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Part II

SAMPLING DESIGNS FOR RARE SPECIES AND POPULATIONS

Part II of this volume describes sampling designs for efficiently estimating abundance of rare species and populations, with a greater emphasis on the first stage of a two-stage design, that is, probability-based selection of sampling units. Consequently, Part II serves as a starting point when developing a design for sampling rare or elusive species.

Adaptive cluster sampling is a relatively recent design for sampling individuals that are spatially clustered within a relatively small portion of a study area. Although much recent work has been devoted to its theoretical development, Smith et al. (Chapter 5) venture beyond theory to provide an evaluation of adaptive cluster sampling when applied to real populations. They describe practical examples of this design and offer guidelines for its usage. In the next chapter, Manly describes an alternative adaptive approach to estimating abundance of rare species based on a two-phase, stratified sampling regime. Christman completes this section by reviewing the sequential sampling design, another form of adaptive sampling, and uses it to estimate abundance of a waterfowl population.

5

Application of Adaptive Sampling to Biological Populations

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Adaptive sampling is appealing because it mimics how biologists would like to collect data—at least more so than most statistical sampling techniques. When adaptively sampling, biologists search for a species of interest at predetermined locations, and if the species is found, searching continues nearby. This procedure usually produces a biased sample when applied to spatially clustered species because occupied habitat will be sampled disproportionately. Fortunately, Thompson (1990 and subsequent papers) showed how unbiased estimators of density and abundance could be obtained by following the adaptive cluster sampling procedure.

Additional appeal of adaptive cluster sampling can be attributed to its statistical properties. For species that tend to be rare and spatially clustered, adaptive cluster sampling has the potential to be efficient; that is, it can result in estimators of population density or abundance with smaller variance than conventional sampling methods for equal effort (Roesch 1993; Brown 1994; Smith et al. 1995; Christman 1997; Lo et al. 1997). Getting reliable information on rare and spatially clustered species can be challenging and costly, so any increase in reliability of information or reduction in survey cost is welcome and desirable.

It must be noted, however, that a theoretical increase in efficiency alone is not sufficient motivation to move a statistical method from theory to practice. There is little gain if a method, no matter how promising, is not put into practice. Paraphrasing John Tukey (1986:97), practical efficiency is equal to the statistical efficiency of a method times the probability that the method will be put into practice.

Despite its promise, there have been few real applications of adaptive cluster sampling in the published literature. By far, studies have focused on theoretical considerations and simulation studies (e.g., see Thompson 2003 and articles therein). The reason for this pattern, we believe, is two-fold. First, the methodology is still relatively young, and it takes time for new methods to work their way into common practice. Second, a set of challenges tempers the appeal of adaptive cluster sampling. In our view, challenges when applying adaptive cluster sampling include:

1) Increased efficiency is not guaranteed, and in fact efficiency depends critically on the spatial distribution of the target population.
2) The final sample size is random and, as such, not known prior to the survey.
3) Data collection can be complex under field situations.
4) Adaptive sampling may need to be modified for mobile animals or sensitive species and habitats.

Our objective in this paper is to present the challenges that a biologist will face when considering the application of adaptive sampling, to offer suggestions for overcoming those challenges, and to highlight areas where method development will improve the practical efficiency of adaptive sampling. We first introduce adaptive sampling and review its literature. We then outline the main challenges that a biologist faces when putting adaptive sampling into practice. Afterward, we present case studies to illustrate the application of adaptive sampling to biological populations. Finally, we summarize and discuss future directions.

Application of Adaptive Cluster Sampling

Since Thompson (1990) introduced the adaptive cluster sampling design, a substantial literature has developed. The literature can be classified into three categories: modifications of the basic design; simulation studies to provide guidelines on effective application; and most recently, applications to real biological populations from which practical issues have emerged.

Introduction and Review of Adaptive Cluster Sampling

Adaptive cluster sampling, which was created by Thompson (1990), has a large number of possible designs. With the most basic adaptive sampling

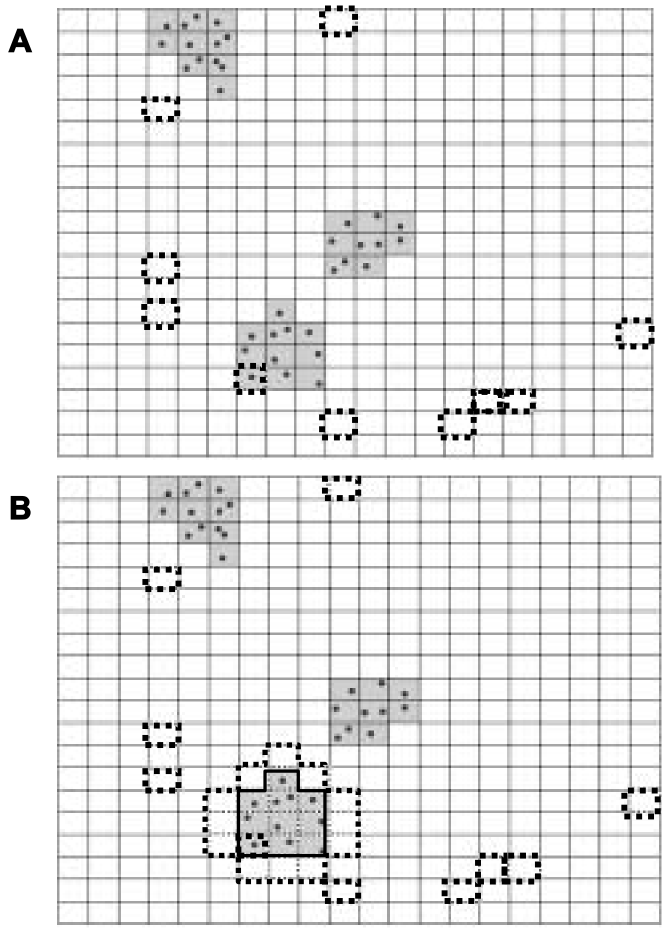

Figure 5.1. An example of adaptive cluster sampling. The study area consists of 400 units. The value within a unit is the count of black dots. There are three networks of black dots in the population. An initial simple random sample of 10 units is shown in (A). One of the initial units lands in a network of black dots, triggering adaptive sampling. The final sample of units is shown in (B).

design, initial sampling units are selected from a defined population according to a conventional probability-based sampling design. For example, the process could begin with simple random sampling without replacement as shown in Figure 5.1A. Observations in the initial sample units determine whether additional (adaptive) units are selected. If the observation in an initial unit meets some condition, adaptive units are selected in its neighborhood. The neighborhood of a unit, which includes itself and nearby units, can take a variety of shapes (Figure 5.2). However, a neighborhood must be symmetric in that if unit A is in the neighborhood of unit B then unit B is in the neighborhood of unit A.

For biological populations, the condition to adapt is typically based on the count of organisms exceeding some predefined level, such as a count > 0. In turn, if the count in an adaptive unit meets the condition then neighboring units are selected as long as the condition is met (Figure 5.1B). As a result of this adaptive process, clusters of sampling units are selected. Within each cluster there are units that meet the condition; this set of units is called a network. Because of neighborhood symmetry, if one unit in a network is selected, then all units in the network are selected. The number of units in a network is the network size. In addition, there are units in a cluster that do not meet the condition. These units are called edge units because in a cluster they define the network's edge. An initial unit that does not meet the condition is considered a network of size one.

There are several important choices to be made when implementing adaptive sampling. First, there is the initial sampling design, including sampling unit size and shape, selection scheme, and sample size. Second, there are choices that are particular to adaptive sampling, including the condition to determine whether adaptive units are selected and the configuration of the neighborhood. Typically, the condition to adapt is based on the observation of a unit meeting or exceeding a predetermined value. For example, a typical condition is to adapt if a species is present in a unit (i.e., count > 0). The neighborhood configuration is flexible (Figure 5.2), but a cross pattern (Figure 5.2B) is currently a common choice. Finally, there is a choice of estimators. Thompson (1990) derived two unbiased estimators, based on the Horvitz-Thompson and Hansen-Hurwitz estimators, for application to adaptive cluster sampling, and he showed how these estimators could be improved using the Rao-Blackwell method. In most compar-

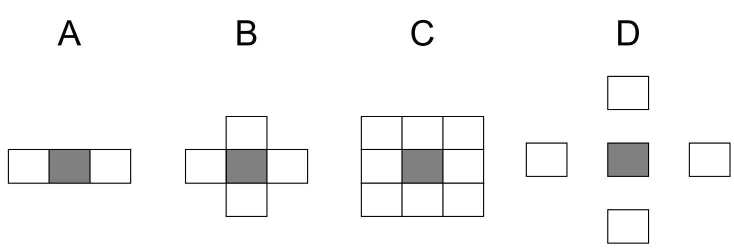

Figure 5.2. Possible neighborhood shapes for adaptive sampling. The gray-shaded unit represents a unit that meets the condition to adapt. The remaining units make up the gray unit's neighborhood.

isons, the Horvitz-Thompson estimator appears to be the superior choice (Salehi 1999, 2003).

The combination of these choices results in a wide variety of possible adaptive sampling designs. There has been considerable work on designs resulting from changes to the initial sampling design (see Thompson and Seber 1996 for an in-depth review of early work). Thompson developed adaptive sampling designs that use systematic and stratified sampling to select the initial sample (Thompson 1991a,b). Several authors have considered incorporating adaptive sampling in two-stage designs (Salehi and Seber 1997; Zhang et al. 2000; Muttlak and Kahn 2002; Christman 2003). Roesch (1993) and Pontius (1997) developed adaptive sampling designs that incorporate selection of the initial sample with probability proportional to size. Adaptive Latin square sampling was considered by Munholland and Borkowski (1996) and Borkowski (1999). Pollard and Buckland (1997) developed a strategy to combine adaptive sampling in a line transect survey. Palka and Pollard (1999) applied this strategy to survey harbor porpoise and found the strategy easy to implement and effective at reducing estimator variance.

Another area that has received considerable attention is the use of stopping rules to restrict adaptive sampling. Brown (1994) and Brown and Manly (1998) were the first to explore the performance of adaptive sampling with a stopping rule. The objective of Brown's stopping rule, which was triggered when a preset sample size was reached, was to limit the size of the final sample. Brown's stopping rule limited final sample size effectively but introduced some positive bias (in many cases) and the final sample size remained random (Salehi and Seber 2002). Lo et al. (1997) presented a restricted adaptive sampling strategy in which the stopping rule limited the amount of adaptive sampling per network. Lo and colleagues' strategy was applied to estimate Pacific hake larval (*Merluccius productus*) abundance, and they concluded that although the estimators were biased, restricted adaptive sampling resulted in a substantial variance reduction. Su and Quinn (2003) used simulation to evaluate a stopping rule that was similar to the one used by Lo et al. They added the stopping rule to an "adaptive sampling design with order statistics" and found that the magnitude of bias depended on the order statistic, stopping rule, and spatial distribution of the population.

