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Integrating land cover modeling and adaptive management to conserve endangered species and reduce catastrophic fire risk

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Abstract: Land cover modeling is used to inform land management, but most often via a two-step process where science informs how management alternatives can influence resources and then decision makers can use this to make decisions. A more efficient process is to directly integrate science and decision making, where science allows us to learn to better accomplish management objectives and is developed to address specific decisions. Co-development of management and science is especially productive when decisions are complicated by multiple objectives and impeded by uncertainty.

Multiple objectives can be met by specification of tradeoffs, and relevant uncertainty can be addressed through targeted science (i.e., models and monitoring). We describe how to integrate habitat and fuels monitoring with decision making focused on dual objectives of managing for endangered species and minimizing catastrophic fire risk. Under certain conditions, both objectives might be achieved by a similar management policy, but habitat trajectories suggest tradeoffs. Knowledge about system responses to actions can be informed by applying competing management actions to different land units in the same system state and by ideas about fire behavior. Monitoring and management integration is important to optimize state-specific management decisions and increase knowledge about system responses. We believe this approach has broad utility for and cover modeling programs intended to inform decision making.

Keywords: adaptive management; fire management; Florida scrub-jays; structured decision making; state transitions; landcover modeling

1. Introduction

Landcover modeling is becoming increasingly important to inform natural resource management [1,2]. A common approach is for scientists either to develop landcover maps corresponding to snapshots in time or to actually model landcover dynamics in a manner that permits projection of future landcover patterns. In either case, scientists conduct these studies that have potential to inform land management and then provide these results and findings to decision makers, who choose whether and how to use the information. This 2-step process is inefficient, at best, providing little opportunity for real interaction between scientists and decision makers and frequently leading to the dissatisfaction of both groups. Decision makers often complain of scientific results that, although somewhat relevant, do not fill the critical information needs of the decision process. Scientists frequently complain that decision makers do not pay adequate attention to the scientific information that they provide. Adaptive resource management (ARM) [3,4] provides an alternative approach to management that better integrates science into the decision making process [5]. Adaptive management was developed as an approach to making recurrent decisions that are characterized by potentially resolvable uncertainty. Adaptive management essentially embeds science within a broader management process, providing an opportunity to learn about system responses to management actions and a clear path to use what is learned to make better decisions. Hypotheses are compared and tested under ARM, but the hypotheses are precisely those most relevant to management, and test results are directly used in subsequent decisions.

We have been involved with one ARM project in which landcover modeling plays an important role, but believe that there are many more opportunities for the integration of landcover modeling and ARM. Virtually all land management programs that take actions to modify habitat and landcover require model-based projections of landcover changes expected to accompany such actions [6]. Even for management actions that are not directed at modifying habitat, landcover dynamics are frequently relevant to system responses to management and hence to management programs [7]. This relevance is especially true as rapid global change associated with increasing human populations, climate change, etc., results in substantial alterations in landcover patterns and dynamics. For these reasons we expect landcover modeling to become increasingly important to ARM programs directed at a variety of different conservation problems.

The current program in which landcover modeling supports ARM is based on managing habitat to assist in the recovery of the Florida scrub-jay (FSJ) *Aphelocoma coerulescens*, an endangered bird that resides in scrub ecosystems adapted to frequent fire but that has been subjected to substantial habitat loss, fragmentation, and degradation. In our approach, landcover is characterized by discrete successional stages that represent habitat quality, as defined by a geographic scale (10 ha) representing average territory size and therefore relevant to FSJ recruitment and survival (Table 1).

Table 1. Habitat states used to quantify landscape units as potential territories (10 ha) of FSJs directly related to long –term demographic performance (yearling production rates – breeder mortality rates) and fire history successional patterns (adapted from [8–10]. Populations are expected to increase in landscapes dominated by source territories (positive demographic performance) or decrease in landscapes dominated by sink territories (negative demographic performance).

