

# PROCEEDINGS OF THE 22<sup>ND</sup> NORTH AMERICAN PRAIRIE CONFERENCE



Held August 1 - 5, 2010  
University of Northern Iowa  
Cedar Falls, Iowa

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# AN ADAPTIVE APPROACH TO INVASIVE PLANT MANAGEMENT ON U.S. FISH AND WILDLIFE SERVICE-OWNED NATIVE PRAIRIES IN THE PRAIRIE POTHOLE REGION: DECISION SUPPORT UNDER UNCERTAINTY

JILL J. GANNON, U.S. Geological Survey, Northern Prairie Wildlife Research Center, University of Georgia, 180 E. Green St, Athens, GA 30602, jillgannon@gmail.com

CLINTON T. MOORE, U.S. Geological Survey, Patuxent Wildlife Research Center, University of Georgia, 180 E. Green St, Athens, GA 30602

TERRY L. SHAFFER, U.S. Geological Survey, Northern Prairie Wildlife Research Center, 8711 37th St SE, Jamestown, ND 58401

BRIDGETTE FLANDERS-WANNER, U.S. Fish and Wildlife Service, Pacific Region, Branch of Refuge Biology, 1211 SE Cardinal Court, Vancouver, WA 98683

**Abstract:** Much of the native prairie managed by the U.S. Fish and Wildlife Service (Service) in the Prairie Pothole Region (PPR) of the northern Great Plains is extensively invaded by the introduced cool-season grasses smooth brome (*Bromus inermis*) and Kentucky bluegrass (*Poa pratensis*). Management to suppress these invasive plants has had poor to inconsistent success. The central challenge to managers is selecting appropriate management actions in the face of biological and environmental uncertainties. In partnership with the Service, the U.S. Geological Survey is developing an adaptive decision support framework to assist managers in selecting management actions under uncertainty and maximizing learning from management outcomes. The framework is built around practical constraints faced by refuge managers and includes identification of the management objective and strategies, analysis of uncertainty and construction of competing decision models, monitoring, and mechanisms for model feedback and decision selection. Nineteen Service field stations, spanning four states of the PPR, are participating in the project. They share a common management objective, available management strategies, and biological uncertainties. While the scope is broad, the project interfaces with individual land managers who provide refuge-specific information and receive updated decision guidance that incorporates understanding gained from the collective experience of all cooperators. We describe the technical components of this approach, how the components integrate and inform each other, how data feedback from individual cooperators serves to reduce uncertainty across the whole region, and how a successful adaptive management project is coordinated and maintained on a large scale.

**Key Words/Search Terms:** smooth brome, *Bromus inermis*, Kentucky bluegrass, *Poa pratensis*, native prairie, adaptive management, decision support, uncertainty, utility, learning, National Wildlife Refuge System, Prairie Pothole Region

## INTRODUCTION

The extent of native prairie in North America has greatly declined from presettlement conditions. Native mixed-grass prairie has declined 30%–99% and native tallgrass prairie has declined more than 95% (Samson et al. 2004), primarily due to agricultural conversion. In the fragments of native prairie that remain, historic disturbances, such as grazing by native ungulates and frequent fire, have largely been excluded (Murphy and Grant 2005).

More than 100,000 ha of native prairie remnants are found in the Prairie Pothole Region (PPR) within the collection of National Wildlife Refuge System (NWRS) lands of the U.S. Fish and Wildlife Service (Service), which is charged with managing this large public land base. Given the decline of this ecosystem throughout the PPR, these refuge lands have become increasingly important conservation reservoirs for native prairie. Unfortunately, recent surveys of Service prairies revealed that these remaining fragments of native prairie are afflicted by a widespread invasion of two exotic cool-season grasses, smooth brome (*Bromus inermis*) and Kentucky bluegrass (*Poa pratensis*) (Grant et al. 2009). These invasions of Service-owned prairies are believed to stem in part from a common management history (circa 1935–85) of long-term rest and little or no defoliation by natural processes (e.g. grazing or fire) that historically shaped native vegetation communities (Grant et al. 2009).

Refuges are presently attempting to manage for native prairie and against these invasive grasses by reintroducing various forms of disturbance, including prescribed fire, grazing, and haying; however, results to date have been poor to inconsistent. Prairies differ by geographic location, tract size, degree of invasion, soils, etc., making their management an inherently complex undertaking. Managers face considerable uncertainties and operational constraints as they make decisions about the lands under their care (Smiley 2008). Success can be further hindered by a lack of coordinated effort among

refuges in addressing prairie management. Refuges enjoy a high degree of autonomy, which can be an inducement for each station to act on its own, using different tactics to meet different objectives (Moore et al. 2011). Additionally, while monitoring has a long tradition in the NWRS, it has been less common for monitoring to be focused in a way that informs managers about the resource consequences of specific actions they take (Nichols and Williams 2006, Moore et al. 2011). A traditional go-it-alone approach to prairie management can therefore make it difficult to make sense of piecemeal outcomes that may be anecdotal, inconclusive, or contradictory.

