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Decision-Making and Monitoring Strategies in Natural Resource Management and Conservation

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Introduction

Natural resource management is an exercise in decision-making: choosing to act, how to act, or even to not act. These decisions are rarely simple, because of uncertainty in (i) the current state of the system, (ii) ecosystem processes, (iii) the effect of management actions on system processes, and (iv) implementing the intended action. For example, let's consider these uncertainties in the context of sustainably managing the harvest of wildlife and fisheries populations. To decide on the annual allowable harvest, we should ideally understand the size and distribution of the population to be harvested (i). Yet, counting wild animals is often challenging, especially at large spatial scales, commonly leading to sampling errors [1] that require explicit consideration [2,3]. Further, we should know about factors that affect population dynamics, such as abiotic and biotic processes (ii) and harvest decisions (iii). The how and why of population change has been a central focus of ecology [4], including the creation of global databases on demography [5]. Yet, there are still substantial knowledge gaps across many taxonomic groups and geographic areas [5], including many well-known species of conservation concern [6]. Last, controlling the number of animals harvested is not always straightforward (iv). We may only be able to control harvest indirectly through local, state, or federal regulation, such as the length of time harvest is allowed, or the method of harvest (e.g., wildlife: archery, rifle, shotgun; fisheries: long-line, seine net, trawl). These regulations partially control the number of harvested animals, but there is a lot of variability in the number of harvested animals that can occur within these regulations [7].

An additional complexity in natural resource management is that many decisions are recurrent, such that current decisions will affect the system and thus all future decisions [8]. For example, consider a manager aiming to conserve grassland breeding birds within a wildlife refuge. They may be managing for open grasslands by using prescribed fire and need to decide on a fire-return interval [9]. The timing of the prescribed fire will affect the grassland, the soil, the breeding birds, and thus all future decisions of when to burn. Further, resource managers almost always have multiple (and potentially competing) objectives motivated by a diverse set of policies and stakeholders [10]. The manger may also be considering the frequency and timing of the burn to minimize the financial costs and disruption to recreational users of the refuge, such that a short burn-interval will be more costly and disruptive than a longer one; however, a shorter interval may be more beneficial for grassland birds. Making a decision that balances the effects on birds, people, and budgets now and in the future is not intuitive.

Managing renewable natural resources for human exploitation requires recurrent decision-making, such as deciding annual fishing and wildlife harvest quotas, the interval between forest cuttings, drawing down of water reservoirs, and agricultural crop rotations. Managing non-renewable natural resources (e.g., oil and natural gas) can also lead to recurrent decisions when managing extraction rates to maximize profit with fluctuating commodity prices. The compounding of recurrent state, process, action, and control uncertainties (i–iv, respectively) along with competing multiple objectives can be overwhelming for decision-makers. This may lead to inaction despite a strong need for immediate action [11]. This may also lead to the complacency for an institutionalized decision process that ignores uncertainties, favoring simplicity over realism. The result of which may lead to decisions that jeopardize meeting long-term management goals [12].

Overcoming the complexities of a decision process requires embracing uncertainty [13] as an inherent reality of perhaps all natural resource management decisions. We suggest management questions be framed in a formal decision process, which is a powerful strategy to deconstruct the decision into essential and manageable elements that can be examined using decision-analytic tools [14,15]. Here, we briefly outline the essential elements for making empirical, logical, and transparent decisions in the face of uncertainty, specifically using a structured decision-making (SDM) framework [16,17]. Second, we focus on sampling strategies to monitor state variables of interest (i.e., measures of the natural resource being managed) as a necessary element of any decision-making process. Monitoring is the key to decrease state, process, and action uncertainty, and thus improve future decisions [18–20]. Furthermore, there is perhaps a lack of appreciation in natural resource management for sampling options and their relevant advantages and disadvantages.

