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Aerial Survey Design: A Systems-Analytic Perspective

Explicit analysis enables selection of improved survey designs.

Abstract: *In recent years there has been a progressively greater emphasis on the efficiency, rather than simply the feasibility, of aerial surveys for various applications. This paper describes a systems-analysis perspective to the design of an aerial survey. Specifically, it sets forth and illustrates a five-step process for the efficient design of an aerial survey. These steps include the (1) identification of survey objectives, (2) enumeration of survey options, (3) screening of these alternatives to identify candidates for detailed analysis, (4) evaluation of these candidates, and (5) selection of a final survey plan. Though both mathematical and statistical models are employed, the principal objective of this survey paper is to provide a conceptual framework for understanding the design process.*

Introduction

There are many articles and texts that introduce remote sensing and explain both practical and technical aspects of the design and execution of an aerial survey. The American Society of Photogrammetry's *Manual of Photogrammetry* and *Manual of Remote Sensing* contain relevant material as do books by Lintz and Simonett (1976) and Sabins (1978). From time-to-time, articles on the relative costs and efficiency of aerial survey and analysis options have also appeared (e.g., Ulliman, 1975; Maxim and Cullen, 1977; Ferguson *et al.*, 1981; and Stephens *et al.*, 1981). However, these papers are highly specialized. There is a dearth of material that addresses the more general design questions from a systems-analysis perspective (see, however, work of Philipson (1980)). This approach can be useful in survey design.

Diverse Perspectives

At the outset it should be noted that there are diverse perspectives to aerial survey design. The photointerpreter, for example, might wish multiple target images from various access geometries, sun angles, stereo coverage, absence of hot spots, etc. The survey pilot wants straight flight tracks, constant and safe altitudes, and flexible "time-windows" for imaging. Remote sensing specialists are interested in multispectral coverage, and the survey sponsors want their questions answered at reasonable cost. The key element of a successful survey is how these considerations are integrated into an effective design.

In this context the task of the systems analyst is to help sort through manifold design options, and technological and operational alternatives, etc., in order to integrate these into an overall plan that accomplishes the survey objectives efficiently. Useful general descriptions of systems analysis are those of Kahn and Mann (1956), Quade (1967), Quade and Boucher (1968), Churchman (1968), Kaufmann (1968), Breipohl (1970), and Fisher (1974).

Steps in the Process

Broadly, the job of the systems analyst in survey design can be described by the five steps shown following:

- Identifying the survey objective(s) and stating it (these) in precise terms,
- Enumerating the possible alternatives for survey design,
- Screening these alternatives to select good candidates for detailed analysis and comparison,
- Evaluating these candidates for cost and effectiveness, and finally,
- Selecting the best option(s) for consideration and implementation.

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These are discussed below.

Definition of Objectives

First, the need to identify the survey objective(s) is both obvious and important. It is important because, along with cost, it is one of the principal criteria by which a survey design is judged. Survey designs that are efficient for some objectives need not be efficient for others. In sampling a stratified population, for example, if the objective is to maximize the number of discovered "objects of interest," only those areas most likely to contain these objects should be selected;[1] yet this design would not provide information on other areas nor the population as a whole. Even when there is general agreement on the overall survey objectives, fine points can have significant leverage on choice of design. Maxim and Harrington (1982a), for example, present a discussion of optimal designs for aerial surveys taken at two time periods. Designs that maximize the precision of these estimated period-to-period changes require examination of the *same* (i.e., matched) quadrats in both time periods and differ from those designs that maximize the precision of the current period's estimate. Other examples are presented later. Objectives, therefore, need to be stated as precisely as possible; care is required in translating broad statements of objectives into useful operational criteria or measures of effectiveness.

The definition of objectives is facilitated if the important sources of error of the survey are identified beforehand. Table 1, for example, shows the general types of errors relevant to aerial surveys of agriculture and how these errors are quantified and measured. Some of these errors may be large while others may be sufficiently small to be disregarded. The contribution of these errors to various survey objectives is important. For example, an overall survey objective might require high precision for the final estimate of regional agricultural production. But often sub-objectives are also relevant, such as the precision of estimates for various geographic subdivisions. In addition, the precision of intermediate estimates such as hectareage or agricultural yield may be relevant to survey goals and, if so, should be reflected in the statement of objectives.