To tackle this problem, scientists from the U.S. Geological Survey Northern Prairie and Patuxent Wildlife Research Centers are partnering with Service biologists and managers to develop an adaptive management-based system for making decisions about prairie management. This system will coordinate local efforts, recognize uncertainties that make management difficult, assist managers with making transparent and scientifically based management decisions given these uncertainties, and maximize the learning potential from management outcomes to reduce these uncertainties, thereby improving decision making and management through time. The framework of the adaptive management decision support system is built around the practical constraints of the refuges. The project interfaces with individual land managers who provide refuge-specific information and receive annual decision guidance that incorporates understanding gained from the collective experience of all cooperators. That is, individual cooperators learn from the dispersed efforts of all cooperators, as information feedback from each serves to reduce uncertainty across the whole region.

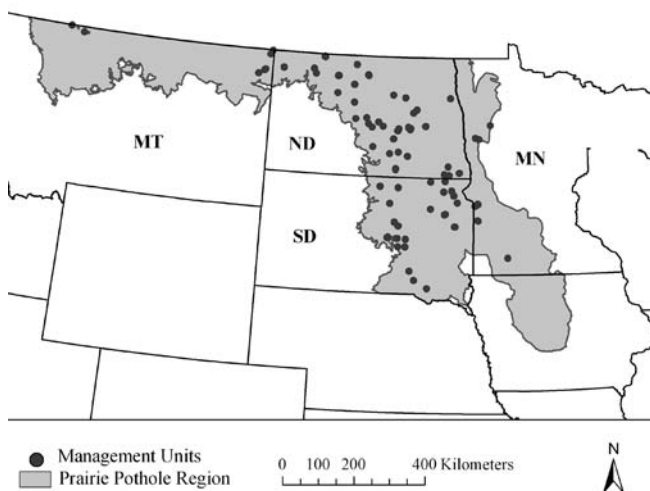


Figure 1. The project is focused on U.S. Fish and Wildlife Service National Wildlife Refuge System lands within the Prairie Pothole Region of the northern Great Plains. Service cooperators from nineteen different stations have enrolled in the project, resulting in 120 management units that span the boundaries of two Service regions (3 & 6) and four states (North Dakota, South Dakota, Minnesota, and Montana).

## STUDY AREA

This project focuses on Service NWRS lands within the PPR of the northern Great Plains (Figure 1; Appendix A). Within the PPR, 19 refuge complexes and wetland management districts (hereafter referred to as refuges, stations, or cooperators) contributed 120 management units to the project. Management units are parcels that receive a single management treatment at any one time over its entire extent; average unit size was 35 hectares (range 3.5-241 ha). These units span the boundaries of two Service regions (3 and 6) and four states (North Dakota, South Dakota, Minnesota, and Montana).

## ADAPTIVE MANAGEMENT-BASED DECISION SUPPORT SYSTEM

Adaptive management is an approach to recurrent decision making laid upon a foundation of predictive modeling, monitoring, and knowledge updating. Management decisions are chosen to pursue specifically identified management objectives, with the choice of best decision conditional on the present state of the managed system, and what is currently understood about behavior of the system. Adaptive management provides a formal framework for the improvement of management performance through the incremental reduction of uncertainty, an outcome achieved through repeated assessment of decision models against observed system response (Williams 1997, Kendall 2001, Moore and Conroy 2006, McCarthy and Possingham 2007).

The adaptive management framework consists of two stages: a setup phase, which is carried out only once or at infrequent intervals, and an iterative phase, which constitutes the recurrent steps of the annual decision-making process (Williams et al. 2007; Figure 2).

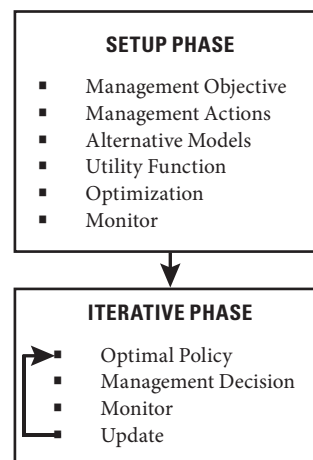


Figure 2. The adaptive management framework consists of two stages: the setup phase consists of six components and is carried out only once, while the iterative phase consists of four components and constitutes the recurrent steps of the annual decision-making process.

There are six components of the setup phase: (1) define the management objective, (2) establish the potential management actions, (3) identify uncertainties and develop alternative models, (4) determine the utility function, (5) compute the optimal decision table, and (6) develop and implement a monitoring protocol. The iterative phase consists of four components: (1) identify the optimal policy, (2) make and implement a management decision, (3) monitor the outcome, and (4) assess the outcome relative to model predictions and update model weights. The focus of this paper is to describe our decision-support system within the structure of these adaptive management framework elements; the framework we describe here is a work in progress.

