocarbons, although nothing could be inferred about other unsampled areas.

Random sampling of an area is particularly useful if one wishes only to detect the presence or absence of thermogenic hydrocarbons or to obtain compositional information. Random sampling does not ensure uniform coverage of an area. Indeed, it usually results in spatial clustering (Krumbein and Graybill, 1965). This type of sampling is appropriate when spatial information is unimportant to answering the questions posed and the area is considered as a single homogeneous population. Random sampling is also useful in obtaining unbiased estimates of two areas for comparison purposes. This is particularly useful in comparing two basins, two parts of a basin, or two prospective areas. The error of estimating the population mean is directly proportional to the variation of the population and inversely proportional to the square root of the number of samples taken (Dixon and Massey, 1957). Thus, a larger number of samples are needed for an area with a greater range of magnitudes than for one where all the values are similar.

Most land hydrocarbon surveys and marine sniffer or airborne surveys are generally concerned with high-grading selected areas within a larger region. This requires that spatial variation of hydrocarbon seepage be mapped in adequate detail to unambiguously resolve features that are large enough to be considered interesting (targets) from the natural background variation and smaller features. Two sampling techniques are commonly used: *line profiles* (one dimensional) and *grids* (two dimensional).

Designing a line profile sampling program is relatively straightforward. Once the number, orientation, and location of the lines are selected, the remaining parameters to be chosen are the method of sampling, the depth or depths of sampling, and the sample spacing along the line. Information gathered along a line is, strictly speaking, only useful for inferences in behavior along that line because it does not provide an unbiased sample of the area. This sampling design is typical of offshore surveys by sniffers or onshore in seismic shot holes. An array of several line surveys is transitional between one- and two-dimensional information and is often presented as a map. If this is done, care should be exercised in forming trends between lines because of the bias introduced by the line locations.

When two-dimensional information is needed, some type of gridded or stratified survey is preferred to ensure an approximately equal distribution of points. For many people, the word *grid* brings up the image of a regular, square grid, such as the squares on a checkerboard. There are, however, many types of grid designs (Yates, 1960; Krumbein and Graybill, 1965). Within each grid element, a fixed number of samples is taken. These can be chosen by a variety of methods, such as regular positions (corners or centers), random positions (using a random number generator), haphazard (chosen for convenience), or even purposeful selection.

In practice, I prefer a combination of sampling methods. Within each grid element, two or more sample locations are chosen, with the first one purposefully located (if there is a reason to do so). The others are chosen randomly or to achieve a combination of (1) no large internal unsampled areas, (2) ease of access, and (3) close proximity to other samples to enable estimation of short-distance variability and the potential of aliasing. It should be remembered, however, that as the sampling program departs from unbiased selection criteria, statistical inferences become weaker. Included within each survey should be a few replicate samples to estimate sampling repeatability. I believe the majority of surface seepage studies that have failed or yielded ambiguous results have done so because of undersampling. This results in aliasing the targets and the inability to resolve a target from natural variations in background noise and stray signals.

Surface seep detection is considered to be an inexpensive technique, but in our zeal to keep it inexpensive, it has been made "cheap" and does not always provide the data necessary to evaluate its usefulness properly. By analogy, the cost of acquiring and processing seismic data can be significantly reduced if only single-fold data are gathered. The redundancy in multifold data reduces noise, justifying the additional cost.

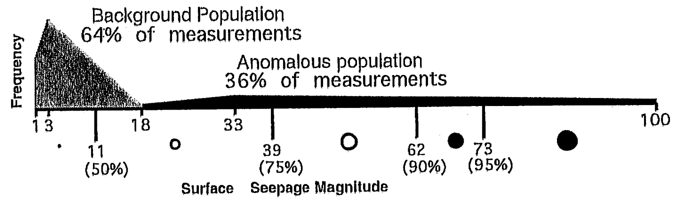

Figure 1—Background and anomalous populations used in Figures 5 through 8. The anomalous population is bounded between 18 and 100, with a mode at 33 and comprises about 36% of the total population. The background population comprises the remaining 64% and is bounded between 1 and 18 with a mode at 3. Symbols for magnitude classes are used in Figures 6a–d.

I believe similar results can be achieved in surface geochemical surveys by increasing the spatial density of sampling and looking for spatial clustering of high-magnitude sites of homogeneous composition. This can be achieved by visual inspection of the data and application of a variety of spatial statistical techniques, such as the one used by Dickinson and Matthews (1993) or those summarized in Davis (1973). The increased ability to interpret geochemical survey data resulting from increased sampling density is shown by Burtell et al. (1986). To quantify the effect of both sample design and density, the following simulation technique was used.

DESIGN OF SIMULATION

Traditionally, surface geochemical measurements from a survey are treated as either a log normal distribution (with part of the high-magnitude tail of the population defined as anomalous) or as two or more normal populations with the lowest magnitude population considered as background and the highest as anomalous. Whether there are, in reality, multiple populations or a continuous multicompositional population is an academic question. In practice, a threshold value is selected for each compositional class and magnitudes above this threshold are considered to be anomalous and values below are considered to be background. Dividing a distribution of seepage magnitudes into these two populations is commonly achieved by the selection of a cut-off value, often coincident with a natural break or frequency minimum in the measurements as determined by inspection of a histogram, plotting on probability paper (Krumbein and Pettijohn, 1938; Harding, 1949), or other statistical tests (Court, 1949; Dixon and Massey, 1957).

