USDA Forest Service
U.S. DEPARTMENT OF AGRICULTURE

Pacific Northwest Research Station | General Technical Report PNW-GTR-1044 | July 2026

Wildland Fire and Fuels Science Synthesis:
Supporting Landscape and Community Resilience in the Pacific Northwest

Avoiding Common Pitfalls in the Implementation of Adaptive Forest Wildlife Management

Adam Duarte and James T. Peterson[1]

Background

Forest managers and their partners aim to increase the pace and scale of forest management to improve the health of millions of acres on national forests across the United States. Developing forest management strategies requires the evaluation of tradeoffs to meet multiple objectives, including reducing wildfire risk, increasing timber production, and providing the habitat required to sustain wildlife populations. However, the responses of wildlife to wildfires and active forest management are complex, as species inhabiting forests have vastly different life history requirements. Using avian species as an example, some birds primarily depend on early-successional habitats—the olive-sided flycatcher (*Contopus cooperi*) and black-backed woodpecker (*Picoides arcticus*), for example—while others primarily rely on mature habitats that take decades to regenerate, such as the marbled murrelet (*Brachyramphus marmoratus*), northern spotted owl (*Strix occidentalis caurina*), and American goshawk (*Astur atricapillus*). Of course, classifying species according to

Purpose

This synthesis provides an overview of adaptive management for forest wildlife communities with a specific focus on what we believe to be some of the missing components of many adaptive management programs. We highlight useful approaches to guide the application of adaptive management for forest management planning and implementation.

Clockwise from top left: olive-sided flycatcher (*Contopus cooperi*), black-backed woodpecker (*Picoides arcticus*), northern spotted owl (*Strix occidentalis caurina*), American goshawk (*Astur atricapillus*), marbled murrelet (*Brachyramphus marmoratus*).

[1] Adam Duarte is a research wildlife biologist, U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station, 3625 93rd Ave SW, Olympia, WA 98512-5623; James T. Peterson is a unit leader and professor, U.S. Geological Survey, Oregon Cooperative Fish and Wildlife Research Unit, Oregon State University, Department of Fisheries, Wildlife, and Conservation Sciences, 104 Nash Hall, Corvallis, OR 97331–3803.

early- or late-seral habitat can be overly simplistic given that there is often a gradient of habitat preferences, with many avian species requiring a mosaic of habitats. Careful consideration of these varying ecological needs, particularly when considered across taxa, would be beneficial when implementing forest management that aims to meet wildlife objectives.

Despite a seeming wealth of information on the responses of wildlife species to wildfire and forest management, developing prescriptive strategies is complicated by the fact that studies in the literature have largely focused on a single or focal species, or on wildlife communities at shorter time scales and smaller spatial scales. Indeed, relatively few data are available to quantify the effect of forest disturbance on larger wildlife communities at broad temporal and spatial scales, and the species we know the least about are often the species of the highest conservation and management concern. Nevertheless, it is becoming increasingly clear that wildlife responses are highly nuanced, and context plays a crucial role when predicting the responses of wildlife communities to wildfire and forest management. Thus, for example, even if the sole management objective is to maximize avian biodiversity, evaluating management tradeoffs still requires balancing multiple, sometimes competing objectives related to each species' life history requirements amid considerable ecological uncertainty.

We believe that adaptive management processes based on close collaboration between researchers and managers (e.g., coproduction) are valuable for integrating wildlife monitoring with predictive models that can help inform adaptive forest wildlife management. Although there are different philosophies on how to implement adaptive management (see "Adaptive Management Philosophies"), this framework represents a formal process that managers can use to evaluate tradeoffs in potential management actions, while acknowledging and considering various sources of uncertainty. Notably, this process requires managers to agree on a quantifiable management objective(s); to implement management actions that recur across space or time, or both; and to have a desire to reduce uncertainties following the implementation of management actions (i.e., learning by doing).

Importantly, our objective here is not to provide an exhaustive review of adaptive management. Excellent reviews of this framework are readily available in the literature (e.g., Conroy and Peterson 2009, 2013; Runge et al. 2020). However, even though managers and researchers have long touted that adaptive management is an effective framework to inform management, it is our view that many adaptive management programs have fallen short of the requisite steps needed to fit within the adaptive management framework. Thus, we outline what we believe to be some of the missing components of adaptive management efforts in hopes of guiding future coordination among local and regional programs that seek to implement adaptive management for forest wildlife.