**ADAPTIVE MANAGEMENT FRAMEWORK:  
SETUP PHASE  
MANAGEMENT OBJECTIVE**

Under adaptive management, the selection of decisions is driven by an explicit, measurable management objective (Williams et al. 2002). The objective statement must (1) be quantifiable and measurable in the field, (2) define a quantity that can be generated as output from a decision model, and (3) balance tradeoffs among multiple objectives. One of our first tasks was to hold an initial, facilitated problem-scoping workshop to define the management objective. The workshop was held in July 2008 and was attended by 25 Service personnel (managers, biologists, project leaders) representing 19 different refuges from across the PPR of Service regions 3 and 6. During the workshop, participants considered various management goals and constraints and developed a consensus management-objective statement: *increase the composition of native grasses and forbs on native sod while minimizing cost.*

**MANAGEMENT ALTERNATIVES**

We next defined the menu of admissible decision alternatives that managers can use to pursue the management objective. Management decisions are supplied as input to decision models, and different decisions should yield different expected outcomes under the models. Management of grasslands is characterized by considerable uncontrolled natural variability; thus, it is important that differences in outcome among management alternatives be large and distinct if management is to be informative. A decision set containing a few, coarse-grained alternatives is more likely to provide rapid gains in learning than one containing a large number of subtly distinguished options. Therefore, construction of the set of decision alternatives was guided by actions likely to generate the greatest diversity in outcomes, and by logistical and political feasibility.

During the initial workshop, we elicited ideas from the participants about treatment options, identified constraints in their use, and narrowed the management alternatives to a manageable number to facilitate learning. The cooperators outlined five alternative management actions: *rest, hay, graze, burn, and burn/graze combination*. Each of the five management alternatives was generally defined with broad sideboards for timing, repetition, and intensity of application; within these sideboards, specific implementation of the action was left to the discretion of the manager. In each management year (defined as September 1-August 31), for each management unit, a manager selects one management action from this menu to apply to the unit.

**UNCERTAINTY AND ALTERNATIVE MODELS  
DESCRIBING THE SYSTEM**

We define the state of the biological system on each management unit at a particular time by two characteristics: the amount of cover of native grasses and forbs and the type of invasive grass that is dominant. We recognize five discrete states of native prairie cover: greater than 95%, 80%-95%, 50%-80%, 20%-50%, and less than 20%. Within each of the latter four states of native prairie cover, where some degree of invasion occurs, we recognize the dominant invasive as smooth brome, Kentucky bluegrass, or something other than either of these two invasive grasses. We also recognize smooth brome/Kentucky bluegrass codominance when native prairie cover is less than 80%. The five states of native prairie cover in combination with the dominant invasive results in 16 discrete possible states of the system (Figure 3).

		DOMINANT INVASIVE			
		SB	SB KB	KB	OT
NATIVE PRAIRIE	> 95%	1			
	80 - 95%	2	3		4
	50 - 80%	5	6	7	8
	20 - 50%	9	10	11	12
	< 20%	13	14	15	16

Figure 3. The composition of each management unit is categorized into one of 16 discrete states, depending on its amount of native grasses and forbs (>95%, 80%-95%, 50%-80%, 20%-50%, < 20%) and its dominant invasive (smooth brome [SB], smooth brome/Kentucky bluegrass codominant [SB|KB], Kentucky bluegrass [KB], and other [OT]). We do not recognize codominant invasion status when native prairie cover is greater than 80%, and we do not recognize the dominant invasive when native prairie cover is greater than 95%. We define dominance as follows: smooth brome dominant if  $SB/(SB + KB) \geq 0.67$ ; Kentucky bluegrass dominant if  $KB/(SB + KB) \geq 0.67$ ; and other dominant if  $OT/(SB + KB + OT) \geq 0.67$ . If none of these conditions are met, then a unit is categorized as codominant smooth brome and Kentucky bluegrass.

