Urban, D.L. 2002

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Tactical monitoring of landscapes

11.1 Introduction

Landscapes are large by conventional definitions (Forman and Godron, 1981, 1986; Urban *et al.*, 1987; Turner, 1989) and data at that scale are dearly bought. Yet with the advent of ecosystem management (Christensen *et al.*, 1996) – which implies a larger scale of reference than prior approaches to resource management – researchers and managers are increasingly faced with pursuing sampling and monitoring programs at these larger scales. A significant component of such programs should be the establishment of long-term monitoring systems designed to detect trends in resources, prioritize management needs, and gauge the success of management activities. This goal can be especially daunting in cases where the study area is especially large, where the signal to be detected is uncertain (e.g., potential responses to climatic change), or where the objects of concern are simply difficult to locate (e.g., rare species).

Here I consider some approaches that may prove useful in designing sampling and monitoring programs for landscape management. In contrast with large-scale efforts that are coarse-grained and intended as "first approximations" (Hunsaker *et al.*, 1990), or more location- or taxon-specific methods (e.g., examples in Goldsmith, 1991), my concern here is with problems that are simultaneously fine-grained and of large extent. This is essentially a sampling problem at first, with the goal of capturing fine-grained pattern in an efficient manner. In many cases, however, even an efficient blanketing of the study area is logistically infeasible and so a second concern will be to focus sampling as powerfully as possible on a specific application or hypothesis. Two key attributes of this approach are the explicit pursuit of multi-scale designs and the integration of models as a guide to sampling. This latter aspect of the approach has much to offer in the implementation of adaptive management of natural resources, as I discuss in a closing section.

11.2 Terms and scope of discussion

The issue of sampling designs for monitoring natural resources is not new and my intent here is not to review – nor even echo – a huge and growing literature. General references (Cochran, 1997) and more application-specific texts (Goldsmith, 1991; Schreuder *et al.*, 1993) are widely available. In particular, a collection of articles spawned from a workshop by the Sustainable Biosphere Initiative provides an authoritative statement of the state of the art (Dixon *et al.*, 1998, and other articles in same special feature). As a bridge to this literature, however, some definition of terms and scope will be useful. Insofar as possible, I will try to follow the terminology of Nusser *et al.* (1998).

It is useful to distinguish multiple components of the monitoring process. *Sampling design* pertains to schemes devised for collecting measurements. This aspect has a natural correspondence to *experimental design*, the framework for statistical estimation and inference. For example, a completely random sampling design corresponds to a completely randomized design in estimating the effects; a stratified sampling design corresponds to a randomized complete block design (and see below). This distinction is important for two reasons. First, it separates the process of *acquisition* of the data from the task of *estimation* of statistical parameters for the population of inference. In general, a sample is a set of observations (cases, units, or elements) from a finite population or sampling frame. This is the scope of sampling designs. By contrast, statistical estimation typically is carried out subject to assumptions about the distribution of data (assumptions presumed of infinite populations). In this chapter I focus on the sampling problem, echoing Stow *et al.* (1998) in the opinion that if the data have a high signal-to-noise ratio and sample sizes are adequate, the analysis phase is less of a challenge.

Some elements of sampling design are especially pertinent to the illustrations I discuss in this chapter. Samples are often *stratified* over various criteria (*strata*) to achieve a balanced coverage in the sample. For example, one might stratify samples over vegetation types, topographic positions, or soil types. In landscape ecology, the stratification is often over *space*: the strata are geographic.

Monitoring programs often rely on rather complicated hybrid designs to meet multiple objectives. These designs include *multi-stage sampling* and *multi-phase sampling*. In the former, a (large) set of primary sampling units is identified and then subsequently resampled in a restricted way to generate the samples. In multi-phase sampling, the initial sample is surveyed for (typically) readily measured, coarse-resolution variables and then in a subsequent phase, some subset of these samples is revisited and a *different* set of (typically) more logistically demanding variables are measured. This second set is then related to the initial set, e.g. via regression, and thus is used to leverage additional information from the initial, coarse-resolution data set. I mention these designs because, while I do not address these explicitly in the discussion to follow, the recommendations I make are consistent with more complicated designs.