State	Characteristics	Demographic performance
Short	Oak <1.2 m tall & recent fires (<4 years ago) that completely burned territories	-0.32
Open-medium	Medium-height (1.2–1.7 m) oak >0.4 ha often as a mosaic amongst short but no tall patches (>1.7 m) > 0.4 ha, no openings	0.49
Open-closed	Medium-height (1.2–1.7 m) oak >0.4 ha often as a mosaic amongst short but no tall patches (>1.7 m) > 0.4 ha openings	0.15
Tall mix	Mosaic of short or medium patches amongst tall oak > 0.4 ha	-0.24
Tall	All scrub >1.7 m tall and unburned >20 years	-0.31

The highest quality habitat (open-medium) for FSJ is a transitional state and, therefore, recovering the species requires imposing a disturbance regime using prescribed fires, which are necessary because habitat fragmentation restricts spread of natural fires across landscapes and society generally requires that wildfires be suppressed [10,11]. Because optimal habitat conditions for FSJ are generally those needed by other scrub-adapted species, the species is considered a management indicator species [12].

The need to apply decision theory to balance conflicts between protected species conservation and fire management to protect human interests is well-established on many continents [13]. Funding for conducting prescribed fires is often specified for fuels management and not necessarily for species habitat management; administrators from agencies often measure performance of prescribed fire programs using the acreage burned each year, which provides little information on habitat quality trajectories because fire intensity and outcomes are heterogeneous [10]. Our studies have shown that an emphasis on fuels management will not achieve species conservation goals on many conservation lands [14]. Wildland fire managers and ecologists agree that prescribed fires are beneficial, and we

believe that differences in management approaches are reconcilable, but require stakeholders to acknowledge multiple values and agree (1) on the legitimacy of objectives arising from these values, (2) on how to measure whether management is attaining those objectives, and (3) on how resources should be optimized.

Our objectives here are to describe approaches that can be used to integrate both fuels and habitat management, specific to the Florida scrub system. We provide examples of approaches to perform this integration of science and management because we believe that it is broadly applicable to other fire risk and endangered species applications worldwide. Landcover modeling and landcover monitoring, endeavors that are sometimes viewed as stand-alone activities, are given important and explicit roles in this integrated process. Here, we take a general approach to integrating landcover and ecological sciences with natural resource management because implementing a specific ARM would consider a broader group of stakeholders who are particularly important in defining objectives.

There are a large number of studies associated with fuels management that focus on risk assessment and associated uncertainties in decision making [15-17]. Strategies have been attempted to balance fuels and species management recognizing that there are potential conflicts [18-21]. Our approach differs from these other, two-step efforts by that fact that we explicitly integrate management objectives, available actions, predictive modeling and learning in a transparent way to recommend conditionally optimal decisions.

2. Management of Florida Scrub: Fuels management vs. Ecological benefit

Landcover studies have shown that Florida ecosystems have been severely degraded by a reduction in fire frequency due to wildfire suppression and because human landscape features (cities, highways, etc.) minimize the spread of natural lightning fires across landscapes [11,22]. This degradation has resulted in catastrophic impacts to biological diversity; fire managers and ecologists agree that introducing fire back into the system is a priority [23]. Prescribed fires differ from wildfires because of their size, spatial pattern, season, and differences in weather when these events occur [24]. One reason that prescribed fires often have limited ecological benefit is that fire managers often burn out the flammable parts of a burn unit in order that patches are less likely to reignite, ignite unburned fuels in surrounding management units, or produce smoke and other hazards. The success of prescribed fire programs is often measured as the annual burn acreage rather by remaining fuel levels or the ecological value of the fires. Extensive fires that produce a large proportion of short territories (Table 1) result in poor FSJ survival and repeated extensive fires can result in catastrophic population declines [8]. Scrub management guidelines, focused on biological diversity, specify mosaic fires that produce mostly open-medium territories [12]. The second reason prescribed fires alone have limited success is that long unburned scrub generally does not burn without mechanical cutting, an expensive management option [25]. Because scrub regrowth is often a function of underground biomass, many ecologists have observed that scrub that is long unburned recovers much faster than scrub that has been subjected to more frequent fire. Thus, fire history may be an important component to include in landcover models, but has not received much attention in the literature [9,26].