Structured Decision-Making

The six elements of an SDM process are where the decision-makers (i) explicitly state the management objectives, (ii) list all possible alternative actions, (iii) predict the consequence of each action on the management objectives, (iv) choose an action by optimizing the objectives while considering trade-offs, (v) implement the decision, and (vi) monitor the system to evaluate whether the objectives were achieved [15–17,21]. This separation helps identify the distinct roles of stakeholders (e.g., managers, policymakers, resource users) and scientists, such that stakeholders communicate the objectives and their relative importance [9], while scientists make predictions and evaluate trade-offs; both groups identify potential actions.

Perhaps the most obvious and yet underappreciated aspect of a decision process is that a 'good' or 'best' decision is impossible to identify without clear, explicit, and measurable objectives [16,17]. Objectives are typically quantifiable statements (i.e., via an objective/loss function) that contain at least one measure of system performance that can be maximized (or minimized) [9,10,22]; however, alternative approaches are available that seek satisfactory performance, rather than optimal performance [23]. Predicting the consequences of possible actions entails describing a model of the system. Such a model may be qualitative or intuitive expectations, but often are quantitative [20], which lends to being explicit, transparent, objective, and amenable to analyses; quantitative models can synthetically incorporate empirical and expert knowledge [13]. The means of being able to predict the consequences of potential actions, identify the current state of the resource, and evaluate management performance is often through monitoring data [24]. Monitoring is essential to recurrent decisions and the means to which learning can occur through an adaptive management process to improve decision-making over time [19]. However, monitoring natural resources requires careful sampling considerations to ensure data are able to provide accurate and precise estimates of state variables.

Monitoring Strategies

To evaluate the effectiveness of natural resource management, we require quantitative information on how the system responds to management actions. We acquire this information via monitoring. Monitoring has always been a critical component of scientific investigation and natural resource management, and therefore, monitoring methods have, and continue to be, well studied and described. Monitoring programs designed to inform management and conservation of natural resources are inherently spatial, and therefore, we focus on spatial sampling designs. Spatial sampling designs can be classified into two broad types: *model-free approaches* and *model-based approaches* [25]. What exactly to monitor is problem-specific and depends on the objectives of the study and the processes that are considered in models used to predict the consequences of proposed actions; we provide a high-level overview of spatial sampling concepts that is applicable for monitoring many types of natural resources.

Model-Free Sampling Designs

No specific model is assumed for data when using model-free sampling designs. This is advantageous because we are not required to adhere to any assumptions regarding underlining ecological/ecosystem processes, precluding the possibility of selection bias that can occur when relying on a mis-specified model to collect a sample. Model-free approaches include the relatively well-known *probability-based sampling methods* such as simple random sampling, systematic sampling, stratified sampling, stratified sampling with random tessellation, cluster sampling, and Markov sampling [26]. They also include the lesser-known geometrically based *space-filling designs* [27].

Probability-based sampling methods assume the underlining spatial process of interest is fixed, but randomness is introduced in sample selection using a probability sampling design. A probability sampling design consists of both a sampling frame, a set of all elements in the population of interest, and a probability measure defined on the frame; a systematic method for assigning a probability to the selection of any subset (i.e., any sample) from the frame. The statistical properties (e.g., unbiased-ness) of the estimators used to make inference on the population are based entirely on the probability measure that defines the design. For this reason, inference from probability-based sampling methods is often referred to as *design-based inference.* The objective of design-based inference is to quantify a population parameter of interest. Typically, these include summary statistics such as the mean, total, variance, or proportion. Probability-based sampling methods are one of the most common and widely used sampling methods in natural resources. When probability-based sampling designs are combined with the appropriate estimators, investigators obtain objective, unbiased estimates of the population. Both [26] and [28] provide in-depth discussion of probability-based sampling methods and numerous extensions.