Finally, a potential source of some confusion relates to the statistical estimation of parameters from sample survey data. Classical survey statistics are *design-based estimators* in that the sampling design (or experimental design) dictates the form of the statistical estimators. For example, each sample's contribution to a parameter might be *weighted* by its probability of selection or inclusion; for many sampling designs, this probability depends on the sample's areal representation (e.g., how common that cover type is on a landscape). By contrast, auxiliary information may be used to control or calibrate these weights, leading to *model-based* or *model- assisted* estimators. In the discussion that follows, I present a different perspective on model-based sampling designs, one aimed at data collection rather than statistical estimation. I trust that this distinction will be apparent from the context of the discussion.

11.3 Sampling spatial heterogeneity: Multi-scale designs

A significant challenge to sampling over large areas is that many processes ecologists wish to capture are implicitly fine-grained but play out at large scales. For example, the process of seed dispersal takes place over distances of tens of meters but may be manifest in species distributions over larger gradients (hillslopes or landscapes; Clark *et al.*, 1999), and perhaps even at subcontinental-scale species migration (Clark *et al.*, 1998). Similarly, microtopographic effects on soil moisture gradients vary over distances of tens to hundreds of meters but are fundamental to landscape-scale patterns in plant species abundances (Halpin, 1995; Stephenson, 1998; Urban *et al.*, 2000). These patterns mandate a sampling design that can capture fine-grained details over large extent, a challenge that is not well met by simple sampling designs such as uniform, random or stratified-random designs.

The essential challenge in sampling such patterns is to collect samples such that they cover most of the study area (i.e., the sampling frame is the entire population of interest) but also to include samples that are sufficiently close together to capture the fine-grain pattern – an important consideration if geostatistical methods are to be used in analyses. For example, a uniform sampling grid provides a finite set of between-quadrat distances (i.e., x, SQRT($2x$), $2x$, SQRT($5x$), . . . where x is the interval of the sampling grid) and this can degrade geostatistical analyses by constraining sample sizes within some distance classes. In the uniform case, the spacing of samples depends only on sampling

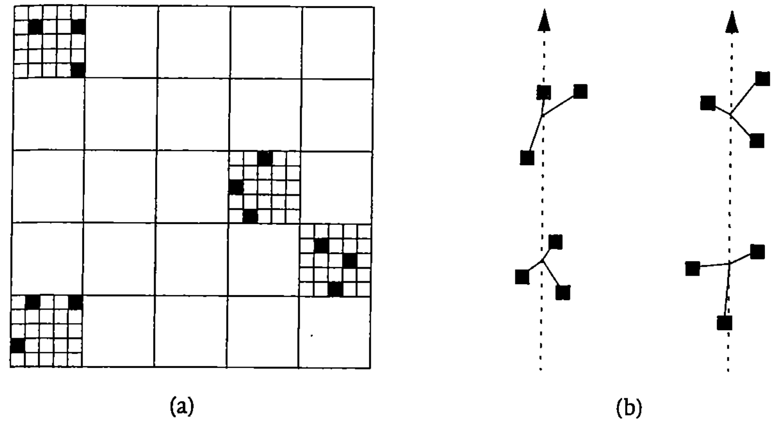

FIGURE 11.1
Examples of multi-scale sampling designs. (a) Nested non-aligned blocks, in which four of the cells have been selected for sampling and each cell is subdivided by a nested grid, itself sampled with three sub-cells (filled). (b) Stratified clusters, in which four cluster centroids are stratified over the study area and three sampling points are located at random distances and azimuths from each centroid.

intensity, or the number of sample elements in the study area. Thus, for large landscapes that are sparsely sampled, the sample elements would be far apart and fine-grained patterns would be missed. Random or stratified-random sampling designs do not have as severe a drawback in terms of geostatistical analyses, but they still suffer the dependency that sampling intensity dictates the frequency of samples within short distances.

The solution to this challenge is to devise multi-scaled sampling designs to collect measurements over short distances while also covering a large study area. Two sampling designs seem especially well suited to this. *Nested non-aligned block designs* use a grid as a basic sampling template, with samples located randomly in some of the grid cells. For example, in a non-aligned block design one might specify some percentage of the grid to sample, randomly select the corresponding number of cells, and then randomly locate a quadrat within each of these cells. A *nested* nonaligned block design follows the same procedure for subsampling within the selected grid cells, by using a finer-scaled grid within each selected cell of the larger grid (Fig. 11.1a). The blocks can be nested further, as deeply as is necessary to capture the details of interest. A nested non-aligned block design is roughly equivalent to a multi-stage stratified random design (see below); nesting the blocks makes it multi-scaled and allows the samples to capture fine-grained information over large areas. The level of nesting and cell size in the grid dictates the grain of sampling.

