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A Decision Support Tool for Adaptive Management of Native Prairie Ecosystems

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The Native Prairie Adaptive Management initiative is a decision support framework that provides cooperators with management-action recommendations to help them conserve native species and suppress invasive species on prairie lands. We developed a Web-based decision support tool (DST) for the U.S. Fish and Wildlife Service and the U.S. Geological Survey initiative. The DST facilitates cross-organizational data sharing, performs analyses to improve conservation delivery, and requires no technical expertise to operate. Each year since 2012, the DST has used monitoring data to update ecological knowledge that it translates into situation-specific management-action recommendations (e.g., controlled burn or prescribed graze). The DST provides annual recommendations for more than 10,000 acres on 20 refuge complexes in four U.S. states. We describe how the DST promotes the long-term implementation of the program for which it was designed and may facilitate decision support and improve ecological outcomes of other conservation efforts.

Keywords: adaptive management; Bayesian statistics; conservation; databases; decision support tool.
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Background of the Native Prairie Adaptive Management Initiative

Prairie dominated by endemic plant species (native prairie) is arguably the most endangered type of ecosystem in North America (Sampson and Knopf 1994). As much as 82–99 percent of tallgrass prairie and 30–99 percent of mixed-grass prairie have been converted to agriculture in the past 200 years (Sampson and Knopf 1994). Invasive grasses, including Kentucky bluegrass (*Poa pratensis*) and smooth brome (*Bromus inermis*), displace desirable native plant species and pose serious threats to remaining native prairie ecosystems (Grant et al. 2009). Endemic prairie plants evolved with periodic disturbance from fire and grazing. The management of native prairie strives to mimic historic disturbance regimes, thus promoting native species and suppressing invasive species (Sampson and Knopf 1994).

The U.S. Fish and Wildlife Service, steward of significant tracts of native prairie in North America, recognized the potential to improve ecological outcomes of management-action decisions by strategically collecting and synthesizing information about invasive species management of prairies on National

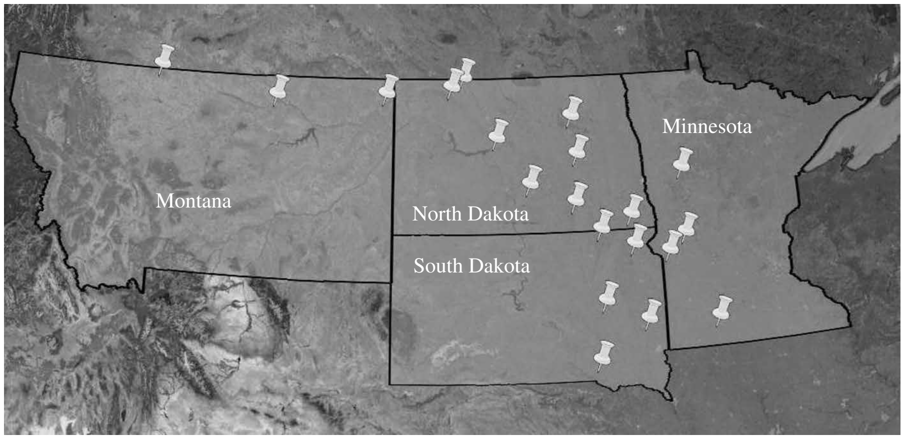

Figure 1: The map indicates 20 National Wildlife Refuge complexes that participate in the Native Prairie Adaptive Management initiative. Base map data: Google, Landsat, NOAA.

Wildlife Refuges (hereafter, refuges). To this end, the U.S. Fish and Wildlife Service and the U.S. Geological Survey developed the Native Prairie Adaptive Management (NPAM) initiative in 2008; hereafter, we refer to this collaboration as the NPAM development team (Gannon et al. 2013). NPAM is a cyclical process of decision making, management implementation, and monitoring. Refuge personnel participating in the initiative (hereafter, cooperators) have enrolled 120 management units comprising more than 10,000 acres in 20 refuge complexes scattered across Minnesota, North Dakota, South Dakota, and Montana (Figure 1).