For simplicity in these simulations, I have defined two nonoverlapping populations: (1) an anomalous population representative of the target and (2) a background population representative of the area in general. These two populations are shown in Figure 1. In these examples, the anomalous population is bound between measured values of 18 and 100 (with a mode at 33) and com-

Table 1—Division of Population into Five Classes

Class	Range of Values	Percentage of Population
1	1–11	Lower 50%
2	11–39	50–75%
3	39–62	75–90%
4	62–73	90–95%
5	73–100	Upper 5%

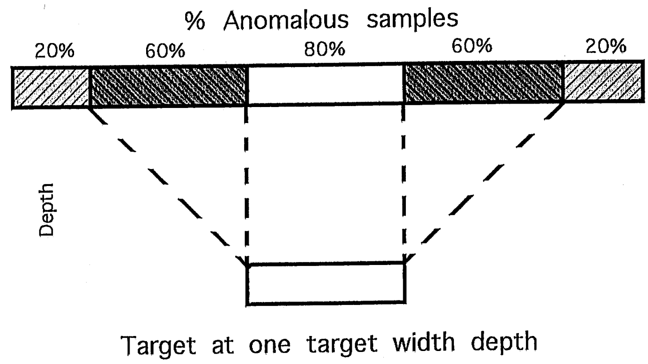

Figure 2—Relationship of anomalous surface data to the subsurface target used in Figures 5 through 8. In the heart (directly over the target), 80% of the data is defined as belonging to the anomalous population. In the fringe (extending outward from the heart a distance equal to the vertical distance from the target to the surface), 60% is defined as belonging to the anomalous population. In the background region (at the greatest distance from the heart), 20% belongs to the anomalous population.

prises about 36% of the total population. The background population comprises the remaining 64% of the total population and is bounded between values of 1 and 18 (with a mode at 3).

Two techniques have been used for purposes of display. In the line profile examples, the data have been presented as a continuously varying bar. In the grid examples, for ease of recognition, the continuous population has been divided into five classes, shown in Table 1. The lowest class is entirely within the background class, while the upper three classes are entirely within the anomalous population. The class with values between 11 and 39 comprises 25% of the population and contains samples from both background and anomalous populations. This class thus represents an uncertainty in defining the separation point of the two anomalous populations. This is commonly encountered in the real world, where the boundary between the two populations is unknown and subject to finite and biased sampling.

The spatial distribution of these two populations, and therefore the five classes, is defined by artificially dividing the sampled area into three zones (Figure 2). Those samples in the heart (directly over the subsurface target) are defined to have an anomalous population percentage of 80%. Those samples in the fringe (extending outward from the heart a distance equal to the vertical distance from the target to the surface) are defined to have an anomalous population percentage of 60%. Those samples in the background region (at the greatest distance from the heart) are defined to have an anomalous population percentage of 20%.

Surface geochemical data are notoriously noisy, with large magnitude changes in concentration over short distances. I believe much of this variation is due to undersampling. The nature of the migration process (Matthews, this volume) is also responsible for some of the noise, as illustrated in Figure 3 (Matthews et al., 1984). In these simulations, I have assumed homogeneous strata from the subsurface target to the surface with randomly scattered fractures that act as high-permeability pathways. The frequency of occurrence of anomalous or background populations in each of the three zones is therefore controlled by the connection of these fractures to a subsurface occurrence of hydrocarbons and the location of a sampling point relative to these fractures. The relationship in the heart zone is based on the assumption that migration of hydrocarbons is dominantly vertical. The greatest concentration of subsurface hydrocarbons is within the target and therefore the greatest concentration of anomalous seepage is directly over the target.

The relationship in the fringe zone is based on the assumption that migration of hydrocarbons from the target also moves outward in a zone no wider than 45° off vertical from the edge of the target to the surface. The dispersion of signal and decrease in frequency of occurrence is caused by a mechanical dispersion process as the hydrocarbons move through the pore network as a separate phase (Matthews, this volume). This angle is chosen because it is halfway between dominantly vertical and dominantly horizontal migration. The background zone is dominated by hydrocarbons in low concentrations derived from biogenic activity and solution-diffusion transport in the water column (Matthews, this volume). The occurrences of samples from the anomalous population are assumed to have originated directly from the source rock or from subeconomic accumulations between the source and the surface.