Fire managers usually rely on a return interval to determine when a managed area needs to burn, which differs from our previous ARM modeling that recommends using time-specific state variables (e.g., habitat states from Table 1) to determine the optimal management action. This approach has resulted

in recommendations for a much more frequent fire return interval than has been customary [14]. Many ecologists agree that burning more frequently might hasten returning the system to a more desired ecological state, but this would require significant management effort and willingness to value mosaic fires for ecological benefit. Fire managers recognize that mosaic fires are difficult to achieve and observe that burning early in the vegetation recovery cycle often achieves less reduction in fuels than waiting until fuels become mature and more continuous. Although mosaic fires may increase the risk of flare-ups and smoke, burning early might reduce the threat of wild fires between prescribed fires. Many fire managers hold the view that the habitat states used to describe FSJ habitat are largely reflective of fuels loads and continuities, although this topic represents an area needing more research. Landscapes dominated by short and open-medium territories have relatively low fuels and high fuel discontinuities, whereas as landscape dominated by closed-medium and tall mix have high fuels loading and possibly high fuels continuities. Burning earlier requires fire managers to recognize that actions to further ecological objectives may also be of value to fuels management - e.g., fires that only burn small extents create open sandy areas interspersed with oak scrub which promote both valuable ecological objectives and possibly minimize the risk of more extensive fires in the future [10]. We argue that objectives and measurement of the efficacy of management should be based on the risk of fuels present on landscapes, rather than the total acreage burned. Because fire risks to humans are difficult to measure and specify, fuels are generally used as surrogates and we chose to focus our efforts here on habitat and fuels states recognizing that stakeholders will collaboratively define the objective function to describe the trade-offs of fuel risks and habitat benefits.

3. Adaptive resource management

ARM has come to be defined and viewed in many different ways, so we begin with a brief description of our specific view of this process. As noted above, we view ARM as a process for making informed decisions for recurrent management problems characterized by potentially resolvable uncertainty. ARM requires the following components essential to any informed decision process [27-29]: clearly specified objectives, a set of potential management actions, models for projecting system response to actions, monitoring for estimating the state of the system and other relevant parameters, and a decision algorithm that uses these components to select the appropriate decision. The establishment of an ARM program begins with a deliberative or setup phase during which the listed components are developed and assembled. Objectives drive the entire process and must be developed in a manner that engages, and obtains input from, all relevant stakeholders. Development of the set of potential actions is based on the specified objectives and again typically requires input from relevant stakeholders. Based on specified objectives and actions, models are developed to predict consequences of potential actions to the managed system. Because substantial uncertainty frequently characterizes predictive modeling, it is often necessary to develop multiple models in order to include all of the uncertainty about system response to actions. Relative degrees of confidence in the different models are reflected by model “weights”, numbers that sum to 1 for all the members of the model set. A monitoring program is then established for the specific purpose of informing the decision process, and a decision algorithm is selected in order to translate information from all of these process components into a recommended decision. The decision algorithm can be very formal, as with a dynamic optimization algorithm [30-32].

This deliberative phase is then followed by actual implementation of ARM in an iterative phase. At each decision point, the decision algorithm is used to select the appropriate action based on the

objectives, available actions, models, and current estimates of system state (from the monitoring program). The selected action is implemented and drives the system to a new state, which is identified by the monitoring program. In the typical case of multiple models, the estimated system state is compared with the predictions made by each of the system models. Model weights are increased for models that predicted well and decreased for models that predicted poorly, using Bayes' theorem (e.g., [31]). At the next decision point, armed with these new model weights and the new estimate of system state, the decision algorithm is again used with the existing objectives, actions and models to select the next action. The iterative process proceeds in this manner with model weights and estimates of system state changing from one decision point to the next. Learning is accomplished by the comparison of model predictions with estimated system state at each time step, and is reflected in the updating of model weights. Because the model weights determine the relative influence of the different models in the decision algorithm, the learning is incorporated directly into each decision. Note that this step of evolving degrees of confidence in different models based on a comparison of predictions against observations (i.e., an estimate of the true system response) effectively incorporates science within the larger management process.