Salehi and Seber (2002) presented unbiased estimators for designs similar to Brown's restricted adaptive cluster sampling design. They found in a simulated example that the unbiased estimators yielded smaller mean square errors (MSE) than biased estimators when sample size was small, but that the biased estimators had smaller MSE as sample size increased. Salehi and Seber (2002) developed stopping rules to reduce the final sample size. However, Christman and Lan (2001) looked at the problem from the perspective that conventional sampling might not generate a large enough sample or yield sufficient observations from a rare population. This prompted Christman and Lan (2001) to develop an inverse adaptive cluster sampling design that allows sampling until a predefined number of nonzero units are selected. Salehi and Seber (2004) presented an unbiased estimator for Christman and Lan's design and proposed a new design, the general inverse sampling design, that avoids selecting an unfeasibly large sample.

The issue of how to select an appropriate condition has received attention because the condition to adapt can have a profound effect on efficiency and expected final sample size (Smith et al. 1995; Brown 2003). If the condition is too liberal, adaptive sampling might be triggered too frequently and the expected final sample size might be excessively large—even too large to complete the planned survey. Conversely, if the condition is too restrictive, adaptive sampling might not be triggered at all and sampling might be insufficient to achieve desired precision. To help make an effective choice, Thompson (1996) suggested basing the condition on the order statistics from the initial sample. This approach, which Su and Quinn (2003) labeled *acsord* for "adaptive cluster sampling with order statistics," is feasible when the initial sample can be selected in its entirety prior to selecting the adaptive units. After the initial units are sampled, the observations are ordered, and the condition is set equal to the r^{th} order statistic (Su and Quinn 2003). Of course, there remains the challenge of choosing the appropriate order statistic. Su and Quinn (2003) conducted extensive simulations of *acsord* sampling of five populations with various degrees of aggregation. They found that efficiency and relative bias were determined by the interaction between population characteristics, initial sample size, stopping rule, order statistic, and estimator used. Similarly, other simulation studies have shown complex effects of population characteristics and design factors on the efficiency of adaptive sampling (Smith et al. 1995; Christman 1997; Brown 2003).

Thompson (1994) identified analytically the factors that affect the efficiency of adaptive cluster sampling. There have been additional simulation studies to determine what affects efficiency (Brown 1994; Smith et al. 1995; Christman 1997; Brown 2003). In general, factors affecting efficiency fall into categories of population distribution, relative and absolute size of the expected final sample, unit size, or per unit sampling cost. For adaptive cluster sampling to even have a chance of being efficient the population must be geographically rare (meaning that organisms should occupy a small percentage of the units in the population) and the spatial distribution of the population should be highly aggregated or clustered. Although bias is not dependent on spatial distribution, efficiency is. Thus, prior knowledge of spatial distribution of the population is important when deciding whether to apply adaptive sampling. Brown (2003) showed how neighborhood definition and condition to adapt can affect the spatial characteristics of the population and improve the efficiency of adaptive sampling.

The closeness of the final and initial sample sizes is another important factor that determines efficiency. Analytically and empirically it has been shown that efficiency tends to be high when the expected final sample size is a small percentage increase of the initial sample size (Thompson 1994; Smith et al. 1995; Brown 2003). However, Christman (1997) noted that high efficiencies often are reached only when the expected final sample size is a large proportion of the population. This has implications on whether adaptive cluster sampling is practical in real applications. By necessity, sample sizes in real applications are a small proportion of the population, so achieving the high efficiencies observed in simulated studies might not be possible in real applications.

Thompson (1994) also noted that efficiency could be increased when per-unit sampling costs are taken into account. Adaptive sampling will tend to be efficient when travel cost to sampling units is high, so that cost of sampling neighboring units is less than sampling units at random, and when the cost of making observations on units not meeting the condition is less than on units that do meet the condition. This latter condition could be satisfied when the condition is based on an auxiliary variable that can be inexpensively measured—for example, by basing the condition on a rapid assessment or catch per unit effort (CPUE).

Additional work has focused on application of adaptive sampling when there are multiple variables of interest (Thompson 1993; di Battista 2002; Dryver 2003; Smith et al. 2003), when observations are incomplete and detectability is an issue (Thompson and Seber 1994), and when the objective of the survey is to describe spatial distribution or spatial prediction (Hanselman et al. 2001; Curriero et al. 2002; Chapter 14, this volume). Although di Battista (2002) found that adaptive sampling resulted in lower MSE for estimates of diversity for clustered populations compared to simple random sampling, he noted a bias and devised a jackknife procedure to reduce the bias. Dryver (2003) cautioned that the performance of adaptive cluster sampling depends on the covariance between species when the condition is based on one species but abundance of another species is being estimated. In multispecies assemblages of freshwater mussels, Smith et al. (2003) found that the probability of detecting rare species was greater in adaptive units. Thompson and Seber (1994) presented a general approach for incorporating detectability estimates. Pollard and Buckland (1997) combined adaptive sampling with distance sampling methods to account for imperfect detectability. The effect of preferential sampling on kriging methods was examined by Curriero et al. (2002), who used adaptive cluster sampling as an example of preferential sampling. Hanselman et al. (2001) used variograms to assess degree of spatial clustering and gauge the likely efficiency of adaptive cluster sampling of rockfish in the Gulf of Alaska.

Aside from adaptive cluster sampling, adaptive allocation sampling (Thompson et al. 1992) is an attractive alternative in that observations can be used to stratify the survey area even when prior knowledge of within-strata variances and means is unavailable. Various sampling designs are available under adaptive allocation (Thompson and Seber 1996). Some designs require two passes over the population area (cf. double sampling or two-phase sampling), whereas others require one pass where the level of sampling in a particular stratum depends on observations in the previous stratum. Estimators can be either design-based or model-based (Thompson et al. 1992).

The list of applications of adaptive sampling to real biological populations is small, but it is growing and covers a diverse set of taxa. It took several years from the introduction of adaptive cluster sampling (Thompson 1990) before the first real applications to biological populations were reported (Lo et al. 1997; Strayer et al. 1997; Woodby 1998). Up to that point applications to biological populations were based on simulations (Roesch 1993; Brown 1994; Smith et al. 1995; Christman 1997; Woodby 1998).

Lo et al. (1997) applied a restricted adaptive sampling design to estimate Pacific hake larval abundance. They concluded that their adaptive sampling scheme was easy to implement and resulted in a more precise estimator than a conventional alternative. Also, Lo et al. (1997) noted that adaptive sampling provided information on patch size, which is an interesting biological characteristic.

Strayer et al. (1997) applied adaptive cluster sampling to survey of freshwater mussels (Unionidae). Their design was essentially that presented by Thompson (1990) with simple random sampling of 0.25 m^2 quadrats at the initial sample and a cross-shaped neighborhood. Because freshwater mussel density varied among the multiple sites that were sampled, Strayer et al. (1997) used a different condition at each site; the condition was based on a rapid assessment of density that preceded adaptive sampling.

McDonald et al. (1999) applied an adaptive version of line transect sampling in an aerial survey of polar bears (*Ursus maritimus*). Their condition for adaptive sampling was the detection of polar bears or fresh seal kills along a 37-km transect line. The neighborhood was defined as parallel transect lines 9 km on each side of the initially sampled line. The condition was met on five transect lines, but neither polar bears nor fresh seal kills were found on any adaptively sampled lines.

Palka and Pollard (1999) combined adaptive and line transect sampling for a survey of harbor porpoises (*Phocoena phocoena*). Their design was based on a strategy presented by Pollard and Buckland (1997) (see also Pollard et al. 2002). Palka and Pollard (1999) concluded that the strategy was easy to implement in the field and resulted in more precise estimates of density compared to traditional line transect sampling.

Bradbury (2000 and pers. comm.) described an application of a modified adaptive sampling design to estimate density of red sea urchin (*Strongylocentrotus franciscanus*). His design was based on a systematic adaptive cluster sampling design modified for sampling in one dimension (Thompson 1991a). However, the final sample size was constrained by defining the neighborhood to include the units halfway between the initial systematically sampled units (Woodby 1998); in that way, the final sample size was constrained to be no more than twice the initial sample size. Bradbury (pers. comm.) concluded that the modified adaptive sampling design was easy to implement.

Systematic adaptive cluster sampling was also the basis for an application by Acharya et al. (2000) to assess rare tree species. The tree species under study were found in clusters, and Acharya et al. (2000) concluded that efficiency of adaptive sampling depended on cluster size, with greatest efficiency observed for the species that formed the largest clusters.

Conners and Schwager (2002) implemented adaptive cluster sampling in a hydroacoustic survey of rainbow smelt (*Osmerus morax*) in Lake Erie. Their field trial was limited to one initial transect with adaptive transect segments parallel to and 1.5 km from the initial transect. The length of the adaptive transect segments was equal to the distance over which the condition was met on the initial transect. Conners and Schwager (2002) concluded that application of adaptive cluster sampling is feasible but pointed out several potential problems, including the need for (1) real-time data processing to assess the condition; (2) accurate georeferencing to find the adaptive units; and (3) effective condition and neighborhood definition to control the expected final sample size.

Hanselman et al. (2003) applied adaptive cluster sampling to surveys of Gulf of Alaska rockfish (*Sebastes alutus*, *S. borealis*, and *S. aleutianus*) (see also Chapter 14, this volume). They based the condition on percentiles of past survey results, allowed a distance of 0.1 nautical miles (nm) between adaptive tows, and included a stopping rule to restrict the expected final sample size. Their evaluation focused on the effect of condition and species distribution on efficiency. Hanselman et al. (2003) compared adaptive cluster sampling to simple random sampling if sample size was equal to the final sample size minus the edge units and found adaptive cluster sampling to be efficient.

Smith et al. (2003) applied adaptive cluster sampling to surveys of freshwater mussels (Unionidae) at 24 independent sites. Their initial sample was selected systematically, the condition was species presence, and the neighborhood was the standard cross shape (Figure 5.2B). Smith et al. (2003) compared adaptive cluster sampling to simple random sampling if sample size was equal to the final sample size including edge units. They found that adaptive cluster sampling did not result in lower sampling error for fixed sample size. However, application of adaptive sampling substantially increased both the number of individuals sampled and the probability of detecting the presence of rare species.

Challenges When Implementing Adaptive Cluster Sampling

There are four important challenges that a biologist will face when contemplating the application of adaptive cluster sampling. Before applying adaptive sampling, biologists should ask themselves the following questions:

1) Should I apply adaptive cluster sampling to this population?
2) How large should I expect the final sample size to be?
3) How do I implement adaptive sampling under field conditions?

4) How can I modify adaptive sampling to account for species biology, behavior, and habitat?

Should I Apply Adaptive Cluster Sampling to This Population?

The basic challenge is to determine whether adaptive cluster sampling is appropriate for the population of interest—in other words, "When is it a good idea to apply adaptive sampling?" In general, adaptive sampling is a good idea when it is efficient *and* the uncertainty in final sample size is not too great. A sampling design is efficient when it leads to smaller variance for fixed cost compared to an alternative design, which is often simple random sampling. The remainder of this section addresses the issue of efficiency, and the next section discusses methods to reduce the uncertainty in the final sample size.

From a statistical point of view, conventional cluster sampling tends to be efficient when clusters comprise most of the variation in the variable of interest. The same rule applies to adaptive cluster sampling, which is efficient when the within-network variance is a high proportion of total variance. In addition, efficiency of adaptive sampling tends to increase when the final sample size is close to the initial sample size.