Selecting Candidate Survey Designs

A definition of survey errors (as shown on Table 1) is often helpful for structuring the search for alternatives and screening and evaluating these alternatives, the next steps in systems analysis. A common mistake in survey design is a premature specification and fixation on only a few alternatives, foreclosing consideration of other (possibly more attractive) choices. There are almost always alternatives to any proposed design and, within limits, the more of these considered the better. It is convenient to think of alternatives in several functional categories:

Table 1. Types of Errors Relevant to Aerial Surveys with an Agricultural Illustration

Error Type	Brief Description	How Quantified	How Measured
1. Detection Error	1. Failure to detect an agricultural field	Detection Probability p_d	Comparison of imagery-determined number of fields with ground-truth data
2. Identification Error	2a. Misidentification of target crop as other	False Negative Probability	Comparison of imagery field classification with ground-truth data
	2b. Misidentification of other crop as target	False Positive Probability (May be more than one if multiple crops involved)	
4. Yield Errors	4. Misestimating the yield per hectare	Standard error of yield estimate	Comparison of yield from prediction equation to fields of known yield or sampling studies on ground-truth plots
5. Sampling Error	5. Chance errors inherent in using a sample as an estimate of the population	Standard error of estimate	Standard statistical models

choice of platforms and sensor(s); exploitation technology (e.g., manual versus automated interpretation); statistical sampling schemes; statistical estimation (scale-up or classification) methodology; and, finally, such issues as survey timing and other operational details. Choices within each of these categories often have a hierarchical or tree-like structure. Figure 1 illustrates this with a partial list of statistical sampling options. Similar charts can be prepared for options in each of the other functional categories. Taken together, these options have a multiplicative or combinatorial quality. For example, if there are only six choices within each of seven categories, there are 6^7 or nearly 280,000 choices in all. It is, therefore, necessary to reduce the number of alternatives to a managable set for further detailed evaluation. This screening process can also be systematized by identifying and applying relevant criteria of choice for comparison of alternatives.

In some cases there are hard-and-fast survey specifications that must be met, and these constraints can be used to eliminate certain alternatives from consideration. From the viewpoint of the individual user, for example, Landsat's frequency of access is not a decision variable. If the survey application absolutely required more frequent access than is provided by Landsat, this option could be deleted (though composite strategies including data from several sensors might be viable). Likewise, long time lags for image receipt and processing might prevent use of a given option, etc. This all falls under the rubric of deleting infeasible alternatives.

Dominance arguments can sometimes be invoked to eliminate alternatives. One alternative is said to dominate another if, considering all relevant attributes, it is at least as good or better in every respect. For example, it is generally true that optimal stratified sampling plans result in a higher survey precision than those which use simple random sampling (though the differences can sometimes be small; see Cochran (1977) for examples where detection and identification errors are not considered). If the costs of the additional complexity of design and analysis are minimal, and if sufficient information is at hand to design a stratified plan, it follows that simple random sampling can be omitted from consideration. Likewise, color or color-infrared imagery is superior to panchromatic imagery for many applications involving detection and identification of vegetation (though costs may differ) and the black-and-white alternative can be eliminated.

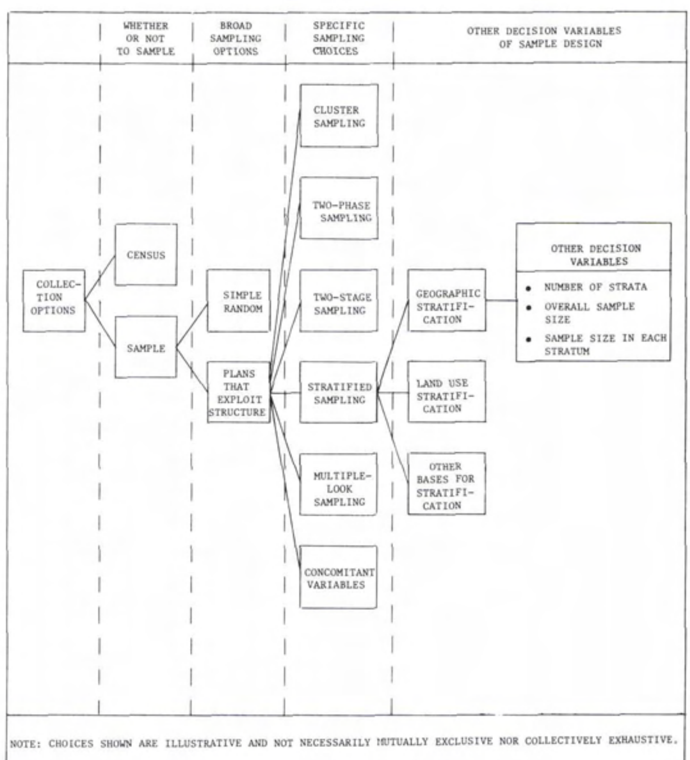

FIG. 1. A partial list of statistical sampling options for survey design.

Figure 2 shows the relevant steps in the design of an aerial survey, possible criteria for choice, and a partial listing of options and other details. The inputs shown to the left of the steps also imply relevant screening criteria. To illustrate, the first step given in Figure 2 refers to the specification of a sampling plan. Possible options are shown to the right, while relevant considerations and inputs are shown to the left. One criterion shown on this figure is the availability of exogenous information. As noted by Maxim (1982) exogenous or prior information can be used to develop efficient sampling plans, identify improved estimators, determine hybrid estimation schemes, and check the plausibility of survey estimates. Each sample design (e.g., *stratified random* sampling, two-stage sampling) has unique information requirements, however, and lack of the requisite prior knowledge serves to limit choices. To develop an optimal stratified sampling plan, for example, requires knowledge of, among other things, the areal extent of each stratum and estimates of the strata means and variances. If these are not known (at least approximately), then a stratified plan cannot be employed and the set of options is narrowed. Space constraints do not permit an extensive discussion of Figure 2, but it summarizes many relevant considerations in survey design.