The iterative phase proceeds in this manner, simultaneously promoting both wise management and learning for better management in the future. However, at any time during the iterative phase it is possible to revisit any of the ARM components, effectively returning to the deliberative phase. Stakeholder objectives may change, ineffectiveness of management actions may motivate a search for new actions, system response may not be predicted well by any members of the model set, or monitoring may be ineffective at estimating relevant quantities. Returns to the deliberative phase after obtaining experience with the ARM process are referred to as double-loop learning [33,34]. Any changes made to process components during this double-loop deliberative phase are then incorporated into ARM for the next round of iterative phase decisions. Finally, we reiterate that adaptive management is viewed in different ways by many managers and scientists. Our purpose in laying out our view of this process is not to suggest to readers that this view is in any sense the only "correct" perspective, but rather to insure that the reader has a clear idea of what we mean by ARM.

4. Defining objective functions

For any informed decision, the decision maker and stakeholders are required to formulate the problem with clearly defined and quantifiable management objectives. In decision theory, objectives are representative statements about how we value the outcomes of alternative management actions. An objective function is the formalized, mathematical expression of such statements, translated into measurable management goals, and can be written to capture multiple (possibly competing) benefits as well as conditional constraints and management costs. By quantifying the costs and benefits (the 'return') expected to result from implementing a management policy, the objective function serves as the basis for an optimization or tradeoff analysis [31,35]. A common formulation of conservation objectives is the maximal coverage problem, where the goal is to find the solution that achieves the greatest return given budget (or personnel) constraints [36,37]. If the management problem has multiple-objectives, we would define the system state (e.g., of a habitat patch) based on variables that represent each objective. We could then assign a management return to that state variable reflecting its benefit to each objective. For example, a habitat patch may be observed as being of high quality for FSJ, but of moderate risk for wildfire. These components would define a single system state for the patch (high/moderate), and we assign a value to each component and sum values to produce the

management return for that patch. There are many ways to assign management values to system states, including utility functions that describe the relationship between state variables and benefits or values can be assigned directly to each level of the state variable (e.g., high (FSJ) = 1, moderate (fuel) = 0.5) which could reflect both the level of the variable and an implicit weighting of objectives. A generalized objective function for a multiple objective problem is

$$\max \sum_j \sum_i f(r_{ij}|x_i, a_i) \quad , \quad (1)$$

given that

$$\sum_i c(a)_i \leq B \quad ,$$

where $f(r_{ij}|x_i, a_i)$ is a function that identifies the management return for objective j at site i , conditional on being in system state x after implementing action a . The cost of implementing action a at site i is $c(a)_i$ and B is the total resources (dollars, staff hours) available for allocation. The utility function f can take on a number of functional forms (e.g., linear, convex/concave, step, etc.) to describe state-dependent management values or can simply be used to assign a return to each possible state of the system.

The objectives of the National Fire Plan, followed by the U.S. Fish and Wildlife Service, are to reduce the risk of catastrophic wildfire by reducing hazardous fuel loads (especially near communities), restore fire-adapted ecosystems and reduce suppression costs. The Fire Plan includes implicit recognition of a state-dependent Markov process by specifying that decisions will be based on objectives to minimize fuel hazard by maximizing the probability of system state transitioning from high to low risk, while minimizing the probability of the system transitioning from low to high risk.

The objectives of habitat management for FSJ recovery can be specified in multiple ways, and we present 2 examples. Johnson et al. [14] describe an adaptive management program in which FSJ population growth rate is modeled as a function of scrub-height classes (Table 1). The management objective is to maximize population growth rates by implementing habitat treatments at the management-unit level and the utility function increases linearly with growth rate. A related scrub habitat management program in mainland Florida has chosen territory occupancy of FSJ as an appropriate state variable (ψ is the probability that a local site is occupied). Probabilities of a site transitioning between occupancy states are functions of scrub-height class, soil substrate and the presence of FSJ in neighboring territories. The management objective under this program is to maximize the number of occupied territories within each management unit, with a sigmoidal utility function to represent a species recovery goal of 0.70 occupancy in a given conservation reserve (Eaton et al., unpublished). In both cases, the goal of the analysis was to produce unconstrained optimal decisions, so neither cost nor other objectives such as fuel load were included in the objective function. However, cost constraints were recognized as an important consideration for future iterations of the decision model.