From a practical point of view, adaptive cluster sampling tends to be efficient when organisms are clustered and the clusters are geographically rare. Geographic rarity means that the sampling units that are occupied by organisms are a small proportion of all units in the study area. Rarity of clusters is the most important characteristic. Individuals could be rare, but not clustered. In that case, networks would be small—typically a solitary unit—and the within-network variance would be negligible. Conversely, individuals in a population could be clustered, but the clusters could be common and numerous. In that case, the expected final sample size would likely be much larger than the initial sample size. For adaptive cluster sampling to be efficient individuals in the population must be clustered and the clusters must be rare.

Many ecological populations are clustered. However, it does not follow that adaptive cluster sampling is appropriate for most clustered or ecological populations. For instance, Figure 5.3 shows three populations each with the same abundance, but with different spatial distributions. The population in Figure 5.3A has a few large clusters; its variance to mean ratio is 1.3, 6.75% of the units are occupied, and the within-network variance is 44% of total variance. The population in Figure 5.3B has many small clus-

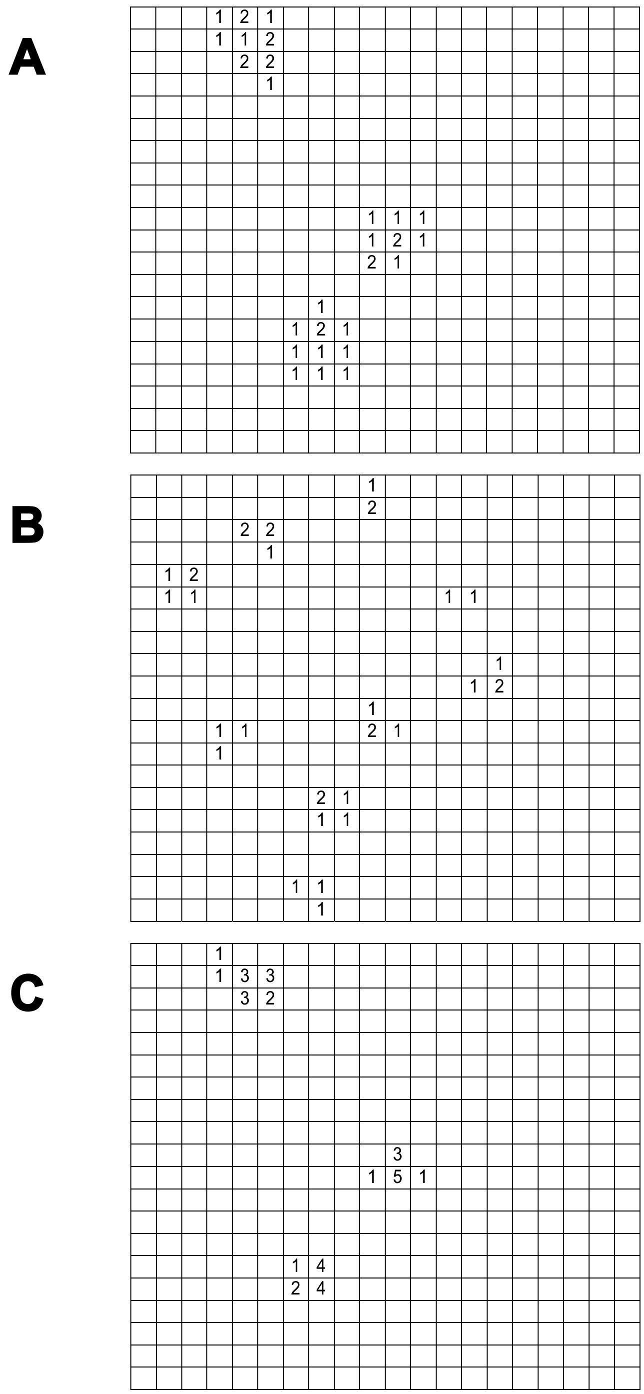

Figure 5.3. Three hypothetical populations showing various degrees of spatial clustering and rarity.

ters; its variance to mean ratio is 1.3, 6.75% of the units are occupied, and the within-network variance is 45% of total variance. The population in Figure 5.3C has a few small clusters; its variance to mean ratio is 3, 3.5% of the units are occupied, and the within-network variance is 48% of total variance. It is not obvious which populations would be appropriate for adaptive cluster sampling. Clustering appears in all populations. The degree of rarity, as measured by occupancy, is lowest in Figure 5.3C but does not vary between the other two populations. However, efficiency of adaptive cluster sampling differs among the three populations (Figure 5.4). Efficiency is defined here as the ratio of simple random sampling variance to adaptive sampling variance with sample size equal to the expected final sample size from adaptive sampling. For population 5.3A, efficiency of adaptive sampling depends on sample size with efficiency > 1 only for expected final sample size ≥ 90. A sample size of 90 translates to 23% of the study site being sampled, which seems high for ecological studies. For population 5.3B, adaptive cluster sampling is not efficient for a wide range of sample sizes. For population 5.3C, adaptive cluster sampling is efficient

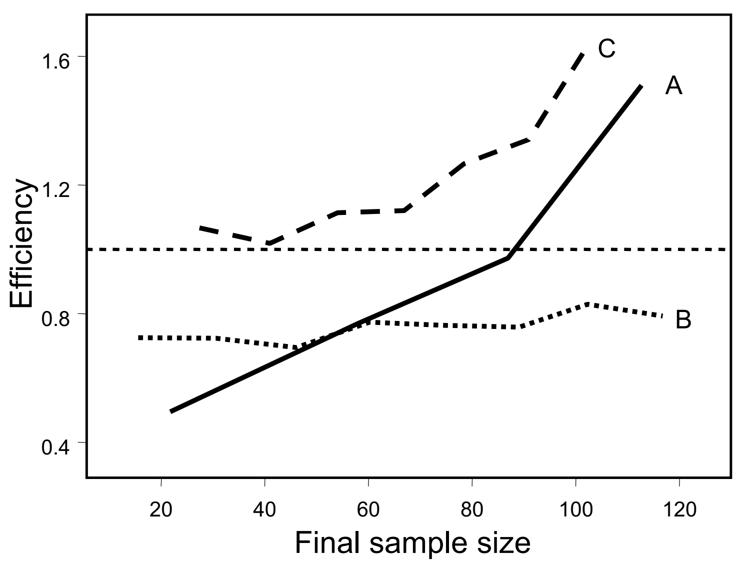

Figure 5.4. Results from simulated adaptive sampling of the populations shown in Figure 5.3. Efficiency is the ratio of simple random sampling variance to adaptive sampling variance with sample size equal to the expected final sample size from adaptive sampling. Efficiency greater than 1 indicates that adaptive sampling is the better design, and efficiency less than 1 indicates that simple random sampling is the better design.

and appropriate. So this example indicates that adaptive cluster sampling is efficient when clusters are small and geographically rare, that it is not efficient when clusters are small and numerous, and that efficiency depends on sample size when clusters are large and rare.

Other factors affect efficiency in addition to spatial distribution. For example, both the condition to adapt and the neighborhood definition affect efficiency through their effect on within-network variance and expected final sample size. Because the factors interact, simulation is invaluable for evaluating the efficiency of adaptive cluster sampling. Case study 1 illustrates the use of simulation to help design an adaptive survey.

How Large Should I Expect the Final Sample Size to Be?

Another challenge is to plan for uncertainty in the final sample size. Unlike conventional sampling designs in which sample size is fixed, the final sample size in adaptive sampling designs depends on what you find as you sample. The expected final sample size depends on the spatial distribution of the target population, the condition to adapt, the neighborhood definition, and whether stopping rules are employed in the sampling scheme. Because final sample size is random, techniques to predict final sample size are important for project planning. There are no hard and fast rules to predict final sample size, but there are some guidelines that are useful for anticipating final sample size in a qualitative sense.

Final sample size will tend to be highly variable in populations that contain only a few large clusters. If by chance the initial sample intersects a large cluster, many adaptive units will be sampled. If a large cluster is not intersected, the final sample size will be equal to the initial sample size. In populations that contain many small clusters, final sample size will tend to be much higher than the initial sample size.

The condition that triggers adaptive sampling will affect the size of networks in the population and, in turn, the final sample size. As the condition is made more restrictive by increasing the critical value, networks will, in effect, become smaller and adaptive sampling will be triggered less frequently, resulting in a smaller final sample size. Conversely, a liberal condition that triggers adaptive sampling much more often (a "hair-trigger" condition) will result in a final sample size considerably larger than the initial sample size.

Small neighborhoods (e.g., Figure 5.2A or 5.2B) will generate smaller final sample sizes than large neighborhoods (e.g., Figure 5.2C). Neighborhoods that contain discontinuities where adjacent units are "leap-frogged" (e.g., Figure 5.2D) will generate smaller final sample sizes than neighborhoods that include adjacent units (e.g., Figure 5.2B).

Stopping rules will reduce the maximum final sample size but will not eliminate variation in final sample size. Stopping rules also bias results, but the extent of the bias might not be large, depending on how it is implemented (Brown and Manly 1998). Several real-world applications have incorporated some sort of stopping rule (Lo et al. 1997; Woodby 1998; Hanselman et al. 2003) in which the potential for bias seems to have been outweighed by the need to control for the final sample size. Case study 2 illustrates the use of a stopping rule.

How Do I Implement Adaptive Sampling in the Field?

Adaptive sampling can be a complex procedure to implement under field conditions. In addition to the usual challenge of conventional probability sampling, which is required to take the initial sample, biologists must navigate among adaptively sampled units within a cluster. The key to successful implementation of adaptive sampling is keeping careful records to track which adaptive units have been sampled and which units remain to be sampled. In addition, choice of neighborhood, stopping rules, and design to take initial sample can help ease implementation.

When sampling freshwater mussels in rivers, we find it helpful to start a map on the reverse side of our data sheet whenever adaptive sampling is triggered. For example, Figure 5.5A shows a grid that maps the units within a large adaptive cluster; the numbers refer to the count within a sampling unit. This grid map of a cluster came from one of our data sheets. Adaptive sampling was triggered when two mussels were observed in a unit (indicated by a circle in Figure 5.5). The remaining observations were mapped and recorded on the data sheet grid as sampling progressed. The map was indispensable for navigating within the cluster.