One of the interesting choices highlighted in

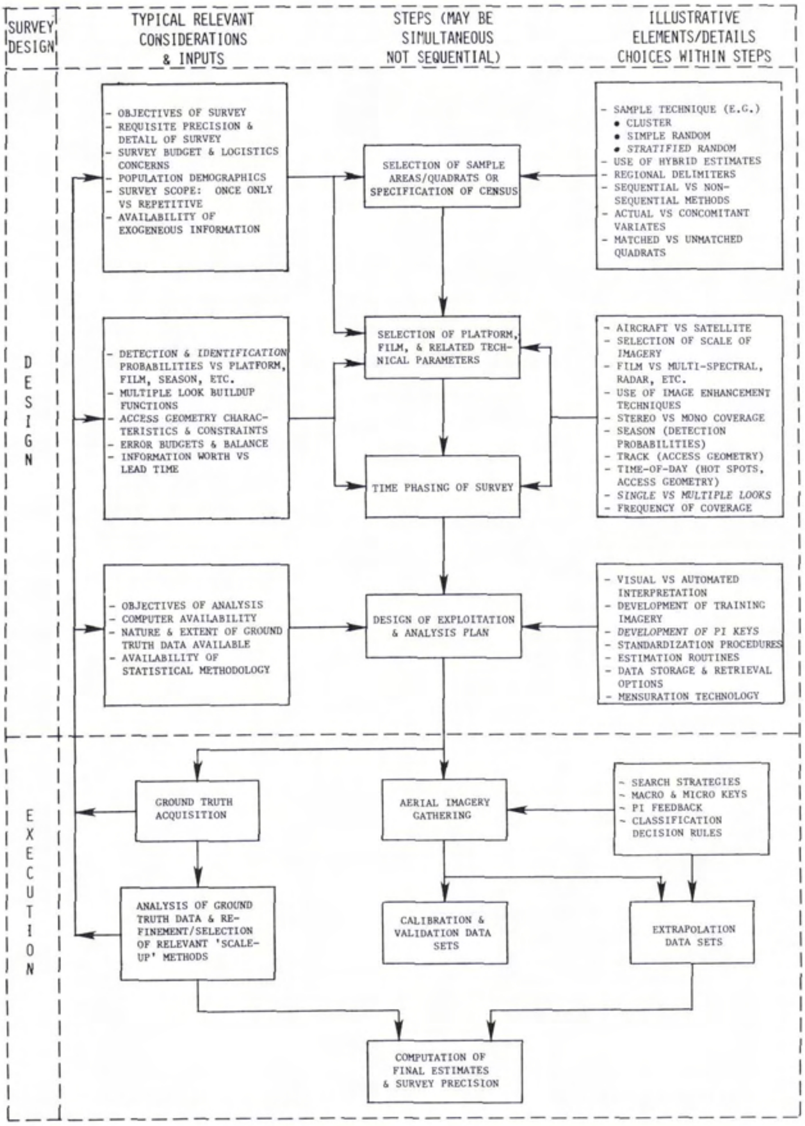

FIG. 2. A systems-analytic overview of steps in the development and execution of an aerial survey.

Figure 2 is the question of whether to sample or take a complete census of the population; or possibly to do both. For many purposes (e.g., mapmaking), a complete survey or census is required. For others, such as crop production estimates, a sample may offer sufficient precision at lower cost. For yet others, the choice of sample versus survey cannot be resolved beforehand, and a composite or sequential strategy merits consideration. Lamb (in Johannsen and Sanders, 1982) provides an example in this latter category. Lamb describes the use of low-altitude aerial photography to identify problem agricultural areas in the southern part of the Columbia River Basin. Specifically, low-altitude color-infrared aerial photographs can be used to detect a variety of problems (e.g., irrigation sprinkler malfunction, overfertilization, poor fertilizer distribution, improper spraying, soil problems, etc.) in center-pivot irrigated farming areas. Detection of one or more of these problems in a given field enables corrective action to be taken, preventing later yield losses. In a real sense, each detected problem is worth money, and a simple model, shown in footnote 2, can be used to compute the profitability of an aerial survey. The actual survey, incidentally, is a census, not a sample. But a key factor in the profitability equation is the number of "problem pivots" in the farm—too low a number implies that the costs of the survey outweigh its savings. This number may not be known beforehand—an observation which suggests a composite or sequential strategy. That is, conduct a preliminary survey based on only a sample of fields in order to estimate this quantity and, if "sufficiently high," fly a complete census; otherwise, defer any action to a later cycle when this series of actions is repeated. Where feasible, such sequential strategies merit consideration.