Common Adaptive Management Pitfalls

Assuming Everyone Knows the Problem Is a Problem

The first step in adaptive management is to define the problem so that all managers have a shared understanding of the issue(s) that they are addressing. In our experience, a common misconception is that most managers think about the system in a similar-enough way that vague problem statements are sufficient. Such an assumption will undoubtedly lead to conflict as managers talk past each other while attempting to address different, albeit often related, problems. Problem statements clearly convey the context of the problem but do not need to be overly long or complicated. They also specify the decision makers and the relevant background on what is motivating the decision, such as statutes, mandates, and stakeholder values. Moreover, problem statements define the spatial and temporal extent of the decision, while recognizing any constraints or limitations (e.g., budgets, policy).

Tell Us What You Really Want

Each adaptive management program will need to develop a statement tailored to its specific objective(s) and centered around the problem. Defining objective statements is a challenging task that requires examining human values to identify desirable outcomes. These statements may include outcomes focused on economic objectives and constraints, species- or foraging-guild-specific objectives, multitaxa objectives, and much more. In our experience, maximizing specificity in the objectives statement and clearly communicating all objectives usually leads to more productive conversations during

Definitions

adaptive management—a management framework that incorporates the reduction of uncertainty to improve management as recurrent actions are implemented across space or time, or both.

Bayes' rule—a central theorem of probability that describes the relationship between prior and posterior information using conditional probability.

conceptual model—a model that is visually depicted within a diagram, usually to facilitate communication and understanding.

constraint—a limitation on the range of values that are acceptable, such as a maximum amount of resources that can be invested in management or a minimum management objective value that is tolerable.

decision-support model—a quantitative model that helps decision makers evaluate tradeoffs in management decisions based on management objectives and the current understanding of system dynamics.

fundamental objective—an outcome or set of outcomes that truly matter to managers and stakeholders.

heuristic approaches—flexible mathematical approaches to identify near-optimal solutions to optimization routines.

management action—a tactic that is implemented to achieve management objectives, typically at a specific time and place.

management objective—quantifiable outcome(s) that reflects the values of decision makers and stakeholders that management decisions can influence.

management strategy—an overarching vision or plan to achieve management objectives through a coordinated set of management actions, typically over the long term.

means objective—an outcome or set of outcomes that are thought to be needed to achieve the fundamental objective(s).

mental model—an internal model that is usually developed from personal experiences and beliefs.

model—a simplified abstraction of reality used in communication, prediction, and decision analysis.

optimization routine—a process that uses a mathematical algorithm to identify management actions that achieve a desired management objective value (usually maximizing or minimizing the value).

parameter—a constant or coefficient value used to make predictions within a decision-support model.

prediction error—uncertainty in the predicted outcome(s) from a model.

propagation of error—a process where uncertainties in parameters and submodels combine to influence uncertainty in the predicted outcome.

sensitivity analysis—a process where an analyst systematically varies decision-support model components to gauge the strength of the effect (if any) that uncertainty in the component has on the preferred management action(s).

state-dependent decision making—a process where decisions are made after the current system state (e.g., population abundance, forest conditions) is observed.

submodel—a collection of parameters used to make predictions within a larger decision-support model, such as a linear model used to predict survival within a larger population model.

system dynamics—processes that determine how system states change through space or time, or both.

Key Takeaways

- Adaptive management with close collaboration between managers and researchers is valuable to meet multiple objectives while managing forests in the face of ecological uncertainty.
- Common pitfalls of successfully implementing adaptive management include vague problem statements and management objectives, confusing means objectives with fundamental objectives, omission of objectives, avoiding quantitative decision-support model (DSM) development because of data limitations, overcomplicating DSMs, and lack of a targeted monitoring program.
- Two types of uncertainty exist in natural systems—some can be reduced through better knowledge and adaptive management, while others reflect inherent natural variability; both can be explicitly incorporated into management frameworks.
- Monitoring to inform adaptive management should be targeted toward management objectives and key uncertainties identified through DSMs.
- DSMs are tools that managers can use to facilitate transparency and reproducibility, but they are not decision makers or a replacement for human intuition and subjectivity.

later steps of any management program. Conversely, failing to clearly define the objectives at the outset can result in conflict, the implementation of ineffective management strategies, and wasted management resources.

Objectives govern every aspect of an adaptive management process, so it is important to develop objectives using unambiguous and measurable terms (McGowan et al. 2015). As an example, the statement "respond to wildfire risks" is too vague to be a meaningful objective. The statement "reduce wildfire risk, promote timber production, and conserve avian communities" may seem more specific, but it still lacks clarity and specificity for each objective. Having such broad objectives could lead to conflict if different managers prioritize one outcome (e.g., avian diversity) over another (e.g., wildfire risk). A stronger objectives statement aims to be more explicit and transparent, incorporating a set of actions that are assumed to lead to outcomes that help achieve defined objectives. For instance, we can frame one of the desired outcomes as a constraint to clarify and simplify the objectives statement: "Implement forest management to increase timber production by 25 percent, and reduce wildfire risk below 20 percent over the next 10 years, while maintaining avian species richness and composition at current levels." Notably, this assumes that "avian species richness and composition" has also been explicitly defined.