		FUTURE STATE AT TIME $t+1$															
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
STARTING STATE AT TIME $t$	1	0.61	0.05	0.16	0.16	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	2	0.08	0.47	0.11	0.08	0.14	0.07	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00
	3	0.05	0.06	0.46	0.06	0.12	0.09	<b>0.16</b>	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	4	0.06	0.02	0.14	0.47	0.04	0.01	0.22	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	5	0.00	0.07	0.00	0.02	0.60	0.13	0.03	0.03	0.09	0.01	0.01	0.00	0.00	0.00	0.01	0.00
	6	0.02	<b>0.03</b>	0.00	0.01	0.06	0.60	0.10	0.03	0.02	0.06	0.03	0.01	0.00	0.02	0.00	0.00
	7	0.01	0.00	0.04	0.01	0.00	0.02	0.84	0.02	0.00	0.00	0.04	0.00	0.00	0.00	0.01	0.00
	8	0.01	0.01	0.01	0.03	0.03	0.10	0.20	0.50	0.01	0.01	0.01	0.04	0.01	0.01	0.00	0.01
	9	0.01	0.02	0.01	0.00	0.05	0.03	0.02	0.00	0.67	0.08	0.03	0.00	0.07	0.01	0.00	0.01
	10	0.00	0.01	0.00	0.00	0.00	0.04	0.01	0.01	0.06	<b>0.68</b>	0.07	0.03	0.01	0.07	0.02	0.00
	11	0.01	0.00	0.01	0.01	0.01	0.02	0.11	0.01	0.02	0.08	0.66	0.00	0.00	0.02	0.00	0.02
	12	0.01	0.01	0.01	0.02	0.01	0.03	0.01	0.05	0.13	0.09	0.24	0.26	0.01	0.02	0.03	0.07
	13	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.11	0.05	0.00	0.02	0.68	0.07	0.03	0.03
	14	0.01	0.00	0.00	0.00	0.01	0.04	0.00	0.00	0.05	0.04	0.03	0.00	0.02	0.73	0.06	0.00
	15	0.00	0.00	0.01	0.00	0.00	0.01	0.01	0.01	0.02	0.04	0.04	0.04	0.04	0.12	0.59	0.06
	16	0.00	0.00	0.01	0.01	0.01	0.02	0.01	0.03	0.01	0.02	0.04	0.03	0.11	0.18	0.18	0.34

Figure 4. A 16 x 16 transition matrix describes the probability of a unit transitioning from any of the 16 resource states at time  $t$  (vertical axis) into some other state at time  $t + 1$  (horizontal axis), after a particular management action is applied. For example, the matrix depicted represents transition probabilities (provisional; subject to further analysis) under the management action Rest. Probabilities within each of these 256 cells describe how likely each of the transitions is to occur under the management Rest. For example, a management unit starting in state 3 (80%-95% NP, KB dominant), has a 16% chance of degrading to the lower state 7 (50%-80% NP, KB dominant) under rest management. A unit starting in state 6 (50%-80% NP, SB|KB codominant) has a 3% chance of improving to state 2 (80%-95% NP, SB dominant), while a unit starting in state 10 (20%-50% NP, SB|KB codominant) has a 68% chance of remaining in that state.

### STATE TRANSITION PROBABILITY MODEL

We use a state transition probability model to describe how we think the biological system behaves in response to management (Figure 4). A 16 x 16 transition matrix describes the probability of transitioning from state  $x$  at time  $t$  to state  $y$  at time  $t+1$ , given a particular management action. Because management actions are likely to influence transition probabilities from one state to another, a complete model consists of five matrices, one for each alternative management action. Given the current state of the unit and the management action applied, the model provides a probabilistic prediction of the state of the unit after applying the management action.

Work is ongoing to estimate baseline transition probabilities for each matrix via a meta-analysis of data from several long-term studies. We estimated average transition probabilities across studies, and we placed vague prior probability distributions on the transition matrices to provide inference support for the many parameters where we had sparse data. To complete a prototype of our decision framework, we estimated provisional transition probabilities for mixed-grass prairies and tallgrass prairies separately, resulting in two empirically derived models; final estimates will be a focus of forthcoming work.

## REPRESENTING UNCERTAINTY THROUGH ALTERNATIVE MODELS

Sole reliance on any one particular model implies that the behavior of the system is well understood and that responses to management decisions are predictable with a degree of accuracy. This is not the case in prairie management, where the wide range of site characteristics, current conditions, and variability in treatment execution makes the outcome of any treatment difficult to predict. Under adaptive management, uncertainties about response to management actions are cast in the form of plausible, competing decision models. Each model in the set represents an alternative hypothesis about how the system behaves.

Building alternative models proceeded from an initial synthesis of information about grassland restoration efforts, including expert opinions elicited from participants at the initial scoping workshop. By asking “What makes decision making difficult in grassland management?”, we were able to identify and classify different areas of uncertainty in decision making. More targeted inquiry of the Service biologists serving on the project’s Science Team allowed us to identify general areas of agreement about the behavior of the system, as well as to distinguish four major sources of uncertainty: (1) the effect of haying on native prairie, smooth brome, and Kentucky bluegrass, (2) the effectiveness of burning in suppressing smooth brome, (3) the effectiveness of grazing in suppressing Kentucky bluegrass, and (4) the existence of a threshold of native prairie composition, below which there is no benefit gained by active management.