Under these assumptions, single points with anomalously high concentrations of surface hydrocarbons, such as those that occur in the background zone, are not of spatial interest. Although they do support the existence of a subsurface hydrocarbon source, there is a significant chance that they are not associated with the tail end of a major migration route. However, a large number of adjacent sites with anomalously large values are of interest. The real question is "How are numbers of adjacent sites between these two extremes classified?" Unfortunately, there are no fixed rules to aid in this decision process. In the interpretation section, an oversimplified rule-based decision process is used for illustrative purposes. In an interpretation of a real survey, the relationships that are defined for this simulation are unknown. They are, however, inferred from an understanding of the subsurface

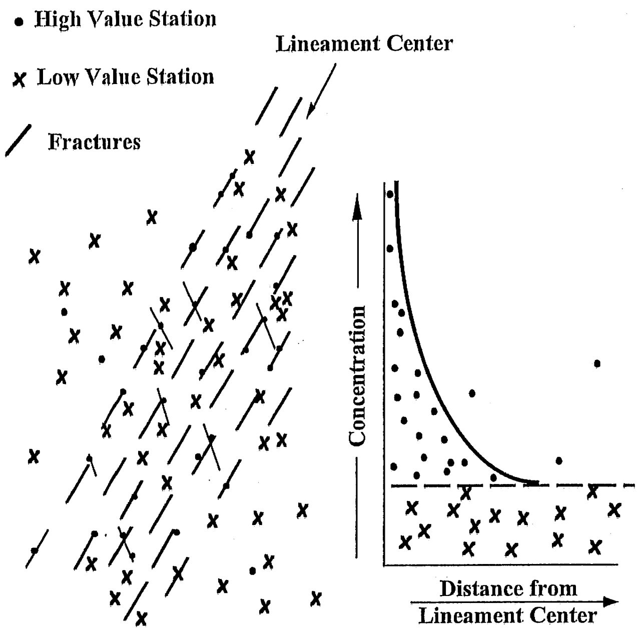

Figure 3—In the seepage model, seepage is focused along preferential pathways, shown here as fractures associated with a lineament zone. The high-magnitude sites are preferentially associated with the lineament zone. Note that even inside the lineament zone, the samples do not always intersect fractures.

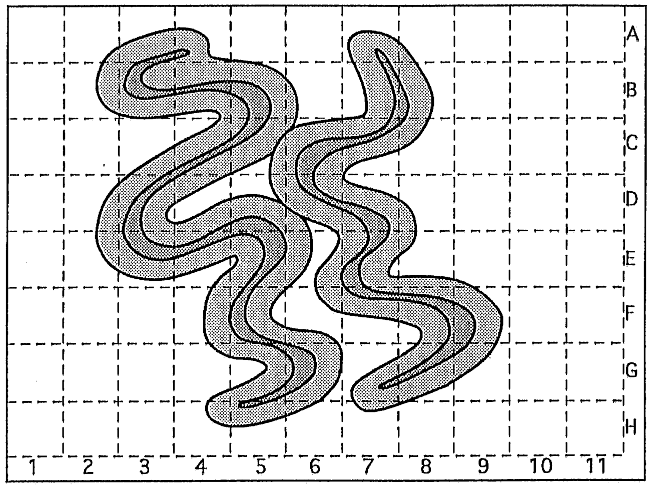

Figure 4—A "mask" showing the location of two hypothetical meandering river deposits superimposed on the sampling design. The idealized heart (dark gray) and fringe (light gray) areas were used to generate Figures 5 through 8.

geology of the area, compositional information, and appropriate analog surveys over known accumulations.

It should be emphasized that this is only one of several relationships between the target and the surface pattern. It is a simple one, constructed to allow the interpreter to focus on the effect of sample spacing. The real world is much more complex and variable. One of the significant challenges in interpretation of surface geochemical data is understanding the relationship of its pattern to the subsurface.

THE MODEL

In the simulations that follow, I have defined the existence of hydrocarbon accumulations in two meandering river channels. Therefore, the patterns of anomalous samples are expected to be longer than they are wide, to have a preferred trend with some variation about this trend, and to have variable width. The sands are defined to be as deep as their average width, causing the fringe zone around the main trend to be approximately as wide as the target itself. There is no implied scale to the simulations. The relationships are entirely dependent on the sampling density per minimum anomaly width and the continuity of the anomaly along is greatest length.

A regular grid of simulated sampling locations was chosen to be 81 samples wide and 61 samples tall (giving a total of 4941 locations). A mask showing the location of the two idealized river channels and their representative fringe areas was superimposed on the sampling design to determine which stations would fall into background, fringe, and heart areas (Figure 4). Within each area, stations were chosen randomly and assigned to either anomalous or nonanomalous populations in the appropriate proportions (20%, 60%, and 80% anomalous, respectively) and to which of the five magnitude classes they belonged. Once this gridded data set had been created, it was decimated to create the various line and grid sampling patterns.

Reference cells (A–H, 1–11) have been provided to facilitate comparison between the target locations and simulations of the various surface expressions. Note that the widest heart area is one-half the width of a reference cell and the width of the fringe plus heart is about 1–1.5 cells. Note also that even longer adjacent line segments encompass both heart and fringe areas and are dependent on the angular relationship of the sampling program with the orientation of the target. Since interpretation is a personal task, the reader is encouraged to interpret the simulations shown in Figures 5 and 6 and compare their interpretation to Figure 4.