Once the screening step has been completed, more detailed evaluation of the remaining survey alternatives can be undertaken. Mathematical and statistical models of the estimation logic and survey error propagation are essential for this detailed evaluation. Work by Bauer *et al.* (1978), Frazier and Shovic (1980), Todd *et al.* (1980), Hixson *et al.* (1981), Maxim *et al.* (1981 a, b, c, 1982 a, b), Maxim (1982), and Cochran (1977) serve as examples. Several uses of such models are illustrated here. The next sections cover some important issues to be examined as part of the evaluation step.

Survey Precision: How Much Is Enough?

A basic question to be answered early in the design of any aerial survey is, "How much precision is required?" Generally, the precision of an aerial survey can be increased if more resources are expended. More and better sensors can be employed, sophisticated image-enhancement techniques can be used, the scale of the imagery can be altered, the size of a statistical sample can be increased, etc. However, a basic principle governs these choices: Increases in survey effort or expenditure often bring about less-than-proportional increases in survey precision. This is a well known result for sampling: Figure 3 illustrates this square root dependence. In this illustration, "objects of interest" are being counted in an area subdivided into 1000 quadrats—identification errors are neglected and curves are presented for two assumed values of the detection probability. For the numerical assumptions shown, a sample size of 40 quadrats is sufficient to estimate the total number of objects in the population, T, to within about 25 percent (i.e., $\sigma_T/T = 12.5\%$) if the detection probability $p = 0.2$ and there is no misclassification.[3] Doubling the sample size increases the precision to within about 18 percent—an improvement to be sure, but not a *doubling* of precision (halving of the standard error of the estimate). Economists term this "diminishing marginal returns" (DMR). Experience suggests, however, that this DMR effect is not limited to sampling laws alone, but applies more broadly (see also Slater (1980) for additional perspective). Thus, it is of central importance to establish targets for survey precision early in the design effort.

Setting targets for survey precision requires careful thought about the objectives of the survey and the consequences of imprecise estimates. It is often a matter of judgment, though explicit models can be used in some cases (e.g., discussions on "the value of information" in texts on decision theory such as Raiffa (1977)) to structure this judgment. At a minimum, it is worthwhile to compute curves, such as those shown in Figure 3, to enable "the price of precision" to be known. This is a convenient starting point for thinking about how much precision is required, particularly when the x axis is converted to units of survey cost rather than sample size.

It is often true that survey precision *per se* is not the relevant measure of effectiveness. Rather, the *value of the information* is what is really at issue. Nelson (1981), for example, did an interesting study of the use of Landsat (specifically the ratio of band 7 to band 5) for monitoring forest canopy defoliation by gypsy moths. A major research question was the optimal time for such a survey. If the survey was conducted "too early" in the season, little detectable defoliation had occurred. If the survey was "too late," refoliation may have occurred and infestation was again difficult to detect. Nelson found that June was an optimal time for detection. But suppose that, following the survey, some corrective action (e.g., spraying) was planned. It is reasonable to suppose that the benefits of spraying would be greater if the infested trees were detected earlier. This consideration might alter the optimal survey timing substantially. The survey user might well prefer a less precise answer earlier in the season than a highly accurate estimate after considerable damage had been done. These statements are not intended to be critical of Nelson's analysis. If no corrective ac-

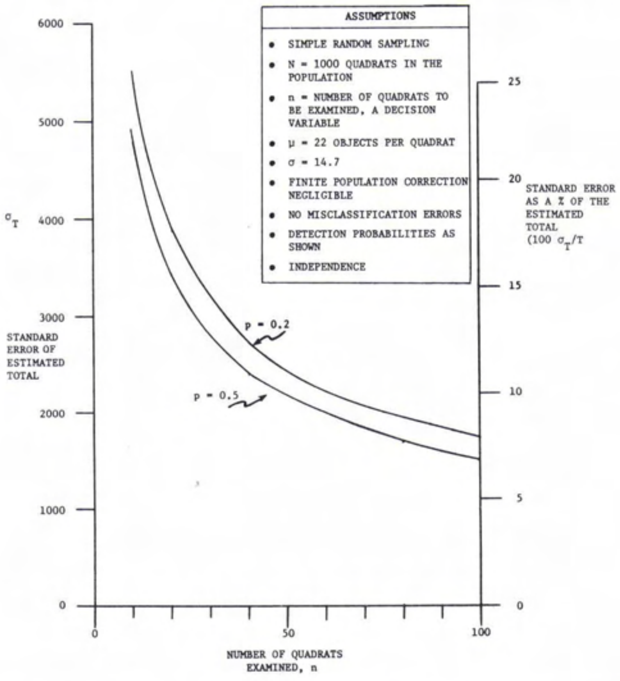

FIG. 3. A basic characteristic of sampling problems—diminishing marginal returns.