We constructed four alternative models—four different notions of how we think the system may behave—to represent the four major sources of uncertainty. We formulated these four models by directed modification of the baseline, empirically derived transition probabilities. Model 1 serves as a reference point, expressing several baseline statements about system behavior, as follows: natural mimics of disturbance (i.e., graze, burn, and burn/graze combination) are equally effective at increasing native prairie, haying is equivalent to rest, and graze and burn are differentially effective against specific invasive species—grazing is more effective than burning against smooth brome and burning is more effective than grazing against Kentucky bluegrass. Models 2-4 differ from Model 1 in ways that isolate identified areas of uncertainty. Model 2 focuses on the first uncertainty, and states that while haying is less effective than the natural mimics of disturbance at increasing native prairie, it is more effective than rest. Model 3 targets the second and third uncertainties, and proposes that burning is not effective against smooth brome and grazing is not effective against Kentucky bluegrass. Model 4 aims at the fourth uncertainty and introduces the existence of a threshold (< 20% native prairie cover) below which active management is no better than rest. We have two sets of these four alternative models—one set for mixed-grass prairies and one set for tallgrass prairies—based on the same four concepts but derived from different initial transition probabilities, depending on the prairie type.

The mere existence of multiple models speaks to our uncertainty about the behavior of the system; however, we further quantify this uncertainty by assigning a weight to each model that connotes our current belief in each model as the best representation of system behavior. Model weights are an important element of adaptive management because they are a quantitative expression of current understanding about the system (also referred to as the belief state). Model weights determine the influence of each model on the decision at each point; models with greater weight exert more influence on the selection of a management action. However, model weights continually change through time in response to decisions made, as feedback from the monitoring data informs us about how well or how poorly each model performs as a predictor of management effect. The influence of each model changes through time as our understanding about the system changes. At the outset of decision making, where uncertainty is greatest, it may be reasonable to assign each model equal initial weight. Thus, we assigned equal initial weights of 0.25 to each of our four competing models.

## IRREDUCIBLE FORMS OF UNCERTAINTY

The sources of uncertainty described above, around which our alternative models were created, are considered *structural uncertainty*—the type of uncertainty that adaptive management is intended to address and reduce. Three other sources of uncertainty exist, however, and include: (1) *environmental stochasticity*, unexpected outcomes brought about by chance events (e.g., unanticipated differences in treatment efficacy due to temporal and spatial variation in precipitation), (2) *partial controllability*, the inability to carry out an action as intended (e.g., an incomplete burn), and (3) *partial observability*, the inability to see or measure the system accurately (e.g., sampling variability in monitoring) (Nichols et al. 1995, Williams 1997). These sources of uncertainty are themselves irreducible; nevertheless, because they can have an impact upon decision making, they must be addressed and implicitly or explicitly accounted for in the predictive models. In our decision framework, environmental stochasticity is reflected through the probabilities contained in the state transition models; that is, because of the effects of the random environment, the transition from a given state into the same or some other state is not known with certainty, but only probabilistically. Partial controllability will be accounted for in a model component that makes a probabilistic determination of which action is carried out given which action was indicated as “best”; we will elicit from our cooperators information that will help parameterize this model component. Finally, we plan to account for partial observability in the updating step of our framework; inaccuracy in measuring the resource should result in reduced learning from management actions.

## UTILITY FUNCTION

The utility function describes what we want from the system through management. It combines both the resource and cost aspects of the management objective by balancing the *value* of having native prairie with the *cost* of achieving it. The utility function is a subjective expression of the value system (i.e., importance of having native prairie, undesirability of invasive species, willingness to direct resources to address either) of the cooperators. As such, parameterizing the utility function is a process that stands completely apart from the process that expresses our beliefs about the science of the system (i.e., construction of the model set). Utility is the annual measure of what the manager receives from the system in return for what he/she invests; therefore, it is reasonable to describe sound management as the sequence of decisions over many years that makes accumulated utility as large as possible.

We distinguish three main characteristics that cooperators value: (1) high cover of native prairie, (2) increasing the amount of native prairie cover, and (3) gaining more native prairie cover for less investment. We have constructed the utility function to recognize these three values by accounting for three corresponding elements: (1) the future native prairie

		FUTURE STATE				
		> 95%	80 - 95%	50 - 80%	20 - 50%	< 20%
STARTING STATE	> 95%	1.0	<b>0.40</b>	0.03	0.006	0.001
	80 - 95%	1.0	<b>0.80</b>	0.13	0.009	0.003
	50 - 80%	1.0	<b>0.90</b>	0.35	0.02	0.006
	20 - 50%	1.0	<b>0.95</b>	0.58	0.10	0.008
	< 20%	1.0	<b>0.98</b>	0.74	0.23	0.01