Line Profiles

Line profiles, which have been used for many years, offer a compromise between cost and density of information. This can be a real advantage in regional investigations or if the target's shape and orientation are known. This sampling design is particularly cost-effective for any technique that is approximately continuous, such as seismic profiles or marine sniffers. Figures 5a–d have a constant line separation of one cell and increase from a den-

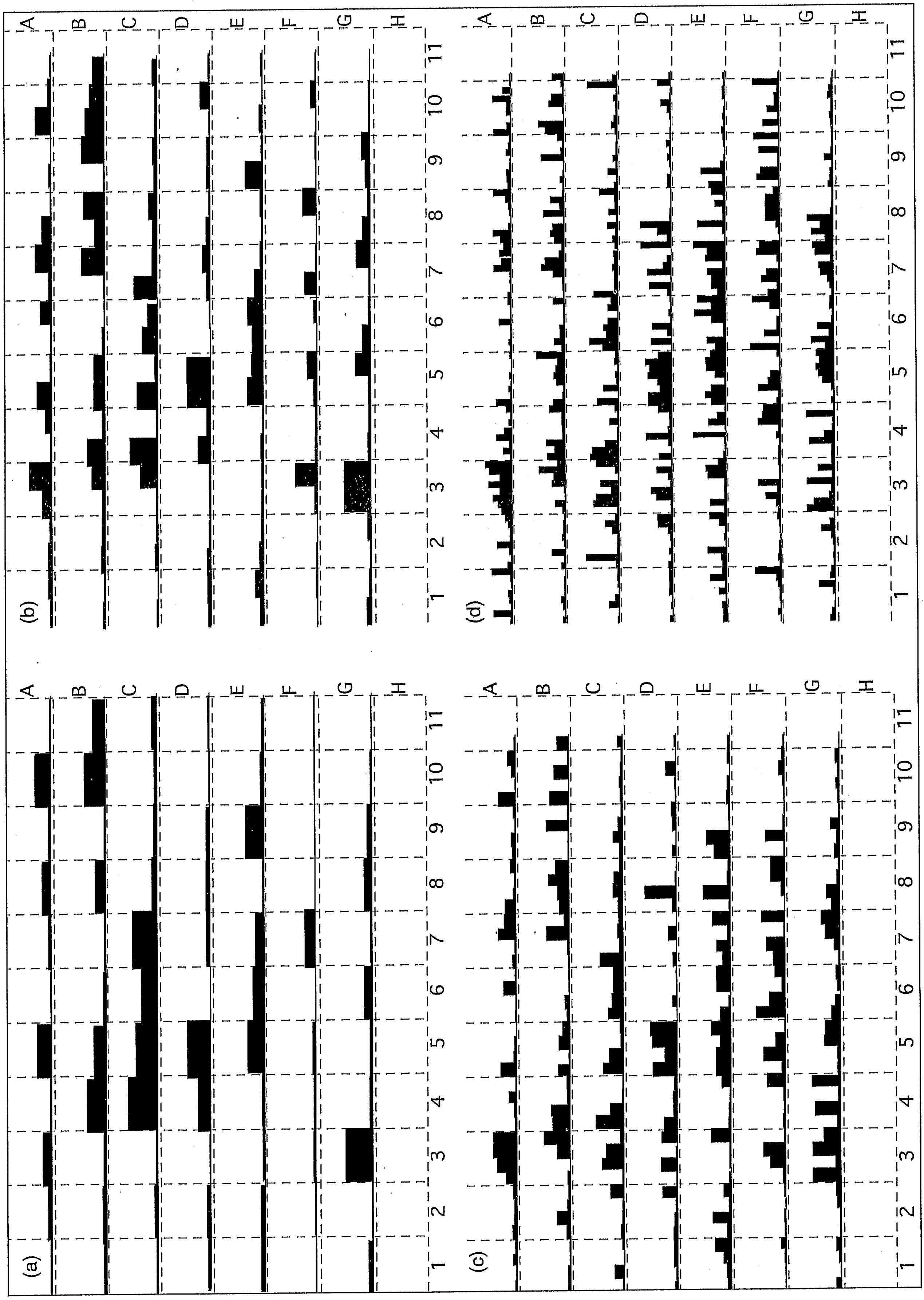

Figure 5—Seepage magnitude simulation of the line profile sampling technique shown at various sampling densities: (a) one sample per cell, (b) two per cell, (c) four per cell, and (d) eight per cell.