NPAM coordinates local efforts of refuges, provides transparent decision support for selecting management actions under uncertainty, maximizes learning from management outcomes, and improves decision making through time. To reduce uncertainty about the extent to which various management actions suppress invasive plants, NPAM uses adaptive management, a decision-analytic approach in which competing models represent hypotheses about the effects of management actions on the system being managed (Walters 1986). Insights from repeated assessment of predictive abilities of competing models guide future management-action decisions (Walters 1986). The combination of shared management challenges, biological uncertainties, and recurrent management-action decisions made adaptive management a natural fit for addressing concerns about invasive species on prairie lands.

The U.S. Geological Survey provided technical expertise and specialized software during the first two adaptive-management cycles in 2010 and 2011, and in 2012 and 2013, as the work we describe was phased into operation. A formal transfer of the system from the U.S. Geological Survey to the U.S. Fish and Wildlife Service, at which point the U.S. Fish and Wildlife Service would run the system autonomously, was envisioned from the beginning. However, inefficiencies in NPAM's original data management, quality-assessment, and analytical processes hindered this transfer. We developed a decision support tool (DST) that made this transfer feasible and promotes the long-term implementation and success of NPAM. The DST provides Web-based data entry, integrated analytical routines, and improved data-quality assessment. Herein, we describe the DST, which encapsulates NPAM's original analytical framework and workflow, and explain its benefits in comparison to the previous implementation of decision support.

Adaptive-Management Framework

Adaptive-management projects have four requisite components: objective(s), a monitoring plan, management actions (decision alternatives), and competing models (Williams et al. 2009).

Gannon et al. (2013) described these components in their implementation of NPAM:

(1) Objective: The NPAM management objective is to increase the relative proportion of native prairie

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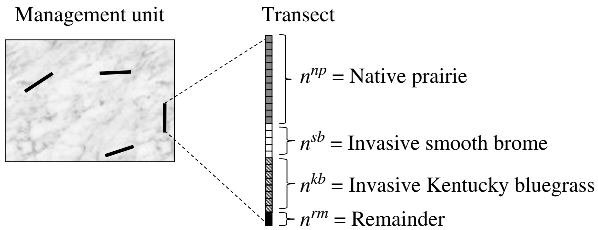

Figure 2: Observers annually collect data at 50 intervals along multiple transects randomly oriented within each management unit. A transect is characterized by a vector of 50 elements with each element taking one of four values shown above.

plants by reducing the proportion of invasive plants, while minimizing management costs.

(2) Monitoring plan: Each summer, the dominant vegetation type is recorded along fixed 25-meter (m) belt transects. Each transect consists of 50 regular interval belts that are 0.1 m wide by 0.5 m long (Grant et al. 2004). Transects are used to sample vegetation in management units. Species or species-group observations recorded along transects are classified into four mutually exclusive categories: native prairie, invasive smooth brome, invasive Kentucky bluegrass, and other nondesirable species (i.e., the remainder) (Figure 2).

Each management unit is assigned one of 16 possible vegetation states and one of seven management-history states based on monitoring data. Vegetation states have two components: proportion of native prairie (0–30 percent, 30–45 percent, 45–60 percent, or 60–100 percent) and a dominance classification of the remaining plant community (smooth brome dominant, Kentucky bluegrass dominant, smooth brome and Kentucky bluegrass codominant, or dominated by another nondesirable species) (Table 1).

	Proportion of native vegetation (%)			
Dominant invasive species	60–100	45–60	30–45	0–30
Smooth brome	1	5	9	13
Smooth brome and Kentucky bluegrass codominant	2	6	10	14
Kentucky bluegrass	3	7	11	15
Other nondesirable species	4	8	12	16

Table 1: Management units are assigned vegetation states (1–16) using monitoring data collected on transects. Vegetation states have two components: dominant invasive species and proportion of native vegetation.

Management-history states convey the frequency of management actions that disturbed the vegetation community (e.g., controlled burn) in the preceding seven years and timing of the most recent disturbance. The combination of vegetation and management-history state is the basis of predictive models and decision support. Herein, references to state without modifier pertain to this combination of vegetation state and management-history state; for simplicity, however, we often refer only to vegetation state.

(3) Management actions (decision alternatives): One management action from a discrete set of actions may be applied during each iterative cycle per management unit. The set of management actions is specific to a geographic stratification to which the management unit belongs. For example, one set includes resting (no action), and three defined forms of disturbance: conducting a controlled burn, prescribed grazing, and performing a controlled burn and a prescribed graze in the same cycle (burn-graze combination).