Figure 5. This is an example of how we quantify the values cooperators place on having high cover of native prairie (NP) and gaining more NP. These values are expressed in a two-dimensional utility matrix indexed by the NP cover before (starting state) and after (future state) a management action. We assign values of utility to each possible transition between the starting and future states, where utility is expressed with a value ranging between 0 and 1. These values represent cooperator satisfaction with each outcome (0 is the least and 1 is the most satisfied). Values along the diagonal represent cooperator satisfaction with staying in a given state; satisfaction is greatest with the highest NP cover and declines with lower NP cover. Cooperators also value making improvements from a lower to a higher NP state and disfavor degrading from a higher to a lower NP state. Values in the matrix beneath and above the diagonal represent transitions where NP was gained and lost, respectively. Given a future NP state of 80%-95% (bolded values), satisfaction is relatively high (0.8) when that condition was maintained from its starting state, is greater (0.90) when that condition was an improvement from a lower state of 50%-80% NP, and is greatly reduced (0.4) when that condition resulted from a degradation from >95% NP. The third element of the utility function, cost, is not shown here. The complete utility function, encompassing all three aspects of the cooperators' value system, consists of five utility matrices like the one depicted here—one for each management action; each matrix contains the same internal relationship among values, but the utilities are discounted according to the relative cost of management actions, which are ranked from most expensive (burn/graze) to least expensive (rest).

state resulting from an action, (2) the starting native prairie state before applying an action (comparison between elements 1 and 2 allow us to distinguish between improvements and degradations in prairie state), and (3) the management action that was taken to prompt the transition between the starting and future states. Because subjective preferences are hard to draw out and evaluate, and because different stakeholders will have different perspectives of how they value these three elements, quantifying the utility function will require expertise to elicit and resolve these values. While the actual quantification of the values may vary, the utility function will follow the structure outlined above (Figure 5).

## OPTIMIZATION

Optimization is the search for best management actions through a process that integrates the model, which describes how we think the system works, and the utility function, which describes our values. Dynamic programming is a form of optimization for decisions and the resulting rewards (utility values) that occur through time (Dreyfus and Law 1977). We use adaptive stochastic dynamic programming (ASDP; Lubow 1995, 1997), which accounts for current and future expected rewards, future dynamics of system state and knowledge gain, and the degree of management control (partial controllability). The procedure determines the trajectory of decisions through time that will maximize expected cumulative utility, thereby achieving the management objective. The end product of the optimization is a large table that contains every possible combination of resource state (i.e., 1-16) and belief state (i.e., weights assigned to the four alternative models), and identifies the optimal management decision for each combination (Table 1).

The optimal decision table generated by ASDP provides a best decision for the current condition of the resource and for the degree of confidence (model weights) we currently place on each of the four alternative models. The current condition of the resource is management-unit specific and ascertained annually via a standardized monitoring program (see "Monitoring" below). The current understanding of the system, indicated by the weights assigned to each model, is specific to prairie type (i.e., mixed or tall) and is determined annually via an updating procedure (see "Compare and Update" below). Because we have two sets of alternative models, one for mixed-grass prairies and one for tallgrass prairies, we obtain two optimal decision tables, one for each prairie type.

## MONITORING

The monitoring protocol is designed to provide data for three purposes: (1) determining current system state (i.e., prairie composition) on each management unit, (2) evaluating progress toward the management objective, and (3) assessing predictive performance of the alternative models. We adopted a protocol that employs a modified belt-transect sampling method (Grant et al. 2004) and was familiar to many

Table 1. Excerpt from an optimal decision table produced from the adaptive stochastic dynamic optimization. The full table contains all possible combinations of native prairie state (i.e., 1-16) and belief state (i.e., weights assigned to the four alternative models), and identifies the optimal management decision for each combination. We discretized model weights by 0.125, making 165 possible combinations of the four model weights (three of which are shown in the excerpted portion of the table). Combining 165 belief states with 16 resource states results in 2,640 possible combinations. As an example, if our current understanding of system behavior is perfect, with 100% of confidence on Model 1, then the optimal decision for a management unit in state 3 would be to Burn. However, if our current understanding of system behavior is imperfect, with 37.5 % of confidence in Model 1, 37.5% in Model 2, 0% in Model 3, and 25% in Model 4, then the optimal decision for the same resource conditions would be to Burn/Graze.

STATE	MODEL 1	MODEL 2	MODEL 3	MODEL 4	OPTIMAL DECISION
1	1	0	0	0	Hay
2	1	0	0	0	Graze
3	1	0	0	0	Burn
4	1	0	0	0	Graze
⋮	⋮	⋮	⋮	⋮	⋮
16	1	0	0	0	Graze
1	0.625	0.125	0.125	0.125	Rest
2	0.625	0.125	0.125	0.125	Graze
3	0.625	0.125	0.125	0.125	Burn
4	0.625	0.125	0.125	0.125	Burn/Graze
⋮	⋮	⋮	⋮	⋮	⋮
16	0.625	0.125	0.125	0.125	Graze
1	0.375	0.375	0	0.25	Rest
2	0.375	0.375	0	0.25	Graze
3	0.375	0.375	0	0.25	Burn/Graze
4	0.375	0.375	0	0.25	Burn/Graze
⋮	⋮	⋮	⋮	⋮	⋮
16	0.375	0.375	0	0.25	Graze