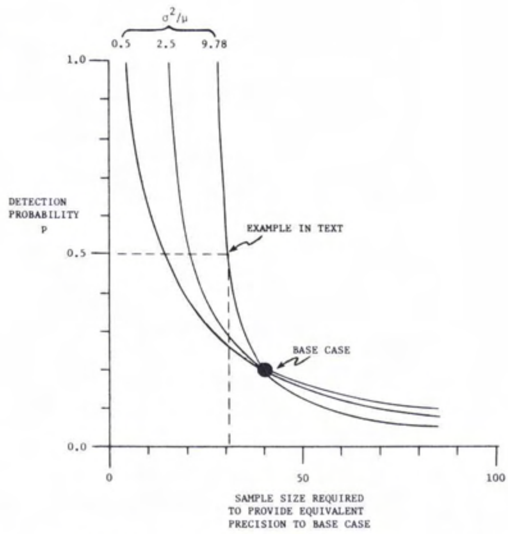

FIG. 4. Parametric Analysis characterizes trade-off possibilities.

tion is contemplated or if timely information is not essential, then maximizing detection probabilities is a reasonable basis for survey scheduling.

As a second example, the United Nation's Food and Agriculture Organization has initiated a pilot project on the use of remote sensing to detect areas where locusts might breed. As a recent article (*The Economist*, 1982) notes, "There is no mystery in predicting where and when locusts are going to breed: dry areas where there has just been heavy rainfall. But speed is essential. Locusts start breeding within days of a triggering fall of rain." Both response time and accuracy are important in this application.

These are examples of the sense in which the phrase "information worth versus lead time" is used in Figure 2.

ENTER TRADEOFFS—A SECOND IMPORTANT CONCEPT

Setting forth information as shown in Figure 3 suggests other relevant issues. This figure details replicate computations at two assumed detection probabilities, $p = 0.2$ and $p = 0.5$. As noted for $p = 0.2$, a sample size, n, of 40 quadrats result in a precision of about plus or minus 25 percent. But, if p were raised to 0.5, as a result of some technological improvement, a sample size of only slightly more than 30 would produce equivalent precision. It ultimately becomes a matter of relative cost which of the two alternatives is more efficient. Here savings in sampling effort are balanced against the (presumably) higher cost of employing a technology with a higher detection probability. Sample size is being "traded-off" against detection probability. While the *existence* of this trade-off is independent of other factors, the *magnitude* of the exchange depends upon the characteristics of the population: in this case specifically, the ratio of σ^2/μ. Here σ^2 is the variance in number of objects per quadrat and μ the mean number of objects per quadrat. If the population is more homogeneous (i.e., σ^2/μ is smaller), sampling errors (which can be reduced by examining more quadrats) are less important than detection errors. This is shown in Figure 4 by plotting the detection probability sample size trade-off for various values of the ratio σ^2/μ. Note that as σ^2/μ *decreases*, the potential sample size savings associated with higher detection probabilities *increases*. This example also shows why it is difficult to establish rules-of-thumb that are sufficiently general to be useful; efficient survey design is often "application-specific."

A second example of a trade-off is furnished by an application studied by Best *et al.* (1982). They considered the problem of estimating the number of Canada geese on the mainstem reservoirs of the Missouri River in central South Dakota during the annual fall migration. Low-altitude daylight aerial photography offered high detection probabilities for geese, but the birds feed in agricultural areas surrounding the reservoirs during the day, increasing the aerial coverage necessary for estimation purposes (and possibly lowering bird-concentration-dependent detection probabilities). At night the geese rest on the reservoirs, and thus present a more attractive "target" for imaging, but only by less capable sensors (thermal imaging). This application likewise requires a trade-off to find the right compromise between detection and sampling errors. This example is also instructive because it shows an interaction between the characteristics of the population being studied and the array of feasible sensor systems.

Uses of Models

The first example directly above illustrates the utility of simple calculations, and their underlying mathematical statistical models. The problem description implied that technological alternatives with higher detection probabilities were available. In practice, it might not be known what these are or even if they exist. Still, it is instructive to ask "what if?" For the problem posed originally, these computations would save a fruitless search for improved sensors. If the population parameters were different, however—say a ratio σ^2/μ of 2.5 or less—the potential gains of high detection-probability options would be more attractive and the search for such options may be justified.

The term "sampling error limited" is used to describe this situation. Loosely, this means that the contribution of sampling error to total error is high. In other surveys, detection or identification may be the critical process; these are said to be "detection limited" or "identification limited." Note that this condition is a function of the values of *all* of the variables. In the example's base case, the detection probability is only 0.2; yet sampling error and not detection error is controlling because of the large value for σ^2/μ.

Trade-Offs Among Error Sources; An Overlooked Aspect of Survey Design?