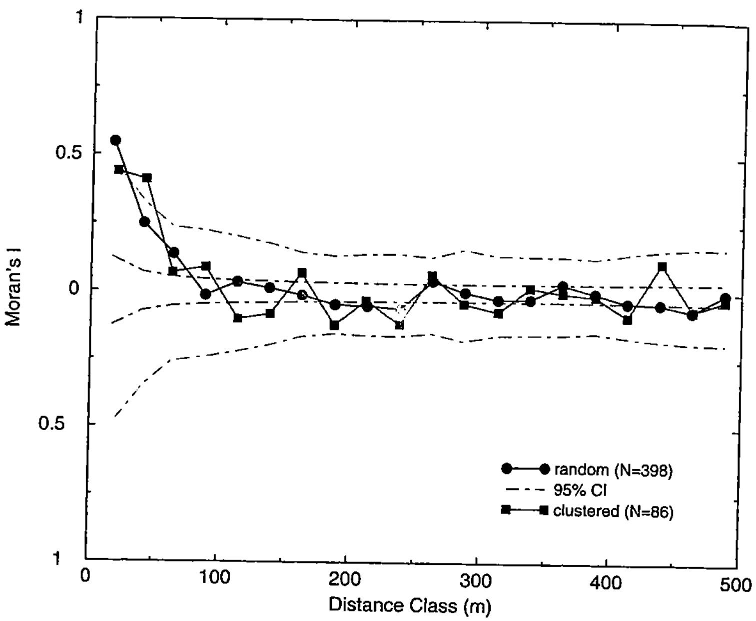

FIGURE 11.2
Examples of computer-based sampling experiments in which alternative sampling designs and intensities are compared in terms of their efficiency in reproducing a reference correlogram based on an arbitrarily large (and logistically infeasible) number of samples. Here the reference case is a correlogram of a topographic convergence index derived from a digital elevation model of a small watershed in the Sierra Nevada; the reference case was sampled using 398 random points. In comparison, the clustered design used cluster centroids arranged on a grid over the watershed, with three samples randomly located within <100 m of 29 cluster centroids (one sample fell outside the watershed boundary and was discarded). The clustered design reproduced the reference correlogram with about one-fifth the sampling intensity.

Equivalently, a multi-stage stratified random or *stratified cluster design* begins as a stratified-random design but locates multiple sample quadrats near each stratification point. A convenient method for achieving this design in the field is to lay out transects and locate cluster centers at (perhaps staggered) intervals along the transect, then locate sample units at random distances and azimuths from the cluster center (Fig. 11.1b). (This design is essentially equivalent to the multi-stage design described by Nusser *et al.* [1998], although the process for locating elements is slightly different.) The net result of a stratified cluster design and nested non-aligned blocks is the same: sets of sample elements (quadrats) with some separated by close distances yet with samples covering the entire study area. The difference in the two designs is in how they are laid out in the field; non-aligned blocks use a grid while clusters use transect lines. The choice depends largely on ease of implementation in the field.

In computer-based sampling experiments with known patterns, clustered designs often can capture the pattern (as a correlogram) using five-fold fewer samples than random samples (Fig. 11.2). Similar computer-based sampling experiments suggest that order-of-magnitude reductions in sampling intensity might be feasible for larger study areas (Urban *et al.*, 2000). To sample variables with unknown grain or pattern, a multi-scale pilot study would seem necessary to develop the most efficient possible design for actual sampling.

In designing field studies, the exercise illustrated in Fig. 11.2 can provide a useful pilot study and guide to actual sampling. For example, digital elevation models (DEMs) can provide a variety of indices that can be used as proxies for soil moisture or edaphic gradients (Moore *et al.*, 1991). DEMs (or derived secondary indices) can be sampled using a variety of designs to find a sample arrangement (number of points per cluster, cluster spacing) and intensity (number of samples) that can capture the pattern with a logistically feasible sampling effort.

11.4 Model-integrated sampling designs

Multi-scaled sampling designs are efficient when the pattern to be described is simultaneously fine-grained and of large extent. But in many cases, even a multi-scaled design is simply not supportable for logistical reasons. For example, a design to capture topographic grain in Sequoia-Kings Canyon National Park (the case considered by Urban *et al.*, 2000), might require thousands of sample points – probably too many for a single inventory, and certainly too many to consider resampling through time. In these cases, it is important to consider that all data are *not* created equal: some observations are much more informative about specific hypotheses while other data might not provide any insight at all.