(4) Competing models: Monitoring data are used to assess the performance of predictive models that reflect specific uncertainties about the relative effectiveness of management actions under key scenarios. For example, one model proposes that compared with rest (no action), all methods of disturbance suppress invasive plants and increase the proportion of native plants equally well. A competing model hypothesizes that management-action efficacy depends on which invasive plant species dominates in the management unit; smooth brome may be more effectively reduced by prescribed grazing than by a controlled burn. Gannon et al. (2013) describe the competing models.

Competing models are represented by state and transition matrices. Each matrix contains probabilities of transitioning from one discrete state to another under a specific management action, for all possible combinations of states and management actions (Westoby et al. 1989) (Figure 3).

Monitoring data are used to assess the performance of predictive models and to incrementally learn through the application of Bayes' theorem (Moore et al. 2013):

$$P_{t+1,\,j} = \frac{P_{t,\,j} L_j(S_{t+1})}{\sum_i P_{t,\,i} L_i(S_{t+1})}, \tag{1}$$

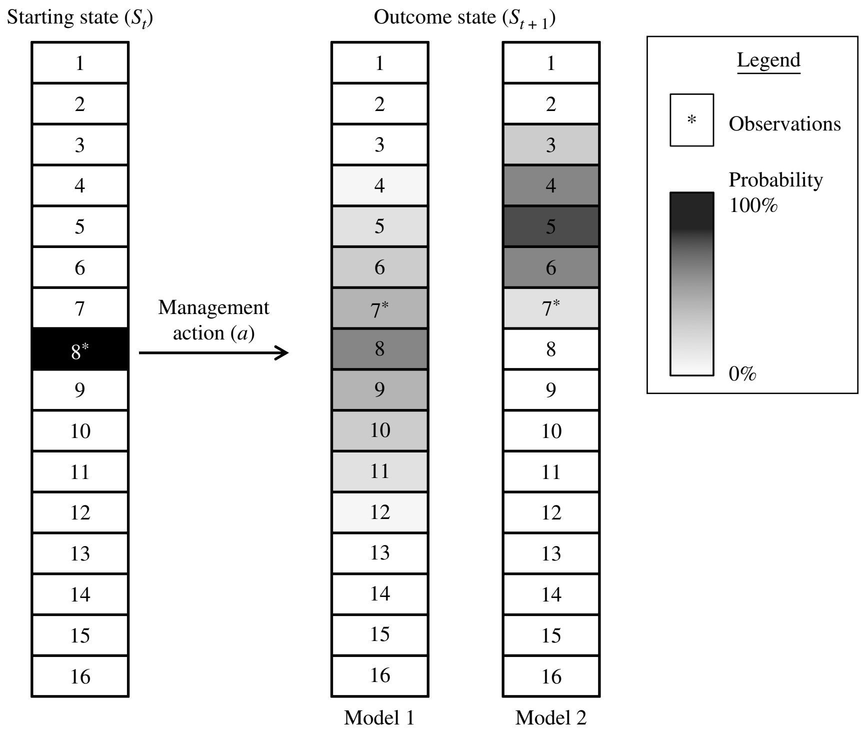

Figure 3: The graphic depicts the probabilities of transitioning from state 8 under management action (a) for two different models. Given that the observed final state was 7, Model 1 has better predictive ability.

where $P_{t,j}$ is the weight of model j at time t, $P_{t+1,j}$ is the updated weight of model j after management actions are taken, and $L_j(S_{t+1})$ is the likelihood of outcome state, S_{t+1} under model j. The likelihood term incorporates state-to-state transition probability and uncertainty as a result of spatial heterogeneity of vegetation composition within management units. Bayes' theorem resolves a model's predictive performance with prior belief by assigning relatively more weight to models that support observed outcomes. In 2010, each competing model received equal weight reflecting a noninformative prior. Model weights are subsequently updated each cycle.

Each combination of starting vegetation state, outcome vegetation state, and management action has an associated utility value indicating the cooperators' relative strength of preference for one combination over another, factoring in cost. Given optimization of competing models and current model weights, management-action recommendations specific to the current state of each management unit are distributed to cooperators for use in the next iterative cycle (Figure 4).