Neither of the existing approaches explicitly considers fuels management, focusing instead on objectives that concern FSJ status. To account for the distinctions in objectives between fuel hazard and habitat-species management, we believe there would be considerable benefit to development of an

objective function that integrates the goals of both resource management programs. One approach to developing an objective function that incorporates 2 components is similar to the maximal coverage problem, where we would optimize the return for one component of the system state (i.e., one of the variables used to classify patches to state), conditional on achieving a minimum level (a constraint) for a second system state variable. For example, we could produce a policy to minimize the number of territories in a management unit that contains fuels biomass in a high-risk state, conditional on achieving a minimum occupancy level of 0.70.

$$\min \sum_i^N \Pr(\text{fuels risk} = \text{high})_i \quad ,$$

given that

(2)

$$\frac{\sum_i^N \psi_i}{N} \geq 0.7 \quad ,$$

where N is the count of territories. The objective function could also be written to maximize FSJ occupancy subject to the constraint of maintaining fuel load below some threshold level.

Alternatively, we could address the problem by maximizing the total return for each objective (fuels reduction, FSJ), subject to a budget constraint (as in Eq. 1). If we value one objective more than another, we can reflect this either by assigning relative values to each component of the system state (e.g., if fuels management is of higher priority, a larger value can be assigned for low fire risk relative to the value of high quality FSJ habitat) or by appropriately weighting the return for each variable summed across all sites. A third option is to evaluate the return on management actions for each objective separately and seek a Pareto-efficient solution [38,39]. Pareto optimality identifies a multi-dimensional efficient frontier of possible solutions in which improvement in one component of objectives cannot occur without a loss to another. This efficiency frontier would represent an optimal range of trade-offs between (un-weighted) habitat and fuels management objectives for which a negotiated solution based on managers' values could then be reached.

5. Management actions

Decision analysis in general, and ARM in particular, entail selection of one element of a finite (often small) number of potential management actions. The set of possible actions usually includes “do nothing” as well as possible actions selected for their potential to move the system in a direction consistent with program objectives. In the specific case of scrub management, the action set might include “do nothing”, “burn”, and “chop”. Optimal FSJ habitat needed for population recovery requires open sandy areas exposing mineral soil adjacent to medium height scrub that has often not burned in 10 years [10]. The open sandy areas are often less than 2 years post-fire so that optimal habitat often results from a mosaic of age classes. Ecologists ask managers to use mosaic fires when scrub-jays are present, implying that two types of fire could be conducted depending on system state: extensive or mosaic. Fire managers are often reluctant to distinguish these types of fire because desired results are difficult to achieve, but many managers are amenable to not reigniting patches that do not burn unless unburned areas are immediately adjacent to highways or management unit boundaries. With this distinction of fire types in mind, the action set might expand to include “do nothing”, “burn (mosaic)”, burn (extensive)”and “chop”.

6. Models

When land cover states can be classified in terms that represent progress towards or away from something we hope to achieve, estimates of land cover transition probabilities under differing management regimes can be used to guide optimal decision making for realizing positive impacts on resources, processes and ecosystem services [14]. Most habitats are subject to natural succession dynamics, and the application of a management action is intended, by definition, to transition land cover states in an intended direction, although often with considerable uncertainty. Therefore, land cover change can be effectively described using discrete-time, first-order Markov models, characterized as random processes in which the system state at any point in time depends only on the state in the previous time step. A vector of probabilities describes the transition from a single known state in time t to any of a finite number of other states in time $t+1$. Because the state space (X) for a Markov model is discrete and comprehensive, we constrain these probabilities as

$$\sum_{i=1}^X \Pr(x_{i,t+1} | x_{j,t}, a_t) = 1 \quad ,$$

where the transition probabilities at time t are conditional not only on the state at time t , but also on the management action a selected at that time. Although some management actions can produce deterministic outcomes (i.e., the vector of transition probabilities comprises all zeroes except for one state with a value of 1), it is more common that management actions result in probabilistic outcomes due to partial controllability of the action achieving its intended result, variation in environmental conditions under which the action is implemented or averaging across unmodeled variation in the conditions of the managed sites.