Implementation can be streamlined and simplified by choice of neighborhood. For example, the sampling units in case studies 2 and 3 are transects (or tows) and the neighborhoods are defined as transects that run parallel to, but some distance from, the condition-meeting transect. In this way sampling is simplified because you are adaptively sampling in only two directions rather than four (or more), similar to the neighborhood in Figure 5.2A. An extreme example of this was presented by Woodby (1998), in which the neighboring transects were placed halfway between the initial transects. In Woodby's design, adaptive sampling always stopped after one set of adaptive transects was sampled because sampling further would

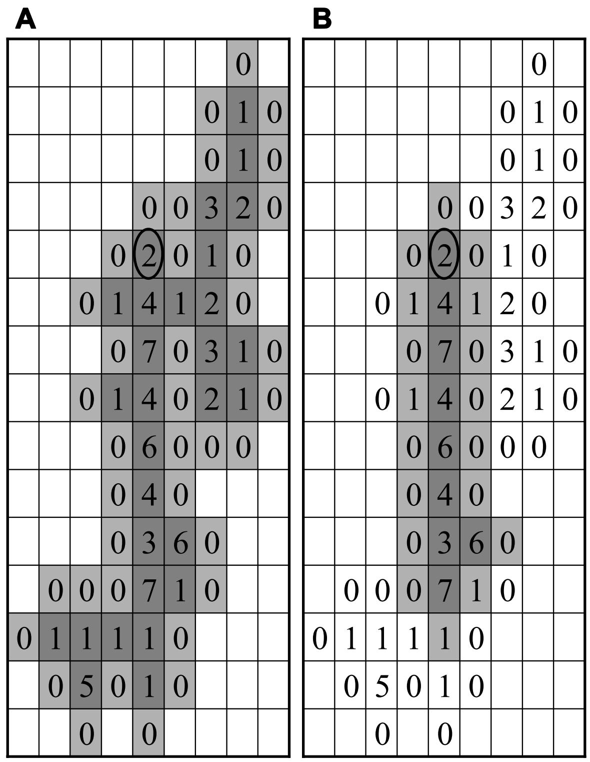

Figure 5.5. A cluster of units showing edge units in light gray and network units in dark gray. The initially sampled unit is circled and has a value of two. (A) shows the result when adaptive sampling is triggered whenever a selected unit's value is greater than zero. (B) shows the result when adaptive sampling is triggered whenever a selected unit's value is greater than one.

overlap other initial transects. Woodby's design essentially uses the neighborhood definition to create a stopping rule.

Stopping rules can ease implementation by reducing the spatial extent of adaptive sampling. Complexities associated with navigating to adaptive units and planning difficulties associated with an open-ended final sample size are diminished when adaptive sampling has a predetermined cutoff. Case study 2 provides a good practical example of the use of a stopping rule. Lo et al. (1997) incorporated a stopping rule in a survey of Pacific hake larvae. In this case, adaptive sampling would not have been possible without a stopping rule because of the large scale of the survey area.

Choice of design to take the initial sample will influence ease of implementation. Simple random sampling often is cumbersome under field conditions. Systematic sampling is an attractive alternative for taking the initial sample because it is relatively easy to implement (Thompson 1991a; Acharya et al. 2000; Hanselman et al. 2003; Smith et al. 2003). Systematic sampling with multiple random starts, which supports valid estimation of sampling variance and does not add much complexity to implementation, is preferred over single-start systematic sampling, which is commonly applied under field conditions. Systematic sampling is known to be an efficient sampling design for clustered populations, regardless of adaptive sampling (Christman 2000). Case studies 2 and 3 incorporate some form of systematic sampling for initial sample selection. Case study 1 does not include systematic sampling but uses simple random sampling instead because it is a computer simulation of freshwater mussel sampling. When we have actually applied adaptive sampling to freshwater mussel surveys, we have used systematic sampling to take the initial sample (Smith et al. 2003).

How Can I Modify Adaptive Sampling to Account for Species Biology, Behavior, and Habitat?

Special consideration is required when adaptive sampling is applied to species that are mobile, elusive, or sensitive to handling. The potential for double-counting is high when animals could be flushed into adjacent sampling units as a result of adaptive sampling. Imperfect detectability is an issue when sampling elusive animals whether sampling is adaptive or conventional (Thompson and Seber 1994). Because adaptive sampling tends to result in selection of occupied habitat, the potential for habitat disturbance is greater than in conventional sampling. If sampling is destructive or species or their habitats are sensitive to sampling, adaptive sampling might need to be modified to reduce disturbance.

A solution to problems caused by mobile species is to define neighborhoods that do not include adjacent units (e.g., Figure 5.2D). The separation between within-neighborhood units can be selected to exceed flushing distance. If aggregation size is smaller than the flushing distance, adaptive sampling methods would not be advantageous. There would be no value in adaptively sampling if the neighborhood jumps over the aggregation. Another approach for mobile species is to base the assessment on an index of species presence, as was done in case study 2.

Imperfect detectability is a pervasive issue in field studies of animal populations (Seber 1982). Numerous strategies have been developed to adjust for imperfect detectability, which would lead to underestimates of animal abundance if left unadjusted. In the context of finite population sampling, such as when sampling units are selected and then counts of animals are made on the selected units, imperfect detectability is dealt with by first adjusting for detectability on selected units, then expanding the adjusted per-unit counts to the entire sampling frame. This approach works for conventional sampling because selection of units does not depend on detectability, so adjustment for detectability can be handled prior to estimating totals or means. However, detectability can influence the selection of adaptively sampled units because the condition to adapt is typically based on a count of detected animals (Thompson and Seber 1994). For example, suppose that in truth an initial unit should trigger adaptive sampling because it is occupied by a species. In practice, neighboring units might not be selected because the animal in the initial unit might not be detected, in which case adaptive sampling would not be triggered. Thompson and Seber (1994) solve this dilemma by turning the problem around and first estimating the population of detectable animals and then adjusting that estimate by an independent estimate of detection.

Let us consider an example of how to design adaptive sampling to account for imperfect detectability. Detectability is an issue in surveys of freshwater mussels because they are benthic organisms that position themselves at various depths of the substrate. Some mussels are readily detectable at the substrate surface by visual or tactile observation, but some are buried below the surface and must be excavated for detection. To estimate total abundance or density, some amount of excavation is required and double sampling can be used to adjust for detectability in an optimal way that balances effort and precision (Smith et al. 2000). Double sampling in this case involves excavating a subsample of quadrats. The ratio of mussels detected on the substrate surface in excavated quadrats to total mussels in excavated quadrats is used to estimate detectability. Double sampling can be applied to an adaptive sampling design by excavating a subsample of the initial sample of quadrats. Adaptive sampling is used to estimate the detectable portion of the population; then the estimate of detectability from double sampling is used to adjust and estimate total abundance. Thompson and Seber (1994:219–220) provided a formula for incorporating an estimate of detectability into adaptive sampling estimates of abundance.

Some organisms are so sensitive that the mere act of sampling can be detrimental by interfering with survival or reproduction. In some situations, animals must be captured to be observed, habitat must be altered to collect animals, or plants must be removed to measure biomass. In such situations, sample size is of concern not only to control survey cost but also to reduce disturbance. The potential for disturbance is elevated for adaptive sampling because it tends to allocate effort into occupied habitat.

When sampling-related disturbance is a concern, a potential solution is to base the condition to adapt on a less invasive method of sampling. In that way, the impact from sampling the edge units, which form a large portion of the final sample, will be reduced or even eliminated. For example, American ginseng (*Panax quinquefolium*) is a rare, low-growing plant that is susceptible to trampling when being surveyed (John Young, U.S. Geological Survey, pers. comm.). One strategy to reduce disturbance during sampling would be to base the condition to adapt on a geographic information system (GIS)-based prediction of habitat (Boetsch et al. 2003). All sampling units (both initial and adaptive units) could be selected using GIS. The initial sample selection would be probabilistic and clusters of adaptive units could be selected based on predictions of habitat. In that way, edge units would never have to be visited in the field and travel to and among sampling units could be planned to minimize potential for disturbance and to reduce travel time.

Case Studies

We present three case studies to illustrate the design and application of adaptive sampling methods. These examples do not illustrate all potential challenges, but are based on our experiences and represent some of the practical challenges faced when implementing adaptive sampling.

Case study 1, from D.R.S., demonstrates the use of simulation to design an effective adaptive sampling survey. The objective was to estimate density of freshwater mussels, a class of often rare and endangered organisms. In this case, simulation helped to identify an adaptive sampling design that would be appropriate for populations similar to the study population and to plan for final sample size that would result from the design's implementation.

Case study 2, from J.A.B., discusses the application of adaptive sampling to a monitoring protocol for Australian brushtail possum (*Trichosurus vulpecula*), which is a nuisance species in New Zealand. In this case, the basic adaptive cluster sampling design had to be modified because the target organism could not be observed directly. Instead, an index of possum activity was observable, which created a time lag between selection of the sampling unit and the observed response.

Case study 3, from N.C.H.L., demonstrates the generality of adaptive sampling procedures. In an application to Pacific sardine (*Sardinops sagax*) assessment, adaptive sampling procedures are incorporated in a complex survey to allocate effort among strata and to reduce variance. This case study also illustrates application of adaptive sampling in a large-scale survey, where navigating among sampling units is a costly endeavor.

Case Study 1: Assessing the Effect of Condition to Adapt on Estimates of Freshwater Mussel Density

Freshwater mussels (Unionidae) represent a diverse assemblage including more than 300 species that are suffering an extinction rate higher than any other North American fauna (Ricciardi and Rasmussen 1999). Efficient sampling to assess and monitor mussel populations has become a critical need for malacologists and managers (Smith et al. 2001; Strayer and Smith 2003). The fauna tend to cluster and are often rare and at low density (Smith et al. 2003; Strayer and Smith 2003). Thus, freshwater mussels appear to be good candidates for adaptive cluster sampling.

Here we use freshwater mussels as an example to demonstrate how simulation can help determine how best to design an efficient adaptive cluster sampling survey. Application of adaptive cluster sampling is logistically feasible because freshwater mussels are not readily mobile and they can be observed directly (Smith et al. 2003; Strayer and Smith 2003). However, as in many real-world situations, selecting a proper value for the condition to adaptively sample presents a challenge. Simulations provide an excellent method to compare a range of alternatives prior to implementation. For this study we had access to a complete count (census) of freshwater mussels at a river site. Alternatively, a population can be generated based on a sample of data and assumptions about the spatial distribution.

Methods

We counted all mussels on a section of riffle habitat in the Cacapon River near Capon Bridge, West Virginia. The river section was approximately rectangular and measured approximately 40 m wide (bank to bank) by 90 m long. The substrate surface was thoroughly searched within a grid of 0.25 m^2 cells, and mussels were measured lengthwise and returned to the substrate. Figure 5.6A shows clustering in the population of freshwater mussels (*Elliptio complanata*) at the site (black squares in Figure 5.6A represent areas that were occupied by mussels).