Reference Points Can Miss the Point

Although there are plenty of pitfalls associated with misspecified objectives (reviewed in Conroy and Peterson 2013), the most common pitfall is the improper structuring of objectives (i.e., fundamental versus means objectives). A common example of misplaced focus on means objectives is the use of reference points that represent rigid management targets. Setting rigid management targets may oversimplify the complexity of ecological processes. It also presupposes that managers are certain that achieving these targets is both necessary and sufficient for achieving the broader fundamental objective(s). For example, a fundamental objective for managers might be to maintain the long-term viability of the white-headed woodpecker (*Leuconotopicus albolarvatus*). One way to help achieve this goal—among many possible means objectives—could be restoring important nesting habitat. Focusing on the amount of nesting habitat as a management target assumes that nesting habitat is limited and proportional to the fundamental objective, which may or may not be the case depending on the system that is being managed. Improper structuring or omission of objectives may result in achieving a means objective (e.g., nesting habitat restoration) at the cost of not achieving the fundamental objective (e.g., species persistence), particularly when there may be other unidentified limiting factors (e.g., lack of foraging habitat, increased nest predation). In our experience, managers often focus on prioritizing management targets that represent means objectives that are within their

Adaptive Management Philosophies

Two distinct philosophical approaches (schools) help guide adaptive management implementation: the decision-theoretic and the resilience-experimentalist (reviewed by McFadden et al. 2011). Both schools require explicit articulation of management objectives and potential management actions that can be implemented to achieve objectives. However, they emphasize different approaches to learning (see the table below). In general, the decision-theoretic school involves the integration of modeling and monitoring to learn while implementing management. In contrast, the resilience-experimentalist school tends to treat management interventions as controlled experiments, prioritizing learning through hypothesis testing with replicated treatments. It is worth noting that real-world adaptive management programs often borrow from each school depending on the need to learn quickly versus the opportunity to learn over time. Moreover, the U.S. Department of Agriculture, Forest Service is uniquely positioned to implement both approaches by learning through experiments on experimental forests and ranges and through active management on national forests and grasslands.

Characteristics of two adaptive management philosophies

Characteristic	Decision-theoretic	Resilience-experimentalist
Primary focus	Optimizing management decisions under uncertainty	Generating scientific knowledge through experimentation
Treatment of uncertainty	Explicitly quantified through probability and mathematical models	Addressed through hypothesis testing and experimental design
Management objectives	Central to the decision-making process	Secondary to learning objectives
Learning	Systematic reduction of key uncertainties affecting decisions	Hypothesis testing through controlled experiments
Implementation	Structured decision making with formal models	Experimental design with replicated treatments
Key tools	Alternative mathematical models, Bayesian updating, value of information analysis	Analysis of variance, experimental controls, replication, statistical power analysis
Timeframe emphasis	Balance between short-term objectives and long-term learning	Emphasis on rapid learning for future management
Decision criteria	Expected value or utility maximization	Statistical significance of experimental results
Tradeoffs	Between management objectives (using current knowledge) and exploration (reducing uncertainty)	Between experimental rigor and management objectives

control or perhaps easier to monitor, while assuming that achieving them will produce the desired outcomes (i.e., fundamental objectives). Given the significant uncertainty in managing natural systems, this assumption is highly optimistic at best.

Another common practice is to use reference points to trigger management actions—for example, restoring foraging habitat if population growth rate estimates indicate that the white-headed woodpecker population is decreasing. Although it is common practice to use trigger points to facilitate this type of state-dependent decision making, it is worthwhile to understand the properties of the chosen metric when defining trigger points. First, trigger points are often based on hypotheses or models related to system dynamics, so it is important to evaluate how uncertainty influences trigger points. Second, it is beneficial for trigger points to represent information that can be gathered in a timeframe that is meaningful to managers and ecosystem dynamics. Although population growth rate is a common trigger point used in wildlife management, trigger points such as this are problematic. For example, it takes three or more years to estimate this metric in the best of cases, and estimating meaningful changes in population growth rates requires a considerable amount of data. Therefore, using a trigger point such as this often leads to delayed reactionary management strategies, which managers may then implement too late to reverse population declines.

The use of reference points is common in management decision making, likely because of their ease of use. We are not advocating for the omission of reference points in management decision making but are simply highlighting some common pitfalls with reference points that managers can avoid. Notably, managers can develop reference points within an adaptive management framework that recognizes uncertainties, focuses on fundamental objectives, and considers any potential mismatch in the time it takes to estimate reference points and implement management (Irwin and Conroy 2013).