Space-filling designs were developed to sample such that large unsampled gaps in the study area were avoided. When there is little prior spatial information about an ecological process of interest (e.g., how to stratify a sample), an intuitive approach to collecting data might be to select a sample that has good spatial coverage of the area interest. This provides an alternative to simple random sampling, which does not guarantee good spatial coverage. A *minimax design* is a type of space-filling design that chooses a sample that minimizes the maximum distance between points. That is, it guarantees that all points in the sample are within a certain distance of at least one point in the design; there are no spatial gaps with a distance larger than a specified distance. Similarly, a *maximin* design maximizes the minimum distance between points so that points are as far away from each other as possible. Justification for a maximin design is that areas close in proximity are more similar than distant sites, and therefore, samples in close proximity may provide redundant information.

Model-Based Sampling Designs

To fully realize the benefits of the probabilistic sampling designs, appropriate estimators that are associated with the probability measure defining the design must be used to make inference on the population. However, data are increasingly being used to fit models to make model-based inference, regardless of how the data were collected. Using data to fit and evaluate statistical models of ecological processes is fundamental to ecology and management. Yet, monitoring designs for collecting data, and the statistical models used to analyze the data, are typically developed independently of each other. When monitoring designs are developed independently of statistical models, monitoring effort can be inefficient and fail to capture essential spatial, temporal, or spatio-temporal variability of an ecological process [20]. Formally linking monitoring designs with statistical modeling using an *optimal monitoring design* permits several advantages over traditional model-free sampling designs (when a model is going to be used to make inference) including increased efficiency, more precise parameter estimation, and reduced prediction uncertainty. These improvements translate to increased reliability of scientists to evaluate the consequences of management actions and thus lead to improved decisions. Optimal monitoring designs permit extraction of the most information from the data that can be affordably collected, helping to improve our understanding of the ecological system, despite limited or shrinking financial resources.

Broadly speaking, a model-based sampling design consists of several steps, with each step being conceptually straightforward. These steps are similar to the steps described above for SDM. In fact, optimal monitoring is a type of SDM, where the decision is the optimal place to collect data to help inform our understanding of some process of interest. In the first step of optimal monitoring, an ecological process such as the occurrence or abundance of a species or resource is modeled using baseline data. Second, using the model from the first step, a statistical forecast of a process of interest is made. The forecast provides a basis for examining potential monitoring designs that could be implemented in the future. Third, managers and stakeholders identify the objectives or criteria they wish to achieve with their monitoring, and formalize this using an objective function [9]. Objectives typically include minimizing prediction uncertainty or minimizing variance of parameter estimates, but could also include minimizing multi-modal uncertainty or cost. Fourth, after a forecast is made, and an objective function is chosen, a monitoring design that optimizes the objective function, relative to the ecological forecast is chosen. Fifth, data are collected using the optimal monitoring design. The model is then updated with the new data, and ecological learning occurs. The process can be iterated through time (a recurrent decision), increasing our understanding of the ecological mechanisms governing the data (a process analogous to adaptive resource management), and lead to improved evaluation of management actions.

While there are several advantages of model-based sampling described in the previous paragraph, there are two potential disadvantages. The first disadvantage is computational and analytic complexity required to obtain an optimal model-based design. It is simple to develop a simple/stratified/systematic random sample. However, identifying an optimal model-based sample requires a large amount of computation, and the ability to forecast sometimes-complex ecological processes. The second potential disadvantage is the optimal survey design is conditional on the selected model used to make inference. If a mis-specified model is used for inference, the resulting errors in mis-specification may be propagated through to the data, resulting in data that are sub-optimal. To address the second point, several researchers have developed 'hybrid designs' that consist of both an optimal, model-based sample, and a model-free sample [29]. Model-based sampling designs have been used disproportionately less in natural resources than model-free designs. However, in recent years, there have been several natural resource applications that have used model-based or hybrid sampling designs [20,29–31].

Conclusions

Managing natural resources can be complex, necessitating careful consideration about the process to which information is gathered and decisions are made. We outline the essential elements of making empirical, logical, and transparent decisions in the face of common uncertainties and when designing sampling strategies for monitoring natural resources. We encourage resource managers tasked with managing public and valued resources (e.g., air, water, soil, and plant and animal species) to strive towards adopting an empirically based logical and transparent decision process informed via a robust monitoring strategy.

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