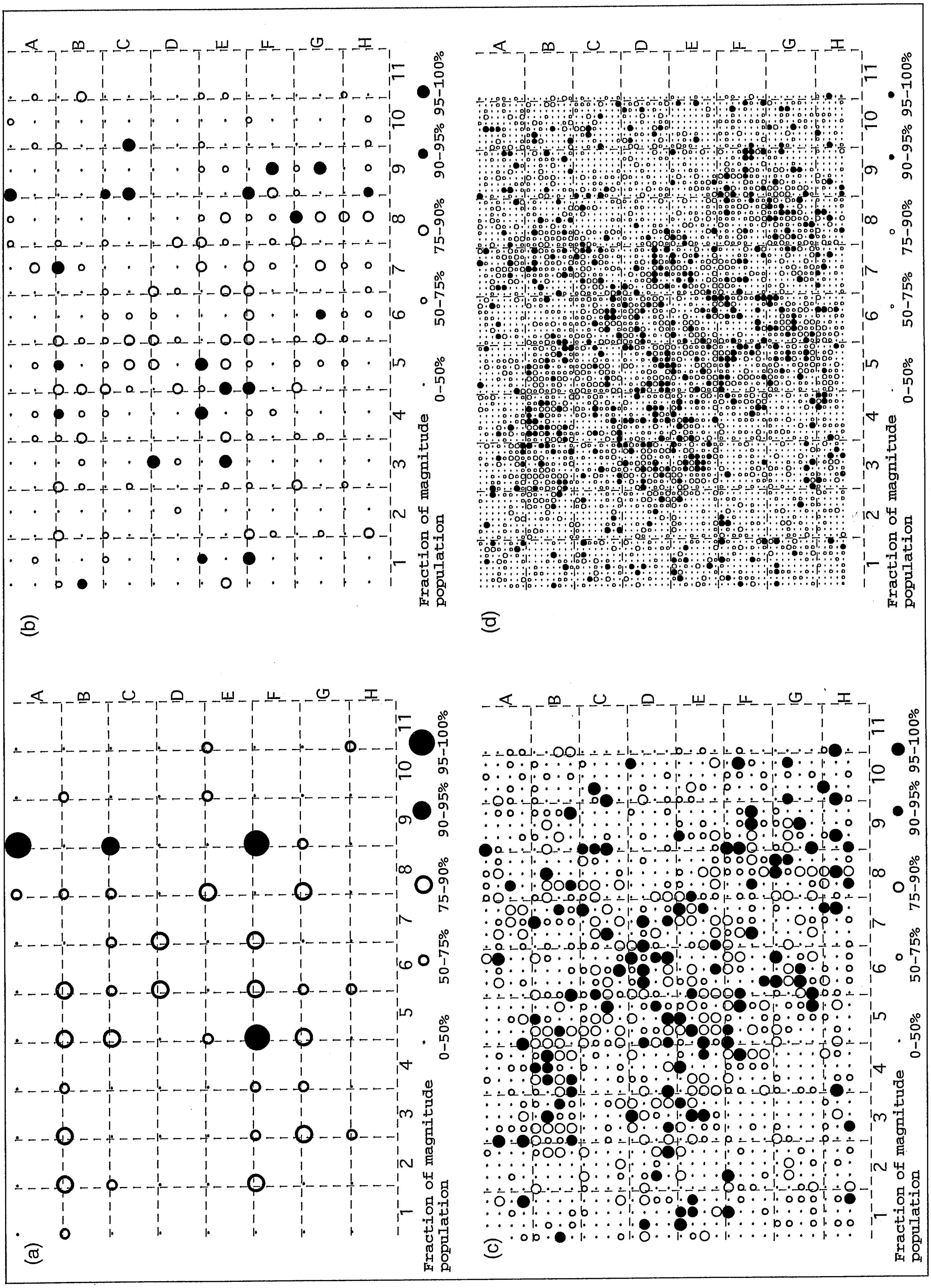

Figure 6—Seepage magnitude simulation of the grid sampling technique shown at various sampling densities: (a) one sample per cell, (b) four per cell, (c) sixteen per cell, and (d) sixty-four per cell.

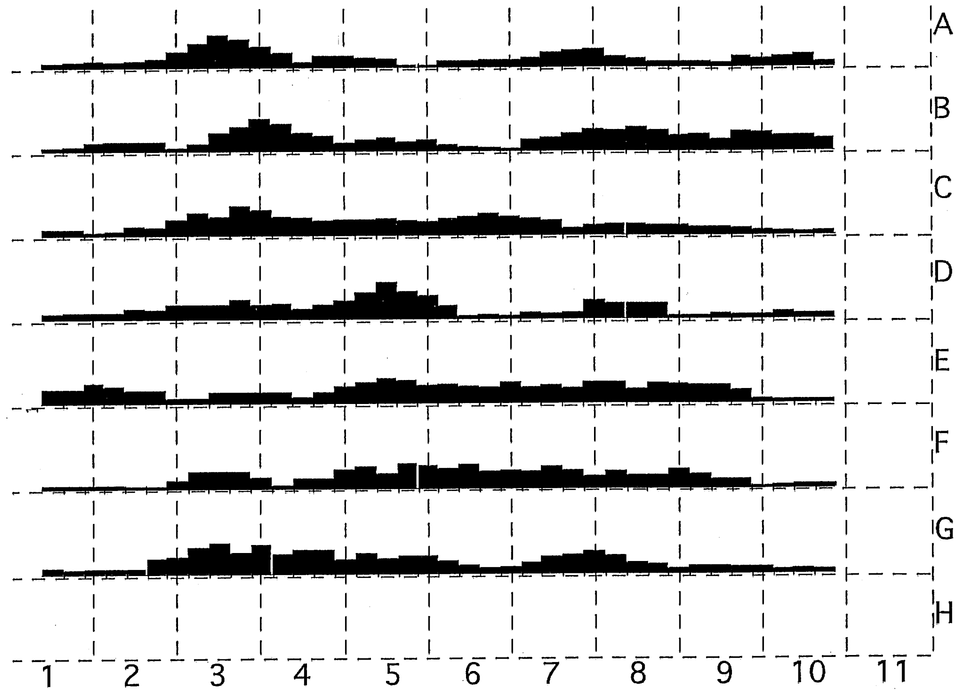

Figure 7—Four-point running average of the seepage magnitude simulation in Figure 5c.