Essential considerations when modelling land cover change in this way include 1) defining the possible states of the system in terms that are appropriate to the management context, 2) matching the time step of state transition probabilities to the management cycle and, 3) specifying a transition matrix for each action available to managers. With regard to the first consideration, habitat state selection, for example, should encompass characteristics or quantities that represent different values that we might assign to management outcomes. Choice of habitat states must also take into account the spatial scale at which actions are applied and practicalities of identifying the system state at any point in time with minimal error (i.e., via monitoring), both of which permit state-dependent decision making. In the case of scrub management, one way to define the system state is as a combination of discrete states corresponding to the demographic performance of the FSJ (Table 1). The spatial scale at which we describe habitat state is that at which burn decisions are implemented, the fire management unit (FMU), and the time step of the state transition estimates is the annual decision cycle used by land managers. With the additional objective of managing habitat for fuels reduction, we expect that it could be necessary to modify how habitat state is defined (see above, **Defining objective functions**). We might instead characterize the state space as a combination of vegetation structure and discrete categories of fuels biomass, biomass connectivity (i.e., ability to carry a fire) or adjacency to another site with high fuels biomass (i.e., as a measure of risk).

Finally, individual transition probabilities must be specified for all system states and for all possible management actions from which the decision maker is able to select. When novel management actions are being considered, these probabilities must be elicited as best estimates from experts [40,41]. When

land cover history data exist, state-action transition probabilities can be estimated empirically using a variety of techniques including binomial or multinomial logit models implemented using Bayesian MCMC methods (e.g., using Dirichlet priors; [42]) or maximum-likelihood approaches ([9,43]). If the history of system state and management action is known for each managed site over time, modeling individual site histories (e.g., land cover state at each time step) using maximum-likelihood methods is an efficient way to estimate transition parameters as a function of management actions and site conditions. The resulting transition parameters will be in the form of a matrices of X by X dimension, where a is the number of available management actions and X is the number of landcover states. For example, a system that can be described using five relevant habitat states and whose units are managed using either prescribed fire or cutting would require a model with 3, 5 x 5 transition matrices ($a = 3$ actions, including a no-action alternative), for a total of 75 parameters. Note that when landcover state histories are observed imperfectly (e.g., using remote sensing), methods to account for state misclassification have been developed ([42,44,45]).

7. Monitoring

Monitoring programs provide data that play at least 4 important roles in management programs. (1) Estimates of system state variables (e.g., the number of sites in the management unit in each habitat or habitat + fuel load state) are used to make state-dependent management decisions. (2) Estimates of state variables and other quantities related to objectives are used to assess progress towards management objectives. (3) Estimates of state variables and other parameters (e.g., model vital rates) can be compared against model-based predictions in order to discriminate among competing models. This comparison of empirical data against model-based predictions for the purpose of discriminating among competing hypotheses constitutes the key step in science. Thus, this role of monitoring entails the embedding of a scientific step in the larger management program. (4) Monitoring data are also used to obtain updated estimates of key model parameters used to predict system responses to management. As with other elements of the ARM program, the nature of the monitoring program is driven by the management context. If management focus is on sites characterized by habitat state and fuel load state, then a monitoring program would ideally provide estimates of habitat-fuel load state each year for all, or a subset, of sites that are in the management program.

Landcover monitoring can be conducted either remotely (e.g., satellite imagery, aerial photography) or with actual visits to each monitored site. One of the greatest challenges in landcover monitoring to support ARM is obtaining imagery to classify habitat states in a timely manner, for example where high resolution is necessary to detect small but important habitat features. The states used herein are simple enough that they can be practically classified in the field each year in all but the largest conservation areas, which may need to rely on new technologies such as unmanned aerial systems [14]. We also use time series satellite imagery to maintain a fire history database and to map fire boundaries [24,46]. Such data are used to obtain estimates that populate the transition probability matrices described above. For example, we would like to estimate the probability that a burn was successful in moving a site from one habitat state to another as a function of the initial habitat state and environmental conditions [9].