Optimization entails maximizing cumulative expected utility over 1,000 years (Gannon et al. 2013):

$$\max_{a_{t+1}} \sum_{t=t_o}^{t_{1000}} \lambda \times u(S_t, S_{t+1}, a_{t+1}), \tag{2}$$

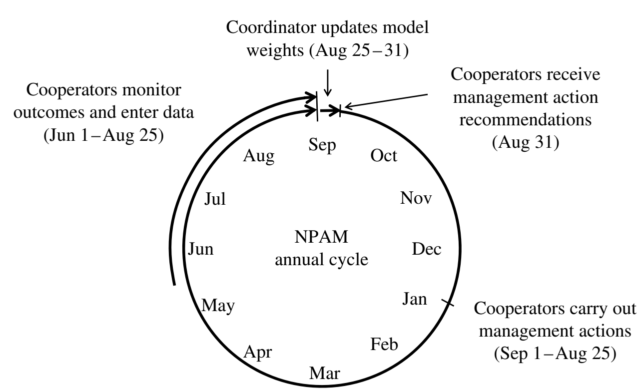

Figure 4: The Native Prairie Adaptive Management initiative's iterative adaptive-management cycle spans from September 1 to August 31.

where $u(S_t, S_{t+1}, a_{t+1})$ is the expected utility of a state transition (starting state S_t and outcome state S_{t+1}) under management action a_{t+1} chosen from a discrete set of alternatives, and λ discounts the value of the utility expected to be accrued in the distant versus near future. An adaptive stochastic dynamic-programming algorithm (Lubow 1995, 1997) produces tables of recommended management actions.

Original Data Management Process

In the first two adaptive-management cycles of NPAM, data processing, analysis, and decision support required significant personnel resources, expertise, and oversight. Next, we describe methods used in 2010 and 2011 that we collectively refer to as the original process.

(1) After completing management actions and data collection, the U.S. Fish and Wildlife Service coordinator emailed copies of a compound Microsoft Access database to the cooperators. The database required a specific configuration of linkages that could easily be broken during data entry.

(2) Cooperators entered management actions and monitoring data into local copies of the database.

(3) Because the database files were too large to email, the cooperators compressed the databases into archival (i.e., zipped) format and uploaded them to a FTP host. The coordinator retrieved and collated the data.

(4) A U.S. Geological Survey member of the NPAM development team (hereafter, researcher) ran a SAS (SAS Institute Inc. 2010) program, translating monitoring data into state variables. The researcher computed likelihoods under competing models and updated model weights using SAS (Gannon et al. 2013). Updated model weights in combination with the state of each management unit determined optimal management actions for the next iterative cycle. Recommended management actions were drawn from static optimization tables generated by an adaptive stochastic dynamic-programming algorithm developed by Gannon et al. (2013). Technical expertise was required to run the SAS code and efficiently search large optimization tables.

(5) The researcher emailed the results to the coordinator.

(6) The coordinator emailed management-action recommendations to the cooperators. This concluded an iteration of the adaptive-management cycle.

Evaluation of the Original Process

Inefficiencies the NPAM development team observed in the 2010 and 2011 cycles, as we describe next, became development needs to be addressed with a DST that would replace the original process.

(1) Ineffective communication and information transfer: The distributed database necessitated email-based communication among the coordinator and cooperators regarding protocols, deadlines, and management-action recommendations. This inefficient communication was prone to inconsistent and misunderstood messaging. The coordinator could not revise the database without disseminating a new product and could not observe data entry progress. Supervising cooperators could only verify data entered by field technicians if the supervisor and technicians accessed the same database copy.

The original process relied on a distributed database in which portions of the data set were stored in parallel across 20 computers. This introduced the possibility of data loss if database copies were corrupted or irretrievable (i.e., hard drive failure). The NPAM development team observed problems characteristic of distributed databases in general: database maintenance required redundancies, isolating and correcting inconsistencies among database copies was difficult and time consuming, and the process required cooperators to have specific software.

(2) Inefficient analytical performance: The original process was not robust to errors compounded across many users and multiple steps, thus complicating decision support. Rectification of questionable data values involved generation of a list of such values by the U.S. Geological Survey researcher, who passed the list to the U.S. Fish and Wildlife Service coordinator for resolution, who then passed the resolved list to a database manager for data entry. Model weight updating and the generation of optimal management-action recommendations were similarly labor-intensive processes.