In field studies over small extent, ecologists sometimes can get away with over-sampling – essentially a "shotgun" approach that collects the appropriate data along with extraneous data that are not useful for the specific application at hand. This can work for small study areas but is simply unsupportable for large-scale efforts. An alternative approach is to use a model to help discover which observations will be most useful for a specific application or research task. Here I illustrate this approach with three examples, proceeding from simple (conceptual) models to more complicated simulation models.

11.4.1 The rare herb *Fusilli puttanesca*

The first example is purely hypothetical and is used to present a logical structure for guiding sampling schemes. *Fusilli puttanesca* is a relic herb that grows in riparian meadows in the southern Appalachian foothills. Because of its showy flowers it is much prized by hikers and nature buffs, who decimate its populations near roads and trails. The research question at hand is, What limits the local abundance of this species? Is its distribution habitat-limited? Does it behave as a metapopulation (a "population of populations" in more-or-less discrete habitat patches; Harrison, 1994; Hanksi, 1998) and is it dispersal-limited? Or is human impact the chief constraint on its distribution? The key to this application is that only a few observations might be needed to shed light on these questions; the task is to isolate these observational cases. Importantly, a naive approach of simply combing the study area for the plants will be woefully inefficient and may not answer the question at hand.

First, assume that this task can be simplified by collapsing all habitat patches into binary cases: good habitat versus non-habitat, connected versus isolated in terms of population dispersal, and near versus far from trails as an index of the likelihood of disturbance by hikers. Then note that the three factors and two levels yield only eight combinations of conditions; these combinations can be represented readily in a decision tree (Fig. 11.3). From a standpoint of thoroughness, sampling each branch of the tree, with some replication, completely addresses the questions at hand. In terms of experimental design, this is a full factorial design corresponding to a balanced ANOVA model.

Sampling a decision tree is a straightforward task if it can be posed within the framework of a geographic information system (GIS). In a GIS the identification of locations that meet a number of conditions simultaneously (e.g., meet the definition of "habitat," within a threshold distance of other habitat, and farther than a threshold distance from roads or trails) is accomplished via "map algebra" (intersection), and these locations can then be subsampled using a random or stratified design (see below).

This decision-tree structure is contrived, but for a reason. This approach is consistent with a powerful statistical approach to this sort of question, that of classification and regression tree (CART) modeling (Breiman *et al.*, 1984; Moore *et al.*, 1990). A CART model is a nested regression approach in which data cases (observations) are partitioned recursively in a tree-like structure. In a typical case, the samples might be labelled occupied versus unoccupied samples for a given species, or similarly, habitat versus non-habitat, or near versus far and so on. In the case of a binary dependent variable (e.g., habitat versus non-habitat) and interval-scale predictor variables (e.g., elevation, slope, rockiness, and so on), the solution is equivalent to a set of nested logistic regressions that identify critical values on the independent variables that best classify the input samples. The final classification tree is comparable to the dichotomous trees used as taxonomic keys.

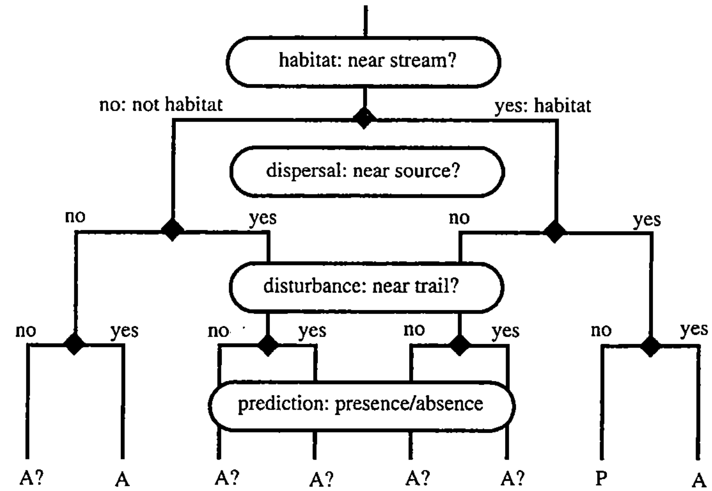

FIGURE 11.3
A decision tree highlighting the role of habitat availability, accessibility (dispersal limitation), and local disturbance (decimation by hikers) in governing the local distribution of a hypothetical species. Branches are labelled A (absent) or P (present); ? indicates an uncertain or indeterminate branch. Note that if disturbance is the primary agent of concern, only two of the branches provide data that are unconfounded by other factors. Note also that few cases seem unequivocal, depending on the strength of the three constraints.