of the refuges across the Dakotas. A primary consideration when deciding upon the monitoring effort was that it be sustainable by the refuge personnel who are charged with carrying it out each year. For this reason, only necessary attributes that inform the models are measured. In addition to being sustainable, the monitoring protocol reliably conveys prairie composition, is flexible for use in both mixed- and tallgrass prairie, is quick and efficient, and is robust to multiple observers. Along with monitoring prairie composition, refuge managers are responsible for keeping detailed descriptions of the management activities they carry out on each management unit each year (e.g., burn intensity, stocking rate, timing

of application, etc.) so that over time a fuller picture of management practices emerges, facilitating future study of native prairie response to management.

A centralized database was developed to standardize, organize, and maintain the vegetation monitoring data and the management activity data collected by project cooperators. Vegetation monitoring occurs annually during the growing season (between June and August).

**ADAPTIVE MANAGEMENT FRAMEWORK:  
ITERATIVE PHASE  
LOOK UP THE OPTIMAL DECISION POLICY**

Given the current state of the system and the current understanding of the system, identifying the current best management decision is a matter of looking up the combination (i.e., system state and belief state) in the appropriate (i.e., mixed- or tallgrass prairie) optimal decision table (e.g., Table 1). Given complete uncertainty at the outset of decision making, 0.25 is a reasonable initial assignment of weight to each model. The decisions in the optimal decision table that correspond to this current level of understanding constitute the current optimal decision policy (Figure 6). Following monitoring, which informs cooperators about the current composition of native prairie on their sites, we identify the recommended management actions for each unit with respect to its system state and its prairie type (mixed or tall) by consulting the current optimal decision policy. By 31 August of each year, we provide individual cooperators with a recommended management action for each of their management units for the upcoming management year (September 1-August 31).

In future iterations of the decision cycle, the current state of the system will be ascertained by the annual monitoring program (see “Monitor” below) and the current understanding of the system (i.e. weights on each alternative model) will be determined by the annual updating procedure (see “Compare and Update” below).

**MAKE AND IMPLEMENT A MANAGEMENT DECISION**

Upon receiving the management recommendations for their units, managers consider the recommendation, along with other relevant information (e.g., funding constraints; access to a burn crew, cattle, or haying cooperator; fuel load; weather conditions), and decide what management action to implement on each unit that year. The management action is carried out at some point during the management year (September 1-August 31).

**MONITOR**

During the period of the growing season when both cool-season and warm-season grasses are visible (June-August), refuge personnel carry out the annual monitoring protocol. Cooperators individually enter their vegetation and management data in the standardized database and trans-





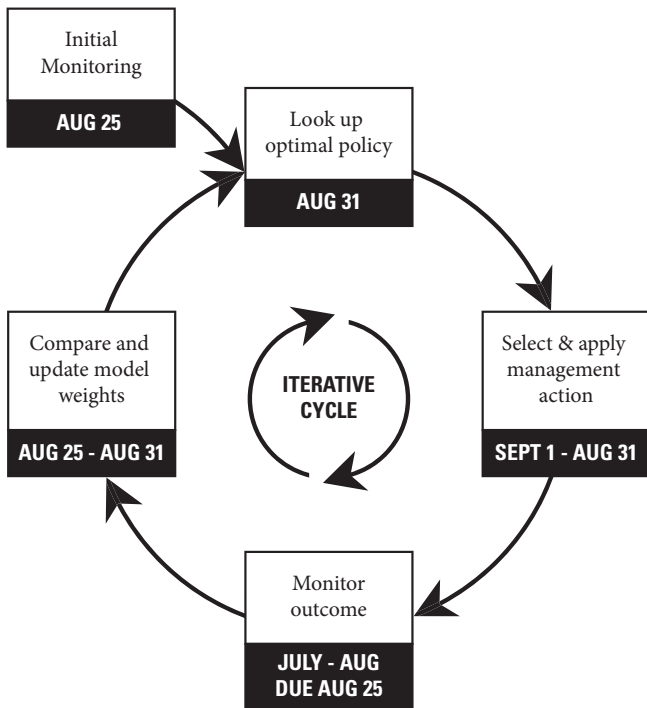


Figure 7. After initial monitoring of all management units during the setup phase, we know the current state of each of the management units and move into the iterative cycle of the adaptive management framework. Here we enter into an annual cycle that includes (1) identifying the optimal policy and generating recommended management actions for each unit with respect to its current state (August 31); (2) selecting a management action for each unit and then applying that action (September 1-August 31); (3) monitoring the units for their new state after management has been applied (July-August), and entering and transmitting the data (August 25); and (4) comparing the predicted outcomes of each alternative model to the observed outcomes from the monitoring data and updating the confidence weights on each model. With the updated model weights in hand, we return to the first step of the iterative cycle and look up the new decision policy that corresponds to the newly realized model weights. Because the optimal decision policy is influenced by the model weights, when it comes to making the next decision, models that have garnered more weight will assert more influence on the resulting policy and thus on the recommended next decision.

tial and temporal replication. Third, the gain in knowledge is directed back to improve management at both the local and the system-wide scales. Each station benefits from the collective gain in understanding achieved by all stations.