Show Us Your Model

All natural resource management involves the use of models, whether explicit quantitative models or implicit mental models. Even without formal quantitative modeling, managers rely on mental cause-and-effect relationships based on assumptions, experience, and expectations about how management actions will influence ecological or economic outcomes. Admittedly, some mental models have high predictive accuracy, which is great. However, mental models are not repeatable. Different managers may predict different outcomes for the same management actions even when using similar mental models. They also are not transferable, as one manager cannot simply "give" their mental model to another. Finally, mental models lack transparency because there is no formal way to evaluate assumptions or to determine which assumptions have the greatest influence on decision making.

In contrast, adaptive management relies on the use of quantitative decision-support models (DSMs) to evaluate tradeoffs among different potential management actions. DSMs are explicit, albeit simplified, representations of system dynamics that can be tested and evaluated. Depending on the nature of the DSM, they may also be transferable from one system to another.

Converting conceptual models to quantitative DSMs forces researchers and managers to collate existing information and data streams to evaluate whether data are being collected in a way that is useful within the spatial and temporal dimensions of the decision context. We have found that data collection efforts to fill information gaps identified with conceptual models often fail to provide information at the scale that directly informs quantitative DSMs. For example, decades of research and monitoring on stream ecosystem responses to forest management activities at local scales were not useful for evaluating broad-scale conservation actions in the interior Columbia River Basin (Reiman et al. 2001).

Uncertainty and data limitations are common in natural resource management, and a common misconception among managers and researchers is that they need more data or need to resolve uncertainty to develop useful DSMs. Consequently, management programs often pause DSM development after creating conceptual models with the expectation that they will develop a quantitative DSM after collecting more data. Uncertainty in decision analysis takes two basic forms: (1) reducible uncertainty through better knowledge and adaptive management and (2) irreducible uncertainty that reflects inherent natural variability. Thus, some uncertainties will never be fully resolved. The misconception that managers and researchers must resolve uncertainty before they develop a useful DSM is a significant barrier to successfully implementing adaptive management.

Gaps in existing data or a belief that currently available data are inadequate for model building need not prevent the development of a useful quantitative DSM. There are multiple rigorous and defensible approaches for addressing data gaps, ranging from quantitative meta-analysis to expert elicitation. Furthermore, reducible and irreducible uncertainties can both be represented or accounted for within adaptive management programs by incorporating them directly into DSMs (Peterson and Duarte 2020). It is important to remember that a decision will be made regardless of whether a quantitative DSM exists. Having a DSM enhances transparency, allows for the evaluation of the influence of model assumptions, and helps identify and prioritize two key uncertainties—(1) the elements of the model that have the greatest effect on forecasted outcomes and (2) the evaluation of tradeoffs among different potential management actions (see “Addressing Uncertainty In Decision Analysis”).

Keeping It Simple Is Smart

Ecology and mathematics are complicated, but DSMs do not have to be. Useful DSMs focus on the decision at hand and chiefly aim to accurately represent the system that is being managed at the resolution of the problem (i.e., a requisite DSM) (Phillips 1984). Although complex models may better characterize the complexity of the ecological processes that they are trying to represent, they may not constitute good DSMs. We are not advocating for overly simple DSMs that fail to provide a useful representation of the system that is being managed. However, in our experience, uncertainty in fewer than 10 DSM parameters or submodels often governs what is considered the preferred management action—no matter how complicated the original DSM. If uncertainty in a parameter or submodel does not influence the decision, including it in the analysis comes at a cost. In particular, unnecessary DSM complexity can lead to superfluous propagation of error, and, from a practical perspective, a more complicated model can be difficult to understand, troubleshoot, and run within a timeframe that meets the needs of management programs.

Addressing Uncertainty in Decision Analysis

Given that uncertainty is inherent in natural systems, implementation of management actions may differ from what was planned, and it can be difficult to decide how to weigh the relative importance of management objectives. Evaluations made using decision-support models (DSMs) benefit from followup sensitivity analyses. Sensitivity analyses can help explain why certain decisions were made in the face of—sometimes considerable—uncertainties and can ultimately provide the transparency often needed to gather more support for management strategies.

Managers and researchers can use sensitivity analyses for at least four useful evaluations, as follows:

1. To understand how the DSM works and, by extension, to evaluate whether uncertainty in DSM inputs, parameters, or submodels leads to changes in the preferred management action(s).
2. To calculate the value of information, which is what managers may expect to be the return on investment when reducing uncertainty in components of a DSM. For example, this can allow managers to make statements such as, “We can expect to increase harvests by 10 percent of board feet per watershed if we reduce uncertainty in the relationship between American goshawk occupancy and forest composition and structure.”
3. To evaluate how uncertainty in management implementation (such as acres actually treated versus what was initially planned) may lead to changes in the preferred management action(s).
4. To understand how much managers would need to value one objective over another before they implement a different management decision. For example, this can enable managers to make statements such as, “We would need to value avian diversity three times more than timber production before we would ever change our management decisions.”