For my present purpose, it is especially useful that one can posit a decision tree as a guide to sampling, in effect posing a working hypothesis about the relevant factors controlling species distribution. Field data collected according to this design can then be used in CART analysis to actually estimate the model – that is, to find the actual critical values that define habitat, isolation, or disturbance probability. Of course, this approach also assumes that the first decision tree is fairly reasonable or else the sampling might miss the solution badly! Fortunately, this approach can also be self-mending in that as samples accrue, a better estimate of the overall situation (explanatory model and CART solution) can be refined.

Note that in terms of sampling efficiency, a design that represents all branches of the decision tree is thorough but not necessarily efficient. Indeed, for a complicated or multi-levelled tree, the implied sampling effort might be untenable for logistical reasons. In these cases, it is worth noting that some hypotheses can be isolated quite parsimoniously in the decision tree. For example, if the primary interest in these herbs is in hiker impact, then note that the only cases that offer any clean insight into this are those samples that are good habitat and not dispersal-limited. Samples that are isolated or poor habitat might be unoccupied for those reasons and thus can tell us nothing about disturbance. That is, only two of the branches of the tree are of immediate interest (the two farthest to the right in Fig. 11.3) and sampling effort can be adjusted accordingly. Likewise, if dispersal limitations are the primary concern then habitats close to trails or otherwise prone to disturbance are confounded and not useful for a study of dispersal. Thus, by focusing on specific hypotheses, the sample effort can be drastically reduced and focused in a tactical way. Indeed, the level of statistical control over extraneous factors might well lead to increased statistical power.

Of course, in some cases the underlying model is sufficiently complex that a simple decision tree does not provide enough leverage on the problem to be useful as a guide to sampling or monitoring. In these cases, more complicated models can be applied.

11.4.2 The Mexican spotted owl

The Mexican spotted owl (*Strix occidentalis lucida*), a sister subspecies of the more notorious northern spotted owl, occupies mixed-conifer and pine–oak forests of the American Southwest including southern Utah and Colorado, Arizona and New Mexico, and parts of northern Mexico. It was listed as federally threatened in 1993, largely under threat of habitat loss. Over parts of its range, primary habitat occurs as higher-elevation forests on mountains separated by desert (so-called "sky islands") and it is easy to envision the species acting as a classical metapopulation (Harrison, 1994; Hanski, 1998) in the sense of spatially discrete populations coupled by infrequent dispersal. The Recovery Plan mandated by the Endangered Species Act (US Department of the Interior Fish and Wildlife Service, 1995) specifically considered landscape context and connectivity in its deliberations and recommendations (Keitt *et al.*, 1995).

Keitt *et al.* (1995, 1997) devised an approach in which they attempted to identify those habitat patches that might be especially important to long-term persistence of the owl. Habitat patches might be important for two reasons. Large patches are important simply through their area alone; larger patches produce more owls and consequently have a significant impact on metapopulation recruitment. More interestingly, a patch might also be important because of its spatial location and role as a dispersal conduit or stepping-stone; these patches needn't be large yet can still have an important effect on the metapopulation via immigration and emigration.

Keitt *et al.* (1997) defined landscape connectivity in terms of average traversability, indexed as correlation length. The index is computed from raster data in which a habitat patch is a cluster of adjacent cells of "potential owl habitat" as defined by forest cover types. Correlation length depends on patch areas and shapes:

$$C_L = \sum_{i=1}^{n} A_i \cdot R_i \tag{11.1}$$

where A_i is patch area as a proportion of total map area; R_i is the patch's radius of gyration (Stauffer, 1985), the mean Euclidean distance from each cell in the cluster to that cluster's centroid (compact clusters have smaller radii than long or irregular clusters); and there are n patches in the landscape. Correlation length is the expected distance that one might traverse the map while remaining in "habitat" and thus serves as a useful index of connectivity.

The authors performed a patch-removal sensitivity analysis in which they sequentially removed each habitat cluster and recomputed correlation length for the landscape. They then ranked the patches in terms of the magnitude of change in correlation length on patch removal; that is, the highest-ranking patch was the one whose removal resulted in the largest decrease in correlation length. Raw ranks tended to highlight the largest patches as being most important, because of the area term in the formula (eq. 11.1) (Fig. 11.4a, color plate). By dividing each patch's effect (loss of correlation length) by its area, they focused on the area-corrected importance of each patch (Fig. 11.4b, color plate). This area-relativization emphasized small patches that were located in key places for dispersal: stepping-stones.