As in any effort over a large and heterogeneous system, there are tradeoffs. The flexibility exercised by individual stations and the large geographic scale make for a noisy system, which means that learning is slower compared with a controlled experiment that has strict protocols and dictated actions. But, if the framework is adhered to, learning will occur.

It is beyond the scope of this paper to address the process of consultation and negotiation with cooperators on the many difficult aspects of this problem. Discussions concerning the choice of the annual time step, the state structure, the date which demarcates successive management years, and the model set were thoughtfully considered and negotiated. The science team and resource managers conducted these inter-

actions with the understanding that the inherent complexity of the system had to be simplified to make the problem manageable, and that the desire to represent the complexity had to be balanced with the need to be parsimonious.

### ATTRIBUTES OF SUCCESSFUL IMPLEMENTATION

We agree with Moore et al. (2011) that there are three elements at the heart of a successful, integrated, large-scale adaptive management effort: components, collaboration, and commitment. The first, *components*, has been the focus of this paper and includes all the steps of the setup and iterative phases of the adaptive management framework (i.e., management objective, management action alternatives, alternative models, utility function, optimization, monitoring program, decision selection, and assessing and updating). The second is *collaboration* that is well-structured and broad. Team members should include people who are knowledgeable about management issues, operational procedures, and refuge capabilities and constraints; skilled in coordination, communication, organization, elicitation, and facilitation; and have expertise in decision structuring and modeling. Regular communication among members of the project team and between the team and cooperators, as well as a common understanding of roles and responsibilities among team members, are requisite for successful collaboration. Adaptive management is a challenging undertaking, especially in environments that operate in short-term budgetary and priority-setting horizons; thus, long-term *commitment* to the process at the station, coordinator, and administrative levels is vital to project success. All three elements are essential to successfully develop, implement, and reap the benefits of a large-scale adaptive management project.

### ACKNOWLEDGMENTS

This project could not succeed without the excellent collaboration, energetic commitment, and abundant knowledge of the U.S. Fish and Wildlife Service (USFWS) members of our bi-agency Science Team. Besides coauthor BFW, these members, all wildlife biologists, include: Todd Grant, Sara Vacek, Vanessa Fields, Kim Bousquet, and Pauline Drobney. We were incredibly fortunate to have the talent and time of Kevin McAbee (USFWS), who developed the centralized project database. Todd Sutherland (USFWS) also provided expertise and assistance with the database. Justin Dupuy (USFWS) was instrumental in maintaining the database and integrating the GIS aspects. We also want to recognize all of our cooperators—the numerous Service personnel (project leaders, managers, and biologists) from the participating refuges—who are fully engaged in this project. We are grateful to Bob Patton, James Stubbendieck, and Gene Town for granting us access to their rare and valuable long-term datasets. Lastly, we thank Mitch Eaton, Conor McGowan, and an anonymous reviewer who provided manuscript reviews and valuable insight for its improvement. The findings

and conclusions in this article do not necessarily represent the views of the U.S. Fish and Wildlife Service. Use of trade, product, or firm names does not imply endorsement by the U.S. government.

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Appendix A. List of U.S. Fish and Wildlife Service project cooperators. National Wildlife Refuge (NWR). Wetland Management District (WMD).

COMPLEX	NO. OF UNITS	GRASS TYPE	STATE	USFWS REGION
Arrowwood NWR Complex	16	Mixed	ND	6
Audubon NWR Complex	11	Mixed	ND	6
Benton Lake WMD	2	Mixed	MT	6
Big Stone NWR	1	Tall	MN	3
Detroit Lakes WMD	3	Tall	MN	3
Devils Lake WMD	2 1	Mixed Tall	ND	6
Huron WMD	10	Mixed	SD	6
Kulm WMD	10	Mixed	ND	6
Lake Andes NWR	3	Mixed	SD	6
Long Lake WMD	5	Mixed	ND	6
Lostwood NWR Complex	3	Mixed	ND	6
Madison WMD	3	Tall	SD	6
Medicine Lake NWR	6	Mixed	MT	6
Morris WMD	9	Tall	MN	3
Sand Lake NWR Complex	3 2	Mixed Tall	SD	6
Souris River Basin NWR Complex	10	Mixed	ND	6
Tewaukon WMD	7	Tall	ND	6
Waubay NWR Complex	11	Tall	SD	6
Windom WMD	2	Tall	MN	3