The example shown in Figure 4 illustrates trade-offs among error sources. Here detection error is being exchanged for sampling error. This is a common (though not always recognized) situation in aerial survey design. Lillesand *et al.* (1981), for example, investigated various approaches for detection of Dutch Elm disease. Their approach was to use 1:6,000 scale imagery taken in early May (when leaves were off the trees) to identify elm trees and prepare a base map. This was compared with imagery taken in mid-season (25 July) when the health of these trees was inferred from various photographic signatures. Mid-season photography was not used for identification of elms because "accomplishing these tasks with leaf-on images is much more difficult given overlap between crowns and the similar appearance of elms and other species." For a fixed imagery budget, however, using observations at two time periods might not be possible or the size of the sample that can be taken in mid-season might have to be reduced. That is, *identification* error is reduced but *sampling* error is increased—another trade-off between errors in an aerial survey. In their published work Lillesand *et al.* did not present data showing the merits of this trade-off, presumably because the answer was believed self-evident. The objective of this example is not to take a contrary position, but rather to indicate the pervasive, and sometimes subtle, nature of possible trade-offs or "latent options."

In agricultural surveys the trade-off between errors in estimating hectareage and yield may be worth exploring. Total production of a crop is the *product* of the number of hectares with the yield per hectare. The variance of the estimate of total production is a function of the variances of each of the estimates of hectareage and yield. In some cases, agricultural yield is exogeneous to the survey and, therefore, not a design option. If the uncertainty in this exogeneous yield estimate is known, it can be used to compute the resulting uncertainty in production. But, in other cases yield estimation is an integral part of the survey effort. If yield measurement is part of the survey, then it consumes resources which might be otherwise allocated, and the concept of a trade-off between yield and hectareage errors is relevant. Overall, survey precision can be improved by increasing the precision of either the hectarage or the yield estimate. The trade-off occurs because, if total survey effort is held constant, any increase in the precision of one estimate may only come about at the expense of a decrease in the precision of the other.

Trade-Offs Not Resolved by Cost Considerations

In the trade-offs presented thus far, it is possible (in principle at least) to select a best design by evaluating the costs of various alternatives described by the trade-off curves (survey precision held constant). There are circumstances, however, where this is more complex. Such is the case if there is more than one survey objective. As noted earlier, survey designs that are optimal for one objective often differ from those that are optimal for another, and thus the objectives themselves need to be balanced in survey planning.

Table 2 shows an example of a stratified sampling plan that illustrates this point (Maxim, 1982). The plan in this illustration was designed to select the number of quadrats to be sampled in each of three strata in order to maximize the precision of the estimated total number of objects in the survey population. For a sample size of 100 quadrats, the resulting precision of the estimate of the population total (as measured by the proportional error, σ_T/T) is 5.5%.[4] (Note the improvement offered by this sampling plan over simple random sampling of the same population shown in Figure 3.)

Column 10 of Table 2 shows the proportional error

TABLE 2. COMPUTATION OF OPTIMAL STRATIFIED SAMPLING PLAN; DETECTION PROBABILITY $p = 0.2$

	1	2	3	4	5	6	7	8	9	10
Stratum	Number of Quadrats in Stratum N_j	Stratum Mean μ_j	Stratum Variance σ_j^2	$\mu_j(1-p)/p$	K_j^2	K_j	K_jN_j	$n_j = \frac{100\ N_jK_j}{\Sigma N_jK_j}$	Integer n_j	Proportional Error σ_T/T
1	300	20	64	80	144	12	3600	29.80	30	10.95
2	300	40	25	160	185	13.60	4080.4	33.77	34	5.83
3	400	10	81	40	121	11	4400	36.40	36	18.33
Total or average	$N = 100$	$\mu = 22$	$\sigma^2 = 215.23$			$\Sigma N_jK_j = 12080.4$		$n = 100$	100	5.49

$$\sigma_T^2 = (\Sigma n_jK_j)^2/n = 1,459,336 \quad \sigma_T = 1208$$

for estimation of each stratum total. In particular, the proportional error for stratum 3 is 18.3 percent. Holding the design, strata definitions, and number of strata fixed, the proportional error in stratum 3 can be reduced by increasing the number of quadrats sampled from this stratum, denoted by n_3. But this choice *increases* the proportional error in the other strata, as well as that of the estimated population total. Figure 5 shows these points graphically. If, for example, n_3 were to be increased to from 36 to 60, the optimal values for n_1 and n_2 would shift to 19 and 21, respectively; the proportional error in stratum 3 would be reduced to 14.2 percent, but those for strata 1 and 2 would increase to 13.8 percent and 7.4 percent, while the overall proportional error would increase by nearly 11 percent, from 5.5 percent to 6.09 percent. Which plan is best depends upon how the various objectives are weighted—a trade-off not resolved by cost considerations directly because survey effort is held constant among these options. This example further illustrates the importance of *precise stipulation* of survey objectives and measures of effectiveness.