Moreover, unnecessary DSM complexity can hinder adaptive management programs because DSM prediction error significantly reduces the ability to learn and, by extension, appropriately adapt management (see "Adaptive Updating"). Notably, there is a formal process that managers and researchers can use to develop a requisite DSM (see "Developing a Decision-Support Model").

Some management programs may choose to use DSMs to evaluate predefined management scenarios to find a set of decisions that work well in most cases (i.e., scenario evaluation). Although this can certainly be useful, it is worth considering that this approach does not fully leverage the capabilities of a DSM. In particular, managers and researchers can use a DSM to provide

Adaptive Updating

To demonstrate how decision-support model (DSM) prediction error affects learning, consider a simplified forest fuel management decision with two objectives: (1) minimizing wildfire risk—quantified as wildfire probability—and, (2) maximizing avian species diversity—measured by number of bird species. In this example, there are three potential management actions that can be implemented: (1) no action, allowing natural processes to continue; (2) prescribed burning to reduce surface fuels; and (3) mechanical thinning to selectively remove small-diameter trees and understory vegetation (fig. 1). Let's assume that avian biologists dispute the response of bird species to fuel reduction management actions. One group believes that forest structural complexity primarily drives avian diversity, while the other believes that avian diversity depends on the type and intensity of forest disturbance. Two alternative models represent these competing hypotheses:

1. The structural complexity hypothesis predicts that in the next 3 to 5 years, avian diversity will remain unchanged under no action but will increase 10 percent with prescribed burning and increase 20 percent with mechanical thinning.
2. The disturbance hypothesis predicts that in the next 3 to 5 years, avian diversity will remain unchanged under no action but will increase 30 percent with prescribed burning and decrease 10 percent with mechanical thinning.

Model weights are typically applied when alternative models are used in DSMs to estimate a single outcome for a given proposed management action. For simplicity, both models that represent each hypothesis are initially weighted equally—0.5 each—to predict avian diversity under each management action. Based on these equally weighted predictions, prescribed burning emerges as the preferred action for maximizing short-term avian diversity and minimizing wildfire probability, with an expected utility score of 11.9 (fig. 1). The utility score combines wildfire probability and avian diversity objectives into a single value, where a higher utility score represents a preferred outcome based on the management objectives.

Learning (i.e., uncertainty reduction) occurs when model predictions are compared to real-world monitoring results and model weights are updated using Bayes' rule. However, DSM prediction error—expressed here as a coefficient of variation—significantly influences the learning rate. If the aforementioned disturbance hypothesis represents the true underlying mechanism, its model weight increases rapidly when prediction error is low at 0.1 (fig. 2). When prediction error increases to 0.5, the rate of weight adjustment

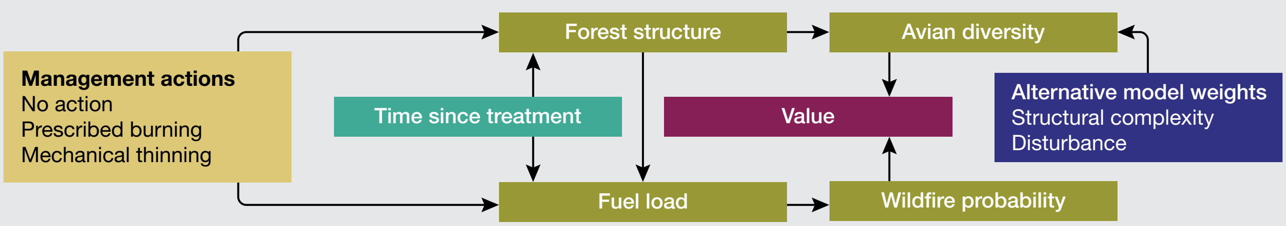

Figure 1—Graphical depiction of a simplified forest fuel management decision-support model, where "value" represents the utility score when combining the wildfire probability and avian diversity objectives into a single value.

generalizable guidelines to form a management strategy that can be applied across similar management units. Using a scenario-evaluation approach would require one to consider both the actions to implement and their temporal sequence to maximize gains in the objective(s). Evaluating every combination of actions and sequence of actions in this way may be time prohibitive even in relatively simple cases. For instance, considering just five types of actions (i.e., thinning, prescribed fire, mastication, salvage logging, and no action) at a single site across 10 years would require 5^{10} or 9,765,625 unique management scenarios to represent all the possibilities. This number increases exponentially as the number of sites increases, making a comprehensive

decreases substantially. Importantly, no learning can occur under the no-action alternative because models that represent each hypothesis predict identical outcomes. Learning within adaptive management leads to more accurate DSMs by design and, by extension, to an improved ability to evaluate tradeoffs in management actions.