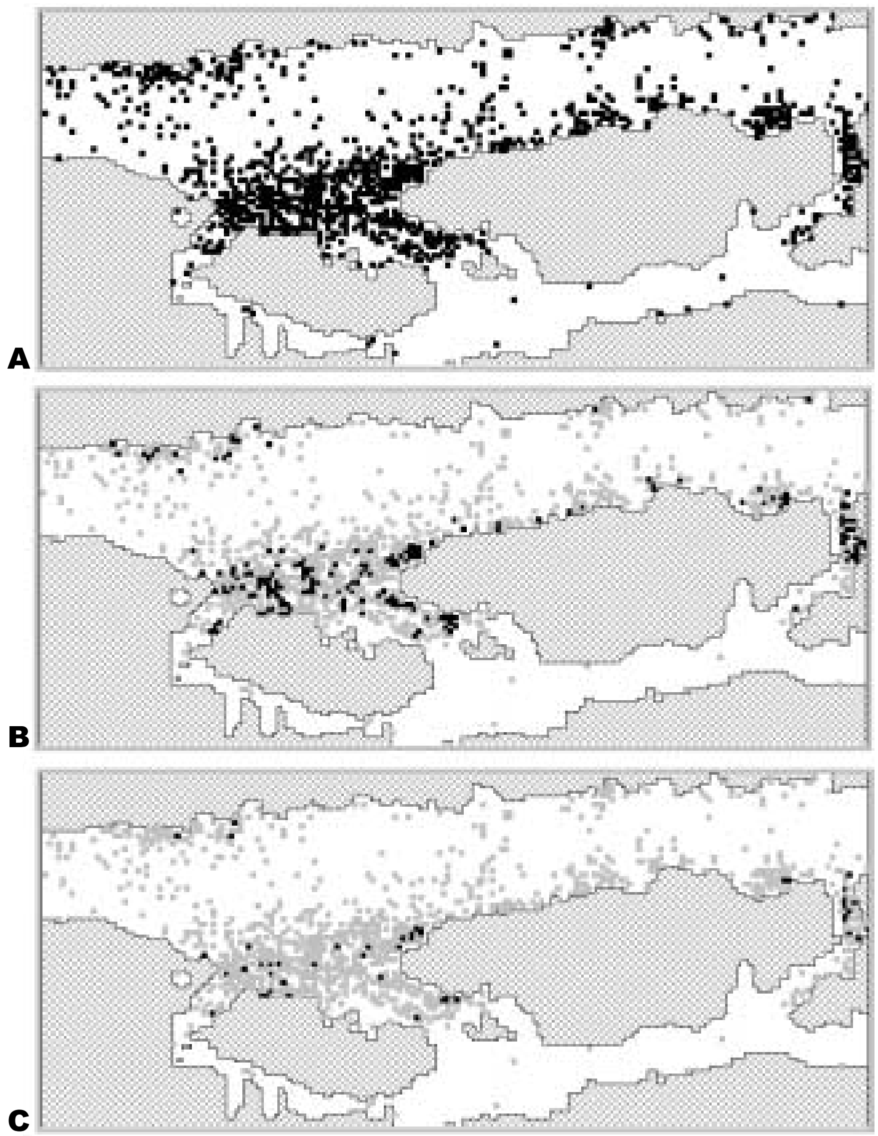

Figure 5.6. Population of freshwater mussels in a riffle in the Cacapon River at Capon Bridge, West Virginia. The cross-hatch indicates land. White indicates river substrate unoccupied by mussels. The remaining area is occupied by at least one mussel. Black squares show areas that meet the condition to adapt in a sample unit. Gray squares show areas that are occupied but do not meet the condition to adapt in a sample unit. The condition, which is based on the count per 0.25 m^2, changes among the panels. In (A), adaptive sampling would be triggered if any mussels were found. In (B), adaptive sampling would be triggered if at least three mussels were found. In (C), adaptive sampling would be triggered if at least five mussels were found.

We simulated the implementation of adaptive cluster sampling with 0.25 m^2 quadrats as the sampling unit, simple random sampling to take the initial sample, and a cross-shaped neighborhood (Figure 5.2B). Sampling was simulated using a range of conditions to adapt. The condition to adapt was of the form $y_i \geq c$, where y_i was the count of mussels in the i^{th} quadrat and c was the critical or threshold value. We considered c from 1 to 5. For example, when any mussels are present in a quadrat and $c = 1$, then adaptive sampling is triggered. We compared within-network to population variance, initial to final sample size, and sampling efficiency that resulted from each condition. Efficiency was defined as the ratio of sampling variance from simple random sampling to adaptive cluster sampling given equal sample size, that is, sample size for simple random sampling was set to be the expected final sample size from adaptive cluster sampling. Simulations were replicated 1,000 times and results were averaged across the replications. Software used for this simulation can be found at http://www.lsc.usgs.gov/AEB/davids/acs/.

Results

The condition to adapt, in effect, partitions the study area into networks. In Figure 5.6, black squares indicate areas of the population that form the networks that meet the condition. Each panel in Figure 5.6 shows results from a different condition.

In this population, the condition to adapt had a strong effect on the within-network variance, ratio of final to initial sample size, and efficiency (Figure 5.7). For a condition of $y_i \geq 1$, the within-network variance was more than 40% of total variance, final sample size was nine times initial sample size, and efficiency was only 0.2. Within-network variance decreased, final sample size decreased, and efficiency increased as the condition became more stringent (Figure 5.7).

Discussion

As the condition becomes more restrictive the proportion of the population that meets the condition shrinks. This leads to two important results. First, the within-network variance decreases as the range of values within a network is truncated. For example, when the condition is $y_i \geq 1$ a network could contain values ranging from 1 to the maximum count; only units with counts equal to 0 would be excluded from networks that meet the condition. However, when the condition is $y_i \geq 5$ the range of a network's values would be limited from five to the maximum count. Second, as the

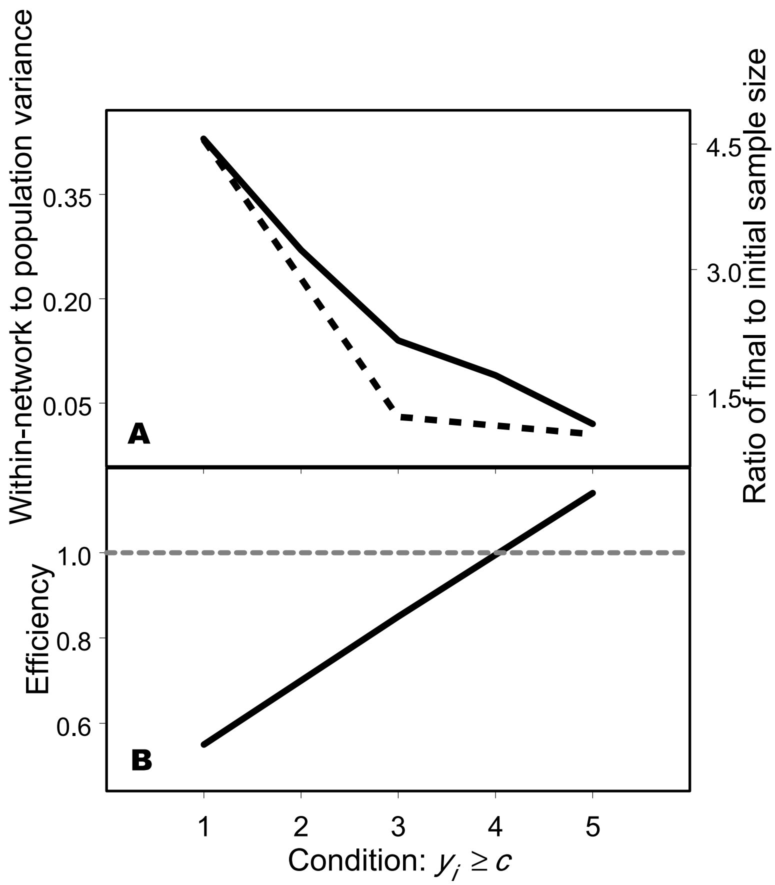

Figure 5.7. Results from simulated adaptive sampling of the population shown in Figure 5.6. Sampling was simulated for a range of conditions to adapt ($y_i \geq c$, where c = 1, 2, 3, 4, and 5). (A) shows ratio of within-network variance to population variance (solid line) and ratio of final to initial sample size (dashed line). (B) shows efficiency, which is the ratio of simple random sampling variance to adaptive cluster sampling variance with sample size fixed at the expected final sample size. Efficiency is a function of relationships shown in (A). Adaptive cluster sampling is more efficient when efficiency is greater than one, as indicated by the horizontal dashed line in (B).

condition becomes more restrictive, the expected final sample size approaches the initial sample size. This is caused by the reduction in network size—there are simply fewer sampling units in networks as the condition becomes more restrictive.

Interestingly, these two results act in opposite directions on the sampling efficiency. A reduction in within-network variance reduces efficiency, all else being equal. In contrast, efficiency increases as expected final sample size approaches initial sample size. The ultimate effect on efficiency depends on the net effect of the interaction between within-network variance and final sample size. In this case study, the reduction in final sample size had a greater effect on efficiency than reduction in within-network variance, but this will not always be true.

From the simulation we learned that adaptive cluster sampling would be a good idea only if we set the condition correctly. A restrictive condition was correct for this population. We also learned that it would have been a bad idea if the condition were set too liberally. In retrospect, it is apparent that the freshwater mussel population, although clustered, was not rare enough for adaptive cluster sampling to be efficient. By restricting the condition to adapt, we effectively made the population "rare," or at least the networks that met the condition became rare. If density was lower at the site, as Smith et al. (2003) found, a more liberal condition would have been feasible.

This result is specific to this population. In general, it is not necessary for efficiency to increase as the condition becomes more restrictive. This case study points out the utility of simulation before implementation. Simulation is a powerful method to evaluate efficiency across a wide range of alternative designs. In the absence of simulation we would not have been able to predict an efficient condition without a lengthy and expensive series of field trials.

Case Study 2: Monitoring Possum Abundance in New Zealand

The Australian brushtail (*Trichosurus vulpecula*) is a major environmental pest in New Zealand. These marsupials were first successfully introduced from Australia in 1858 to establish a fur industry. They rapidly spread so that today, about 70 million possums live throughout more than 90% of mainland New Zealand (Pracy 1974; Cowan 1990; Clout and Erickson 2000). Possums are considered a serious pest in New Zealand, primarily because they defoliate preferred plant species, predate bird eggs and chicks, and carry bovine tuberculosis, which poses a major threat to New Zealand's beef and venison industries (Green 1984; Cowan 1990; Brown et al. 1993; Coleman and Livingstone 2000).

Various government and private agencies in New Zealand expend considerable effort to control possums using either traps or poisons. Therefore, an accurate and efficient method for monitoring possums is necessary to assess whether control strategies are effective. Until recently, the primary index of possum density was based on lines of leghold traps. The major disadvantage of monitoring possums using traps is that it limits sample sizes to low levels because of the amount of labor required to transport and check traps (Brown and Thomas 2000; Thomas et al. 2003). A new monitoring method is being developed in New Zealand using a device called WaxTag, which contains a possum-specific attractant. The possum bites a wax block on the end of the tag, and the frequency of bite marks is used to calculate an index of possum density. Bite marks from other species can be distinguished from possum bite marks (Thomas et al. 1999).

Possum distribution is known to be clustered, and if residual hot spots can be detected, follow-up control can be targeted to specific locations. Adaptive sampling could be used to assess residual possum population size and to provide information on the spatial pattern of the remaining animals. The use of WaxTags creates the potential to use more informative survey designs, such as adaptive sampling, because large sample sizes are possible.

It is important to note that when using WaxTags for monitoring, the frequency of bite marks is considered an index of possum activity rather than an estimate of possum numbers because one possum can bite more than one WaxTag. An index based on possum activity is more biologically meaningful than an estimate for low possum densities because the environmental effect of one possum compared with the effect of multiple possums is of less concern than the environmental effect of some possums compared with no possums.

In this study, we assessed a practical application of using WaxTags and adaptive cluster sampling to monitor possums. The aim was to develop a survey protocol similar to the existing protocol for leghold traps but which also provided information on possum population size and spatial pattern. Thus, tag lines were set up using systematic sampling, and then additional lines were set up on either side of the initial lines during an adaptive phase. The new monitoring protocol needed to be modeled on the existing trap protocol because of the widespread use of the existing method. The possum control industry would be more likely to respond positively to incremental changes in the monitoring methodology than to a completely new model. For this reason, lines of WaxTags were used as the sample unit as prescribed for traps by the existing protocol.