The above advice to specify objectives carefully is sound and important, particularly if survey efficiency is critical. But, as a practical matter, it is not always possible to be so explicit. Many surveys have

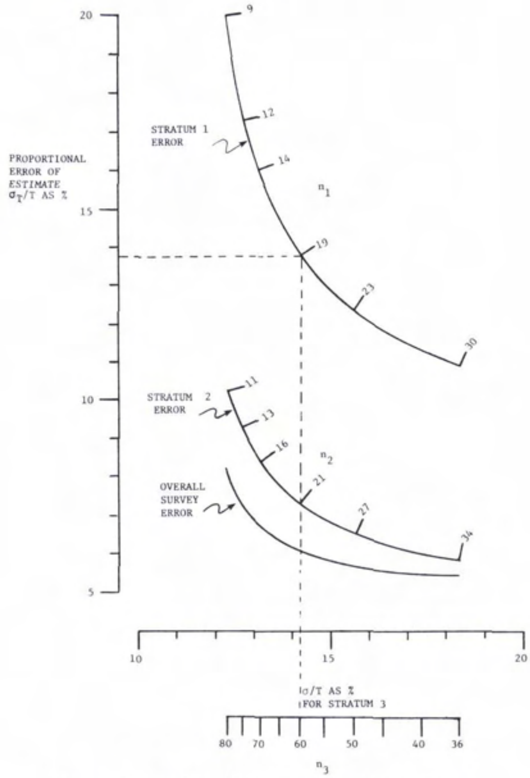

FIG. 5. Trade-offs in stratified sampling.

a strong research component, and survey objectives are less clear cut and emerge only gradually as the data are analyzed. In terms of the above example, stratum 3 may only become "interesting" after some of its characteristics are discovered. A better approach in this case is to abandon the search for a "perfect" survey design (in terms of any one objective) and settle instead on a survey design which is acceptable for many objectives. *Robust* designs, as they are called, reflect exactly this idea. Central to the construction of robust designs are a series of computations to evaluate the design efficiency in terms of several candidate objectives. This is another way in which the computations summarized in Figure 5 can be used. According to these computations, "small" increases in the precision of the estimate for stratum 3 can only be purchased at the expense of "large" decreases in the precision of other estimates (when survey effort is held constant); perhaps an unacceptable exchange. Graphs such as Figure 5 help the analyst to see the consequences of these options and make informed choices.

A Key Concept—Sensitivity Analysis

Many structural, logical, and numerical assumptions underlie the choice of survey design and analysis techniques. Logical assumptions about the nature of measurement error, for example, affect the appropriate models for analysis (independence/dependence of detection outcomes, whether or not detection or identification are size-dependent, how detection probabilities increase with the number of looks, etc.). Numerical assumptions often underlie the choice of sampling design (e.g., population statistics μ and σ^2 are used directly in determination of the optimal sample size for each stratum if a stratified sample is selected extrapolation methodology) and specific scale-up equations (e.g., detection and identification probabilities as used in scale-up formulas), to cite just two instances. Some of these inputs may be known exactly, but most have varying degrees of uncertainty. As well, not all assumptions are of equal *importance* to the choice of survey design or analysis technique.

Sensitivity analysis is the name given to a systematic procedure for evaluating the leverage of uncertain assumptions on the decisions at hand. In its simplest form a sensitivity analysis can be conducted by varying each of the numerical inputs by a stated amount (e.g., 10 percent, 20 percent) and noting the changes in the relevant decision variables or measure(s) of effectiveness. In this way, assumptions can be rank-ordered in terms of importance. Special attention can be accorded critical assumptions and, in some cases, validation experiments can be included as part of the survey plan. Alternatively, survey designs and analysis techniques can be selected that, though not necessarily optimal given complete information, are more robust to misinformation. The importance of sensitivity analysis cannot be overstated.

Survey Plan Selection: The End of the Beginning

The last step in the survey planning process is the selection of the final survey and analysis plan from among the best alternatives. This work includes the obvious tasks of translating the survey data into requisite estimates and their associated precision. But it should also include a program of monitoring the results as they become available. Monitoring activities often include:

- *Validation checks of important assumptions* where these can be made. For example, a simple scale-up rule for crop estimation in a multi-crop environment might assume that there are only two crops; the crop of interest and "all others." If misclassification probabilities among these other crops are constant and/or if the mix of other crops is constant, the two-crop representation is adequate and subsequent interpretation effort can be simplified. The adequacy of the two-crop representation can be tested as part of the survey.
- *Exploiting early returns to shift collection emphasis.* Unexpected rainfall or temperatures during the growing season of a crop, for example, may result in a different geographic distribution of crop production for that year and hence a need to re-evaluate sampling plans. The discovery of a promising mineral "target" in an area to be explored might alter the subsequent search strategy. Obviously, the feasibility and utility of sequential strategies varies among specific applications but (as noted earlier) these are worthy of consideration.
- *Exploiting early returns to shift analysis emphasis.* There are circumstances where the imagery acquisition plan cannot readily be altered (e.g., with Landsat), but the exploitation and analysis plan can be adjusted in response to the survey data. In two-stage sampling, for example, the sampling frame may consist of "large" quadrats which can be further divided into several "small" quadrats. If data analysis indicates that the objects of interest are fairly evenly distributed over small quadrats within a large quadrat, but appreciable differences exist among large quadrats, then it may be optimal to select only a few small quadrats within each large quadrat. The exploitation effort "saved" by this cluster sampling procedure can be better "spent" by examining a greater number of large quadrats. (See Cochran (1977) for applicable models absent detection or identification errors.)