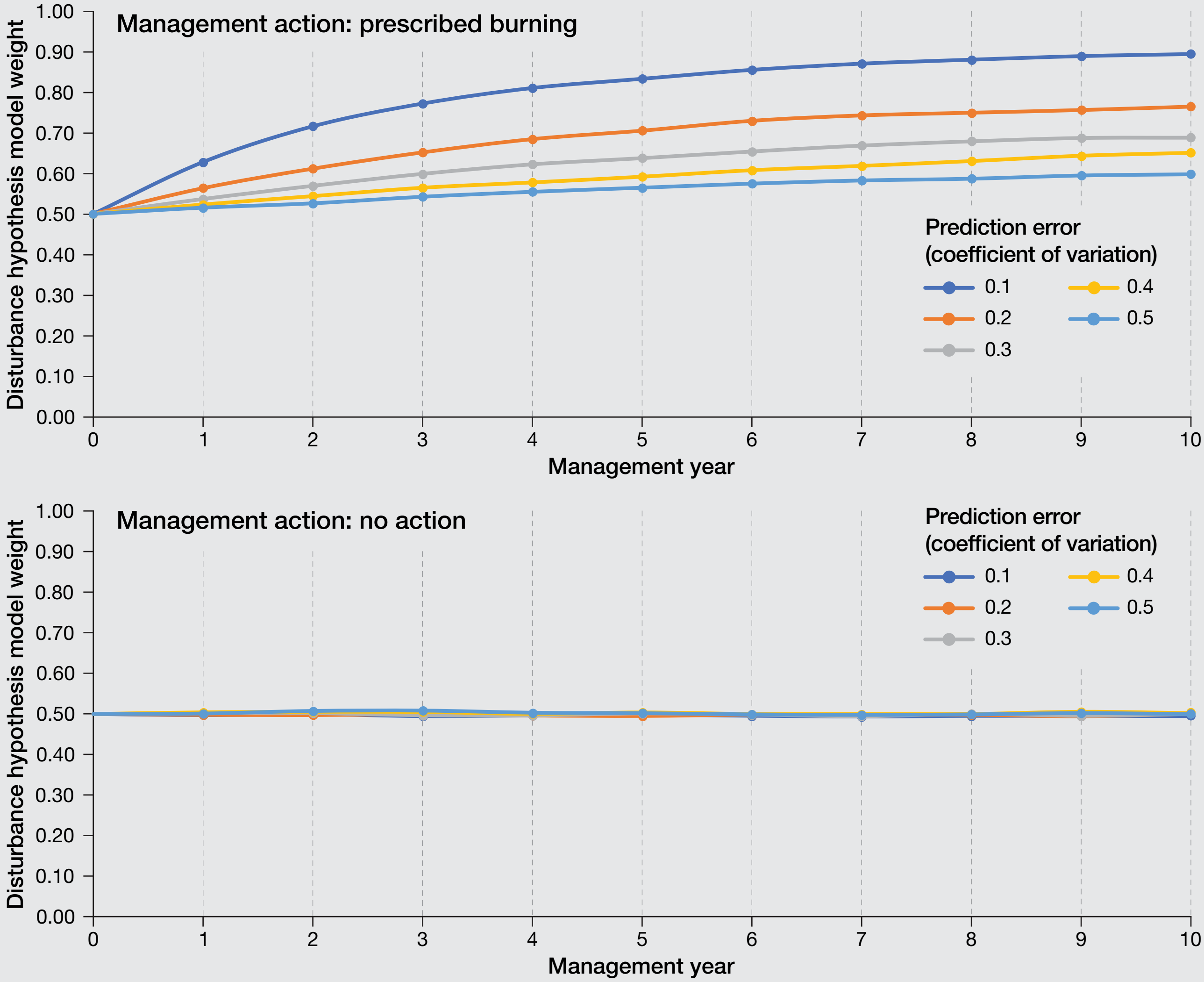

Figure 2—Change in disturbance hypothesis model weights over time following the implementation of two different management actions: prescribed burning and no action. Model weights are updated by comparing model predicted avian diversity with observed values (avian monitoring data) using Bayes' rule. When implementing prescribed burning, lower prediction error (expressed as a coefficient of variation) leads to faster learning. When implementing no action, no learning can occur because the models that represent both hypotheses predict identical outcomes.

evaluation across management units intractable using this approach.