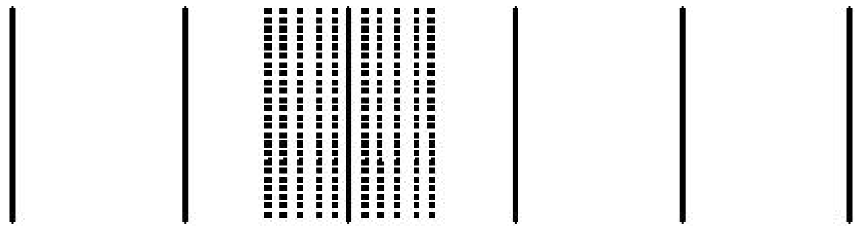

Figure 5.8. Layout of possum monitoring lines. There were fifteen lines at each site; six are shown here (solid lines). Lines were spaced 500 m apart, and along each line there were 10 WaxTag stations spaced 20 m apart. In the figure, the third solid line from the left "triggered" adaptive sampling and five parallel lines on both sides, spaced 50 m apart, were set (dashed lines). There were 10 stations spaced 20 m apart along each adaptive line.

Methods

Two sites were used to test adaptive sampling using WaxTags: Balmoral Forest and Eyrewell Forest in North Canterbury, New Zealand. At each site, an initial sample of 15 lines was placed at 500-m intervals (Figure 5.8). Each line consisted of 10 WaxTag stations spaced 20 m apart. At each station, two WaxTags were nailed to opposite sides of a tree. The WaxTags were left for three nights, and on the fourth day the number of stations with possum interference was recorded.

The adaptive phase of the study was designed according to the results from the initial lines. The three lines with the highest frequency of bite marks were chosen as the lines that "triggered" adaptive sampling, and five parallel lines spaced 50 m apart were set on both sides of each of these three lines. The WaxTags on these lines were left for a further three nights and the number of stations with possum interference was recorded.

The adaptive lines were all set at the same time rather than in a sequential pattern typical of most adaptive cluster sampling. This method was chosen because the sample units could not be assessed immediately. The lines were left out for three consecutive nights because possums are nocturnal and because it can be difficult to detect possums when populations are small.

Results

The possum population at Balmoral Forest was extremely small. After three nights, only three initial lines had any possum bite marks (Lines 6, 8, and 15; Table 5.1). On each of these lines, only one station had bite

Table 5.1.

Number of WaxTag stations with possum interference on 15 initial lines and 30 adaptive lines at Balmoral Forest, New Zealand. The initial lines were left out for three nights, and then five adaptive lines were set on each side of the three initial lines with the highest interference. Blank cells indicate no data because adaptive lines were not placed parallel to 12 of the initial lines.

	Initial line number														
Line	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Adaptive line A						0		0							0
Adaptive line B						0		0							0
Adaptive line C						0		0							0
Adaptive line D						0		0							0
Adaptive line E						0		0							0
Initial line	0	0	0	0	0	1	0	1	0	0	0	0	0	0	1
Adaptive line F						0		0							1
Adaptive line G						0		0							0
Adaptive line H						0		0							0
Adaptive line I						0		0							0
Adaptive line J						0		0							0

marks and hence the condition to trigger adaptive selection was one (see Discussion section for elaboration on this point). The frequency of bite marks on the adaptive lines that were placed parallel to lines 6, 8, and 15 was also very low. In fact, after three nights, throughout the 30 adaptive lines, bite marks were recorded at only one station on the first adaptive line adjacent to line 15 (Table 5.1).

Higher rates of bite marks were observed at Eyrewell Forest than at Balmoral Forest; 13 lines detected possums (Table 5.2) at Eyrewell. Lines 6 and 11 clearly had the highest frequency of bite marks (eight and nine stations, respectively), but four lines had five stations with bite marks. However, the spatial pattern of possum activity differed among these lines. Only Line 1 had three adjacent stations with bite marks; the other three lines had only two adjacent stations with bite marks. Thus, the condition for adaptive selection was given an extra layer of complexity by counting first the number of stations with bite marks (five), and then second, the number of consecutive stations with bite marks (three). The spatial aggregation component was introduced into the condition because one goal of this study was to detect aggregates of possum activity.

Table 5.2.

Number of WaxTag stations with possum interference on 15 initial lines and 30 adaptive lines at Eyrewell Forest, New Zealand. The initial lines were left out for three nights, and then five adaptive lines were set on each side of the three initial lines with the highest interference. Blank cells indicate no data because adaptive lines were not placed parallel to 12 of the initial lines. All adaptive lines parallel to the three initial lines had possum interference, but only those shown in bold were above the adaptive selection condition.

	Initial line number														
Line	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Adaptive line A	4					4					**8**				
Adaptive line B	3					**7**					**9**				
Adaptive line C	**7**					**6**					4				
Adaptive line D	**5**					4					**6**				
Adaptive line E	2					3					**8**				
Initial line	5	4	5	4	2	8	4	4	3	5	9	5	0	0	4
Adaptive line F	**9**					**6**					**10**				
Adaptive line G	**7**					5					**8**				
Adaptive line H	**6**					**8**					**5**				
Adaptive line I	**5**					**9**					**5**				
Adaptive line J	3					**9**					4				

Discussion

The sampling design used in this study is a modification of the usual adaptive cluster design. These modifications were made because of the specific challenges of monitoring low-density possum populations in New Zealand.

The first challenge was that the sample units in this case could not be assessed immediately. WaxTags, or any other device used to record possum activity, must be left overnight because the species is nocturnal. Furthermore, when animal numbers are low, the devices need to be left for more than one night (three is the standard practice) to ensure that resident possums have an adequate chance of encountering the device. As a result, it would have been too time-consuming to sequentially sample within a detected cluster. Instead, a maximum of five lines on either side of the initial triggered line was used, which limited the maximum size of a cluster but was the most practical option for a monitoring technique that will need to be both efficient and cost effective.

The practice of setting all five lines on either side of an initial line does raise some important analytical questions. First, the design restricts the maximum size of a network to five lines on either side of the initial line, which introduces bias because the network size and inclusion probability are incorrectly calculated for large networks. Second, given that this design yields data on the rate of bite marks from all 10 lines (five on either side), should all of this information be used to estimate the possum index, or should we use only the information that would have been gained if lines were sequentially set? For example, if we had set the adaptive lines sequentially next to Line 1 at Eyrewell Forest, the adjacent Adaptive Line 1E would have been set first. However, because it had a value of 2, which was less than the condition (5), the next four adaptive lines (1A–1D) strictly should not have been set. Similarly, for initial Line 6, an edge to the network would have been found in the first adaptive line on one side (Line 6E) and in the second adaptive line to the other side (Line 6G). We feel that the ideal analysis would use all of the data gathered from all of the lines because the additional information could add to a more robust analysis.

A more subtle question that arises is how to determine the value that triggered adaptive selection of adjacent lines. The initial line values given in Tables 5.1 and 5.2 represent the number of stations with bite marks recorded after the first three nights. However, at the end of the three nights when the adaptive lines were set, the initial lines were also reset so that any WaxTag with bite marks was replaced with a new WaxTag. A second value then was recorded for all of the lines after an additional three nights. In many cases, this second value did not correspond to the first value recorded on the initial lines. For example, Line 1 at Eyrewell Forest had an initial value of five stations with bite marks. However, when all of the bitten tags were replaced and the lines were set for an additional three nights, the Line 1 value increased to six stations with interference. Similarly, Line 6 had a first value of 8 but a second value of 6, and Line 11 had an initial value of 11 and a second value of 10. It seems sensible from a biological standpoint to use the initial values because those values triggered the adaptive selection. The second values, on the other hand, can be considered a measure of the temporal change in possum activity on that line. This temporal change could be a result of possums becoming conditioned to the presence of WaxTags or to any other source of temporal variation (e.g., changes in food supply or weather).

The second challenge in this application of adaptive cluster sampling is the practical limitations of setting and checking WaxTags. In particular, the survey effort must be divided into units of person-days, and the number of days required to complete the entire survey must be known in advance. This is because much of the possum monitoring in New Zealand is conducted by commercial businesses that need to run efficiently for the industry to be sustainable. Thus, it is not feasible to have surveys with unknown completion times, which is characteristic of traditional adaptive cluster sampling.

This challenge was met by using a constant number of lines in the initial sample that triggered adaptive selection as well as a predetermined number of adaptive lines. The sampling protocol was designed around the need to divide the work into units that one person could complete in a full day. Thus, the initial sample was set at 15 lines because one person can comfortably set this many lines in one day. Similarly, the 30 adaptive lines (i.e., 10 lines adjacent to three initial lines) could be completed in two person-days (i.e., two people in one day). In contrast, if we had chosen, for example, four initial lines and 10 adaptive lines, this would have equated to 2.67 person-days of work, which would make monitoring operations inefficient and costly.

The third challenge in this application is that the condition for adaptive selection was not known (nor could it be predicted) prior to the survey. Over time, it might eventually be possible to set the condition a priori, but in this trial we were able to overcome this problem by having a two-phase design. This design meant that lines had to be checked twice: once in Phase I to collect the initial sample values and to place out the adaptive lines and then again in Phase II to check all of the lines again. However, there are some advantages to this two-phase design. First, the survey effort required for an initial assessment of the possum activity level (the 15 initial lines) is clearly differentiated from the survey effort required for the second adaptive sampling phase. The first phase is analogous to current monitoring protocol, which uses traps, and it can be used to assess whether contractual target levels for control have been met. In contrast, the second phase can be used to concentrate follow-up control operations on hot spots or local areas of patchiness. There also are advantages to being able to separate these two phases for budgeting and financial accounting.

This example illustrates how the adaptive cluster sampling technique can be modified to help with a real biological problem with practical limitations. The challenges in using adaptive cluster sampling for monitoring possums are that the sample unit value can not be immediately gained in the field, that there are very practical limitations to sample sizes and expenditure of field effort, and that with limited knowledge the adaptive condition can not be set prior to sampling. Given these challenges, adaptive cluster sampling can be "adapted" and is a very useful tool for possum monitoring.

Case Study 3: Adaptive Allocation Sampling to Estimate Egg Production of Pacific Sardine

The Pacific sardine (*Sardinops sagax*) was once one of the more important fisheries off the west coast of the American continents. The estimated biomass peaked at 3.6 million metric tons (mt) in 1934 but fell to less than 100,000 mt in the late 1950s and mid-1960s as the fishery collapsed (Murphy 1966; MacCall 1979). In 1949, a survey was launched to help understand the decline of sardines and to monitor their population. The Southwest Fisheries Science Center of the National Marine Fisheries Service has been responsible for monitoring the spawning biomass of Pacific sardine by conducting a routine ichthyoplankton survey, commonly referred to as the California Cooperative Fisheries Investigations (CalCOFI).

The daily egg production method (Parker 1985; Hunter and Lo 1997) has been used to estimate spawning biomass of Pacific sardine (Wolf 1988a,b; Lo et al. 1996; Scannel et al. 1996; Barnes et al. 1997). The daily egg production method estimates spawning biomass by (1) calculating the daily egg production from ichthyoplankton survey data; (2) estimating the maturity and fecundity of females from adult fish samples; and (3) calculating the biomass of spawning adults. In this report, we concentrated on the ichthyoplankton survey.