Though unexpected results can always occur in the survey-analysis phase, it is wise to do as much pre-planning as possible. A well-structured analysis plan can anticipate many contingencies.

Merits of The Overall Design Approach

Key features of the approach described here include:

- Explicit—Models that underlie analysis often force consideration of relevant issues. Assumptions are made explicit and can be more readily examined and challenged.
- Systematic—The process of structured search for improved design alternatives is highly systematic. This lowers the likelihood that efficient alternatives will be overlooked.
- Efficient—The systems analysis approach captures, however imperfectly, both the benefits and costs of design alternatives. There is at least a guarantee of efficiency over the set of alternatives considered (sub-optimization).
- Verifiable—Some of the analytic computations are verifiable. Explicit computation of the final precision (or other measure(s) of effectiveness) of the survey is possible. The sensitivity of the computed measure(s) of effectiveness to various assumptions can be evaluated and many of these assumptions can be tested.

Concluding Comments

George S. Morrison, in discussing the planning for the so-called Culebra Cut, a famous and difficult part of the Panama Canal, remarked that: "It is a piece of work that reminds me of what a teacher said to me when I was in Exeter over forty years ago; that, if he had five minutes in which to solve a problem, he would spend three deciding the best way to do it," (see McCullough, 1977)—a sentiment echoed here.

Notwithstanding the above, the relative text area allocated to the design and execution phases of the survey shown on Figure 2 reflects the emphasis of this paper, not an estimate of the resources that should be allocated to each phase. As with other activities, the depth and extent of analysis is subject to trade-offs. An elaborate and expensive survey may justify substantial planning and analysis in search of efficiency gains, but it must be remembered that these activities are a means to an end—and not ends themselves. Such effort need not be elaborate in order to be useful, and it is important not to confuse the *scale* of analysis with the *content* of analysis. Even simple analyses can address the relevant issues.

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Footnotes

1. This assumes that the sample size is smaller than the number of quadrats in the richest stratum, and that detection probabilities are constant across all strata. If not, other strategies may be best. Problems of this sort are in the domain of what is called "search theory"—a sophisticated and well-developed branch of operations research. For interesting geological examples see Koopman (1956-1957), Brown (1960), and Koch and Link (1980).

2. Let N be the number of center-pivot irrigated fields in a region, f the number of frames of imagery required for a census, μ the average number of problems per field (presumably significantly less than 1), ω the "worth" of a detected problem, F the fixed cost of a photo-mission, and c the average acquisition and exploitation cost per frame. Then, the "profit" of an aerial census, Π, is

$$\Pi = \text{“Revenues”} - \text{Costs}$$

$$\Pi = N \mu \omega - F - cf.$$

A necessary and sufficient condition for Π to be positive is

$$\mu > \frac{F + cf}{N \omega}.$$

It should be noted that the sequential option discussed in the text is only one strategy for estimating μ. Over time, historical data may be used to estimate μ or alternatively to estimate survey timing. Lamb (1982) apparently chose the latter approach, flying photo-missions every week during the growing season. Depending upon the values of the various cost factors and the size of the farm, this may be a preferred strategy; models can describe this choice.

3. The equation for the variance of the estimated total, σ_T^2, is given by

$$\sigma_T^2 = \frac{N^2}{n}\left[\frac{\mu(1-p)}{p} + \sigma^2\right]$$

where N = number of quadrats in the population,
n = number of quadrats in the sample (assumed small relative to N),
μ = mean number of objects per quadrat,
σ^2 = variance of the number of objects per quadrat, and
p = detection probability.

Several assumptions underlie this model (Maxim *et al.*, 1981b).

4. The variance of the estimated total, σ_T^2, from a stratified sampling plan (given some simplifying assumptions) is

$$\sigma_T^2 = \sum \frac{N_j^2}{n_j}\left[\frac{\mu_j(1-p)}{p} + \sigma_j^2\right]$$

where the subscript j refers to the stratum. Otherwise, the terms are as defined in footnote 2. The design that minimizes this variance for a fixed number of quadrats to be sampled, n, is given by

$$n_j = \frac{n\, N_j K_j}{\Sigma\, N_j K_j} \quad \text{where} \quad K_j = \left[\frac{\mu_j(1-p)}{p} + \sigma_j^2\right].$$

See Maxim *et al.* (1981c) for details.

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