Fortunately, the decision sciences have developed multiple ways of solving DSMs that can fit a large variety of decision situations. Here, solving a DSM means being able to use optimization routines to efficiently examine all model combinations to meet management objective(s). This avoids having to consider each unique management scenario in isolation but achieves the same outcome. For example, Gustafson et al. (2006) used linear programming to solve a DSM to evaluate alternative timber harvest schedules under a forest plan revision in the Midwest. Furthermore, Moore and Conroy (2006) used adaptive stochastic dynamic programming to solve a dynamic forest growth DSM to evaluate timber harvest strategies that maximized the amount of red-cockaded woodpecker (*Leuconotopicus borealis*) nesting habitat on a wildlife refuge in the Southeast. Both optimization routines, however, benefitted from using relatively simple DSMs.

We recognize that the use of a relatively simple DSM may represent a misalignment with forest management across landscapes given that managers often implement management actions within multiple project areas across scales (i.e., watersheds to forest districts to national forests to regions). However, heuristic approaches can handle more complex DSMs and provide near-optimal solutions when exact optimization is not computationally feasible. Our point here is to emphasize that, although natural systems are complex, simplifying the representation of a decision problem (i.e., the DSM) can facilitate the use of multiple, efficient algorithmic approaches to solve DSMs and, ultimately, to develop effective management strategies in reasonable timelines.

Monitoring a Few Things Well Is Better than Monitoring a Lot of Things Okay

Monitoring is an important, albeit often omitted, task when implementing adaptive management. Although some propose that there is a difference between "research grade" monitoring data that scientific studies use and "management grade" monitoring data that managers use, this is a fallacy that often leads to less rigorous monitoring. Undeniably, monitoring programs should be targeted to achieve monitoring objectives, which may be related to management or research, or both. Although it can be difficult to prioritize what to monitor, monitoring the parameters or metrics associated with the management objective(s) is a good start. This allows managers to know the current state of the system that is being managed and whether management actions are accomplishing management objectives.

Developing a Decision-Support Model

Decision-support models (DSMs) to predict natural systems have become increasingly more complex as technological advancements and analytical approaches allow for more advanced computing. As noted in the main text, however, there are multiple advantages to developing DSMs that only contain those elements that are necessary to solve the problem (i.e., a requisite DSM).

Here we outline basic steps that managers and researchers can use to develop a requisite DSM to help inform decisions within an adaptive management program:

1. Develop a conceptual model that represents all potential model components and linkages that may influence the managed system (e.g., fig. 1).
2. Compile existing information to parameterize the conceptual model within a quantitative DSM.
3. Identify remaining conceptual model components and linkages that lack information.
4. Decide to omit missing model components and linkages, or parameterize missing model components using expert elicitation, meta-analysis, etc.
5. Run potential management strategies through the DSM via scenario analysis.
6. Run sensitivity analyses to identify which model components influence the identity of the preferred management action(s).
7. Absorb (i.e., make it a constant parameter), remove, or omit model components that do not influence the decision-making process.
8. Use the simplified, requisite DSM within optimization routines to help inform management strategy development.

Importantly, managers and researchers could also use a DSM to prioritize monitoring efforts. The process of building DSMs forces managers and researchers to (1) critically assess what they need to know to make informed decisions, (2) identify key information needs using sensitivity analyses (see "Addressing Uncertainty in Decision Analysis"), and (3) define the scale at which data must be collected to inform management. For example, an effective monitoring prioritization strategy would identify two types of critical information needs: (1) those representing essential information needs for the specific decision being made based on sensitivity analyses, and (2) those currently lacking sufficient empirical data to support robust predictions when using the DSMs. Focusing monitoring efforts on components that meet both criteria maximizes knowledge gain that is relevant to decisions at a scale that can directly inform management.

Given the increasingly limited resources available to invest in wildlife monitoring and the pressing need to implement active forest management, it is essential to find creative ways to do more with less to establish effective monitoring programs within real-world budgetary and time constraints. This will undoubtedly require flexibility on how data are collected to fill critical information needs. For example, technological advancements for monitoring wildlife (e.g., camera traps, autonomous recording units, drones) and the development of more sophisticated analytical approaches (e.g., Bayesian hierarchical models, data integration, convolutional neural networks) are lowering some barriers to collecting relatively fine-resolution data across large spatial extents that can quantify wildlife population dynamics and species' distributions. However, there is often a time lag in adopting these relatively new methods over traditional wildlife monitoring approaches (e.g., point counts, trapping and tagging, nest searching or checks). Although we agree that these advancements do not represent a panacea for information gathering, these new approaches often come with advantages (e.g., noninvasive, cost effective) and ought to be considered when they represent a viable option toward collecting critical information to inform management.