Because sardine eggs are aggregated (Lo et al. 1996), efficient sampling methods have been sought. Before 1996, sardine egg production was estimated from plankton net sampling only, like CalVET (Smith et al. 1985). Since 1996, in addition to plankton nets, Bongo nets and the Continuous Underway Fish Egg Sampler (CUFES; Checkley et al. 1997) have been used to sample fish eggs (Hill et al. 1998, 1999).

Since 2001, we have used an adaptive allocation sampling design to estimate daily egg production. This design allocates additional net tows according to egg densities observed from the CUFES. Plankton net samples of eggs and yolk-sac larvae are allocated to the high-density area as determined by CUFES to estimate the daily egg production at age 0 (P_0), which then is incorporated in the daily egg production method to estimate spawning biomass.

Methods

In 2002, we conducted a full-scale survey to estimate the spawning biomass of Pacific sardine (Lo et al. 2001). We sampled ichthyoplankton with plankton nets and CUFES aboard the R/V *McArthur* (March 21–April 19) and R/V *David Starr Jordan* (March 27–April 14). The Jordan segment of the survey was the routine CalCOFI April survey (http://swfsc.nmfs.noaa.gov/frd/CalCOFI/CurrentCruise.htm). In addition, we sampled adult sardine aboard R/V *David Starr Jordan* (April 14–25) after the routine CalCOFI cruise to estimate reproductive parameters.

We used egg counts from the CUFES from the 2002 survey to allocate placement of plankton net tows and to map the spatial distribution of the sardine spawning population. Following the adaptive sampling procedure, we towed plankton nets at 4-nautical mile (nm) intervals on each line after the egg density from each of two consecutive CUFES samples exceeded the critical value of 1 egg/min. Plankton net tows continued until the egg density from each of two consecutive CUFES samples was less than 1 egg/min.

We post-stratified the survey area into a high-density area (Region 1) and a low-density area (Region 2) according to the egg density from CUFES collections. We determined the stage of eggs from the plankton net tows and identified yolk-sac larvae from plankton and Bongo net tows in the high-density area. These responses were incorporated into a model of the embryonic mortality curve in the high-density area and later converted to the daily egg production, P_0, for the whole survey area. We employed this adaptive allocation sampling, which is similar to a 1997 survey of Pacific hake larvae (Lo et al. 2001), aboard the *McArthur* but not aboard the *Jordan* because the latter was conducting the routine CalCOFI survey.

We used eggs from plankton tows and yolk-sac larvae from both plankton and Bongo tows in Region 1 to compute egg production (P_0) assuming the embryonic mortality curve was exponential: $P_t = P_{0,1}\exp(zt)$, where P_t was daily egg or yolk-sac production/0.05 m^2 at age t days and z was the daily instantaneous mortality rate (Lo et al. 1996; Lo et al. 2001). We examined eggs for their developmental stages and converted them to age (Lo et al. 1996). Due to the small number of tows with eggs, we obtained egg production in Region 2 ($P_{0,2}$) by calibration: $P_{0,2} = P_{0,1} \times q$, where q was ratio of egg density in Region 2 to Region 1 from CUFES. The egg production for the entire survey area, P_0, was a weighted average of $P_{0,1}$ and $P_{0,2}$, where the weights were the area sizes.

We used the estimate of P_0 together with estimates of four adult parameters to compute the spawning biomass (B_s) according to

$$B_s = \frac{P_0 AC}{RSF/W_f}, \tag{5.1}$$

where A is the survey area in units of 0.05 m^2, C is the conversion factor from g to mt, $P_0 \times A$ is the total daily egg production in the survey area, and the denominator (RSF/W_f) is the daily specific fecundity (number of eggs/population weight (g)/day). The fecundity estimate was calculated from the daily spawning fraction or the number of spawning females per mature female per day (S), the average batch fecundity (F), the proportion of mature female fish by weight (sex ratio or R), and the average weight (in g) of mature females (W_f) (Parker 1985; Picquelle and Stauffer 1985; Lo et al. 1996; Lo and Macewicz 2002).

Regarding sampling gear, the diameter of the CalVET net frame was 25 cm, the tow was vertical to minimize the volume of water filtered per unit depth, the mesh size was 0.15 mm, and the tow depth was 70 m. The diameter of the Bongo net frame was 71 cm, the tow was oblique at a 45° wire angle, the mesh size was 0.505 mm, and the tow depth was 210 m when 300 m of wire was deployed. CUFES can be installed midship on a research vessel with the intake pipe over the side of the vessel or in the bowl. It extends 3 m below the water surface (see illustration in Checkley et al. 1997). Eggs were sieved from the water flow with the 0.5 mm nylon mesh of the CUFES concentrator.

Results

The survey area was post-stratified into a high-density area (Region 1) and a low-density area (Region 2, Figure 5.9). Region 1 encompassed the area where the egg density (eggs/min) in CUFES collections was at least 1/min. The rest of the survey area was Region 2 (Figure 5.9). One egg/min was equivalent to two to four eggs/plankton tow, depending on the degree of water mixing.

We collected 1,622 CUFES samples from *McArthur* (1,165) and *Jordan* (457) at intervals ranging from 1 to 47 min with a mean of 24.4 min and median of 30 min. In Table 5.3 we present gear-, region-, and vessel-specific incidence of eggs and yolk-sac larvae. Catches of eggs are shown in Figure 5.9 and catches of yolk-sac larvae are presented in Figure 5.10.

The daily egg production in Region 1 ($P_{0,1}$) was 2.33/0.05 m^2 (CV = 0.17, Lo and Macewicz 2002) and egg mortality was $z = 0.4$ (CV = 0.15) for an area of 88,403 km^2 (25,830 nm^2). The ratio (q) of egg density between Region 2 and Region 1 from CUFES samples was 0.056 (CV = 0.025). In

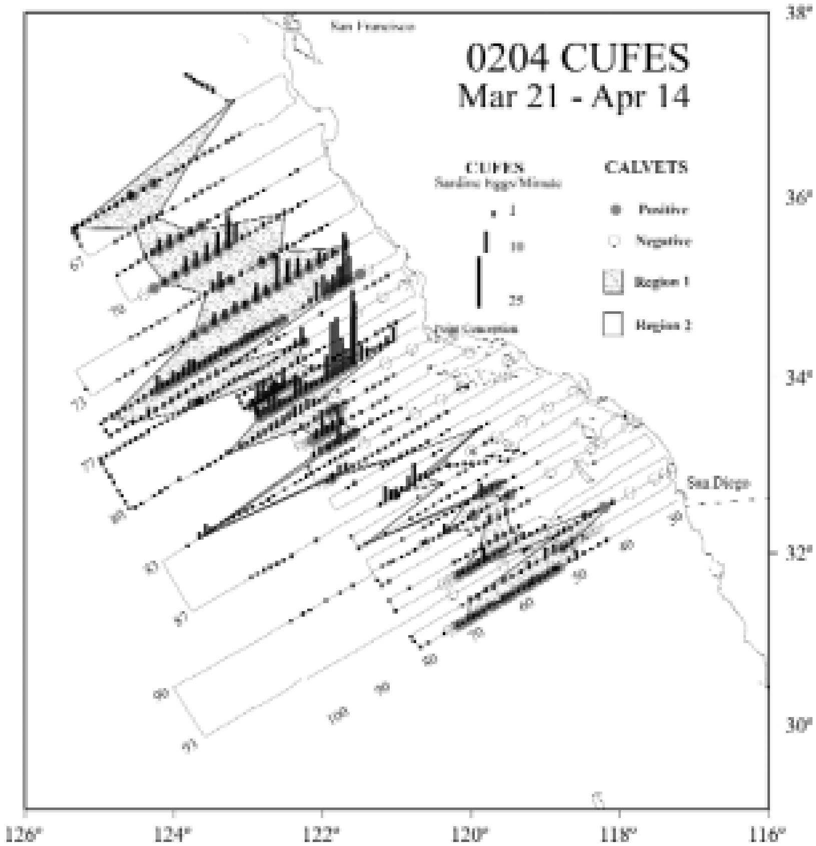

Figure 5.9. Sardine eggs from plankton net tows (solid circle denotes positive catch and open circle denotes zero catch) and from CUFES (stick denotes positive collection) in March–April 2002 survey. The numbers on line 93 are California Cooperative Fisheries Investigations (CalCOFI) station numbers. Region 1 is stippled area.

Region 2, egg production ($P_{0,2}$) was 0.13/0.05 m^2/day (CV = 0.22) for an area of 236,679 km^2 (69,154 nm^2). For the entire survey area of 325,082 km^2 (94,984 nm^2), daily egg production was 0.728/0.05 m^2 (CV = 0.17) and egg mortality was 0.4 (CV = 0.15).

Discussion

We compared results from the 2002 survey to results from a conventional survey conducted in 1994 (Lo et al. 1996) to illustrate how changing to a CUFES-aided adaptive allocation design affected the Pacific sardine assessment (Table 5.4). We believe the comparison is instructive even though the two surveys differed somewhat in area and population size. The conven-

Table 5.3.

Number of positive tows of sardine eggs from plankton nets, yolk–sac larvae from plankton and Bongo nets, and eggs from CUFES in Region 1 (eggs/min ≥ 1) and Region 2 (eggs/min < 1) for both McArthur (Mc) and Jordan (Jord) cruises.

		Region								
		1			2					
Sampling Type	Outcome	Total	Mc	Jord	Total	Mc	Jord	Total	Mc	Jord
Plankton net eggs	positive	130	112	18	12	6	6	142	118	24
	Total	149	127	22	68	25	43	217	152	65
Plankton net yolk–sac	positive	83	76	7	29	13	16	112	89	23
	Total	149	127	22	68	25	43	217	152	65
Bongo net yolk–sac	positive	4	–	4	23	–	23	27	–	27
	Total	7	–	7	58	–	58	65	–	65
CUFES eggs	positive	453	389	64	372	252	120	825	641	184
	Total	495	428	67	1,127	737	390	1,622	1,165	457

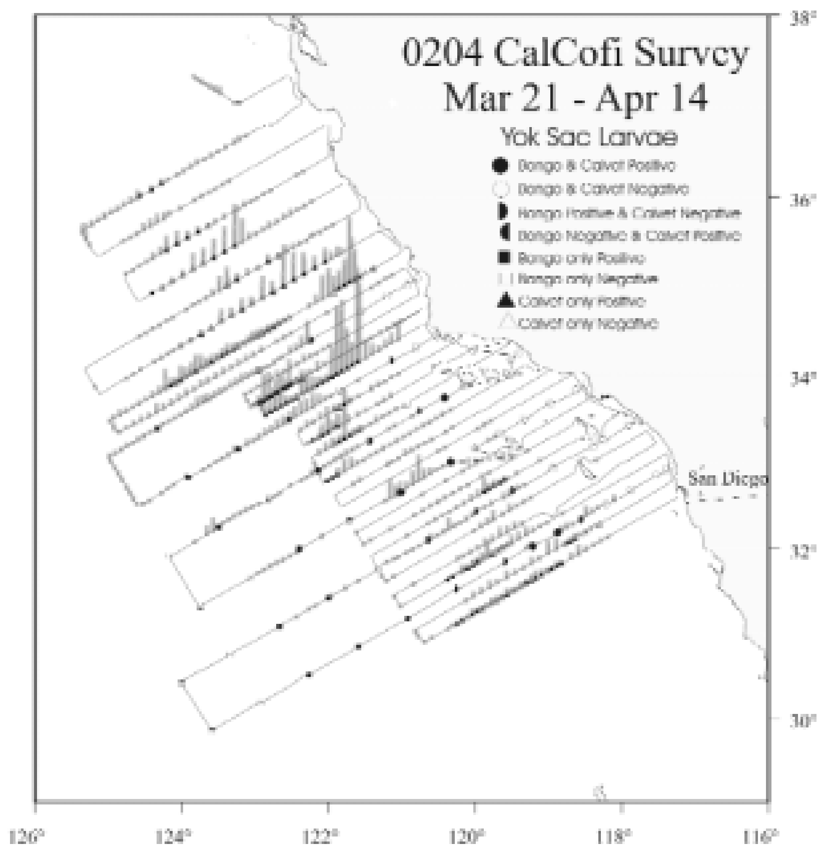

Figure 5.10. Sardine yolk-sac larvae from plankton net tows (circle and triangle) and from Bongo net tows (circle and square) in March–April 2002 survey. Solid symbols are positive and open symbols are zero catch.