This ranking was not intended as a definitive statement on owl population biology. Rather, the goal was to develop and illustrate a macroscopic approach that would identify key habitat patches from the perspective of landscape connectivity and metapopulation structure. For my present purpose, it is sufficient to note that these patches offer themselves as candidate study areas and monitoring locations if we wish to learn more about owl dispersal in a metapopulation context. Importantly, it should be noted that these patches (highlighted in Fig. 11.4b, color plate) tend *not* to be the places one might naturally choose as study areas when working with rare or threatened species. For logistical reasons, one would quite naturally choose locations that are prime habitat and probably large, simply because a large number of observations could be collected. The analysis of Keitt *et al.* (1997) suggests that, for spatially distributed metapopulations, the most informative locations for monitoring might not be obvious, indeed, might not even support appreciable populations.

Urban and Keitt (2001) have since extended this approach to embrace the computational framework of graph theory (Harary, 1969; Gross and Yellen, 1999). Graph theory is a well-developed body of theory concerning flux or routing in networks, broadly defined. Urban and Keitt used graph theory to index patch importance to the metapopulation in terms of recruitment flux, in the sense of Pulliam's (1988) metapopulation model, and also in terms of long-distance traversability, in the sense of Levins's (1969) original "spreading-of-risk" model of metapopulations. Patch-removal sensitivity analysis thus permits ranking habitat patches on multiple criteria in a computationally expedient framework. Again, because the approach is macroscopic, it need not provide a definitive answer about the actual importance of each habitat patch in the landscape; but the patches thus identified are certainly prime candidates for further study or monitoring.

The macroscopic approach amounts to a sensitivity analysis of an underlying explanatory model couched in metapopulation theory. The approach is macroscopic in that it relies on map analysis without actually invoking details of a metapopulation model (i.e., there is no explicit parameterization of demographic processes or dispersal). In the next example, I consider a more explicit simulation model.

11.4.3 Climatically sensitive sites in the Sierra Nevada

The mixed-conifer forests of the Sierra Nevada of California are climatically sensitive over multiple time-scales (Stephenson, 1998) and are currently the focus of an integrated research program in Sequoia-Kings Canyon and Yosemite National Parks, aimed at anticipating the possible consequences of anthropogenic global change (Stephenson and Parsons, 1993). These forests are host to a variety of species including the giant sequoia (*Sequoiadendron giganteum*), whose narrow distribution with respect to elevation (a proxy for temperature in steep mountains) suggests potentially drastic impacts of rapid climate change in a greenhouse world.

One goal of the Sierra Nevada Global Change Research Program is to identify sites that might serve as potential "early warning" sites and thus form the backbone of a monitoring program. Our approach to this has been to use a simulation model to characterize the physical template of these landscapes, and then to analyze the model to find locations that might be most sensitive to climatic change.

The Sierra has a Mediterranean climate with mild winters and very dry summers. With an increase in elevation, temperature decreases while precipitation increases; importantly, the precipitation changes from rain to snow at middle elevations, and it is the persistent snowpack that develops at middle elevations that provides growing-season soil moisture which supports the mixed-conifer zone. The soil moisture balance represents a complex interaction with temperature as it affects the partitioning of precipitation into

snow versus rain, the dynamics of snowmelt in the spring, the onset and end of the growing season in terms of plant phenology, and evaporative demand during the summer. Urban *et al.* (2000) developed a simulation model that adjusts monthly temperature, radiation, and precipitation for topographic position (elevation, slope, and aspect) and that, in conjunction with soils data and plant canopy characteristics, simulates the soil water balance for these sites. Urban (2000) then performed a sensitivity analysis of the model to quantify the sensitivity of soil moisture to variation in temperature and precipitation. The sensitivity analysis was conducted across the full parametric space of the model, so that the relative sensitivity of different elevations, slopes, and aspects could be defined. Model sensitivity was then regressed on these terrain variables and these regressions were used in a GIS to map model sensitivity from parameter space into geographic space. The analysis also included a measure of uncertainty in the model. Because the model simulates a discrete point in space it could not attend the complexities of lateral hydrologic flow and consequent microtopographic effects on soil water drainage. Uncertainty due to topographic drainage was included by highlighting locations in the study area with contrasting topographic drainage indices. A false-color grid composite was generated to highlight regions of the Kaweah Basin, one of three large basins comprising Sequoia-Kings Canyon National Park, in terms of their relative sensitivity and uncertainty (Fig. 11.5, color plate).