(3) Requirement for specialized technical expertise and proprietary software: The original process required a U.S. Geological Survey researcher to provide expertise in and access to proprietary software

(SAS). The NPAM development team sought a system that could be operated by an in-house U.S. Fish and Wildlife Service coordinator without requiring the coordinator to have specialized technical expertise.

Development Needs and Literature Review

The NPAM development team required a DST that would increase the automation of decision support and result in a system that could be carried forward autonomously by the U.S. Fish and Wildlife Service. Primary requirements were to facilitate cross-organizational data sharing, efficiently perform analyses, and eliminate the need of the coordinator and cooperators for specialized software or technical expertise. When we set out to develop a DST, we first looked for existing systems with requisite attributes. A literature review yielded no potential systems that we could adapt for our purposes. Considering the logistical challenges of coordinated, broadscale monitoring and the need for rapid integration of monitoring data and updated learning, this finding was not surprising. Next, we describe existing DSTs for adaptive management in conservation, focusing on features NPAM required, and explain why we could not adapt an existing system.

Miradi, an open-source and popular DST for conservation applications, guides users through problem assessment, model design, implementation of management actions, and monitoring. Over 5,500 users downloaded Miradi and used it in 115 projects in the five years following its launch (Schwartz et al. 2012). However, Miradi does not facilitate cross-organizational data sharing and cannot perform analytical tasks related to knowledge updating and the selection of optimal management actions under uncertainty, making it unsuitable for NPAM.

We avoided using proprietary software for modeling Bayesian networks. For example, Netica (Norsys Software), which has been used in wetland-management decision support (Gawne et al. 2012), requires some technical expertise and does not adequately facilitate analyses for iterative decision making for our purposes. Open-source Bayesian software packages such as GeNIe (Decision Systems Laboratory) have been applied in natural resource management, for example, in decision support for fisheries surveillance (Tessem et al. 2009). We avoided open-source Bayesian software because of the technical expertise required.

We needed to centralize data across a large spatial area from multiple cooperators. Some DSTs support adaptive management; however, because they fall short of this requirement, they could not serve us as templates. For example, a DST for adaptive management of water resources developed by Westphal et al. (2003), the CLAM model for integrated adaptive management of coastal lakes (Ticehurst 2008), and Landscapes ToolKit (Bohnet et al. 2011) do not facilitate centralizing data contributed by multiple cooperators. These DSTs provide valuable decision support; however, each lacks a critical element for distributed decision making. Thus, we concluded our literature review and developed a novel approach.

A Decision Support Tool for Native Prairie Adaptive Management

We constructed a DST consisting of an online platform for data entry and an integrated database, which is maintained on the coordinator's local machine, that performed analyses and data processing. Next, we discuss the steps in our DST.

Step 1: Data Entry

Vegetation monitoring and management-action data are centralized in real time and online. Cooperators interact with a secure Web portal maintained by the U.S. Department of the Interior. Data entry requires a four-character pass code specific to a refuge.

A standardized form-based interface (e.g., Figure 5) provides quality control by preventing the entry of duplicate information and disallowing incompatible field combinations. The DST strengthens and augments quality-control measures from the original data management process. Validation errors trigger descriptive screen tips, for example, "Start date of a management action must be before the end date." In the absence of errors, other screen tips confirm data entry.

We developed the online data entry portal and form-based interface using Microsoft SharePoint and InfoPath. This software is institutionally available to U.S. Fish and Wildlife Service employees and is thus cost effective.