sity along the line of one station per cell to a maximum of eight per cell. In Figure 5a, it is relatively easy to pick out major trends by emphasizing clusters of high-magnitude values. There are few samples, and most of the statistical chance of identifying the background area works for you. Hence, it should be easy to divide the region into areas of potential interest and no interest.

However, there is a high degree of aliasing of information, as can be seen by a comparison with Figure 5d. Figure 5a uses the first of the eight samples in each cell shown in Figure 5d. If the second or any other of the eight samples had been chosen, the results would have been quite different. Because there is a high chance of not identifying some of the potential target area, some opportunities may not be recognized. If individual high values are identified as being of interest, the risk of selecting background locations as areas of interest is increased. As the density along the lines increases (Figures 5b–d), decisions become more important. The chance of spurious high values increases, while the clustering tends to break into smaller areas. The chance of aliasing along the line decreases, but the aliasing between lines remains constant because the line spacing has not changed. It becomes increasingly difficult to correlate the smaller areas of interest detectable along the lines across the much greater distances between lines. It is difficult to identify the trend because of this spatial bias, except as a broad generality.

Grid Surveys

Grid designs keep the spatial density of sampling approximately constant. This is a significant advantage over line profiles in preparing maps. In Figures 6a–d, sample density increases from a spacing of one sample per cell to sixty-four samples per cell. Sample density in Figure 6a is identical to that of Figure 5a. The only difference is that the first row of data in each cell was used instead of the last, and the magnitude information has been grouped into the five classes. All discussion of Figure 5a applies equally well to Figure 6a. The effect of aliasing can be seen by comparison with Figure 6d. As the sampling density increases (Figures 6b–d), decisions again become more important because as the aliasing decreases, the visual appearance of the sampling noise increases. The tendency to focus on the individual rather than the larger pattern can be overcome by defocusing your eyes while looking at Figure 6d or by looking at it from a distance. A good relationship can be seen with the heart and fringe area of Figure 4. Simulation of higher density grids does not increase the relationship but simply reaffirms the assumed statistical chances that anomalous values correspond to the heart, fringe, and background areas.

Comparing Line and Grid Surveys

Because Figures 5c and 6b both have the same sampling density, they can be directly compared to determine the information gained for similar costs. The effect of smoothing the data by calculating a four-station running average is shown in Figures 7 and 8. This was accomplished in discrete steps for the line profiles that are shown at the same scale as Figure 5c. The gridded data were averaged by a running box and rescaled into five classes with the same percentage values previously discussed. Note that this spatial stacking suppresses the magnitude of isolated stray sites (see cell D3 in Figures 6b and 8), reinforces clustered high values (cell E5), and

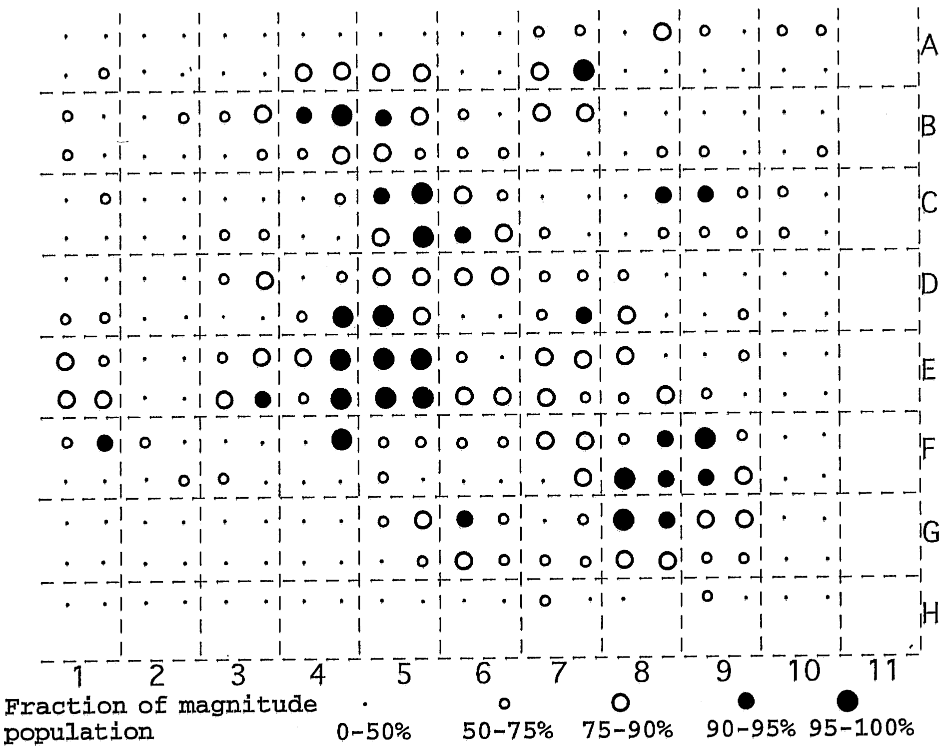

Figure 8—Four-point running average of the seepage magnitude simulation in Figure 6b.

diminishes but spreads out smaller isolated clusters of high values (cell C9). The readers are encouraged to draw their own conclusions about the relative values of the information derived from Figures 5–8. My personal preference is to examine a combination of raw and smoothed gridded data and to use an objective statistical test such as the technique described by Dickinson and Matthews (1993).