In this figure the magenta zone is simultaneously sensitive to variation in temperature and precipitation. This zone represents roughly 17% of the basin. That is, the potential monitoring sites that seem most sensitive to climate change represent only about one-sixth of the study area – an appreciable focusing of any monitoring effort.

Urban (2000) went further, to select climatically sensitive sites that would also allow the placement of sample quadrats on contrasting topographic positions within a logisitically reasonable distance (100 m) and close to roads or major trails (500 m, a concession to the rough terrain and a humanitarian gesture to field crews!). These further restrictions reduced the target sampling domain to less than 2% of the study area: a substantial focusing of sampling effort and efficacy.

In these examples, note the trend toward increasing complexity of the "model" underlying the sampling. In the first example the model was a simple hypothesis; in the case of the spotted owl, a static analysis of an implicit model; and in this last example, a formal analysis of a dynamic simulation model. The underlying principle is the same in each case, however: by using a model as a guide to designing a sampling scheme, the scheme can be focused substantially and with greater efficiency than conventional designs.

11.5 Monitoring temporal change: Trend detection and efficiency

Note in the case of metapopulation dynamics there is a long-term commitment to monitoring implicit in the underlying model: metapopulations are defined by between-patch dispersal events that might occur only once per generation or so (Harrison, 1994; Hanski, 1998). Similarly, monitoring for the effects of anthropogenic climate change mandates an investment in monitoring that extends well beyond the scope of typical research programs. The temporal aspects of large-scale monitoring programs, however, have not received as much attention as they might warrant.

A contrived example illustrates the potential implications of ignoring spatiotemporal dynamics in long-term monitoring programs. Consider a species whose distribution is patchy and which disperses from population centers. Over time, such a population would exhibit spatial drift, as is typically seen in population models implemented as cellular automata or explicitly spatial partial differential equations. Clearly, if one were to establish a set of monitoring stations randomly (i.e., without reference to initial occupancy), then the actual stations occupied by the species would change over time. On average, one might expect the proportion of occupied stations to remain relatively constant for a stable population – a classical definition of a metapopulation. If, however, the species of interest is quite rare, then it would be completely reasonable to set up monitoring stations in locations where the species actually occurred. This would be especially likely if initial studies of the species led to site selection such that adequate sample sizes could be garnered for demographic studies. If such sites were retained for monitoring (recognizing the value of extending the initial studies), then over time the monitoring will almost certainly show a population decline as the species drifts away from the initial site. This sort of bias would seem especially awkward, to say the least, for monitoring programs aimed at rare or threatened species.

While contrived, the example is not unrealistic. For example, Sutter (1986) compared a variety of monitoring approaches for the rough-leafed loosestrife (*Lysimachia asperulaefolia*) in savanna–pocosin ecotones, a fire-maintained habitat in the southeastern coastal plain of North Carolina. Resamplings of fixed locations showed a marked population decline over as little as two years. But *Lysimachia* is rhizomatous, and in fact the population seems to be persisting quite well, even increasing: it merely moved.

Similarly, for species with fine-grained microhabitat affinities for particular successional stages, succession itself would lead to an apparent change in species abundances as monitoring sites succeed to other microhabitats and species move to find suitable sites. The "shifting mosaic" nature of vegetation (Watt, 1947; Bormann and Likens, 1979; Smith and Urban, 1988) predicts that as vegetation undergoes succession/disturbance dynamics, any species dependent on microhabitats must also ride these dynamics in space and time (Urban and Smith, 1989).

One solution to the complexities implied by spatiotemporal dynamics is to use what are called rotating-panel (Duncan and Kalton, 1987; Schreuder *et al.*, 1993) or partial resampling (Usher, 1991) designs. In this, a fixed number of sample points is established for the initial survey. At the next survey time, a percentage of the original samples is resampled (say 80%), and a set of new samples is established to fill out the sample size (here, 20% new plots). At the next survey, the procedure is repeated: some samples are discarded and some new samples are established. While it may seem costly to discard samples each time, the overall sample is in a sense refreshed by the new samples. In monitoring spatial processes, this design ensures that as populations drift the sampling can discover them. Rotating-panel designs are not much used in ecology (but see Lesser and Kalsbeek, 1997; White *et al.*, 1999), but certainly warrant further consideration.