8. Decision Algorithm

The final component of an informed decision process is a decision algorithm that uses the other process components described above, objectives, actions, models and monitoring, to decide which action is most likely to produce returns that are “best” with respect to the specified objectives. Dynamic optimization methods are often used for solving sequential decision problems in natural resource management [47–49]. Sequential decision problems are ubiquitous in conservation; examples include the harvesting or stocking of animals, the control of invasive plants and animals, and habitat management for imperiled species [50,51].

Dynamic optimization methods combine objective functions that value present and future consequences of alternative management actions with models of ecological system change (see Objectives and Modeling sections, above). The general resource management problem involves a temporal sequence of decisions, where the optimal action at each decision point depends on time and/or system state [49]. The goal of the manager is to develop a decision rule (or management policy) that prescribes management actions for each time and system state that are optimal with respect to the objective function. A key advantage of dynamic optimization is its ability to produce a feedback policy specifying optimal decisions for possible future system states rather than expected future states [47]. In practice this makes optimization appropriate for systems that behave stochastically, absent any assumptions about the system remaining in an equilibrium state or about the production of a constant stream of resource returns.

Similar to our organization of the preceding discussion, a framework for dynamic optimization requires specification of (1) an objective function for evaluating alternative management policies; (2) predictive models of system dynamics that are formulated using quantities relevant to the stated management objectives; (3) a finite set of alternative management actions, including any constraints on their use; and (4) a monitoring program to follow the system's evolution and responses to management. More formally, let

$$\underline{x}_{t+1} = \underline{x}_t + f(\underline{x}_t, a_t, \underline{z}_t) \quad (3)$$

characterize system dynamics, where \underline{x}_t is a vectorized representation of system state at time t and a_t and \underline{z}_t represent management actions and environmental variation, respectively. Environmental and other sources of variation induce Markovian transition probabilities $p(\underline{x}_{t+1} | \underline{x}_t, a_t)$. Let policy A_t specify an action for every system state \underline{x}_t at every time in the time frame $\{t, t + 1, \dots, T\}$. Benefits and costs attend management actions, which are included in returns $R(a_t | \underline{x}_t)$ that in turn are accumulated in an objective or value function:

$$V(A_t | \underline{x}_t) = E\left\{\sum_{\tau=t}^T \alpha^{\tau-t} R(a_\tau | \underline{x}_\tau) | \underline{x}_t\right\}, \quad (4)$$

where the expectation is with respect to stochastic influences on the process and α discounts future returns. This function can be decomposed into current returns and future values by:

$$V(A_t | \underline{x}_t) = R(a_t | \underline{x}_t) + \alpha \sum_{\underline{x}_{t+1}} p(\underline{x}_{t+1} | \underline{x}_t, a_t) V(A_{t+1} | \underline{x}_{t+1}), \quad (5)$$

which makes clear that future values are conditioned on the effect of current actions on future states. A value $V(A_t | \underline{x}_t)$ can be obtained for every possible policy A_t over the time frame, and the optimal policy satisfies [52,53].

$$V^*(\underline{x}_t) = \max_{a_t} \{R(a_t|\underline{x}_t) + \alpha \sum_{\underline{x}_{t+1}} p(\underline{x}_{t+1}|\underline{x}_t, a_t) V^*(\underline{x}_{t+1})\}. \quad (6)$$

A key consideration in dynamic optimization is the uncertainty attendant to management outcomes. This uncertainty may stem from environmental variation, errors in measurement and sampling of ecological systems (partial system observability), incomplete control of management actions (partial controllability), and incomplete knowledge of system behavior (structural or model uncertainty) (Williams et al. 1996). Model uncertainty, an issue of particular importance in adaptive management, can be characterized by continuous or discrete probability distributions of model parameters, or by discrete distributions of alternative model forms that are hypothesized or estimated from historic data. Important advances have followed from the recognition that these probability distributions are not static, but evolve over time as new observations of system behaviors are accumulated from the management process. Indeed, the defining characteristic of adaptive management is the attempt to account for the temporal dynamics of this uncertainty in making management decisions [3] [54] [55–57]. State-dependent decisions produced by stochastic dynamic optimization are thus optimal with respect to the other decision process components and their associated uncertainties.