Table 5.4.

Sardine daily egg production (P_0) from a conventional survey (1994) compared to an adaptive allocation survey (2002). We used the adaptive allocation survey observations from a CUFES to allocate plankton net tows.

	Survey	
Variable	Conventional	Adaptive allocation
Survey area (km^2)	380,175	325,082
Plankton tows		
Total	684	217
Positive for eggs	72	142
Percent positive	11	65
CUFES Samples		
Total	–	1,622
Positive for eggs	–	825
Percent positive	–	51
High-density stratum	–	91
Low-density stratum	–	33
Daily egg production		
P_0 (per 0.05 m^2)	0.19	0.73
CV	0.22	0.17
Daily specific fecundity (eggs/g)	11.39	22.94
Spawning biomass (mt)	127,102	206,033

tional 1994 survey covered a slightly larger area than the 2002 survey (380,175 km^2 vs. 325,082 km^2), and the total biomass of sardine was lower in 1994 than in 2002 (127,000 mt in 1994 vs. 206,000 mt in 2002).

An obvious difference in the results of the two surveys was that only 11% (74/684) of CalVET net tows were positive for sardine eggs in the 1994 conventional survey, whereas 65% (142/217) were positive in the 2002 survey (Table 5.4). This indicates that CUFES-aided adaptive allocation sampling was effective in allocating plankton net tows and thereby reducing ship time costs. The coefficients of variation for the estimates of P_0 were similar: 0.22 for the conventional survey compared to 0.17 for the CUFES-aided adaptive allocation survey. Thus, the variance penalty for using the ratio estimator q did not greatly diminish the benefit in using CUFES to post-stratify and allocate all plankton net tows to Region 1. This simple statistical comparison, however, does not reveal the greatest potential benefits in using CUFES-aided adaptive allocation sampling. Adaptive allocation would be most useful when the population is at a lower level, as it was in 1994, because at such levels one must survey a large area to ensure an unbiased estimator, but the population is probably concentrated in a very small fraction of the survey area. In addition, the high resolution maps of spatial distribution of eggs provided by CUFES have not as yet been incorporated into the survey design like Hanselman et al. (2001) did, but we plan to do so in the future. We also will develop new insights into the processes involved in selection of spawning habitats by the parents.

Any adaptive sampling requires a critical value to determine when to take additional observations. In our case, the critical value was an egg density from CUFES that triggered full water column sampling using the plankton net tows. We used a critical value of 1 egg/min, which was equivalent to 2–4 eggs/tow, depending on the degree of water mixing. In the past, the critical value was 2 eggs/min, which was equivalent to 4–8 eggs/tow. This range of critical values (2–8 eggs/tow) was similar to the value (5 eggs/tow) used in a stratified sampling design for an anchovy survey in Biscay Bay in Spain (Petitgas 1997).

An optimal critical value exists for each species and survey area. The critical value can be determined prior to the survey or during the survey using order statistics (Thompson and Seber 1996; Quinn et al. 1999). The extent to which the critical value can be fine-tuned to deliver an optimum balance between CUFES and plankton net tows for a particular region, species, and season is unknown. One factor is the large difference in catch ratios of eggs/plankton net tow to eggs/min from CUFES among years; this ratio ranged from 0.145 (2001) to 0.73 (1996), with most values around 0.25. This wide range does not support the idea of fine-tuning. These differences may overstate the expected variability for sardine because the areas were different; 1996 samples were taken over a very limited portion of the survey area, whereas in other years, the samples were collected from high-density spawning areas. Interestingly, our 2002 estimate (0.24) was similar to that we computed for sardines off the coast of South Africa (van der Lingen et al. 1998) and in previous years (Lo and Macewicz 2002).

In effect, the egg density from CUFES was used as an auxiliary variable to allocate plankton net tows. Fish eggs are constantly monitored while the CUFES is continuously pumping water. As a result, CUFES is a labor-intensive operation. To apply the adaptive allocation sampling using CUFES, fish eggs have to be easily identified by CUFES operators on the ship. Misidentification of eggs leads to large variance and possible bias. If that is not possible, other variables that are easier to measure and are somehow correlated with the variables of interest (sardine eggs in our case) can be used to base the adaptive allocation (Thompson and Seber 1996). Auxiliary variables include sea surface temperature, chlorophyll, plankton volumes for fish populations, and birds for some marine mammals.

Discussion and Future Directions

Ultimately, the practical efficiency (see Tukey 1986:97) of adaptive sampling will depend on the extent that the method is put into practice, which in turn depends on resolving (or alleviating) the challenges outlined in this chapter. It has been slightly more than a decade since Thompson (1990) introduced adaptive cluster sampling, and there is now a rich and growing base of literature focusing on adaptive sampling. However, practical application has lagged behind theoretical and methodological development. We note that 10 years after its introduction the Jolly-Seber method (Jolly 1965; Seber 1965) had not been practiced much, although it is now widely practiced in its many extensions. Hopefully, some of the material in this chapter will encourage statisticians to continue method development and stimulate biologists to experiment with adaptive sampling procedures. Although we outlined some challenges, we also offered possible solutions, and we firmly believe that more and better solutions will be discovered as biologists practice adaptive sampling on a variety of populations and under a variety of field conditions.

To help overcome the challenges that we outlined, we see a need for further method development on several fronts. First, guidelines need to be developed to help biologists identify populations that are candidates for adaptive procedures. Second, there is a need for continued work on strategies and alternative designs for restricting the final sample size. Third, because detectability is such a pervasive issue in animal ecology, methods of incorporating detectability into the finite population framework must be applied. Finally, user-friendly software would be helpful to simulate sampling before implementation and to analyze data from adaptive sampling designs.

We see at least three approaches to identifying candidate populations for adaptive sampling. Identification can be made for a specific population through a pilot survey (Salehi and Seber 1997), for a particular species (or taxonomic group) through experimental applications, ideally over multiple populations/sites (Lo et al. 1997; Hanselman et al. 2003; Smith et al. 2003), or for statistical populations that then could be compared to biological populations (Thompson 1994; Brown 2003). We expect that examples of the first and second approaches will multiply as biologists experiment with adaptive sampling procedures. Adaptive sampling might catch on within studies of certain taxa. For example, benthic organisms and pelagic fisheries are taxonomic groups that appear to be good candidates for adaptive sampling. We expect that statisticians will make substantial progress on establishing statistical criteria to guide application. Brown (2003) found that adaptive sampling generally performed well on statistical populations with small network sizes. The next step is to quantify the statistical criteria so that empirical measures can be used to guide application. For example, what are the network sizes or values for dispersion indices that correspond to appropriate application of adaptive sampling? Once we know the answers to that question, we can compare those values to population measurements taken in pilot surveys or to prior data to decide whether and how to apply adaptive sampling.

There will likely be substantial progress on methods to restrict the final sample size. In our experience, the open-endedness of the final sample size is a major deterrent to application of adaptive sampling. In applications to real populations, stopping rules have often been used because of the need to restrict final sample size (Lo et al. 1997; Hanselman et al. 2003; see also case study 2). Recent theoretical work by Salehi and Seber (2001) holds the promise that unbiased estimators will be derived for restricted designs. Other promising developments on the horizon include adaptive sampling designs that do not require a neighborhood. The absence of a neighborhood eliminates edge units and can remove much of the uncertainty in the final sample size. Neighborhood-free designs include adaptive allocation (Lo et al. 2001; see also case study 3) and sequential sampling designs (Christman 2003). A neighborhood-free adaptive sampling design called two-stage sequential sampling (TSS), recently developed by M. Salehi (Isfahan University of Technology, Isfahan, Iran), has been shown to perform well on a variety of populations compared to both conventional sampling designs and neighborhood-based adaptive sampling designs (Salehi and Smith, 2004). In the TSS design, an initial sample of secondary units (u_1) is selected within a sample of primary units. A condition is evaluated independently within each primary unit. If the condition is met, an additional sample of secondary units (u_2) is selected, but sampling stops there regardless of observations in the u_2 units. So under the TSS design the final sample size is restricted to be no more than $u_1 + u_2$ in each primary unit.

Because detectability is an issue for many species, biologists might be reluctant to even consider adaptive sampling until procedures that account for detectability have been well established and demonstrated on species at least closely related to the study species. Thompson and Seber (1994) presented methodology to account for detectability in adaptive sampling. Pollard and Buckland (1997) developed a technique to combine adaptive sampling with line transect sampling that adjusts for imperfect detectability. When applied in a survey of harbor porpoise, adaptive sampling reduced the variance in density estimates compared to traditional line transect sampling because increased observations resulted in improved estimates of detectability (Palka and Pollard 1999). Smith et al. (2000, 2001) demonstrated methods to incorporate detectability via double sampling in freshwater mussel surveys that use conventional finite sampling designs, and those methods can be extended to similar surveys that use adaptive sampling. Because mark-recapture sampling is an important technique used to account for imperfect detectability, combining mark-recapture and adaptive sampling would be productive.

Not many statistical techniques gain widespread acceptance without full-featured software that performs the necessary calculations. A software program called Visual Sampling Plan (VSP) produced by Battelle Memorial Institute (download at http://dqo.pnl.gov/vsp/vspsoft.htm) is a very powerful tool for sampling design, and it includes modern designs such as adaptive cluster sampling and ranked set sampling. VSP was developed to support contaminant monitoring and assessment, so the language used to describe sampling does not match how a biologist might discuss sampling. For example, sampling goals are framed in terms of comparisons to thresholds and reference values rather than estimating density, abundance, or biomass. Also, the range of adaptive sampling designs that are implemented in VSP is limited to selecting the initial sample by simple random sampling, two neighborhood shapes, and no option for stopping rules. We see a need for a similarly featured software package focusing on biological applications and including a much wider range of adaptive sampling designs.

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