REGIONAL AND PROSPECT INTERPRETATION

Although the readers are encouraged to interpret the figures for themselves, the following observations are offered as a guide to a numerical comparison of interpreting the different sampling densities. The interpretation style chosen for this comparison is a simple rule-based technique. Sampled areas are considered to be homogeneous squares extending from a single data point located in the upper left-hand corner to the next data point to the right and down. For the purpose of regional high-grading, anomalous areas are those that contain a sample in the upper 50% of the measurements and are adjacent to at least four other such samples. The measure of efficiency in this paper is the percentage of total target retained in the high-graded region. For the purpose of prospect high-grading, anomalous areas are those that contain a sample in the upper 25% of the measurements and are adjacent to at least four other such samples. The percentage of the anomalous areas occupied by target is calculated and used as an efficiency measure. Different interpretation schemes will generate different but often not too dissimilar results.

The results of applying this technique to regional high-grading of the grid data are shown in Figure 9. The percentage of the total target area included in the high-graded region is maximized at slightly above four samples per cell. These values can be compared to an expected 4.5% value achieved by a random selection of 50% of the total area (about one-half the 8.9% of the target area). Actual high-graded areas were 40–43% of the total area for a sampling density of greater than four per cell and 48% for a sampling density of one per cell.

The results of applying this technique to high-grade prospect areas using the grid survey data are shown in Figure 10. The efficiency percentages on the graph are equivalent to the probabilities of being vertically over a portion of the target. They can be compared to the probability of hitting a portion of the target by random drilling in the entire area (8.9%), and the probability of hitting the target by confining random drilling to only the heart plus fringe areas (24.8%). Note that the efficiency of the survey, as defined by this measure, increases rapidly to a density of sixteen samples per cell and then increases much more slowly as the sampling density increases. This density ensures that four or more adjacent samples will be taken through the heart and fringe areas in any grid direction. The continuity along the length of the heart and fringe areas builds spatial sample correlation, while the requirement that four or more adjacent values must occur in the upper 25% of the population minimizes the selection of areas in the background region.

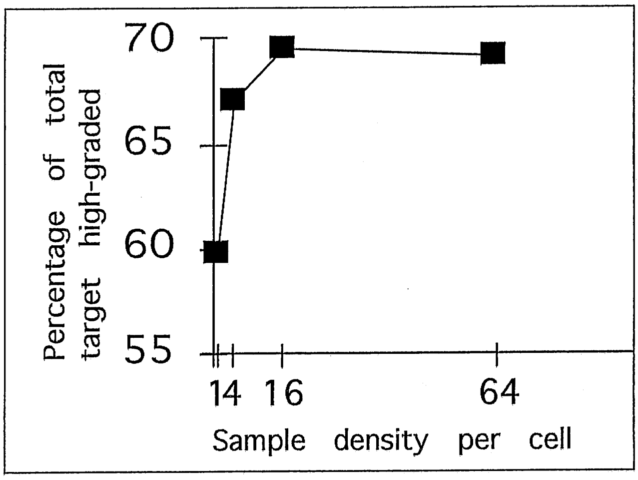

Figure 9—Percentage of the target that is high-graded by regional sampling using a grid survey.

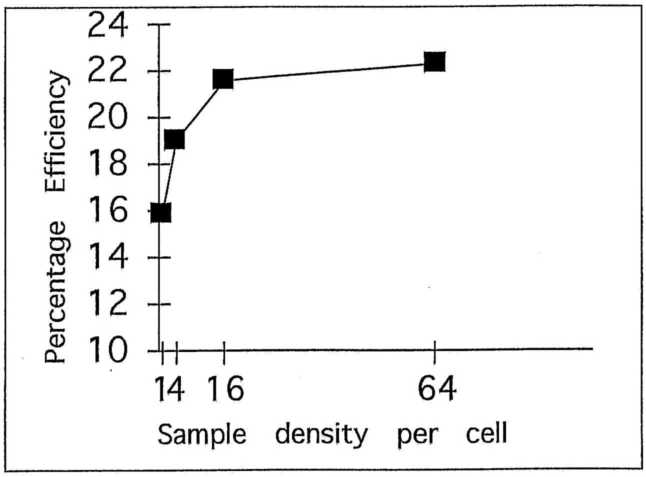

Figure 10—Efficiency (in %) of the target definition using a grid survey.