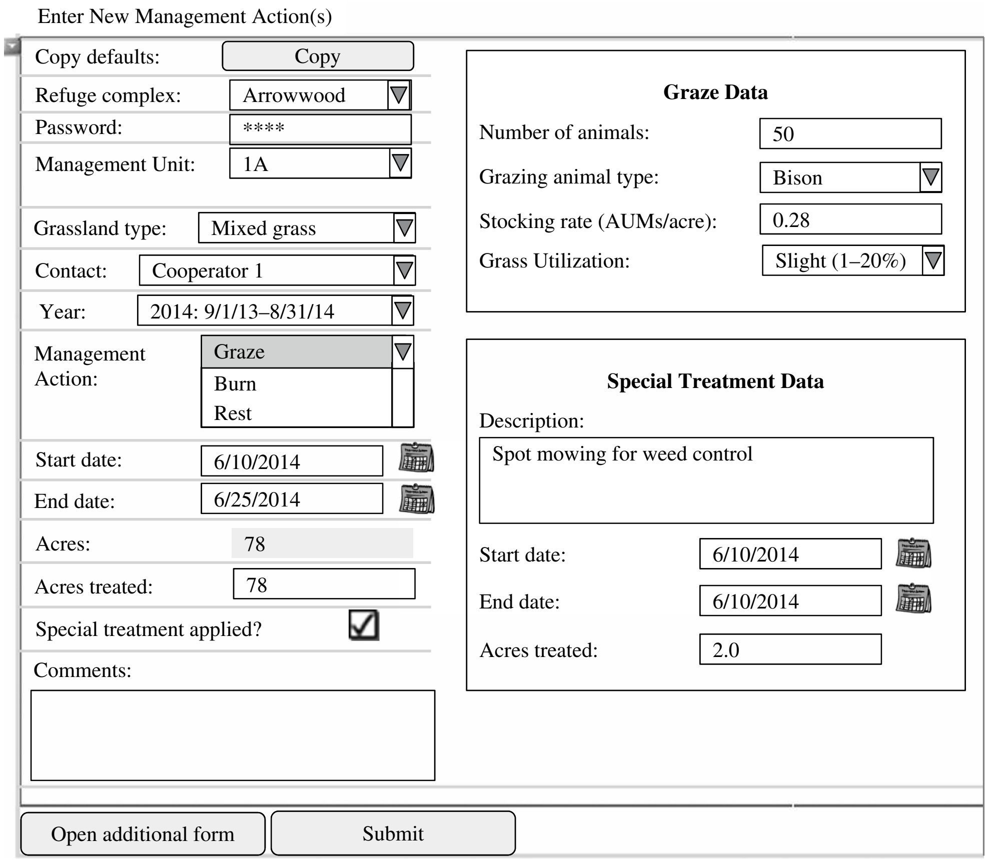

Figure 5: An example data entry form on the Native Prairie Adaptive Management initiative's website illustrates how cooperators record details about management actions implemented.

Step 2: Data Processing

The coordinator imports data from the online database into a locally stored, relational database by clicking a button. The relational database archives data, making them accessible whether or not the Internet is available, and generates summaries of aggregated data (e.g., Figure 6). Summaries serve as the basis for potential hypothesis testing beyond NPAM. Cooperators consider summaries an added value of participation and use them for their personal records and reports.

The DST provides interactive features for methodical data-quality review. The coordinator performs custom validation of flagged records that meet specific criteria. For example, the DST flags management-action records for prescribed graze if grass utilization is "Slight (1–20 percent)." In this example, the coordinator could reclassify the management action from prescribed graze to "rest," if the management action taken is deemed insufficient to qualify as prescribed graze. The NPAM development team determined that flagging and reviewing could not be automated because, although based on defined criteria, potential interactions among multiple triggers for flagging mean reclassification must be determined under coordinator discretion.

Step 3: Evaluation of Competing Models

NPAM's primary objective is to increase the proportion of native plant species on U.S. Fish and Wildlife Service-owned prairies. To this end, cooperators receive situation-specific management-action recommendations. Generation of these recommendations entails using monitoring data to update model belief weights that describe the relative influence

Ten Plant Code Categories by U.S. State in 2014 — Friday, April 10, 2015 4:49:47 PM

U.S. State	Description	Percentage	Number of Stops Along Transects
MN	Crested Wheatgrass	0.00%	0
MN	Kentucky Bluegrass	21.06%	1,411
MN	Low Shrub	2.66%	178
MN	Not Applicable	0.73%	49
MN	Native Grass-Forb	52.81%	3,538
MN	Noxious & Other Weeds	0.07%	5
MN	Other	2.10%	141
MN	Quackgrass	0.03%	2
MN	Reed-Canarygrass	4.12%	276
MN	Smooth Brome	13.72%	919
MN	Tall Shrub/Tree	2.70%	181
	Total:	100.00%	6,700

Figure 6: An example summary provided to cooperators shows frequencies of 10 plant cover types, grouped by U.S. state.

of each model on the current management-action recommendation.