We also caution against monitoring for the sake of monitoring. Too often monitoring programs continue simply because they were already established. We are not trying to discredit the value of long-term monitoring programs and the data they collect; there are several legitimate reasons to invest in long-term monitoring programs. However, in the face of limited resources, it may be worthwhile to consider how much data is enough, whether modifications to existing monitoring programs can improve efficiencies while maintaining or increasing their rigor, and whether redirecting monitoring resources toward monitoring efforts that reduce uncertainty associated with newly identified priority information needs would be a better investment.

Conclusion

Given the uncertainty about the response of wildlife communities to wildfires and forest management and the pressing need to implement active forest management, we believe proper adaptive management processes that managers and researchers jointly develop will be key to meeting multiple forest management objectives. Adaptive management requires clear communication among participants and the formal integration of monitoring, modeling, and management to evaluate management tradeoffs in the face of uncertainty. We stress that a good DSM helps guide conversations within a decision-making process, and DSMs are simply tools that managers can use as one line of evidence when making decisions. DSMs do not replace human intuition and subjectivity. Rather, when used properly, they assist decision making and facilitate transparency. We also stress that monitoring is an essential component of adaptive management. A well-designed monitoring program is intentionally designed—with budgetary constraints in mind—to understand the current state of the system that is being managed. It serves as a basis for evaluating system performance in response to management and enables DSM predictions to be confronted with real-world data to learn, adapt, and answer specific research questions. We hope this synthesis informs the design of effective adaptive management programs that maximize the success of forest management to meet multiple objectives when dealing with considerable ecological uncertainty.

Suggested Citation

Duarte, A.; Peterson, J.T. 2026. Avoiding common pitfalls in the implementation of adaptive forest wildlife management. In Wright, V.; Keville, M., tech. eds. Wildland fire and fuels science synthesis: supporting landscape and community resilience in the Pacific Northwest. Gen. Tech. Rep. PNW-GTR-1044. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station.

References

Conroy, M.J.; Peterson, J.T. 2009. Integrating management, research, and monitoring: balancing the 3-legged stool. National Quail Symposium Proceedings. 6: 1. https://doi.org/10.7290/nqsp06864y.

Conroy, M.J.; Peterson, J.T. 2013. Decision making in natural resource management: a structured, adaptive approach. Hoboken, NJ: John Wiley & Sons, Ltd. 474 p. https://doi.org/10.1002/9781118506196.

Gustafson, E.J.; Roberts, L.J.; Leefers, L.A. 2006. Linking linear programming and spatial simulation models to predict landscape effects of forest management alternatives. Journal of Environmental Management. 81(4): 339–350. https://doi.org/10.1016/j.jenvman.2005.11.009.

Irwin, B.J.; Conroy, M.J. 2013. Consideration of reference points for the management of renewable resources under an adaptive management paradigm. Environmental Conservation. 40(4): 302–309. https://doi.org/10.1017/S0376892913000222.

McFadden, J.E.; Hiller, T.L.; Tyre, A.J. 2011. Evaluating the efficacy of adaptive management approaches: Is there a formula for success? Journal of Environmental Management. 92(5): 1354–1359. https://doi.org/10.1016/j.jenvman.2010.10.038.

McGowan, C.P.; Lyons, J.E.; Smith, D.R. 2015. Developing objectives with multiple stakeholders: adaptive management of horseshoe crabs and red knots in the Delaware Bay. Environmental Management. 55: 972–982. https://doi.org/10.1007/s00267-014-0422-8.

Moore, C.T.; Conroy, M.J. 2006. Optimal regeneration planning for old-growth forest: addressing scientific uncertainty in endangered species recovery through adaptive management. Forest Science. 52(2): 155–172. https://doi.org/10.1093/forestscience/52.2.155.

Peterson, J.T.; Duarte, A. 2020. Decision analysis for greater insights into the development and evaluation of Chinook salmon restoration strategies in California's Central Valley. Restoration Ecology. 28(6): 1596–1609. https://doi.org/10.1111/rec.13244.

Phillips, L.D. 1984. A theory of requisite decision models. Acta Psychologica. 56(1–3): 29–48. https://doi.org/10.1016/0001-6918(84)90005-2.

Reiman, B.; Peterson, J.T.; Clayton, J.; Howell, P.; Thurow, R.; Thompson, W.; Lee, D. 2001. Evaluation of the potential effects of federal land management alternatives on trends of salmonids and their habitats in the Interior Columbia River basin. Forest Ecology and Management. 153(1–3): 43–62. https://doi.org/10.1016/S0378-1127(01)00453-4.

Runge, M.C.; Converse, S.J.; Lyons, J.E.; Smith, D.R., eds. 2020. Structured decision making: case studies in natural resource management. Baltimore, MD: Johns Hopkins University Press. 288 p. https://doi.org/10.1353/book.74951.