9. Valuing Information

The value of information has been an important concept in fields such as economics, medicine, and engineering, but there are few applications in natural resource management [58]. A useful tool for addressing questions about the nature and implications of uncertainty is the expected value of information [59]. In particular, the expected value of perfect information (EVPI) expresses the gain in the management performance if uncertainty were to be eliminated. EVPI is simply the difference between the objective value expected if there were no uncertainty and the best that could be expected with values that are averaged over uncertain outcomes. EVPI is often expressed in dollars, but any relevant performance metric will suffice. Expressing EVPI in dollars is useful, however, for determining what managers should be willing to spend on monitoring and other data-collection programs designed to reduce the uncertainty.

EVPI can be useful for the design and implementation of effective monitoring programs to support either state-dependent or adaptive management [60]. Even if a rigorous assessment of information value is not possible, the expected-value heuristic can be helpful for bringing clarity of thought and purpose to questions concerning monitoring design [61]. For example, because of the direct and opportunity costs of monitoring, some authors have begun to explore the optimal frequency of resource monitoring. Here the notion of optimality concerns the ability of a monitoring program to provide information that will improve management performance in a demonstrable and cost-effective way [62–64].

10. Landscape Resilience and Restoration

Not everyone concerned with the conservation of natural resources agrees about the utility of decision analysis and optimization [65–67]. Proponents of “resilience thinking” have been particularly critical [68]. Resilience is defined as the magnitude of disturbance a system can absorb while still retaining essentially the same function, structure, identity, and feedbacks [69] or as the disturbance that can be absorbed without shifting the system to an alternative stability regime (or “domain of attraction”) [70].

Important concerns for ecosystem management are: (1) the loss of resilience as the system state approaches a (perhaps unknown) threshold, and the attendant increase in probability that some disturbance will shift the system to a less desirable stability regime; and (2) changes in the parameters governing the size and shape of the domains of attraction that make system shifts more or less likely [71]. Systems with alternative stable states can also exhibit hysteresis, in which a loss of resilience is followed by a system change and thereafter with an increase in resilience so that reversing the change is difficult [72,73].

In our example, scrub that has been subject to long periods of fire suppression exhibits hysteresis, and an optimal burning regime alone does not appear sufficient to return the system to its historic state [22]. Approaches to the conduct of dynamic optimization for systems whose dynamics are influenced by history and characterized by substantive time lags have been developed conceptually [28], but implementation can be challenging. Although a number of researchers have begun to formulate models that can be used to explore properties of resilience [72-74], more needs to be done to develop models that can be used to provide practical advice for those concerned with ecosystem management. We believe that a useful approach will be to use the described methods of decision analysis, but to modify objectives (stressing outcomes that are robust) and models in a manner consistent with resilience ideas [75].

11. Conclusions

We proposed a general approach to how landcover modeling can be directly integrated with management decision making to support natural resource management programs where repetitive decisions are characterized by uncertainty that can be hopefully reduced by learning. Under this approach, landcover modeling does not “inform” decisions in a vague, unspecified manner, but rather provides the predicted responses to management actions that form the basis for optimization. Similarly, learning, as evidenced by increased confidence in one or more particular models, leads directly to increased influence of such models in subsequent decisions. Our application was specific to fire prone ecosystems managed by prescribed fire needed to reduce wild fire risk and manage habitat for species of conservation concern. Our approach relies on stakeholders to forge agreements about objectives, management actions, monitoring, and their integration. Landcover modeling provides predictions about the effects of specific management decisions or forcings (natural and man-made) using transition probabilities that can be updated by monitoring. We believe this adaptive approach to management can be very useful in many applications, and that landcover modeling can be a key component of decision making.

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Author Contributions

All authors contributed to writing and editing of the manuscript and have been collaborating on an adaptive resource management program for Florida scrub-jays and fire management.

Conflicts of Interest

The authors declare no conflict of interest.

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