The coordinator launches an executable script to compute model-specific likelihoods (i.e., probability of the data given correctness of the model), based on observed state transitions. Likelihoods inform Bayesian updating of model belief weights. Static optimal decision-policy tables generated externally by an adaptive stochastic dynamic-programming algorithm prior to DST development (Gannon et al. 2013) are searched using updated model belief weights. From decision-policy tables, optimal state-specific management-action recommendations for each management unit in the subsequent cycle are identified (Figure 7).

Step 4: Dissemination

The coordinator uploads a table of management-action recommendations to the data entry website. The management action expected to provide the optimal outcome, factoring in cost, is reported per management unit. Cooperators retrieve management-action recommendations from the same website used for data entry, completing an iteration of the adaptive-management cycle.

Results

The DST has been used and incrementally improved over three management cycles in 2012–2014. Features described in preceding sections became fully operational in 2014, allowing the complete replacement of the original process. Here, we describe quantitative and qualitative measures of success.

(1) Cross-organizational data sharing: In 2014, 20 refuge complexes representing 120 management units used this DST. Thus, the DST has the distinction of being adopted successfully for adaptive management, which is relatively rare (Stankey et al. 2005). It facilitates data sharing across widespread refuges that have no history of formalized information sharing prior to enrollment in NPAM.

The application of adaptive management in distributed decision-making environments, as are often found in conservation, requires sharing data. In adaptive management, learning is more efficient with replication of management actions and monitoring (Moore et al. 2013). The DST facilitates the annual entry of vegetation monitoring data collected along approximately 2,000 transects (about 100,000 observations), and details of management actions implemented.

(2) Perform analyses efficiently to improve conservation delivery: Improving the understanding of biological systems through the evaluation of competing models is the hallmark of adaptive management and the foundation of NPAM. In NPAM, iterative reallocation of weight among competing models reflects learning over time, as models with consistently better predictive performance acquire weight at the expense of other models. Gannon et al. (2013) report model weights through three cycles of updating. The DST efficiently integrates what had previously been a disconnected, standalone process, and facilitates the improvement of conservation outcomes for native prairie brought about by knowledge-guided management.

A key feature of the DST, absent in the original process, is its facility that allows the coordinator to methodically review and resolve flagged records. This feature eliminates cumbersome steps that involved three people, streamlines flagging and reviewing, and more quickly brings about the generation of

Management Recommendations in 2015

August 28, 2014
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Management Unit	Year	NP Proportion	SB Proportion	KB Proportion	RM Proportion	Vegetation State	Recommended Management Action
G14 Pasture 1	2014	0.30	0.27	0.40	0.04	{0–30, Co}	GRAZE
G14 Pasture 2	2014	0.39	0.19	0.25	0.18	{30–45,Co}	BURN/GRAZE
G26 Paddock 1	2014	0.16	0.06	0.68	0.10	{0–30,KB}	BURN
G26 Paddock 2	2014	0.36	0.08	0.52	0.03	{30–45, KB}	REST
G26 Paddock 3	2014	0.11	0.06	0.60	0.22	{0–30, KB}	BURN
G26 Paddock 4	2014	0.12	0.18	0.48	0.22	{0–30, KB}	BURN

Figure 7: Management-action recommendations (far right) for each management unit (far left). Vegetation states and components (NP: native prairie, SB: smooth brome, KB: Kentucky bluegrass, and RM: remainder) are listed. This report is abbreviated for purposes of presentation; the full version contains management-history state attributes that, in combination with vegetation state, determine management-action recommendations.

management-action recommendations. This improvement enables a complete data review within NPAM's deadlines, while requiring less personnel effort.

(3) Does not require technical expertise or specialized proprietary software to operate: The NPAM development team realized early on that the initiative's success would hinge on the ability of the U.S. Fish and Wildlife Service to implement sustained adaptive-management cycles without external technical support from the U.S. Geological Survey. Therefore, we designed the DST such that it could be administered indefinitely by a coordinator who does not have specialized technical expertise.

DST administration requires MS Access that, as part of the Microsoft Office Professional Suite, is frequently available institutionally. MS Access licenses cost approximately $140 at the time of this writing. We run computationally intensive analyses via a standalone executable module written in Python, an open-source platform. Analyses in Microsoft's Structured Query Language (SQL) and Visual Basic for Applications are implemented using button clicks. Therefore, the coordinator does not need to interact with code to perform analyses.