Note that this discussion has focused on correctly detecting the trend in population dynamics through monitoring. While this is important, even crucial, to natural resource management, it begs an equally important issue of detecting the processes or constraints responsible for the observed trend. For example, is the population declining because of habitat area in itself, is habitat isolation important, or is it some other constraint or process? More in-depth goals in monitoring would seem to require sampling schemes based on model analysis, such as described above.

11.6 Opportunities in adaptive management

The issue of effective monitoring of landscapes fits neatly into a larger framework of adaptive management. Adaptive management (called "learning by doing" by Walters, 1986) is not new (Holling, 1978) but is emerging to play a central (but not uncontroversial) role in resource management (Walters and Holling, 1990; McLain and Lee, 1996; Johnson 1999a,b; Lee, 1999). Key to the concept of adaptive management are several defining elements (Lee, 1999): that management is bioregional (landscape-scale or larger), that governance and implementation are collaborative (involving stakeholders), and importantly, that managers rarely know enough about the systems they hope to manage. The framework of adaptive management is intuitive, involving an underlying model of the system which leads to a management strategy or policy, a monitoring program, and a mechanism for evaluation and reaction (Fig. 11.6). The approaches to model-based monitoring schemes described above are an attempt to strongly couple the initial stages of this

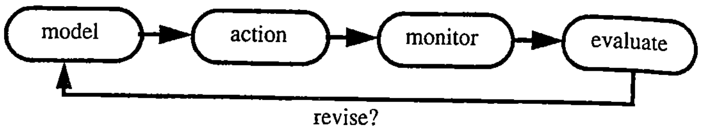

FIGURE 11.6
Schematic of the adaptive management approach. Stakeholders are involved actively in the modeling, action (management strategy or policy), and evaluation phases. Approaches to model-based monitoring schemes discussed in this paper strongly couple the first and third stages of the process.

process, by forcing the monitoring scheme to proceed directly from the underlying model.

This approach is consistent with Lee's (1999) appraisal of adaptive management on several important issues. First, the approach recognizes that a rigorous model-based approach to sampling will likely yield useful and reliable data at lowest cost and most rapidly. Second, the model analysis implicit in the decision-tree approach, and explicit in the later examples, provides a means of emphasizing the central factors identified as being important to the underlying model, while also providing a means of controlling or excluding extraneous factors. Again, data are expensive and some focus on specific factors is logically and logistically necessary. The approach using sensitivity or uncertainty analysis recognizes that "our ignorance is uneven" (Lee, 1999) and thus the most important uncertainties should be addressed rigorously and early. This is also in agreement with Johnson's (1995) advocacy of simulation models as learning tools that can be used to identify critical uncertainties for adaptive management. Finally, because model-based or experimental approaches always run some risk of "surprise" or unanticipated results, the feedback from evaluation to model revision – and by extension, to a revised monitoring scheme – provides for a flexible approach that evolves as we learn (Ringold *et al.*, 1996).

11.7 Summary

I make two points in this discussion. First, landscapes are large and often comprise patterns that are fine-grained, and so conventional sampling approaches will seldom perform as efficiently as designs geared explicitly toward capturing such patterns. Multi-staged stratified designs tend to be more efficient, capturing spatial patterns with fewer samples than simple designs (stratified or random). Importantly, sampling designs often can be tested and fine-tuned in advance by experimenting with alternative designs using digital data from a study area, such as terrain-based indices or land-cover maps. Such cyber-sampling pilot studies can lead to a substantial reduction in the sampling intensity and consequent logistical expense of sampling, while still capturing the patterns of interest. Any design, of course, should be confirmed and further modified as necessary through a pilot study in the field.

Second, I emphasize that all data are *not* created equal: some observations are more informative about particular hypotheses than others. Thus, when the goal is to provide as much leverage as possible for a particular hypothesis or working model, sampling can be focused dramatically by explicitly incorporating the model into the sampling design. This can be accomplished in a simple manner using tree-based guides (decision trees, classification trees), or more formally through the use of computer simulation models.

It should be emphasized that model-guided designs also test the model efficiently, gathering observations that would confirm or disprove the model. Thus, using a model as a guide can be useful even if the model is preliminary or inadequate, because data collected subject to the model's assumptions can only improve the model (note that the most effective way to improve a model is to force it to fail: Mankin *et al.*, 1975). Model-guided designs thus can emerge as a component of adaptive management, with the underlying model providing tests that will ultimately improve the model itself. This approach thus elevates monitoring from a rather passive role to a more active and integrative role in resource management and landscape ecology.

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