COST–BENEFIT ANALYSIS

One of the premises of this study is that taking too few samples is a false economy. To judge this, it is necessary to compare the expected direct cost of a survey to an estimate of the total exploration costs that could be saved by increasing the sampling. The costs used are only an example of one way to evaluate this decision. The comparison requires a measure of scale. Assuming the target occurs at a depth of 1.6 km (1 mi), the width of the fringe area (about one-half a cell width) is 1.6 km on each side of the heart of the anomaly. Thus, each cell is about 3.2 km (2 mi) wide. For purposes of discussion, I use a cost of $100 per station as the cost of a surface geochemical sample.

As an example of the cost versus benefit for a regional survey, consider the cost of increasing the sampling density from one to four samples per cell. For the surveys shown in Figures 6a and b, this would increase the number of samples from 88 to 336 and increase costs by $24,800. The cost of seismic data and processing is estimated at $3750/km ($6000/mi). A conservative regional program for the surveyed area (25.7 km north-south and 32 km east-west) would be three east-west regional lines, each 32 km long (ignoring the extra data needed to attain full stack over the entire length of the line). The total cost of this survey would thus be $360,000. The elimination of 6.7 km (4.2 mi) from this regional program (7%) would pay for the survey. If the regional seismic lines can be optimally placed by a surface geochemical survey to provide needed information, the total cost of the exploration program can be reduced.

As an example of the cost versus benefit for a program of several wildcat wells, consider the cost of increasing the sampling density on each prospect from four to sixteen samples per cell. For the surveys shown in Figures 6b and c, this would increase the number of samples from 336 to 1312 and increase costs by $97,600. The dry hole cost of drilling each well to 1.6 km is estimated at $250,000. Thus the break-even point for a wildcat program would be the elimination of 0.4 dry hole.

The greatest improvement in cost effectiveness would be achieved by a two-stage surface geochemical sampling program. For the 336 mi^2 area described above, this would entail an initial low-density regional survey at four samples per cell (one per square mile) at a cost of $33,600, followed by a prospect-scale survey of sixteen samples per cell over the 168-mi^2 high-graded area at a cost of $67,200. The total cost of this two-stage survey would be $100,800. The break-even point would be the cost equivalent of either 0.4 dry hole or 17 mi of seismic, or some combination of these.

SUMMARY

True comparisons of the effectiveness of particular sampling designs or densities can only be achieved if the answer is known without error. In the real world, there are too many uncontrolled variables, such as the permeability structure of the earth, the location of the reservoir, the action of bacteria, the location of the source rock, the effects of groundwater, and other factors. In this paper, the comparison is achieved by creating a known, simulated target and its constructed relationship to a survey whose results are determined by fixed probabilities of results. It should be emphasized that the measurement patterns shown here are not only a function of target shape and sampling design. They are also dependent upon the assumed model of seepage (vertical with a 45° fringe area), the probability of anomalous and background sample occurrences (80%, 60%, and 20% in the heart, fringe, and background, respectively), the range of values within the two populations, and the break points chosen for plotting purposes. Real-world measurements also include compositional information that can be helpful in identifying populations.

The effect of assumptions about the existence of a fringe zone on the interpretation of these simulations deserves special consideration. The proportion of anomalies assigned to the fringe zone is much closer to that assigned to the heart than it is to the background regions. This effectively enlarges the areal extent of the interpreted anomalous region, increasing the chance of the target being included within the regional interpretation scheme but simultaneously reducing the percentage of prospect-scale anomaly that is underlain by target. The larger the fringe zone, the lower the sample density needed for a regional survey, but the more difficult it becomes to locate the target within this zone. Conversely, a smaller fringe zone requires a denser sample spacing for the regional survey but results in a higher probability of locating the target within it.

Sampling designs for surface geochemical surveys must be designed to meet the goal of the survey. Is the goal to determine (1) if there is an active hydrocarbon system, (2) the type of hydrocarbons present, if any, (3) regions of general interest for further work, or (4) prospect definition? Because interpretation of data involves many decisions and choices, the readers will ultimately be required to draw their own conclusions and weigh the cost versus benefit of interpretation derived from the two designs and the different densities.

The most straightforward application of surface geochemistry, and the easiest to interpret, involves hypothesis testing using purposeful sampling. Spatial high-grading of areas within a larger region is more difficult. On the basis of simulations presented here, I believe the sampling method that is most interpretable with respect to defining the original target is the highest density grid (sixty-four samples per cell, Figure 6d). It seems, however, that a gridded sampling density of four samples per cell could provide sufficient regional resolution. A density of sixteen samples per cell would provide sufficient prospect resolution. Interpretation of a regional survey, followed by detailed sampling in the high-graded region, is the most cost-effective technique. If a different model was constructed, with a different fringe zone, proportions of anomalous and background populations, and continuity of target, the details of the results would certainly be different. However, the following basic principles should still hold: (1) at least two samples per line within the heart and fringe zone for regional high-grading, (2) a minimum of four samples per expected target width for prospect-scale surveys, and (3) sufficient samples in the background region to define the areas of interest (about five times as many as within the area of interest).

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