Cooperators interact with the Web-based portion of the DST via a Web browser of their choosing. SharePoint is institutionally available for the U.S. Fish and Wildlife Service, and the U.S. Department of the Interior grants access to the data entry portal to non-U.S. Fish and Wildlife Service partners. SharePoint costs vary by usage; the small business (fewer than 250 computers) package costs about $6,300.

We developed a cost-effective DST by avoiding the use of expensive proprietary software. For example, a business license for the database platform Microsoft SQL Server 2012 costs approximately $9,000 per server. The realized cost is higher when the associated cost of a professional database manager is included. SQL Server requires expertise to maintain and develop; the average SQL database manager's salary is $91,000 (Indeed 2015). In future applications, we will explore open-source options to replace SharePoint, for example, MySQL paired with Python.

Conclusions

The DST we describe performs as a comprehensive application supporting collection, management, analysis, and interpretation of data for broadscale conservation. The system helps NPAM meet program objectives in a coordinated and sustainable manner. Adaptive management requires the technical marriage of field observation and model prediction, often across long periods of time and large areas; our tool facilitates this integration and promotes cross-organizational data sharing. The potential impact of the DST, which could serve as a template for other conservation efforts, extends beyond the scope of the specific application we describe.

One clear opportunity for further application of the DST is in other adaptive-management projects led by the U.S. Fish and Wildlife Service. Under the leadership of its parent agency, the U.S. Department of the Interior, the U.S. Fish and Wildlife Service, which manages 150 million acres in National Wildlife refuges, is increasingly using adaptive management (U.S. Fish and Wildlife Service 2014). Other U.S. agencies, such as the U.S. Department of Agriculture, apply adaptive management, as do private and government organizations around the world, including in Australia, Canada, Europe, and South Africa (Stankey et al. 2005). By facilitating all aspects of adaptive management, we believe this DST could serve as a template for other programs, and result in more optimal decision support and conservation delivery.

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Verification Letter

Cami Dixon, U.S. Fish and Wildlife Service, Region 6, Biological Resources Division, 5924 19th St. SE, Woodworth, ND 58496, writes:

"I am writing to verify the actual use of the application described in the manuscript, "A Decision Support Tool for Adaptive Management of Native Prairie Ecosystems," by Victoria Hunt et al. The manuscript accurately describes the use and resulting benefits of the application."

Victoria M. Hunt is a biologist with over six years of experience developing decision support tools and predictive models for large-scale collaborative conservation efforts. She earned a BSc from Cornell University and has dual MSc degrees from Wageningen University, Netherlands and The University of Natural Resources and Life Sciences in Vienna, Austria. She is employed by the Chicago Botanic Garden and earned a PhD in ecology and evolutionary biology from the University of Illinois at Chicago.

Sarah K. Jacobi works at the Chicago Botanic Garden in the Plant Science and Conservation Department. As a conservation scientist, Jacobi applies structured decision-making techniques to natural resource management. Her research focuses on developing decision support tools that efficiently utilize limited resources, while explicitly incorporating uncertainty in the decision-making process. Jacobi earned her PhD in environmental engineering from Johns Hopkins University.

Jill J. Gannon is a research ecologist with the U.S. Geological Survey; she provides decision analysis support, expertise, and technical guidance for agencies with natural resource management decision problems. She earned a PhD in wildlife ecology and management from the University of Georgia, Warnell School of Forestry and Natural Resources and a BSc in ecology, behavior, and evolution from the University of California, San Diego.

Jennifer E. Zorn works for the U.S. Fish and Wildlife Service under Region 6 Division of Biological Resources as a data manager for the Inventory and Monitoring Initiative. She earned her BS in biological science from South Dakota State University and a Graduate Certificate in geographic information science from University of North Dakota.

Clinton T. Moore is a research scientist in the U.S. Geological Survey, and he serves as assistant leader of the Georgia Cooperative Fish and Wildlife Research Unit at the University of Georgia. He works in areas of estimation, modeling, and decision analysis for the management of natural resources.

Eric V. Lonsdorf is a research associate at Franklin & Marshall College. He develops decision models for large-scale conservation and resource allocation problems. He earned a BA in biology from Carleton College and a PhD in ecology, evolution and behavior from the University of Minnesota Twin Cities.